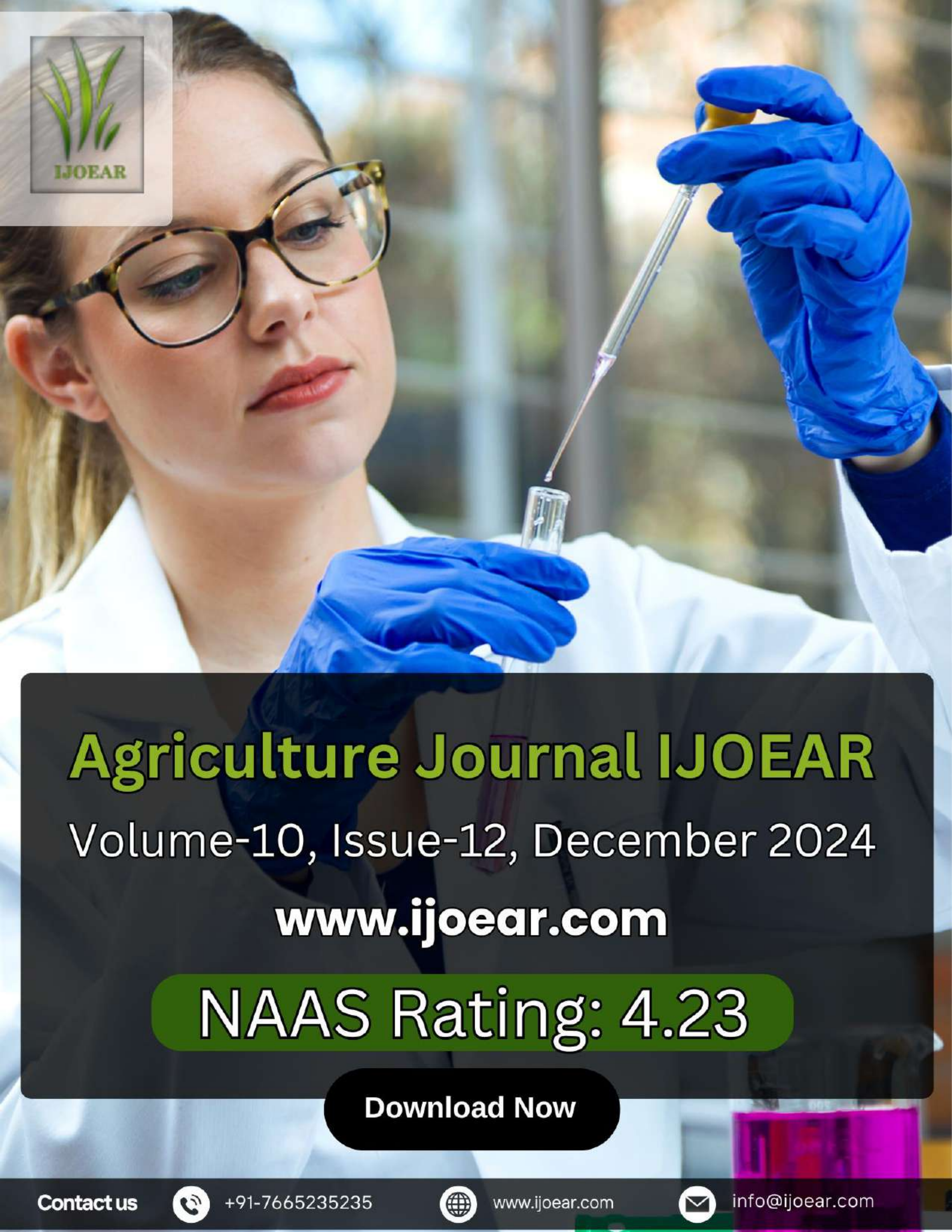

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Preface

We would like to present, with great pleasure, the inaugural volume-10, Issue-12, December 2024, of a scholarly journal, *International Journal of Environmental & Agriculture Research*. This journal is part of the AD Publications series *in the field of Environmental & Agriculture Research Development*, and is devoted to the gamut of Environmental & Agriculture issues, from theoretical aspects to application-dependent studies and the validation of emerging technologies.

This journal was envisioned and founded to represent the growing needs of Environmental & Agriculture as an emerging and increasingly vital field, now widely recognized as an integral part of scientific and technical investigations. Its mission is to become a voice of the Environmental & Agriculture community, addressing researchers and practitioners in below areas.

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Environmental science and regulation, Ecotoxicology, Environmental health issues, Atmosphere and climate, Terrestric ecosystems, Aquatic ecosystems, Energy and environment, Marine research, Biodiversity, Pharmaceuticals in the environment, Genetically modified organisms, Biotechnology, Risk assessment, Environment society, Agricultural engineering, Animal science, Agronomy, including plant science, theoretical production ecology, horticulture, plant, breeding, plant fertilization, soil science and all field related to Environmental Research.

Agriculture Research:

Agriculture, Biological engineering, including genetic engineering, microbiology, Environmental impacts of agriculture, forestry, Food science, Husbandry, Irrigation and water management, Land use, Waste management and all fields related to Agriculture.

Each article in this issue provides an example of a concrete industrial application or a case study of the presented methodology to amplify the impact of the contribution. We are very thankful to everybody within that community who supported the idea of creating a new Research with *IJOEAR*. We are certain that this issue will be followed by many others, reporting new developments in the Environment and Agriculture Research Science field. This issue would not have been possible without the great support of the Reviewer, Editorial Board members and also with our Advisory Board Members, and we would like to express our sincere thanks to all of them. We would also like to express our gratitude to the editorial staff of AD Publications, who supported us at every stage of the project. It is our hope that this fine collection of articles will be a valuable resource for *IJOEAR* readers and will stimulate further research into the vibrant area of Environmental & Agriculture Research.

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Vegetable crops or Olericulture: Crops utilized fresh or whole (wholefood crop, no or limited processing, i.e., fresh cut salad); (Lettuce, Cabbage, Carrots, Potatoes, Tomatoes, Herbs, etc.)	Tree Fruit crops: apples, oranges, stone fruit (i.e., peaches, plums, cherries)
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Impact of Agroforestry on Physical Health and Screen Time: A Study in Garhwal Himalaya, India

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***Abstract*—** *Contribution of agroforestry towards ecosystem services is being recognized globally. The benefit people gains from an ecosystem are crucial to community health serving as a bridge between nature and society. Forests and agriculture, particularly agroforestry, are some of the vital natural resources for rural and subsistence communities, offering a range of ecosystem services such as food, fodder, fuelwood, timber, medicines and other non-timber forest products. Cultural services are non-material benefits that people derive from ecosystems, contributing to physical health, spiritual enrichment, recreation, ecotourism, cognitive development, and leisure. Cultural services support physical, cultural and intellectual development, including arts, music, and other recreational activities. This study was conducted on people owning and managing Grewia optiva (Bhimal) based agroforestry systems of Garhwal Himalaya in Uttarakhand state of India and mainly focuses on physical health of elderly agroforestry farm owners in the form of physically active hours and reduced screen time. Nowadays, where maintaining health as well as physical activities are considered crucial, this study highlights the role of agroforestry in lifestyle of elderly people. An increase in active hours and a considerable reduction in screen time have been observed in elderly people from study area as compared to elderly people who were not involved in agroforestry practices. This is an important aspect of agroforestry besides climate change adaptation and mitigation which is yet to be analysed, quantified and studied.*

***Keywords*— Agroforestry, Ecosystem services, Physical activity, Screen time.**

I. INTRODUCTION

Agroforestry is a land-use system integrating shrubs and trees into rural landscapes and agricultural lands to enhance ecosystem sustainability, productivity and diversity. It is a combination of modern and traditional land-use practices, including the management of trees alongside agricultural crops and livestock on the same unit of land [1]. Most abundant tree species on trees outside forests are *Grewia optiva* (Bhimal), *Quercus leucotrichophora* (Banj oak), *Mangifera indica* (Mango), *Ficus spp*., *Pinus roxburghii* (Chir pine), *Cedrus deodara* (Deodar) and *Cupressus spp*.. Among these, bhimal and banj oak trees are the most abundant tree species in rural areas [2]. *Grewia optiva* is a multipurpose tree species and is an important agroforestry tree that provides valuable resources such as leaf fodder, fiber, and fuelwood. It is highly preferred and generally retained by farmers, particularly for feeding livestock due to its high digestibility and preference among cattle [3, 4]. It is a very good source of fiber and used locally to make tokris, ropes and scrubs for cattle. The trees on farms are seasonally lopped for fuelwood. *Grewia optiva* in agroforestry systems significantly influence the socio-economics of the rural population of Garhwal Himalaya.

The tree based agroforestry systems not only provide direct benefits but also the indirect ones in the form of cultural, regulatory and supporting ecosystem services. Although the studies regarding cultural ecosystem services provided by agroforestry systems are there but most of them are very much limited to the recreational and tourism values. Past studies on physical and psychological health due to agroforestry systems are almost none and are an underexplored and underrated area of interest. Present study helps understanding the basic lifestyle activities of two people group in study area and how it may affect health outcomes in elderly people.

II. MATERIAL AND METHODS

District Tehri Garhwal, located in the Garhwal Himalayan region of district Uttarakhand, India, is characterized by its lush green mixed and coniferous forests along with pleasant summer climate, and cold winters. Agriculture is the primary occupation in rural areas, with most villages situated near forested regions. Agroforestry serves as a predominant land-use pattern, with agricultural fields and bunds often supporting fruit and forest trees, grasses, and livestock rearing. Local communities rely heavily on trees to meet their daily requirements for fodder, fuelwood, and small timber.

Six villages in district Tehri Garhwal, Uttarakhand with three elevation ranges (table 1) having *Grewia optiva* (Bhimal) based agroforestry systems were selected. Respondents aged above 60 years were asked question regarding their socio-economic status, existing physical conditions, illnesses, various physical activities they perform throughout the day as well as time spend on smartphone/television. Two groups of 50 respondent families each were selected and analyzed with one group actively managing agroforestry farm and livestock while other group with abandoned farms or inactive in agroforestry practices through questionnaire survey and personal interview. The respondents selected for the survey were healthy elderly people without any serious chronic or life threatening illnesses. Male and female respondents were surveyed separately from each family regarding their activities and involvement in agroforestry practices.

TABLE 1
DESCRIPTION OF STUDY AREA

Elevation range	Village	Latitude	Longitude
500-1000 m amsl	Bhandar gaun	78º 22' 06" E	30º 17' 07" N
	Khemda	78º 27' 58" E	30º 22' 31" N
1000-1500 m amsl	Dandasali	78º 23' 51" E	30º 21' 39" N
	Chatti	78º 28' 22" E	30º 18' 52" N
1500-2000 m amsl	Dargi	78º 24' 28" E	30º 19' 14" N
	Khatiyad	78º 23' 18" E	30º 18' 21" N

III. RESULT AND DISCUSSION

The observation regarding physical activities of elderly men and women dedicated to the management of agroforestry farm and livestock have been summarized in table 2 and table 3 respectively. Among all the elderly men involved in agroforestry management in all villages, most (51.67% were physically active for 35-49 hours per week followed by 21.67% of elderly men being physically active for 21-35 hours in a week as compared to elderly men not involved in agroforestry management with most elderly men (38.33%) being physically active in a week for 21-35 hours followed by 35% of elderly men who were physically active for less than 21 hours a week.

TABLE 2
NUMBER OF ELDERLY RESPONDENTS (MALE) WITH THEIR PHYSICALLY ACTIVE HOURS THROUGHOUT A WEEK

Parameters	Elevation	500-1000m amsl		500-1000m amsl		500-1000m amsl		Total	%
	Hours/week	Bhandargaun	Khemda	Dandasali	Chatti	Dargi	Khatiyad		
Elderly men involved in agroforestry management	Less than 21	5	7	5	3	8	7	35	11.67
	21-35	12	9	13	11	9	11	65	21.67
	35-49	27	24	22	29	30	23	155	51.67
	49-63	6	10	10	7	3	9	45	15
Elderly men not involved in agroforestry management	Less than 21	19	14	15	21	18	18	105	35
	21-35	18	22	20	18	21	16	115	38.33
	35-49	12	11	11	6	10	13	63	21
	49-63	1	3	4	5	1	3	17	5.67

Role of female in agroforestry is very significant as they spend much more time than men especially in the management of livestock. Even the elderly women had a fair share in agroforestry and livestock management. Among the elderly women surveyed in study area (table 3), most of the elderly women (47%) involved in agroforestry management were active for 34-49 hours in a week followed by 36.33% women active for 49-63 hours in a week. Majority (45.33%) of elderly women not involved in agroforestry were physically active for 21-35 hours a week followed by 26.33% women staying active for 35-49 hours a week.

TABLE 3
NUMBER OF ELDERLY RESPONDENTS (FEMALE) WITH THEIR PHYSICALLY ACTIVE HOURS THROUGHOUT A WEEK

Parameters	Elevation	500-1000m amsl		500-1000m amsl		500-1000m amsl		Total	%
	Hours/week	Bhandargaun	Khemda	Dandasali	Chatti	Dargi	Khatiyad		
Elderly women involved in agroforestry management	Less than 21	2	1	0	4	6	1	14	4.67
	21-35	8	7	4	8	2	7	36	12
	35-49	25	23	28	22	22	21	141	47
	49-63	15	19	18	16	20	21	109	36.33
Elderly women not involved in agroforestry management	Less than 21	10	15	11	9	16	10	71	23.67
	21-35	21	19	20	25	26	25	136	45.33
	35-49	17	16	16	14	5	11	79	26.33
	49-63	2	0	3	2	3	4	14	4.67

Another aspect contrasting physical activity is screen time. Among all surveyed elderly men involved in agroforestry (table 4), majority (41%) were having screen time less than 14 hours in a week followed by 39.67% spending 14-28 hours weekly. Among elderly men not involved in agroforestry, majority (45%) had a screen time of 28-42 weeks followed by 23.33% elderly men with less than 14 hours a week screen time.

TABLE 4
NUMBER OF ELDERLY RESPONDENTS (MALE) WITH THEIR SCREEN TIME THROUGHOUT A WEEK

Parameters	Elevation	500-1000m amsl		500-1000m amsl		500-1000m amsl		Total	%
	Hours/week	Bhandargaun	Khemda	Dandasali	Chatti	Dargi	Khatiyad		
Elderly men involved in agroforestry management	Less than 14	21	20	18	19	21	24	123	41
	14-28	20	20	19	21	17	22	119	39.67
	28-42	9	9	12	8	10	3	51	17
	42-56	0	1	1	2	2	1	7	2.33
Elderly men not involved in agroforestry management	Less than 14	12	13	12	10	14	9	70	23.33
	14-28	9	11	8	9	12	7	56	18.67
	28-42	21	19	24	22	22	27	135	45
	42-56	8	7	6	9	2	7	39	13

Among the elderly women surveyed (table 5), majority (52%) of women involved in agroforestry practices spend less than 14 hours a week screen time followed by 34% women spending 14-28 hours a week screen time with no women spending more than 42 hours per week screen time in study area. Out of total surveyed elderly women who were not involved in agroforestry, 39% spend 28-42 hours a week screen time followed by 25% women spending 14-28 hours screen time.

TABLE 5
NUMBER OF ELDERLY RESPONDENTS (FEMALE) WITH THEIR SCREEN TIME THROUGHOUT A WEEK

Parameters	Elevation	500-1000m amsl		500-1000m amsl		500-1000m amsl		Total	%
	Hours/week	Bhandargaun	Khemda	Dandasali	Chatti	Dargi	Khatiyad		
Elderly women involved in agroforestry management	Less than 14	26	28	27	24	28	25	158	52.67
	14-28	18	17	15	20	12	20	102	34
	28-42	6	5	8	6	10	5	40	13.33
	42-56	0	0	0	0	0	0	0	0
Elderly women not involved in agroforestry management	Less than 14	10	12	11	8	11	12	64	21.33
	14-28	12	11	12	14	10	16	75	25
	28-42	20	18	18	21	21	19	117	39
	42-56	8	9	9	7	8	3	44	14.67

Outdoor activities and physical health are positively interlinked phenomena in younger as well as elderly people with former benefitting in later. A decrease in medical expenditure with increased outdoor activities in elderly people has been observed [5]. Interaction with forest and nature has been linked to reduced stress in people [6]. Reduced stress levels were observed in peoples after short term forest bathing as compared to people in city areas [7]. A significant decreased levels of pro-inflammatory cytokines and stress hormones were seen in Elderly patients with COPD (Chronic Obstructive Pulmonary Disease) stating the positive health effect of forest bathing trip on elderly COPD patients by reducing inflammation and stress level [8].

On contrary to maintaining physical health and an active lifestyle, people overusing smartphones are prone to anxiety, irregular eating habits, blurred visions, sleep disorder and fatigue [9, 10, 11, 12, 13]. Excessive use of smartphone has been linked to reduction in sleep time, insomnia, lower sleep efficiency and fatigue. Use of smartphone in bed has also been linked to depression, anxiety and stress [14].

It can be inferred by the study that the elderly people involved in agroforestry management spend far more on physical activities as compared to elderly people not involved in agroforestry practices. Similarly, elderly men not involved in agroforestry practices spend their spare time taking walks or on their smartphones/television. Elderly women were comparatively more active than elderly men as they spend more time on farm and livestock management. Besides, women also collect fodder for livestock which is rarely done by men in study area. Elderly women spent far less screen time as compared to elderly men in both categories. This was because apart from physically active time, elderly women also spend more time as compared to elderly men in study area doing household Chores such as cooking and cleaning as well as caring for their grandchildren.

Study on linkage between forest/nature and human is very limited and have not been properly explored yet. Similarly, impact of agroforestry practices on human physical and mental health is an important and interesting aspect to study as it may help improve chronic physical and mental wellbeing of people. From the study it was also observed that people involved in agroforestry make more social connections to other nearby people just for helping each other such as helping during seed sowing, harvesting, soil working and even helping with livestock management. People often work on others farm for few days and in return others work on their farm when work is more hectic. As the role of agroforestry in climate change adaptation, mitigation and livelihood support is well studied however; large scale studies to identify the indirect role of agroforestry on people's lives should be conducted.

IV. CONCLUSION

From the forgoing result and discussion, it can be concluded that involvement of people with nature yields an increase in physical health and reducing the need of smartphone, television or other screen time. These studies need to be further elaborately conducted to know more about the impact of agroforestry on peoples' physical, mental and social status.

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Anatomical Insights into Orchid Roots: Adaptive Mechanisms in *Polystachya concreta, Liparis viridiflora, & Coelogyne nervosa*

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Abstract**—** *Orchids exhibit remarkable anatomical adaptations in their roots, enabling them to thrive in diverse ecological conditions. This study investigates the root anatomical features of three orchid species: Polystachya concreta, Liparis viridiflora, and Coelogyne nervosa. Specimens were collected from the Eunoia Orchid Garden, Ambalavayal, and analyzed using histological techniques. Observations revealed significant variations in root structures, including velamen layers, cortical organization, vascular bundle arrangements, and pith characteristics.*

Polystachya concreta exhibited a three-layered velamen with hexagonal cortical cells and eight vascular bundles. Liparis viridiflora demonstrated a four-layered velamen, twelve vascular bundles, and pronounced protoxylem. Coelogyne nervosa displayed a six-layered velamen, over eighteen vascular bundles, and a well-developed parenchymatous pith. These anatomical features underscore the adaptive strategies of orchids to different environmental conditions, enhancing water retention, nutrient absorption, and resilience against abiotic stressors.

This comparative analysis highlights the morphological diversity among orchid species and provides insights into their ecological adaptations. The findings contribute to the understanding of orchid biology and support conservation efforts by identifying key anatomical traits essential for survival in varied habitats.

Keywords**— *Orchidaceae, Root anatomy, Velamen structure, Polystachya concreta, Liparis viridiflora, Coelogyne nervosa, Vascular bundles, Adaptations, Histological analysis, Conservation biology.***

I. INTRODUCTION

Orchids, belonging to the family Orchidaceae, represent one of the largest and most diverse groups in the plant kingdom, with over 25,000 species and numerous hybrids distributed across the globe. Renowned for their unique morphology, ecological adaptations, and intricate relationships with pollinators, orchids are a focal point of botanical research. They are found in diverse habitats ranging from tropical rainforests to arid regions, displaying remarkable structural and functional adaptations that contribute to their ecological success. Among these, root anatomy plays a pivotal role in nutrient absorption, water retention, and plant stability, particularly for epiphytic and terrestrial orchids that encounter a wide range of environmental challenges.

The Western Ghats, a UNESCO World Heritage site and one of the world's eight "hottest hotspots" of biodiversity, harbors a rich array of orchid species. This region, known for its unique climatic conditions and varied topography, provides an ideal habitat for both epiphytic and terrestrial orchids. However, habitat loss, deforestation, and climate change pose significant threats to the survival of many orchid species. The conservation and understanding of these orchids, particularly their anatomical and physiological features, are essential for their survival and ecological role.

Roots are among the most critical structures in orchids, especially in epiphytic species, which rely on them not only for water and nutrient uptake but also for anchorage on host plants. The velamen, a specialized tissue layer unique to orchid roots, serves as an efficient water absorption system while protecting the plant from desiccation. Anatomical studies of orchid roots provide insights into their adaptations to various habitats, shedding light on their survival strategies in nutrient-poor environments. Such studies are particularly valuable for conservation biology and offer guidance for sustainable cultivation practices.

This study focuses on the anatomical features of the roots of selected orchid species: *Polystachya concreta*, *Liparis viridiflora*, and *Coelogyne nervosa*. These species, representative of the diverse morphological and ecological adaptations within Orchidaceae, were selected for their varying habitats and root structures. *Polystachya concreta* is a rare species known for its sympodial growth habit and unique velamen anatomy. *Liparis viridiflora*, on the other hand, is a common species with distinct vascular bundles and cortical structures, while *Coelogyne nervosa* exhibits adaptations typical of epiphytic orchids thriving in the cooler climates of the Himalayan foothills and Southeast Asia.

The roots of orchids are highly specialized structures, featuring multiple layers of velamen, parenchymatous cortex, and well-defined vascular bundles. These structures are not only essential for water absorption but also facilitate gas exchange and provide mechanical support. The endodermis, pericycle, and pith further contribute to the functionality of orchid roots, enabling them to thrive in a range of ecological niches. The adaptations observed in these root structures highlight the evolutionary ingenuity of orchids, allowing them to establish themselves in diverse environments.

In this study, specimens were collected from the Eunoia Orchid Garden in Ambalavayal, Kerala, and analyzed for their root anatomical features. The species selected represent both epiphytic and terrestrial growth forms, offering a comprehensive understanding of the anatomical variations across different orchid habitats. The roots were processed and studied using standard anatomical techniques, and detailed observations were made regarding the structure and function of the velamen, cortex, vascular bundles, and associated tissues.

The findings from this research contribute to the understanding of orchid root biology, emphasizing their ecological adaptations and anatomical diversity. By analyzing the root anatomy of these species, the study provides valuable insights into the structural-functional relationships in orchids, which are crucial for their conservation and sustainable management. This research highlights the need for continued investigation into the unique adaptations of orchids, particularly in biodiversity hotspots such as the Western Ghats, to ensure their survival in the face of environmental challenges.

II. METHODOLOGY

The present study investigates the root anatomical features of selected members of the Orchidaceae family to understand their structural adaptations and ecological significance. Specimen collection was conducted on April 8, 2021, at the Eunoia Orchids Garden in Ambalavayal, Wayanad, with the support of Mr. Sabu V. U. The specimens collected included roots from *Liparis viridiflora* (Blume) Lindl., *Polystachya concreta* (Jacq.) Garay, and *Coelogyne nervosa* A. Rich. Photographs of the plants were captured using a Canon EOS 200D camera for documentation.

Among the collected specimens, the best samples were selected for anatomical studies, ensuring that they were in optimal condition for microscopic examination. Fresh materials were processed in the MSc. Botany lab at St. Mary’s College.

2.1 Sample Preparation:

The roots were sectioned manually using a sharp blade, ensuring the slices were as thin as possible to enhance visibility under a microscope. Sufficient water was applied to the blade edge to prevent air bubble entrapment in the sections. The cut sections were immediately transferred to a watch glass containing distilled water using a fine brush.

2.2 Staining and Mounting:

The sections were stained with 1% safranin for enhanced tissue contrast. Microslides were prepared by carefully transferring the stained sections using a brush. A drop of glycerine was applied to each slide as a mounting medium. Coverslips were gently placed over the sections with a needle to avoid trapping air bubbles. Excess glycerine was removed with tissue paper.

2.3 Microscopic Analysis:

The prepared slides were observed under a research microscope to analyze and document the anatomical features. Special attention was paid to tissue layers such as the epi-velamen, velamen, cortex, endodermis, pericycle, and vascular bundles.

III. IMPORTANCE OF THE SPECIES

The study focuses on the anatomical adaptations of roots in three selected members of the Orchidaceae family: *Polystachya concreta*, *Liparis viridiflora*, and *Coelogyne nervosa*. These orchids represent a diverse range of growth forms, including epiphytic, lithophytic, and terrestrial habits. Understanding their root anatomy is vital to comprehending their ecological success, survival strategies, and potential applications in conservation and biodiversity preservation.

3.1 Species Overview and Ecological Significance:

3.1.1 Polystachya concreta:

This species is a sympodial epiphyte with occasional lithophytic and terrestrial growth forms. Widely distributed in pantropical regions, including Asia, Africa, and the Americas, *P. concreta* is noted for its ecological flexibility. Anatomical studies revealed its uniseriate epi-velamen, three-layered velamen, and a relatively thick cortex with parenchymatous cells. The arrangement of vascular bundles, with exarch xylem and multiple phloem patches, highlights its efficient nutrient and water transport system. These features enable it to adapt to nutrient-poor soils and varying water availability. Despite its adaptability, this species is classified as rare, emphasizing the importance of its conservation.

3.1.2 Liparis viridiflora:

Commonly known as the Green-Flowered Liparis, this species thrives in terrestrial environments, particularly in the forests and hilly regions of South and Southeast Asia. It is widely distributed in India, including in Kerala, where it is frequently observed in the Western Ghats. Anatomical observations show its four-layered velamen, rounded cortical cells, and radial polyarch vascular bundles. These adaptations allow *L. viridiflora* to withstand varying moisture levels and support efficient water and nutrient transport. As a common species, its ecological role includes stabilizing soil in its native habitats and contributing to local biodiversity.

3.1.3 Coelogyne nervosa:

This primarily epiphytic orchid is distributed across the Himalayan region and Southeast Asia. It is recognized for its striking floral display and adaptability to cool climates. Anatomically, *C. nervosa* features a six-layered velamen, a thick cortex, and a large pith region. The numerous vascular bundles (more than 18) and polyarch arrangement indicate a robust system for nutrient storage and transport, critical for its survival in nutrient-poor epiphytic habitats. This species' ecological importance extends to its role in supporting pollinators and maintaining forest biodiversity.

3.2 Importance of the Study:

The anatomical analysis of these orchids provides insights into their survival strategies, particularly their root adaptations to varying environmental conditions. The velamen, a critical feature, aids in water absorption and storage, enabling orchids to survive in epiphytic and terrestrial habitats. The vascular bundle arrangements reveal their efficiency in nutrient transport and resilience to environmental stressors.

This study underscores the importance of conserving these species, as they play crucial roles in maintaining ecological balance. By understanding their structural and ecological attributes, the findings contribute to conservation strategies aimed at protecting orchids and the fragile ecosystems they inhabit, particularly in biodiversity hotspots like the Western Ghats.

Studies:

1. **Polystachya concreta:** Known for its single-layered epi-velamen and three-layered velamen, this species exhibits parenchymatous cortical cells and a radial arrangement of vascular bundles with exarch xylem.
2. **Liparis viridiflora:** Features a single-layered epi-velamen and four-layered velamen, with polyarch vascular bundles and well-defined endodermis and pith.
3. **Coelogyne nervosa:** Displays a six-layered velamen and more than eighteen vascular bundles. The cortex is thick and parenchymatous, with a prominent pith region.

These anatomical studies provide insights into the unique structural adaptations of terrestrial and epiphytic orchids, enabling them to thrive in diverse ecological niches. Observations of features such as velamen thickness, vascular organization, and cortical structure offer valuable data for understanding orchid ecology and aiding conservation efforts.

This methodology lays the foundation for future comparative studies on root anatomy and its role in the ecological success of Orchidaceae species in varying habitats.

IV. RESULTS

The anatomical study of the roots of three orchid species (*Polystachya concreta*, *Liparis viridiflora*, and *Coelogyne nervosa*) revealed significant structural adaptations supporting their survival and ecological function in diverse environments.

1. **Polystachya concreta** exhibited a uniseriate epi-velamen and a compactly arranged three-layered velamen, providing effective moisture absorption and retention. The cortex was parenchymatous with hexagonal cells containing chlorophyll, facilitating photosynthesis. The vascular bundle arrangement was exarch with eight radial bundles, with protoxylem located at the periphery and metaxylem at the center.
2. **Liparis viridiflora** displayed a four-layered velamen with thick-walled parenchymatous cortex cells. The vascular bundles were polyarch, with 12 distinct bundles organized radially. The xylem showed spiral and reticulate thickenings, optimizing water transport. A well-defined pith was composed of parenchymatous cells.
3. **Coelogyne nervosa** exhibited a six-layered velamen and a thick parenchymatous cortex with well-defined endodermis and pith. The vascular bundles, numbering more than 18, were exarch and polyarch. Protoxylem with spiral thickenings and metaxylem with annular thickenings enhanced water conduction efficiency.

The observed variations in root anatomy demonstrate adaptations for moisture absorption, nutrient transport, and photosynthesis, underscoring the ecological diversity and survival strategies of these orchid species. These findings highlight the intricate relationship between structure and function in orchids' adaptation to their habitats.

A. Habit **B. Collected specimen** **C. T.S. of the root**

PLATE 1. *Polystachya concreta*

A. Habit **B. Collected specimen** **C. T.S. of the root**

PLATE 2. *Liparis viridiflora*

A. Habit **B. Collected specimen** **C. T.S. of the root**

PLATE 3. *Coelogyne nervosa*

V. DISCUSSION

The root anatomical study of *Polystachya concreta*, *Liparis viridiflora*, and *Coelogyne nervosa* highlights the unique structural adaptations that enable these orchids to thrive in diverse environments. These adaptations are vital for nutrient acquisition, water retention, and ecological resilience.

The presence of velamen in all three species, albeit with different layering, is a hallmark adaptation in orchids. The uniseriate epi-velamen followed by multiseriate velamen in *Polystachya concreta* (three layers), *Liparis viridiflora* (four layers), and *Coelogyne nervosa* (six layers) plays a critical role in water absorption and prevention of desiccation. This layered structure also facilitates the storage and slow release of moisture, which is particularly important for epiphytic orchids in fluctuating water conditions.

The cortex, composed of parenchymatous cells, varies in thickness and shape among the species, providing mechanical support and aiding in photosynthesis due to chlorophyll-containing cells. The specialized endodermis, distinct in all studied species, functions as a barrier regulating water and nutrient flow into the vascular tissues. Notably, the vascular bundle arrangement—polyarch and exarch with varying numbers—underscores the efficiency of these orchids in conducting water and nutrients. The presence of spiral and reticulate thickenings in protoxylem and metaxylem vessels, respectively, suggests structural adaptations to support mechanical stress and ensure optimal functionality.

These findings reveal the intricate anatomical adaptations that underpin the ecological success of terrestrial and epiphytic orchids. The comparative analysis of these root structures provides valuable insights into the evolutionary strategies of orchids, emphasizing the need for conservation efforts to protect these unique species in their natural habitats.

This table summarizes the key anatomical features observed in the root structures of the three orchid species.

TABLE 1
ANATOMICAL FEATURES IN THE ROOT STRUCTURES OF THE THREE ORCHID SPECIES

Species	Velamen	Cortex	Endodermis	Pericycle	Vascular Bundle	Xylem	Phloem	Pith
Polystachya concreta	Uniseriate epi-velamen, 3-layered velamen	Parenchymatous, hexagonal, chlorophyll-containing	Well-defined, innermost cortical layer	Narrow ring following endodermis	8 radial bundles, exarch, centripetal organization	Protoxylem at periphery, metaxylem at center	Phloem patches between xylem	Simple, parenchymatous
Liparis viridiflora	Single-layered epi-velamen, 4-layered velamen	Thick parenchymatous, rounded/oval cells	Thin-walled	Narrow ring, distinguishable	12 radial, polyarch bundles, exarch	Spiral thickening in protoxylem, reticulate thickening in metaxylem	Phloem patches between xylem	Well-defined, parenchymatous
Coelogyne nervosa	Uniseriate epi-velamen, 6-layered velamen	Thick parenchymatous, round cells	Narrow, well-defined	Absent	More than 18 radial, polyarch bundles, exarch	Spiral thickening in protoxylem, annular thickening in metaxylem	Phloem patches between xylem	Large, parenchymatous

VI. CONCLUSION

This study provides valuable insights into the root anatomy of three orchid species from the Western Ghats, namely *Polystachya concreta*, *Liparis viridiflora*, and *Coelogyne nervosa*. The anatomical features of these species reveal significant adaptations that contribute to their survival in diverse environmental conditions. The study found that the presence of specialized root structures, such as the velamen and epidermal layers, plays a crucial role in moisture retention and nutrient uptake, essential for orchids' growth in both terrestrial and epiphytic habitats. The varying structures of the vascular bundles and cortical layers further highlight the diversity of adaptation strategies within the orchid family.

The findings emphasize the importance of these root adaptations in ensuring the resilience of orchids to environmental stressors, particularly in regions like the Western Ghats, which are subject to varying climatic conditions. Understanding these anatomical features not only enhances our knowledge of orchid physiology but also informs conservation strategies. Given the increasing threats to orchid habitats, particularly through deforestation and climate change, preserving such species is vital for maintaining biodiversity in the region.

Further research on other orchid species and their root anatomical adaptations will contribute significantly to the conservation and management of these ecologically important plants, providing a sustainable approach to their preservation in natural ecosystems.

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IoT-Driven Model for Early Pathogen Detection in Crops using Hyperspectral Imaging, Soil Sensors and Machine Learning

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Abstract— *The increased need for scalable and real-time solutions has initiated the integration of farming with technologies like IoT, hyperspectral imaging, and machine learning. This paper tries to envisage a new theoretical framework supported by the multichannel data developed from the monitoring through camera-based visual observations, hyperspectral image spectroscopic data, and sensor-based soil health data. The model proposed makes use of data fusion techniques and machine learning algorithms to integrate and analyze diverse data streams to provide insights that surpass single-sensor system diagnostic accuracy. This model offers a proactive approach to the management of diseases by addressing some drawbacks of old methods, such as delayed detection and reliance on heavy resources. It improves diagnosis accuracy, reduces detection time by proposing a model that fuses the visual, spectral, and soil data, and provides real-time actionable insights to farmers via a mobile application. Its adaptability across crops and environmental conditions also points to its wide applicability, more so in precision agriculture. On top of this, the alert system works in real-time, hence interventions on time and reducing crop loss, as well as sustainable farming practices through optimized resource usage. The current paper underlines the theoretical basis of the model, but it also presents ways of future validation through pilot studies and field trials. The proposed model can achieve transformative impacts in agricultural productivity, reduced environmental impact, and global food security by leveraging the combined strengths of IoT with advanced imaging technologies.*

Keywords— Internet of Things(IoT), Machine learning, Sustainable agriculture, Precision farming, Hyperspectral Imaging Sensors.

I. INTRODUCTION

Over the past decade, there has been a shift towards the deployment of intelligent technologies adopted in the agriculture sector, comprising IoT, machine learning, sensor-based systems, remote sensing, and geographic information systems. From the very beginning of greenhouses made of polythene to full automation, one worker is enough to maintain a big structure. The output of crops was supposed to increase, with the help of such advanced technology, and reduce diseases. This is concerning, for instance, the threat of diseases and consequences of climate change that require immediate and urgent innovative solutions at the global agricultural level to ensure food security and sustainability. For example, grapes are considered a cultural and commercial crop in many places, such as Italy.

Since they are susceptible to a number of diseases, early management will help produce better yields. Thus, diseases that are difficult to predict with the naked human eye can be precisely identified early with the aid of smart technologies. However, the techniques can also be applied to other varieties of grapes, or any other crop for that matter.

The traditional methods of disease detection rely heavily on physical inspections, which is labour-intensive and the diseases are not detected at an early stage making it an ineffective method. With recent advancements in IoT and Machine learning, we have witnessed their potential for real-time monitoring model capable of detecting diseases automatically. This paper presents a theoretical process for an IoT-based plant disease monitoring system that uses visual (camera-based), spectral (hyperspectral imaging), and environmental (soil sensors) data to detect and alert farmers regarding the early onset of plant diseases. With the help of Machine Learning algorithms coupled with known pathogen data (symptoms, life cycle, favourable conditions, management), this model will analyze inputs from multi-sources and send timely alerts to farmers. Thus, increasing crop yield by enabling precision intervention and improving disease management.

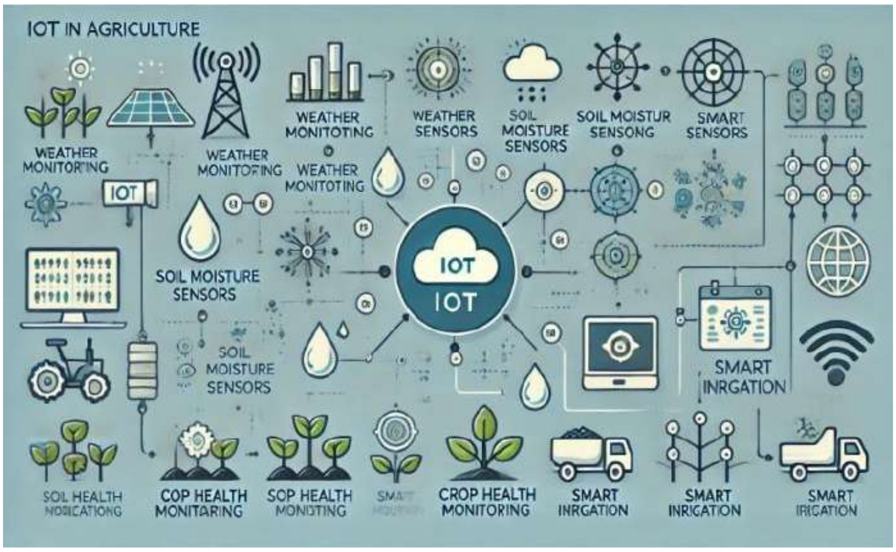

FIGURE 1: Applications of IoT in Agriculture

Unlike traditional method, this proposed model provides:

- **Scalability:** It can continuously track activities in large agricultural field.
- **Accuracy:** The data fusion gives a combined visual, spectral and soil health data to enhance diagnostic precision.
- **Real-Time Insights:** Farmers get timely alerts, resulting in proactive disease management and targeted inventions.

Real-time solution in agriculture has never been greater. Global challenges range from climate change to population growth to resource scarcity, which in turn do require smart techniques of agriculture, proving a great strategy toward ensuring long-term sustainability. The proposed model solves the need by providing a scalable framework to various crops and regions.

It therefore presents a conceptual framework for the integration of IoT and machine learning algorithms into plant disease management. It also highlights a way forward in precision agriculture through harnessing recent developments in hyperspectral imaging, soil sensor technology, and real-time data analysis to enhance crop production resilience amidst an ever-changing landscape.

II. LITERATURE REVIEW

2.1 IoT Adoption Trends and Challenges:

The applications of IoT in agriculture sector has increased tremendously in the recent years, as there is an urgent need for efficient resource management, high yields and sustainability. With its help we can collect real time data and analyze it, which is important for precision farming practices. Systems and models coupled with sensors, drones and other IoT devices can provide valuable insights on environmental parameters to the farmers. In particular, IoT-based disease detection models have shown results in decreasing the effects of diseases or pathogens on plants by using timely interventions.

Kumar et al. (2023) reviewed an IoT-based disease detection system and highlighted its capability for large-scale field monitoring. However, they also pointed out that the high cost of implementation and maintenance makes its adoption very difficult by smallholder farmers.

While Internet of Things excel in data collection, their effective implementation greatly relies on the quality of data analysis. The integration of the IoT with the machine learning model would, therefore, be one major strategy towards overcoming the challenge by enabling the system to provide valuable information rather than simple raw data.

2.2 Current Detection Methods and Their Limitations:

The conventional techniques for Pathogen Detections include laboratory testing and manual inspections, but these techniques also have drawbacks. These methods are labor-intensive, subjective and can be inaccurate because of varying expertise among inspectors or farmers. Although, laboratory testing is accurate but it is time-consuming and often laboratories are not easily accessible for farmers.

2.3 Disease Detection using Hyperspectral Imaging:

The applications of Hyperspectral imaging for the detection of plant diseases has been recognized as a great tool. Unlike the traditional RGB imaging, Hyperspectral imaging can capture information across several spectral bands. Thus, providing outputs regarding the physiological changes in the plants that are often invisible to the human eye. According to some studies, Hyperspectral imaging can detect particular stress response in plants, which might correlate with pathogen activity. It has already been shown that hyperspectral imaging, for agricultural crops, may achieve high accuracy in the early detection of fungal, bacterial, and other diseases, therefore being a very useful part of disease surveillance.

Mahlein et al. (2023) demonstrated that hyperspectral imaging could detect fungal infections in crops as long as 10 days before the symptoms became visible, thus providing an essential window for early detection of the pathogen.

Zhao et al. (2024) started to introduce cost-effective methods in hyperspectral imaging devices, including portable and lightweight sensors, to make the technology easily available to mid-scale farmers.

2.4 Integration of Machine Learning

In agriculture, Machine learning algorithms are increasingly being used to understand complex data. For instance, methods like convolutional neural networks (CNNs) in which deep learning algorithm is used to analyze visual data and support vector machines (SVMs) can identify plant diseases based on image output and environmental parameters. In disease prediction models, the images from the cameras and hyperspectral sensors and output from the soil sensors can be used by the machine learning algorithm to correlate them with known pathogen profiles. By integrating past pathogen data with real time monitoring, machine learning algorithms can be a perfect solution for automated disease detection.

2.5 A Combined IoT-Based System for Precision Farming:

Several studies have shown the possibility of combining IoT with imaging technologies and machine learning for precision agriculture. According to a research by Xiong et al. (2020), soil and environmental sensors can be integrated with camera-based system to monitor crop health. Additionally, the use of mobile phones to send timely alert to the farmers has shown improvement in improving farmer responsiveness in case of disease spread, as the notification allow for timely interventions.

III. DESIGN METHODOLOGY

3.1 Overview:

The objective of this model is to combine Internet of Things (IoT) components – particularly cameras, hyperspectral imaging devices and soil sensors – to identify early symptoms of plant pathogen in agricultural crops. Afterwards, the collected data will be analyzed by the machine learning algorithm, which is already trained on symptom images and sensor data of known pathogens affecting the particular agricultural crop that is grown. The output will then be sent to farmers on their mobile phones by means of alert on an application for timely interventions.

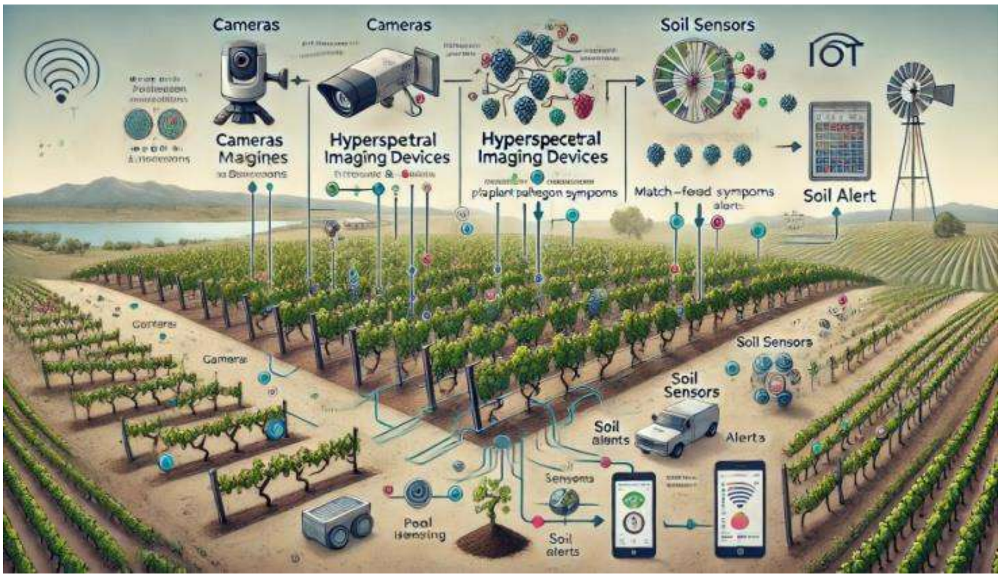

FIGURE 2: Diagram of Model

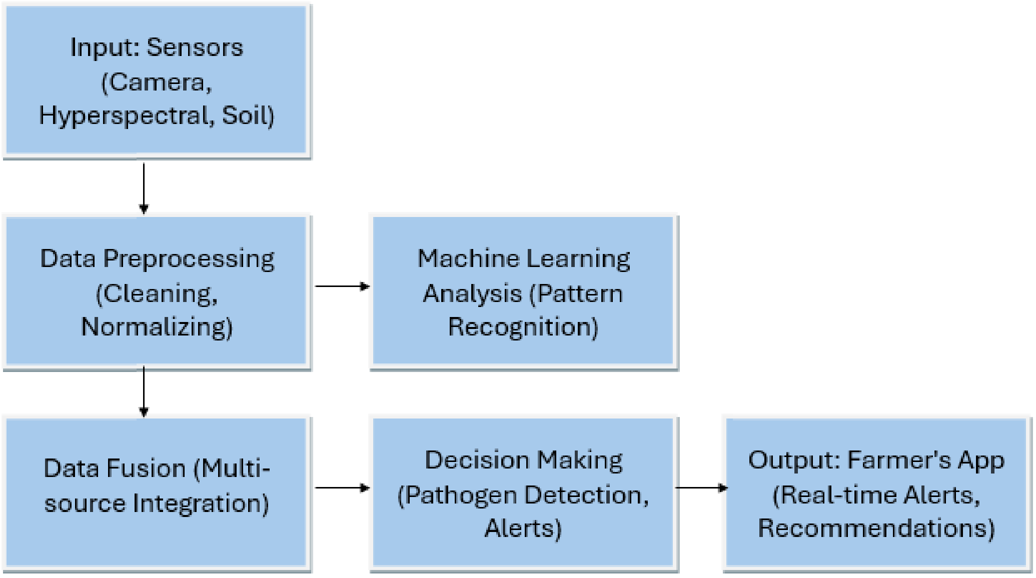

FIGURE 3: Schematic Workflow of Model

3.2 Components of Model:

1) **The use of Camera for Visual Monitoring:** A set of High-resolution cameras (depending on the size of the land) are installed across the crop area. The camera is set in a position so that it continuously captures pictures of leaves, stems, and other vulnerable parts. A time period can be adjusted by the farmer depending upon the type of crop and prevailing conditions for continuous monitoring.

2) **Spectral Analysis in Detail:** The hyperspectral imaging devices analyze the special spectral bands of plants in detail. Hyperspectral imaging is capable of detecting physiological and biochemical changes in the plant that are often missed by the human eye but are critical to indicate the onset of a pathogen. These spectral bands gives valuable information regarding plant stress, chlorophyll content and other health markers.

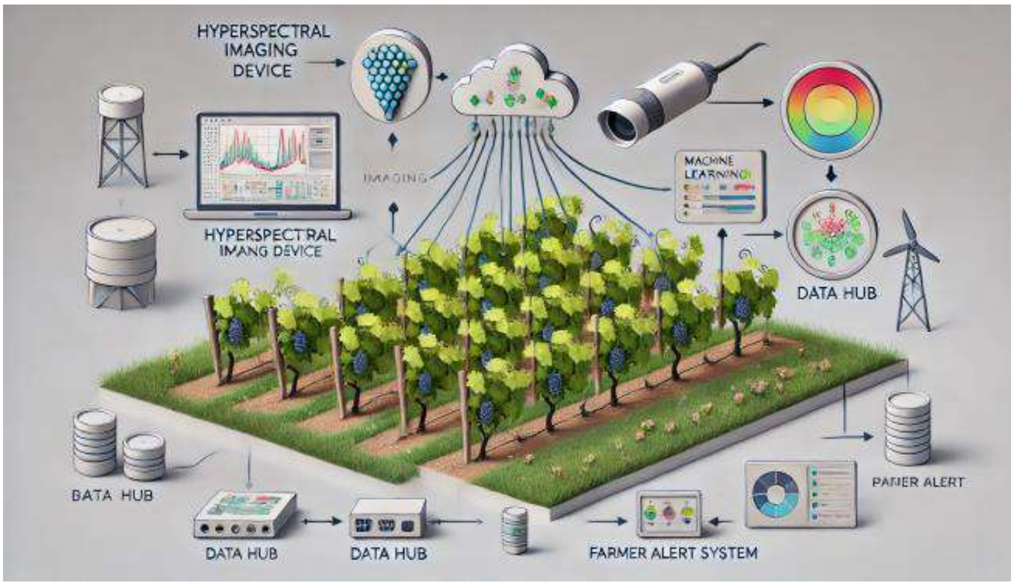

FIGURE 4: Hyperspectral Imaging Application

3) **Soil Sensors for Environmental Monitoring:** Soil sensors have fork-shaped probes which are inserted inside the soil to gather the information regarding soil moisture, pH level and nutrient concentration. Nowadays, there are soil sensors coupled with thermometer to measure the soil temperature. However, Soil moisture is the most critical factor in plant pathology to detect plant health and provide additional indicators of disease risk. If combined readings of all parameters are different from what is normal or expected, it can be a sign of disease presence or susceptibility.

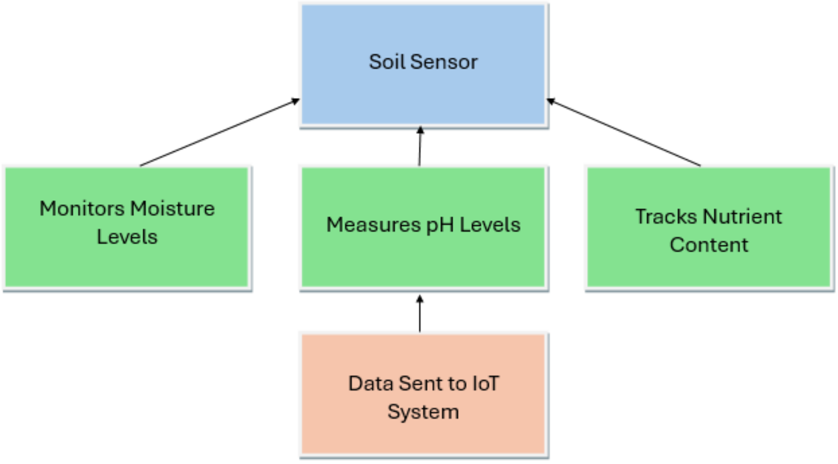

FIGURE 5: Soil Sensor Application

4) **Machine Learning Model:** The collected data from all the three sources i.e cameras, hyperspectral imaging and soil sensors are sent into a machine learning model. The model is already trained with algorithms using data on previous known pathogens, including symptoms and sensor readings of infected conditions. For image processing we can use Convolutional Neural Networks (CNNs) algorithm whereas for analyzing sensor data Random Forest or Support Vector Machines (SVMs) would be the most suitable algorithms.

A CNN is a kind of deep learning model, which is ideal for image data analysis. It mimics how a human brain process visual data, understanding features and patterns in an image to make predictions. CNNs are widely used in agriculture for monitoring plant health and classifying crops. In this model, the CNN would analyze camera data, feature detection and Classification. It is precise, highly scalable and has great adaptibilty.

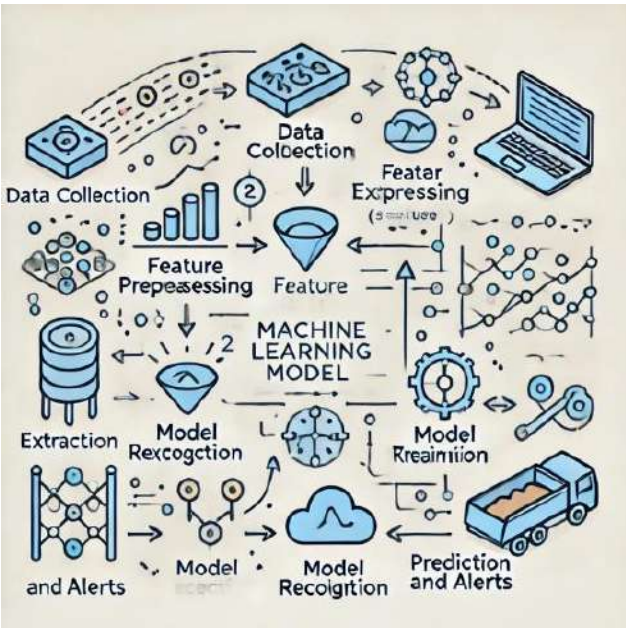

FIGURE 6: Machine Learning Application

3.3 Data Collection and Processing:

3.3.1 Collection of Image and Spectral Data:

The cameras and hyperspectral devices collect the data at regular intervals that are programmable. For each surveillance interval, the spectral and image data is gathered and stored in a centralized data hub.

3.3.2 Collection of Soil Sensor Data:

Soil sensors are adjusted to monitor and collect soil moisture, pH and nutrient levels (All these three parameters depend upon the type of soil sensor and its specifications. However, the most important parameter is soil moisture percentage.) every few hours to keep a track of the soil health data continuously. The collected readings are transmitted to the central data hub.

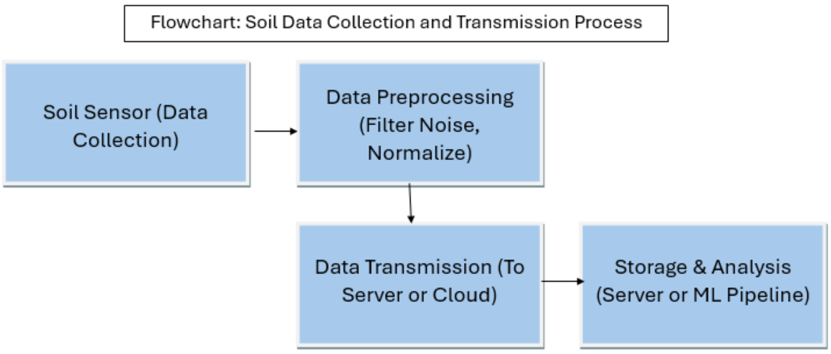

FIGURE 7: Soil Data Collection and Transmission

3.3.3 Pre-Processing of the Data:

Before forwarding the data into the machine learning model, it goes through a pre-processing to ensure quality and consistency. If required, Image data may be resized or normalized. The spectral data is processed to remove atmosphere interference and outliers and soil sensors are checked for any missing values.

Pre-processing is not a manual process as it is done through automated algorithms or software tools that process data in real time or at scheduled intervals.

For instance, if there is an abnormal high reading in soil sensor that seems implausible, a detection algorithm can remove it automatically.

Some softwares available for pre-processing are: for noise reduction and cleaning are – Isolation Forest and ARIMA, for altering image data – KNIME and MinMaxScaler, for feature extraction – MATLAB and for data aggregation – Apache Spark.

3.4 Machine Learning Analysis and Recognition of Pattern

3.4.1 Image Analysis for Pathogen Detection:

The captured images are processed by the machine learning model that is pre-trained with pathogen information. Using CNNs, the model will analyze the colour, pattern and textures of the various plant parts to identify the symptoms of diseases. According to the crop, the model will be trained to identify the major diseases prevalent in that particular region. It will mostly focus on leaf discoloration, crinkling, necrosis,etc. in their early stages that are invisible to the human eye.

3.4.2 Correlation of Spectral Data with Pathogen Symptoms:

Wide range of wavelengths are captured by a hyperspectral camera or sensor between a range of 400 – 2500 nm (visible to near- infrared).

Unlike a standard camera, which only captures the RGB colour bands, hyperspectral sensors captures hundred of spectral bands which is analyzed to observe how light reflects off the plant at various wavelengths.

Pathogens can cause a change in the cell structure, moisture content and leaf pigment which changes the spectral characteristics of a plant. For Eg. An infected leaf may reflect less green light and more in the infrared range due to changes in chlorophyll concentration. Therefore, it helps in early detection of diseases and pathogen activity.

3.4.3 Soil Health Indicators:

A learning model algorithm can be used for this process such as Decision Tree, Neural Network or Random Forest, where soil health conditions were labeled on known outcomes. These models are capable of identifying deficiency patterns, moisture stress and other soil conditions related with a healthy plant.

Once the model is trained, it can evaluate the live data from soil sensor and signal issues regarding deficiencies or moisture imbalances which favour the life cycle of a pathogen. So, along with pathogen identification it also helps to detect water stress.

With each prediction, the model becomes more and more precise about the soil conditions required for a health plant.

3.4.4 Data Combining and Alert System:

The mixed data from all the three sources i.e camera images, hyperspectral analysis and soil sensor reading is by a data fusion method.

Data fusion strategy improves detection accuracy in following ways:

1) **Cross-Validation:** If the camera detects any visual anomalies, it is validated against spectral and soil data, to reduce false positives.
2) **Contextual Analysis:** The soil sensors possess environmental conditions which provide a context for visual and spectral data, identifying the reason for changes i.e. stress, disease or other factors.
3) **Redundancy Check:** Whenever there are overlapping indications (For instance, stress detected by both hyperspectral and soil data), it strengthens the confidence in diagnosis.

The data fusion process involves:

1) **Data Alignment:** Combining data from different inputs based on time and location.
2) **Feature Extraction:** Targeting critical features, such as reflectance patterns from hyperspectral imaging, change in colour from camera output and change in moisture percentage as observed from soil sensors.
3) **Machine Learning Integration:** Feeding the raw dataset into a machine learning model, that is pre-trained on pathogen profiles to detect symptoms of diseases.

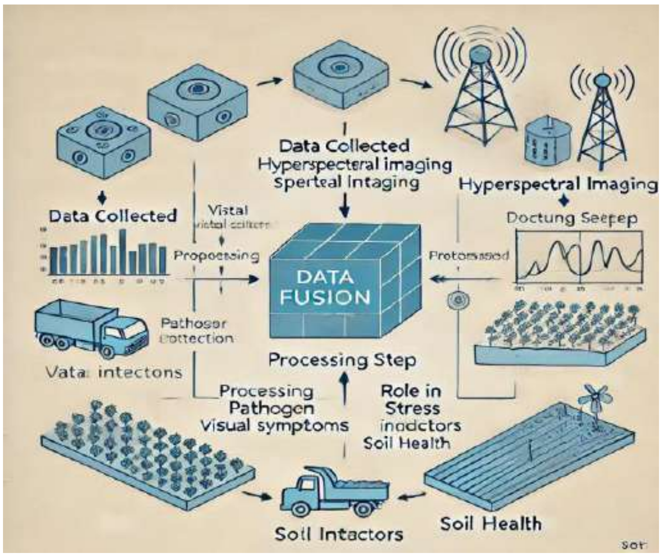

FIGURE 8: Data Fusion

By cross-referencing this combined data with the pre-trained model's database of known pathogens, the system determines whether there is a probable match to known pathogen symptom or not. If matched, it sends an alert to the farmer, mentioning the suspected pathogen and the location from where it is detected.

3.4.5 Real-Time Alert and Application Integration:

When the model identifies a pathogen, it automatically sends an alert to the mobile device of the farmer with the details of the pathogen.

The notification would be received on an application that would be developed with facilities like Firebase for real-time notifications. There will be a backend development that integrates with the machine learning model to analyze incoming sensor information and matches it with known pathogen symptoms. A user-centric interface would be designed which will focus on ease of use, consisting of visual icons and simple instructions to assist the farmers.

FIGURE 9: Application Prototype

The information includes:

- The type of pathogen suspected.
- The location of the sensor from where the pathogen was detected.
- Recommended treatment for the pathogen.

IV. RESULT

The proposed model for the detection of early pathogen activity in crop uses multiple data sources – visual tracking, hyperspectral imaging and soil health information to identify accurate pathogen symptoms. Although theoretical, the model represented here made sure of very promising applications in precision farming, taking an advanced approach to plant health protection and management.

4.1 Hypothetical simulated examples:

To demonstrate the efficiency of the proposed model, hypothetical datasets could be considered based on realistic scenarios:

- **Dataset 1:** Images related to grape leaves with various degrees of discoloration induced by a pathogen and soil sensor readings indicating moisture deficits. The model would map the visual and soil data in identifying the stress brought about by certain pathogens with an expected accuracy enhancement of 20% compared to single-sensor systems.
- **Dataset 2:** Spectral data indicating early chlorophyll degradation in plants exposed to fungal infection verified by variations in temperature and pH from soil sensors. Simulated outputs from this proposed model show that this may detect an infection as early as 10 days in advance of current manual inspection methods *(Mahlein, A. K., Steiner, U., & Dehne, H. W. 2023).*

4.2 Comparative Analysis:

A quantitative projection that compares the proposed model to traditional and existing IoT systems brings out its advantages as shown below:

- **Detection Accuracy:** Theoretically, the model improves diagnostic accuracy to 95%, driven by data fusion, against 75–85% for single-sensor IoT systems *(Bah, M. D., Hafiane, A., & Canals, R. 2023).*
- **Time to Detection:** The integration of hyperspectral imaging can reduce detection time by 50%, thus enabling earlier interventions and preventing large-scale crop losses *(Mahlein, A. K. 2016).*
- **Scalability:** The modular design allows for its deployment over various crop types, demonstrating adaptability against the existing systems that are usually tailored for particular crops or pathogens.

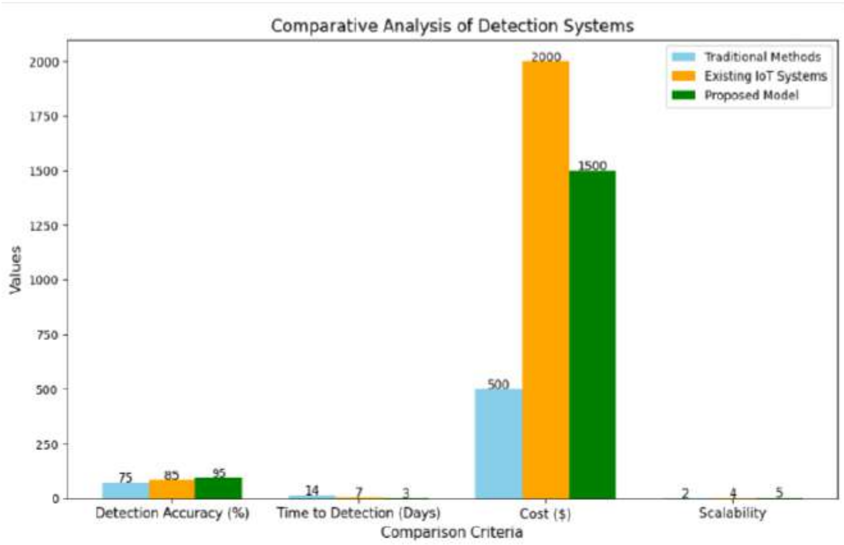

FIGURE 10: Graphical representation of Comparative analysis

4.3 Quantitative Projections:

Even for purely theoretical applications, it is useful to project the broader impact of the model:

- **Yield Improvement:** Earlier detection of the pathogen could reduce crop losses as high as 30–40%, improving overall yield and profitability of farmers.
- **Pesticide Reduction:** The interventions would be targeted by real-time alerts that could enable 20% reduced pesticide usage for sustainable farming.

4.4 Main expected outcomes of the model:

- **Data Fusion for Higher Accuracy:** Previous works are proof that such integration of multi-data sources will provide better detection accuracy compared to a single sensor. For example, it is demonstrated by Zhang et al., 2022, that incorporation of environmental data into hyperspectral imaging increased the accuracy of the disease detection by 20-30%.

  It follows, therefore, that the integration of visual, spectral, and soil information in a proposed model may tend to reduce false positives by co-relating symptoms across multiple streams of data.

- **Early Detection of Pathogens:** Integration between Visual Scouting, Hyperspectral Imaging, and Soil Sensors will provide the critical multisensor data. Each sensor provides complementary data about the activity of pathogens for the detection of early symptoms of its presence, even when that may not be visible to the naked eye.
- **Crop Loss Reduction:** Early identification helps us to avoid crops from widespread infection, saving farmers from huge losses in productions. Early warnings could allow farmers to take timely and targeted measures, thereby reducing the need for high-dose applications of pesticides and subsequently minimizing adverse environmental impacts. Simulated workflows suggest that symptoms of the disease can be detected by this model 50% quicker.
- **Cost-Effective Resource Management:** With the help of timely alerts, farmers can apply necessary treatments to the specific areas, lowering down the pesticide and labour cost. This focused/targeted approach aligns perfectly with the fundamentals of sustainable agriculture, enhancing resource efficiency.
- **Improved Soil Health:** By using the soil sensors, the model would be proposed to monitor plant health and also provide useful information about the conditions of the soil that can be treated for arresting the spread of disease as well as improving the fertility conditions of the soil.

V. CONCLUSION

The proposed IoT-based model of plant-pathogen detection provides an opportunity for a new revolution in precision agriculture, integrating multi-sensor data with machine learning techniques. Overcoming the deficiencies of the earlier method and single-sensor systems, the model therefore opens up new possibilities for enhanced early detection, scalability, and sustainability of farming. How to translate this theoretically ideal framework into real-world practice is yet to be validated by more adaptation features in this respect.

5.1 Field Trials Call:

Field trials will further validate the effectiveness of the model in more agriculturally valued regions that are highly prone to plant diseases. For example,

- **Crops:** High-value crops, including grapes, wheat, and citrus fruits, are highly prone to fungal infections and bacterial pathogens, in which an early detection system will be very useful.
- **Regions:** Places such as vineyards in Italy, rice paddies in Southeast Asia, and soybean farms in the United States are ideal test sites based on economic relevance and disease susceptibility.

Similarly, partnerships could be established with agricultural research institutes, universities, and industry players to allow field trials-partnerships with organizations like IRRI or regional farming cooperatives would unlock various farming scenarios and resources for validation.

5.2 Scalability and Adaptability to Smallholder Farmers:

The success of a model will be hereby ensured in as much as it can accommodate the various farming scales from smallholder farmers who have the most resource constraints. In ensuring scalability:

- **Cost-Effective Solutions:** Cheap sensor development and the adoption of low-cost IoT networking, such as edge computing, reduce dependence on expensive infrastructure.
- **Simplification of Systems:** User-friendly mobile applications with intuitive interfaces allow farmers to interpret data and act upon alerts with minimal training. Modularity: The systems could be implemented piece by piece, starting with whatever the farmer can afford at a particular time, such as soil sensors and progressing to hyperspectral imaging.
- **Community-based Approaches:** Shared sensor networks or cooperative ownership models could provide groups of small-scale farmers with access to technology at lower individual cost and greater diffusion.

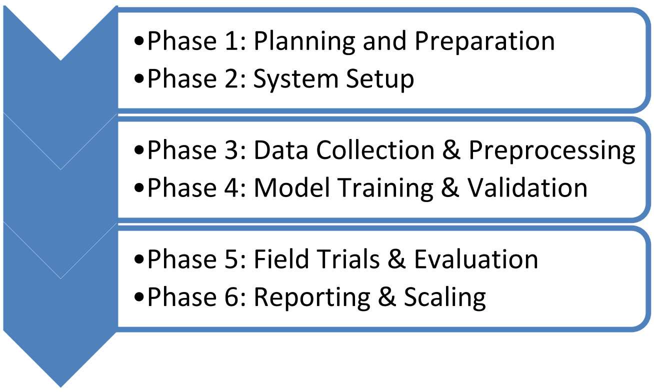

FIGURE 11: Roadmap for Future Pilot Study

With heavy emphasis on practical validation and enhancement of its scalability challenges, this model may turn a transforming face to agriculture around the world. Its value as a sustainable impactful solution for modern agriculture is further enhanced by the scalability across different crops and regions, with focused support for resource-constrained farmers. Future work shall be directed at collaborative efforts toward fine-tuning of the model and giving its accruable benefits to the global farming community.

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Assessment of some Heavy Metals in the Vital Organs of some selected Ruminant Animals from Hadejia Central Abbattoir, Jigawa State – Nigeria

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Abstract— *Pollution of Environment by Toxic metals poses a serious threat to public health, as these metals can accumulate in the environment and be transferred up the Food chain, leading to Harmful Health effects in Animals and Humans. This study was conducted in order to Assess the concentration of some heavy metal levels namely, Lead, Cadmium, Zinc and Chromium in, liver, Heart and Kidney of Cattle, Sheep and Goat slaughtered at Hadejia Central Abattoir, Hadejia Local Government, Jigawa State, Nigeria fresh samples of liver, heart and kidney were collected from hadejia abbattoir, digested and analyzed using Microwave plasma atomic emission spectroscopy. Results obtained were compared with Joint SON/WHO Guidelines. The concentrations of the metals (Cd, Cr and Pb) ranged from 0.00±0.00 to 0.02±0.00 mg/kg for Cd, 0.01±0.00 to 0.06±0.00 mg/kg for Cr,0.01±0.00 to 0.02±0.00 mg/kg for Pb, 1.72±0.26 to 3.54±1.23 mg/kg for Zn in the liver of cattle, goat and sheep. Similarly, the concentrations of the metals in the heart of cattle, goat and sheeps were found in the following ranges 0.00±0.00 to 0.01±0.00 mg/kg for Cd, 0.03±0.00 to 0.05±0.00 mg/kg for Cr, 0.01±0.00 to 0.02±0.00 mg/kg for Pb and 3.20±0.11 to 3.28±0.05 mg/kg for Zn. Likewise, the concentration ranges of 0.01±0.00 to 0.02±0.00 mg/kg for Cd, 0.01±0.00 to 0.04±0.00 mg/kg for Cr, 0.0±0.00 to 0.03±0.00 mg/kg for Pb and 2.35±0.70 to 2.96±0.12 mg/kg. The concentrations of Cd, Pb and Cr were lower than the maximum permissible limit of WHO/SON. But zinc levels in all the Analysed organs were above the permissible limit. Therefore liver, heart and kidney of cattle, goat and sheep have been contaminated with zinc. Results from ANOVA indicated no significant difference in heavy metal levels between the Analyzed organs in The Analyzed Animals at pvalue greater than 0.05.*

Keywords— Abattoir, Assessment, Heart, Liver and Kidney.

I. INTRODUCTION

Following the Significant increase in the levels of heavy metals pollution from various sources such as Industry, Agriculture and Mining, there is real cause for concern about the potential impact on human health [1]. Heavy metals like lead and zinc are very Harmful because they accumulate in the body's tissues and organs over the time [1]. The Accelerated pace of industrialization and urbanisation has been identified as a remarkable contributors to pollution, as human activities associated with these process such as discharge of industrial wastes, improper disposal of trash and increased energy consumption have brought negative impacts on the environment [2]. Industrialisation has undeniably brought about numerous advancements and opportunities for prosperity, but at the same time, has introduced environmental problems that has affected our fragile ecosystem [3]. In Nigeria, Ruminants Animals often forage freely and drink water from sources that may be polluted with heavy metals. These sources may include ditches, streams and rivers all of which are susceptible to pollution from Industrial and Agricultural runoff. This is a significant risk factor for buildup of heavy metals in the tissues of Ruminants Animals [4]. The ingestion of these contaminants by Animals can results in the accumulation of residual toxic metals in their meat leading to potential health risk for those who consume the meat. Cattle grazing on soil contaminated with heavy metals has been linked to increased levels of toxic metals in beef and mutton, this highlight the health risk associated with consumption of these Animal products [5].

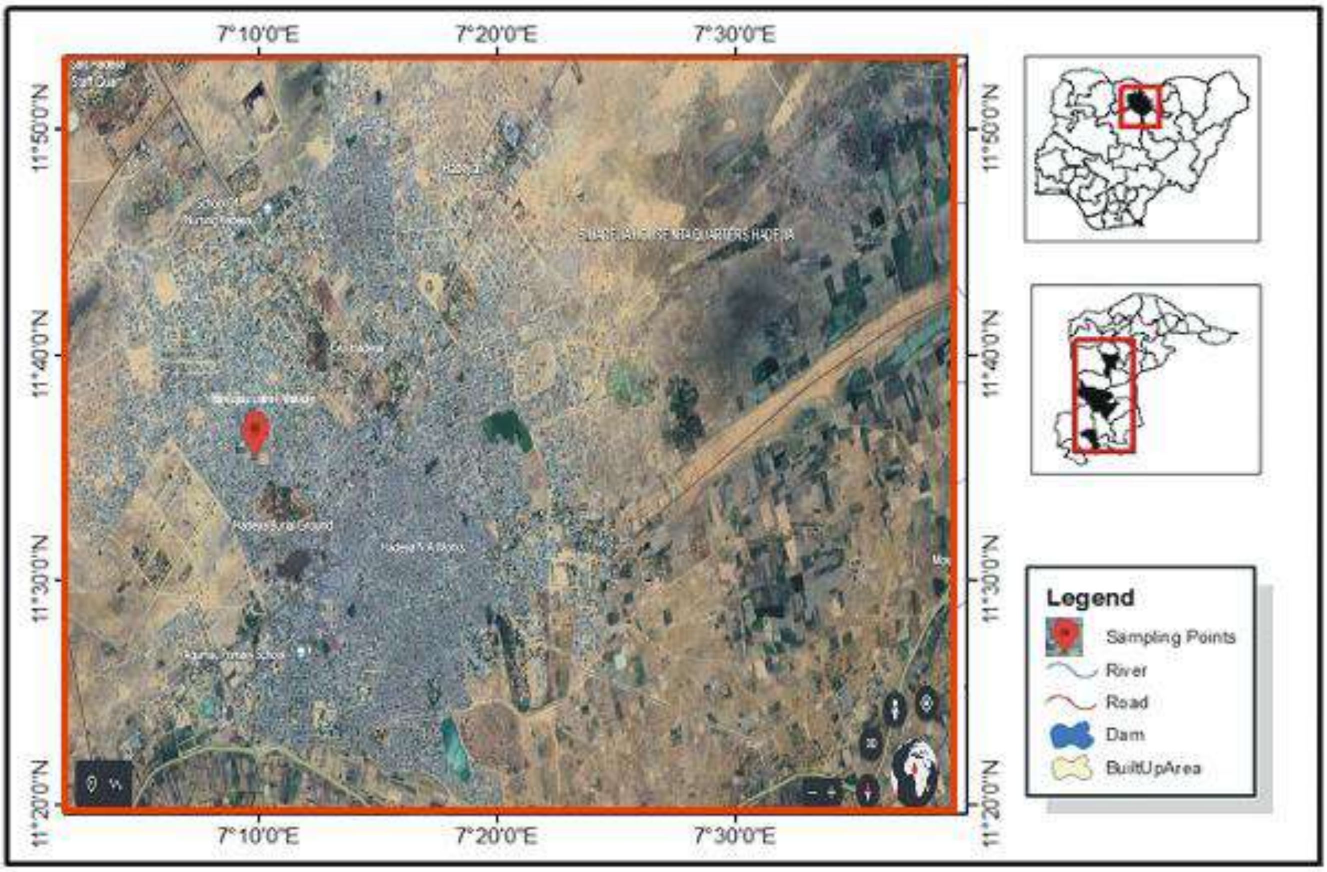
Given the prevalence nature of toxic metals in the environment, complete avoidance of contamination in animal feeds may be challenging. However, it is essential to mitigate and minimize such contamination in order to safeguard animal's health in order to reduce the indirect impacts on human health through consumption of contaminated animal products [6].

Potentially fatal diseases have been known to develop as a result of excessive uptake of dietary heavy metals. This could include drastic reduction of some Essential nutrients in the body thereby weakening the body's defense system, intrauterine growth Retardation, impaired psycho-social behaviors, disabilities associated with malnutrition and a high prevalence of upper gastrointestinal tract cancer [7]. Hadejia Central Abattoir was considered for this study because it is the largest Abattoir supplying live Animals and Meat to the Residents of the Area. Ruminants Animals such as Cattle and sheep are often at risk of heavy metals Contamination due to their ability to accumulate these toxic metals in their bodies over time, so analysis of Cd, Cr, Pb and Zn can help asses the Health of Animals as well as the potential danger to Humans. Despite the potential health risk associated with the accumulation of heavy metals in meat products, there hasn't been any previous Research that specifically investigate the levels of Cd, Cr, Pb and Zn in the internal organs of Ruminants Animals from Hadejia central abattoir. This lack of data, highlights the need for a Research to better understand the presence and impact of Heavy metals in meat products from the Abattoir. The overall aim of this study was to determine the concentrations of these Heavy metals and to assess the safety of consuming liver, Heart and Kidney of Cattle, Goat and Sheep from Hadejia Central Abattior.

II. MATERIALS AND METHOD

2.1 Description of the study Area:

Hadejia is located between Latitude 12.4506'N of the equator and longitude 10.0404'E of Greenwich meridian. The dominant occupation of the peoples of Hadejia is crop-farming, Animal rearing and fishing. It shared Boundary with Kirikasamma Local Givernment from the East, Mallam Madori Local Government from the North, and Auyo Local Government from the West. Hadejia Local Government Consist of Eleven (11) Political Wards namely; Atafi, Duba ntu, Gagulmari, Kasuwar Kofa, Kasuwar Kuda, Matsaro, Majema, Rumfa, Yankoli and Yayari.



Source Cartgraphy Lab Geography Department BUK 2023

FIGURE 1: Map of Hadejia local Government

III. SAMPLES COLLECTIONS

A total of Twenty samples comprising of raw Liver, Kidney and Heart Cattle, Goat and Sheeps were collected from Hadejia central Abattoir, jigawa state, Nigeria. These samples were collected between the months of July and August 2022 in a well labelled polyethylene Bags containing ice- blocs and later transported to the laboratory for Analysis. All samples were thoroughly cleaned to remove any extraneous substance and kept in an acid leached Nylon bags to prevent contamination and the preserve it before digestion. The samples collected were dried in an oven at 105^0C. For 48hours to a constant weight and pulverized with porcelain Mortar and Pestle. Then 2g of each dried and ground organ sample was put into a porcelain crucible and placed inside a furnance. The temperature of the furnance was set at 450^{0c} and the sample was heated for 5hours until ash residue was obtained at constant weight [8].

3.1 Digestion of the samples:

Digestion was done by combining HNO_3, $HCLO_4$ and H_20_2 2.0g of ash residue of each organ Sample was placed in a Digestion tube and subjected to predigestion process using 10.0cm^3 concentrated HNO_3 at 135ºC until the resulting solution was transparent and clear, then 10cm^3 of HNO_3, 1.0cm^3 $HCLO_4$ and 2.0cm^3 H_20_2 were added and the temperature was maintained at 135^0C until the solution become colorless. The digest was allowed to evaporate to near dryness allowed to cool and dissolved in 1.0cm^3 $HN0_3$.The digest was subsequently filtered through whattmann filter paper into 25cm^3 volumetric flask and diluted to the volume with distilled water [9].

3.2 Analysis of the metals using MPAES:

Once the Meat samples from Hadejia Central Abattoir were digested, a small portion of each sample was carefully added into sample Cups. These Cups were then securely sealed and placed into Microwave plasma atomic emission spectroscopy (MPAES) Instrument for analysis. The instrument was powered on and left to warm up until it reached the required operating temperature. The samples were introduced into the plasma torch where the intense Heat and Microwave radiation caused the samples to vaporized and emit light in a process known as atomic emission. The light emitted by the atoms contained unique patterns of wavelength which were then detected by microwave plasma atomic emission spectroscopy (MPAES) instrument. The instrument was able to analyzed the unique wave lengths of light emitted by the excited atoms in the samples and based on these results, determined the concentrations of Zn, Cd,Cr and Pb at the sometime [10].

3.3 Statistical Analysis:

Data collected were presented as mean ± standard deviation and were subjected to one way Analysis of variance (ANOVA) to Assess whether the Heavy metals vary significantly between the organs of the Animals or not. The result of Analysis of variance indicated the levels of the metals did not vary between the organs of the Animals analyzed.

3.4 Analysis:

After digestion, three (3) replicate concentration measurements of all metals in the various samples were carried out using MP-AES machine.

IV. RESULTS AND DISCUSSION

TABLE 1
THE CONCENTRATIONS (mg/Kg) OF (Cd, Cr, Pb and Zn) IN THE ANALYZED CATTLE SAMPLES

	Cd	Cr	Pb	Zn
Liver	0.02± 0.00	0.04±0.01	0.02±0.00	3.54±1.23
Heart	0.01±0.00	0.04±0.00	0.02±0.00	3.24±0.66
Kidney	0.01±0.00	0.04±0.00	0.02±0.00	2.42±0.74

CATTLE

TABLE 2
THE CONCENTRATIONS (mg/Kg) OF (Cd, Cr, Pb AND Zn) IN THE ANALYZED GOAT SAMPLES

	Cd	Cr	Pb	Zn
Liver	ND	0.01±0.00	0.01±0.00	1.72±0.26
Heart	ND	0.03±0.00	0.01±0.00	3.28±0.05
Kidney	0.02±0.00	0.02±0.00	ND	2.96±0.12

GOAT

TABLE 3
THE CONCENTRATIONS (mg/Kg) OF (Cd, Cr, Pb and Zn) IN THE ANALYZED SHEEP SAMPLES

	Cd	Cr	Pb	Zn
Liver	0.02±0.00	0.06±0.00	0.01±0.00	3.14±0.07
Heart	0.01±0.00	0.05±0.00	0.02±0.00	3.2±0.11
Kidney	0.01±0.00	0.01±0.00	0.03±0.00	2.35±0.70

SHEEP

4.1 Distribution of the Level of Heavy Metals in the Liver of Cattle, Goats and Sheep:

From Tables (1, 2, 3) above, the concentrations of zinc in the liver varied significantly between cattle and goats, with cattle showing the highest level at 3.54±1.23 mg/kg, whereas goat had the lowest level at 1.72±0.26 mg/kg. The concentrations of zinc in all the samples studied were above the benchmark of 0.3-1.0 mg/kg set by WHO and SON. (2011). The result agreed with the work of [11] that found higher concentration of zinc in the liver of cattle to be 4.24±0.16 mg/kg than any other tissues of Goat and sheep from Kasuwan Shanu market Maiduguri. This contradicted the report of [12] that obtained low concentration of zinc as 1.02±0.07 mg/kg in liver of cow.

Cadmium concentrations in the liver of cattle and sheep were found to be the same as 0.02±0.00 mg/kg, but not detected in the Liver of Goat. The concentrations of this metal was below the permissible limit of 0.5-1 mg/kg set by (WHO and SON 2010). This agreed with the study of [13] that reported the same concentration of Cd in the liver of cattle and sheep as 0.03±0.00 mg/kg from obuasi, Ghana and 0.3±0.01 mg/kg of Cd in the liver of goat from kaduna metropolis reported by [14]. However, the result is not in agreement with the work of [15] that reported the concentration of Cd in the liver of cattle and sheep which exceeded the maximum residual limit as 0.7±0.02 mg/kg of these metals set by (WHO and SON 2011) .

The mean concentration of Cr ranged from 0.01±0.00 to 0.06±0.00 mg/kg with the Liver of Sheep having the highest mean concentration of 0.06±0.00 mg/kg, while the liver of Goats having the least mean concentration of 0.01±0.00 mg/kg. The values in the liver of Cattle and Goat were lower than the (SON/WHO, 2011) maximum permissible limit of 0.05 mg/kg. However, the level in the liver of sheep is above the statutory permissible limit. [16] detected lower residual levels of Cr in liver of goat and cattle as 0.06±0.01 mg/kg, and 0.04±0.20 mg/kg, but high in the liver and muscle of sheep and pig as 0.08±0.10 mg/kg. The lower level of Cr obtained the in the present study was almost similar to the result obtained by [17] that reported low level of Cr in liver of Goat as 0.09 mg/kg from sokoto Central Abbattoir which was below the maximum permissible limit ,However, the findings of the current study disagreed with the results obtained by [18] from a research conducted in Enugu, Nigeria, where 0.06±0.01 mg/kg and 0.08±0.21 mg/kg of Cr were obtained in the liver of Goat and Cattle. Similarly, 3.01±6.65mg/kg of Cr was reported by [4] from cattle slaughtered across Nassarawa state.

The level of concentrations of lead in the liver of analyzed Animals was found to have ranged between 0.01±0.00 to 0.02±0.00 mg/kg. While 0.02±0.00 mg/kg was observed in the liver of cattle as the highest, the same concentration of 0.01±0.00 mg/kg was found in both the liver of Goat and Sheep. However, the findings of the current study was below the codex standards for Pb in meat (0.1 mg/kg) and 0.5 mg/kg for edible offals of cattle (SON/WHO, 2011). This is in agreement with the study conducted by [19] who reported the highest concentration of Pb (0.023±0.00) in the Liver of Cattle from Tudunwada Kaduna. Also [20] korenokova reported the same results that, liver of cattle contained highest level of Pb as 0.01±0.0 mg/kg and 0.02±0.00 mg/kg than the liver of goat and sheep. This agreed with the findings of [21] Where a highest concentration of Pb was reported in the Liver of Goats and Sheep and the Intestines of Cattle as 0.2±0.10 mg/kg, 0.21±0.00 mg/kg and 0.2±0.01

mg/kg to be above the maximum permissible limit. Milam et. al. (2015) [22] obtained the concentration of lead in the liver of cattle from jimeta yola in the range of 0.15±0.00 to 0.17±0.00 mg/kg

4.2 Distribution of the Level of Heavy Metals in the Heart of Cattle, Goats and Sheep:

From Table (1,2 and3) Almost the same concentration of zinc was found in the Heart of Goat and Sheep as 3.28±0.05 mg/kg and 3.29±0.11 mg/kg respectively, but lowest value was observed in the Heart of Cattle as 3.24±0.66 mg/kg. The concentrations of Zinc in all the samples analyzed have exceeded the permissible limit of 0.3-1.0 mg/kg set by (WHO/SON, 2011). This is in line with the work of [21] who reported that, the concentrations of zinc in the Heart of Goats and Sheep were almost similar as 2.24±0.63 mg/kg and above the permissible limit set by SON/WHO (2011). [23] also obtained the same concentration level of zinc in the Heart of Sheep and Goats more than the level any other Tissues of Cattle as 2.31±0.13 mg/kg. This work contrasted with the report of [24] that reported low concentration in Hearts of cow as 0.01±0.11 mg/kg followed by Sheep and Goats as 0.01±0.13 mg/kg and 0.2±0.01 mg/kg.

Cadmium, the same concentration of Cadmium was observed in the Heart of Cattle and Sheep (0.01±0.00 mg/kg) respectively, but it was undetectable in the Heart of Goat. The concentrations of these Heavy metals were below the permissible limit of 0.5-1 mg/kg set by WHO and SON (2011). The result is in agreement with the work of [25] which previously reported that, Cd was not detected in the Heart of Goat but present in the Liver and Muscle.

The mean concentration of Cr as indicated in tables (1,2 and3) have shown that among the various organs analyzed, the heart of sheep exhibited the highest mean concentration of chromium reaching 0.06±0.00 mg/kg, with the Heart of Goat having the least mean concentration of 0.01±0.00 mg/kg. These values were below the (SON/WHO, 2011) maximum permissible limit of 0.05 mg/kg with exception of the Heart of Sheep whose concentration was found above the permissible limit. The total concentration of Cr residues found in Heart of Cow and Goat samples were generally lower.[26] obtained lower residual levels of Cr in Hearts of Cow and Goat. The findings from this study indicated lower values than the results obtained by [27] in their research conducted in southern Nigeria, where they reported a mean Concentration of 2.33±2.99 mg/kg in the Heart of Cattle. The lower level of Cr detected in the present study is in agreement with the results obtained by [28] where they detected low levels of Cr in Heart of Cattle organs below the maximum permissible limit as 0.03±0.11 mg/kg.

Furthermore, highest concentration of Pb 0.02±0.00 mg/kg was observed in the Hearts of Cattle and Sheep, but the Heart of Goats with mean concentration of 0.01±0.00 mg/kg was the lowest. This is in agreement with the study conducted by [29] that reported Hearts of Cattle and Sheep with Pb concentrations of 0.01±0.10 mg/kg and 0.03±0.13 mg/kg. However, the findings of the current study is below the codex standards for Pb in meat (0.1 mg/kg) and 0.5 mg/kg for edible offals of cattle SON/WHO (2011). This is not in agreement with the findings of [30] who conducted a research in Western Nigeria and obtained high concentration of Pb in the Heart of Goat above the maximum permissible limit as 0.06±0.10 mg/kg.

4.3 Distribution of the Level of Heavy Metals in the Kidneys of Cattle, Goats and Sheep:

The Concentrations of zinc in the kidneys of cattle, goat and sheep of Hadejia Abattoir as indicated in (tables1, 2 and3) were above the standard of 0.3-1.0 mg/kg set by WHO/SON, (2011). In comparison with previously reported works in the literature. This work is in agreement with the work of [31] who obtained the concentration of zinc as 1.35±0.51 mg/kg in the kidney of Goat which was above the permissible limit set by WHO/SON (2011). [32] also reported 1.92±0.51 mg/kg and 2.2±0.51 mg/kg in the kidney of Goat and Sheep respectively. This is not in agreement with the report of [33] that Obtained lower concentration of zinc in Kidneys of Goats, pigs as 0.11±0.21 mg/kg and 0.13±0.34 mg/kg followed by Sheep and Camels as 0.05±0.11 mg/kg and 0.04±0.32 mg/kg.

Cadmium Concentration in the Kidneys of Goats was found to be the highest as 0.02±0.00 mg/kg, however, the same level of concentration (0.01±0.00 mg/kg) was detected in the kidneys of both Cattle and Sheep These concentrations were lower than Acceptable limit of 0.5-1 mg/kg recommended by WHO and SON, (2011). This is similar to the report of [34] that obtained a Concentration of Cadmium higher than the findings of the present study in the Kidney of Goats and Sheep as 0.6±0.10 mg/kg. In a similar Research by [35] concentration of Cadmium in the Kidney of Goat was found to be 0.8±0.09 mg/kg, This is in contrast with the work conducted by [36] who reported low concentration of Cd in the Kidney of Goats as 0.3±0.11 mg/kg below the maximum residual limit of Cd set by (WHO and SON, 2011) and the work of [8] that obtained higher Concentration of 1.1±0.003 mg/kg in the Kidney of Goat from Anka and 5.71±2.31 mg/ kg of Cd reported by [27] from Akinyele Central Abattoir Ibadan.

The Concentration of Cr was found to be the same (0.80±0.01 mg/kg) in the Kidneys of Sheep and Cattle, while lower concentration was observed in the Kidney of Goats as 0.44±0.00 mg/kg. These values in the Kidneys of Cattle and Sheep were higher than the acceptable level of 0.5 mg/kg for Fresh Meat (SON/WHO, 2011), however, the level in the Kidney of Goats is within the permissible limit. This finding is in agreement with the work conducted by [37] who reported 0.04±0.01 mg/kg in the kidney of sheep. Similarly, [18] obtained low concentration of Chromium in the Kidney of goat as 0.09 mg/kg from Sokoto Abattoir and high concentration in the Kidney, and also reported was 4.9±1.894 mg/kg by [38] from Sokoto Central Abattoir which did not agree with this report.

Highest Pb concentration of 0.03±0.00 mg/kg was observed in the Kidney of Sheep, while the lo west value of 0.02±0.00 mg/kg, was detected in the kidney of cattle. However, Pb was not detected in the Kidney of Goats. Results from this findings were below the Codex standards for Pb in meat (0.1 mg/kg) and 0.5 mg/kg for edible offals of Cattle (SON/WHO, 2011). This is in agreement with the study conducted by [39] who reported that Pb was not detected in the Kidney of Goats. In a Similar study by [40] 0.04±0.20 mg/kg was obtained kidney of sheep but not detected in the Kidney of Goats. This is not in agreement with the findings of [11] that reported high concentration of Pb in the Kidney of Cattle as 0.15±0.01 mg/kg from Kasuwan Shanu market in Maiduguri metropolis and the finding of [22] that obtained higher concentration of Pb 0.17±0.05 mg/kg in the Kidney of cow from jimeta Central Abattoir.

The variations in the levels of Heavy metals in the Meat samples might be due to Differences in the level of Exposure that the Animals had to Heavy metals in their Environment. This can depend on where the Animals were raised, as Different Geographical Locations may have varying amount of Heavy metals in their Soil, the use of contaminated water or Equipment during processing or handling of the meat and the type of feed given to animals leading to Different levels of Accumulation in Animals [41].

V. CONCLUSION

The study successfully determined the concentrations of Cr, Cd, Pb and Zn in the liver, heart and kidney of cattle, goat and sheep from Hadejia Abattoi**r.**

Zinc levels are Above the permissible limit but other Heavy metals (Cr, Cd, and Pb) are within the safe limits set by WHO and SON. This suggest that the Cattle, Goat and Sheep in Hadejia Abattoir might have been exposed to high level of Zinc, but other Metals are not a concern. This high Concentration of Zinc might come from the Ingestion of Food and water that is high in zinc by Cattle, Goat and Sheep. Therefore Liver, Heart and Kidney of Cattle, Goat and Sheep from Hadejia central Abbatior might not to be safe for Consumption with regard to Zn concentrations. However, they might be safe for consumption with respect to observed concentrations of Cr, Cd and Pb. The present study has exposed the potential risk associated with consumption of these organs considering the high concentration of zinc detected in them. Further Research should be carried out to ensure that these toxic metals are maintained at an acceptable limit. Also because of the priority the Recent study has Accorded to the safety of the peoples consuming this meat, other toxic metals and vital organs not considered in this Research should also be studied

CONFLICT OF INTEREST

The Authors have declares that no conflict of interest exist

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Early Laboratory Packet Diagnosis for Successful Fighting MDS and AML (ITP and LGC)

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Abstract— *RNAi induce variable mutation which the prevalence is very high nowadays, ever diagnose Large Granular Chronic (LGC) patients.*

Problem: *High prevalence of mortality cases in ITP, MDS, and AML in which the complaint is only nausea/ vomitus, bloated, fatigue or lethargic, and progress to deadly ITP/AML we meet in everyday practice. Anemia and thrombocytopenia progress to death of ITP/AML in 2 weeks- 5 months after first time hospitalized to get transfusion and dextrose 5% infusion for the used-up energy/ glycogen in the liver. The laboratory packet should support "bridge therapy" to surgery or invasive procedure, splenectomy and or chemotherapy. Method: Case report and review of my Library recommendation of Google Scholar, ChatGPT, elaborate to ScienceDirect and EBSCOHost MEDLINE full text. Recorded all the Laboratory found in the case report and references.*

Result: Case Report and References of Dx/ associated with phases of ITP/MDS/AML.

Discussion: Laboratory of the symptoms in each phase ITP and MDS/AML. Conclusion: Complex biomarker vs. simple laboratory packet in early RNAi induce ITP and AML in the mapping of ITP/AML phase to fight high mortality, stay calm with right nutrition to support the body metabolism of ITP progression to AML/ MDS. High Protein Low Carbohydrate on low Albumin plasma is already built-in in all phases.

Keywords— Hemoglobin, Platelet count, Thrombopoietin, Aplastic Anemia, ITP, Splenectomy.

I. INTRODUCTION

Anemia and thrombocytopenia progress to dead of Immune Thrombocytopenia /Acute Myeloid Leukemia (ITP/AML) in 2 weeks- 5 months after first time hospitalized to get Red Blood Cell (RBC) transfusion, and dextrose 5% infusion for the used up depleted energy/ glycogen in the liver, are often high prevalence causes of this disease in our everyday practice.[1] The patients come with nausea/vomitus complaint, later, loss of appetite. Broad diagnosis and Differential Diagnosis from typhus to DHF, hepatitis, and feverish observation-hypoglycemic become high-cost, laboratory and imaging investigation, whereas clonal hematopoiesis (CH) is a common premalignant state.[2] The aims of this study is to reveal the Laboratory Parsimony packet in the progress advancing hematologic malignancy in all phases to support the curing phase and tapering off. Hypothesis: Hemoglobin and platelet count lead the whole phase of chronic Myelodysplastic Syndrome (MDS)/AML, which thrombopoietin (TPO) level could play a role in classifying disease severity in AA and ITP.[3] Patients with thrombocytopenia usually do not experience serious bleeding until their platelet count is very low. Previous studies have defined a new inflammatory index induce ITP, and the progression to MDS, then AML.

II. METHOD

Case report and review on hybrid My library recommendation of Google Scholar, ChatGPT, and academic search engine ScienceDirect, and EBSCOHost MEDLINE with Full Text. Inclusive and exclusive using keywords ITP/AML/MDS laboratory with Bayesian network and analysis.

III. RESULTS

Case Report and References of diagnosis associated with phase of ITP/AML/MDS. This anemia and thrombocytopenia cases ends with mortality post splenectomy, cauda pancreatectomy, or post chemotherapy full or half dose. The complete clinical and hematology response, the relapsed/refractory autoimmune cytopenia, chronic refractory ITP,[4] complete remission with and without venetoclax.[5]

MDS develops to AML, which is cancer of the white blood cells. This is known as the "transformation" phase. It can take a few months or up to several years before transformation takes place.[6] Transformation of MDS to AML: A case with whole-body 2-[F18] fluoro-2-deoxy-D-glucose positron emission tomography (PET).[6,7]

TABLE 1. THE PHASE OF ITP/MDS/AML: TRANSFORMATION

Packet Laboratory	DHF and other ssRNAi infection	ITP	MDS	AML
Hb	N	↓	↓↓	↓↓↓
Platelet account	↓	↓↓	↓↓↓	↓↓↓
Lymphocyte/Monocyte account	↓	↑↑	↑↑	↑↑↑

The decreasing of platelet count is in negatively correlation with disease severity, and positively with the prognosis of this ITP,[7] which is associated with splenomegaly.[8]

Albumin plasma level and nutritional status has also been made more clearly defined in various studies as a great significance factor affecting the prognosis.[9]

Inflammation reaction/ cytokine storm, and many arrangements of elements of inflammatory parameters have been used to estimate the prognosis.

The parameters should be validated, easily identifiable at diagnosis, and cost-effective.[9]

IV. DISCUSSION

Immune Thrombocytopenia (ITP) is an Autoimmune bleeding disorder characterized by excessive reticuloendothelial platelet (Mononuclear Phagocytic System) destruction & inadequate compensatory platelet production.[10]

MDS is a group of various bone marrow disorders which are being typical by the bone marrow not producing blood cells to a satisfactory. Patients in the early phase, absolute low blood counts cell or maybe need blood transfusion. But in the progressed phase, the patient's condition is not different with AML. This study recorded these three cases (ITP/MDS/AML) laboratory in the finding references in chronic unmanageable cases.[4] Entire blood count and a peripheral blood smear has also been stated. Haemoglobin, Albumin, Lymphocyte, Platelet (HALP) score which are the biomarkers of nutrition and inflammation status are monitored.[9] Pathogenesis of the symptoms in each phase ITP and AML/MDS induced by nutritional and inflammation status.[9] A streamline laboratory to intensify the diagnostic for detecting and the progression to MDS and AML.

Anemia vs. bleeding score,[4] & platelet count (thrombocytopenia) has been stated in Refractory cases. Anemia marks prognosis, figures the failure of the bone marrow to produce mature healthy cells is a gradual process. The anemia also relies on bleeding score, which is increased risk of bleeding in patients receiving anticoagulant, so a parameter prothrombin time (PT) and activated partial thromboplastin time (APTT), are evaluate to monitor the coagulation status of the patient. Both can describe the blood disorder of bleeding or clotting process. Hypercoagulation is also usual in hematology malignancy, should be monitored also by D-Dimer. Hyper aggregation means thick blood so that clotting or easy to become solid if the Hb is more than 18-19 gr/dL and hematocrit is more than 50-60%. Polycythemia vera and D-dimer are reported in these cases.

- Inflammation biomarker IL-1b, TNF, IL23, IL33, IFN3g, IFN-a2 where as IL-6, and IL-1b with the moment to first RBC transfusion for Dx/ and prognostic utility.[11]
- Plasmapheresis in cytokine storm phase while aspirin failed as rescue therapy.[12]
- Serum EPO position < 500U/L, 5FSB1 mutation status, and ring sideroblastic status.[13]
- Thrombocytopenia notice, and positive CMV IgG and IgM antibodies.[8]

Also, IgG and IgM of 4 serotype DENV especially -4 in endemic DHF area. Whereas routine hematology in all serotypes has different figures in hemoglobin, hematocrit, thrombocyte in each serotype. DENV2 has the highest hematocrit value, lowest thrombocytopenia, and lowest hemoglobin.[14] Lowest Leukocyte count is found in DENV-2, then followed by DENV-4, and DENV-3.[14]

CD 38,[4] CD 34 Blast, CD16-granulocytes.[15] is associated with antibodies differentiating the low & high-risk MDS patients. These 2 cases dead report of Lymphoma malignant ever report as Large Granular Lymphocytic Leukemia patient (Large Granular Chronic/LGC).

Pre-emptive discovery and evolution of relapse in AML by flow cytometric measurable residual disease surveillance, such as CD4, CD8, Hb and platelet count.[16]

Germline Genetic Evaluation in the maintenance of patients with MDS and AML challenged a traditional outpatient.[17] We already know and could chased mutation, but they are all associated with Hemoglobin, Albumin, Lymphocyte, and Platelet (HALP) count.[9]

Mutated JAK2 and variant allele frequency (VAF) in polycythemia vera and essential thrombocytopenia.[18] Another mutation is also reported, but all are in correlation with HALP and therapy genetic and epigenetic silencer. Ivermectin and Decitabine should not be sequencing again and again, the clinical symptom will figure the patient's condition. Associated with cytokine storm, bi-implicative, cytokine storm induce mutation and/ or mutation induce cytokine storm. HALP score as Prognostic factor xp MDS.[9] An FLT3 mutation is the most common genetic mutation in AML.[19] FMS-like tyrosine kinase 3 (FLT3). The FLT3 gene manages the production of fms-like tyrosine kinase 3 (FLT3). FLT3 is a protein that undertaking the growth and division of various cells, including some blood cells.

Enhancement of erythropoietic output by Cas9-mediated insertion of a natural variant in hematopoietic stem and progenitor cells (HSPCCs). Congenital erythrocytosis-the non-pathogenic hyper-production of RBCs-that is caused by a truncated erythropoietin receptor. Cas9-mediated genome editing in CD34+ human HSPCs can create again the truncated form of erythropoietin receptor, leading to substantial intensity in erythropoietic output.[20] These phenomena has been described and laboratory monitoring in application can only with hemoglobin level. Phase II clinical study anemia-thrombocytopenia, and in accordance with symptoms are observed and checked the progress. The primary trial endpoint was bone marrow response. The secondary endpoints included cause on diseases to happen such as anemia, thrombocytopenia.[21]

Gene editing support immunologic benefit for in utero gene editing in mice, and inform maternal preprocedural testing protocols and exclusion criteria for clinical trial caused by limiting postnatal gene editing.[22] CRISPR/Cas9 screens in mutant HSPCs are suggested as contributing factors to MDS and AML, which is mutant cells exist is depends on the genome and gene instability (epigenetic) cases.[2] Poly (ADP-ribose) polymerase (PARP) inhibition leads to synthetic lethality with key splicing-factor mutations in MDS.[23] PARP is a protein in cells that helps make good damaged DNA.

Impact of pacritinib on symptoms in with thrombocytopenia and myofibrosis who require RBC transfusion has been reported.[24]

A first-in-human phase 1, CB-012, a next-generation (NG) CRISPR-edited allogeneic anti-CLL-1 CAR-T cell therapy for adults with relapsed/refractory (RR) AML.[25]

NG CRISPR-edited allogeneic antiCLL-1 CAR-T cell therapy for adults with RR dose escalation portion, and this JAK-2 inhibitor have to be change by anti-inflammation storm such as aspirin and plasmapheresis. Does RR ITP/MDS/AML need HALP monitoring? Following each therapeutic dose doesn't need the recovery of mutant genetic/epigenetic, and clinical symptoms such as Quality of Life (QL), could substitute mutation and CDs test, enzyme, and physical fitness, not only

Hemoglobin, Albumin, Lymphocyte, Platelet Count (HALP) and TNF-a or CRP, and serum TPO. D-Dimer and PT APTT for knowing the first liner, and albumin plasma is now already covered by high protein low carbohydrate nutritional intake, and inflammation is covered by aspirin. Both are important factors affecting the progression of ITP/MDS/AML. Hemoglobin, albumin, lymphocyte, platelet has also been a new inflammatory index.[9]

V. LIMITATION

Phase of ITP/MDS/AML has not been specifically recorded in each reference, but the direction of the phase could already be seen. HALP, TNF-a/CRP, CDs without sequencing could fight the RR. The progression of MDS/AML should be elaborated. It is a transformation signaling phase matter.[6,7,8,9,11,15,119,21,23,25]

VI. CONCLUSION

Complex biomarker vs. simple laboratory packet in early RNAi induce ITP-MDS-AML in the mapping of ITP/AML phase to fight high mortality. Stay calm with right nutrition to support the body metabolism of ITP transformation to MDS/AML.

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CONFLICT OF INTERESTS

The author declares to not having vested interest into conflict of interest.

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Management of Root Rot Disease in Soybean

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Abstract— *A field experiment was conducted at Agricultural Research Station, S. D. Agricultural University, Ladol during 2019-20, 2020-21 and 2021-22 for management of root rot disease in soybean. The eight different treatments were evaluated. Based on pooled data of three years, the result revealed that minimum mean disease incidence (2.45%) was observed with seed treatment of Penflufen 13.28 % + Trifloxystrobin 13.28 % FS found lowest per cent disease incidence in throughout the crop season in all three years followed by seed treatment with Thiophanate Methyl 45 % + Pyraclostrobin 5 % FS (2.95%).*

Keywords— Soybean, Root rot, Fungicides, Seed treatments and Grain yield.

I. INTRODUCTION

Soybean (*Glycine max* L.) having both protein and oil, is an important oilseed crop. Cultivation of soybean in India was negligible till 1970, but Production increased rapidly thereafter, crossing over 11.87 million tonnes in 2023-24 (Anon. 2023). In India, annual losses due to various diseases are estimated as 12 per cent of its total production (M. Santha, 2007). More than hundreds of pathogens are known to affect soybean where sixty-six fungi, six bacteria, eight viruses and seven nematodes (Sinclair, 1978). Among these, soil borne diseases like root rot or collar rot caused by *Rhizoctonia* sp., *Sclerotium rolfsii* and *Fusarium* sp. are gaining more importance as they reduce plant population in the field resulting in the heavy yield losses. The pathogens are soil inhabitants and polyphagous facultative parasites. Muthusamy and Mariappan (1991) reported 77 per cent losses due to *Rhizoctonia bataticola* and 14 – 74 per cent due to *Sclerotium rolfsii*. Manglekar and Raut (1997) have reported 30 per cent yield loss in soybean due to Rhizoctonia root/stem rot in Vidharbha region of Maharashtra. In Gujarat, this disease occurs every year and contributing to yield loss in unsprayed crop of the farmers. Therefore, an experiment was conducting to investigate the performances of fungicides under this agro-climatic region which can reduce loss with effective and economic approach.

II. MATERIALS AND METHODOLOGY

Soybean crop (*var*. NRC-37) was raised following standard agronomical practices adopting flood irrigation method on Agricultural Research Station, S. D. Agricultural University, Ladol. The experiment was laid out in a randomized block design with eight treatments including untreated control with three replications. The planting was done at spacing of 45 x 10 cm. The recommended dosage of fertilizers 45 kg N and 60 kg P per hectare was applied. Seeds treatment was imposed before the time of seeds sowing as per the treatments given. The per cent disease incidence of root rot was recorded at 45 DAS, 60 DAS, 75 DAS and 90 DAS by selecting total plants comes in net plot area in each representative plots.

Per cent disease incidence (PDI) was calculated by using the following formula:

$$PDI = \frac{No.of\ plant\ showing\ symptoms}{Total\ no.of\ plant\ observed} \times 100 \quad (1)$$

Based on these observations, per cent disease incidence (PDI) of soybean root rot was carried out. Yield (kg/ha) and economics of treatments were also calculated

TREATMENT DETAILS

Sr. No	Treatments	Dosage/100 kg seed	
		a.i. (g)	Formulation g/ml/100 kg seed
1	Seed Treatment with Carboxin 37.5 % + Thiram 37.5 % DS	2.25	300
2	Seed Treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS	15.4 + 15.4	100
3	Seed Treatment with Thiophanate Methyl 45 % + Pyraclostrobin 5 % FS	12.5	250
4	Seed Treatment with *Trichoderma harzianum* 1.0 % WP	10	1000
5	Seed Treatment with *Pseudomonas fluorescens* 1.0 % WP	10	1000
6	T_4 + Soil Application of *T. harzianum* 1.0 % WP + *Pseudomonas fluorescens* 1.0 % WP (Enrich with each 2.5 kg in FYM @ 250 kg/ha)	-	5 kg/ha
7	T_5 + Soil Application of *T. harzianum* 1.0 % WP + *Pseudomonas fluorescens* 1.0 % WP (Enrich with each 2.5 kg in FYM @250 kg/ha)	-	5 kg/ha
8	Untreated Control	-	-

III. RESULTS AND DISCUSSION

3.1 Percent disease incidence:

In soybean wilt disease was not observed during all three years So, the data on PDI of root rot disease of soybean was recorded periodically at 45, 60, 75 and 90 days after the sowing with different seed treatments. It is revealed from the data that there was significant difference in percent disease Incidence during 2019-20, 2020-21, and 2021-22 and pooled also (Table 1, 2, 3 and 4).

TABLE 1
EFFECT OF DIFFERENT TREATMENTS ON ROOT ROT DISEASE IN SOYABEAN IN 2019-20

Tr. No.	Treatment	Per cent disease incidence (PDI)				Pooled Mean
		45 DAS	60 DAS	75 DAS	90 DAS	
T_1	Seed Treatment with Carboxin 37.5 % + Thiram 37.5 % DS @ 3 g/kg of seed	10.18^{e}	9.65e	9.09^{e}	8.30^{de}	9.30^{de}
		-3.13	-2.82	-2.5	-2.09	-2.63
T_2	Seed Treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS @ 1 ml/kg of seed	9.28^{f}	8.70^{d}	8.09^{f}	6.38^{f}	8.11^{f}
		-2.61	-2.29	-1.98	-1.25	-2.03
T_3	Seed Treatment with Thiophanate Methyl 45 % + Pyraclostrobin 5 % FS@2.5 ml/kg of seed	10.00^{e}	9.46^{e}	8.70^{ef}	7.64^{e}	8.95^{ef}
		-3.03	-2.71	-2.29	-1.77	-2.45
T_4	Seed Treatment with *Trichoderma harzianum* 1.0 % WP @ 10 gm/kg of seed	12.64^{c}	12.36^{bc}	11.92^{c}	11.00^{bc}	11.98^{bc}
		-4.79	-4.59	-4.27	-3.65	-4.33
T_5	Seed Treatment with *Pseudomonas fluorescens* 1.0 % WP @ 10 gm/kg of seed	13.71^{b}	13.05^{b}	12.64^{b}	11.62^{b}	12.76^{b}
		-5.63	-5.11	-4.79	-4.06	-4.9
T_6	T_4 + Soil Application of *T. harzianum* 1.0 % WP + *Pseudomonas fluorescens* 1.0 % WP (Enrich with each 2.5 kg in FYM @ 250 kg/ha)	11.16^{d}	10.68^{d}	10.01^{d}	8.70^{d}	10.14^{d}
		-3.75	-3.44	-3.03	-2.29	-3.13
T_7	T_5 + Soil Application of *T. harzianum* 1.0 % WP + *Pseudomonas fluorescens* 1.0 % WP (Enrich with each 2.5 kg in FYM @250 kg/ha)	12.07^{c}	11.77^{c}	11.47^{c}	10.52^{c}	11.46^{c}
		-4.38	-4.17	-3.96	-3.34	-3.96
T_8	Untreated Control	14.47^{a}	14.84^{a}	15.31^{a}	16.55^{a}	15.29^{a}
		-6.25	-6.56	-6.98	-8.13	-6.98
S.Em.±	**Y**	-	-	-	-	0.08
	T	0.23	0.25	0.22	0.24	0.34
	Y x T	-	-	-	-	0.23
C.D. at 5%	**T**	0.69	0.75	0.66	0.73	0.99
	Y x T	-	-	-	-	0.66
C.V. %		3.37	3.76	3.45	4.14	3.67

Figures in parenthesis are retransformed values of arcsin transformation
Treatment mean with common letter(s) are not significant by DNMRT at 5% level of significance

Table 1 revealed per cent disease incidence in 2019-20, at 45 DAS seed treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS (2.61%) found significantly less disease incidence over rest of the treatments followed T3 and T1. At 60 DAS same trends were found where seed treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS (2.29%) recorded minimum disease incidence, which was followed T3 and T1. At 75 DAS, seed treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS (1.98%) was found repeatedly superior over rest of the treatment and at par with Thiophanate Methyl 45 % + Pyraclostrobin 5 % FS (2.29%). At 90 DAS, seed treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS (1.25%) found significantly less disease incidence over rest of the treatments. In pooled over period data indicated that seed Treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS (2.03%) found minimum disease incidence which was followed by seed treatment with Thiophanate Methyl 45 % + Pyraclostrobin 5 % FS (2.45%).

TABLE 2
EFFECT OF DIFFERENT TREATMENTS ON ROOT ROT DISEASE IN SOYABEAN IN 2020-21

Tr. No.	Treatment	Per cent disease incidence (PDI)				Pooled Mean
		45 DAS	60 DAS	75 DAS	90 DAS	
T_1	Seed Treatment with Carboxin 37.5 % + Thiram 37.5 % DS @ 3 g/kg of seed	12.09[cd]	11.47[cd]	10.17[c]	8.68[bc]	10.60[bcd]
		-4.4	-3.96	-3.13	-2.29	-3.44
T_2	Seed Treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS @ 1 ml/kg of seed	11.00[e]	10.67[e]	9.08[d]	7.16[c]	9.47[d]
		-3.65	-3.44	-2.5	-1.56	-2.79
T_3	Seed Treatment with Thiophanate Methyl 45 % + Pyraclostrobin 5 % FS@2.5 ml/kg of seed	11.65[de]	11.16[de]	9.64[cd]	8.49[bc]	10.23[cd]
		-4.08	-3.75	-2.81	-2.19	-3.21
T_4	Seed Treatment with *Trichoderma harzianum* 1.0 % WP @ 10 gm/kg of seed	12.53[bc]	12.08[bc]	11.77[b]	9.79[b]	11.54[bc]
		-4.71	-4.38	-4.17	-2.92	-4.05
T_5	Seed Treatment with *Pseudomonas fluorescens* 1.0 % WP @ 10 gm/kg of seed	12.91[b]	12.51[b]	11.77[b]	9.99[b]	11.80[b]
		-5	-4.7	-4.17	-3.02	-4.22
T_6	T_4 + Soil Application of *T. harzianum* 1.0 % WP + *Pseudomonas fluorescens* 1.0 % WP (Enrich with each 2.5 kg in FYM @ 250 kg/ha)	12.27[bcd]	11.63[cd]	11.00[b]	9.64[b]	11.14[bc]
		-4.52	-4.07	-3.65	-2.81	-3.76
T_7	T_5 + Soil Application of *T. harzianum* 1.0 % WP + *Pseudomonas fluorescens* 1.0 % WP (Enrich with each 2.5 kg in FYM @250 kg/ha)	12.39[bc]	11.78[cd]	11.16[b]	9.79[b]	11.28[bc]
		-4.61	-4.17	-3.75	-2.92	-3.86
T_8	Untreated Control	14.47[a]	15.19[a]	15.66[a]	15.55[a]	15.47[a]
		-6.25	-6.88	-7.29	-8.13	-7.14
S.Em.±	**Y**	-	-	-	-	0.11
	T	0.22	0.23	0.25	0.49	0.41
	Y x T	-	-	-	-	0.32
C.D. at 5%	**T**	0.66	0.7	0.77	1.5	1.22
	Y x T	-	-	-	-	0.91
C.V. %		3.03	3.32	3.9	8.54	4.84

Figures in parenthesis are retransformed values of arcsin transformation
Treatment mean with common letter(s) are not significant by DNMRT at 5% level of significance

Table 2 revealed that the disease incidence in 2020-21. At 45 DAS, seed treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS (3.65%) found significantly less disease incidence over rest of the treatments. At 60 DAS, same trends were found where seed treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS (3.44%) recorded minimum disease incidence, which was found at par with seed Treatment with Thiophanate Methyl 45 % + Pyraclostrobin 5 % FS (3.75%). At 75 DAS, seed treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS (2.50%) was found repeatedly superior over rest of the treatment which was found at par with T3. At 90 DAS, seed treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS (1.56%) found significantly less disease incidence over rest of the treatments. In pooled over period data indicated that seed Treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS (2.79%) found minimum disease incidence which was found at par with seed treatment with Thiophanate Methyl 45 % + Pyraclostrobin 5 % FS (3.21%) and seed Treatment with Carboxin 37.5 % + Thiram 37.5 % DS (3.44%)

TABLE 3
EFFECT OF DIFFERENT TREATMENTS ON ROOT ROT DISEASE IN SOYABEAN IN 2021-22

Tr. No.	Treatment	Per cent disease incidence (PDI)				Pooled Mean
		45 DAS	60 DAS	75 DAS	90 DAS	
T_1	Seed Treatment with Carboxin 37.5 % + Thiram 37.5 % DS @ 3 g/kg of seed	11.99^{de}	11.30^{de}	10.16^{c}	9.39^{b}	10.71^{bc}
		-4.32	-3.85	-3.12	-2.69	-3.5
T_2	Seed Treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS @ 1 ml/kg of seed	9.33^{f}	10.60^{e}	8.95^{d}	7.25^{c}	9.03^{d}
		-2.63	-3.39	-2.43	-1.61	-2.52
T_3	Seed Treatment with Thiophanate Methyl 45 % + Pyraclostrobin 5 % FS@2.5 ml/kg of seed	11.50^{e}	10.98^{e}	9.73^{cd}	8.63^{bc}	10.21^{cd}
		-3.98	-3.64	-2.87	-2.26	-3.19
T_4	Seed Treatment with *Trichoderma harzianum* 1.0 % WP @ 10 gm/kg of seed	12.69^{bc}	12.24^{bc}	11.84^{b}	10.04^{b}	11.70^{b}
		-4.83	-4.5	-4.21	-3.07	-4.15
T_5	Seed Treatment with *Pseudomonas fluorescens* 1.0 % WP @ 10 gm/kg of seed	13.09^{b}	12.65^{b}	11.89^{b}	10.33^{b}	11.99^{b}
		-5.13	-4.8	-4.25	-3.23	-4.35
T_6	T_4 + Soil Application of *T. harzianum* 1.0 % WP + *Pseudomonas fluorescens* 1.0 % WP (Enrich with each 2.5 kg in FYM @ 250 kg/ha)	12.18^{cd}	11.85^{cd}	11.16^{b}	9.78^{b}	11.24^{bc}
		-4.45	-4.22	-3.75	-2.9	-3.83
T_7	T_5 + Soil Application of *T. harzianum* 1.0 % WP + *Pseudomonas fluorescens* 1.0 % WP (Enrich with each 2.5 kg in FYM @250 kg/ha)	12.55^{bcd}	11.88^{cd}	11.47^{b}	10.09^{b}	11.50^{b}
		-4.73	-4.25	-3.96	-3.11	-4.01
T_8	Untreated Control	14.60a	15.51^{a}	15.87^{a}	16.75^{a}	15.68^{a}
		-6.36	-7.16	-7.48	-8.32	-7.33
S.Em.±	**Y**	-	-	-	-	0.12
	T	0.2	0.24	0.26	0.54	0.39
	Y x T	-	-	-	-	0.34
C.D. at 5%	**T**	0.6	0.73	0.79	1.65	1.14
	Y x T	-	-	-	-	0.96
C.V. %		2.81	3.44	3.95	9.14	5.1

Figures in parenthesis are retransformed values of arcsin transformation
Treatment mean with common letter(s) are not significant by DNMRT at 5% level of significance

Table 3 revealed that the disease incidence. In 2021-22, At 45 DAS, seed treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS (2.63%) found minimum disease incidence which was followed by T3 and T1. At 60 DAS, seed treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS (3.39%) found repeatedly superior over rest of the treatment, which was found at par with seed Treatment with Thiophanate Methyl 45 % + Pyraclostrobin 5 % FS (3.64%). At 75 DAS, seed treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS (2.43%) was found lower disease incidence, it was found at par with T3. At 90 DAS, seed treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS (1.61%) found significantly less disease incidence over rest of the treatments. In pooled over peroid data indicated that seed Treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS (2.52%) significantly lower percent disease intensity as compared to control (7.25%), it was found at par with T3 (3.19%).

In pooled over year analysis seed treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS (2.45%) found lowest per cent disease incidence in throughout the crop season in all three years followed by seed treatment with Thiophanate Methyl 45 % + Pyraclostrobin 5 % FS (2.95%)

3.2 Yield:

Effect of different treatments on soyabean grain yield was found significant as compared to untreated check during all the years and pooled also (Table 5). During the year 2019-20 to 2021-22, seed Treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS was found very effective against soil borne diseases of soybean. The grain yield was recorded significantly higher over rest of the treatments. In 2019-20, treatment T2 *i.e.* seed Treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS recorded maximum grain yield (18.10 q/ha) and it was found at par with treatments T3, T1, T6 and T7. In second year (2020-21) same trends were recorded in grain yield. Treatment T2 *i.e.* seed Treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS repeatedly showed superior performance of grain yield. In the last year (2021-22) also where it was recorded 18.35 q/ha and it was found at par with T3, T1 and T6. In case of pooled yield, the maximum yield was recorded from treatment T2. It showed maximum grain yield 18.01 q/ha. Treatment T3 *i.e.* seed Treatment with Thiophanate Methyl 45 % + Pyraclostrobin 5 % FS was also found statistically very near with the treatments T2. Apart from all the treatments, treatment T3 and T1 were recorded at par with overall superior treatment T2.

TABLE 4
EFFECT OF DIFFERENT TREATMENTS ON ROOT ROT DISEASE OF SOYABEAN (POOLED OVER YEAR)

Tr. No.	Treatment	Per cent disease incidence (PDI)			Pooled Mean
		2019-20	2020-21	2021-22	
T_1	Seed Treatment with Carboxin 37.5 % + Thiram 37.5 % DS @ 3 g/kg of seed	9.30^{de}	10.60^{bcd}	10.71^{bc}	10.21^{de}
		-2.63	-3.44	-3.5	-3.19
T_2	Seed Treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS @ 1 ml/kg of seed	8.11^{f}	9.47^{d}	9.03^{d}	8.87^{f}
		-2.03	-2.79	-2.52	-2.45
T_3	Seed Treatment with Thiophanate Methyl 45 % + Pyraclostrobin 5 % FS@2.5 ml/kg of seed	8.95^{ef}	10.23^{cd}	10.21^{cd}	9.80^{e}
		-2.45	-3.21	-3.19	-2.95
T_4	Seed Treatment with *Trichoderma harzianum* 1.0 % WP @ 10 gm/kg of seed	11.98^{bc}	11.54^{bc}	11.70^{b}	11.74^{bc}
		-4.33	-4.05	-4.15	-4.18
T_5	Seed Treatment with *Pseudomonas fluorescens* 1.0 % WP @ 10 gm/kg of seed	12.76^{b}	11.80^{b}	11.99^{b}	12.18^{b}
		-4.9	-4.22	-4.35	-4.49
T_6	T_4 + Soil Application of *T. harzianum* 1.0 % WP + *Pseudomonas fluorescens* 1.0 % WP (Enrich with each 2.5 kg in FYM @ 250 kg/ha)	10.14^{d}	11.14^{bc}	11.24^{bc}	10.84^{cd}
		-3.13	-3.76	-3.83	-3.57
T_7	T_5 + Soil Application of *T. harzianum* 1.0 % WP + *Pseudomonas fluorescens* 1.0 % WP (Enrich with each 2.5 kg in FYM @250 kg/ha)	11.46^{c}	11.28^{bc}	11.50^{b}	11.41^{bc}
		-3.96	-3.86	-4.01	-3.94
T_8	Untreated Control	15.29^{a}	15.47^{a}	15.68^{a}	15.48^{a}
		-6.98	-7.14	-7.33	-7.15
S. Em.±	**Y**	0.08	0.11	0.12	0.05
	P	-	-	-	0.12
	T	0.34	0.41	0.39	0.29
	Y x P	-	-	-	0.11
	Y x T	0.23	0.32	0.34	0.16
	P x T	-	-	-	0.18
	Y x P x T	-	-	-	0.31
C.D. at 5%	**T**	0.99	1.22	1.14	0.88
	Y x T	0.66	0.91	0.96	0.44
	Y x P x T	-	-	-	NS
C.V. %		3.37	4.84	5.1	4.79

Figures in parenthesis are retransformed values of arcsin transformation
Treatment mean with common letter(s) are not significant by DNMRT at 5% level of significance

TABLE 5
EFFECT OF DIFFERENT TREATMENTS ON GRAIN YIELD OF SOYABEAN (POOLED)

Tr. No.	Treatment	Yield q/ha			Pooled Mean
		2019-20	**2020-21**	**2021-22**	
T_1	Seed Treatment with Carboxin 37.5 % + Tiram 37.5 % DS @ 3 g/kg of seed	16.22^{ab}	15.79^{ab}	16.40^{abc}	16.14^{ab}
T_2	Seed Treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS @ 1 ml/kg of seed	18.10^{a}	17.59^{a}	18.35^{a}	18.01^{a}
T_3	Seed Treatment with Thiophanate Methyl 45 % + Pyraclostrobin 5 % FS@2.5 ml/kg of seed	18.01^{a}	17.56^{a}	17.16^{ab}	17.57^{a}
T_4	Seed Treatment with *Trichoderma harzianum* 1.0 % WP @ 10 gm/kg of seed	14.05^{bc}	13.07^{b}	13.21^{cd}	13.44^{cd}
T_5	Seed Treatment with *Pseudomonas fluorescens* 1.0 % WP @ 10 gm/kg of seed	13.10^{bc}	13.06^{b}	13.12^{cd}	13.09^{cd}
T_6	T_4 + Soil Application of *T. harzianum* 1.0 % WP + *Pseudomonas fluorescens* 1.0 % WP (Enrich with each 2.5 kg in FYM @ 250 kg/ha)	15.36^{abc}	15.28^{ab}	16.12^{abc}	15.59^{b}
T_7	T_5 + Soil Application of *T. harzianum* 1.0 % WP + *Pseudomonas fluorescens* 1.0 % WP (Enrich with each 2.5 kg in FYM @250 kg/ha)	14.64^{abc}	14.48^{ab}	14.55^{bcd}	14.56^{bc}
T_8	Untreated Control	12.56^{c}	12.47^{b}	12.21^{d}	12.41^{d}
S. Em.±	**T**	1.07	1.18	1.12	0.65
	Y	-	-	-	0.4
	T x Y	-	-	-	0.65
C.D. at 5%	**T**	3.27	3.57	3.4	1.86
	Y x T	-	-	-	NS
C.V. %		12.23	13.66	12.84	12.91

Treatment mean with common letter(s) are not significant by DNMRT at 5% level of significance

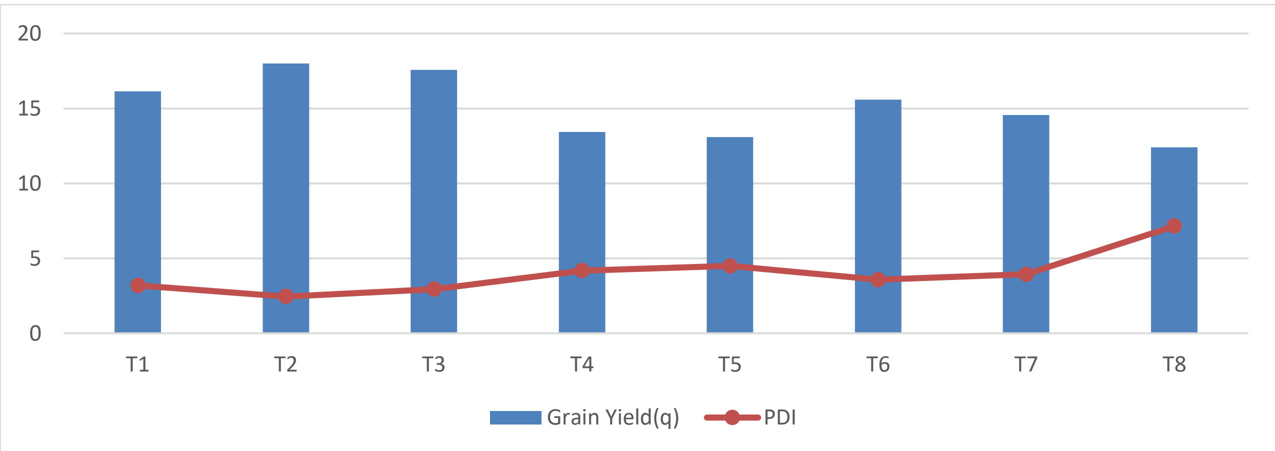

FIGURE 1: Effect of different treatments on per cent disease incidence and grain yield of soyabean (Pooled)

TABLE 6
ECONOMICS OF VARIOUS TREATMENTS

Tr.No.	Treatment	g or ml / 100kg of seed	Cost of material (Rs./ha)	Labour cost (Rs.)	Total cost of treatment (Rs.)	Yield (q/ha)	Gross realization (Rs./ha)	Net realization (Rs./ha)	Net gain (Rs./ha)	PCBR
T_1	Seed Treatment with Carboxin 37.5 % + Thiram 37.5 % DS	300	600	355	955	16.14	83928	19396	18441	01:19.3
T_2	Seed Treatment with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS	100	740	355	1095	18.01	93652	29120	28025	01:25.6
T_3	Seed Treatment with Thiophanate Methyl 45 % + Pyraclostrobin 5 % FS	250	600	355	955	17.57	91364	26832	25877	01:27.1
T_4	Seed Treatment with *Trichoderma harzianum* 1.0 % WP	1000	300	355	655	13.44	69888	5356	4701	01:07.2
T_5	Seed Treatment with *Pseudomonas fluorescens* 1.0 % WP	1000	390	355	745	13.09	68068	3536	2791	01:03.7
T_6	T_4 + Soil Application of *T. harzianum* 1.0 % WP + *Pseudomonas fluorescens* 1.0 % WP (Enrich with each 2.5 kg in FYM @ 250 kg/ha)	5 kg/ha	3025	1775	4800	1559	81068	16536	11736	01:02.4
T_7	T_5 + Soil Application of *T. harzianum* 1.0 % WP + *Pseudomonas fluorescens* 1.0 % WP (Enrich with each 2.5 kg in FYM @250 kg/ha)	5 kg/ha	3115	1775	4890	1456	75712	11180	6290	01:01.3
T_8	Untreated Control	-	-	-	-	12.41	64532	-	--	-

Labour cost: Rs. 355/- (for seed treatment) 2 labour extra for 2 days to enrich FYM and soil application, Soybean: Rs. 52/kg, FYM: Rs. 1000/- for 500 kg.

IV. CONCLUSION

Treat the seed with Penflufen 13.28 % + Trifloxystrobin 13.28 % FS at the rate of 1 ml/kg of seed for effective and economic management of root rot disease of soybean.

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Evaluation of different Insecticides against Sucking Pests Infesting Brinjal

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Abstract— *A field experiment was conducted at Agricultural Research Station, S. D. Agricultural University, Ladol during 2019-20, 2020-21, 2021-22 and 2022-23 for evaluation of different insecticides against sucking pests infesting brinjal. The eleven different treatments were evaluated. There was no any sucking pest infestation in kharif 2019-20. Based on pooled data of three years, Sulfoxaflor 21.8 SC 0.03 per cent @ 12.5 ml/10 liter of water recorded minimum white fly and jassid population (2.79/leaf and 1.21/leaf), no effect on predator and highest yield (286.61 q/ha) followed by Sulfoxaflor 21.8 SC 0.024 per cent @ 10 ml/10 liter of water and Cyantraniliprole 10.26 OD 0.0072 per cent @ 7.02 ml/10 liter of water.*

***Keywords—* Brinjal, Jassids, Whiteflies, LLB, Predator, Insecticides.**

I. INTRODUCTION

Brinjal, solanum melongena L. also known as eggplant belong to family solanaceae is cultivated in almost all the seasons across India. Brinjal is often described as the ‘King of vegetables ‘due to its versatility use in Indian food (Choudhary and Gaur, 2009). India is one of the largest producers of brinjal in the world. Due to its nutritive value, consisting of minerals like iron, phosphorous, calcium and vitamins like A, B and C, unripe fruits are used primarily as vegetable in the country. Brinjal is subjected to attack by number of insect pests right from nursery stage till harvesting (Regupathy et al., 1997). Among them, shoot and fruit borer, *Leucinodes orbonalis* (Guen.), whitefly, *Bemicia tabaci* (Genn.), leafhopper, *Amrasca biguttula biguttula* (Ishida) and red spider mite, *Tetranychus macfurlanei* (Baker and Pritchard). Of these, sucking pests is considered as one of the main constraints as it damages the crop throughout the year. The extensive and indiscriminate use of pesticides for controlling brinjal pests has led to several problems like resurgence of secondary pests, health hazards and pesticide residues in edible fruits (Kabir et al., 1996). The objective of the present investigation is to test the efficacy of newer insecticides for the management of sucking pests of brinjal.

II. MATERIALS AND METHODOLOGY

Brinjal (*var*. Guj. Anand oblong brinjal-2) was raised following standard agronomical practices adopting flood irrigation method on Agricultural Research Station, S. D. Agricultural University, Ladol. The experiment was laid out in a randomized block design with elevan treatments including untreated control with three replications. The planting was done at spacing of 90 x 60 cm. The recommended dosage of fertilizers 100 kg N, 50 kg P and 50 kg K per hectare was applied. The observations on population of sucking pests *viz*. aphid, jassid and white fly was recorded from five randomly selected plants per treatments. On each plant, three leaves (one each from bottom, middle and top portion of the plant) was observed for the pest count. Observation on sucking pests was recorded before spray and 1, 3, 5, 7 and 14 days after spray. Two foliar sprays were undertaken. 1st spray at ETL, 5 Insect population/leaf per plant and subsequent foliar spray made 15 days after first spray.

TREATMENT DETAILS:

Tr. No.	Treatments	Conc. (%)	Dose g.a.i./ha	Dose /10 lit water
1.	Thiamethoxam 25 WG	0.0084	42	3.36 g
2.	Cyantraniliprole 10.26 OD	0.0054	27	5.26 ml
3.	Cyantraniliprole 10.26 OD	0.0072	36	7.02 ml
4.	Cyantraniliprole 10.26 OD	0.0090	45	8.78 ml
5.	Sulfoxaflor 21.8 SC	0.0180	82	7.5 ml
6.	Sulfoxaflor 21.8 SC	0.0240	109	10 ml
7.	Sulfoxaflor 21.8 SC	0.0300	136	12.5 ml
8.	Flupyradifuron 17.9 EC	0.0067	32	3.75 ml
9	Flupyradifuron 17.9 EC	0.0089	43	5.0 ml
10.	Flupyradifuron 17.9 EC	0.0112	53	6.25 ml
11.	Untreated Control	--	--	--

III. RESULTS AND DISCUSSION

The results presented in table 1 to 6 showed effect of different insecticides on populations of sucking pests in brinjal. During entire period aphid populations is below ETL or less. There are no any sucking pests infestation during *kharif* 2019-20 in brinjal.

3.1 Efficacy of insecticides against white fly:

In pooled over year data of three years (Table 1), lowest white fly population (2.79/leaf) observed in Sulfoxaflor 21.8 SC 0.03 per cent @ 12.5 ml/10 liter of water which was followed by Sulfoxaflor 21.8 SC 0.024 per cent @ 10 ml/10 liter of water and Cyantraniliprole 10.26 OD 0.0072 per cent @ 7.02 ml/10 liter of water.

3.2 Efficacy of insecticides against jassid:

In pooled over year data of three years (Table 2), lowest jassid fly population (1.21/leaf) observed in Sulfoxaflor 21.8 SC 0.03 per cent @ 12.5 ml/10 liter of water the treatment which was followed by Sulfoxaflor 21.8 SC 0.024 per cent @ 10 ml/10 liter of water and Thiamethoxam 25 WG 0.0084 per cent @ 3.36 g/10 liter of water.

3.3 Effect of insecticides predator:

During the year 2020-21, 2021-22 and 2022-23, there was no significant difference observed among the mean population of predators at before spray and at different days after both the sprays (Table 3).

TABLE 1
EFFECT OF DIFFERENT INSECTICIDES ON WHITE FLY POPULATION IN BRINJAL (POOLED)

Sr. No.	Treatments	Conc. (%)	No. of white fly /leaf				Pooled over year
			Before spray	2020-21	2021-22	2022-23	
1	Thiamethoxam 25 WG	0.0084	2.87^{a}	1.90^{b}	1.97^{bc}	1.99^{bc}	1.95^{bcd}
			-7.54	-3.18	-3.45	-3.56	-3.4
2	Cyantraniliprole 10.26 OD	0.0054	2.89^{a}	1.90^{b}	1.99^{bc}	2.03^{bc}	1.97^{bcd}
			-7.49	-3.21	-3.54	-3.69	-3.48
3	Cyantraniliprole 10.26 OD	0.0072	2.89^{a}	1.87^{b}	1.96^{bc}	2.00^{bc}	1.94^{cd}
			-7.58	-3.1	-3.44	-3.6	-3.38
4	Cyantraniliprole 10.26 OD	0.009	2.88^{a}	1.90^{b}	1.95^{bc}	1.99^{bc}	1.94^{cd}
			-7.57	-3.19	-3.4	-3.54	-3.38
5	Sulfoxaflor 21.8 SC	0.018	2.87^{a}	1.92^{b}	1.96^{bc}	2.01^{bc}	1.96^{bcd}
			-7.56	-3.27	-3.45	-3.62	-3.45
6	Sulfoxaflor 21.8 SC	0.024	2.88^{a}	1.89^{b}	1.90^{c}	1.95^{c}	1.91^{d}
			-7.49	-3.13	-3.22	-3.43	-3.26
7	Sulfoxaflor 21.8 SC	0.03	2.87^{a}	1.70^{c}	1.77^{d}	1.86^{d}	1.78^{e}
			-7.59	-2.52	-2.79	-3.06	-2.79
8	Flupyradifuron 17.9 EC	0.0067	2.86^{a}	1.94^{b}	2.03b	2.06^{b}	2.01^{b}
			-7.56	-3.38	-3.71	-3.83	-3.64
9	Flupyradifuron 17.9 EC	0.0089	2.89^{a}	1.93^{b}	2.02^{b}	2.04^{bc}	2.00^{bc}
			-7.59	-3.31	-3.68	-3.77	-3.59
10	Flupyradifuron 17.9 EC	0.0112	2.88^{a}	1.91^{b}	2.02^{b}	2.04^{bc}	1.99^{bc}
			-7.61	-3.24	-3.65	-3.75	-3.55
11	Untreated Control	--	2.90^{a}	2.69^{a}	2.73^{a}	2.77^{a}	2.73^{a}
			-7.59	-6.74	-6.99	-7.18	-6.97
S.Em.±		T	0.05	0.03	0.03	0.03	0.02
		P	-	0.02	0.02	0.02	0.01
		S	-	0.01	0.01	0.01	0.01
		Y	0.03	-	-	-	0.01
		T×P	-	0.06	0.07	0.07	0.04
		T×S	-	0.04	0.05	0.05	0.02
		P×S	-	0.03	0.03	0.03	0.02
		Y×T	0.11	-	-	-	0.03
		Y×P	-	-	-	-	0.02
		Y×S	-	-	-	-	0.01
		T×P×S	-	0.08	0.09	0.1	0.05
		Y×S×T	-	-	-	-	0.04
		Y×S×P	-	-	-	-	0.03
		Y×P×T	-	-	-	-	0.07
		Y×S×P×T	-	-	-	-	0.09
C. D. at 5%		T	NS	0.07	0.08	0.09	0.05
		Y×S×P×T	-	-	-	-	NS
C.V. (%)			6.39	7.2	7.83	8.44	7.86

Figures in parentheses are retransformed values, those outside are $\sqrt{x + 0.5}$ ***transformed values***

Treatment means with the letter(s) in common are not significant by DNMRT at 5% level of significance

TABLE 2
EFFECT OF DIFFERENT INSECTICIDES ON JASSID POPULATION IN BRINJAL (POOLED)

Sr. No.	Treatments	Conc. (%)	No. of jassid /leaf				Pooled over year
			Before spray	2020-21	2021-22	2022-23	
1	Thiamethoxam 25 WG	0.0084	1.80^{a}	1.36^{b}	1.44^{bc}	1.46^{b}	1.42^{de}
			-2.73	-1.36	-1.59	-1.65	-1.53
2	Cyantraniliprole 10.26 OD	0.0054	1.80^{a}	1.39^{b}	1.46^{bc}	1.50^{b}	1.45^{bcd}
			-2.75	-1.44	-1.64	-1.77	-1.62
3	Cyantraniliprole 10.26 OD	0.0072	1.80^{a}	1.37^{b}	1.45^{bc}	1.48^{b}	1.43^{cde}
			-2.76	-1.38	-1.62	-1.72	-1.57
4	Cyantraniliprole 10.26 OD	0.009	1.79^{a}	1.36^{b}	1.44^{bc}	1.48^{b}	1.43^{cde}
			-2.72	-1.37	-1.6	-1.7	-1.56
5	Sulfoxaflor 21.8 SC	0.018	1.76^{a}	1.38^{b}	1.45^{bc}	1.48^{b}	1.43^{cde}
			-2.61	-1.42	-1.6	-1.71	-1.58
6	Sulfoxaflor 21.8 SC	0.024	1.79^{a}	1.35^{b}	1.41^{c}	1.44^{b}	1.40^{e}
			-2.73	-1.35	-1.51	-1.61	-1.49
7	Sulfoxaflor 21.8 SC	0.03	1.78^{a}	1.26^{c}	1.29^{d}	1.35^{c}	1.30^{f}
			-2.7	-1.09	-1.19	-1.35	-1.21
8	Flupyradifuron 17.9 EC	0.0067	1.77^{a}	1.39^{b}	1.50^{b}	1.53^{b}	1.48^{b}
			-2.67	-1.46	-1.78	-1.87	-1.7
9	Flupyradifuron 17.9 EC	0.0089	1.76^{a}	1.39^{b}	1.48^{b}	1.51^{b}	1.46^{bc}
			-2.62	-1.46	-1.72	-1.8	-1.66
10	Flupyradifuron 17.9 EC	0.0112	1.75^{a}	1.36^{b}	1.47^{bc}	1.50^{b}	1.74^{a}
			-2.59	-1.37	-1.68	-1.76	-1.6
11	Untreated Control	--	1.81^{a}	1.72^{a}	1.76^{a}	1.80^{a}	1.76^{a}
			-2.75	-2.46	-2.62	-2.76	-2.61
S.Em.±		T	0.05	0.02	0.02	0.03	0.01
		P	-	0.03	0.02	0.02	0.01
		S	-	0.01	0.01	0.01	0.06
		Y	0.03	-	-	-	0.07
		T×P	-	0.04	0.06	0.04	0.03
		T×S	-	0.03	0.04	0.03	0.02
		P×S	-	0.02	0.02	0.02	0.01
		Y×T	0.09	-	-	-	0.02
		Y×P	-	-	-	-	0.02
		Y×S	-	-	-	-	0.01
		T×P×S	-	0.06	0.08	0.08	0.04
		Y×S×T	-	-	-	-	0.03
		Y×S×P	-	-	-	-	0.02
		Y×P×T	-	-	-	-	0.05
		Y×S×P×T	-	-	-	-	0.07
C. D. at 5%		T	NS	0.06	0.07	0.07	0.04
		Y×S×P×T	-	-	-	-	NS
C.V. (%)			9.11	7.78	9.13	9.3	9.13

Figures in parentheses are retransformed values, those outside are $\sqrt{x+0.5}$ transformed values

Treatment means with the letter(s) in common are not significant by DNMRT at 5% level of significance

TABLE 3
EFFECT OF DIFFERENT INSECTICIDES ON PREDATOR POPULATION IN BRINJAL (POOLED)

Sr. No.	Treatments	Conc. (%)	No. of predator/plant				Pooled over year
			Before spray	2020-21	2021-22	2022-23	
1	Thiamethoxam 25 WG	0.0084	1.20^{a}	1.07^{bc}	1.10^{c}	1.20^{c}	1.12^{cd}
			-1.16	-0.67	-0.72	-0.95	-0.78
2	Cyantraniliprole 10.26 OD	0.0054	1.22^{a}	1.07^{bc}	1.11^{c}	1.19^{c}	1.13^{cd}
			-1.16	-0.67	-0.74	-0.94	-0.78
3	Cyantraniliprole 10.26 OD	0.0072	1.20^{a}	1.05^{c}	1.10^{c}	1.20^{c}	1.12^{cd}
			-1.18	-0.62	-0.73	-0.94	-0.76
4	Cyantraniliprole 10.26 OD	0.009	1.24^{a}	1.07^{bc}	1.12^{c}	1.20^{c}	1.13^{cd}
			-1.24	-0.66	-0.78	-0.95	-0.8
5	Sulfoxaflor 21.8 SC	0.018	1.22^{a}	1.09^{bc}	1.13^{bc}	1.21^{bc}	1.14^{cd}
			-1.2	-0.69	-0.79	-0.98	-0.82
6	Sulfoxaflor 21.8 SC	0.024	1.24^{a}	1.09^{bc}	1.15^{bc}	1.22^{bc}	1.15^{c}
			-1.2	-0.69	-0.84	-1.01	-0.85
7	Sulfoxaflor 21.8 SC	0.03	1.23^{a}	1.13^{b}	1.19^{b}	1.27^{b}	1.20^{b}
			-1.16	-0.8	-0.93	-1.12	-0.95
8	Flupyradifuron 17.9 EC	0.0067	1.23^{a}	1.06^{c}	1.10^{c}	1.18^{c}	1.11^{d}
			-1.22	-0.64	-0.71	-0.89	-0.75
9	Flupyradifuron 17.9 EC	0.0089	1.21^{a}	1.06^{c}	1.11^{c}	1.20^{c}	1.12^{cd}
			-1.22	-0.64	-0.74	-0.95	-0.78
10	Flupyradifuron 17.9 EC	0.0112	1.22^{a}	1.08^{bc}	1.11^{c}	1.20^{c}	1.13^{cd}
			-1.24	-0.64	-0.75	-0.95	-0.78
11	Untreated Control	--	1.30^{a}	1.24^{a}	1.29^{a}	1.35^{a}	1.29^{a}
			-1.22	-1.03	-1.18	-1.34	-1.18
S.Em.±		T	0.03	0.02	0.02	0.02	0.01
		P	-	0.01	0.01	0.01	0.01
		S	-	0.01	0.01	0.01	0.01
		Y	0.02	-	-	-	0.01
		T×P	-	0.04	0.03	0.05	0.03
		T×S	-	0.02	0.03	0.03	0.02
		P×S	-	0.02	0.02	0.02	0.01
		Y×T	0.06	-	-	-	0.02
		Y×P	-	-	-	-	0.01
		Y×S	-	-	-	-	0.01
		T×P×S	-	0.05	0.05	0.07	0.04
		Y×S×T	-	-	-	-	0.02
		Y×S×P	-	-	-	-	0.03
		Y×P×T	-	-	-	-	0.02
		Y×S×P×T	-	-	-	-	0.04
C. D. at 5%		T	NS	0.05	NS	NS	0.03
		Y×S×P×T	-	-	-	-	NS
C.V. (%)			8.61	8.41	10.27	9.23	8.41

Figures in parentheses are retransformed values, those outside are $\sqrt{x + 0.5}$ ***transformed values***

Treatment means with the letter(s) in common are not significant by DNMRT at 5% level of significance

3.4 Impact on yield:

The data on brinjal yield presented in Table 4 clearly reveled that plot sprayed with sulfoxaflor 21.8 SC 0.03 per cent @ 12.5 ml/10 liter of water recorded maximum yield duringfirst (286.61 q/ha) followed by the treatment sulfoxaflor 21.8 SC 0.024 per cent @ 10 ml/10 liter of water (255.68 q/ha) and Thiamethoxam 25 WG 0.0084 per cent @ 3.36 g/10 liter of water (248.97). While Lowest yield was observed in untreated control with 182.24 q/ha.

3.5 % LLB (Little leaf of brinjal) infestation:

There was no significant difference in % BLB infestation observed among all the treatments. Minimum % BLB infestation (4.36%) was observed in the plots treated with Sulfoxaflor 21.8 SC, 0.0300% (Table 5).

3.6 Pesticide Residue Analysis:

Pesticide residue analysis for the best treatment was made at Bio science Research Centre, S. D. Agricultural University, Sardarkrushinagar and it can be seen from the results that the residue of sulfoxaflor 21.8 SC 0.03 per cent @ 12.5 ml/10 liter of water was found below quantification limit (Table 6).

TABLE 4
EFFECT OF DIFFERENT INSECTICIDES ON FRUIT YIELD OF BRINJAL (POOLED)

Sr. No.	Treatments	Conc. (%)	Yield (q/ha)			
			2020-21	2021-22	2022-23	Pooled over year
1	Thiamethoxam 25 WG	0.0084	218.64^{abc}	244.69^{b}	283.58^{ab}	248.97^{bc}
2	Cyantraniliprole 10.26 OD	0.0054	189.81^{cd}	221.54^{bc}	251.11^{abc}	220.82^{de}
3	Cyantraniliprole 10.26 OD	0.0072	200.86^{bcd}	228.52^{b}	260.31^{abc}	229.90^{bcde}
4	Cyantraniliprole 10.26 OD	0.009	215.12^{abc}	245.19^{b}	274.14^{ab}	244.81^{bcd}
5	Sulfoxaflor 21.8 SC	0.018	211.23^{bc}	239.81^{b}	274.32^{ab}	241.79^{bcde}
6	Sulfoxaflor 21.8 SC	0.024	232.04^{ab}	251.85^{ab}	283.15^{ab}	255.68^{b}
7	Sulfoxaflor 21.8 SC	0.03	249.88^{a}	288.95^{a}	320.99^{a}	286.61^{a}
8	Flupyradifuron 17.9 EC	0.0067	196.05^{bcd}	209.88^{bc}	242.04^{bc}	215.99^{e}
9	Flupyradifuron 17.9 EC	0.0089	205.62^{bcd}	216.30^{bc}	239.38^{bc}	220.43^{de}
10	Flupyradifuron 17.9 EC	0.0112	206.98^{bcd}	217.35^{bc}	250.55^{abc}	224.96^{cde}
11	Untreated Control	--	169.57^{d}	184.51^{c}	192.66^{c}	182.24^{f}
S.Em.±		T	11.89	12.91	20.97	8.21
		Y	-	-	-	4.76
		Y×T	-	-	-	15.89
C. D. at 5%		T	35.08	38.08	61.86	23.11
		Y ×T	-	-		NS
C.V. (%)			9.87	9.65	13.91	11.69

Treatment means with the letter(s) in common are not significant by DNMRT at 5% level ofsignificance

TABLE 5
EFFECT OF DIFFERENT INSECTICIDES ON LLB INFESTATION IN BRINJAL (POOLED).

Sr. No.	Treatments	Conc. (%)	LLB infestation (%)			
			2020-21	2021-22	2022-23	Pooled over year
1	Thiamethoxam 25 WG	0.0084	12.42^{a}	13.96^{a}	13.10^{b}	13.59^{cde}
			-4.76	-5.95	-4.76	-5.16
2	Cyantraniliprole 10.26 OD	0.0054	13.96^{a}	16.36^{a}	15.74^{ab}	15.74^{abcd}
			-5.95	-8.33	-7.14	-7.14
3	Cyantraniliprole 10.26 OD	0.0072	12.42^{a}	15.16^{a}	15.74^{ab}	14.86^{abcde}
			-4.76	-7.14	-7.14	-6.35
4	Cyantraniliprole 10.26 OD	0.009	10.89^{a} (3.76)	13.96^{a}	13.10^{b}	13.10^{de}
				-5.95	-4.76	-4.82
5	Sulfoxaflor 21.8 SC	0.018	12.42^{a} (4.76)	15.16^{a}	15.75^{ab}	14.86^{abcde}
				-7.14	-7.14	-76.35
6	Sulfoxaflor 21.8 SC	0.024	12.42^{a} (4.76)	15.49^{a}	14.57^{ab}	14.57^{bcde}
				-7.14	-5.95	-5.95
7	Sulfoxaflor 21.8 SC	0.03	10.89^{a} (3.57)	12.42^{a}	13.10^{b}	12.61^{e}
				-4.76	-4.76	-4.36
8	Flupyradifuron 17.9 EC	0.0067	13.96^{a} (5.95)	17.89^{a}	18.38^{a}	17.11^{ab}
				-9.52	-9.52	-8.33
9	Flupyradifuron 17.9 EC	0.0089	13.96^{a} (5.95)	17.89^{a}	17.21^{ab}	16.72^{ab}
				-9.52	-9.52	-8.33
10	Flupyradifuron 17.9 EC	0.0112	12.42^{a} (4.76)	16.69^{a}	17.21^{ab}	15.84^{abc}
				-8.33	-8.33	-7.14
11	Untreated Control	--	15.16^{a} (7.14)	17.89^{a}	18.38^{a}	17.50^{a}
				-9.52	-9.52	-8.73
S.Em.±		T	1.56	1.758	1.5	0.81
		Y	-	-	-	0.47
		Y×T	-	-	-	1.57
C. D. at 5%		T	NS	NS	NS	2.27
		Y ×T	-	-		NS
C.V. (%)			21.08	19.372	16.62	17.93

Treatment means with the letter(s) in common are not significant by DNMRT at 5% level of significance

TABLE 6
PESTICIDE RESIDUE ANALYSIS FROM THE FRUIT OF BRINJAL

Sr. No.	Sample Name	Pesticide tested	Results ppm	LoD ppm	LoQ ppm	Maximum residue limits MRL (ppm) in raw feed		
						Codex	EU	Other country
1.00	Harvest after spray “0” day	Sulfoxaflor	BQL	0.00	0.01	1.5 Vegetables	0.30	2.00
2.00	Harvest after spray “1” day	Sulfoxaflor	BQL					
3.00	Harvest after spray “3” day	Sulfoxaflor	BQL					
4.00	Harvest after spray “5” day	Sulfoxaflor	BQL					
5.00	Harvest after spray “7” day	Sulfoxaflor	BQL					
6.00	Harvest after spray “14” day	Sulfoxaflor	BQL					
7.00	Untreated Control	Sulfoxaflor	BDL					

IV. CONCLUSION

Sulfoxaflor 21.8 SC 0.03 per cent @ 12.5 ml/10 liter of water recorded minimum white fly and jassid population, no effect on predator and highest yield and proved to be the most effective treatment against sucking pests of brinjal.

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Application of Remote Sensing in Horticulture Precision Farming System- A Review

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Abstract— *Horticulture crops play significant role in improving the productivity of land, generating employment, enhancing exports, improving economic conditions of the farmers and entrepreneurs and providing food and nutritional security to the people. For better management of the existing crops and to bring more area under horticulture crops, updated and accurate database is necessary for systematic planning and decision making. Remote sensing (RS) is an advanced tool that aids in gathering and updating information to develop scientific management plans. Many types of sensors namely microwave radiometers, laser meters, magnetic sensors and cameras collect electromagnetic information to derive accurate, large-scale information about the Earth's surface and atmosphere. Because these data and images are digital, they can easily be quantified and manipulated using computers. RS can be used in efforts to reduce the risk and minimize damage. The same data can be analyzed in different ways for different applications. A number of studies were aiming at identification of crop, area estimation, disease and pest identification, etc. using satellite data in horticulture. The potential use of RS techniques in Horticulture is briefly reviewed in order to exploit the available techniques for efficient crop management.*

Keywords— Remote sensing, Crop acreage estimation, Crop growth monitoring, Crop stress detection, Yield assessment, Weather forecasting.

I. INTRODUCTION

Horticulture crops comprising of fruits, vegetables, flowers, spices, plantation crops and medicinal plants play a significant role in economy, employment, national self reliance, health, food and nutritional security of the country. During the past few years, horticulture development has emerged as one of the major thrust area in agriculture sector. For optimum utilization of available horticultural land resources on a sustainable basis, timely and reliable information regarding their nature, extent and spatial distribution along with their potential and limitations is very important. The key factors that contribute towards crop growth and production are different soil characteristics (soil pH, nutrient levels, drainage efficiency, texture, permeability and water holding capacity), climatic conditions (temperature, rainfall, solar radiation, chilling hours, growing degree days) and land-use type (soil properties, topography), plant population, fertilization, irrigation, and pest infestations. All these physical factors must be part of a geospatial database (Schumann and Zaman, 2003, Panda et al., 2011). RS systems due to regular, synoptic, multispectral and multi temporal coverage of an area provide accurate database on spectral behaviour of crops as well as their growing environment, i.e. soil and atmosphere.

II. AGRICULTURAL APPLICATIONS - BASIC ASPECTS

During the early stages of the satellite remote sensing, most researchers are focused on the use of data for classification of land cover types with crop types being a major focus among those interested in agricultural applications. In recent years, the work in agricultural remote sensing has focused more on characterization of plant biophysical properties. Remote sensing has long been used in monitoring and analyzing of agricultural activities. Remote sensing of agricultural canopies has provided valuable insights into various agronomic parameters. The advantage of remote sensing is its ability to provide repeated information without destructive sampling of the crop, which can be used for providing valuable information for precision agricultural applications. Remote sensing provides a cheap alternative for data acquisition over large geographical areas (De beurs and Townsend, 2008). In India, the satellite remote sensing is mainly used for the crop acreage and production estimation of agricultural crops.

III. CROP YIELD AND PRODUCTION FORECASTING

Remote sensing has been used to forecast crop yields primarily based upon statistical– empirical relationships between yield and vegetation indices (Thenkabail et al., 2002, Casa and Jones 2005).The information on production of crops before the harvest is important for national food policy planning. Reliable crop yield is an important component of crop production forecasting purpose. The crop yield is dependent on many factors such as crop variety, water and nutrient status of field, influence by weeds, pest and disease infestation, weather parameters. The spectral response curve is dependent on these factors. The growth and decay in the spectral response curve indicates the crop condition and its performance. By using IRS P3 WiFS (Wide Field Sensor) and IRS-1C WiFS and LISS3 which have a good periodicity, it may be possible to construct growth profiles and retrieve yield related parameters at region level (Menon, 2012).

IV. PRECISION HORTICULTURE

Remote sensing technology is a key component of precision farming and is being used by an increasing number of scientists, engineers and large-scale crop growers (Liaghat and Balasundram, 2010). The main aim of precision farming is reduced cost of cultivation, improved control and improved resource use efficiency with the help of information received by the sensors fitted in the farm machineries. Variable rate technology (VRT) is the most advanced component of precision farming. Sensors are mounted on the moving farm machineries containing a computer which provides input recommendation maps and thereby controls the application of inputs based on the information received from GPS receiver (NRC, 1997). The advantage of precision farming is the acquisition of information on crops at temporal frequency and spatial resolution required for making management decisions. Remote sensing is a no doubt valuable tool for providing such informations. Bagheri et al., (2013) used multispectral remote sensing for site- specific nitrogen fertilizer management. Satellite imagery from the advanced spaceborne thermal emission and reflection radiometer (Aster) was acquired in a 23 ha corn- planted area in Iran.

V. CONCLUSION

In conclusion, remote sensing has emerged as an indispensable tool for modern horticulture. Its ability to provide timely, spatially comprehensive, and non-destructive information on crop growth, health, and yield offers significant advantages over traditional ground-based methods. From monitoring crop acreage and assessing stress conditions to optimizing resource management through precision agriculture techniques, remote sensing empowers horticulturists with valuable insights for informed decision-making.

As remote sensing technology continues to evolve, with advancements in sensor technology, data processing algorithms, and integration with other data sources, its potential to revolutionize horticulture further is immense. Continued research and development are crucial to unlock the full potential of remote sensing in addressing the challenges and maximizing the opportunities within this vital sector.

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Integrated Management of Bacterial Leaf Blight of Rice under Field Condition

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Abstract— *The present study was conducted on evaluation of different fungicides, antibiotics and antagonists against bacterial blight disease under field conditions. Among them, combi fungicide streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v (200ppm)+ trifloxystrobin 25 + tebuconazole 50 (75WG) at 0.03 per cent was found significantly superior and most effective for the control of bacterial blight and recorded minimum disease intensity (26.28%), the highest grain yield (5.63 kg/plot), highest straw yield (7.08kg/plot) and the highest test grain weight (27.43g) which was statistically at par with streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v (200ppm) + azoxystrobin 18.2 + difenconazole 11.4 SC at 0.03 per cent. Followed by streptomycin sulphate 90 w/v + tetracycline hydrochloride 10 w/v at 1000ppm and copper oxychloride 50 WP at 1.25 per cent, respectively.*

Keywords— Rice, Bacterial Blight, Fungicides, Antibiotics, Bioagents.

I. INTRODUCTION

Rice (*Oryza sativa* L.) is often referred to as the "queen of cereal crops" due to its critical role as a staple food for roughly half of the global population (Qudsia *et al.*, 2017). Rice crop is not only vital for global food security but also plays a significant role in economic development, job creation, social stability, and regional peace (Yadev and Kumar, 2018). In the 2023-2024 period, global rice production reached approximately 518.14 million metric tons, marking a 0.87 percent increase. In India, the production was around 134 million metric tons, reflecting a 7 percent increase compared to the average over the previous five years. India cultivated rice on 43.66 million hectares, yielding 118.87 million tonnes with a productivity rate of 2722 kg per hectare (Anonymous, 2021). In contrast, Gujarat's rice cultivation covers 0.90 million hectares, producing 2.14 million tonnes with a yield of 2365 kg per hectare (Anonymous, 2022). Bacterial leaf blight caused by *Xanthomonas oryzae* pv. oryzae Ish. is found worldwide and particularly destructive in Asia. The disease was endemic in Bihar (Srivastava and Rao, 1963) and Tamil Nadu (Rajagopalan *et al.*, 1969). Reduction in rice yield may be as high as 50 per cent was also recorded, when the crop was severely infected (Mew *et al.*, 1993). It became a destructive disease of rice in Punjab and appeared in Ludhiana, Jalandhar, Patiala and Sangur districts and caused about 30 per cent yield loss (Chahal, 2005). The disease could be characterized mainly into two distinct phases; leaf blight phase, and the "Kresek phase" (acute wilting of young plants) which is the destructive one for the epidemic of disease (Reddy and Ou, 1976). Identification of less hazardous and effective measures, including bio control agent and chemical control measure is needed for the effective management of BLB disease. Therefore, suitable management option is the most important for for increasing production and productivity of rice and improves the food security.

II. MATERIALS AND METHODS

The field experiment was laid out in randomized block design for the evaluation of different fungicides, antibiotics and antagonists with ten treatments and three replications by using susceptible *cv*. GR-11 at Main Rice Research Centre, Navsari Agricultural University, Navsari during *Kharif*-2023. Seeds of susceptible *cv*. GR-11 were sown in the nursery on 17th July 2023, seedlings were transplanted in the puddled soil in the main field at an age of 20-25 days. High fertilizer dose of 150:30:00 kg/ha N: P_2O_5:K_2O was used for creating a favorable environment for the incidence of bacterial blight disease. In all the experiments, fertilizers were applied as per the recommended practice *i.e*., half N, full P and K as basal dose at planting and remaining 50 per cent N in two equal splits at tillering and panicle initiation stages. The experimental plots were artificially inoculated by standard clip inoculation method at tillering stage to get sufficient disease incidence for the evaluation of the efficacy of chemicals and antagonists against bacterial blight disease. Two sprays were carried out, the first spray was given at the initiation of the disease and the second spray was applied at 15 days after the first spray mentioned in Table 1.

TABLE 1
TREATMENTS DETAILS OF INTEGRATED DISEASE MANAGEMENT OF BACTERIAL BLIGHT

Tr. No.	Technical name	Conc. (%)/ppm	Dose (g or ml/l)
T_1	Streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v	200 ppm	0.2 g
T_2	Streptomycin sulphate 90 w/v + tetracycline hydrochloride 10 w/v	1000 ppm	1.0 g
T_3	Copper oxychloride 50 WP	1.25	2.5 g
T_4	Streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v + trifloxystrobin 25 + tebuconazole 50 (75WG)	200 ppm + 0.03	0.2 +0.4g
T_5	Trifloxystrobin 25 + tebuconazole 50 (75WG)	0.03	0.4 g
T_6	Streptomycin sulphate e 18.75 w/v + oxy tetracycline 2 w/v + azoxystrobin 18.2 + difenconazole 11.4 SC	200 ppm + 0.03	0.2g+1.0 ml
T_7	*Bacillus subtilis* 2x10^8 cfu/ml	0.50	5.0 ml
T_8	*Trichoderma viride* 2x10^6 cfu/gm	0.50	5.0 g
T_9	*Pseudomonas fluorescens* 2x10^8 cfu/ml	0.50	5ml/l
T_{10}	Control (Water spray)	-	-

Formula for calculating per cent disease intensity is:

$$PDI = \frac{Sum\ of\ the\ score \times 100}{No.of\ observations \times highest\ number\ of\ rating\ scale} \quad (1)$$

III. RESULTS AND DISCUSSIONS

The results of the effect of fungicides, antibiotics and antagonists on disease intensity of bacterial blight of rice are presented in Table 2. The results indicated that the per cent disease intensity ranged from 26.28 to 54.65 per cent during *Kharif* crop season 2023.

TABLE 2
EFFECT OF FUNGICIDES AND ANTAGONISTS ON PER CENT DISEASE INTENSITY OF BACTERIAL BLIGHT OF RICE

Treat. No.	Technical Name	Concentration (%)	Per cent Disease intensity (%)	Disease control (%)
T1	Streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v	200 ppm	40.12 (39.27)	26.59
T2	Streptomycin sulphate 90 w/v + tetracycline hydrochloride 10 w/v	1000 ppm	33.18 (35.12)	39.28
T3	Copper oxychloride 50 WP	1.25	35.45 (36.49)	35.13
T4	Streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v + trifloxystrobin 25 + tebuconazole 50 (75WG)	200 ppm + 0.03	26.28 (30.83)	51.91
T5	Trifloxystrobin 25 + tebuconazole 50 (75WG)	0.03	37.53 (37.68)	31.33
T6	Streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v + azoxystrobin 18.2 + difenconazole 11.4 SC	200 ppm + 0.03	29.58 (32.93)	45.87
T7	*Bacillus subtilis*	0.50	44.15 (41.63)	19.21
T8	*Trichoderma viride*	0.50	47.82 (43.74)	12.50
T9	*Pseudomonas fluorescens*	0.50	42.83 (40.83)	21.63
T10	Control (Water spray)	-	54.65 (47.68)	-
		S.Em±	1.31	
		CD at 5 %	3.80	
		CV (%)	6.78	

Figures in parenthesis are arc sine transformed values and outside the parenthesis are original values.

3.1 Per cent disease intensity of bacterial blight:

The experiment was conducted with an objective to evaluate the relative field efficacy of different fungicides, antibiotics and antagonists *viz.*, streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v at 200 ppm, streptomycin sulphate 90 w/v + tetracycline hydrochloride 10 w/v at 1000 ppm, copper oxychloride 50 WP at 1.25 per cent, streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v at (200ppm) + trifloxystrobin 25 + tebuconazole 50 (75WG) at 0.03 per cent, trifloxystrobin 25 + tebuconazole 50 (75WG) at 0.03 per cent and streptomycin sulphate e 18.75 w/v + oxy tetracycline 2 w/v (200 ppm) + azoxystrobin 18.2 + difenconazole 11.4 SC at 0.03 per cent, antagonists *viz., Pseudomonas fluorescens* at 0.50 per cent, *Trichoderma viride* at 0.50 per cent and *Bacillus subtillis* at 0.50 per cent, respectively.

The data on per cent disease intensity of bacterial blight during *Kharif* 2023 indicated that all the treatments were significantly superior in reducing bacterial blight intensity as compared to untreated control. Among them, combi fungicide streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v (200ppm) + trifloxystrobin 25 + tebuconazole 50 (75WG) at 0.03 per cent was found significantly superior and most effective for the control of bacterial blight and recorded minimum disease intensity (26.28%) which was statistically at par with streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v (200ppm) + azoxystrobin 18.2 + difenconazole 11.4 SC at 0.03 per cent with disease intensity of 29.58 per cent followed by streptomycin sulphate 90 w/v + tetracycline hydrochloride 10 w/v at 1000ppm (33.18%), copper oxychloride 50 WP at 1.25 per cent (35.45%), trifloxystrobin 25 + tebuconazole 50 (75WG) at 0.03 per cent (37.53%), streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v at 200ppm (40.12%), *Pseudomonas fluorescens* at 0.50 per cent (42.83%), *Bacillus subtilis* at 0.50 per cent (44.15%) and *Trichoderma viride* at 0.50 per cent (47.82%), respectively.

The maximum disease control was recorded in streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v (200ppm) + trifloxystrobin 25 + tebuconazole 50 (75WG) at 0.03 per cent (51.91%) followed by streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v (200ppm) + azoxystrobin 18.2 + difenconazole 11.4 SC at 0.03 per cent (45.87%), streptomycin sulphate 90 w/v + tetracycline hydrochloride 10 w/v at 1000ppm (39.28%) and so on, respectively.

3.2 Effect of fungicides, antibiotics and antagonists on Yield of Rice:

The consequences of the fungicides, antibiotics and antagonists on grain yield, straw yield and test weight of rice are presented in Table 3 and 4. The results indicated that the grain yield ranged from 3.6 to 5.63 kg/plot and straw yield ranged from 4.89 to 7.08 kg/plot, respectively.

TABLE 3
EFFECT OF FUNGICIDES AND ANTAGONISTS ON GRAIN AND STRAW YIELD OF RICE (*CV*. GR-11)

Treat. No.	Technical Name	Conc. (%)	Grain Yield		Straw Yield	
			Kg/plot	Kg/ha	Kg/plot	Kg/ha
T_1	Streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v	200 ppm	4.37	4726	5.73	6205
T_2	Streptomycin sulphate 90 w/v + Tetracycline hydrochloride 10 w/v	1000 ppm	4.83	5231	6.10	6602
T_3	Copper oxychloride 50 WP	1.25	4.67	5051	6.07	6566
T_4	Streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v + trifloxystrobin 25 + tebuconazole 50 (75WG)	200 ppm +0.03	5.63	6097	7.08	7666
T_5	Trifloxystrobin 25 + tebuconazole 50 (75WG)	0.03	4.60	4978	5.97	6457
T_6	Streptomycin sulphate e 18.75 w/v + oxy tetracycline 2 w/v + Azoxystrobin 18.2 + difenconazole 11.4 SC	200 ppm +0.03	5.43	5880	6.83	7395
T_7	*Bacillus subtilis*	0.50	4.20	4545	5.58	6043
T_8	*Trichoderma viride*	0.50	4.10	4437	5.47	5916
T_9	*Pseudomonas fluorescens*	0.50	4.27	4618	5.66	6122
T_{10}	Control (Water spray)	-	3.62	3914	4.89	5292
		S.Em±	0.26	280.3	0.29	312.1
		CD at 5 %	0.77	832.9	0.86	927.4
		CV (%)	9.81	9.81	8.41	8.41

TABLE 4
EFFECT OF FUNGICIDES AND ANTAGONISTS ON TEST WEIGHT OF RICE

Treat. No.	Technical Name	Concentration (%)	Test grain weight (g)
T_1	Streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v	200 ppm	22.30
T_2	Streptomycin sulphate 90 w/v + Tetracycline hydrochloride 10 w/v	1000 ppm	24.15
T_3	Copper oxychloride 50 WP	1.25	22.65
T_4	Streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v + trifloxystrobin 25 + tebuconazole 50(75WG)	200 ppm + 0.03	27.43
T_5	Trifloxystrobin 25 + tebuconazole 50 (75WG)	0.03	22.33
T_6	Streptomycin sulphate e 18.75 w/v + oxy tetracycline 2 w/v + azoxystrobin 18.2 + difenconazole 11.4 SC	200 ppm + 0.03	26.13
T_7	*Bacillus subtilis*	0.50	19.60
T_8	*Trichoderma viride*	0.50	18.83
T_9	*Pseudomonas fluorescens*	0.50	20.17
T_{10}	Control (Water spray)	-	15.23
		S.Em±	1.09
		CD at 5 %	3.24
		CV (%)	8.62

3.2.1 Grain yield:

The significantly highest grain yield (5.63 kg/plot) was recorded in streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v (200ppm) + trifloxystrobin 25 + tebuconazole 50 (75WG) at 0.03 per cent which was statistically at par with streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v (200ppm) + azoxystrobin 18.2 + difenconazole 11.4 SC at 0.03 per cent 5.43 kg/plot). Next best in order of merit were streptomycin sulphate 90 w/v + tetracycline hydrochloride 10 w/v at 1000ppm (4.83kg/plot), copper oxychloride 50 WP at 1.25 per cent (4.67kg/plot), trifloxystrobin 25 + tebuconazole 50 (75WG) at 0.03 per cent (4.60kg/plot), streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v at 200ppm (4.37 kg/plot), *Pseudomonas fluorescens* at 0.50 per cent (4.27kg/plot), *Bacillus subtilis* at 0.50 per cent (4.20kg/plot) and *Trichoderma viride* at 0.50 per cent (4.10kg/plot), respectively.

3.2.2 Straw yield:

The results of straw yield revealed that, significantly highest straw yield (7.08kg/plot) was recorded in streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v (200ppm) + trifloxystrobin 25 + tebuconazole 50 (75WG) at 0.03 per cent which was statistically at par with streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v (200ppm) + azoxystrobin 18.2 + difenconazole 11.4 SC at 0.03 per cent (6.83kg/plot) followed by streptomycin sulphate 90 w/v + tetracycline hydrochloride 10 w/v at 1000ppm (6.10kg/plot), copper oxychloride 50 WP at 1.25 per cent (6.07kg/plot), trifloxystrobin 25 + tebuconazole 50 (75WG) at 0.03 per cent (5.97kg/plot), streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v at 200ppm (5.73kg/plot), *Pseudomonas fluorescens* at 0.50 per cent (5.66kg/plot), *Bacillus subtilis* at 0.50 per cent (5.58 kg/plot) and *Trichoderma viride* at 0.50 per cent (5.47kg/plot), respectively.

3.3 Effect of fungicides and antagonists on test weight of rice:

The result on test grain weight indicated that significantly highest test grain weight (27.43g) was recorded in plot sprayed with streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v (200ppm) + trifloxystrobin 25 + tebuconazole 50 (75WG) at 0.03 per cent which was statistically at par with streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v (200ppm) + azoxystrobin

18.2 + difenconazole 11.4 SC at 0.03 per cent (26.13g), streptomycin sulphate 90 w/v + tetracycline hydrochloride 10 w/v at 1000ppm (24.15g), copper oxychloride 50 WP at 1.25 per cent (22.65g), trifloxystrobin 25 + tebuconazole 50 (75WG) at 0.03 per cent (22.33g), streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v at 200ppm (22.30g), *Pseudomonas fluorescens* at 0.50 per cent (20.17g), *Bacillus subtilis* at 0.50 per cent (19.60g) and *Trichoderma viride* at 0.50 per cent (18.83g), respectively.

Evaluation of different fungicides, antibiotics and antagonists were carried out by different researchers earlier. Mandal *et al.* (2017) conducted an experiment to know the effects of streptocycline, copper oxychloride and their combination, bioagents (*Trichoderma viride* and *Pseudomonas fluorescens*) on disease severity of bacterial blight. The result revealed that, all the treatments were superior over control in reducing the disease severity. Patil *et al*. (2017) carried out an experiment with eight treatments under field condition against the bacterial leaf blight of rice. Streptocycline 72 WP + copper oxychloride 50 WP combined treated plots showed the lowest disease incidence of 22.33 per cent followed by bacterinashak, agrimycin 100, kasugamycin 4 WP and the highest disease severity was recorded in control (55.53%). The highest grain yield of 56.49 q/ha was recorded in streptocycline + copper oxychloride followed by bacterinashak (54.24 q/ha). Roat *et al*. (2018) conducted a field experiment to test the efficacy of different fungicides, antibiotics and antagonists and revealed that the combined application of streptocycline @ 250 ppm + copper oxychloride @ 0.25 per cent were the best combination for the control of bacterial blight and was followed by foliar application of streptocycline @ 250 ppm + copper oxychloride @ 0.25 per cent + *Pseudomonas fluorescens* 10^8 cfu ml^{-1} @ $8g1^{-1}$ and streptocycline alone @ 250 ppm. The *P. fluorescens* 10^8 cfu ml^{-1} also reduced the disease incidence and increased the yield. Nasir *et al*. (2019) evaluated comparative efficacy of three antibiotics *viz.,* streptomycin sulphate 72 WP, kasugamycin 4 WP and kasugamycin + copper oxychloride (50 WP) along with four fungicides *viz*., copper oxychloride 50 WP, tebuconazole + trifloxystrobin (75 WDG), Gem Star Super 325 SC and Bordeaux mixture (1%) against BLB of rice. Among the antibiotics, streptomycin sulphate 72 WP performed best with 92.23 per cent disease control and increase in rice yield upto 3.55 per cent over the untreated control. Among the fungicides, copper oxychloride 50 WP was found effective upto 76.48 per cent with 2.67 per cent increase in yield of rice. Bordeaux mixture (1%) found effective upto 84.08 per cent with 2.78 per cent yield increase over untreated control.

IV. CONCLUSION

Among the tested fungicides, antibiotics and antagonists *viz*., streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v (200ppm) + azoxystrobin 25 + tebuconazole 50 (75WG) at 0.03 per cent was found significantly superior and most effective for the control of bacterial blight with the minimum disease intensity (26.28%) and maximum disease control (51.91%), which was statistically at par with streptomycin sulphate 18.75 w/v + oxy tetracycline 2 w/v (200ppm) + azoxystrobin 18.2 + difenconazole 11.4 SC at 0.03 per cent with disease intensity of 29.58 per cent and also recorded the highest grain yield, straw yield and test weight.

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Determination of HSV Colour Indices of Dragon Fruit

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Abstract— *Dragonfruit (Hylocereus spp.) is a vibrant tropical fruit gaining attention for its unique appearance, nutritional value, and market potential. Its color serves as a critical determinant of consumer preference, reflecting fruit quality and maturity. This study aimed to quantify the HSV (hue, saturation, and value) color indices of dragonfruit at different maturity stages—unmature, mature, and overmature—using advanced image processing techniques. Images were collected under controlled conditions, preprocessed for segmentation, and analyzed using MATLAB R2023a. The HSV parameters were calculated for 400 samples, revealing distinct variations in color attributes across developmental stages. Mature dragonfruit exhibited the highest hue values, indicating peak coloration, while overmature fruits showed a decline due to potential discoloration. Saturation values were most vivid in mature fruits, signifying optimal pigmentation, whereas unmature fruits displayed subdued colors. Brightness progressively increased with maturity but slightly decreased in overmature samples. Combined HSV indices provided a robust metric for differentiating between maturity stages, with the highest values observed at the mature stage. These findings underscore the utility of HSV color indices as reliable indicators for maturity classification, contributing to quality control, automated sorting, and improved postharvest management.*

Keywords— Dragonfruit, HSV color indices, Image processing, Color analysis.

I. INTRODUCTION

Dragonfruit, commonly known as *Hylocereus spp.*, is a tropical fruit gaining global attention due to its vibrant color, unique appearance, and nutritional value. The fruit is not only consumed fresh but also processed into products such as juices, jams, and food colorants, making its visual appeal a critical determinant of consumer preference [7]. Among the visual characteristics, color plays a pivotal role as it is often associated with quality, ripeness, and overall marketability [8]. Color indices, such as those derived from L*a*b* (lightness, chromaticity), RGB (red, green, blue), and HSV (hue, saturation, value) color spaces, offer an objective method to quantify color attributes. These indices have been widely used in agricultural research to evaluate fruit quality and ripening stages [2]. For dragonfruit, however, research on standardized color indices remains limited, despite its expanding commercial relevance. This study aims to determine and evaluate the color indices of dragonfruit under varying conditions, including ripeness levels and storage treatments. By establishing reliable color metrics, this research intends to contribute to better quality control and postharvest management practices for dragonfruit. Furthermore, it seeks to bridge existing gaps in literature regarding color quantification and its applications in the dragonfruit value chain.

II. METHODOLOGY

The study aimed to determine the HSV color indices of mature dragonfruit by employing advanced image processing techniques. The methodology was divided into four main stages: field data collection, image preprocessing, computation of HSV indices, and statistical analysis.

2.1 Field Data Collection:

The images of mature dragonfruit were collected from agricultural fields in Asola village, located near Vasantrao Naik Marathwada Krishi Vidyapeeth (VNMKV), Parbhani, Maharashtra. This region is known for its favorable agro-climatic conditions conducive to dragonfruit cultivation. To ensure uniformity and minimize variability, only fully mature fruits exhibiting consistent morphological characteristics were selected. Images were captured under controlled lighting conditions using a DSLR camera equipped with a fixed focal length lens, ensuring high resolution and minimal distortion. Each dragonfruit sample was photographed against a neutral background to facilitate subsequent image analysis, as recommended by Du and Sun (2004).

2.2 Image Import and Preprocessing:

The collected images were imported into MATLAB R2023a software, a powerful tool for image processing and computational analysis. Image preprocessing steps included resizing and segmentation. All images were resized to a standard resolution of 512 × 512 pixels to maintain uniformity across the dataset and optimize computational efficiency. This step was crucial for ensuring consistency in subsequent image analysis processes, as noted by Gonzalez and Woods (2018). Segmentation was performed to isolate the region of interest (the dragonfruit skin) from the background. A color thresholding technique based on the RGB color space was employed initially to differentiate the dragonfruit from the neutral background. Subsequently, morphological operations, such as erosion and dilation, were applied to refine the segmented regions and remove noise, following the approach outlined by Jain et al. (1995). The segmented regions were then converted to grayscale and overlaid with the original image to extract color information specific to the dragonfruit.

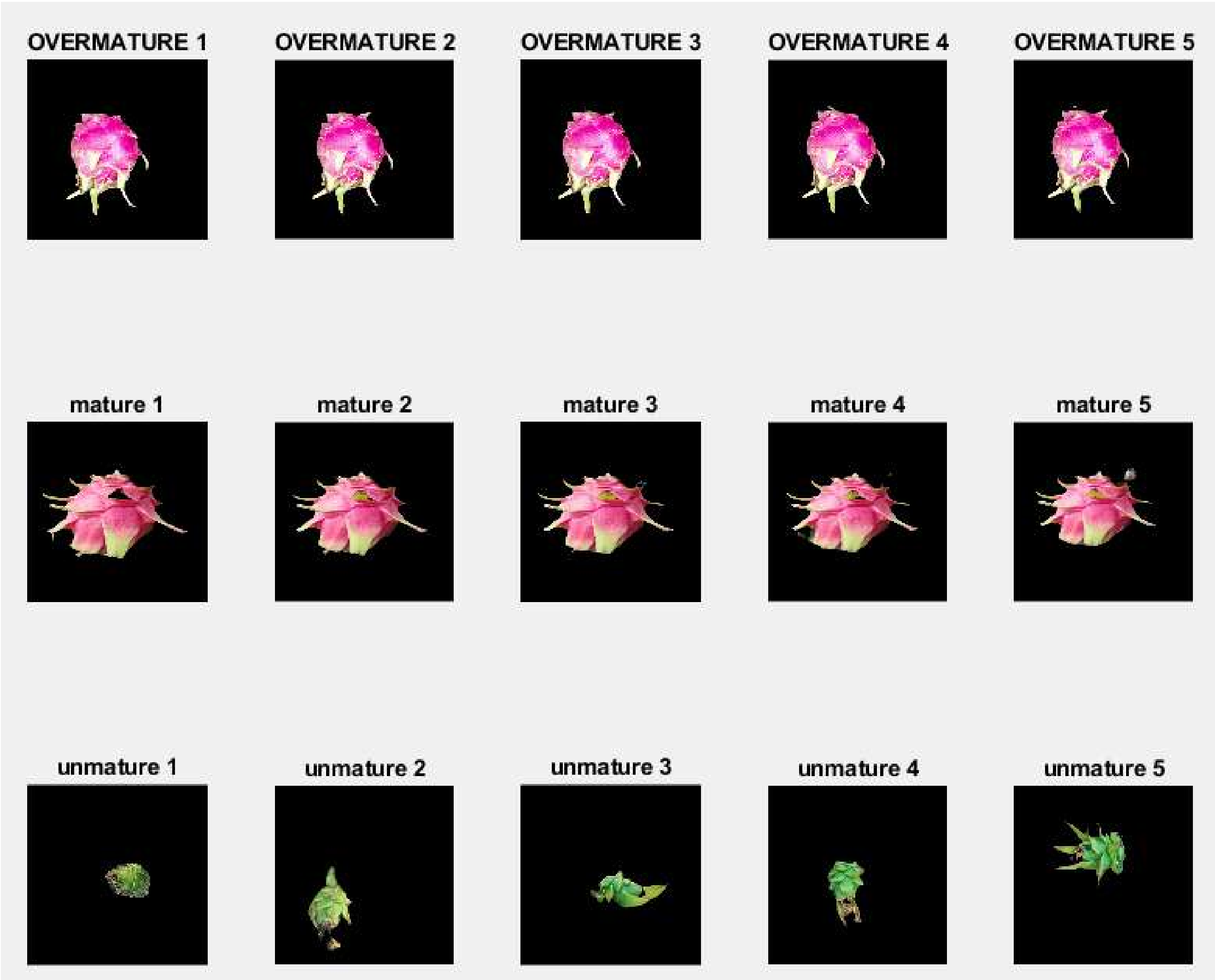

FIGURE 1: Segmented dragon fruit images

2.3 HSV Color Space Conversion:

After segmentation, the images were converted from the RGB color space to the HSV (hue, saturation, value) color space. This conversion is widely used in agricultural imaging studies due to its ability to represent perceptually relevant color attributes (Cheng et al., 2001).

- **Hue (H):** Represents the dominant wavelength of the color, ranging from 0° to 360°. For dragonfruit, this parameter was critical in identifying the characteristic reddish-pink hue.
- **Saturation (S):** Indicates the intensity or purity of the color. Higher saturation values correspond to more vivid colors.
- **Value (V):** Corresponds to the brightness of the color, ranging from 0 (black) to 1 (white).

Each pixel in the segmented region was analyzed to extract its HSV values. MATLAB's built-in rgb2hsv function was employed for this purpose. The extracted HSV values were stored in a matrix format for further processing.

III. RESULTS AND DISCUSSION

The results of this study provide a comprehensive analysis of the color indices of dragonfruit at three maturity stages—unmature, mature, and overmature. By calculating the HSV (hue, saturation, and value) parameters for 400 dragonfruit images, the differences in color characteristics across these maturity classes were quantified. The findings offer insights into the relationship between fruit maturity and color metrics, which are critical for quality assessment and classification in the agricultural sector.

TABLE 1
HSV COLOUR INDEX OF DRAGON FRUIT DURING FRUIT DEVELOPMENT STAGES

	Unmature	Mature	Overmature
Average H	0.0349	0.1030	0.8055
Average S	0.0845	0.0838	0.0813
Average V	0.1000	0.1216	0.1245
Average HSV	0.0731	0.1028	0.3371

3.1 Hue (H):

The hue values (H) were calculated for all images to determine the dominant wavelength or color of the dragonfruit. The results indicated significant variation across the three maturity stages. The unmature fruits exhibited the lowest average hue value (0.04248), indicating a weaker representation of red tones, as red hues are typically associated with ripeness in dragonfruit. On the other hand, mature fruits had the highest average hue value (0.13306), signifying the peak development of the characteristic reddish-pink coloration. The hue value slightly decreased for overmature fruits (0.10357), suggesting a potential loss of vibrancy or the onset of discoloration due to over-ripening (Pathare et al., 2013).

These results align with existing studies that highlight the transition in color hues as fruits progress through maturity stages. For instance, Cayuela (2008) observed similar trends in citrus fruits, where changes in hue corresponded to biochemical modifications during ripening. For dragonfruit, the increased hue values during the mature stage reflect the accumulation of pigments such as betalains, which are responsible for the vibrant coloration (Stintzing et al., 2002).

3.2 Saturation (S):

Saturation represents the intensity or purity of the color. The average saturation values were relatively consistent across the three classes: 0.09620 for unmature, 0.09979 for mature, and 0.09587 for overmature fruits. Mature dragonfruit exhibited the highest saturation, indicating more vivid and pure colors compared to the other two classes. In unmature fruits, lower saturation values suggest a duller or less pronounced coloration, likely due to the underdevelopment of pigments.

Interestingly, the overmature fruits showed a slight decline in saturation compared to the mature fruits. This decrease may be attributed to physiological changes such as pigment degradation or moisture loss, which are common in post-harvest stages (Du & Sun, 2004). The stability in saturation values across stages suggests that this parameter may serve as a robust indicator of fruit maturity, with peak values coinciding with the optimal harvest period.

3.3 Value (V):

The value parameter, which corresponds to the brightness of the color, exhibited noticeable differences among the three classes. Unmature fruits had an average brightness value of 0.11270, which increased to 0.15239 in mature fruits. The overmature class showed a slight reduction in brightness (0.14609) compared to the mature stage. These results suggest that the brightness of dragonfruit increases with ripening but slightly diminishes as the fruit becomes overripe.

The brighter appearance of mature fruits may be attributed to the optimal development of surface pigments and increased reflectance under uniform lighting conditions during imaging. Similar findings were reported by Pathare et al. (2013), who noted a correlation between increased brightness and the ripening process in various horticultural crops. The slight decline in brightness for overmature fruits could be linked to surface dullness or textural changes that affect light reflection.

3.4 Combined HSV Indices:

The overall HSV indices, calculated as the average of hue, saturation, and value parameters, revealed distinct differences among the three maturity classes. Unmature fruits had the lowest average HSV value (0.08379), while mature fruits displayed the highest value (0.12841). Overmature fruits showed an intermediate value of 0.11518. These results emphasize that the combined HSV indices provide a reliable metric for distinguishing between maturity stages.

The increase in HSV values from unmature to mature stages underscores the progressive development of color attributes associated with ripening. This trend highlights the utility of HSV indices in capturing multidimensional color information, as also noted by Cheng et al. (2001) in their study on color image segmentation. For dragonfruit, the peak HSV value at the mature stage represents the optimal visual quality, aligning with consumer preferences for vibrant and appealing fruits.

IV. DISCUSSION

Immature **Mature** **Overmature**

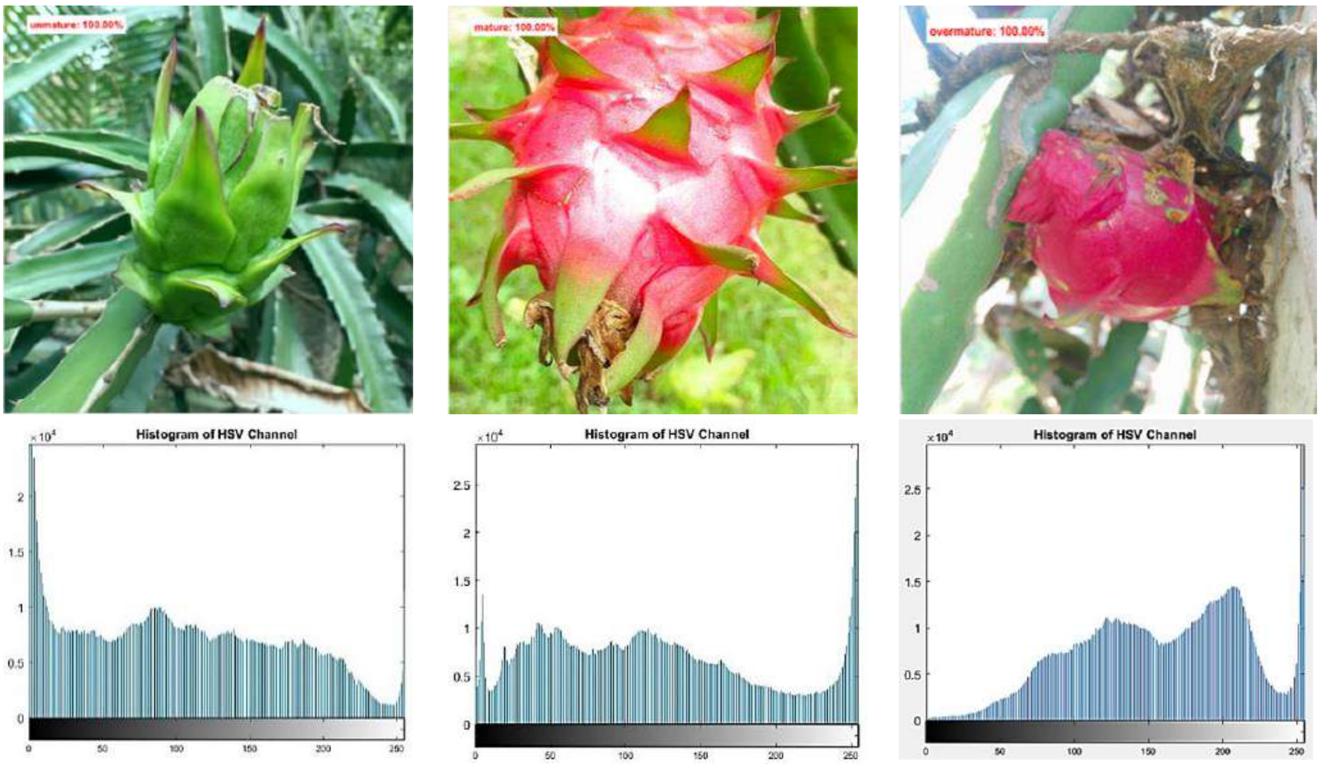

FIGURE 2: HSV colour index of Dragon fruit

The observed variations in HSV parameters across maturity stages are consistent with the physiological and biochemical changes that occur during fruit development. Unmature dragon fruits, characterized by lower hue, saturation, and brightness values, lack the vivid coloration. The transition to mature fruits is marked by significant increases in these parameters, reflecting the culmination of ripening processes. However, the slight decline in color indices for overmature fruits indicates the onset of senescence and potential quality degradation.

These findings have important implications for the postharvest management and marketing of dragonfruit. By utilizing HSV indices as objective metrics, it is possible to establish standardized criteria for classifying fruits based on their maturity stage.

This approach not only enhances quality control but also facilitates automation in sorting and grading processes, as demonstrated by recent advances in agricultural imaging technologies (Du & Sun, 2004).

Moreover, the results contribute to the broader understanding of color as a quality attribute in horticultural products. The correlation between HSV parameters and dragonfruit maturity stages aligns with similar studies on other fruits, such as mangoes, apples, and citrus (Cayuela, 2008; Pathare et al., 2013). This reinforces the applicability of HSV-based analyses across diverse crop types and highlights their potential for wider adoption in the agricultural industry.

V. CONCLUSIONS

The comprehensive methodology employed in this study combines field-based data collection, advanced image processing, and robust statistical analysis to establish reliable HSV color indices for mature dragon fruit. This systematic approach ensures the accuracy and reproducibility of results, paving the way for future research on the visual quality assessment of dragon fruit and other horticultural crops.

The study successfully quantified the HSV color indices of dragonfruit at different maturity stages using image processing techniques. The results demonstrated clear distinctions in hue, saturation, and brightness values between unmature, mature, and overmature fruits. The mature stage exhibited the most desirable color characteristics, as indicated by the highest HSV values, while the overmature stage showed signs of quality decline. These findings underscore the importance of HSV indices as reliable and objective indicators for fruit maturity classification. Future research could explore the integration of these indices with machine learning algorithms for automated maturity detection. Additionally, investigating the relationship between HSV parameters and biochemical attributes, such as pigment concentration and sugar content, could provide deeper insights into the ripening process. Such advancements would further enhance the applicability of color indices in improving the quality and marketability of dragonfruit.

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Precision Farming in Nepal: A Machine Learning Perspective

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Abstract— *This paper encompasses three different machine learning models that we built to help Nepali farmers in selecting ideal crops for their land, using the right fertilizers, and predicting plant diseases. We tried about five models each for crop recommendation and fertilizer recommendation and a single model for plant disease prediction. We chose "Decision Trees" for both our Crop Recommendation and Fertilizer Recommendation and "Convolutional Neural Networks (CNN)" for Plant Disease Prediction. All models achieved over 95% accuracy. Our GitHub repository houses all the code, making it accessible for future researchers and ML developers working on related tasks.*

(https://github.com/anamgiri/uunchai).

Keywords— Machine learning, Algorithms, Nepal, Agriculture, Plant disease, fertilizers, crop, recommendation, Plant Disease Prediction Nepal, Decision Tree, Random Forest, Convolutional Neural Networks (CNN), Deep Learning.

I. INTRODUCTION

Most of the foodstuffs in Nepal are still imported from foreign countries, despite the fact that agriculture is the primary occupation for most people. While technology has significantly advanced in other sectors in Nepal, the agricultural sector still relies on traditional farming methods, which are more time-consuming and less productive. Farmers are uneducated about various modern farming practices that could be very beneficial to them. Therefore, we developed machine learning models to assist Nepali farmers in integrating technology into their farming methods. Our focus is solely on the agricultural sector, including both professional farmers and individuals growing crops at home. Through this paper, we aim to demonstrate how our model can identify the right crops to plant under optimal conditions, recommend appropriate fertilizers, and accurately predict plant diseases in a timely manner, which will greatly assist in precision farming for Nepali farmers.

II. LITERATURE REVIEW:

In Hema MS, Niteesha Sharma, and Ch. Santoshini's research paper on "Plant Disease Prediction Using Convolutional Neural Networks," they emphasized that many people pursue agriculture in India, but many crops die due to unidentified diseases. Furthermore, employing professionals costs a lot for small and medium-scale farms, so using machine learning and deep learning models is a more viable alternative for this sector.

In Mahendra N's research on "Crop Prediction Using Machine Learning Approaches," he explains how to design a model that recommends crops and fertilizers based on soil to solve soil and fertilizer-related problems. He used Decision Tree algorithms for crop prediction and SVG for rainfall prediction.

Musanase, Vodacek, Hanyurwimfura, Uwitonze, and Kabandana, in their paper, explain their crop recommendation system that utilizes different machine learning models, where Random Forest performed the best. Soil nutrient parameters (N, P, K) were used to predict the ideal crop for soil. The research provides insight into the benefits of using ML for crop recommendations, showcasing a critical development in precision agriculture.

Lili Li, Shujuan Zhang, and Bing Wang developed an image recognition disease model using deep learning models. This model overviewed the diseases through images and facilitated farmers in using the right fertilizers. Various imaging techniques like Support Vector Machines (SVM), K-means clustering, and K-nearest neighbors (KNN) were employed. A comparison of deep learning models was conducted, and accurate plant leaf disease recognition was achieved using deep learning.

In the research paper “Crop Recommendation System to Maximize Crop Yield Using Machine Learning Technique” by Rohit, Ankit, Mitalee, Pooja, Suresh, and Avinash, they explained their system for recommending crops based on soil conditions to enhance productivity. They addressed the need for precision agriculture, particularly in small, rain-fed farms, by utilizing machine learning models like SVM, ANN, Random Forest, and Naïve Bayes.

In the research paper “Crop Prediction and Fertilizer Recommendation Using Machine Learning” by Prof. Kiran, Priyanka, Pooja, Tushar, and Mayuri, their study focuses on using machine learning, specifically the Support Vector Machine (SVM) algorithm, to predict crop yields and recommend fertilizers based on soil and environmental data. The research involves collecting and preprocessing a dataset with parameters like calcium, magnesium, potassium, and nitrogen, crucial for assessing crop suitability and yield potential. By employing SVM, the study creates a model integrated into a web application where farmers can input soil details to receive tailored crop and fertilizer suggestions. The results indicate high accuracy in predictions, showcasing the significant impact of data-driven insights on improving agricultural productivity and practices. Overall, the study demonstrates the transformative potential of machine learning in agriculture, enhancing decision-making and crop management. It shows that integrating technology with agriculture can significantly enhance crop yield predictions and guide better decision-making for farmers.

III. MATERIALS AND METHODS

3.1 Datasets:

We used secondary sources of data for our research and modeling purposes. We used datasets publicly available on Kaggle for this purpose. Due to the lack of a dataset specifically focused on Nepal, we chose datasets from other countries that contain parameters closely resembling those of Nepal. The fertilizer recommendation dataset contained 100 rows and 8 features (temperature, humidity, moisture, soil type, crop type, nitrogen, potassium, phosphorus) with the fertilizer name as the label. The crop recommendation dataset contained 2,200 rows with 7 features (nitrogen, phosphorus, potassium, temperature, pH, rainfall) and plant name as the label. The plant disease dataset consists of about 87K RGB images of healthy and diseased crop leaves categorized into 38 different classes. For the fertilizer recommendation and crop recommendation systems, we used a 60/20/20 ratio for train, validation, and test sets, whereas for disease prediction, we used an 80/20 ratio for train and validation sets and a separate test images directory.

3.2 Proposed Models:

For the Crop recommendation system: We tried four different models for this system. Decision tree and Random forest both gave us pretty good results. Results for Decision tree were: Test Accuracy: 0.95, Test Precision: 0.96, Test Recall: 0.95, Test F1 Score: 0.95 Results for Random Forest were: Test Precision: 0.98, Test Recall: 0.97, Test F1 Score: 0.97 We also tried SVC and gradient boosting but they couldn’t show better results than the previous two because we believe our data also contained non-linear relationships, so SVC couldn’t perform as well as other models. Gradient boosting requires more hyperparameters and is sensitive to overfitting, so decision trees and random forest performed slightly better than these models for our data. We finalized the decision tree as our model as it had a slightly better classification report than random forest.

For the Fertilizer recommendation System: We tried four different models for both of these systems. Decision tree and Random forest both gave us pretty good results. Results for decision tree were: Test Accuracy: 1.0, Test Precision: 1.0, Test Recall: 1.0, Test F1 Score: 1.0 Results for Random Forest were: Test Accuracy: 0.95, Test Precision: 1.0, Test Recall: 0.95, Test F1 Score: 0.97 We also tried SVC and Naive Bayes but they couldn’t show better results than the previous two because we believe our data also contained non-linear relationships, so SVC couldn’t perform as well as other models. Naives Bayes, although with high accuracy, usually assumes data to be independent which is untrue in our case. So, we finalized the decision tree as our model as it had a slightly better classification report than random forest.

For the Plant Disease Prediction System: We used CNN for disease classification as it uses filters and multilayers to detect patterns and edges which is very convenient for image processing. Also, the max pooling layer reduces the spatial dimensions of the image which helps the model become invariant to small translations and distortions.

3.3 Training Process:

3.3.1 Fertilizer Recommendation and Crop Recommendation:

We used ordinal encoder for encoding in all 4 models. The decision tree and random forest models encountered overfitting problems. So, we observed the accuracy for their depths and selected ideal depths for solving the problem.

3.3.2 For the Plant Disease Prediction System:

We used multiple layers for CNN. The first layers were Conv2D, Conv2D, MaxPool2D. These layers were repeated 5 times with different filter sizes (32, 64, 128, 256, 512). We used multiple Conv2D layers with increasing filter sizes to allow the network to learn features at various levels of abstraction. The initial layers with smaller filter sizes (e.g., 32, 64) detect simple, low-level features like edges and textures. As you move deeper into the network, the larger filter sizes (e.g., 128, 256, 512) help the network capture more complex, high-level patterns and structures, such as shapes and objects relevant to plant diseases. The activation function used was 'relu'. Then the layers were Dropout, Flatten, Dense and Dropout respectively. Then, the final layer was Dense with activation as softmax. The optimizer we used was Adam. We did 10 epochs on the training set.

IV. CONCLUSION AND FUTURE WORK:

In summary, we successfully developed three ML models to assist Nepali farmers in choosing the right crops, selecting appropriate fertilizers, and predicting plant diseases. For the Plant Disease Prediction System, our future work includes using different CNN architectures with early stopping to address potential overfitting. Moving forward, we plan to utilize more complex and pre-trained models to analyze their accuracies. For the Crop and Fertilizer Recommendation Systems, our future efforts will focus on finding datasets with more parameters. We aim to collect larger and updated datasets specific to Nepal, which could revolutionize precision agriculture with technology. Additionally, we plan to integrate these three systems into our website. Currently, the models are only hyperlinked to our site, but in the future, we intend to develop an interactive UI where users can input their parameters and receive recommendations or predictions directly.

V. DISCUSSION

5.1 Potential Impact:

- **Increased Productivity:** By optimizing crop selection, fertilizer use, and disease management, these models can significantly boost agricultural yields in Nepal.
- **Reduced Costs:** Precision farming minimizes resource wastage (fertilizers, pesticides) and reduces labor costs by automating certain tasks.
- **Improved Food Security:** Increased productivity can contribute to greater food security for Nepal, potentially reducing reliance on imports.
- **Sustainability:** Optimized resource use can lead to more sustainable agricultural practices, minimizing environmental impact.

5.2 Technological Advancement:

- The successful implementation of these models demonstrates the potential of machine learning in modernizing Nepalese agriculture.
- This can encourage further research and development in this area, leading to more sophisticated and impactful solutions.

5.3 Farmer Empowerment:

By providing farmers with data-driven insights and decision-making tools, these models can empower them to make informed choices and improve their livelihoods.

VI. LIMITATIONS

6.1 Data Limitations:

- **Data Availability:** Relying on datasets from other countries can introduce biases and limit the model's accuracy in the specific context of Nepal.
- **Data Quality:** The quality of available data significantly impacts model performance. Inaccurate or incomplete data can lead to unreliable predictions.
- **Data Collection:** Collecting high-quality, real-time data from Nepalese farms can be challenging due to limited infrastructure and resources.

6.2 Model Limitations:

- **Generalization:** Models trained on limited datasets may not generalize well to new, unseen situations or variations in environmental conditions.
- **Interpretability:** Some complex models, like deep neural networks, can be difficult to interpret, making it challenging to understand the rationale behind their predictions.
- **Maintenance:** Machine learning models require ongoing maintenance, including retraining with new data and adapting to changing conditions.

6.3 Implementation Challenges:

- **Technology Access:** Ensuring access to technology (smartphones, internet connectivity) for all farmers in Nepal can be a significant hurdle.
- **Digital Literacy:** Farmers may require training and support to effectively use and understand the outputs of these models.
- **Trust and Adoption:** Building trust among farmers in the use of technology and convincing them to adopt new practices can be challenging.

6.4 Addressing Limitations:

- **Data Collection:** Invest in initiatives to collect high-quality, location-specific data on soil, weather, and crop conditions in Nepal.
- **Model Development:** Explore more robust and interpretable models, such as explainable AI techniques.
- **Technology Access:** Improve digital infrastructure in rural areas and provide affordable access to smartphones and internet connectivity.
- **Farmer Education:** Conduct workshops and training programs to educate farmers on the use of these technologies and their benefits.
- **Continuous Improvement:** Regularly monitor model performance, gather feedback from farmers, and continuously refine models based on real-world experience.

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Technical Note on Steps in Baseline Quantification for ARR Carbon Finance Projects using Remote Sensing and GIS

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Abstract— *This technical note outlines a systematic approach to baseline quantification for ARR (Afforestation, Reforestation, and Revegetation) carbon finance projects using advanced remote sensing (RS) and GIS methodologies. This approach particularly addresses India's fragmented landscapes, aiming to integrate small and marginal farmers into carbon finance markets, thus enhancing agroforestry potential and providing additional income generation. The challenges in meeting common practice criteria and additionality, as per VERRA/Gold Standard methodologies, are also discussed, offering recommendations to improve inclusivity and applicability.*

Keywords— Baseline, Carbon Finance, Remote Sensing, GIS, LULC, Afforestation.

I. INTRODUCTION

The increasing emphasis on climate change mitigation has brought afforestation, reforestation, and revegetation (ARR) projects to the forefront as effective tools for sequestering atmospheric carbon dioxide. These projects form a crucial part of global and national climate action strategies. However, ensuring their success requires robust methodologies for baseline quantification and eligibility assessment, particularly in countries like India, where the landscape is highly fragmented, and smallholder participation is key. India's agricultural landscape is characterized by over 86.1% small and marginal landholdings, making it one of the most fragmented in the world. While this fragmentation poses challenges in scaling carbon finance projects, it also presents an opportunity to integrate millions of small and marginal farmers into these initiatives. Existing methodologies, such as those by VERRA and the Gold Standard, provide a strong framework for ARR projects but often fall short in addressing the complexities of fragmented landscapes and ensuring additionality and inclusivity. This technical note proposes a systematic approach to baseline quantification, leveraging high-resolution RS-GIS tools to overcome these challenges. By tailoring the methodology to India's unique landscape, this work highlights how agroforestry potential can be utilized not just for environmental benefits but also for generating additional income for smallholders. Furthermore, the methodology addresses critical gaps in existing frameworks, such as the common practice criteria and additionality, ensuring that projects are both credible and scalable. The revised approach aims to bridge the gap between existing standards and the practical realities of fragmented agricultural landscapes. It emphasizes the role of data-driven models and spatial analyses in creating transparent, scalable, and inclusive ARR carbon finance projects that align with national and international goals.

II. BASELINE QUANTIFICATION IN ARR PROJECTS: CURRENT PRACTICES AND LIMITATIONS

In carbon finance, the baseline serves as a critical benchmark, representing the carbon stock that would naturally exist in the absence of the project. This reference is essential for calculating the additional carbon sequestered due to project activities (Zomer et al., 2007). Traditional methods for baseline estimation predominantly rely on field measurements. While field-based approaches provide ground-truth data, they are labor-intensive, prone to human error, and prohibitively expensive when applied across large and fragmented landscapes, such as those prevalent in India (Pandit & Behera, 2021). Eligibility criteria for ARR projects add further complexity to baseline determination. Standards like the Verified Carbon Standard (VCS) and Gold Standard mandate that ARR projects must be implemented on degraded or non-forest lands. Moreover, to meet additionality requirements, a plot must not have been classified as forest land—based on canopy cover thresholds—at least 10 years prior to the project start date. These stipulations are designed to prevent the displacement of native ecosystems and ensure genuine carbon sequestration (Verra, 2024). In the Indian context, these criteria are further refined. Non-forest land is defined as having a canopy cover below 15%, adding a region-specific layer of specificity to baseline assessments (Government of India, 2023). Meeting these standards necessitates a retrospective analysis of historical land conditions, which is challenging without the integration of advanced technological tools. This is where remote sensing (RS) and geographic information system (GIS) technologies become indispensable. By leveraging high-resolution satellite imagery and geospatial analyses, RS-GIS offers a scalable, accurate, and cost-effective solution for baseline quantification. These tools enable the retrospective evaluation of land use and canopy cover, ensuring compliance with eligibility criteria while reducing the reliance on labor-intensive field surveys. Furthermore, RS-GIS methodologies are particularly suited to fragmented landscapes, allowing for the aggregation and analysis of smallholder plots, which are common in India's agricultural system. This integration of advanced geospatial technologies not only addresses the limitations of traditional methods but also enhances the credibility and scalability of ARR carbon finance projects, aligning them with both national and international standards.

2.1 Leveraging Remote Sensing and GIS for Robust Baseline Quantification:

By employing RS-GIS technology, particularly through high-resolution satellite imagery and linear regression modeling, we propose a method that not only enhances the accuracy of baseline quantification but also verifies the land's eligibility (Roy et al., 2020). This method integrates historical satellite data from at least two to three years before project initiation to capture the baseline carbon stock and extend the analysis back 10 years for compliance with eligibility criteria (Jain & Kumar, 2022).

In this approach, linear regression models are established between remote-sensing-derived predictor variables—such as Leaf Area Index, Fractional Vegetation Cover, Forest Canopy Density, and other vegetation indices—and observed biomass values from field monitoring plots. High correlations between these predictor variables and field biomass data allow for reliable biomass estimations across large areas. This not only facilitates the initial baseline quantification but also enables ongoing assessments of carbon sequestration over time, providing a transparent and credible foundation for carbon credit claims (Nair et al., 2018). This methodology ensures accurate, transparent, and scalable baseline quantification for ARR projects, providing both regulatory confidence and increased potential for smallholder inclusion in carbon finance markets (Ghosh & Sharma, 2024).

2.2 Steps in Baseline Quantification Using RS-GIS and Regression Modeling:

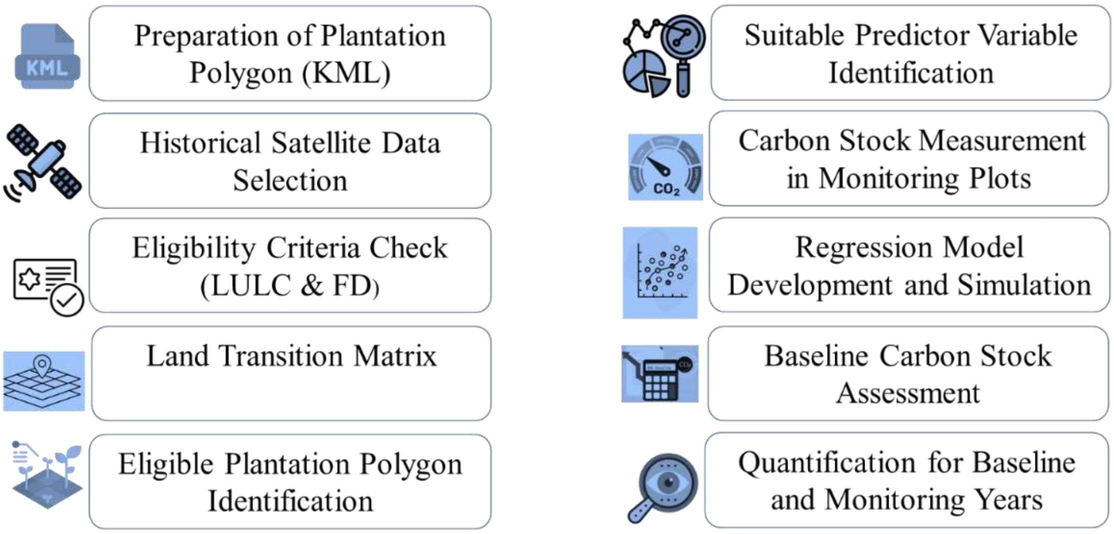

FIGURE 1: Steps in Proposed Baseline Quantification

1. **Preparation of Plantation Polygon (KML)**: Generate project-specific KML files defining the geographic boundaries of the plantation areas. These boundaries guide the spatial analysis and serve as the foundation for subsequent RS-GIS assessments.

2. **Historical Satellite Data Selection**: Historical Satellite Data Selection: Select historical satellite images, ideally dating 10+ years before the project start date, to evaluate prior land conditions and ensure compliance with common practice criteria. High-resolution imagery (e.g., LISS-IV, Sentinel-2) is used to analyze canopy density and land transitions in fragmented landscapes. Cluster-based analysis is applied to aggregate small plots for comprehensive assessments.

3. **Eligibility Criteria Check (LULC and Forest Canopy Density Mapping)**:
   - **Land Use and Land Cover (LULC) Assessment**: Classify historical land use patterns to ensure the project land qualifies as non-forest or degraded land according to project standards.
   - **Forest Canopy Density/Fractional Vegetation Cover (FVC) Mapping**: Conduct canopy density or FVC mapping to confirm that canopy cover was below required thresholds (e.g., <15%) a decade prior to project initiation, as per host-country or national definitions.
4. **Land Transition Matrix**: Use a land transition matrix to analyze historical changes in land use (e.g., non-forest to forest), ensuring that the project complies with the required standards regarding land conversion history.
5. **Eligible Plantation Polygon Identification**: Identify eligible polygons within the project area that meet baseline eligibility requirements, marking them for inclusion in the carbon quantification analysis.
6. **Socio-Economic Integration:** Incorporate socio-economic data of small and marginal farmers to ensure equitable distribution of carbon finance benefits. Data on land ownership, crop patterns, and socio-economic status is integrated with spatial data to design farmer-centric project models.
7. **Suitable Predictor Variable Identification**: Select predictor variables from satellite data, such as Leaf Area Index (LAI), Fractional Vegetation Cover (FVC), and Forest Canopy Density, that correlate well with carbon stock or biomass data observed in the field.
8. **Challenges Addressed in Existing Frameworks:**
   - **Common Practice Criteria:** Traditional approaches often fail to distinguish between historical and new agroforestry activities. This methodology uses retrospective high-resolution analyses to accurately identify additionality.
   - **Fragmented Landscapes:** By clustering smallholder plots and leveraging advanced GIS tools, this approach ensures scalability and compliance with VERRA/Gold Standard frameworks.
   - **Farmer Inclusivity:** The methodology incorporates socio-economic data to ensure that smallholders benefit from carbon finance projects.
9. **Carbon Stock Measurement in Monitoring Plots**: Establish monitoring plots within eligible areas and collect field data on carbon stock or biomass. This data will serve as observed values in the regression model, enhancing model accuracy and validation.
10. **Regression Model Development and Simulation**: Develop a regression model correlating the selected RS-derived predictor variables with field-measured biomass or carbon stock. Simulate the model to confirm a high correlation, ensuring that it can be reliably applied to baseline and monitoring years.
11. **Baseline Carbon Stock Assessment**: Apply the regression model to predict baseline carbon stock across the eligible land area. This quantification establishes the reference carbon stock against which future sequestration will be measured.
12. **Carbon Sequestration Quantification for Baseline and Monitoring Years**:

    Using the model, calculate the carbon sequestration achieved through ARR activities, comparing baseline and monitoring year values. This quantification provides the basis for carbon credit claims, enhancing transparency and reliability.

2.3 Benefits of RS-GIS and Machine Learning for ARR Baselines:

Implementing RS-GIS-based baseline quantification offers several advantages:

- **Scalability**: This approach supports large-scale analysis across fragmented plots typical of Indian landscapes, enabling coverage of regions with multiple small and marginal landholders (Zomer et al., 2007).
- **Accuracy and Reliability**: High-resolution imagery combined with machine learning and regression modeling enhances the accuracy of biomass estimates, bolstering confidence in the baseline quantification (Singh et al., 2023).
- **Transparency**: By archiving historical data and offering reproducible models, this approach provides a transparent baseline that meets the rigor demanded by carbon markets (Pandit & Behera, 2021).

- **Cost-effectiveness**: Remote sensing reduces the need for labor-intensive field measurements, making the monitoring process economically feasible for smallholder-inclusive ARR projects (Roy et al., 2020).

III. APPLICATION TO INDIA'S FRAGMENTED LANDSCAPE AND MEETING CARBON MARKET REQUIREMENTS

International standards require ARR and agroforestry projects to meet criteria for additionality and eligibility to avoid “business-as-usual” scenarios. The RS-GIS-based approach enables retrospective assessments that verify the land’s degraded status and non-forest classification 10 years prior to project start (Verra, 2024). By ensuring compliance with these conditions through objective, data-driven models, this methodology enhances the legitimacy and marketability of such projects. High-confidence baseline estimation builds a credible foundation for claiming carbon credits and ensures additionality by rigorously quantifying the impact of new plantation activities on carbon sequestration (Nair et al., 2018; Ghosh & Sharma, 2024). India’s agroforestry potential is closely tied to its small and fragmented landholdings, which account for 86.1% of agricultural land (Government of India, 2023). The baseline quantification approach, integrating high-resolution RS-GIS and regression modeling, enables precise assessments of small, scattered plots, thus broadening smallholder participation in carbon finance projects. This inclusion not only ensures equitable distribution of benefits but also expands the total area under agroforestry, enhancing carbon sequestration potential. Furthermore, the transparency, scalability, and affordability of this approach make it particularly suited for attracting greater investment in agroforestry carbon finance initiatives, especially in the Indian context.

IV. CONCLUSION

Integrating RS-GIS with linear regression and machine learning enhances baseline quantification for ARR projects in India. This method aligns with eligibility and additionality requirements by providing precise, retrospective carbon stock assessments and enabling continuous monitoring. For India’s agroforestry landscape, where fragmented holdings and smallholder participation are prevalent, this approach offers a practical, transparent, and scalable solution that could significantly improve the confidence of carbon markets. By adopting RS-GIS-based baseline quantification, India can facilitate access to carbon finance for a larger pool of smallholders, transforming agroforestry into a viable tool for sustainable development and climate mitigation. Our enhanced methodology not only addresses the limitations of existing frameworks but also ensures that India’s small and marginal farmers are integral beneficiaries of carbon finance projects. By tailoring the approach to fragmented landscapes, this work contributes to both sustainable development and equitable growth.

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Determination of Crop Coefficient and Water Requirement of Okra Crop by using Lysimeter for Parbhani District, Maharashtra

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Abstract— *Water is a finite and vital resource, making its efficient utilization particularly critical in irrigation, especially during the summer months when water scarcity is most acute. Summer okra (Abelmoschus esculentus), a key vegetable crop in India, depends on precise irrigation scheduling to ensure optimal yields. To address this need, a field experiment was conducted over the summer seasons of 2023 and 2024 at Vasantrao Naik Marathwada Krishi Vidyapeeth (VNMKV), Parbhani, situated in the semi-arid Marathwada region of Maharashtra, India. The study utilized a weighing-type lysimeter to estimate crop coefficient (Kc) values for okra, which are crucial for determining accurate irrigation schedules. In 2023, the Kc values for the okra crop were recorded as follows across different growth stages: initial stage (12 to 14 MW) – 0.63, development stage (15 to 18 MW) – 1.05, mid-season stage (19 to 23 MW) – 1.42, and late season stage (24 to 26 MW) – 0.76. In 2024, the Kc values were slightly different: initial stage (13 to 15 MW) – 0.60, development stage (16 to 19 MW) – 0.99, mid-season stage (20 to 24 MW) – 1.33, and late season stage (25 to 26 MW) – 0.75. The seasonal water requirement for okra was calculated to be 579.18 mm in 2023 and 529.38 mm in 2024. These Kc estimates provide valuable insights for optimizing irrigation management, facilitating more accurate water demand predictions and resource planning. The study's findings contribute to improving water use efficiency in the Marathwada region, where conserving water is vital for sustainable agricultural practices.*

Keywords— Crop coefficient, FAO-56 Penman Monteith method, lysimeter, okra, reference evapotranspiration, crop evapotranspiration, water requirement.

I. INTRODUCTION

Okra (Abelmoschus esculentus L. Moench) is a highly valued crop, particularly for its mucilaginous pods that, due to their soluble fiber content, impart a distinctive slimy texture when cooked. The pods are versatile, consumed in various forms such as cooked, pickled, raw, or added to salads. In developing nations, okra plays a significant role in addressing malnutrition and food insecurity. Nutritionally, raw okra comprises approximately 90% water, 7% carbohydrates, 2% protein, and is a rich source of dietary fiber, vitamin C, and vitamin K (Gemede, 2015). While okra exhibits relative tolerance to water stress, it performs optimally when soil moisture is well-maintained, especially during germination and for achieving high yields. Varughese et al. (2014) emphasize the importance of fertigation with 100% of the recommended fertilizer dose delivered through drip irrigation for optimizing water use and crop yield. Thokal et al. (2020) recommend specific agronomic practices, including a crop spacing of 1200-450 x 150 mm, 100% RDF fertigation, 80% ET_x drip irrigation, and the use of silver-black mulch to enhance productivity and water efficiency, particularly in the lateritic soils of the Konkan region.

Crop water requirements vary throughout the growing season, influenced by changes in canopy structure, climatic conditions, cropping practices, and irrigation methods (Hamdy and Lacirignola, 1999; Katerji and Rana, 2008).

Evapotranspiration (ET), encompassing both soil evaporation and plant transpiration, constitutes approximately 99% of the water uptake by plants. Therefore, measuring daily crop evapotranspiration (ETc) throughout the growth cycle is crucial for determining precise water requirements. Accurate estimation of ETc is essential for effective water management, as misestimating water needs can adversely affect economic, social, and environmental outcomes (Shideed et al., 1995; Katerji and Rana, 2008).

The crop coefficient (Kc), a critical factor in irrigation management, represents the ratio of ETc to reference evapotranspiration (ET_0). Kc values fluctuate during different growth stages and must be calibrated locally to ensure precise irrigation scheduling (Doorenbos and Pruitt, 1977; Milla et al., 2016). While generalized Kc values are available, region-specific data is imperative for effective irrigation planning at the local level.

In Maharashtra, characterized by arid and semi-arid climatic conditions, erratic rainfall patterns present significant challenges to agricultural productivity. The Marathwada region typically cultivates okra during June-July, September-October, and February-March, with the winter-sown crop demanding the highest water input. Given the increasing importance of okra cultivation in the region, a field experiment is proposed to quantify the water requirements and crop coefficients of okra. This research aims to facilitate improved irrigation planning and water resource management in the Marathwada region.

With rising global water demand, irrigation is becoming an increasingly significant cost factor in agriculture. Effective irrigation scheduling, which is key to maximizing yields and enhancing water productivity, requires a solid understanding of crop water needs (Dabhi et al., 2020). One of the most commonly used methods to estimate crop water requirements is the FAO-56 Penman-Monteith (PM) method. This method calculates reference crop evapotranspiration (ETo) and multiplies it by crop coefficients (Kc) to determine crop evapotranspiration (ETc), with Kc values adjusted to account for the specific characteristics of different crops and their growing environments (Allen et al., 1998). Studies by Gul et al. (2018) highlighted the influence of water table depths on okra's water usage and overall productivity, while Nyatuame et al. (2019) emphasized the importance of applying the right amount of water to maximize the efficiency of limited freshwater resources. Similarly, James et al. (2017) used a mini-lysimeter to measure water use in okra, further demonstrating the importance of developing irrigation systems that are specifically tailored to the needs of different crops.

Due to the highly site-specific nature of Kc values, determining them locally is crucial for optimizing irrigation management (Ramachandran et al., 2021). Although generalized Kc values, such as those found in FAO's Irrigation and Drainage Paper No. 24 (Doorenbos and Pruitt, 1977), are widely applied, they can lead to substantial inaccuracies if not calibrated to local conditions. For instance, Vu et al. (2005) discovered a 17% error when using standard Kc values in paddy fields, which highlighted the need for local calibration. Awari et al. (2023) conducted a key study that determined Kc values for okra in the semi-arid Marathwada region of Maharashtra using a weighing-type lysimeter. Additionally, Awari and Khodke (2018) developed modified Kc values for gram in the Parbhani district, which differed significantly from FAO recommendations due to regional climate and farming practices.

Kc values are central to precision irrigation scheduling, as they are derived by dividing ETc by ETo. In a study by Hawari et al. (2023) in the Marathwada region, Kc values for okra ranged between 0.61 and 1.41, with the highest values observed around the 10th week. Their research provided Kc values of 0.64, 1.07, 1.33, and 0.86 for the initial, developmental, mid-season, and late stages of okra growth. These data are essential for developing more efficient irrigation strategies in similar climates.

In sub-humid regions, Patil et al. (2018) examined how subsurface drip irrigation, both with and without plastic mulch, affected okra's water use. Their research showed that plastic mulch reduced total evapotranspiration from 403 mm to 363 mm, as opposed to 512 mm and 468 mm without mulch. Furthermore, Kc values were found to be lower when using plastic mulch (ranging from 0.31 to 0.77) compared to without mulch (0.51 to 0.93). This illustrates how plastic mulch can reduce irrigation demands, lower evaporation losses, and improve crop yields.

Several studies have highlighted the variability of Kc values across different crops and climates. For example, Sagar et al. (2022) used a smart weighing lysimeter to calculate Kc values for Chrysanthemum grown in a greenhouse, with Kc values ranging from 0.43 to 1.27 depending on the crop's growth stage. Similarly, Nigusi Abebe et al. (2021) developed Kc values for onions in Ethiopia using non-weighing lysimeters and found significant differences between local Kc values and FAO-56 recommendations. These findings underline the importance of site-specific calibration in water management. Environmental factors, such as elevated temperatures and vapor pressure deficits, can influence regional Kc values, as noted by Piccinni et al. (2009), reinforcing the need to account for local conditions when determining Kc.

This study aims to determine the water requirements and crop coefficients for okra in Maharashtra's semi-arid Parbhani district using a weighing-type lysimeter. The results will provide more accurate crop water requirement estimates, aiding in reliable crop production and promoting sustainable water use practices in similar regions.

II. MATERIAL AND METHODS

2.1 Study Area:

The experiment on Okra crop cultivation was conducted at the Department of Irrigation and Drainage Engineering, C.A.E.T., V.N.M.K.V., Parbhani, during the years 2022-2023 and 2023-2024. Meteorological data for the study was collected from the IMD-recognized weather station at Vasantrao Naik Marathwada Krishi Vidyapeeth, Parbhani.

2.2 Climate:

The climate of the Marathwada region can be classified as semi-arid. The region experiences hot and dry summers, cold dry winters, and wet, humid monsoon seasons with medium rainfall. The mean annual precipitation is approximately 649.34 mm, mostly received between June and October from the southwest monsoon. Winter rains are scant and uncertain. The mean maximum temperature ranges from 28.6°C in winter (December) to about 41.2°C in summer, while the mean minimum temperature ranges from 10.9°C in winter to 25.6°C in summer. The relative humidity varies between 31% to 62% for minimum and 85% to 96% for maximum throughout the year.

2.3 Soil Data:

The soil in the experimental field was classified as clay, with a field capacity of 26% and a bulk density of 1.4 g/cm³. The variety of Okra used for the lysimeter experiment was Parbhani Kranti (OH/517). Seeds were sown in a 1.5 x 1.5 x 1m weighing-type lysimeter platform at a spacing of 0.25 x 0.50 m on March 24, 2023, and March 26, 2024. To simulate similar growing conditions, the same okra crop was planted around the lysimeter tanks, ensuring a uniform cropping environment.

2.4 Experimental Set-Up:

FIGURE 1: Technical Specifications of Weighing Type Digital Lysimeter
Lysimeter Size; 1.5M X 1.5 M X 1.0 M.

A weighing-type lysimeter, with a platform size of 1.5 x 1.5 x 1 m, was installed in the field as part of a study to measure the actual evapotranspiration of okra by recording the applied water and the amount of water lost through evapotranspiration. The lysimeter consisted of an outer and inner box with a drainage system and a weighing mechanism based on load cells connected to a data logger for recording time-varying water loss due to evapotranspiration and drainage (Schmidt et al., 2013). To install the lysimeter, a pit of 1.5 × 1.5 × 1.0 m was manually dug, with the soil removed in five layers of 200 mm depth each and set aside for backfilling in the same order. The bottom of the pit was compacted, leveled with burnt bricks, and the outer tank was placed with load cells fixed at the base. The inner tank, resting on the load cells, was filled layer-wise with the excavated soil, and its weight was automatically monitored by the load cell assemblies. Moisture sensors were installed at intervals of 200 mm in perforated PVC pipes at a depth of 200 mm below the soil surface to record soil moisture. Field calibration was conducted in 2023, following the methodology of Wheller and Ganji (2010), by recording output from loading and unloading known weights. To replicate field conditions and maintain a controlled environment for water balance measurement, the same crop was grown surrounding the lysimeter to ensure similar micro-environment, nutrient availability, soil moisture, and soil–plant interactions. Additionally, 20 random soil samples were collected from the experimental plot, mixed, and analyzed for physical properties at the Department of Soil Science and Agriculture Chemistry, VNMKV, Parbhani.

2.5 Estimation Parameters:

2.5.1 Calculation of Crop coefficient:

Jensen (1968) introduced the concept of the crop coefficient (Kc) for estimating actual evapotranspiration, which has since been further developed by researchers such as Amayreh and Al-Abed (2005), Fisher (2012), Awari and Khodke (2018), Awari et al. (2019), and Nigusi Abebe et al. (2021). The crop coefficient is defined as the ratio of crop evapotranspiration to reference evapotranspiration, with the latter estimated over a reference grass surface of standard height and with no scarcity of available water (Allen et al., 1998).

$$Kc = ETc / ETo \tag{1}$$

Where,

ETc is the actual crop evapotranspiration (mm day-1)

ETo is the reference crop evapotranspiration (mm day-1)

2.5.2 Determination of crop evapotranspiration (ETc):

Evapotranspiration of the okra crop was measured using the soil water balance method, which considers changes in soil water content within the lysimeter area, including inputs from rainfall and irrigation. The water applied from the lysimeter area served as input data. Crop evapotranspiration was calculated for each growth stage based on the soil water balance equation. This equation estimates evapotranspiration by comparing the soil moisture measured each day against previous measurements. The water balance equation for each successive day during the study period was used to determine the daily crop evapotranspiration.

$$ETc = R+I-DP \pm \Delta S \tag{2}$$

Where,

ETc is crop evapotranspiration,

I= irrigation, mm,

R is rainfall,

DP is deep percolation loss

ΔS is change in storage of soil moisture and all are in mm,

The change in soil moisture (ΔS) was determined by subtracting the moisture content recorded on each day from that of the previous day, with measurements taken from sowing through to the final harvest. Crop evapotranspiration was calculated for different growth stages initial, development, mid-season, and late-season using the appropriate equation. The crop evapotranspiration was estimated based on the water balance equation, considering the daily soil moisture measurements throughout the study period.

2.5.3 Calculation of reference evapotranspiration (ETo):

Reference crop evapotranspiration (ETo) was calculated using the FAO-56 Penman-Monteith method through the DSS-ET version-1, a decision support system developed by the Department of Agricultural and Food Engineering at the Indian Institute of Technology, Kharagpur (George et al., 2002; Bandyopadhyaya et al., 2012). The necessary meteorological data for this calculation were obtained from the weather station at VNMKV, Parbhani.

The FAO Penman Monteith equation is expressed as:

$$ET_0 \frac{[0.408\Delta(\mathrm{Rn} - \mathrm{G}) + \gamma(900\backslash \mathrm{T} + 273)\mathrm{u2}(\mathrm{es} - \mathrm{ea})]}{\Delta + \gamma\, 1 + 0.34\, u_2}$$

where,

ETO - potential evapotranspiration (mm day-1),

Rn - net radiation at the crop surface (MJ m-da1), G - soil heat flux density (MJ m-2 day-1),

T - mean daily air temperature at2m height(°C), u2 - wind speed at 2 m height (m s-1),

es - saturation vapour pressure (kPa), ea - actual vapour pressure (kPa)

es - ea - saturation vapour pressure deficit (kPa), Δ - slope vapour pressure curve (kPa °C-1),

γ - psychrometric constant(kPa°C1).

The total growing period for the okra variety was 98 days in 2023 and 93 days in 2024. During the experiment, the crop growth periods were divided into four stages: initial (21 days), crop development (28 days), mid-season (35 days), same in both year 2023&2024, and late-season (17 days) in 2023 and (12 days) in 2024, based on recommendations from Vasantaro Naik Krishi Vidyapeeth, Parbhani (Holsambare, 1988; Anon., 2021). Real-time weather data was collected daily from an Automatic Weather Station and stored via a cloud server for input into the software. Power for the system was supplied by a storage battery, which was charged by an overhead solar panel installed at the lysimeter's software and data storage panel. These recorded data were used to compute ETo using the FAO-56 Penman-Monteith method. Daily ETo values were logged at regular intervals (every 60 minutes) and averaged to obtain daily values. From these daily averages, ETc and Kc values were calculated. Both daily ETo and Kc values were then averaged on a weekly basis for the crop period.

2.5.4 Soil Parameters:

Soil moisture and temperature were recorded at depths of 200 mm, 400 mm, and 600 mm using in-situ moisture and temperature sensors installed in the lysimeter.

2.5.5 Crop Growth Parameters:

Crop height, number of branches, leaves, flowers, and fruits were recorded manually after 30, 45, 60,75, 90 daysduring study.

III. RESULTS AND DISCUSSION

3.1 Soil analysis of the experimental plot and lysimeter:

The physical properties of the soil were analyzed in 10 cm layers down to 80 cm depth within the lysimeter. The estimated water holding capacity of the experimental soil averaged 25%. It was observed that moisture content increased from the top layer to the bottom of the lysimeter. Field capacity ranged from 23% to 26%, while bulk density varied between 1.37 and 1.41 g/cm³, being higher at the 75 cm depth. The soil type significantly influences water availability to the crop, as the water holding capacity is determined by the amount of moisture retained by the soil particles. The particle size distribution, showing higher clay content in the five layers, contributes to the increased water holding capacity of the soil.

3.2 Crop growth parameters

The crop growth parameters recorded during the experimentation for the lysimeter and field plots are presented in Table 1, 2&3.

TABLE 1
PLANT GROWTH PARAMETERS OF SUMMER OKRA IN LYSIMETER DURING SUMMER 2023&2024

S.No.	Parameter	30 DAS		45 DAS		60 DAS		75 DAS		90 DAS		AT Haevest	
		2023	2024	2023	2024	2023	2024	2023	2024	2023	2024	2023	2024
1	Height, cm	30.7	20.1	69.3	61.09	91.06	90.6	106.1	101.4	111.9	111.8	120.5	111.8
2	Branches, Nos	2.1	1.7	2.3	2.2	3.6	3.2	4.8	3	5.1	3.7	5.5	3.7
3	Leaves, Nos	11.8	9	21.3	14.2	30.4	20.6	33.8	24.7	35.3	23	34	29
4	Flowers, Nos	5	1	3.4	2	2.8	2	4.4	2.6	1.3	0.9	1.1	0.3
5	Fruits, Nos	0	0	5.3	2.3	9.9	4.5	8.7	5.3	5.6	2.9	7.3	3.2
6	Avg yield	**2023- 118.34 gm plant^{-1}, 2024-94.39gm plant^{-1}**											

TABLE 2
PLANT GROWTH PARAMETERS OF SUMMER OKRA IN THE FIELD PLOT-1 OF THE YEAR 2023 AND 2024

Field plot-1	Parameter	30 DAS		45 DAS		60 DAS		75 DAS		90 DAS		AT Haevest	
Sr.no.		2023	2024	2023	2024	2023	2024	2023	2024	2023	2024	2023	2024
1	Height, cm	19.8	19.6	58.2	51.09	80.8	71.32	92.8	83.1	98.9	96.2	102.5	96.2
2	Branches, Nos	1.5	1.3	1.7	1.7	3.1	2.9	3.9	2.4	4.2	3.1	4.6	3.1
3	Leaves, Nos	10.8	7.8	16.9	11	21.8	16	24.8	23.5	25.5	20	24.5	24.5
4	Flowers, Nos	3.4	0.8	2.7	1.6	2.4	1.9	2.8	2.6	1.2	0.6	1	0.4
5	Fruits, Nos	0	0	4.8	1.7	7.7	3.6	6.4	4.2	3.5	2.6	4.6	2.5
6	Avg yield	**2023- 101.27 gm plant^{-1}, 2024-80.20 gm plant^{-1}**											

TABLE 3
PLANT GROWTH PARAMETERS OF SUMMER OKRA IN THE FIELD PLOT-2 OF THE YEAR 2023 AND 2024

Field plot-2	Parameter	30 DAS		45 DAS		60 DAS		75 DAS		90 DAS		AT Haevest	
Sr.no.		2023	2024	2023	2024	2023	2024	2023	2024	2023	2024	2023	2024
1	Height, cm	21.3	18.2	57.9	44.26	77.4	65.15	100.4	78.4	104.1	92.8	106	92.8
2	Branches, Nos	1.2	1.2	1.6	1.9	2.9	2.2	3.3	2.6	3.9	2.7	4.1	2.7
3	Leaves, Nos	11.3	8.8	17.4	14.3	19.9	19	23.1	21.7	24.3	17.8	23.2	22
4	Flowers, Nos	4.3	0.3	3	1.5	2.8	1.7	3	1.9	0.5	0.7	0.5	0.3
5	Fruits, Nos	0	0	4.7	1.2	7.1	2.9	6.2	3.1	3.9	2.7	4.2	2.1
6	Avg yield	**2023- 102.20 gm plant^{-1}, 2024 -74.49 gm plant^{-1}**											

Table 1 represented the growth parameters of summer okra measured in a lysimeter during the summer of 2023 and 2024 at different stages of development, recorded at 30, 45, 60, 75, and 90 days after sowing (DAS), as well as at harvest. In 2023, okra plants showed a greater height, reaching 120.5 cm at harvest compared to 111.8 cm in 2024. Similarly, the number of branches in 2023 peaked at 5.5, whereas in 2024, the maximum was only 3.7. The number of leaves followed a similar trend, with 35.3 leaves in 2023 and 29.0 in 2024 at harvest. Flower production also differed significantly, with a notable reduction in 2024 (only 0.3 flowers at harvest compared to 1.1 in 2023). Fruit production was higher in 2023, with 7.3 fruits at harvest compared to 3.2 in 2024, indicating better overall plant growth and productivity in 2023 than in 2024.

Table 2&3 summarize the growth parameters of summer okra grown in two field plots during 2023 and 2024, with measurements taken at various stages (30, 45, 60, 75, and 90 days after sowing, as well as at harvest). In Field Plot 1, the plants in 2023 generally outperformed those in 2024. The maximum plant height at harvest was 102.5 cm in 2023, compared to 96.2 cm in 2024. Branch and leaf numbers were also higher in 2023, with 4.6 branches and 24.5 leaves compared to 3.1 branches and 24.5 leaves in 2024. Flower and fruit production followed the same pattern, with 4.6 fruits in 2023 compared to 2.5 in 2024. Similarly, Field Plot 2 showed better results in 2023, with plants reaching a height of 106 cm at harvest, while in 2024 they only reached 92.8 cm. The number of branches, leaves, flowers, and fruits were also higher in 2023, with 4.1 branches, 23.2 leaves, and 4.2 fruits compared to 2.7 branches, 22.0 leaves, and 2.1 fruits in 2024. Overall, the data indicates that okra plants showed more vigorous growth and productivity in 2023 compared to 2024 across both field plots.

3.3 Reference Crop Evapotranspiration, Actual crop evapotranspiration, Crop coefficients:

Tables 4 and 5 summarize the weekly average values of reference evapotranspiration (ETo), crop evapotranspiration (ETc), and crop coefficient (Kc) for okra during the 2023 and 2024 growing seasons. In 2023, ETc ranged from 2.26 mm/day during the first week, peaking at 8.71 mm/day in the 8th week, with fluctuations observed until the 15th week. The highest ETc occurred during the 19th standard meteorological week (SMW). In 2024, ETc values ranged from 2.15 mm/day to a maximum of 7.63 mm/day, with the highest recorded during the 20th SMW.

ETo exhibited a rising trend in 2023, starting at 4.34 mm/day and reaching 6.87 mm/day by the 17th SMW. Similarly, in 2024, ETo increased from 4.70 mm/day to 6.49 mm/day, fluctuating due to varying weather conditions. The crop water demand was low in the initial growth stage, increased during mid-season, and decreased in the late season.

Lysimetric Kc values for okra, presented in Figure 3, showed similar patterns for both years. In 2023, Kc values ranged from 0.52 to 1.49, decreasing to 0.65 by the 26th SMW. In 2024, Kc ranged from 0.46 to 1.45, falling to 0.64 by the end of the season. The Kc values for the Parbhani Kranti variety in 2023 were 0.63, 1.05, 1.42, and 0.76 for the initial, development, mid-season, and late-season stages, respectively. In 2024, these values were 0.60, 1.0, 1.33, and 0.75 for the same stages.

The stage-wise Kc values align with findings from previous studies in India, though some variation is noted due to differences in agro-climatic conditions. For instance, Hawari et al. (2023) reported Kc values of 0.64, 1.07, 1.33, and 0.86 for Maharashtra, while Sharma et al. (2021) recorded values ranging from 0.4 to 1.2 for Udaipur, and Patil and Tiwari (2018) reported values between 0.51 and 1.12 for Kharagpur. These variations underscore the importance of developing location-specific Kc values for precise irrigation scheduling.

TABLE 4
WEEKLY LYSIMETRIC ESTIMATED ETc, ETO and Kc VALUES FOR THE OKRA CROP IN 2023

Crop Week	SMW	Crop Growth stage	ETc (mm/day)	ETo (mm/day)	Kc values	Stage Wise kc values
1	12	(21 Days) Initial	2.26	4.34	0.52	0.64
2	13		3.62	5.29	0.68	
3	14		3.44	4.86	0.71	
4	15	(28 Days) Development	4.44	5.31	0.83	1.05
5	16		5.95	6.22	0.96	
6	17		7.89	6.87	1.15	
7	18		7.96	4.43	1.26	
8	19	(35 Days) Mid-season	8.71	6.37	1.37	1.42
9	20		8.53	4.96	1.49	
10	21		8.35	5.64	1.48	
11	22		7.26	4.95	1.45	
12	23		6.21	4.71	1.32	
13	24	(15 Days) Late season	5.08	6.32	0.9	0.76
14	25		2.88	4	0.72	
15	26		2.11	3.25	0.65	

TABLE 5
WEEKLY LYSIMETRIC ESTIMATED ETc, ETO and Kc VALUES FOR THE OKRA CROP IN 2024

Crop Week	SMW	Crop Growth stage	ETc (mm/day)	ETo (mm/day)	Kc values	Stage Wise kc values
1	13	(21 Days) Initial	2.15	4.7	0.46	0.6
2	14		3.57	5.5	0.65	
3	15		3.65	5.27	0.69	
4	16	(28 Days) Development	4.38	5.6	0.78	1
5	17		5.83	6.49	0.9	
6	18		6.21	5.75	1.08	
7	19		7.41	6.09	1.22	
8	20	(35 Days) Mid-season	7.63	5.53	1.38	1.33
9	21		7.52	5.2	1.45	
10	22		7.48	5.6	1.34	
11	23		7.4	5.8	1.28	
12	24		5.95	4.9	1.21	
13	25	(10 Days) Late season	4.11	4.73	0.87	0.75
14	26		3.3	5.23	0.63	

3.4 ETc and ETo during crop growing period:

Reference evapotranspiration (ET_0) and crop evapotranspiration (ETc) during the growing season are presented in the Fig. 2 for year 2023 and 2024. In ETc curve, the fluctuation is regulated by crop growth and development, while in ET_O curve the fluctuation is regulated by weather parameter values.

As shown in the Figure 2 the crop evapotranspiration (ETc) exceeded ET_O at the development stage and midseason stage, whereas in the rest stages ET_O higher than ETc during cropping season. This indicates that during the midseason stage, the crop water demand is high because of the fully developed crop canopies and high evaporative demand to flower, fruit formation and filling.

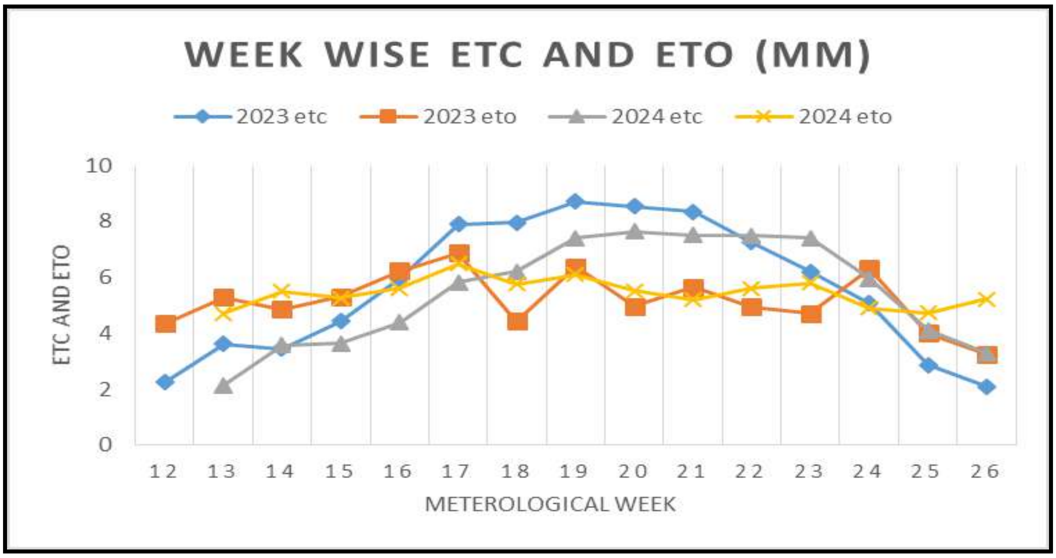

FIGURE 2: Seasonal ETc and ET_O of okra crop as a function of days after sowing

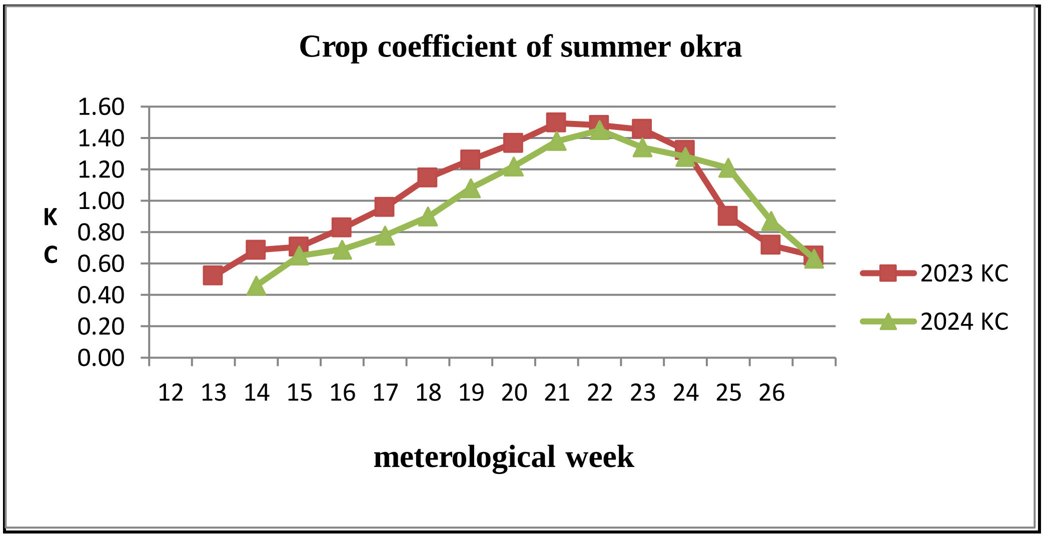

FIGURE 3: Weekwise crop coefficient of summer Okra crop

3.5 Stage-wise water requirement for summer Okra:

The stage-wise crop water requirement of summer Okra at Parbhani presented in the Fig. 4 for year 2023 and 2024, for The initial stage demands of water approximately 65.22 mm 65.57 mm in the year 2023 & 2024 respectively, into the developmental stage, there is a substantial increase in water requirements, totaling 182.66 mm in 2023 where as 166.81 mm in 2024, During the midseason stage it was 273.38 mm of water in 2023 while in 2024 it was ranges 253.20 mm, during late season stage, the water requirement decreases to 57.86 mm and 43.80 mm in 2023 & 2024 respectively. Similar results are in confirmatory with result obtained by Aliku et al. (2022), Ademiju et al. (2017), Hashim et al. (2012), Dahr et al. (2021), Lima et al. (2021), Mehta and Pandey (2016).

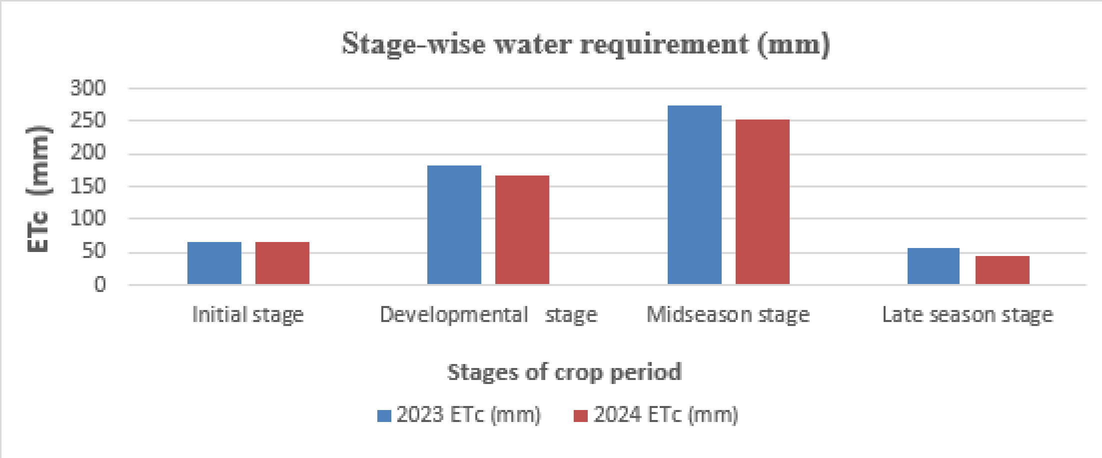

FIGURE 4: Stage-wise water requirement (mm)

IV. CONCLUSION

The study concluded that the total actual evapotranspiration (ETc) for summer Okra was 579.18 mm in 2023 and 529.38 mm in 2024, with the highest water demand observed during the mid-season stage. The reference evapotranspiration (ETo) varied based on climatic conditions, totaling 547.71 mm in 2023 and 513.93 mm in 2024. Stage-wise crop water requirements also fluctuated, with the initial stage requiring approximately 65 mm, while the mid-season had the highest demand, reaching 273.38 mm in 2023 and 253.20 mm in 2024, before decreasing in the late season.

The estimated crop coefficients (Kc) for summer Okra varied across growth stages, with higher values recorded in the mid-season. In 2023, the Kc values were 0.63, 1.05, 1.42, and 0.76 for the initial, developmental, mid-season, and late stages, respectively, while in 2024, they were slightly lower. Notably, the lysimeter-derived Kc values were higher than those recommended by FAO-56, and polynomial crop coefficient equations developed from lysimeter data can be applied to estimate daily or weekly Kc values for different Okra varieties and crop periods.

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An Optimized Hybrid Techniques of Training set reduction for Performance Improvement of k- Nearest Neighbour Classifier to apply it on Agricultural Soil health card dataset

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***Abstract*— *In non-parametric algorithms such as k-nearest neighbour the fundamental predicaments are the larger storage and computational requirements. Moreover, the effectiveness of classification task affected significantly due to uneven distribution of training data. To overcome the drawbacks of lazy learner like k-nearest neighbour classifier, the scope of training set reduction by editing and condensing the training set is explored in this research work. Additionally, the reduction of training set is carried out by hybrid techniques of training set reduction namely TSR-FkNN (Elbow method) and TRS-FkNN (Silhouette value) in optimized way to achieve improvement of classification performance.*

***Keywords*— Machine Learning, k-NN, Hybrid method.**

I. Introduction

In Machine learning (ML) algorithm like the simple k-nearest neighbour (k-NN) classifier the input training set consists of vectors and associated class labels [1]. This training set is used in training phase of ML task and size of the input training set is not changed while taken as input [2]. The ML algorithm calculates the distance between a new input test vector and each vector of the stored training set then assigns a class label to the test vector [3]. Hence, the *k*-NN classifier requires a large amount of memory to store the training dataset and a large amount of time required to execute this algorithm, because in contrast to parametric classification algorithms where parameters are learned from training set and algorithm uses these parameters to compute similarity measure, the non-parametric classifiers stores all training instance [4].

Since non-parametric classifiers stores all training instances, it motivated us to find the solution to reduce time and space of k-NN classifier. There are a few solutions to this problem which are feature selection, training set reduction by removing noisy and unimportant training instances [5]. In this research work, we have evaluated hybrid training set reduction techniques with optimization. These techniques are Training set reduction Fast k-NN by applying SSE (TSR-FkNN, Elbow method) and Training set reduction Fast k-NN by applying silhouette value (TSR-FkNN, silhouette value).

The evaluation of above approaches is carried out on agriculture soil health card dataset. And results suggest that the effectiveness of above approaches is significant to existing methods. This paper is organized as follows. Section 2 presents the background about the research topic. Section 3 is covering proposed research work. Section 4 is about comparison of all methods and analysis. Section 5 is concluding this research work.

II. Background

The ML field is divided into three major areas namely supervised, unsupervised and semi-supervised. In supervised approach the labeled data is used to supervise the algorithms, for example classification [6]. In unsupervised ML approach, learning algorithms learn from the data itself, for example clustering. While in semi-supervised learning approach, the mixture of labeled and unlabeled records are provided as an input to the ML algorithm.

2.1 Soil health card data set (SHCDS):

This research work is concentrated on exploring the applicability of Machine learning techniques on Agricultural Dataset of Soil health card and to propose improved efficient Machine learning algorithm to classify soil sample into the categories of the deficiencies of micro and macro nutrients.

TABLE 1
SOIL HEALTH CARD DATA SET [5]

Sr. No	SHC_POTASS	SHC_SULPHUR	SHC_MG	SHC_PHOSPHORUS	SHC_IRON	SHC_MANGANESE	SHC_ZINC	SHC_CU	Label
1	454	6	6	99	5	6	5	6	MaMi 179
2	429	12.2	1	31	8.36	9.8	0.46	0.98	MaMi 145
3	479	9.7	2	17	0.56	8.46	7.32	0.22	MaMi 130
4	369	8.2	1.5	21	8.44	10.4	0.86	0.32	MaMi 148
5	370	9.3	1	35	7.38	8.4	0.8	0.92	MaMi 145
6	351	12.2	2.5	17	0.98	7.5	7.56	0.48	MaMi 163
7	242	11.6	2	31	8.06	4.12	0.8	0.65	MaMi 145
8	360	14	2	20	9.6	11.44	0.45	0.92	MaMi 133
9	237	14.3	2.5	35	7.12	8.1	0.74	0.23	MaMi 176
10	356	13.5	1	21	8.44	7.56	0.44	0.52	MaMi 145
11	438	10.8	2	31	8.9	7.6	0.46	0.58	MaMi 145
12	315	18.2	2.5	12	7.58	9.2	0.74	0.44	MaMi 161
13	310	16.5	1	33	6.12	8.06	0.74	0.55	MaMi 145
14	233	12.2	2.5	33	9.8	7.52	0.56	0.88	MaMi 177
15	378	18.5	2	26	8.9	7.36	0.56	0.42	MaMi 145
16	397	6.2	1.5	14	11.4	8.9	0.8	0.2	MaMi 136
17	283	9.2	1	35	8.44	9.38	0.5	0.62	MaMi 145

2.2 Applying *k*-NN on SHCDS:

ALGORITHM 1: *k*-Nearest Neighbour (*k*-NN) classifier

Input: A set of Agriculture records R = {R1, R2. . . Rn}, where n is the total number of SHCDS records.
Procedure:

- **Step 1:** Divide the record data into one training set and test set as 50-50 split.
- **Step 2:** For each test record, calculate similarity with each training record.
- **Step 3:** Sort the training records in the descending order of the maximum cosine similarity and select the top k training records.
- **Step 4:** Assign a class to test record which occurs maximum times in the top k training records.
- **Step 5:** Construct a confusion matrix.
- **Step 6:** Calculate performance measures from the confusion matrix.

2.3 Selection of prototype:

k-NN is having a high computational cost requirement and it is a major and severe drawback in spite of various advantages. To achieve two major advantages of the low computational cost and improved storage need to store the subset(a small set from training set) the selecting prototypes is applied for similar of sometimes even an improves classification performance. Different ways of taking an optimized and proper set of representatives have been studied so far. There are two methods which lead to the reduction of the training set size are editing and condensing, they are giving optimized set and referred as Prototype Selection (PS) methods [6].

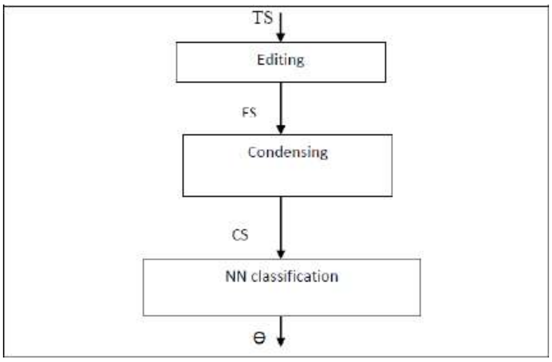

FIGURE 1: Selection of prototype

The learning process is consists of two steps to be finished see Fig 1, editing and condensing in the case when the classifier uses the NN rule. The main focus of editing is to remove noisy instances, and the condensing maintains only the representative instances means it generates prototypes, see Fig. 1. Here, the training set (TS) is the input to the editing, the output of editing is edited set (ES), which in sequence give as input to condensing, whose output is condensed set (CS). Finally, the unknown sample x is classified using the resulting condensed set as input to the classifier. The result: the class ϴ to which the sample x belongs.

III. PROPOSED WORK

In previous section we have discussed training set editing and condensing techniques respectively. In this section, we have proposed a novel techniques which uses both editing and condensing both. These hybrid techniques can be understood from Fig. 2. It takes Initial training set (TS), and then it will condense it followed by applying editing algorithm. Finally, the edited set is applied to the *k*-NN classifier.

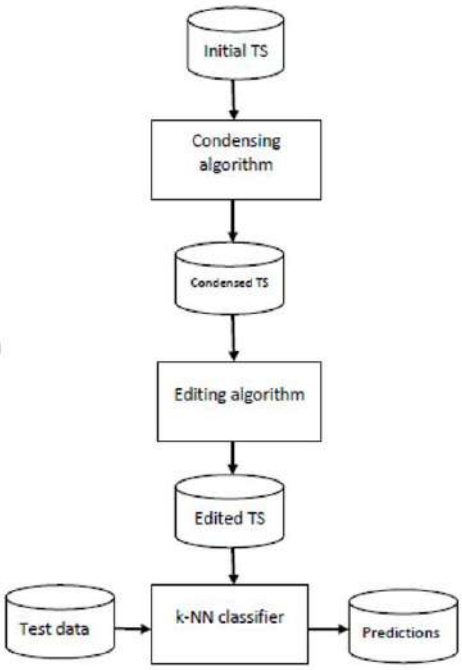

FIGURE 2: Data reduction by hybrid method

Fig. 3 provided an overview of a hybrid approach based on the previous two methods of training set reduction and then clustering. This method is a hybrid method, where we have combined features of both fast k-NN and training set reduction. In hybrid method, the training set reduction techniques are applied on training set feature vector and the technique reduces training set. The reduced training set is given as an input to clustering algorithm and a set of clusters are given as an input to Machine learning algorithm and classifier model is learned. The classifier model assigns a class to a new test instance.

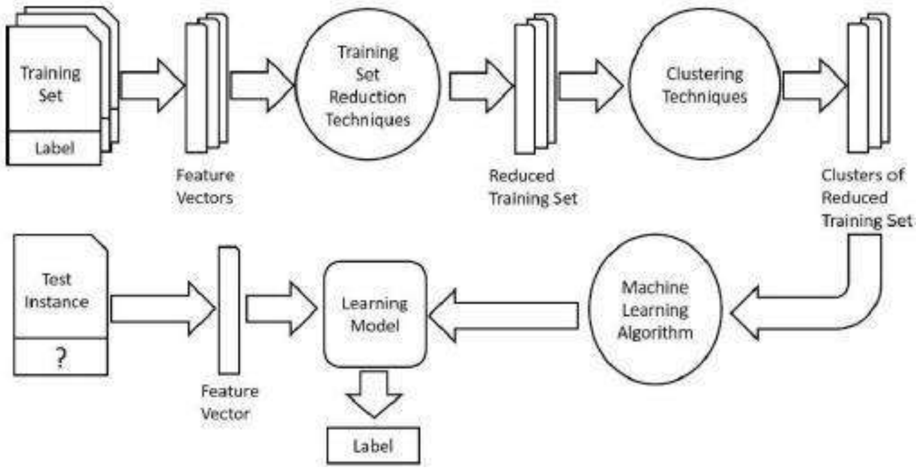

FIGURE 3: Overview of hybrid machine learning technique TSR-FkNN

3.1 Training set reduction fast *k*-nearest neighbour (TRS-FkNN), Elbow method:

This hybrid approach is implemented as per algorithm 2. As shown in step 2, the training set reduction method is applied which reduces the training instances. It is condensing technique the shrink subtractive method which reduces the input training size considerably. The reduced training set is now taken as input to the step 3 where editing method of clustering is applied. To find optimal k value of k-Means clustering algorithm. Here elbow method is applied. It can be noticed that in step 2 and step 3 we are applying editing and condensing techniques consequently. Hence it is a hybrid approach of combining methods for training set reduction.

ALGORITHM 2: Training set reduction Fast k-NN (TRS-FkNN), optimum k-Means by SSE

Input: A set of Agriculture records R = {R1, R2,… Rn}, where n is the total number of agriculture records reduced training record set D.

Procedure:

Step 1: Divide the record data into one training set and test set as 50-50 split. Step 2: Shrink (subtractive) algorithm applied on training set,

- **Step 2.1:** Assign all the training documents into S.
- **Step 2.2:** Select randomly an instance P from S.
- **Step 2.3:** Classify the instance P using remaining instances from S.
- **Step. 2.4:** Remove the instance P if it is correctly classified.
- **Step 2.5:** Repeat step 2.2 to 2.4 till no such instance left in S. Step 2.6: Take the new reduced set S as a training set for step 3.

Step 3: Construct k clusters using k-Means clustering algorithm and validate k value for k-Means clustering by Elbow method step 3.1 to 3.4 and assign a class label to each cluster centroids based on maximum occurrences of a particular class in that cluster.

- **Step 3.1:** Initialize k = 1.
- **Step 3.2:** Increment the value of k.
- **Step 3.3:** Measure the value of SSE for the optimal solution.
- **Step 3.4:** At some point, the effective cost of the solution reaches significantly, then take that value of k and stop. If not then repeat steps 3.2- 3.4.

Step 4: For each test record, calculate similarity with each cluster's centroid.

Step 5: Sort the training records in the descending order of the maximum cosine similarity and select the top k training records.

Step 6: Assign a class to test record which occurs maximum times in the top k training records.

Step 7: Construct a confusion matrix.

Step 8: Calculate performance measures from the confusion matrix.

3.2 Training set reduction fast *k*- nearest neighbour (TRS-FkNN), Silhouette value:

The second proposed hybrid approach is implemented as per algorithm 3. As shown in step 2, the training set reduction method is applied which reduces the training instances. It is condensing technique the shrink subtractive method which reduces the input training size considerably. The reduced training set is now taken as input to the step 3 where editing method of clustering is applied. To find optimal k value of k- Means clustering algorithm, here silhouette value is computed. It can be noticed that in step 2 and step 3 we are applying editing and condensing techniques consequently. Hence it is a hybrid approach of combining methods for training set reduction.

ALGORITHM 3: Training set reduction fast k-NN (TRS-FkNN), optimum k-Means by silhouette value

Input: A set of Agriculture records R = {R1, R2,… Rn}, where n is the total number of agriculture records reduced training record set D.
Procedure:
Step 1: Divide the record data into one training set and test set as 50-50 split.
Step 2: Shrink (subtractive) algorithm applied on training set,
- **Step 2.1:** Assign all the training documents into S.
- **Step 2.2:** Select randomly an instance P from S.
- **Step 2.3:** Classify the instance P using remaining instances from S.
- **Step 2.4:** Remove the instance P if it is correctly classified.
- **Step 2.5:** Repeat step 2.2 to 2.4 till no such instance left in S.
- **Step 2.6:** Take the new reduced set S as a training set for step 3.

Step 3: Construct k clusters using k-Means clustering algorithm and validate k value for k-Means clustering by calculating silhouette value and assign a class label to each cluster centroids based on maximum occurrences of a particular class in that cluster.
Step 4: For each test record, calculate similarity with each cluster's centroid.
Step 5: Sort the training records in the descending order of the maximum cosine similarity and select the top k training records.
Step 6: Assign a class to test record which occurs maximum times in the top k training records.
Step 7: Construct a confusion matrix.
Step 8: Calculate performance measures from the confusion matrix.

IV. COMPARISONS OF RESULTS OF PROPOSED CLASSIFIERS

In this section comparison between different proposed classification techniques is carried out in terms of performance measures and time of classification in milliseconds. For the experiment, we have taken Kutch district data set from SHCDS, having total 14000 entries. These results are performed on a computer with Intel i5 processor and 4GB Ram, the software IDE is NetBeans 8.2. Depends on hardware some of the results may vary. The observed results are on average of five times run.

4.1 Comparison of accuracy of various classifiers:

TABLE 2
COMPARISON OF ACCURACY FOR ALL *k*-NN CLASSIFIERS

	Value *k* for *k*-NN	*k* Nearest Neighbor	Hybrid method	
Sr. No	*k*	*k*-NN	TSR-FkNN (Elbow method)	TSR- FkNN (Silhouette value)
1	31	90.21	88.92	92.64
2	33	88.85	90.42	92.14
3	35	90.41	90.85	93.85
4	37	90	88.85	91.85
5	39	90.35	89.28	92.35
6	41	89.51	90.75	93.34
7	43	90.55	88.75	92.46
8	45	90.27	90.35	91.75

In table 2, the accuracy of different k-NN classifiers is compared. The accuracy presents the ratio between a number of predictions those are correctly classified to the total number of predictions (the number of test data points) [7-10]. It is observed that accuracy of proposed TSR-FkNN (Silhouette value) is high in comparison with other classifiers.

4.2 Training set comparison:

In table 3, different classifiers training instances are compared. In our experimental setup, the simple k-NN classifier trains on 7000 instances which is the benchmark to compare with other reduction techniques. All classifiers start with 7000 instances in training set, then we are applying our proposed prototype selection techniques to reduce the size of the training set and resulting reduced training set it indicated. In our research TSR-FkNN (Elbow method) has lowest training instances when the value of k is 33 and 35 respectively, all other classifiers have higher training instances while k- NN has highest training instances. Here, training instances of all classifiers other than k-NN are reduced by applying novel techniques designed for this research.

TABLE 3
COMPARISON OF TRAINING SET FOR ALL *k*-NN CLASSIFIERS

Sr. No	Value k for k-NN	*k* Nearest Neighbor	Hybrid method	
	k	*k*-NN	TSR-FkNN (Elbow method)	TSR- FkNN (Silhouette value)
1	31	7000	141	131
2	33	7000	61	151
3	35	7000	71	131
4	37	7000	111	141
5	39	7000	151	161
6	41	7000	131	141
7	43	7000	**91**	151
8	45	7000	101	161

4.3 Classification time comparison:

In table 4, comparison of all classifier is done in terms of classification time in millisecond [11-12]. In our research, it is observed that TSR-FkNN (applying SSE) is having lowest classification time when the value of k is 33 and 45 respectively.

TABLE 4
COMPARISON OF CLASSIFICATION TIME FOR ALL *k*-NN CLASSIFIERS

Sr. No	Value k for k-NN	*k* Nearest Neighbor	Hybrid method	
	k	*k*-NN	TSR-FkNN (Elbow method)	TSR- FkNN (Silhouette value)
1	31	5766	248	261
2	33	5779	143	219
3	35	5777	180	192
4	37	5746	217	217
5	39	5749	221	245
6	41	5753	175	217
7	43	5776	185	213
8	45	5745	157	224

V. CONCLUSION

5.1 Storage reduction:

Storage requirement in *k*-NN is very high in comparison to other algorithms.

For TSR- FkNN (Elbow method) storage requirement is lowest when the value of *k* is 33 and 35 respectively followed TSR-FkNN (Silhouette value). Hence, in terms of storage TSR-FkNN is efficient.

5.2 Execution time:

- Execution time is highest in *k*-NN as it store more number of instances for training purpose.
- Execution time is lowest in TSR-FkNN (Elbow method) as it store less number of training instances.

5.3 Generalization accuracy, precision, recall and F1 measure:

- Generalize accuracy of TSR-FkNN (Silhouette value) is highest compared to other algorithms hence in terms of accuracy TSR-FkNN (Silhouette value) is recommended.

In terms of Time, Space and Accuracy comparisons. The proposed novel hybrid algorithm TSR-FkNN (Silhouette value) is the best algorithm hence it can be recommended for classifying soil samples in respective nutrients deficiencies category.

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