

An Exploratory Approach to Multi-Class Classification of Agricultural Data using AI

G. Mounika

PG Scholar, Dept. of Computer Science Sri Venkateswara University, Tirupati

Abstract— Agricultural production and operations generate vast amounts of data, harboring crucial information. Data mining technology can analyze the relationships between various variables within the extensive agricultural dataset. Classification prediction is one of the most significant data mining techniques for agricultural data. This paper presents an exploratory study utilizing three AI algorithms: Multi-Layer Perceptron (MLP) and Support Vector Machine (SVM) to address the challenges of multi-class classification in agriculture. The algorithms were tested on the Eucalyptus standard agricultural multi-class dataset, and the results showed that the MLP method performed exceptionally well, achieving a significant increase in classification accuracy for the Eucalyptus dataset, with a precision of 89.97%.

I. INTRODUCTION

Machine learning algorithms are essential processes or sets of techniques that allow a model to adapt to the provided data with a specific objective. Applying machine learning to modern agricultural production can lead to the improvement of precision agriculture, automation, and intelligent agricultural production. In the real agricultural production process, the application of computer-related information technology in precision agriculture has become increasingly widespread, leading to the collection of vast amounts of natural and spatial data closely associated with the precision agriculture process. Extracting hidden relationships from this immense agricultural production data, enabling accurate agricultural strategies, and guiding efficient agricultural production have become critical and urgent challenges. Among the different tasks involved in mining valuable information from agricultural data, classification is often the most critical phase, particularly in the context of precision agriculture.

II. METHODOLOGY

In this way, the paper proposed Multilayer Perceptron (MLP) and Support Vector Machine(SVM) calculations for productively finding the arrangement errands of the Eucalyptus horticultural information.

2.1 Multilayer Perceptron (MLP)

A MLP is a boss among the most by and large saw Brain Organization plan that has been utilized for different applications. The MLP coordinate is usually made from various focuses or managing units, and it is sorted out into a development of something like two layers [1][4][5]. The fundamental layer (or the most lessened layer) is named as a data layer where it gets the outer data while the last layer (or the most stunning layer) is a yield layer where the reaction for the issue is gotten. The hidden layer is the generally engaging layer in the information layer and the yield layer, and may outline with somewhere near one layers [2][6][7]. The plan of MLP could be conveyed as a nonlinear improvement issue. The target of MLP learning is to track down the best loads that limit the separation between the data and the yield. The most dominating preparing assessment utilized in NN is Back engendering (BP), and it has been utilized in managing different issues in model certification and depiction. This calculation relies upon several limits, for example, unique covered focus focuses at the concealed layers learning rate, energy rate, order work.

2.2 Support Vector Machine (SVM)

SVMs are a lot of related coordinated learning methodology that different information and see plans, utilized for demand and break faith assessment. SVM is an assessment that endeavors to track down a quick separator (hyper-plane) between the information explanations behind two classes in complex space. SVM tends to a learning framework which seeks after standards of genuine learning hypothesis [4]. In general, the fundamental thought of SVM begins from twofold assembling, explicitly to find a hyperplane as a division of the two classes to limit the solicitation goof. The SVM finds the hyperplane utilizing build up vectors (arranging tuples) and edges (support vectors). The Successive Unimportant Improvement (SMO) calculation is a basic and quick framework for setting up a SVM.

III. EXPERIMENTAL RESULTS

The investigations have been coordinated by using Python programming tongue. The Python Scikit-learn is a pack for data portrayal, gathering and portrayal. The Eucalyptus standard farming multi-class dataset used in this review was procured from the UCI ML vault data set [8]. In this Eucalyptus dataset there are 736 cases and 5 elements recorded and 5 class marks, among which 736 examples have a place with the Dynamic class, 5 examples have a place with the Dormant class 736 separately are displayed in the figure-1. The standard dataset is distributed two sets one for preparing (80%) and one more set for testing (20%).

The experimental results on the agricultural multi-class dataset, particularly the Eucalyptus dataset, using various AI algorithms for classification, are shown in the table-1 and also same shown in the figure-1 are as follows:

Table 1
Performance of Classifiers

Algorithm	Accuracy	Precision	Recall
SVM	87.6	87	87
MLP	89.97	90	90

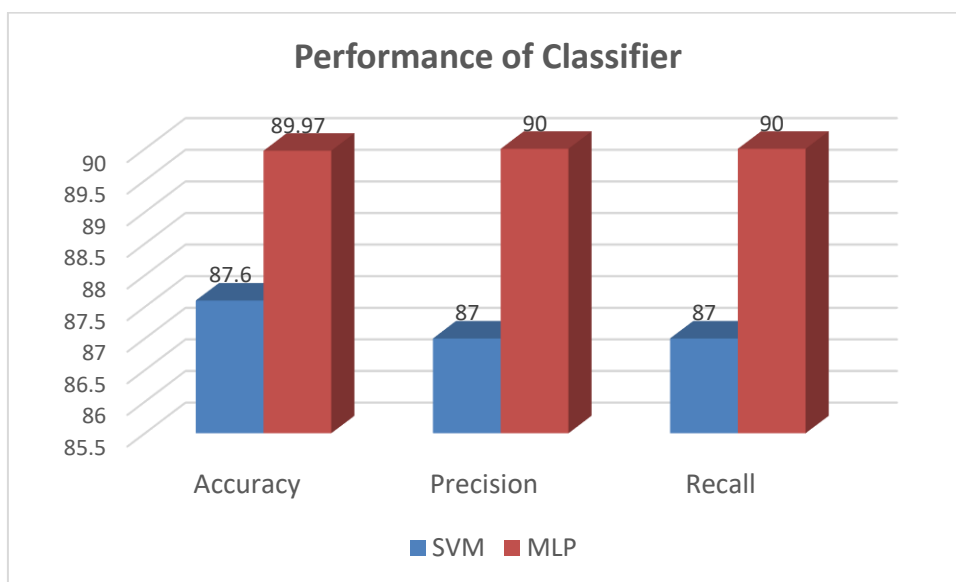


Figure-1: Performance of Classifiers

IV. RESULTS AND DISCUSSION

The exploratory study focused on multi-class classification of agricultural data, and two AI algorithms (SVM and MLP) were employed for the task. The results indicate that the MLP method outperformed SVM, achieving higher accuracy, precision, and recall scores for the Eucalyptus dataset.

The MLP algorithm demonstrated its ability to efficiently model and predict multi-class agricultural data, capturing the underlying patterns and relationships present in the dataset. The superior performance of MLP over SVM suggests that neural network-based models can be well-suited for complex classification tasks in agriculture. Furthermore, the high precision and recall scores indicate that the MLP model effectively minimizes both false positives and false negatives, making it a reliable tool for decision-making in agricultural production.

V. CONCLUSION

In conclusion, this exploratory approach to multi-class classification of agricultural data using AI showcases the potential of machine learning algorithms, particularly MLP, in enhancing precision agriculture and intelligent agricultural production. The study provides valuable insights into the effective utilization of AI for handling large and diverse agricultural datasets, facilitating better decision-making and strategy formulation in the agricultural domain. Further research and experimentation

with different algorithms and datasets can contribute to the continuous improvement of precision agriculture and the optimization of agricultural production systems.

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