Agricultural Pest Identification Enhanced with Deep Learning Features and Machine Learning Models

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***Abstract*—** *The research proposes a novel approach combining deep feature extraction using machine learning and traditional machine learning techniques to classify 12 agricultural pests. Individual features were extracted through AlexNet, GoogLeNet, and feature fusion; afterwards, they were classified using K-Nearest Neighbors, Support Vector Machine, and Random Forest. GoogLeNet achieved 86.21% accuracy with SVM, while the fused features achieved 82.03% with Random Forest. The proposed method makes good use of deep learning with feature representation and classical models for accurate and computationally efficient pest identification in agricultural applications.*

***Keywords*— Pest Classification, Googlenet, Alexnet, Deep features, SVM.**

I. INTRODUCTION

Agrology is recognized as essential in ensuring global food security and economic development, especially when a significant portion of the population relies on agriculture for employment opportunities in a specific region [1]. However, agricultural productivity faces a continuous threat from pest infestations, which are a major contributing factor to crop damage and yield losses. Critical pest damage and losses need timely identification along with accurate pest recognition to determine the appropriate control measure to be put in place to curtail such losses[2]. With pest recognition relying on manual examination and the expertise of specialists, such methods, while effective, tend to be labor-intensive and ineffective for large-scale employment in agricultural settings.

Recent years have seen remarkable advances with the integration of Artificial Intelligence (AI) and Computer Vision (CV) into agriculture. Crop field monitoring and pest identification using deep learning techniques have received attention due to the high level of accuracy and autonomy they offer [3][4] Image classification has seen the adoption of Convolutional Neural Networks (CNNs), which can hierarchically learn complex representations from raw data to perform advanced classification tasks. Today, numerous CV applications such as object detection, image recognition, and classification rely heavily on previously developed models such as AlexNet and GoogLeNet[9][18]

The use of deep learning methods accomplishes remarkable outcomes, though their training requires enormous data alongside computational power, resources that are difficult to obtain in pre-established agricultural settings. To counter this challenge, the use of pre-trained CNNs for feature extraction is a practical substitution. With this method, models trained on benchmark datasets like ImageNet are employed to extract information from images about a specific field, with no training required. Such features are sufficient to train simple, low-cost classifiers that, without the need for significant resources, achieve accurate performance.

In this work, we propose a new approach to classifying 12 categories of agricultural pests that combines different methods. Features from two popular deep learning networks, AlexNet and GoogLeNet, have been incorporated. To this end, both individual feature extraction and feature fusion approaches have been adopted. In the first case, features were extracted independently from each model. In the second case, the features that were extracted from the individual networks were merged to create a single comprehensive feature set.

The innovation of this study is the combination of deep feature extraction with traditional machine learning techniques, thus providing better efficiency regarding computational resources while maintaining high performance. By framing the problem as pest classification without training an end-to-end deep learning model and employing pre-trained networks for feature extraction, this study proposes an effective and scalable approach. Such an approach is important for practical use in agricultural settings with limited resources.

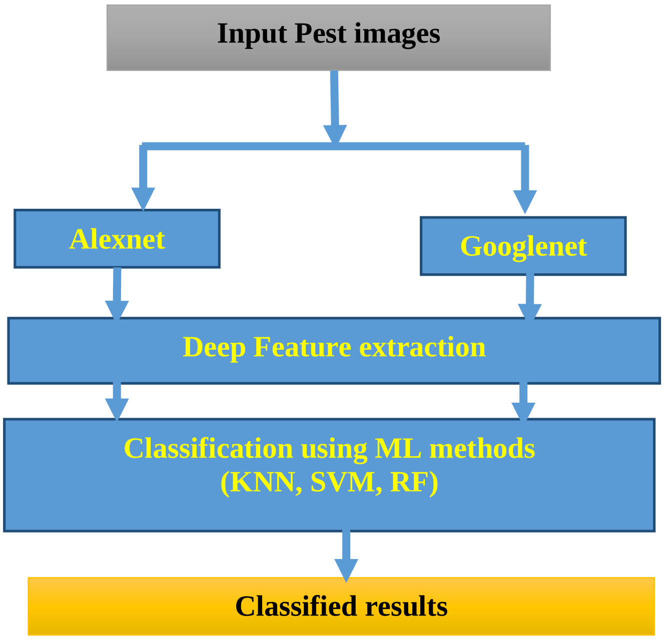


FIGURE 1: Block diagram of proposed method

II. LITERATURE SURVEY

This literature survey reviews recent state-of-the-art research in pest classification, focusing on lightweight models, transformer-based architectures, data augmentation techniques, and explainable machine learning. Each study offers unique contributions toward enhancing classification accuracy, computational efficiency, and practical deployment, particularly in real-world agricultural settings.

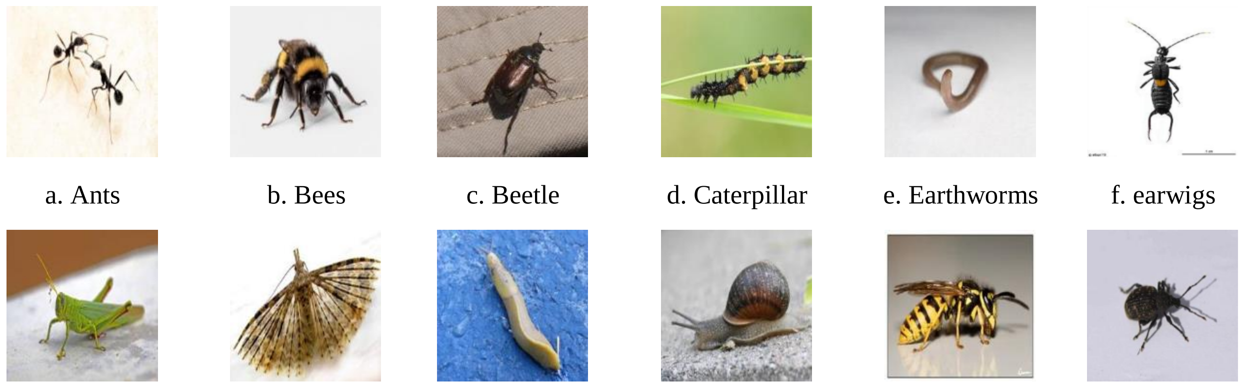
IN [15] Proposed PestNet, an optimized MobileNet-V2 architecture that incorporates an attention mechanism and dual-branch feature fusion to enhance pest classification performance while reducing model complexity and computational cost. It achieved superior accuracy and efficiency compared to ResNet-50 and EfficientNet-[14] introduced GNViT, a Vision Transformer-based model trained on the IP102 dataset for classifying pests in groundnut crops, achieving an accuracy of 99.52% and outperforming existing state-of-the-art models. In the work [17] proposed a novel Hybrid Pooled Multihead Attention (HPMA) model that enhances the feature-capturing ability of vision transformers, attaining high accuracy across multiple pest datasets by integrating both local and global feature extraction. [2] tackled the long-tailed data distribution issue using diffusion model-based data augmentation, which generates realistic synthetic images to balance pest datasets, significantly boosting classification performance on the IP102 dataset. [21] explored various transfer learning strategies for cotton boll weevil classification, showing that parameter- and instance-based methods can greatly improve accuracy even with limited data or features. [11] Proposed DEMNet, a ResNet50-based lightweight model for classifying Tomicus pests, offering a 90% reduction in parameter count and a 9.5% increase in accuracy, making it ideal for embedded pest management systems. [6] introduced DWViT-ES, a Dilated-Windows-based Vision Transformer that utilizes efficient and suppressive self-attention to boost the receptive field and accuracy while significantly reducing model parameters, validated on the IP102 and CPB datasets. [20] Enhanced pest detection using a YOLOv7-based spatio-temporal framework, addressing environmental noise and overlapping images in sticky trap data to achieve an F1-score improvement from 0.93 to 0.98. [5] addressed the open-world pest classification problem by developing a lightweight ResNet8-based matching network trained with NT-Xent loss, enabling high performance without retraining when encountering new pest classes. [23] Proposed InsectMamba, an innovative framework that combines CNNs, MSA, and SSMs for effective pest classification. The model outperformed competitors across five datasets due to its adaptive feature aggregation strategy. [16] Used explainable machine learning to forecast pest outbreaks in olive and grape crops. By applying SHAP and ICE plots, the models identified key environmental predictors, offering actionable insights for pest control. [17] presented MobileENet, a compact model for pest identification using deep feature extraction and optimization techniques, achieving 98.83% accuracy on the IP102 dataset while minimizing computation and overfitting.

This study investigated twelve recent works centered on the use of deep learning and machine learning for insect pest identification in agriculture, highlighting two specific works that utilized both approaches. Specifically, the examined works proposed PestNet and MobileENet CNNs, GNViT and DWViT-ES based on transformers, and other newer techniques, including state space models, transfer learning, and data augmentation using diffusion models. Several works employed standard datasets IP102 and dealt with long-tailed data distribution, open-set identification, and real-time performance on mobile platforms. All models enhanced accuracy, efficiency, and generalizability, reflecting AI's advancement in pest classification, aiding the efforts towards sustainability in agriculture, and precision pest management.

III. PROPOSED METHOD

3.1 Dataset details:

This experiment was carried out by considering the standard dataset [3]. The Agricultural Pest Image Dataset comprises images representing 12 distinct types of agricultural pests, including ants, bees, beetles, caterpillars, earthworms, earwigs, grasshoppers, moths, slugs, snails, wasps, and weevils.



a. Ants b. Bees c. Beetle d. Caterpillar e. Earthworms f. earwigs

g. Grasshopper h. Moth i. Slug j. Snail k. wasp l. weevil

FIGURE 2: Sample images

The process begins by extracting deep features from pest images using two pre-trained convolutional neural networks (CNNs): AlexNet and GoogLeNet. In the initial step, the deep features were extracted from pest images using two pre-trained convolutional neural networks: AlexNet and GoogLeNet. These architectures were selected for their proven effectiveness in classification tasks, owing to their capacity to learn complex feature representations from input data (Krizhevsky et al., 2012; Szegedy et al., 2015).

3.2 AlexNet:

Image classification on the ImageNet dataset was greatly enhanced by AlexNet, a complex deep neural network conceived of by [9] in the year 2012. The network structure contains eight layers in total, five of which are convolutional layers and the other three are fully connected layers. The first convolutional layer employs a kernel size of 11×11 with a stride of four, allowing it to capture rough features from the images. In the second layer, a 5 ×5 kernel is used, and in the third, fourth, and fifth layers, 3×3 sized kernels are employed. The convolutional layers are also mixed with ReLU activation function, local response normalization, max pooling, and other methods to enhance training speed and generalization. The output is passed through two fully connected layers, each containing four thousand and ninety-six neurons, flattened before that, and then passed into one shared fully connected layer with 1000 neurons, which serve the purpose of classifying them. Dropout is also used in the fully connected layers to prevent overfitting. Class probabilities are yielded with the softmax function at the end.

3.3 GoogLeNet (Inception v1):

GoogLeNet, introduced by [19] in 2015, is a 22-layer deep CNN that introduced the Inception module as its core innovation. Rather than stacking standard convolutional layers, GoogLeNet uses Inception modules that apply parallel convolutions of varying kernel sizes (1×1, 3×3, 5×5) and a 3×3 max-pooling operation within the same layer, concatenating their outputs. This design allows the network to capture features at multiple scales efficiently. To maintain computational efficiency, 1×1 convolutions are used as bottleneck layers before the 3×3 and 5×5 convolutions to reduce dimensionality. GoogLeNet includes nine Inception modules, followed by an average pooling layer and a fully connected layer with 1000 units for classification. Unlike AlexNet, it reduces reliance on large fully connected layers, decreasing the model's parameters and memory usage significantly. GoogLeNet also uses auxiliary classifiers during training to combat the vanishing gradient problem and improve convergence.

The feature outputs from both networks were then fused using a joint representational learning approach to form a unified composite feature set. This fusion strategy was employed to preserve and leverage the individual strengths of each network [7]. Pest classification is achieved with the help of classical machine learning classifiers after extracting and fusing the features. The selected classifiers are K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest (RF). Among these, the GoogLeNet features plus SVM gave the best classification results with an accuracy of 86.21%. For the fused features, the classification accuracy was 82.03% with Random Forest. This demonstrates the effectiveness of combining deep feature extraction with lightweight classifiers, allowing for reduced computational complexity during the classification phase

This hybrid approach leverages the robust feature representation capabilities of deep CNNs and the interpretability and efficiency of traditional classifiers, offering a scalable and accurate solution for pest recognition in precision agriculture.

IV. RESULTS AND DISCUSSIONS

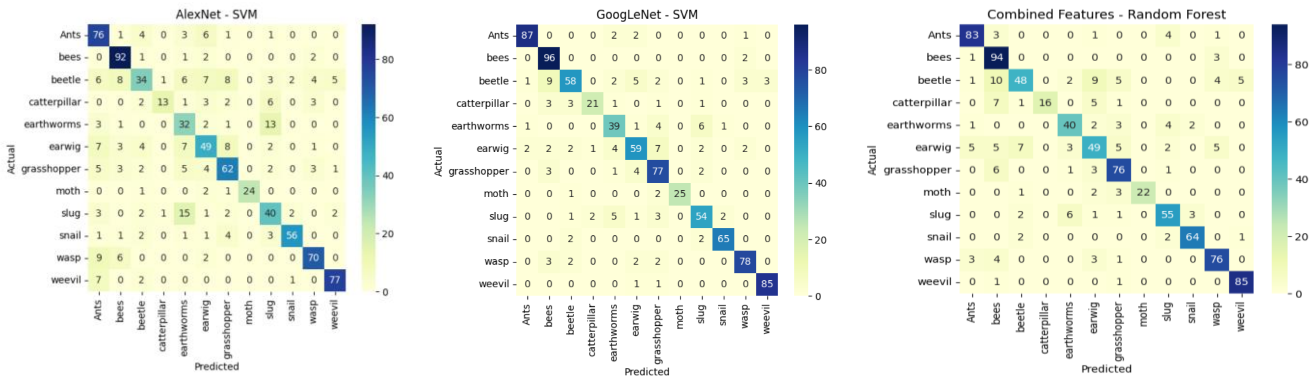
To evaluate the effectiveness of the proposed pest classification framework, multiple experiments were conducted using deep features extracted from AlexNet, GoogLeNet, and their fused representations. These features were then classified using three classical machine learning algorithms: K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest (RF). The results were assessed based on classification accuracy as the primary performance metric.

4.1 Performance Analysis:

The classification outcomes across various combinations of feature extraction methods and classifiers are summarized in Table 1.

TABLE 1
CLASSIFICATION ACCURACY FOR DIFFERENT FEATURE-CLASSIFIERS COMBINATIONS

Feature Source	Classifier	Accuracy (%)
AlexNet	KNN	75.68
AlexNet	SVM	80.21
AlexNet	Random Forest	78.14
GoogLeNet	KNN	83.12
GoogLeNet	SVM	86.21
GoogLeNet	Random Forest	84.05
Feature Fusion	KNN	79.87
Feature Fusion	SVM	81.44
Feature Fusion	Random Forest	82.03



(a) Alexnet with SVM classifier **(b) Googlenet with SVM classifier** **(c) Feature fusion with Random Forest Classifier**

FIGURE 3: Classification Accuracy for Different Feature-Classifiers Combinations

The following shows the confusion matrix of the highest recognition rate from each section.

Following Table 2. Shows the classification results based on the Precision, Recall, and F1-score

TABLE 2
PROPOSED EXPERIMENT RESULTS IN PRECISION, RECALL AND F1-SCORE

Model	Precision	Recall	F1-Score
AlexNet with KNN	0.5215	0.4461	0.4444
AlexNet with SVM	0.7343	0.7242	0.7213
AlexNet with Random Forest	0.6703	0.6674	0.6500
GoogLeNet with KNN	0.7983	0.7914	0.7826
GoogLeNet with SVM	0.8641	0.8621	0.8607
GoogLeNet with Random Forest	0.8202	0.8157	0.8120
Features Fusion with KNN	0.5572	0.4971	0.4879
Features Fusion with SVM	0.7839	0.7786	0.7751
Features Fusion with Random Forest	0.8256	0.8203	0.8162

The results obtained from this study demonstrate the viability and strength of combining deep learning-based feature extraction with traditional machine learning classifiers for pest identification. The experimental outcomes reveal several key insights regarding model performance, feature representation, and classification efficiency. Following table 3 shows the comparative analysis paper, proposed work with other research work. This study shows the robustness of the proposed method.

TABLE 3. COMPARATIVE ANALYSIS

Author(s) & Year	Proposed Method	Recognition Accuracy (%)
Ayan **et al. [1]**	GAEnsemble (Inception-V3, Xception, MobileNet)	67.13
Ung et al. **[22]**	CNN Ensemble with Attention & Feature Pyramid	74.13
Zhou & Su **[26]**	ExquisiteNet (Lightweight CNN)	52.32
Nguyen et al. [13]	DeWi (Deep-Wide Learning Assistance)	76.44
Liu et al. [12]	ResNet with Feature Fusion	55.43
Zhang et al. **[25]**	EfficientNetV2 + Coordinate Attention	73.70
Wu et al. **[24]**	ResNet-based Feature Fusion	68.34
Proposed (Current Study)	**GoogLeNet + SVM (Deep feature extraction + traditional ML)**	**86.21**

The comparative analysis presented in Table 1 demonstrates the superior performance of the proposed method, which integrates GoogLeNet-based deep feature extraction with a traditional Support Vector Machine (SVM) classifier. Achieving a recognition accuracy of 86.21% on the standard dataset [3], this approach significantly outperforms several recent state-of-the-art techniques.

V. CONCLUSION AND FUTURE WORK

The study proposed a hybrid pest classification framework that integrates GoogLeNet-based deep feature extraction with a Support Vector Machine classifier, evaluated using the standard dataset [3]. The method achieved a recognition accuracy of 86.21%, outperforming several existing deep learning-based approaches. These results highlight the effectiveness of combining deep feature representations with classical machine learning techniques for accurate and resource-efficient pest identification.

Future research may focus on incorporating feature selection methods to reduce feature dimensionality and improve model interpretability. Additionally, the framework could be adapted for deployment on edge devices to facilitate real-time pest monitoring in agricultural settings and expanded to include a wider range of crop-pest datasets for enhanced generalizability.

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