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Aerial Vegetable Crop Classification Using CNN Feature Extraction And Machine Learning

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Abstract: Efficient vegetables sorting from aerial images is essential for precision digital farming. Effectively keeping track of. vegetable plants, estimating how much they will produce, and deciding how to use resources carefully. This research work presents an integrated deep learning and machine learning technique for classification of aerial vegetable crops where deep features were extracted from the convolutional neural networks (CNNs) followed by their classification through traditional classification algorithms. Three pretrained CNN models, VGG16, EfficientNetB7, and InceptionV3, have been used to obtain the deep features of the crops. The features obtained through the pretrained CNNs were then classified using SVM, RF, and XGBoost algorithms. Precision, recall, F1-score, and classification accuracy were used as evaluation metrics to assess the proposed models' performance. Experimental results showed that the combination of EfficientNetB7-SVM and VGG16-XGBoost gave the maximum classification accuracy of 95%**.**

Keywords - Aerial crop classification, deep learning, transfer learning, CNN, VGG16, EfficientNetB7, InceptionV3, SVM, Random Forest, XGBoost, precision agriculture

I. Introduction

Data driven farming is becoming more common. It helps farmers work better and get more crops. Checking crop growth, what crops need and resource use.is easy using these techniques. Aerial images from UAVs, drones, and remote sensing are available now days. Because of this, automatic checking of farmland is now possible. There are many uses in agriculture. One important task is vegetable crops identification.

Traditional crop classification depends on people looking at crops and manually picking features. The process takes more time and does not work well for big farming datasets.New deep learning methods, especially CNNs, have made image analysis much better. CNNs can learn useful features on their own from images.Pre trained CNN models using transfer learning are now very popular. Models like VGG16, Efficientnet etc. find rich and helpful features even when there is not much training data.

Hybrid approaches combining CNN-based feature extraction with classical machine learning algorithms given good results in several image classification applications. Machine learning classifiers such as Support Vector Machine (SVM), Random Forest (RF), and XGBoost can effectively utilize deep feature representations for improved categorization performance while reducing computational complexity.

This research proposes a hybrid aerial vegetable crop classification framework using pre-trained CNN models, namely VGG16, EfficientNetB7, and InceptionV3, combined with machine learning classifiers. The extracted deep features are classified using SVM, RF, and XGBoost algorithms, and their performances are comparatively examined. The primary objective of this study is to identify the most effective CNN–ML combination for accurate aerial crop classification

II. REVIEW OF LITERATURE

Deep Learning has brought many innovations to agricultural image analysis. The automatic extraction of relevant visual features from high-resolution aerial and UAV images. In recent times, Convolutional Neural Networks have become the most popular technique used for identifying crops, detecting diseases, and in automated farming. Because of hierarchical representation of feature learning which does not require the crafting of any feature descriptor. Recent literature reviews have shown that CNN models outperform traditional image processing methods in terms of accuracy and robustness. [1], [2].

Deep learning use in agriculture is greatly enhanced through transfer learning for image classification. VGG16, ResNet50, InceptionV3, DenseNet, MobileNet, and EfficientNet have all been widely used as feature extraction architectures. As models have rich semantic features that were learned from large datasets of images. By either fine-tuning these pre-trained networks, or by using them as fixed feature extractors, the cost to compute is greatly reduced. It improves the generalization performance of the classifier for vegetation classification tasks. [1], [3], [4].

The limitations with CNN classifiers are overcome with hybrid deep learning and machine learning frameworks introduced by recent studies. The deep CNNs are used for feature extraction and the traditional machine learning methods are used for classification. This method takes advantage of the representation Learning capability of CNNs. Also, the strong decision boundaries that machine learning classifiers have proven to provide When. missing data from datasets that contain a relatively small amount of data related to agriculture. Based on comparative studies, deep features that were extracted using transfer learning models provide better accuracy when classified with Support Vector Machine (SVM), Random Forest (RF), Extreme Gradient Boosting (XGBoost). Ensemble learning techniques provide good results using completely connected CNN classifiers alone [2], [5].

The machine learning classifiers mentioned in study XGBoost has been identified as the most successful machine learning classifier at classifying deep features extracted from deep learning transfer networks. This success is created through the combination of the gradient boosting framework, regularization mechanism, and ability to model complex non-linear. XGBoost effectively manages the high dimensional feature vectors produced when utilizing a CNN architecture. Also provide excellent classification accuracy when applied to remote sensing, aerial crop mapping, and precision agriculture applications. Random Forest is frequently identified as another great choice. RF classifier is resistance to overfitting, handling the noise associated with real-world data sets. Ability of RF to generalize effectively for multi-class crop classification problems.[5][6]

In addition to this, some recent review articles have stressed the fact that the performance of hybrid classification models depends on the selection of the architecture of CNN used for feature extraction. EfficientNet, DenseNet, and ResNet models create better feature embeddings compared to older CNN models, but they have far fewer parameters than the older CNN models. Thus, designing hybrid models using efficient deep neural network-based feature extractors and machine learning classifiers is a current area of research in agriculture.[1][3][4]

Despite significant advances made in identification of vegetables or crop through the application of satellite and drone images. Few studies have made efforts to evaluate multiple CNN feature extractors based on transfer learning approaches against different machine learning classifiers in classifying aerial vegetables. Most of the existing works have mainly been on deep learning-based solutions or certain crop species. Hence, in this work, we examine multiple CNN networks as deep feature extractors and compare different machine learning classifiers like XGBoost, Random Forest, and SVM.

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III. Proposed Methodology

The proposed methodology consists of image preprocessing, deep feature extraction using CNN architectures, and classification using machine learning algorithms. The workflow of the proposed system is illustrated in Fig. 1.

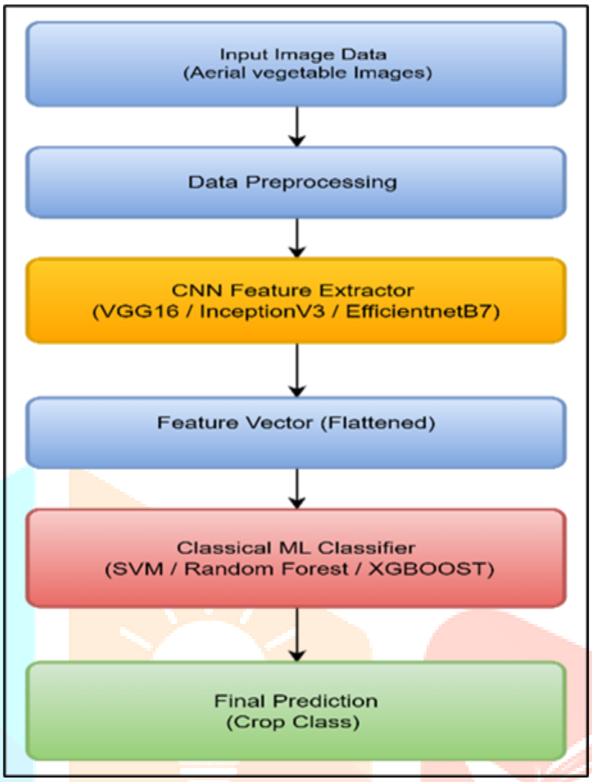

Figure 1. Proposed hybrid CNN and classical ML framework for aerial crop classification

A. Data Preprocessing

The aerial vegetable image dataset was preprocessed before model training. All images were resized to (128 * 128) pixels to ensure consistent input dimensions. Image normalization and formatting operations were performed to improve model convergence and classification performance. The dataset was divided into training and testing subsets for experimental evaluation. This study utilizes UAV-acquired aerial imagery from the Kolkata Agricultural Region Crop (KARC) dataset, collected using low-altitude drone platforms over active agricultural fields in geographically diverse regions of India [7]. The dataset comprises a total of 5,622 annotated samples across 12 crop classes

B. Feature Extraction Using Pre-Trained CNN Models

Three pre-trained CNN architectures, namely VGG16, EfficientNetB7, and InceptionV3, were utilized as feature extractors using transfer learning. The ImageNet-trained weights were employed to leverage previously learned visual representations. The fully connected top layers of each CNN model were removed by setting include_top=False.

The extracted feature maps from the CNN architectures were flattened into one-dimensional feature vectors suitable for machine learning classification. Feature extraction was performed using the prediction function on the training dataset.

C. Machine Learning Classification

The extracted deep features were classified using three machine learning algorithms:

1. Support Vector Machine (SVM)
2. Random Forest (RF)
3. XGBoost

Each classifier was trained independently using the CNN-generated feature vectors. The hybrid CNN+ML combinations were evaluated based on classification accuracy, precision, recall, and F1-score.

IV. Experimental Results and Discussion

The proposed hybrid framework was evaluated using nine CNN+ML combinations. Classification performance was assessed using precision, recall, F1-score, and overall accuracy.

A. EfficientNetB7-Based Models:

The EfficientNetB7+SVM model achieved the highest accuracy of 95%, demonstrating strong classification capability. EfficientNetB7+XGBoost and EfficientNetB7–RF achieved accuracies of 91% and 90%, respectively.

B. VGG16-Based Models:

The VGG16+XGBoost model also achieved 95% accuracy, making it one of the best-performing models. VGG16+RF achieved 94% accuracy, while VGG16+SVM obtained 82% accuracy.

C. InceptionV3-Based Models:

The InceptionV3-based models produced comparatively lower performance. InceptionV3–XGBoost achieved 75% accuracy, followed by InceptionV3+SVM with 74% and InceptionV3+RF with 73%.

Table I: Comparative Performance of Hybrid CNN–ML Models

CNN Model	Classifier	Accuracy
EfficientNetB7	SVM	95%
EfficientNetB7	RF	90%
EfficientNetB7	XGBoost	91%
VGG16	SVM	82%
VGG16	RF	94%
VGG16	XGBoost	95%
InceptionV3	SVM	74%
InceptionV3	RF	73%
InceptionV3	XGBoost	75%

V. COMPARATIVE ANALYSIS

The comparative evaluation indicates that EfficientNetB7 and VGG16 generated more discriminative deep features compared to InceptionV3. Ensemble learning algorithms such as XGBoost and Random Forest generally outperformed standalone SVM classifiers for most CNN feature extractors.

EfficientNetB7+SVM and VGG16+XGBoost emerged as the best-performing hybrid models with 95% classification accuracy. The results demonstrate that combining transfer learning-based CNN feature extraction with machine learning classification significantly enhances aerial crop recognition performance.

Fig. 7.2 presents the comparative accuracy analysis of all hybrid CNN+ML models evaluated in this study. The results indicate that the EfficientNetB7+SVM and VGG16+XGBoost models achieved the highest classification accuracy of 95%, outperforming the remaining combinations. InceptionV3-based models produced comparatively lower accuracies, ranging from 73% to 75%.

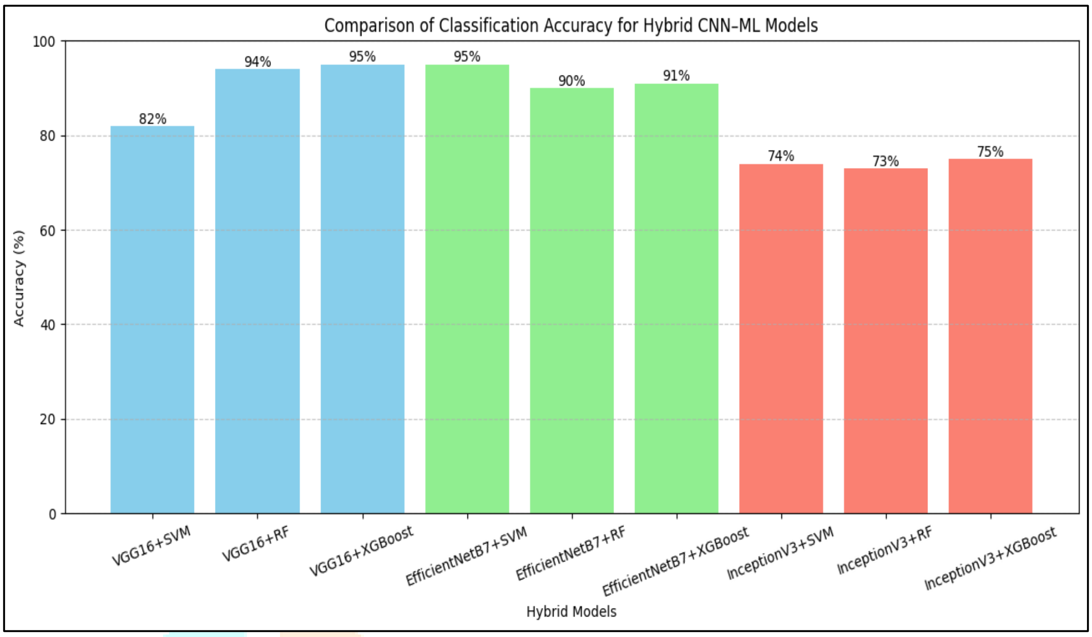

Figure 2. Comparison of classification accuracies achieved by different hybrid CNN+ML models for aerial crop classification

VI. CONCLUSION

This paper presented a hybrid deep learning and machine learning framework for aerial vegetable crop classification. Three CNN architectures VGG16, EfficientNetB7, and InceptionV3 were employed for deep feature extraction, while SVM, Random Forest, and XGBoost were utilized for classification.

Experimental results demonstrated that the EfficientNetB7+SVM and VGG16+XGBoost hybrid models achieved the highest classification accuracy of 95%. The comparative analysis confirmed that deep transfer learning combined with machine learning classifiers can effectively improve crop classification accuracy using aerial imagery.

The proposed framework can support intelligent precision agriculture systems for automated crop monitoring and agricultural decision-making. Future work may include larger datasets, real-time UAV-based classification, and advanced deep learning architectures for further performance improvement.

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