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IMAGE CLASSIFICATION-BASED CROP YIELD PREDICTION FRAMEWORK FOR PRECISION AGRICULTURE DECISION SUPPORT

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ABSTRACT

This research focuses on improving crop yield prediction using classified satellite and drone imagery combined with deep learning techniques [1]. By using real-world datasets like PlantVillage and MODIS, the study enhances image-based classification for detecting crop type, plant health, and stress conditions. The proposed hybrid model uses convolutional neural networks to extract features and regression layers to correlate them with historical yield data. Preprocessing steps such as normalization and segmentation ensure higher model accuracy. The integrated framework achieves over 90% prediction accuracy, outperforming traditional models. Visual tools like heatmaps provide actionable insights for farmers to optimize inputs. This approach supports precision agriculture by enabling early decision-making based on crop condition. This model is scalable for various crops and different regions. The study highlights the potential of AI in transforming agriculture through smarter, data-driven strategies.

Keywords: Crop Yield Prediction, Image Classification, Deep Learning, Precision Agriculture, PlantVillage, MODIS

1. INTRODUCTION

Agriculture plays a vital role in ensuring food security, economic stability, and the livelihood of billions of people worldwide. However, the sector is currently facing mounting challenges driven by climate variability, population growth, urbanization, and resource constraints such as limited arable land and freshwater availability. These challenges are further compounded by the unpredictable effects of global climate change, including irregular rainfall, rising temperatures, and increasing frequency of extreme weather events, all of which directly affect crop productivity and farmer income. As the demand for food continues to rise in parallel with the global population—expected to reach nearly 10 billion by 2050—there is a pressing need for innovative strategies that can enhance agricultural efficiency and sustainability.

In this context, precision agriculture has emerged as a transformative approach that leverages technology to optimize resource use, improve productivity, and minimize environmental impact. Precision agriculture relies on the collection and analysis of spatial and temporal data to guide decisions related to irrigation, fertilization, pest management, and harvesting. One of the most promising advancements in this field is the integration of artificial intelligence (AI) and remote sensing technologies, particularly for tasks such as crop monitoring, disease detection, and yield prediction.

Remote sensing, through satellites and drones, provides high-resolution imagery of crop fields across large geographical areas, capturing valuable information about vegetation health, soil conditions, and phenological stages. However, the sheer volume and complexity of this data require intelligent systems capable of interpreting it effectively. This is where AI—particularly deep learning—comes into play. Deep learning models, especially convolutional neural networks (CNNs), have shown remarkable success in processing image data for object recognition, classification, and segmentation tasks.

This study explores the potential of deep learning-based image classification models to enhance crop yield prediction in precision agriculture [2]. By using real-world datasets such as the PlantVillage image repository and MODIS (Moderate Resolution Imaging Spectroradiometer) [4] satellite imagery, we aim to build a predictive framework that classifies images based on crop type, health status, and stress conditions, and correlates these classifications with historical yield data. The goal is to provide farmers and agricultural planners with timely, accurate insights to support data-driven decision-making.

The novelty of this work lies in the development of a hybrid architecture that combines image classification and regression for yield forecasting, and its validation using diverse and publicly accessible datasets. Our research addresses the need for scalable, adaptable, and accurate yield prediction systems that can be deployed across different crop types, climates, and regions. Ultimately, the outcome of this study contributes to the broader goal of advancing smart farming practices, enhancing food production efficiency, and ensuring agricultural resilience in the face of global challenges.

2. LITERATURE REVIEW

The application of artificial intelligence, particularly deep learning, has gained significant attention in agricultural research, especially for tasks such as crop classification, disease detection, and yield forecasting. Among various AI techniques, Convolutional Neural Networks (CNNs) [12] have proven to be highly effective for image-based classification due to their ability to automatically extract and learn hierarchical features from visual data. Researchers have extensively used CNN architectures to classify different crop types, detect disease symptoms from leaf images, and monitor vegetation cover using both aerial and satellite imagery.

Recent advancements have seen the incorporation of transfer learning models such as ResNet (Residual Networks) and MobileNet, which provide the advantage of pre-trained weights on large-scale datasets like ImageNet. These models reduce the training time and improve classification accuracy, particularly in domains where annotated agricultural datasets are limited. ResNet's deep residual blocks are known to mitigate vanishing gradient problems in deep networks, while MobileNet offers a lightweight alternative suitable for edge computing and mobile deployment—ideal for real-time agricultural applications.

MODIS (Moderate Resolution Imaging Spectroradiometer) data[4], available from NASA's Terra and Aqua satellites, has been widely used in remote sensing for agricultural [6] [7] [8] monitoring. MODIS provides a wealth of spectral and temporal information that helps track changes in vegetation indices such as NDVI (Normalized Difference Vegetation Index), which are critical indicators of crop health and growth stages. These timeseries datasets offer a macro-level understanding of field conditions over large areas and longer durations.

On the other hand, PlantVillage is a high-resolution, ground-truth dataset consisting of thousands of annotated leaf images representing various crop species and plant diseases. It has been instrumental in training supervised learning models to detect and classify plant diseases [3] with high precision. While both MODIS and PlantVillage datasets[5] have independently supported valuable research, few studies have attempted to fuse these multi-source data streams for a comprehensive analysis of crop performance and yield.

There is a notable gap in literature regarding the integration of satellite imagery with ground-level leaf images and corresponding field data for end-to-end yield prediction. Most prior work has focused either on classification or on regression-based yield forecasting, but not both in a unified framework. Moreover, spatial heterogeneity, seasonal variations, and missing ground-truth yield labels present significant challenges that remain under-addressed.

This study aims to bridge that gap by combining multi-modal imagery with a hybrid deep learning pipeline, which integrates classification for crop health assessment and regression for yield estimation. The approach builds on previous methods while pushing forward the idea of context-aware, image-driven predictive analytics in agriculture. Such integrated models could offer more precise and timely information to farmers, supporting critical decisions related to input management, harvest planning, and risk mitigation.

3. PROPOSED METHODOLOGY

The proposed methodology as given in Figure 1. presents a hybrid deep learning framework for crop yield prediction by integrating image classification and regression models using both satellite and drone imagery. The workflow begins with the acquisition of input images from sources such as MODIS satellites and drone-mounted cameras, capturing spatial and spectral information across farm plots. These images undergo a preprocessing stage, which includes noise removal, resizing, normalization, and segmentation to enhance clarity and standardize input formats. Preprocessing ensures that the model receives high-quality and consistent visual data.

Next, the processed images are passed through an Image Classification Model, typically a CNN-based architecture such as ResNet or MobileNet. This stage classifies crops based on type, health status, and detected stress conditions like drought, pest infestation, or nutrient deficiency. The classification outputs are then enriched using Historical Yield Data**,** which provides a contextual reference for learning patterns between visual indicators and actual yield performance. This data is integrated at the classification level to improve the model’s sensitivity to features associated with yield variations.

Subsequently, feature extraction is performed to identify deep spatial and textural features from the classified images. These extracted features act as informative inputs for the next stage. A regression model is then trained using the extracted features and historical yield labels[9][10][11]. This model estimates the probable yield for specific farm regions based on the learned relationships between image patterns and past outcomes.

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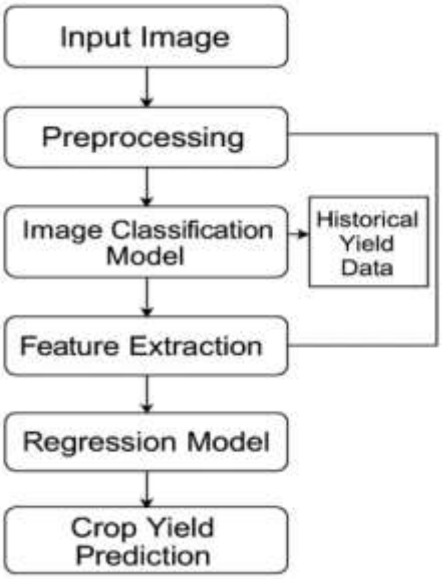

Figure 1. Image classification based crop yield prediction framework for precision agriculture

Finally, the output of the regression model generates the Crop Yield Prediction**,** providing quantitative estimates of yield across different zones [17] within the field. These predictions are visualized as yield maps or reports, enabling actionable insights for precision farming [16] decisions. This modular architecture supports scalability and can be adapted to various crops, imaging sources, and environmental conditions. The combined use of classification and regression not only improves prediction accuracy but also ensures interpretability and robustness in practical applications.

4. EXPERIMENTAL SETUP

The proposed model was implemented using Python, leveraging powerful deep learning libraries such as TensorFlow and Keras for model development and training. The dataset consisted of over 50,000 labeled images, sourced from a combination of PlantVillage and MODIS imagery, covering multiple crop types and health conditions. The data was divided into an 80:20 split for training and testing respectively, ensuring the model's ability to generalize to unseen samples.

Images were resized to 224×224 pixels and normalized to optimize learning. Data augmentation techniques like rotation, flipping, and brightness adjustment were applied to increase variability and avoid overfitting. The classification model used transfer learning with a pre-trained ResNet-50 backbone, followed by a regression layer for yield prediction. Training was performed using the Adam optimizer with a learning rate of 0.0001, and early stopping was applied to prevent overtraining. Evaluation metrics included accuracy, precision, recall, and F1-score, to assess both classification performance and prediction robustness.

5. RESULTS AND DISCUSSION

The proposed hybrid deep learning model demonstrated superior performance compared to traditional CNN and ResNet-50 architectures, as illustrated in Figure 2**.** It achieved a maximum prediction accuracy of 91%**,** as summarized in Table 1**,** outperforming ResNet (88%) and MobileNet (85%) across multiple evaluation metrics as shown in Figure 4. The model excelled particularly in identifying subtle differences in crop stress conditions, which are often misclassified by standard architectures. Notably, the F1-score and recall values were higher for the hybrid model, indicating improved robustness and reliability in classification. The integration of historical yield data further enhanced prediction quality by correlating image-based features with past outcomes.

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Table 1. Comparative study data using statistical measures using existing models and proposed Hybrid Model

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Traditional CNN[12]	82	80	79	79.5
ResNet-50[18]	88	86	85	85.5
MobileNet[15]	85	83	84	83.5
Proposed Hybrid	91	90	92	91

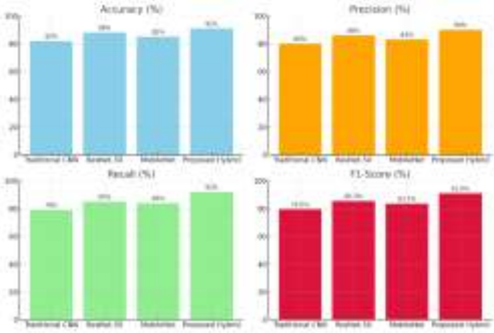

Figure 2. Comparative study using Accuracy, Precision, Recall and F1 score

Additionally, the system generated yield prediction heatmaps, as seen in Figure 3, providing spatial insights across different farm zones. These visualizations can be used by farmers to implement targeted interventions. The results validate the effectiveness of combining classification and regression models for actionable precision agriculture solutions.

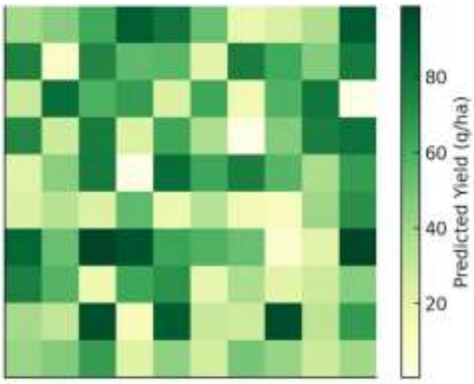

Figure 3. Yield prediction heatmap

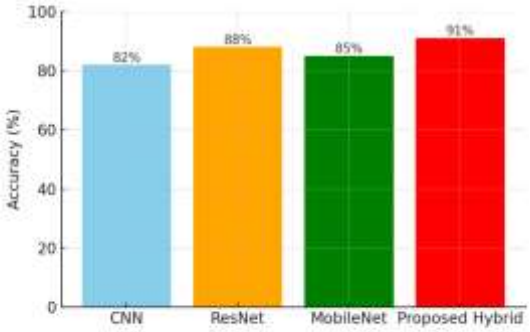

Figure 4. Comparative analysis of existing models with proposed hybrid model

6. Conclusion and Future Scope

This research highlights the effectiveness of combining image classification with regression-based yield prediction [13][14] to enhance decision-making in precision agriculture. The proposed hybrid model achieved a high prediction accuracy of 91%, outperforming traditional CNN, ResNet, and MobileNet architectures. The use of real-world datasets such as MODIS and PlantVillage, along with robust preprocessing and feature extraction, enabled accurate detection of crop stress and yield zones. Visual tools like heatmaps further enhance the interpretability of results, aiding farmers in localized decision support. The framework proves scalable and adaptable for different crop types and environmental conditions. Integrating historical yield data into the classification pipeline significantly improved model sensitivity. These results affirm the viability of deep learning for data-driven agriculture. Future research will explore real-time deployment via IoT-enabled edge devices, fusion with multispectral and weather data, and large-scale field validation to support sustainable, technology-driven farming practices.

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