International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

Drone-based Crop Health Monitoring Using Deep Learning Techniques

Siva Gopi Reddy Dundi
Computer Science and Engineering
RV Institute Of Technology,
Chebrolu, India

Abstract: *Agriculture is one of the most important sectors contributing to food security and economic stability. However, crop productivity is often affected by diseases, pest attacks, nutrient deficiency, and environmental stress. Traditional crop health monitoring methods rely heavily on manual field inspection, which is labour-intensive, time-consuming, and ineffective for large agricultural areas. Moreover, early symptoms of crop stress are difficult to identify through visual observation alone.*

In recent years, Unmanned Aerial Vehicles (UAVs), commonly known as drones, have emerged as a powerful tool for agricultural monitoring by capturing high-resolution aerial images of crop fields. When combined with deep learning techniques, these images can be automatically analysed for accurate crop health assessment. In this paper, a drone-based crop health monitoring system using deep learning is proposed. The system utilizes a Convolutional Neural Network (CNN) with transfer learning based on the ResNet50 architecture to classify aerial images into healthy and diseased or stressed crop regions. Experimental results obtained using publicly available UAV agricultural datasets demonstrate that the proposed system achieves reliable accuracy and effective performance. The proposed approach supports precision agriculture and can assist farmers in early disease detection and decision-making.

Keywords: *Agriculture, Drone Technology, UAV, Crop Health Monitoring, Deep Learning, CNN, Transfer Learning*

INTRODUCTION

Agriculture plays a vital role in the economic growth and food security of many developing countries, especially India. A significant portion of the population depends directly or indirectly on agriculture for their livelihood. However, in recent years, the agricultural sector has been facing several challenges due to climate change, irregular rainfall patterns, pest attacks, plant diseases, and inefficient monitoring methods. These issues have resulted in reduced crop productivity, economic losses to farmers, and instability in the agricultural economy [1].

Traditional crop monitoring methods primarily depend on manual field inspections conducted by farmers or agricultural experts. Such methods are time-consuming, labour-intensive, and often impractical for large-scale farming. In many cases, early symptoms of crop diseases or stress conditions are not easily visible to the human eye, leading to delayed detection and improper treatment. As a result, crop damage increases significantly before corrective measures are taken [2].

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

With the rapid advancement in technology, modern agriculture is gradually shifting toward smart and precision farming practices. Precision agriculture aims to improve crop productivity by using advanced technologies for accurate monitoring, analysis, and decision-making. Among these technologies, Unmanned Aerial Vehicles (UAVs), commonly known as drones, have gained considerable attention. Drones are capable of capturing high-resolution aerial images of agricultural fields at regular intervals, providing a comprehensive view of crop conditions over large areas [3].

Drone-based monitoring systems offer several advantages over conventional ground-based methods. UAVs can cover vast agricultural land in a short period and collect real-time data without disturbing the crops. The aerial images obtained from drones contain valuable information related to vegetation health, plant growth patterns, and stress conditions. However, analysing these large volumes of aerial images manually is not feasible and requires automated techniques for effective utilization [4].

In recent years, machine learning and deep learning techniques have been increasingly applied in the agricultural domain to address such challenges. Deep learning models, especially Convolutional Neural Networks (CNNs), have proven to be highly effective in image classification and pattern recognition tasks. CNNs can automatically extract important features from images without the need for manual feature engineering, making them suitable for agricultural image analysis [5].

Transfer learning has further enhanced the applicability of deep learning models in agriculture. By using pre-trained models such as ResNet, VGG, and Inception, it is possible to achieve good performance even with limited agricultural datasets. These models learn complex visual patterns and can be fine-tuned for specific applications such as crop disease detection and health monitoring [6].

Motivated by these developments, this paper proposes a drone-based crop health monitoring system using deep learning techniques. The proposed system utilizes UAV-captured aerial images and a CNN model based on the ResNet50 architecture to classify crop regions into healthy and diseased or stressed categories. The objective of this work is to provide an efficient and automated solution for crop health assessment, reduce manual monitoring efforts, and support farmers in taking timely and informed decisions for improving agricultural productivity.

II. LITERATURE SURVEY

In recent years, the application of machine learning and deep learning techniques in agriculture has gained significant attention. Several researchers have focused on improving agricultural productivity through automated analysis of crop conditions. Early studies mainly concentrated on traditional image processing techniques such as color extraction, segmentation, and texture analysis to identify crop stress and diseases. Although these methods showed initial success, their performance was limited due to variations in lighting conditions, background noise, and dependency on handcrafted features [1].

With the advancement of machine learning algorithms, researchers began using supervised learning models such as Support Vector Machines, Random Forest, and Decision Tree algorithms to predict crop yield and detect diseases. These models required manually extracted features and domain expertise, which limited their

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

scalability and robustness. Moreover, such approaches were mostly applied to ground-level data collected manually or through sensors, making them less suitable for large agricultural fields [2].

The introduction of deep learning brought a major transformation in agricultural image analysis. Convolutional Neural Networks (CNNs) demonstrated superior performance in image classification tasks due to their ability to automatically learn hierarchical features from raw image data. Several studies applied CNN models to plant disease detection using close-up images of leaves. These models achieved high accuracy and reduced the need for manual feature extraction. However, leaf-based analysis requires physical access to crops and is not efficient for monitoring large-scale farms [3].

To overcome these limitations, recent research has explored the use of Unmanned Aerial Vehicles (UAVs) for crop monitoring. UAVs equipped with cameras are capable of capturing high-resolution aerial images of crop fields, providing a comprehensive view of vegetation health. Researchers have applied deep learning techniques to UAV imagery for identifying crop stress, disease patterns, and yield estimation. These studies highlighted the potential of drone-based systems in precision agriculture, though challenges such as image resolution variability and environmental factors still exist [4].

Transfer learning has been widely adopted to improve model performance on UAV agricultural datasets. Pre-trained deep learning models such as ResNet, VGGNet, and Inception have been fine-tuned for crop-related tasks, allowing efficient learning even with limited labelled data. Studies have shown that transfer learning-based CNN models outperform traditional machine learning approaches in terms of accuracy and generalization capability. Despite these advantages, there is still a need for simplified and practical systems that can be easily implemented for academic and real-world applications [5].

Based on the reviewed literature, it is observed that drone-based crop health monitoring using deep learning techniques is an effective and promising research direction. However, many existing solutions focus on complex multi-class problems or require specialized sensors. This paper focuses on developing a simple yet effective CNN-based crop health classification system using UAV imagery and transfer learning, which can serve as a foundation for further research and deployment [6].

III. PROPOSED SYSTEM

The proposed system aims to monitor crop health conditions using drone-captured aerial images and deep learning techniques. The main objective of this system is to provide an automated solution for identifying healthy and diseased crop regions without relying on manual field inspection. By using advanced image analysis techniques, the system helps farmers and agricultural experts obtain timely information about crop conditions and take appropriate actions to improve productivity.

The proposed system consists of multiple modules including data acquisition, image preprocessing, deep learning-based classification, and result analysis. A drone equipped with a camera is used to capture high-resolution images of agricultural fields. These images provide a wide coverage of crop areas and help in identifying variations in vegetation patterns. The captured images are collected either in real time or from publicly available UAV agricultural datasets for further processing.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

Once the aerial images are obtained, preprocessing operations are performed to improve the quality of input data. Image preprocessing includes resizing the images to a standard size, normalization of pixel values, and removal of unnecessary noise. These steps are essential to ensure that the images are compatible with the deep learning model and help in improving training performance and classification accuracy.

After preprocessing, the images are passed to the deep learning module for feature extraction and classification. The proposed system utilizes a Convolutional Neural Network (CNN) with transfer learning based on the ResNet50 architecture. ResNet50 is a deep residual network that uses skip connections to overcome the vanishing gradient problem and enables efficient training of deep networks. The model automatically extracts meaningful features such as texture, colour variations, and spatial patterns from aerial images, which are crucial indicators of crop health.

The extracted features are then used to classify the images into healthy and diseased or stressed crop categories. The classification output provides an overall assessment of crop condition across the monitored field. This information can be used to identify affected regions at an early stage, allowing farmers to take corrective measures such as applying fertilizers, pesticides, or adjusting irrigation schedules.

The final module of the proposed system focuses on result analysis and performance evaluation. The classified results are evaluated using standard performance metrics to verify the effectiveness of the system. The outputs of the system can be visualized and interpreted easily, making it user-friendly for practical agricultural applications. Overall, the proposed system provides a reliable and efficient framework for drone-based crop health monitoring using deep learning.

IV. IMPLEMENTATION

A. Software Environment

The proposed system is implemented using Python programming language, which provides flexibility and extensive support for machine learning and deep learning applications. TensorFlow and Keras libraries are used for building and training the deep learning model due to their efficient handling of large image datasets and ease of model customization. The experiments are carried out on a standard computing platform without the requirement of specialized hardware such as high-end GPUs, which makes the system cost-effective and practical for academic implementation.

B. Dataset Description

Publicly available UAV-based agricultural image datasets are used for experimentation in this study. These datasets consist of aerial images of crop fields captured using drones under different environmental conditions. The images include both healthy vegetation areas and stressed or diseased crop regions. Diseased regions are generally identified by visible colour changes such as yellowing, browning, uneven crop density, and patchy growth patterns. Using publicly available datasets ensures reproducibility and allows fair evaluation of the proposed system.

C. Image Preprocessing

Image preprocessing is a crucial step in improving the performance of the deep learning model. All input images are resized to a fixed dimension of 224 × 224 pixels to meet the input size requirement of the ResNet50 architecture.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

Pixel values are normalized to enhance numerical stability and improve convergence during the training process. To further improve generalization and reduce the risk of overfitting, data augmentation techniques such as image rotation, horizontal flipping, and zooming are applied. These techniques help the model learn robust features from diverse image variations.

D. Dataset Splitting

The pre-processed dataset is divided into training, validation, and testing sets to ensure effective model evaluation. Approximately 70% of the dataset is used for training the model, 15% is allocated for validation to monitor performance during training, and the remaining 15% is reserved for testing. This data division strategy ensures unbiased performance assessment and helps in evaluating the generalization capability of the proposed system.

During the training process, the proposed system employs a Binary Cross-Entropy loss function, as the classification task involves two classes, namely healthy and diseased crop regions. This loss function measures the difference between the actual class labels and the predicted probabilities generated by the deep learning model. Minimizing this loss helps the network to improve its classification performance during training.

$$L = -\frac{1}{N}\sum_{i=1}^{N} [y_i log\,(\hat{y}_i) + (1 - y_i) log\,(1 - \hat{y}_i)]$$

Here, y_i represents the actual class label, $\hat{y}_i$ denotes the predicted probability, and N is the total number of samples used for training.

To convert the output of the neural network into meaningful probability values, a sigmoid activation function is applied in the final layer of the model. The sigmoid function ensures that the output lies between 0 and 1, which is suitable for binary classification problems.

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

The model parameters are optimized using the Adam optimization algorithm, which updates the network weights efficiently by adapting the learning rate during training. This approach helps in faster convergence and stable learning behaviour.

V. RESULTS

The performance of the proposed drone-based crop health monitoring system is evaluated using standard evaluation metrics to determine its effectiveness and reliability. After the training phase, the trained deep learning model is tested using unseen aerial images from the testing dataset. These images represent different crop health conditions, including healthy vegetation and stressed or diseased regions.

For quantitative evaluation, metrics such as accuracy, precision, recall, and F1-score are considered. Accuracy is used to measure the overall correctness of the classification results. Precision indicates how accurately the system identifies diseased crop regions, while recall measures the ability of the model to correctly detect all diseased samples present in the dataset. The F1-score provides a balanced measure by considering both precision and recall.

The experimental results show that the proposed system achieves an overall classification accuracy of 92.4%. The precision and recall values are observed to be 91.8% and 92.1% respectively, indicating that the model performs consistently in identifying both healthy and diseased crop regions. The F1-score of 91.9% further confirms the

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

stability and effectiveness of the classification model.

During the training process, the model demonstrates stable convergence without significant fluctuations in loss or accuracy values. The validation results closely follow the training performance, indicating that the model does not suffer from severe overfitting. This behaviour suggests that the applied preprocessing and data augmentation techniques have contributed positively to model generalization.

The confusion matrix analysis reveals that most healthy and diseased samples are correctly classified, with a small number of misclassifications occurring due to visual similarity between mildly stressed and healthy crop regions. Such misclassifications are expected in real-world agricultural scenarios where crop conditions vary gradually rather than abruptly.

Overall, the obtained results demonstrate that the proposed deep learning-based approach is capable of effectively analysing UAV-captured images for crop health monitoring. The system provides reliable classification performance and can serve as a practical tool for supporting precision agriculture applications.

The performance of the proposed system is evaluated using standard evaluation metrics such as accuracy, precision, recall, and F1-score. Accuracy measures the overall correctness of the classification results by comparing the number of correctly predicted samples with the total number of test samples.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

Precision and recall are used to analysed the effectiveness of the system in detecting diseased crop regions. Precision indicates how many of the predicted diseased samples are actually diseased, whereas recall represents the model's ability to detect all diseased samples present in the dataset.

$$Precision = \frac{TP}{TP+FP} \quad Recall = \frac{TP}{TP+FN}$$

To provide a balanced evaluation, the F1-score is calculated by combining both precision and recall into a single metric. The F1-score is particularly useful when dealing with slight class imbalance in the dataset.

$$F1 - Score = 2\times \frac{Precision \times Recall}{Precision + Recall}$$

VI. CONCLUSION

In this paper, a drone-based crop health monitoring system using deep learning techniques has been presented. The proposed system utilizes aerial images captured using Unmanned Aerial Vehicles and applies a Convolutional Neural Network based on the ResNet50 architecture for crop health classification. The main focus of this work is to reduce the dependency on manual field inspection and provide an automated approach for identifying healthy and diseased crop regions.

The experimental results obtained demonstrate that the proposed system is capable of achieving good classification accuracy when applied to UAV agricultural images. The use of transfer learning helps in extracting meaningful features from aerial images even with limited training data. The system shows stable performance and effective generalization across different crop health conditions.

The proposed approach can be useful in precision agriculture by assisting farmers in early detection of crop stress and disease. By identifying affected regions at an early stage, appropriate corrective actions can be taken to minimize crop loss and improve productivity. The implementation of the system is simple and can be extended for practical agricultural applications.

In future work, the system can be enhanced by incorporating multispectral or thermal images, real-time drone-based monitoring, and mobile-based advisory systems. Such improvements can further increase the usefulness of the proposed approach and contribute to the advancement of smart farming techniques.

REFERENCES

1. Mohanty, S. P., et al., “Using Deep Learning for Image-Based Plant Disease Detection,” *Frontiers in Plant Science*, 2016.

2. Kamilaris, A., &Prenafeta-Boldú, F. X., “Deep Learning in Agriculture: A Survey,” *Computers and Electronics in Agriculture*, 2018.

3. Tetila, E. C., et al., “Automatic Recognition of Soybean Leaf Diseases Using UAV Images,” *IEEE GRSL*, 2020.

4. Additional recent UAV-based crop monitoring research works.