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RESEARCH PAPER

Multi-modal plant disease detection using a single-stream CNN

Md. Ghouse Mohiuddin[1], Mohd. Yousuf[2]

[1] *Assistant Professor, Department of Computer Science & Application, Palamuru University, Mahabubnagar, Telangana*
[2] *Research Scholar, Department of Computer Science & Application, P.K. University, Shivpuri, Jhansi, M.P*

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Abstract

Application of Artificial intelligence (AI) in agriculture sector plays an important role to enhance the yields by predicting and detecting the plant diseases and improving health of the crop. The early detection of plant diseases is crucial and helpful to the farmers to minimize the crop loss and ensure healthy crop. However, the traditional manual methods, are time consuming, error-prone, and inefficient for large-scale farming. Adopting recent technologies in Artificial Intelligence (AI) and Deep Learning, particularly Convolutional Neural Networks (CNNs) in the recent years have revolutionized the automation process of plant disease detection. However, single-modal approaches depend on only RGB images often fail to capture critical physiological and biochemical changes in plants. To overcome these limitations, we propose a Single-Stream CNN in Multi-Modal Plant Disease Detection, integrating RGB, thermal, and hyperspectral imaging into a unified model. Unlike traditional multi-stream architectures that increase computational complexity, our model processes multi-modal data as a single 4-channel input tensor, optimizing feature fusion while maintaining computational efficiency. The proposed architecture, based on a Modified VGG-16 CNN model, which enhances disease detection accuracy by leveraging complementary information from different imaging modalities. Experimental evaluations demonstrate significant improvements in classification accuracy compared to RGB-only models. Furthermore, our model is optimized for real-time deployment on edge computing devices, making it scalable for precision agriculture applications, including automated greenhouse monitoring, drone-based crop surveillance, and IoT-integrated farming systems. This research work highlights the transformative potential of AI-driven multi-modal plant disease detection, flagging the way for more efficient, cost-effective, and scalable agricultural solutions.

1. Introduction

Agriculture plays a vital role in the supply of food globally. Various environmental factors cause the ill health of plants and effect the crop yields. The early detection of plant diseases is essential to prevent large-scale crop losses. Traditional manual methods of plant disease detection involve visual inspection by experts, which is labor-intensive, time-consuming, and likely to be error-prone. In recent years, machine learning and deep learning techniques have gained popularity for detecting plant diseases, demonstrating high efficiency and accuracy. The application of these techniques in agriculture and farming enhances decision-making regarding crop selection, optimal farming practices, and

Corresponding author: Md. Ghouse Mohiuddin
Email Address: ghouse@palamuruuniversity.ac.in

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seasonal activities. However, traditional approaches primarily rely on unimodal image data, limiting their ability to capture biochemical changes in plants. With the rapid growth of multimedia data, there is an increasing need for AI techniques capable of analyzing heterogeneous data sources. The emergence of multimodal AI techniques addresses these limitations by extracting features from various types of image data, including RGB, thermal, and hyperspectral images.

1.1 Multimodal AI

Multimodal AI models are systems that can process and integrate data from numerous sources, such as text, images, audio, and video. They can be used to improve accuracy and efficiency in a variety of applications, including manufacturing, visual question answering, and image generation. Multimodal AI helps farmers to check the status of the crops by using a combination of satellite images, weather data, and soil information. This integrated analysis assists in making decisions about irrigation and fertilization to optimize crop yields. The key advantages of using multimodal AI system in agriculture includes: Enhanced crop health monitoring, Precision farming, Improved yield prediction, Optimized irrigation management, Pest and disease control, Data-driven decision making, Automated field operations, Reduced labour costs**.** The multimodal data that can be used in agriculture comprises Satellite imagery, drone imagery, IoT based soil sensors data, whether data in text etc**.** Multi-modal imaging, which integrates multiple sources of information such as RGB and thermal imaging, has demonstrated potential in enhancing plant disease detection. Thermal imaging captures temperature variations that may indicate disease-related stress, while RGB images provide essential colour and texture details. In this paper we propose a Single-Stream CNN that fuses these two modalities into a four-channel input tensor, which is then processed using a deep learning model.

The succeeding sections of this paper are structured as follows: **Section 2** presents a review of previous research on plant disease detection using AI techniques, **Section 3** outlines the proposed methodology, **Section 4** discusses result analysis and challenges, and **Section 5** concludes with potential future research directions.

2. Literature Review

Agriculture plays a vital role in ensuring global food security. However, plant diseases posture a major challenge to crop productivity, resulting in substantial economic losses and food shortages. Traditional disease detection methods, such as manual inspection, are time-consuming, labour-intensive, and prone to inaccuracies. Recent advancements in artificial intelligence (AI), image processing and computer vision have introduced promising solutions for automated plant disease detection. Convolutional Neural Networks (CNNs), in particular, have achieved high accuracy in image-based classification tasks [1]. However, relying solely on single-modal image data (e.g., RGB images) has limitations in detecting subtle disease patterns. To address this, a multi-modal imaging approach that combines RGB, thermal, and hyperspectral imaging has been proposed to improve detection accuracy [2].

2.1 Role of AI in Plant Disease Detection

AI-driven models, especially deep learning techniques, have significantly advanced plant disease identification. CNNs have shown robust feature extraction capabilities, making them suitable for classifying plant diseases from leaf images [3]. Traditional machine learning approaches, such as Support Vector Machines (SVM) and Random Forest classifiers, require handcrafted features, limiting their adaptability to diverse disease symptoms. Deep learning, on the other hand, enables automatic feature extraction and classification without manual intervention [4].

2.2 Multi-Modal Image Data: Enhancing Disease Detection

The use of multi-modal image data provides a more comprehensive view of plant health. While RGB images capture surface-level symptoms, thermal imaging detects temperature variations associated with disease-induced stress [5]. Hyperspectral imaging provides spectral signatures that reveal biochemical changes in plants before visible symptoms appear [6]. By integrating these imaging techniques, AI models can achieve higher sensitivity and specificity in disease detection [7].

2.3 CNN-Based Classification Models for Multi-Modal Image Fusion

CNNs have been widely used for plant disease classification due to their ability to learn spatial hierarchies of features. Traditional CNN architectures, such as AlexNet, VGG-16, and ResNet, have been employed for plant disease classification using RGB images [8]. However, to effectively process multi-modal data, specialized architectures, such as Modified VGG-16 or Fusion CNNs, have been developed. These models integrate features from different modalities at various levels, enabling robust decision-making [9]. The Recent advancements from 2020 to 2025 have significantly improved AI-driven plant disease detection which includes:

In a research paper Alnaggar et al. (2023) [10] introduced a dataset comprising multispectral and RGB images to detect rice plant diseases. Their deep learning model demonstrated improved accuracy by integrating Red, Green, and Near-Infrared channels. Sebastian et al. (2024) [11] proposed ViTaL, a Vision Transformer-based model, enhancing feature extraction and model performance in plant disease identification. Under Hybrid Machine Learning and Image Segmentation Techniques, Marques et al. (2024) developed "Plant Doctor," an AI system combining YOLOv8 and Deep SORT algorithms to diagnose urban plant health using video analysis [12]. Emphasizing Multi-Prediction Approaches in

Deep Learning in a research study Yao et al. (2023) [13] proposed the GSMo-CNN model for multi-output plant disease classification, achieving state-of-the-art accuracy on standard datasets. A research study in BMC Plant Biology highlighted the effectiveness of integrating attention mechanisms into Shuffle Net and RestNet-50 for vegetable disease detection for Multisource Information Fusion [14]. Several studies have demonstrated the superiority of multi-modal CNN models over single-modal approaches. A comparative study on apple disease detection showed that a multi-modal CNN model combining RGB and hyperspectral images achieved 96.8% accuracy, whereas an RGB-based model achieved only 87.5% accuracy [15]. Similarly, a fusion model integrating thermal and RGB images improved early disease detection in wheat crops by 12% compared to RGB-only models [16]. These findings emphasize the need for a comprehensive AI-driven approach that leverages multi-modal imaging for improved accuracy and reliability.

2.4 Need for the Proposed Single-Stream CNN Model

Given the advancements and limitations outlined in the literature review, we have proposed a novel model named Single-Stream CNN in Multi-Modal Plant Disease Detection, it aims to address key challenges in existing AI-based models. While multi-modal approaches incorporating RGB, thermal, and hyperspectral imaging have demonstrated improved disease detection accuracy, many of these methods rely on separate processing streams for each modality, increasing computational costs and model complexity. The Single-Stream CNN model integrates features from all three imaging modalities within a unified network, reducing redundant computations and enhancing feature fusion efficiency. This approach is inspired by the success of Fusion CNNs [9] but optimizes processing by employing shared layers for early-stage feature extraction, ensuring better generalization across diverse datasets. Furthermore, our model leverages recent advancements in Vision Transformers [11] and multi-prediction deep learning [13] to improve feature selection and robustness. Additionally, the Single-Stream CNN model is designed to be computationally efficient, making it suitable for real-time deployment in edge devices and cloud-based APIs, enabling broader adoption in precision agriculture [12].

3. Proposed Methodology

Deep learning has been widely applied in plant disease classification using CNNs. Popular architectures like VGG-16, ResNet, and EfficientNet have been fine-tuned for crop monitoring. However, most existing models depend only on RGB images, ignoring other valuable modalities like thermal imaging, text data. Recent studies have explored multi-modal fusion techniques, such as separate CNN streams for different modalities, followed by feature fusion. While multi-stream CNNs have shown improvements, they are computationally expensive and unsuitable for real-time deployment on low-power devices. In this section we present our Single-Stream CNN model architecture (Fig. 1) which provides an efficient alternative by stacking RGB and thermal images into a single input tensor, reducing computational complexity while preserving rich feature representations. The proposed model Architecture for Single-Stream CNN in Multi-Modal Plant Disease Detection is as follows:

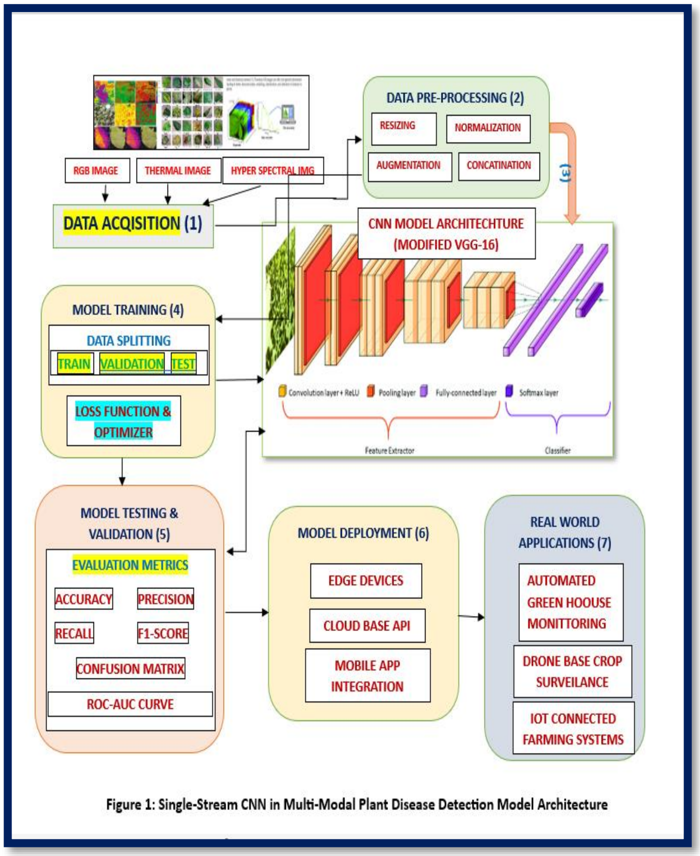

Figure 1: Single-Stream CNN in Multi-Modal Plant Disease Detection Model Architecture

The system architecture in the above Fig. 1 shows the Single-Stream CNN model for plant disease detection used in this research work. The model utilizes multiple types of images (RGB, Thermal, and Hyperspectral) to enhance the accuracy of disease detection. The architecture is broken down into several stages, each playing a crucial role in data processing, model training, validation, and deployment.

3.1 Data Acquisition

The first step in the architecture involves collecting different types of multi-modal images of plant leaves to detect diseases accurately. The three types of images acquired are:

- *RGB Images*: Standard colour images capturing the visible spectrum, commonly used in computer vision tasks.
- *Thermal Images:* Capturing heat variations to detect stress or infections in plants.

- *Hyperspectral Images*: Providing detailed spectral information that can reveal chemical compositions and hidden disease patterns.

These different imaging modalities provide complementary information, helping the model to make more informed predictions.

3.2 Data Pre-Processing

Once the images are collected, they undergo various pre-processing steps to ensure they are in a suitable format for training. The main pre-processing techniques applied are:

- *Resizing:* It ensures all images are of the same dimensions to be compatible with the CNN model.
- *Normalization*: This process standardizes pixel values to a specific range (e.g., 0-1) to stabilize training and improve convergence.
- *Augmentation*: This process applies transformations like flipping, rotation, and brightness adjustments to increase dataset variability and reduce overfitting.
- *Concatenation*: This process merges multiple modalities (RGB, thermal, hyperspectral) to create a unified dataset, enhancing feature extraction.

Pre-processing is a critical step that improves the quality of the dataset and optimizes it for efficient training.

3.3 CNN Model Architecture (Modified VGG-16)

The foundation of the system is a Convolutional Neural Network (CNN), with a Modified VGG-16 architecture shown in Fig. 2 serving as its core. VGG-16, a well-known deep learning model originally designed for image classification tasks, has been adapted to process multi-modal plant images that incorporate both RGB and thermal data. Unlike the standard VGG-16, which typically accepts three-channel (RGB) images, this modified version has been adjusted to handle four-channel input (RGB + Thermal), allowing the model to extract features from both visible and thermal spectrums simultaneously. To efficiently process this data, the system employs a single-stream CNN approach, meaning that both RGB and thermal information are fed into a unified network rather than separate branches. This integration ensures that the network can learn correlations between visible and thermal features, improving the model's ability to detect plant diseases, stress conditions, or other anomalies. Furthermore, the architecture has been optimized for edge deployment, making it lightweight and efficient for real-time inference on edge devices like embedded systems, mobile devices, or IoT-based agricultural monitoring systems. This modification helps reduce computational complexity while maintaining high accuracy, making it ideal for on-field plant health assessments.

The Convolutional Neural Network (CNN) model (Fig. 2) is structured hierarchically to progressively extract features and classify plant diseases with high accuracy. The architecture is based on VGG-16 but has been modified to improve efficiency and adapt to multi-modal inputs (RGB + Thermal) for better disease detection. Key Modifications to VGG-16 includes:

- *Input Shape Modification:* The standard VGG-16 architecture accepts three-channel RGB images (224 × 224 × 3), but the modified version is designed to handle four-channel input (224 × 224 × 4) to integrate both RGB and thermal data. This allows the model to leverage thermal imaging features, which can reveal plant stress, temperature variations, and other disease indicators that may not be visible in standard RGB images.
- *Fewer Fully Connected Layers:* To enhance efficiency, the architecture includes fewer fully connected (dense) layers than the original VGG-16. This reduces the number of parameters, making the model lighter and more suitable for edge deployment, where computational resources are limited.
- *Batch Normalization & Dropout:* Batch Normalization is added after convolutional layers to stabilize training, accelerate convergence, and improve generalization. Dropout layers are introduced in the fully connected layers to reduce overfitting, ensuring the model performs well on unseen plant images.
- *Softmax Output Layer:* The final layer of the network employs a softmax activation function, enabling the system to perform multi-class classification of plant diseases. This means the model can differentiate between multiple plant conditions, such as healthy plants and various disease categories.

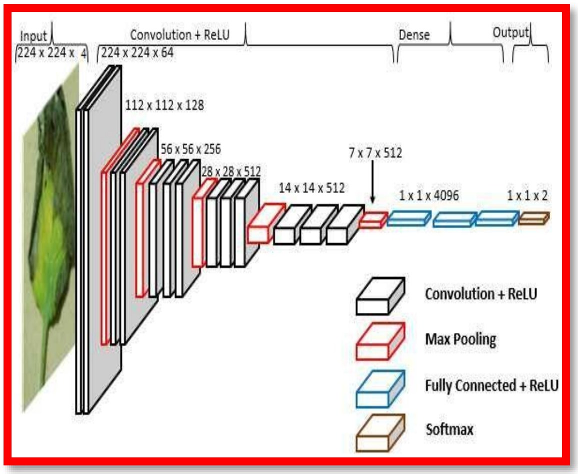

Figure 2: Modified VGG-16 CNN Architecture

3.3.1 Architecture Breakdown

The Modified VGG-16 CNN Architecture depicted in Fig. 2 breakdown in to following layers:

- *Input Layer:* The model accepts a 4-channel input (224 × 224 × 4), where RGB and Thermal images are stacked together to allow the CNN to process fused multi-modal information.

- *Convolutional Blocks (Feature Extraction):* The model retains five convolutional blocks, similar to standard VGG-16, but adapted for four-channel processing. Each block consists of: Conv2D layers with ReLU activation for hierarchical feature extraction, Batch Normalization to enhance training stability, Max-Pooling layers to progressively down sample the feature maps, reducing spatial dimensions while retaining essential information.
- *Fully Connected Layers (Classification):* It includes Flatten Layers, Dense Layers, and Dropout Layers. The extracted features are flattened into a 1D vector using a Flatten layer. Dense (fully connected) layers with ReLU activation are used to learn complex feature relationships. Dropout layers are included to prevent overfitting, ensuring the model generalizes well to new data.
- *Output Layer:* A softmax activation function is applied in the final layer, allowing the model to classify plant images into multiple disease categories (e.g., six plant diseases plus a healthy class).

3.4 Model Training

Once the CNN architecture is defined, the model is trained using the collected and pre-processed dataset. Training involves the following key steps:

3.4.1 Data Splitting

The dataset is divided into three parts: (i) *Training Set:* Here we split the 70% of the data which is used to train the CNN model. (ii) *Validation Set:* In this set we keep 20% of the data to tune hyperparameters and prevent overfitting, and (iii) *Test Set:* Here we used the remaining 10% of the data to evaluate the model's final performance.

3.4.2 Loss Function & Optimizer

Our model uses a loss function (Cross Entropy Loss) to measure the difference between predicted and actual outputs. Cross-entropy, also referred to as logarithmic loss or log loss, is a widely used loss function in machine learning for evaluating the performance of classification models. It quantifies the difference between the actual probability distribution of the target classes and the predicted probabilities generated by the model. Since our model classify the data into multiple classes so here, we use:

Multiclass Cross-Entropy Loss, also known as categorical cross-entropy or softmax loss, is a widely used loss function for training models in multiclass classification problems. For a dataset with N instances, Multiclass Cross-Entropy Loss is calculated with the following formulae:

$$-1N\Sigma i = 1N\Sigma j = 1C(yi,j.\log(pi,j)) \qquad (1)$$

Where, C is the number of classes, yi,j are the true labels for class j for instance i, pi,j is the predicted probability for class j for instance i.

Adam Optimizer is employed here to adjust model parameters, minimizing errors over multiple iterations. Adaptive Moment Estimation (Adam) is an optimization algorithm for gradient descent that is highly efficient, particularly when handling large-scale problems with extensive data or numerous parameters. It is memory-efficient and effectively combines two gradient descent techniques:

- *Momentum-based optimization and RMSProp Momentum:* This technique accelerates gradient descent by incorporating the exponentially weighted average of past gradients, helping the algorithm converge to the minimum more quickly.

$$\mathrm{wt{+}1{=}wt{-}\alpha mt}wt+1=wt-\alpha mt \qquad (2)$$

$$\mathrm{mt} = \beta\mathrm{mt}-1+(1-\beta)\ [\delta\mathrm{L}\delta\mathrm{wt}] \qquad (3)$$

where, m_t = aggregate of gradients at time t [current] (initially, m_t = 0), m_{t-1} = aggregate of gradients at time t-1 [previous], W_t = weights at time t, W_{t+1} = weights at time t+1, α_t = learning rate at time t, ∂L = derivative of Loss Function, ∂W_t = derivative of weights at time t, β = Moving average parameter (const, 0.9).

- *Root Mean Square Propagation (RMSP):* Root Mean Square Prop (RMSprop) is an adaptive learning algorithm designed to enhance AdaGrad. Unlike AdaGrad, which accumulates the sum of squared gradients, RMSprop utilizes an exponential moving average of squared gradients to maintain a more stable and adaptive learning rate.

$$\mathrm{wt}+1 = \mathrm{wt}-\alpha\mathrm{t}(\mathrm{vt}+\varepsilon)1/2*[\delta\mathrm{L}\delta\mathrm{wt}] \qquad (4)$$

$$\mathrm{vt} = \beta\mathrm{vt}-1+(1-\beta)*[\delta\mathrm{L}\delta\mathrm{wt}]2 \qquad (5)$$

where, W_t = weights at time t, W_{t+1} = weights at time t+1, α_t = learning rate at time t, ∂L = derivative of Loss Function, ∂W_t = derivative of weights at time t, V_t = sum of square of past gradients. [i.e sum($\partial L/\partial Wt-1$)] (initially, V_t = 0), β = Moving average parameter (const, 0.9), ϵ = A small positive constant (10^{-8}).

3.4.3 Model Testing & Validation

After training, the model is evaluated using various performance metrics to ensure its reliability in real-world applications. The evaluation includes the following metrics:

- *Accuracy:* It is a measure that calculates how frequently a model correctly predicts the output. It is calculated by dividing the number of correct predicted results with the overall all predicted results [18].

$$\text{Accuracy} = \frac{True_{\text{positive}} + True_{negative}}{True_{\text{positive}} + True_{negative} + False_{\text{positive}} + False_{negative}} \qquad (6)$$

- *Precision:* It indicates the eminence of positive prediction generated by the model. Precision is calculated by dividing the number of True Positive cases by the total number of positive cases [18].

$$\text{Precision} = \frac{True_{\text{positive}}}{True_{\text{positive}}\ False_{\text{positive}}} \qquad (7)$$

- *Recall:* It is a metric that measures how frequently a model identifies correctly True Positive cases from the actual positive samples from the dataset. It is calculated by dividing the number of True Positive cases with the True Positive and False Negative Cases [18].

$$\text{Recall} = \frac{True_{\text{positive}}}{True_{\text{positive}}\ False_{\text{negative}}} \qquad (8)$$

- *F1-Score:* It evaluates the accuracy of the model in a dataset. Evaluation of binary classification systems that categorize samples either 'positive' or 'negative' is done with this measure. It is calculated by taking the harmonic mean of precision and recall. It can be adjusted to emphasize precision upon recall, or the other way around [18].

$$\text{F1 Score} = 2\times\frac{recall\ \times precision}{recall+precision} \qquad (9)$$

- *ROC-AUC Curve:* A Receiver Operating Characteristic (ROC) curve is a graph that shows the performance of a binary classification model. The area under the ROC curve (AUC) is a value that measures the model's performance These metrics provide insights into the model's strengths and weaknesses, guiding further improvements [19].
- *Confusion Matrix*: A confusion matrix for a CNN (convolutional neural network) is a table that visually displays how well the CNN model is performing by comparing its predicted classifications to the actual classifications of images in a test dataset, allowing you to see where the model is making mistakes and which classes it is getting confused between, essentially acting as a detailed report card for the model's performance on different image categories [20].

3.5 Model Deployment

Once the model is trained and validated, it is deployed for real-world applications using various platforms including:

- *Edge Devices:* These devices are used to Integrate the model into embedded systems for on-site plant disease detection.
- *Cloud-Based API:* Through Cloud based API our model able to provide remote access via cloud servers for large-scale agricultural monitoring.
- *Mobile App Integration:* Integration of our model with mobile applications facilitates the farmers to easily detect the diseases instantly in the field.

By deploying the model across different platforms, it becomes accessible and scalable for agricultural users.

3.6 Real-World Applications

At the final stage we focus on applying the trained CNN model to practical agricultural situations. Some key applications in the real world include:

- Automated Greenhouse Monitoring which enables real-time disease detection in controlled farming environments.
- Drone-Based Crop Surveillance, uses drones to scan large fields, identifying diseased plants efficiently.
- IoT-Connected Farming Systems**,** which **i**ntegrates the model with IoT devices to provide continuous plant health monitoring.

These applications determine the practical impact of deep learning in smart agriculture, improving crop yield and reducing losses due to plant diseases.

This architecture outlines a comprehensive AI-driven approach for plant disease detection using multi-modal image data and a CNN-based classification model. By leveraging RGB, thermal, and hyperspectral images, and employing a Modified VGG-16 network, the system enhances disease detection accuracy. Furthermore, its deployment in edge devices, cloud-based APIs, and mobile apps makes it highly accessible for real-world agricultural applications, ultimately supporting smart farming and precision agriculture.

4. Implementation & Results

In this section we discussed the results obtained after implementing the model in python programming language. For implementing the above proposed model, we utilize TensorFlow and Keras to build and train a CNN model for plant disease classification, incorporating layers like Conv2D, MaxPooling2D, Batch Normalization, and Dropout to enhance performance. Image Data Generator is used for image preprocessing and augmentation, while L2 regularization helps prevent overfitting. NumPy facilitates numerical computations, and Scikit-Learn assists in handling class imbalances, generating classification reports, and computing confusion matrices. Matplotlib and Seaborn visualize training performance and results, including accuracy/loss graphs and heatmaps. Additionally, the trained model is converted into a TensorFlow Lite (TFLite) format, making it suitable for deployment on edge devices and mobile applications. The results obtained after executing the python code are discussed in the following paragraphs in various stages:

4.1 Data Acquisition & Data Preprocessing

We have collected the data of groundnut plant leaves dataset from the data repository Mendeley Data. In this dataset Images of leaves are categorized into six distinct groups according to their condition. Collected images are preprocessed and the processed images of groundnut leaves are kept in 6 folders as: the "healthy leaves" folder with 1871 images, the "early leaf spot" folder with 1731 images, the "late leaf spot" folder with 1896 images, the "Nutrition deficiency" folder with 1665 images, the "rust" folder with 1724 images, and the "early rust" folder with 1474 images. The total number of images in the dataset is 10361 [21].

The sample preprocessed training images of the classified leaves in to six classes are depicted in the following Fig. 3.

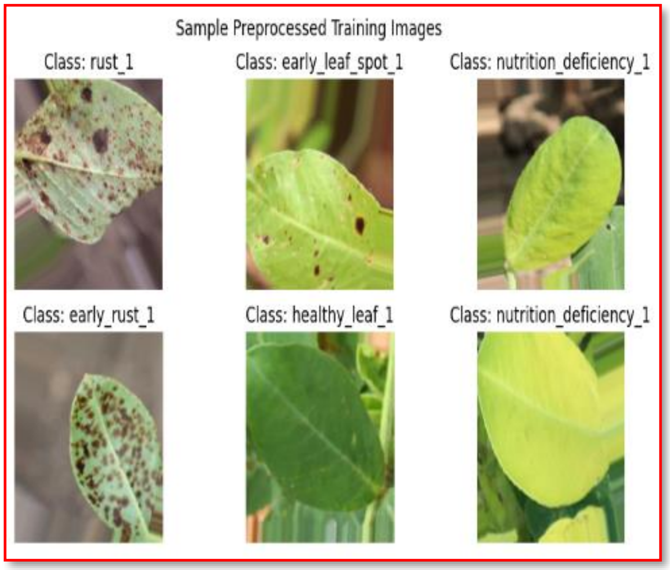
Sample Preprocessed Training Images
Class: rust_1
Class: early_leaf_spot_1
Class: nutrition_deficiency_1
Class: early_rust_1
Class: healthy_leaf_1
Class: nutrition_deficiency_1

Figure 3: Sample Pre-processed Training Images

The Dataset is splitted into training and testing set with the ratio of 80/20 respectively. Feature Scaling is a technique to standardize the independent features present in the data in a fixed range. It is performed during the data pre-processing to handle highly varying magnitudes or values or units. If feature scaling is not done, then a machine learning algorithm tends to weigh greater values, higher and consider smaller values as the lower values, regardless of the unit of the values. Here, we have used Min-Max Scaler. This scaling brings the value between 0 and 1. After features are extracted from the images, they are saved in HDF5 file. The Hierarchical Data Format version 5 (HDF5), is an open-source file format that supports large, complex, heterogeneous data. HDF5 uses a "file directory" like structure that allows us to organize data within the file in many different structured ways.

The images shown in Fig. 4 displays the predicted results of a plant disease classification model, showing four leaf images with their corresponding model predictions and ground truth labels. Each leaf is annotated with "Pred:" (Predicted Class) and "True:" (Actual Class), with correct predictions in green and incorrect predictions in red. From the above resulted image, it is observed that first two images (Left Side) are Correctly Predicted, where both leaves are correctly classified as "rust_1", with predictions perfectly matching the actual class (green text). This suggests that the model is highly accurate in detecting rust disease. Third Image (Middle) is also Correctly Predicted. The model correctly identifies a "healthy_leaf_1", confirming its ability to distinguish disease-free leaves. Fourth Image (Right) is incorrectly Predicted. The model misclassifies an early leaf spot as a healthy leaf (red text), highlighting a common challenge where early-stage infections resemble healthy leaves. This aligns with the confusion matrix findings shown in the next section, where early leaf spot had a high misclassification rate. The model successfully identifies most disease categories, but misclassification of early leaf spot remains a challenge. Addressing this issue will further boost the model’s reliability for real-world applications.

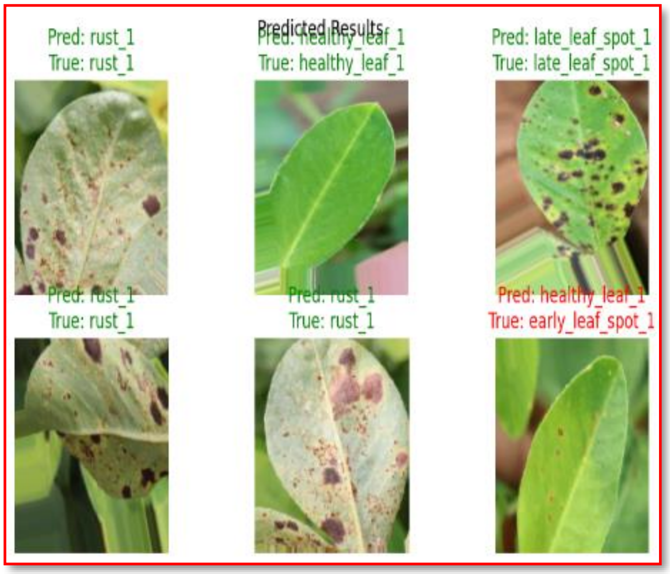

Figure 4: Predicted Results

4.2 Result Analysis

After preprocessing the data, we have trained the proposed model Modified VGG-16 with (80%) of the train data. Then the model is evaluated with respect to the evaluation metrics Precision, Recall, F1-Score, and Support. The results obtained are shown in the following table 1.

Table 1: Experimented results of Valuation Metrics

	Precision	Recall	F1-Score	Support
Early_leaf_spot_1	0.90	0.56	0.96	409
Early_rust_1	1.00	0.98	0.99	409
Healthy_leaf_1	0.68	0.95	0.79	409
Late_leaf_spot_1	0.93	0.98	0.96	405
Nutrition_deficiency_1	0.98	1.00	0.99	410
rust_1	1.00	0.93	0.96	409
Accuracy	0.90			2451
Macro Average	0.92	0.90	0.90	2451
Weighted Average	0.92	0.90	0.90	2451

From the above table 1, we can see that our model has achieved 90% overall accuracy, with high precision and recall across most classes. The early rust, late leaf spot, and nutrition deficiency classes exhibit near-perfect classification, indicating that the model effectively learns features related to these diseases. However, early leaf spot has a low recall (56%), suggesting that many actual cases of this disease are being misclassified. Additionally, the healthy leaf class has a precision of 68%, meaning that some healthy leaves are mistakenly labelled as diseased. This misclassification could be due to similar features shared between healthy and diseased leaves, leading to overlapping decision boundaries.

To address these issues, several optimizations are recommended. Stronger data augmentation, including increased rotation, brightness variation, and zooming, can help the model generalize better for early leaf spot cases. Class weights should be adjusted to prioritize underrepresented or misclassified classes, ensuring a more balanced learning process. To prevent overfitting, introducing learning rate decay will help stabilize training, especially in later epochs. Additionally, integrating transfer learning with VGG-16 can significantly improve feature extraction, leveraging pre-trained filters to capture complex patterns more effectively. Implementing these optimizations is expected to enhance recall for early leaf spot, increase precision for healthy leaf classification, and create a more robust and generalizable model with balanced performance across all classes.

4.2.1 Confusion Matrix

After executing the proposed model on the above said dataset the resulted confusion matrix shown in Fig. 5. It visualizes the model's performance across six different classes. Each row represents the actual class, while each column represents the predicted class. The confusion matrix reveals that the model performs exceptionally well for most classes, achieving high accuracy in Early Rust, Late Leaf Spot, and Nutrition Deficiency, with minimal misclassifications. Healthy Leaf and Rust classes also show strong performance, though some minor errors persist. However, the biggest challenge lies in Early Leaf Spot, where 181 samples are misclassified, mostly as Healthy Leaf, indicating that the model struggles to differentiate between these two categories. This misclassification likely stems from similar visual characteristics between early-stage leaf spots and healthy leaves, leading to overlapping decision boundaries.

Additionally, 26 Rust samples are incorrectly predicted as Healthy Leaf, further reinforcing the need for improved feature extraction. To enhance model performance, transfer learning with VGG-16 or RestNet-50, increased data augmentation, class weight adjustments, and contrast enhancement techniques (CLAHE) can be employed. Fine-tuning the learning rate in later epochs will also refine decision boundaries, ensuring better generalization. Overall, while the model demonstrates strong classification capabilities, targeted optimizations for Early Leaf Spot differentiation can push accuracy beyond 90%, making it even more robust and reliable.

4.2.2 Accuracy & Loss Graph

The accuracy and loss graphs depicted in Fig. 6 indicate a strong learning progression in the optimized model over 20 epochs. The training accuracy steadily improves, reaching approximately 80%, while validation accuracy follows a similar upward trend, stabilizing around 70-75% in later epochs. The small gap between train and validation accuracy suggests that the model is generalizing well, with no significant overfitting. However, minor fluctuations in validation accuracy, particularly between epochs 7-12, may indicate some learning instability, possibly due to class imbalance or challenging features within the dataset.

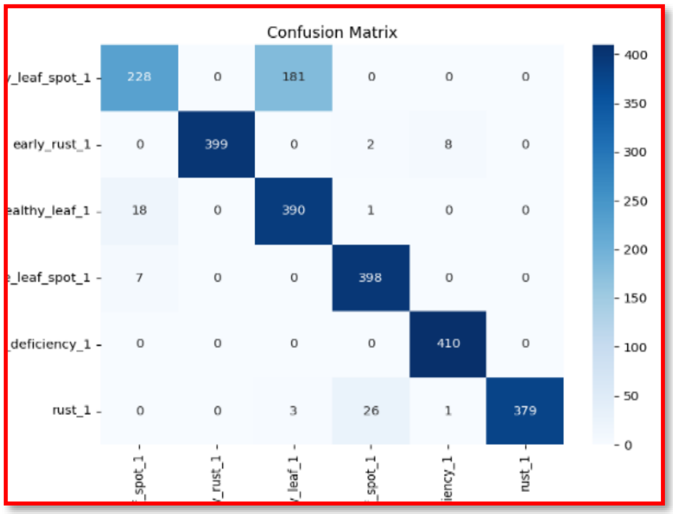

Figure 5: Resulted Confusion Matrix

The loss graph further supports these observations, with both training and validation loss decreasing consistently, demonstrating effective error minimization. While the initial validation loss is quite high (~14), it drops rapidly within the first few epochs, signifying that the model quickly learns key patterns before fine-tuning its performance. Although validation loss remains slightly higher than training loss (~1.5 vs. 1.0), it does not exhibit severe overfitting.

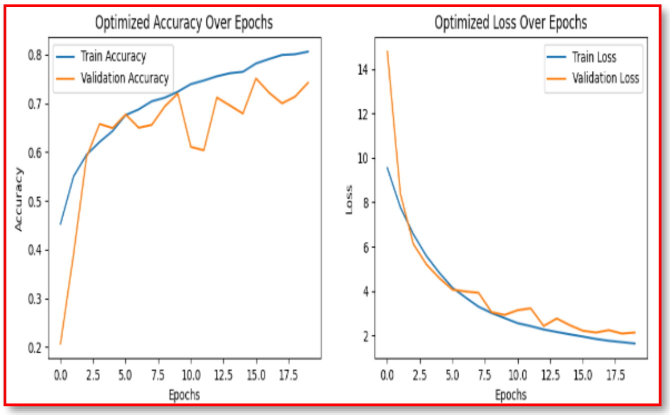

Figure 6: Accuracy & Loss Graph

To further optimize performance, implementing learning rate decay can stabilize fluctuations, while enhanced data augmentation will improve class differentiation. Additionally, fine-tuning dropout and regularization can help refine generalization and prevent potential overfitting. Overall, the model exhibits strong classification capability, achieving 80% accuracy with stable validation performance (~75%), making it highly reliable for real-world applications.

4.3 Discussion

Challenge 1

The high misclassification rate between early leaf spot and healthy leaves in the proposed Modified VGG-16 model is primarily attributed to feature similarities that exist between the two classes, making it difficult for the model to accurately differentiate them. Several key visual similarities contribute to the misclassification, such as:

- Minimal Visual Differences in Early Stages
- Overlapping Color Intensity and Texture Patterns
- Inadequate Feature Differentiation in Early Disease

Future Extension: To address the high misclassification rate, the following advanced feature extraction methods can be integrated:

- Integrate Grad-CAM to visualize misclassified regions and retrain the model to prioritize spot-based features.
- Use attention mechanisms (like Vision Transformers or Self-Attention) to amplify small, localized disease features.
- Augment training data with artificial noise, spot overlays, and color distortions to make the model robust to subtle feature changes.
- Combine RGB and thermal imaging for dual-modality feature extraction, ensuring that thermal stress zones in diseased leaves are captured.
- Introduce class reweighting during training, emphasizing early leaf spot samples to increase model sensitivity toward minimal symptoms.

Challenge 2

Impact of Dataset Distribution on Model's Classification Performance and Class Imbalance effect.

The dataset imbalance in the current research work significantly impacted the model’s performance, particularly for the early leaf spot class, resulting in low precision and recall. The dominance of majority classes (like Nutrition Deficiency and Rust) led to biased learning, reducing the model’s effectiveness in detecting early-stage diseases. However, by applying data augmentation, class weight balancing, and advanced CNN architecture, the model's performance on minority classes significantly improved.

Future Extension: Future research will be focused on synthetic data generation, multi-modal learning, and transfer learning to eliminate bias caused by dataset imbalance and further improve the model’s accuracy, particularly for early leaf spot detection.

5. Conclusion and future work

The integration of multi-modal image data with CNN-based classification models offers a more reliable and precise approach to plant disease detection. By leveraging the strengths of RGB, thermal, and hyperspectral imaging, AI-driven models can detect diseases earlier and with higher accuracy. Although challenges exist, ongoing advancements in deep learning and image fusion techniques will pave the way for more efficient and scalable solutions in smart agriculture. In this paper we present a Single-Stream CNN for multi-modal plant disease detection, integrating RGB and thermal imaging into a unified 4-channel input tensor. The proposed model achieves high classification accuracy while maintaining efficiency for real-time deployment on edge

Our proposed model demonstrates high accuracy (90%), with strong classification performance for most disease categories, particularly “rust, late leaf spot, and nutrition deficiency”, where precision and recall exceed “95%”. The model effectively generalizes across different plant disease types, as evident from its stable accuracy and loss curves, minimal overfitting, and strong performance in predicted results and confusion matrix analysis. However, early leaf spot classification remains a challenge, with a noticeable misclassification rate, often being predicted as a healthy leaf. This suggests the need for more refined feature extraction techniques to distinguish early disease symptoms from normal variations in leaf texture and color.

Future research should focus on enhancing feature learning capabilities by incorporating transfer learning with deep architectures like VGG-16 or RestNet-50, which can extract more detailed and hierarchical patterns. Additionally, contrast enhancement techniques (such as CLAHE) can help improve disease visibility in early stages. Data augmentation strategies should also be expanded, introducing illumination variations and multi-angle image capture, ensuring the model learns robust and diverse disease features. Furthermore, attention mechanisms and transformer-based vision models (e.g., Vision Transformers - ViTs) could be explored to improve classification accuracy in cases where: disease symptoms are subtle or overlapping. Finally, deploying this model in real-world agricultural scenarios via mobile applications or edge computing devices can facilitate real-time disease detection, bridging the gap between research and practical implementation.

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Biographies

Dr. Md. Ghouse Mohiuddin, working as a Asst. Prof. in Computer Science Department, Palamuru University, Mahabubnagar. Completed Ph.D. in Information Technology from Osmania University, Hyderabad. His Research Area is AI & ML.

Mr. Md. Yousuf, Ph.D. Research Scholar, Department of Computer Science & Applications, P.K. University, Shivapuri, Jhansi, MP. His Research Area is AI & ML. He has completed MCA from Osmania University, Hyderabad.

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