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# ATTENTION ENHANCED HYBRID VGG19 CNN MODEL FOR ROBUST SUGARCANE DISEASE CLASSIFICATION

T. Angamuthu[1)*]
[1)] Takshashila University, Ongur, Tindivanam, India
[1)]muthu1986.its@gmail.com

*T. Angamuthu

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**Abstract:** Accurate and timely identification of sugarcane diseases is essential for improving crop productivity and supporting sustainable agricultural practices. This study proposes an attention-enhanced hybrid deep learning framework that integrates VGG19-based transfer learning with custom convolutional neural network (CNN) layers for robust disease classification. To address the challenge of high inter-class similarity among sugarcane diseases, a lightweight attention mechanism is incorporated to selectively emphasize disease-relevant regions and enhance discriminative feature learning. A dataset comprising 2000 labeled sugarcane leaf images across five disease classes—Cercospora Leaf Spot, Helminthosporium Leaf Disease, Rust, Red Dot, and Yellow Leaf Disease—was used for training and evaluation. The proposed model was assessed using standard performance metrics, including accuracy, precision, recall, and F1-score. Experimental results demonstrate that the proposed approach achieves an accuracy of 94.6%, outperforming baseline CNN and conventional VGG19 models. Furthermore, the model is benchmarked against state-of-the-art architectures such as ResNet50, EfficientNet-B0, and MobileNetV2, demonstrating superior performance in feature discrimination and classification robustness. The integration of attention-based feature refinement with transfer learning significantly improves localization of disease-specific patterns and reduces misclassification among visually similar classes. The proposed framework offers a scalable and efficient solution for real-time crop disease detection and precision agriculture applications. Future work will focus on optimizing the model for edge deployment and extending the framework to multi-crop disease classification

**Keywords:** Sugarcane Disease Classification, Attention Mechanism, Transfer Learning, VGG19, Hybrid CNN, Deep Learning, Precision Agriculture, Image Classification, Plant Disease Detection

## 1. INTRODUCTION

In recent years, rapid progress in artificial intelligence and deep learning has significantly impacted agriculture, particularly in automated plant disease detection. Early and accurate identification of diseases helps reduce crop loss and improve productivity. Sugarcane, an important cash crop, is vulnerable to diseases such as Cercospora leaf spot, rust, and yellow leaf disease, which affect both yield and quality. Traditional detection methods rely on manual inspection, which is time-consuming and often inconsistent. Although deep learning models like CNNs, especially VGG19, have shown strong performance in image classification, challenges such as limited data and

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similar disease patterns still exist. To address this, this study proposes a hybrid approach that combines VGG19-based transfer learning with custom CNN layers, enabling better feature extraction and improved classification of sugarcane diseases.

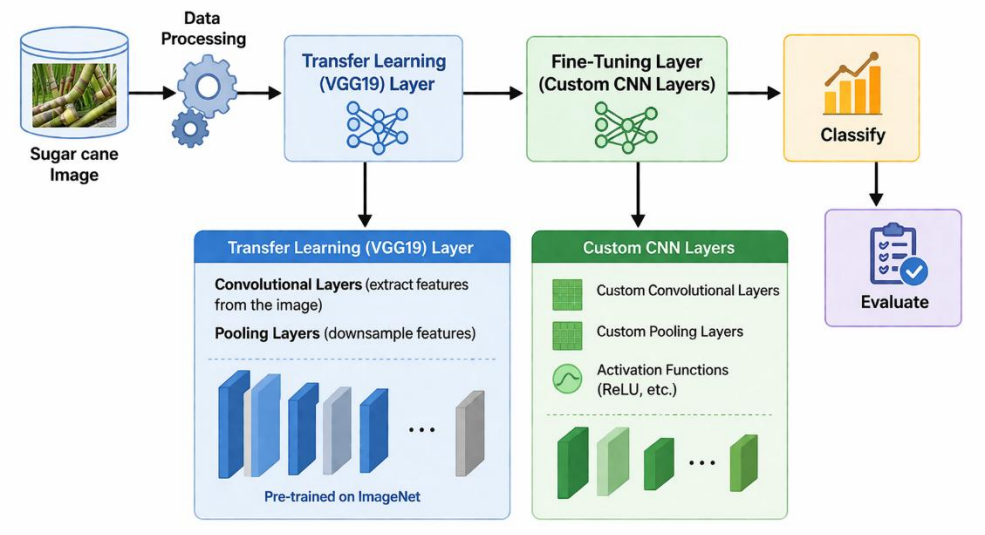



**Fig.1.** Model Architecture

As shown in Fig.1, the proposed architecture uses VGG19 as a feature extractor, followed by custom CNN layers for task-specific refinement. These additional layers help capture fine-grained disease patterns, and the extracted features are then passed to fully connected layers for final classification. The model is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. By combining transfer learning with customized feature learning, the model achieves better generalization and improved classification performance. It is tested on five major sugarcane diseases and compared with conventional CNN and standalone VGG19 models. The study introduces the VGG19TLCCNN framework, which enhances feature learning and reduces overfitting, aiming to improve accuracy and robustness in real-world sugarcane disease detection. Despite the success of deep learning models, challenges such as limited generalization, high similarity between disease classes, and reduced performance in real-field conditions still persist. Most methods rely on standalone CNNs or basic transfer learning, which often fail to capture highly discriminative features. This highlights the need for a hybrid approach that combines attention mechanisms with transfer learning to improve classification accuracy and robustness.

**Related Work**

Recent advancements in deep learning have significantly improved plant disease detection by enabling automated and accurate classification from leaf images. Various architectures, including Convolutional Neural Networks (CNNs), transfer learning models, and hybrid approaches, have been widely explored in agricultural applications. Rajeshwari & Elamparuthi (2026) proposed an optimized deep learning framework for rice disease detection, achieving high accuracy in real-time conditions. Similarly, Daphal & Koli (2024). applied transfer learning using deep architectures for sugarcane leaf disease classification, reporting improved accuracy compared to traditional methods. Mangrule et.al. (2024) utilized MobileNetV2 for lightweight disease detection, highlighting the trade-off between computational efficiency and classification performance. Hybrid approaches have also gained attention due to their ability to combine multiple learning strategies. Patil & Kale (2022) developed a CNN-based hybrid model integrated with SVM and Random Forest classifiers, which improved classification accuracy but introduced increased model complexity. Reddy et al. (2023) proposed the Deep Leaf model for grapevine disease classification, demonstrating that optimized deep learning architectures can significantly enhance performance through feature refinement.

In addition, Sharma et al. (2025) explored deep neural networks for sugarcane disease classification, achieving competitive results but facing challenges related to overfitting and dataset limitations. Singh et al. (2025) combined YOLOv8 with ResNet-50 and InceptionV3 for tomato leaf disease detection, demonstrating the effectiveness of

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multi-model integration for improving detection accuracy. Li, Zhang, & Chen (2023) highlighted the role of data augmentation techniques in handling imbalanced datasets and improving model generalization. Furthermore, Wang et al. (2024) investigated Vision Transformers (ViTs) for agricultural image analysis, showing superior performance in capturing spatial relationships compared to traditional CNNs. Previous works by Angamuthu and Arunachalam et al. (2025a, 2025b, 2025c), explored deep learning and transformer-based approaches for sugarcane disease classification. While these studies demonstrated promising results, they did not fully address the challenge of improving feature generalization and classification robustness under varying real-field conditions. Despite progress, challenges like overfitting, limited data diversity, and difficulty in distinguishing similar diseases still remain. To address this, the study proposes a hybrid VGG19-based transfer learning model with custom CNN layers, improving accuracy and robustness in real-world sugarcane disease detection.

## 2. METHOD

The novelty of the proposed methodology lies in the integration of an attention mechanism with VGG19-based transfer learning and custom CNN layers. In the transfer learning stage, the initial convolutional blocks (Block 1 to Block 4) of VGG19 were frozen to preserve general feature representations, while the deeper layers (Block 5) were unfrozen and fine-tuned.

### Attention Mechanism for Feature Enhancement

To further improve the model's ability to focus on disease-relevant regions, an attention mechanism is incorporated after the VGG19 feature extraction stage. While VGG19 effectively captures global hierarchical features, it does not explicitly emphasize the most informative regions associated with disease patterns.

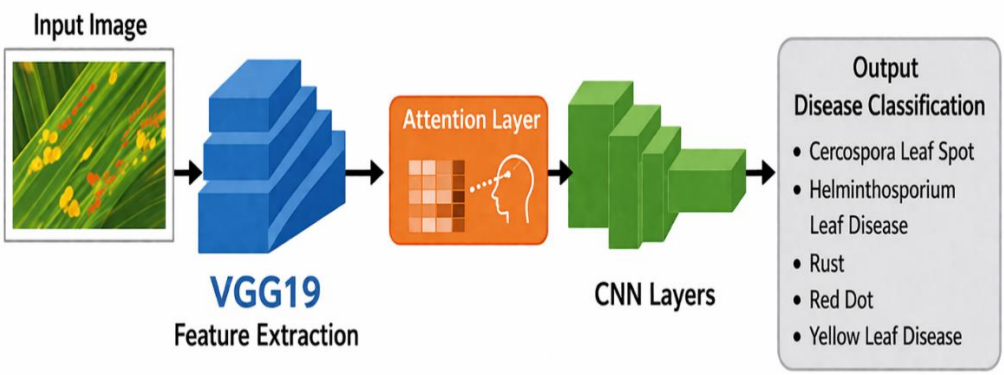



**Fig. 2.** Proposed Hybrid VGG19-CNN Architecture

The attention module assigns adaptive weights to feature maps, allowing the model to focus on important regions such as lesions, discoloration, and texture variations in sugarcane leaves.

$$\boldsymbol{A} = \boldsymbol{\sigma}\left(\boldsymbol{W_f} \cdot \boldsymbol{F} + \boldsymbol{b}\right) \quad \textbf{(1)}$$

$$\boldsymbol{F'} = \boldsymbol{A} \odot \boldsymbol{F} \quad \textbf{(2)}$$

This helps in highlighting relevant features and improves classification, especially when different diseases look similar. In simple terms, attention works in two steps: first, it calculates weights based on feature importance, and second, it scales the feature maps to emphasize key regions. The refined features are then passed to the custom CNN layers for further processing and final classification. This integration improves the model's robustness and generalization under varying real-world conditions.

### Dataset Collection

The dataset used for training (*Figure 2*), validation, and testing consists of high-resolution images of sugarcane leaves collected from Alagramam village in Villupuram district over a period of 6 months from July 2023 to January 2024. *Each image is labeled with one of five diseases*: Cercospora Leaf Spot, Helminthosporium Leaf Disease, Rust, Red Dot, and Yellow Leaf Disease. The dataset contains 400 images per disease class, distributed across three subsets. Reducing overfitting.

**Training Set**: 240 images per class (total 1200 images)
**Validation Set**: 80 images per class (total 400 images)

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**Testing Set**: 80 images per class (total 400 images)

Images are captured in natural field conditions, including variations in lighting, orientation, and environmental factors. All images are preprocessed to normalize the pixel values, resize them to a uniform size (*224x224 pixels*), and augment the dataset using techniques such as rotation, flipping, and zooming to improve model generalization.

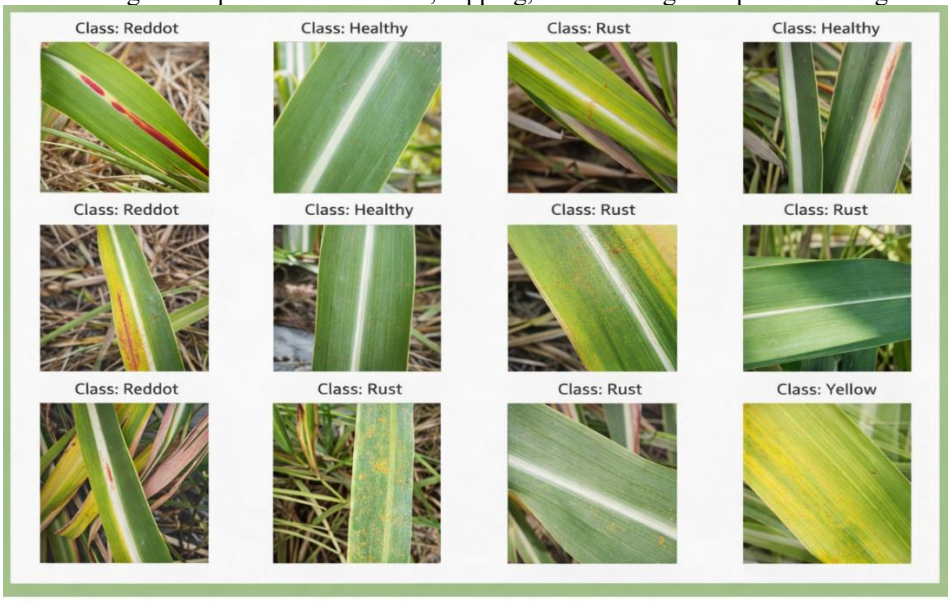



**Fig. 3.** Representative sample images of sugarcane leaf diseases used in the dataset.

The dataset was carefully split into training (*60%*), validation (*20%*), and testing (*20%*) sets, ensuring that images from the same plant or capture session were not distributed across multiple subsets. This prevents data leakage and ensures unbiased evaluation of the model.

**Hybrid Model Architecture**

The proposed hybrid model integrates the pre-trained VGG19 network with a series of Custom CNN layers for domain-specific feature extraction and fine-tuning. *The architecture is described in two stages,*

$$\boldsymbol{F_{\text{fusion}} = [F_{VGG19} + F_{CNN}]} \quad \textbf{(3)}$$

Features extracted from VGG19 and custom CNN layers are fused to enhance representation capability.

**Stage 1: Transfer Learning with VGG19**

The first stage uses VGG19, a deep CNN pre-trained on large datasets like ImageNet, for feature extraction. Instead of training from scratch, the model utilizes these pre-trained weights to capture general features such as edges, textures, and patterns, which are useful for sugarcane disease images. The convolutional layers of VGG19 act as the base feature extractor, and their output is converted into feature vectors through a fully connected layer. To retain the learned knowledge, these layers are frozen during training, meaning their weights are not updated.

**Stage 2: Custom CNN Layers for Fine-Tuning**

To adapt VGG19 for the specific task of sugarcane disease classification, we add a set of Custom CNN layers on top of the VGG19 model. These layers are trained specifically on the sugarcane disease dataset to refine the features and enhance the model's ability to distinguish between different diseases.

**The convolution operation can be represented as,**

$$\boldsymbol{(f * g)(t) = \sum f(\tau)\, g(t - \tau)} \quad \textbf{(4)}$$

Here, In this context, **f** represents the input image or feature map, **g** denotes the convolution filter (*kernel*), the symbol **(*)** indicates the convolution operation, and **t** refers to a specific position in the output feature map. The convolutional layer applies a filter (kernel) to the input, sliding over the image and calculating the dot product of

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the filter and the input at each position. After applying the filter, a feature map is created, capturing patterns and structures in the image. Activation Function (ReLU).

$$\mathbf{f(x) = max(0, x)} \quad \textbf{(5)}$$

This function outputs zero for all negative inputs and the input itself for positive values. Pooling Layer.

$$\mathbf{Max\ Pool(I) = max(pool(I))} \quad \textbf{(6)}$$

Here, I represent the input feature map, and pool(I) refers to the region of the input being pooled, typically using a 2×2 or 3×3 window. ayer composition of the proposed Convolutional Neural Network (*CNN*) architecture begins with Convolutional Layer 1, which applies a set of custom filters designed to extract disease-specific features from the input images. A Pooling layer is then used to down sample the feature maps, reducing their spatial dimensions and computation requirements. Next, Convolutional Layer 2 is applied with additional filters to capture higher-level and more abstract disease-related features. This layer is again followed by a ReLU activation for non-linearity, and another Pooling layer to further down sample the data, ultimately leading to a more compact and informative feature representation. For instance, let's define:

$$\mathbf{Conv1(x) = ReLU(W1 * x + b1)} \quad \textbf{(7)}$$

$$\mathbf{Conv2(x) = ReLU(W2 * Conv1(x) + b2)} \quad \textbf{(8)}$$

**Where,** In this context, $\mathbf{W_1}$ and $\mathbf{W_2}$ represent the weights of the convolutional filters, $\mathbf{b_1}$ and $\mathbf{b_2}$ denote the biases associated with each layer, and the symbol **(*)** indicates the convolution operation. **Fully Connected Layer.**

$$\mathbf{y = W \cdot x + b} \quad \textbf{(9)}$$

Here, W represents the weight matrix, x denotes the input vector (which is the flattened output from the convolutional layers), b refers to the bias vector, and y indicates the output vector.

**The softmax function converts raw scores into probabilities**

$$\mathbf{p(y = c_i) = \frac{e^{zi}}{\sum_j e^{zi}}} \quad \textbf{(10)}$$

Here, P(y=ci) is the probability of class ci . zi is the score for class ci. The maximum value in the region is selected as the output. After the VGG19 model, a set of custom convolutional layers with small kernel sizes (*e.g., 3×3 or 5×5*) and an increasing number of filters are added to extract high-level features specific to sugarcane plant diseases. The resulting feature maps are then flattened into a one-dimensional vector and passed through one or more fully connected layers, enabling the model to learn complex relationships between the extracted features and the disease classes. Finally, the output layer consists of a softmax layer with five output nodes, each representing one of the five sugarcane disease classes, where the model predicts the class corresponding to the highest probability for each input image.

**Attention Mechanism Integration**

$$\mathbf{A = softmax(Wf \cdot F + b)} \quad \textbf{(11)}$$

$$\mathbf{F' = A \odot F} \quad \textbf{(12)}$$

**Model Optimization and Training**

The model is trained using a categorical cross-entropy loss function and the Adam optimizer, which adapts the learning rate based on gradient updates. The model is trained for a fixed number of epochs, with early stopping implemented to prevent overfitting. *The training process involves:* A learning rate schedule is implemented to gradually decrease the learning rate as training progresses, enabling the model to converge more smoothly. Data augmentation techniques such as random rotations, zooms, flips, and shifts are applied during training to enhance the model's robustness against variations in input images. Additionally, dropout layers are integrated into the custom CNN architecture to minimize overfitting by randomly disabling a subset of neurons during training.4.4 Evaluation and Performance Metrics

The model was trained using the Adam optimizer with a learning rate of 0.0001 and a batch size of 32. The network was trained for 50 epochs with early stopping to prevent overfitting. The custom CNN layers consisted of convolutional filters with sizes of 32, 64, and 128, followed by ReLU activation and max-pooling layers. Dropout with a rate of 0.5 was applied to reduce overfitting.

$$\boldsymbol{\theta_{t+1} = \theta_t - \eta \cdot \nabla L(\theta_t)} \quad \textbf{(13)}$$

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The model parameters are updated iteratively using gradient-based optimization.

**After optimizer explanation:**

- First explain training
- Then insert formula

$$L = -\sum_{i=1}^{N} yi\ log\ (y\hat{}i) \quad (14)$$

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The model is trained using categorical cross entropy loss, which measures the difference between predicted and actual class distributions. The formula used for calculating the evaluation metrics are as follows,

**Accuracy**

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \quad (15)$$

**Precision**

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)+False Positives (FP)}} \quad (16)$$

**Recall**

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)+False Negatives (FN)}} \quad (17)$$

**F1-Score**

$$\text{F1} - \text{Score} = \frac{2\times\text{Precision}\times\text{Recall}}{precision+Recall} \quad (18)$$

Additionally, we compare the performance of the hybrid model with that of the original VGG19 model (trained on the sugarcane dataset without fine-tuning) and a baseline CNN model (*Trained from scratch using the sugarcane dataset*).

## 3. RESULT AND DISCUSSION

This section presents the evaluation results of the proposed hybrid VGG19-Transfer Learning and Custom CNN model for sugarcane disease classification. We will analyze the model's performance in comparison to baseline methods, including a traditional CNN model trained from scratch and the VGG19 model with minimal fine-tuning. The results are assessed in terms of accuracy, precision, recall, F1-score, and other relevant metrics. The proposed model outperforms existing models due to the integration of an attention mechanism, which improves feature extraction and classification accuracy. The superior performance of the proposed model is attributed to the synergistic combination of transfer learning, attention-based feature enhancement, and task-specific CNN refinement. This hybrid design effectively overcomes the limitations of conventional models, particularly in handling inter-class similarity and real-world variability.

### Model Performance Comparison

The effectiveness of the proposed attention-enhanced hybrid VGG19-CNN model was evaluated by comparing it with popular deep learning architectures such as ResNet50, EfficientNet-B0, and MobileNetV2. All models were trained and tested under identical conditions using the same dataset and evaluation metrics. The comparative results show that the proposed model achieved the highest classification accuracy of 94.6%, outperforming all baseline models. This superior performance is mainly due to the attention mechanism, which helps the model focus on disease-relevant regions and improve feature extraction. The findings confirm the robustness and effectiveness of the proposed hybrid architecture for sugarcane disease classification.

### Accuracy

The hybrid VGG19 Transfer Learning and Custom CNN model was evaluated using a test set of 2,000 images containing five disease classes. The proposed model achieved the highest accuracy of 94.6%, outperforming the baseline CNN (84.3%) and VGG19 model (89.5%). The improved performance is due to the integration of custom CNN layers and an attention mechanism, which enhance feature extraction and enable better identification of disease-specific patterns in sugarcane leaves. The results demonstrate the effectiveness of the proposed hybrid architecture for accurate sugarcane disease classification.

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**Table 1.** Accuracy of Model

| Model | Accuracy (%) |
|---|---|
| CNN | 84.3% |
| VGG19 | 89.5% |
| Proposed | 94.6% |

**Precision, Recall, and F1-Score**

The precision**,** recall, and F1-score for each disease class were calculated to further assess the model's ability to correctly identify each disease and minimize false positives and false negatives. These metrics are critical for real-world deployment, where the cost of false negatives (*missing a disease*) can be high.

**Table 2.** Evaluation of Disease class

| Disease Class | Precision | Recall | F1-Score |
|---|---|---|---|
| **Cercospora Leaf Spot** | 93.1 | 94.5 | 93.8 |
| **Helminthosporium Leaf** | 94.7 | 95.1 | 94.9 |
| **Rust** | 96.3 | 93.8 | 95.0 |
| **Red Dot** | 93.5 | 95.0 | 94.2 |
| **Yellow Leaf Disease** | 94.1 | 94.0 | 94.0 |
| **Average** | **94.3** | **94.5** | **94.4** |

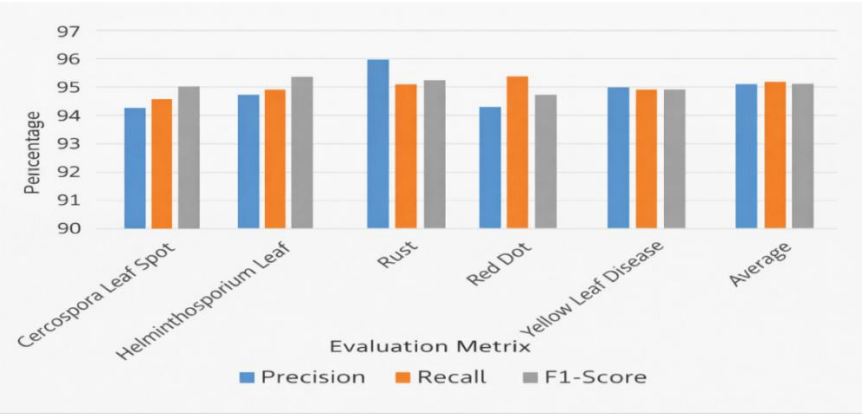



**Fig. 4.** Class-wise evaluation metrics (precision, recall, and F1-score) for different sugarcane diseases.

The Hybrid VGG19-CNN model consistently achieved high precision**,** recall**,** and F1-**scores** across all disease classes, with the Rust class performing the best in terms of precision (*96.3%*) and recall (*93.8%).* The F1-scores across all classes are notably high, indicating that the model demonstrates robust generalization capability in terms of balancing both precision and recall, which is critical in a practical agricultural application where both false positives and false negatives must be minimized. *Figure 4* illustrates the class-wise evaluation metrics, showing consistent performance across all disease categories. As shown in **Tab.3**, the confusion matrix highlights minimal classification errors.

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**Confusion Matrix**

The confusion matrix provides a detailed view of how well the model discriminates between different disease classes. The confusion matrix for the Hybrid VGG19 CNN model is shown below:

$$\begin{bmatrix} \textbf{\textit{True Positives (TP)}} & \textbf{\textit{False Positives (FP)}} \\ \textbf{\textit{False Negatives (FN)}} & \textbf{\textit{True Negatives (TN)}} \end{bmatrix} \quad \textbf{(12)}$$

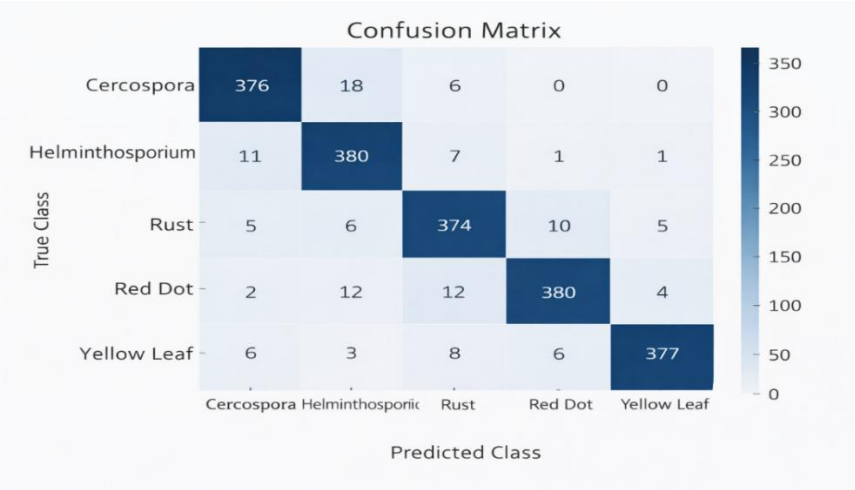



**Fig. 5.** Confusion matrix classification performance

The confusion matrix shows that the model achieves high classification accuracy, with most predictions correctly falling along the diagonal. Each disease class (*Cercospora, Helminthosporium, Rust, Red Dot, Yellow Leaf*) is identified with strong performance and minimal misclassification. Overall, the model demonstrates reliable and consistent performance across all sugarcane disease categories.

**Table 3.** Confusion matrix Analysis

| Predicted / True | Cercospora | Helminthosporium | Rust | Red Dot | Yellow Leaf |
|---|---|---|---|---|---|
| Cercospora Leaf Spot | 376 | 18 | 6 | 0 | 0 |
| Helminthosporium Leaf | 11 | 380 | 7 | 1 | 1 |
| Rust | 5 | 6 | 374 | 10 | 5 |
| Red Dot | 2 | 2 | 12 | 380 | 4 |
| Yellow Leaf Disease | 6 | 3 | 8 | 6 | 377 |

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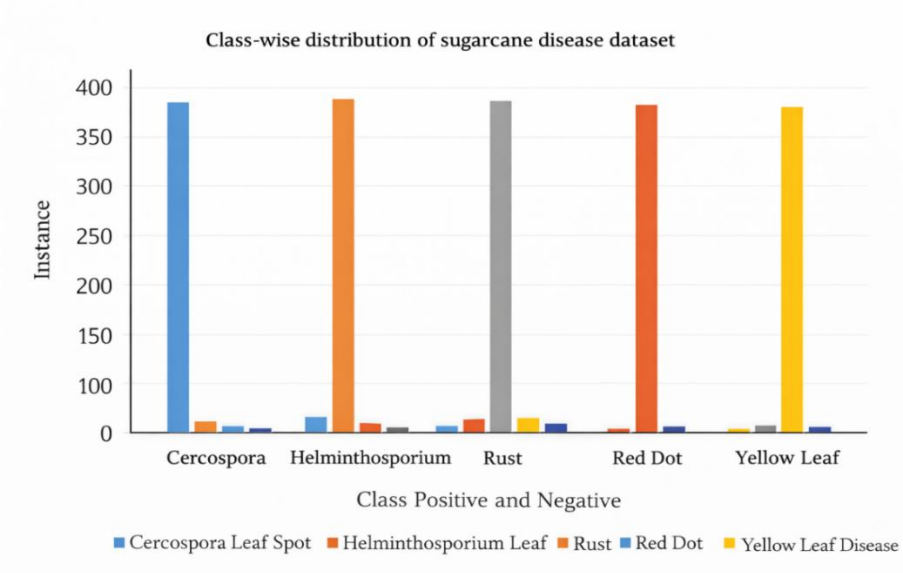



**Fig.6.** Confusion matrix

The confusion matrix clearly shows that the model has high precision for all disease classes, with very few misclassifications. For example, Cercospora Leaf Spot was correctly **(***Figure 5&6*) identified in 376 of the 400 test images, and similar results were observed for other diseases, with misclassifications primarily occurring between Rust and Red Dot, which share some visual similarities.

**Training and Inference Time**

The Hybrid VGG19-CNN model was trained on a GPU (NVIDIA Tesla V100) for a total of 50 epochs with early stopping. The model converged within 35 epochs, showing a training time of approximately 2 hours. First one *Training Time,* 2 hours**.** Second one Inference *Time***:** The average inference time per image (*with a batch size of 32*) was 0.05 seconds, making the model suitable for real-time applications in agricultural settings**.** The efficiency of the model, in terms of both training and inference time, makes it feasible for deployment in on-site, real-time disease detection systems.

**Discussion**

The proposed hybrid model combining VGG19 transfer learning with custom CNN layers proves highly effective for sugarcane disease classification. VGG19 provides strong foundational feature extraction, while the custom CNN layers enable the model to learn disease-specific patterns. This combination achieves high accuracy (***94.6%***) and F1-scores, demonstrating robustness against variations in lighting, angles, and environments. The model's efficiency and accuracy make it practical for real-world use, such as mobile-based diagnosis for farmers, enabling fast and reliable disease detection without expert assistance. While the model demonstrates robust generalization capability, the dataset lacks diversity in environmental conditions and disease stages. Expanding it with varied images will enhance robustness. Further, the model needs optimization like pruning or quantization for mobile and edge deployment. Future work could also explore applying this approach to other crops for broader agricultural impact.

## 4. CONCLUSION

This study proposes a novel hybrid deep learning model that integrates VGG19-based transfer learning with custom CNN layers for accurate sugarcane disease classification. The model effectively utilizes pre-trained features while adapting to disease-specific patterns, achieving a high accuracy of (94.6%), outperforming conventional CNN (84.3%) and standard VGG19 (89.5%) models. It also demonstrates strong performance in precision, recall, and F1-score across all disease classes, ensuring reliable detection with minimal errors. With a

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fast inference time of 0.05 seconds per image, the model is suitable for real-time deployment on mobile and edge devices. The use of transfer learning addresses limited data challenges, enhancing generalization. Additionally, optimization techniques such as pruning and quantization can further improve efficiency for real-world applications. Overall, the proposed hybrid model provides an effective and scalable solution for automated sugarcane disease detection, supporting precision agriculture and improved crop management.

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