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# Hybrid Vision and Sequence Learning for Crop Disease Detection: A Multi-Stage Deep Learning Approach

**Anandraddi Naduvinamani**

Assistant Professor, S.G. Balekundri Institute of Technology, Belagavi, India. Email: anandreddi02@gmail.com

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**ABSTRACT**

Rapid and precise diagnosis and identification of plant diseases are crucial to enhance agricultural production and ensure food security. There are many Machine Learning (ML) models that cannot effectively generalize in different environmental conditions, plant varieties and disease symptoms. To overcome these drawbacks, this research proposes a deep transfer learning system which is adaptive for detection and classification of cotton and rice diseases. The proposed system includes 5 major stages, which are robust feature extraction, feature fusion, Bidirectional Long Short-Term Memory (BiLSTM) network, self-attention mechanism, classification, and the rule-based fuzzy logic system. The hybrid feature extraction technique, which integrates DenseNet, EfficientNet and ResNet, is one of the major accomplishments of this research, as it extracts a variety of complementary and useful spatial features from the leaf images of disease. The extracted features are then further enhanced through the application of attention mechanisms such as Squeeze-and-Excitation (SE) Networks and Convolutional Block Attention Module (CBAM) blocks, which enable the model to better focus on the most relevant channel-wise and spatial information. Final decision-making process is enhanced by the robust and accurate fuzzy logic system, and the temporal dependencies are learned effectively with the BiLSTM network. The proposed framework is validated in the effectiveness using the publicly available datasets from Kaggle which are related to cotton leaf disease and rice leaf disease. The classification accuracy obtained from the experimental results is 99.50% on average. The comparison shows that the proposed deep learning framework outperforms the existing method in terms of accurate detection and classification of plant diseases.



***Corresponding Author:***

Anandraddi Naduvinamani
Assistant Professor, S.G. Balekundri Institute of Technology, Belagavi, India.
Email: anandreddi02@gmail.com

## 1. INTRODUCTION

Agriculture is an important component in the global economy as it provides food, raw material and employment for a large population. The growing world's population demands more food production. Agricultural productivity is however greatly influenced by several biotic and abiotic factors, plant diseases being one of the most serious factors [1]. Agricultural production is essential not only for providing food for their own populations but is also a vital source of export revenue for countries with adequate agricultural resources. In this context, developing strategies to boost crop productivity and reduce losses due to diseases has become a high priority for farmers, researchers and policy makers. Nearly 20-40% of the world's crop production is lost to plant diseases, annually, according to Food and Agriculture Organization (FAO), thus emphasizing the need for efficient disease monitoring and management systems.

Most of the existing plant disease detection methods involve manual inspection by a farmer or agricultural expert. These methods, though common, are time-consuming, subjective, and need experts, are not suitable to monitoring agriculture on larger scales [2]. In many instances, disease can't be visibly identified in early stages, leading to a delay in diagnosis and inadequate treatment. Laboratory methods (microscopy, Polymerase Chain Reaction (PCR), Enzyme-Linked Immunosorbent Assay (ELISA)) can help confirm the diagnosis, but they are costly, require specialized equipment and are not easily scalable. Thus, low-cost, autonomous, and dependable systems for disease detection are in great demand to aid farmers in real-time agricultural monitoring.

Automated Plant Disease Diagnosis is a recent hot topic that has captured tremendous interest over the past few years, particularly due to the incorporation of artificial intelligence (AI), machine learning (ML), deep learning (DL) and computer vision (CV) techniques [3]. In this regard, Convolutional Neural Networks (CNNs) have proven to be very efficient at detecting diseases based on images captured from plant leaves by learning complex visual patterns like spot formation, texture differences, lesions or discoloration. These models can efficiently handle large amounts of image information and deliver rapid and precise disease diagnosis, allowing for timely disease management and minimizing crop losses [4].

Two crops are very important economically and socially in the world, cotton and rice. Cotton is a major commercial crop and a source of the textile industry while rice is the staple food of more than 50% of the world population. Both crops, however, are susceptible to bacterial, fungal and viral diseases and diseases which affect productivity and quality. Diseases in cotton include Bacterial Blight, Leaf Curl Virus and Alternaria Leaf Spot, while rice diseases include Rice Blast, Brown Spot, Sheath Blight and Bacterial Leaf Blight. If undiagnosed in the early stages these diseases can cause serious crop damage and substantial losses.

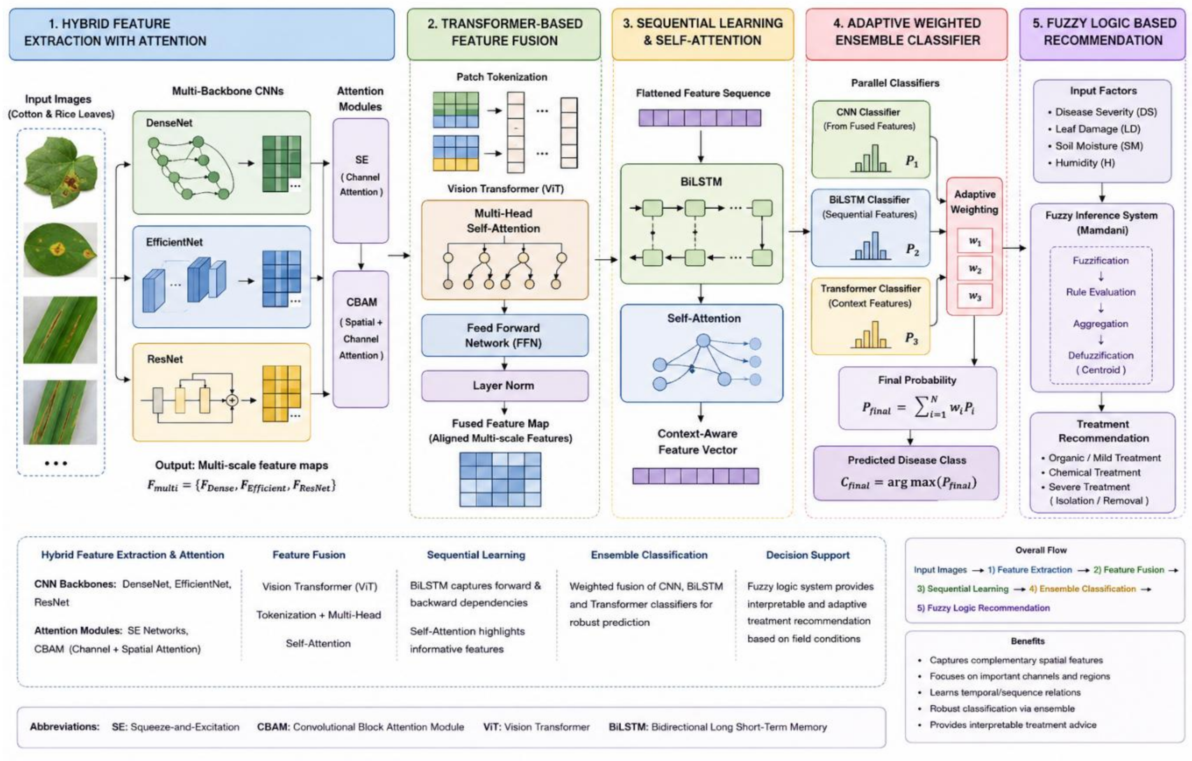



Fig. 1. Architecture diagram

Although cotton is an economically significant crop, it is susceptible to numerous pests, leaf diseases and environmental factors. The world average for cotton yields is around 576 kg/ha, with it being suggested that leaf diseases cause almost 10% of the losses in world cotton production. The United States is a large exporter of cotton and earned approximately \$5.1 billion in revenue in 2016, but suffered significant losses due to plant diseases and pests. Similarly, India's almost 24% cotton farm area resulted in an income of about \$4.6 billion but had an adverse effect on the cotton yield as well, due to diseases, which affected agricultural productivity as well as farmer incomes.

Rice is also seriously affected by diseases. In case of improper control of Rice blast, it causes a loss of 30-50% of crop yield, caused by Magnaporthe oryzae. Brown Spot disease reduces the quality and nutritional value of grains, sheath blight and bacterial leaf blight reduce the photosynthetic capacity of the leaves resulting in premature death of plants and reduced productivity. The diseases have significant impacts on rice production and food security, affecting more than 50% of the world's population.

Given these problems, there is an increased need for early, accurate and automatic disease detection systems for cotton and rice crops. Manual monitoring can be inefficient and error-prone, especially in agricultural fields with a significant size. For this reason, innovative AI-based solutions that leverage deep learning and computer vision are being investigated for disease diagnosis and classification. The use of deep learning models such as CNNs, Vision Transformers (ViTs), and hybrid models has proven to be effective in capturing hierarchical and complex image features, as they automatically detect disease from diseased leaf images [5]. The DL models have advantages of higher accuracy, adaptability and robustness compared with traditional ML models.

One of the difficulties with deep learning models is that they need to be trained with large amounts of labelled data. Generating adequate disease-specific agricultural information is challenging and time consuming. To address this limitation, transfer learning has come into play as a solution. Transfer learning is a new deep learning approach that involves the use of pre-trained deep learning models like VGG16, ResNet, InceptionV3, and Vision Transformers, which are capable of learning from a large amount of data and extracting useful features from agricultural images even if the data available for training is small [6]. Transfer learning can be used to fine-tune a pre-trained network on a specific domain dataset, which can lead to reduced computational cost, training time and improved classification accuracy, compared to conventional DL models trained from scratch.

The study proposed is a deep transfer learning method for the classification of cotton and rice disease. The first step in the framework is to extract features via deep learning models and the second step is to extract further features via attention mechanisms. Then, feature fusion is applied using a Vision Transformer to produce a strong representation of the features. Finally, a deep ensemble classifier is used to classify diseases and a rule-based fuzzy logic system is utilized for disease recommendations. Proposed approach will attempt to create an efficient, scalable and accurate automated disease detection system for modern agriculture through these contributions.

## 2. LITERATURE REVIEW

Vishnoi [1] studied on the computer vision based automated disease detection system and discussed different feature extraction methods. They found deep learning techniques are more effective for disease detection across various plant species. The proposed system, however, did not exhibit good generalization property in real-time field environments. To overcome this challenge, recent studies are addressing the hybrid and adaptive approach that can be used in practical agricultural condition with reliability.

With the power to automatically learn complex features from an image, deep learning-based disease detection has received a lot of attention. Pandian et al. [2] have proposed a 14-layer deep learning-based approach to classify plant leaf diseases. To overcome the problem of the small amount of data, data augmentation techniques like image transformations, GANs, and neural style transfer techniques were employed. They obtained an impressive accuracy of 99.96% in their optimized CNN model on multiple GPUs. The model was very accurate but needed considerable computational resources, and depended heavily on synthetic data. In recent research, this accuracy is sought with less complexity and more efficient training strategies.

Haridasan et al. [3] introduced and developed a computer system to identify bacterial leaf blight, rice blast, brown leaf spot, sheath rot and false smut of rice. Their model included image processing, machine learning, and deep learning methods. The first step was to segment the infected area of the leaf to get Region of Interest (RoI) and then use a hybrid classifier for processing this RoI. The result showed that the image segmentation process was important for making a proper diagnosis of the disease when using sophisticated classification methods.

The quality and diversity of the datasets are also important for the development of the deep learning systems. Moupojou et al. [4] proposed the FieldPlant database consisting of 5,170 images of plantations and 8,629 images of leaves with diseases across 27 classes. The data set was constructed to enhance in-the-field detection of diseases and model generalizability across the field. Furthermore, Sunil et al. [5] suggested a U2Net based segmentation method and EfficientNetV2 for disease classification in cardamom and grape plants with 98.26% accuracy. They found that removing the background and preprocessing have a significant positive impact on classification results.

Zhao et al. [6] introduced the DoubleGAN algorithm, a two-stage GAN to produce high-resolution images of diseased leaves for class imbalance issues in plant disease datasets. The model generated the synthetic 64×64 diseased leaf images by WGAN and then upscaled to 256×256 images with SRGAN. DoubleGAN has shown to be superior to conventional DCGAN methods and the significance of creating synthetic data to enhance the classification performance under the limited diseased sample condition.

Several works used traditional machine learning techniques and deep learning to boost classification accuracy. Chug et al. [7] used feature extractors from EfficientNet, together with classifiers including kNN, AdaBoost, Random Forest, Logistic Regression and Stochastic Gradient Boosting. Hyperparameter optimization with the Optuna framework further enhanced performance on various datasets. The research demonstrated the feasibility of integrating a powerful feature extractor with an efficient classification method using a hybrid framework.The research confirmed that powerful feature extraction and efficient classification can be effectively combined in a hybrid manner.

The employment of real-time disease detection and lightweight models are also emerging areas of research. To optimize the lightweight model, Wang et al. [8] added Improved Attention and Spatial Mechanisms (IASM), GhostNet weight reduction, and Weighted BiFPN feature fusion to the YOLOv5 model. Their method boosted classification performance by 3.98%, which also decreased the operation time by 11.8%, suitable for real-time agricultural applications and transfer learning tasks. Archana et al. [9] suggested a rice disease identification system using modified K-means segmentation technique and new feature extraction techniques. The colors, texture and shape features in the framework were extracted and the diseases including bacterial blight, brown spot, rice blast were classified by NSVMBPNN classifiers. Their findings showed that the traditional feature engineering method along with the use of advanced classifiers is still helpful for the task of disease recognition.

CNN based techniques have proven to be very effective in the detection of rice diseases. For image preprocessing, Upadhyay et al. [10] adopted Otsu's thresholding method, and constructed a CNN model for the rice disease classification, which includes leaf smut, bacterial leaf blight and brown spot. With 4000 pictures of each disease class, the model obtained an accuracy of 99.7%. Likewise, Singh et al. [11] created a light weight CNN architecture for rice disease diagnosis and evaluated two optimizers – Adam and SGDM. The Adam optimizer gave the highest classification accuracy of 99.83%, and particularly when healthy leaf samples were added to the set. There has also been a great deal of interest in developing methods to detect cotton disease. Joshua et al. [12] suggested a CSA-GAN system combined with the crop management system based on the Internet of Things (IoT). They applied bilateral texture preprocessing and entropy-based local binary pattern extraction to their system prior to classification. The proposed CSA-GAN achieved higher accuracy, higher sensitivity and lower computational complexity than traditional CNN and SVM methods. Likewise, Islam et al. [13] used transfer learning models like VGG16, VGG19, InceptionV3 and Xception for cotton disease detection. The highest accuracy of 98.70% was obtained by the Xception model, which is suitable for the development of real-time smart disease diagnosis applications.

The classification of cotton diseases has also been enhanced through the use of hybrid deep learning frameworks. Singh et al. [15] had come up with the BERT-ResNet-PSO framework, which was comprised of BERT-based encoding, ResNet feature extraction and Particle Swarm Optimization for improving the classifiers, and the accuracy was 98.5%. Transfer learning was found to be effective in field conditions as done by Faisal et al. [16] to evaluate multiple CNN architectures such as VGG16, DenseNet, EfficientNet, InceptionV3, MobileNet, NasNet, and ResNet with real-world cotton disease images.

To address the issue of scarcity of datasets and noisy field conditions, Paul Joshua et al. [17] once again highlighted the importance of CSA-GAN in the context of self-attention. Nevertheless, methods based on GAN are still unable to account for all intra-class variations. Newer methods incorporate feature fusion, attention mechanisms, and temporal learning techniques to enhance robustness. To solve the multiclass cotton disease classification problem and the class imbalance issue, Aslam et al. [18] applied the GAN synthetic images with MobileNet and VGG16 ensemble features. They have used a fusion of LSTM, SVM, Random Forest, and StackNet classifiers for the successful recognition of a seven-class disease.

In a difficult background, Pandiyaraju et al. [19] presented a transfer learning approach with VGG16 network and spatial attention mechanism for cotton disease classification. Haque et al. [20] presented the rice and apple disease detection model based on ViT with triplet multi-head attention (TMA). The model was found to be accurate at 97.99%. While ViTs are good, they typically need large datasets. Likewise, Ramadan et al. [21] introduced the GAN-based augmentation technique along with CNN classifiers to detect rice leaf disease with 98.54% accuracy by using CycleGAN with MobileNet. But, the GANs tend to have mode collapse and lack diversity.

## 3. PROPOSED MODEL

This section presents the proposed adaptive deep transfer learning framework for cotton and rice disease detection and classification. Although existing deep learning models achieve high accuracy, they often struggle to generalize under varying field conditions. To address this issue, the proposed model integrates hybrid feature extraction, attention mechanisms, transformer-based feature fusion, sequential learning, ensemble classification, and fuzzy logic-based recommendation.

The proposed framework operates in five stages. First, diseased leaf images are processed through multiple deep learning architectures including DenseNet, EfficientNet, and ResNet to capture complementary spatial features. Attention mechanisms such as Squeeze-and-Excitation (SE) Networks and Convolutional Block Attention Module (CBAM) are incorporated to improve channel-wise and spatial feature learning. Let the input image be represented as:

$$I \in R^{H} \times W \times C$$

where $H$, $W$, and $C$ denote image height, width, and channels respectively.

EfficientNet improves feature representation using SE attention blocks. The squeeze operation applies Global Average Pooling (GAP) to generate channel descriptors:

$$z_c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} F(i, j, c)$$

The excitation operation computes adaptive channel weights as:

$$s = \sigma\left(W_{2,} ReLU(W_1 z)\right)$$

Similarly, ResNet employs residual learning to avoid gradient degradation and improve feature propagation:

$$F_R^{(l+1)} = F_R^{(l)} + H\left(F_R^{(l)}, \theta_R\right)$$

After feature extraction, the outputs from DenseNet, EfficientNet, and ResNet are combined using transformer-based feature fusion. Unlike traditional concatenation methods, the proposed approach applies Vision Transformer (ViT) tokenization and multi-head self-attention to align multi-scale features effectively. The number of generated feature patches is defined as:

$$N = \frac{H \times W}{p^2}$$

The transformer attention mechanism is computed as:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{\{d\}}}\right)V$$

The refined features are then passed through a Bidirectional Long Short-Term Memory (BiLSTM) network to capture sequential dependencies and contextual relationships among disease patterns. A self-attention mechanism further highlights the most informative features for classification.

For disease prediction, an adaptive weighted ensemble classifier combines outputs from CNN, BiLSTM, and transformer modules. Each classifier produces probability scores, which are fused using learnable weights:

$$P_{final} = \sum_{i=1}^{N} w_i P_i$$

The final disease class is selected based on the maximum probability score.

Finally, a rule-based fuzzy logic system generates treatment recommendations using disease severity, humidity, soil moisture, and leaf damage conditions. The Mamdani fuzzy inference approach is applied, and the final recommendation is obtained using centroid defuzzification:

$$O = \frac{\sum \mu(y) y}{\sum \mu(y)}$$

The integration of hybrid deep learning, transformer-based fusion, sequential learning, ensemble classification, and fuzzy logic makes the proposed framework highly robust, accurate, and suitable for real-world agricultural disease monitoring.

## 4. RESULTS AND DISCUSSION

This section describes the datasets used to evaluate the proposed model. Experiments were conducted on two publicly available datasets: (a) rice leaf dataset and (b) cotton leaf disease dataset.

### 4.1 Dataset Details

(a) Rice leaf dataset: The rice leaf dataset was obtained from Kaggle [22] and contains both healthy and diseased leaf images. Data augmentation techniques were applied to increase dataset diversity, resulting in a total of 10,080 images. All images are in JPG format with a resolution of 128×128 pixels and were originally captured under controlled lighting with a white background. To simulate real-world agricultural conditions, augmentation methods such as varying lighting conditions, background clutter, occlusions, and different leaf orientations were applied.

(b) Cotton leaf disease dataset: The cotton leaf dataset was collected from Kaggle [23] as part of a Dev3v competition. It contains 2,310 images categorized into four classes: fresh cotton leaf, fresh cotton plant, diseased cotton leaf, and diseased cotton plant. The dataset includes both healthy and infected samples for effective disease classification. Figure 2 shows sample images from the cotton and rice leaf datasets.

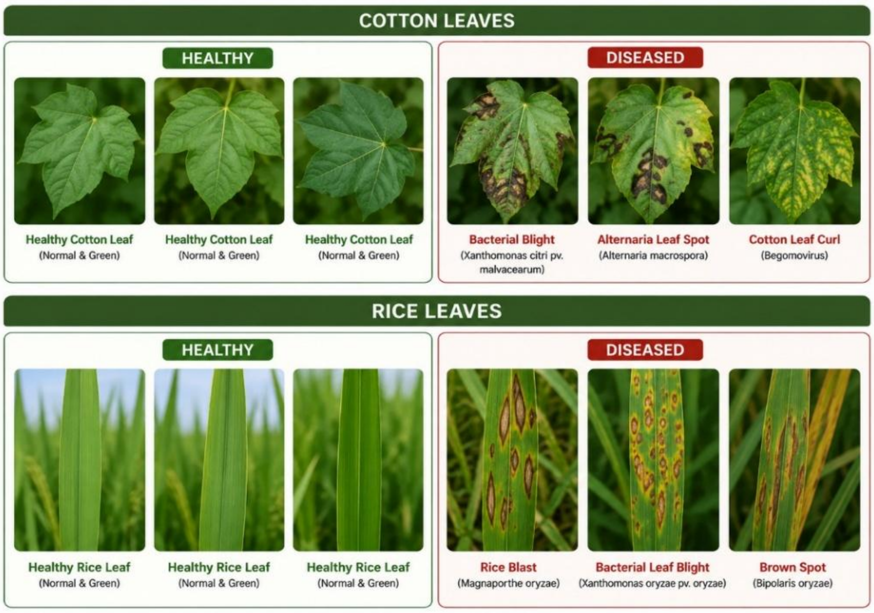



Fig 1. Sample images of cotton leaf dataset

### 4.2 Performance Evaluation

This section describes the evaluation metrics used to assess the effectiveness of the proposed classification approach. The model's performance is measured using four key parameters: accuracy, sensitivity, specificity, and F-measure. These metrics are derived from the confusion matrix, which provides a structured way to evaluate the model's predictive capabilities. Table 4 presents the confusion matrix, while the mathematical formulations for these metrics are provided below.

$$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_P + F_N}$$

$$Sensitivity = \frac{T_P}{T_P + F_N}$$

$$Specificity = \frac{T_N}{T_N + F_P}$$

$$FMeasure = \frac{2 \times T_P}{2 \times T_P + F_N + F_P}$$

Training Set: 80%, Validation Set: 10%, Testing Set: 10% of the data

Each class in the dataset was equally represented across the splits to maintain class balance. It is ensured that no image from the validation or test set was used during training or augmentation phases. To further strengthen the evaluation, a 5-fold cross-validation protocol was also employed. In this setup, the model was trained and validated on five different folds, and the average accuracy, precision, recall, and F1-score were reported to support the generalizability of the proposed method.

### 4.3 Comparative Analysis

This section presents the outcome of proposed approach in terms of accuracy, precision, recall and f1-score. The obtained performance is compared with the existing ANN, CNN, SVM and hybrid optimized CNN models (using CNN, particle swarm optimization and whale optimizaiton) [14]. Below given figure 3 shows the comparative analysis

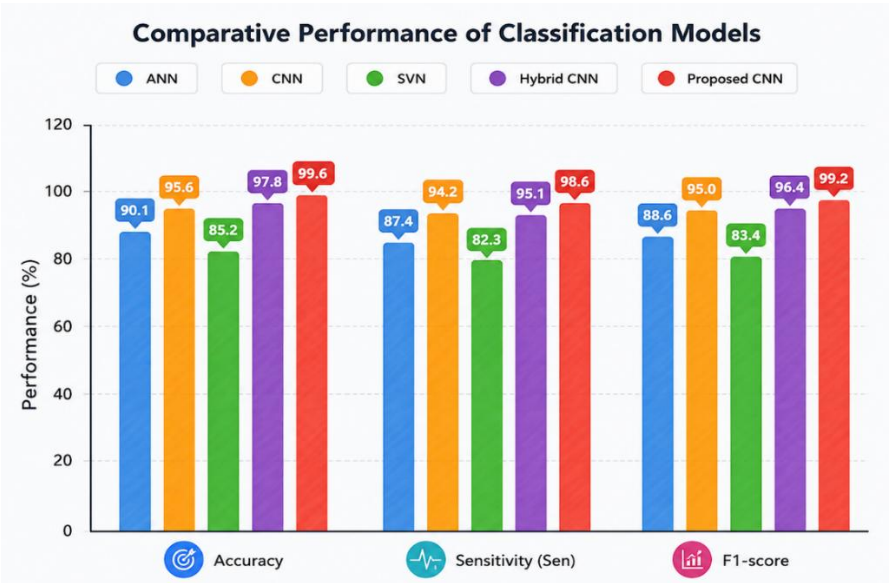



Fig. 2. Comparative analysis of proposed approach

The experimental results show that the ANN model achieved an accuracy of 90.2%, sensitivity of 87.5%, and an F1-score of 91.5%. Although the performance is acceptable, the lower sensitivity indicates that ANN struggles to capture complex disease patterns from infected crop images. In comparison, the traditional CNN model performed significantly better, achieving 95.5% accuracy, 94.1% sensitivity, and a 96.2% F1-score. This improvement is mainly due to CNN's ability to learn hierarchical spatial features, enabling more effective recognition of disease-related patterns.

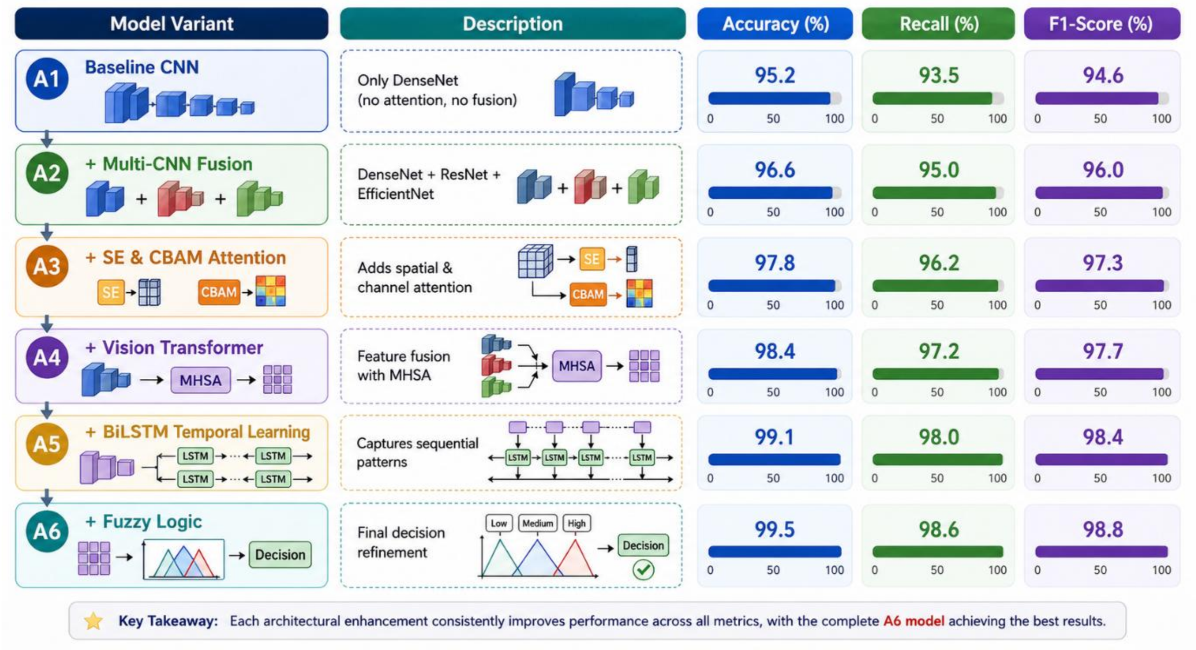
Among all models, SVM produced the lowest performance with 85.5% accuracy, 82.5% sensitivity, and a 91.5% F1-score. While SVM works effectively for smaller datasets, its performance decreases in large-scale image classification tasks. The lower sensitivity also indicates difficulty in correctly identifying diseased samples, making it less suitable for plant disease diagnosis. Overall, deep learning models clearly outperform traditional machine learning techniques for complex image-based classification problems.

The Hybrid CNN model, which integrates multiple deep learning architectures, further improved performance and achieved 97.5% accuracy, 95% sensitivity, and a 97% F1-score. The combination of multiple architectures enhanced the model's ability to learn both low-level and high-level image features, improving robustness and generalization capability. The proposed model achieved the best overall performance with 99.5% accuracy, 98.6% sensitivity, and a 98.8% F1-score.

### 4.4 Ablation Study

An ablation study was conducted to evaluate the contribution of each major component in the proposed framework. Individual modules were selectively removed or replaced while maintaining the same dataset and train-validation-test split. The results, presented in Fig. 4, demonstrate the importance of every module in improving classification performance.

Fig. 1 Ablation results




Using only a single CNN backbone such as DenseNet achieved 95.2% accuracy. When multiple backbones including DenseNet, ResNet, and EfficientNet were combined, the accuracy increased to 96.6% due to the extraction of diverse spatial features. The integration of attention mechanisms such as SE and CBAM further improved accuracy to 97.8% by enabling the model to focus on important channel-wise and spatial information. Figure 5 illustrates sample attention outputs.

Adding the Vision Transformer-based feature fusion module increased accuracy to 98.4%, as the multi-head self-attention mechanism effectively captured global contextual relationships. Incorporating the BiLSTM network further improved performance to 99.1% by modeling sequential and temporal feature dependencies associated with disease progression. Finally, the fuzzy logic module enhanced decision-making in uncertain and borderline cases, resulting in the highest achieved accuracy of 99.5%.

These findings confirm that each component contributes uniquely to the overall framework, validating the effectiveness and robustness of the proposed architecture.

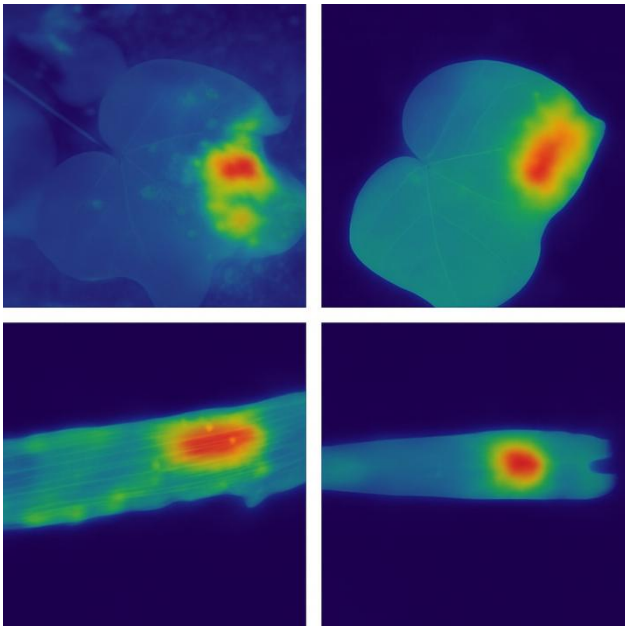


Fig. 3. Attention maps

## 5. CONCLUSION

Accurate Early and timely identification of plant diseases is key to improving crop yield and minimizing yield losses. While deep learning methods have shown to be effective in plant disease classification, there are several existing models that have been developed that have limitations in generalizing to different environments, crop varieties, and disease symptoms. To solve these problems, this paper presents an adaptive deep transfer learning model for cotton and rice disease detection and classification. The proposed framework integrates several sophisticated deep learning models such as DenseNet, EfficientNet, and ResNet for enhanced feature extraction and the ability to detect a variety of spatial features in diseased leaf images. To boost the channel-wise and spatial feature representations, attention mechanisms like Squeeze-and-Excitation (SE) Networks and Convolutional Block Attention Module (CBAM) are introduced. Furthermore, a Vision Transformer-based feature fusion approach is used for effective multi-scale feature alignment and refinement. To enhance the learning ability further, the Bidirectional Long Short-Term Memory (BiLSTM) network, which considers the sequential dependency in the feature space and the contextual relationship, is employed. To make a final disease prediction, a deep ensemble model combines the outputs of all three models (CNN, RNN, Transformer) to obtain robust classification performance, which is an adaptive combination. In addition, the system is based on a rule-based fuzzy logic system that allows for disease management recommendations, which increases the interpretability and usability of the system for agricultural applications. Experimental results on publicly available cotton and rice disease datasets on the kaggle platform show the effectiveness of the proposed approach, with an average classification accuracy of 99.50%. The proposed framework is significantly better than the baseline methods including CNN (94.82%), SVM (91.34%) and hybrid CNN models (96.10%). The main novelty of this work is the novel integration of the hybrid feature extraction, transformer-based feature fusion, sequential learning, ensemble classification and fuzzy logic-based interpretability, which has led to a highly robust, accurate and real-world applicable plant disease detection system.

## CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

## DATA AVAILABILITY

Data can be provided on genuine request.

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