Grenze International Journal of Engineering and Technology, June Issue

Ensemble-based Deep Learning Framework for Robust Sugarcane Leaf Disease Identification

Onkar khavare[1], Y.V. Sawant[2] and L. S. Admuthe[3]
[1-3]DKTE'S Textile and Engineering Institute, Ichlakaranji, India
Email: khavareonkar93@gmail.com, yvsawant@dkte.ac.in

***Abstract*— Early and accurate identification of sugarcane leaf diseases is essential to prevent yield loss and ensure sustainable crop management. Manual inspection methods are often inconsistent and impractical for large-scale farming environments. This paper presents a compact and high-accuracy framework for sugarcane leaf disease detection using an ensemble of CNN, ResNet-50, and EfficientNet models. Preprocessed leaf images are used to capture diverse field conditions. Deep features extracted from each architecture are combined through a weighted ensemble strategy to improve classification reliability and reduce individual model bias. Experimental evaluation demonstrates strong classification performance across multiple disease categories. The proposed hybrid approach attains superior performance in terms of accuracy, precision, recall, and F1-score as compared to standalone models, while remaining robust to variations in lighting, background, and leaf orientation. The suggested framework offers a scalable and effective solution for precision agriculture and supports intelligent crop-monitoring systems.**

***Index Terms*— Sugarcane leaf disease, Convolutional Neural Network, Ensemble learning, Deep learning, Precision agriculture.**

I. INTRODUCTION

Sugarcane cultivation plays a crucial role in supporting the agricultural economy and industrial production of sugar, jaggery and bioethanol. Maintaining healthy crops is essential for achieving high yield and quality; however, sugarcane plants are frequently affected by leaf diseases that spread rapidly and significantly reduce productivity. If not identified at an early stage, these diseases can cause substantial economic losses to farmers and impact overall supply chains.

Traditional disease detection techniques rely on visual assessment by experts or basic image processing methods, which are time-consuming, subjective, and often lack consistency and scalability under real-field conditions. In large farms, continuous monitoring becomes practically difficult, leading to delayed treatment and increased disease severity. Therefore, there is a strong need for an intelligent, automated system capable of accurately detecting and classifying sugarcane leaf diseases in real time.

Recent developments in artificial intelligence, particularly in deep learning, have opened new opportunities in agricultural image analysis. Convolutional Neural Networks (CNNs) have shown remarkable success in extracting meaningful features directly from images without manual feature engineering. These models can learn complex patterns as, texture variations, discoloration, and lesion structures that are characteristic of plant diseases.

Grenze ID: 01.GIJET.12.2.45_26

Single deep learning models, although powerful, may suffer from issues such as overfitting, model bias, or sensitivity to environmental variations like illumination and background noise.

To address these limitations, this paper proposes an ensemble learning-based approach that combines the strengths of Convolutional Neural Networks (CNN), ResNet-50, and EfficientNet. The proposed model overcomes the shortcomings of traditional and single- model techniques by leveraging diverse feature representations and improving generalization capability. By integrating multiple deep architectures through a weighted decision mechanism, the system achieves more stable and accurate predictions across varied conditions.

The objective of this work is to develop a reliable, efficient, and scalable sugarcane leaf disease detection system that can support precision agriculture. As compared to basic deep learning models, the proposed ensemble model not only enhances detection accuracy but also enables early diagnosis, helping farmers take timely preventive measures and reduce crop losses. This approach represents a significant step forward from conventional methods toward intelligent and automated agricultural solutions, enabling timely decision-making for disease control.

II. LITERATURE SURVEY

Automated plant leaf disease detection has gained significant attention due to its potential to enhance crop productivity and enable precision agriculture. Early research primarily relied on traditional computer vision and machine learning techniques, while recent studies emphasize deep learning-based approaches. In fields like healthcare and agriculture, standard, deep learning algorithms are being used more frequently to recognize and diagnose diseases. This is a major development approach in the process of boosting yields and guaranteeing food security and sustainability is the aim of these technologies in agriculture for improved accuracy and scalability.

In [1], Anuja Bhargava et al. proposed a deep learning-inspired framework for plant leaf disease detection, and classification via simple convolutional neural networks (CNNs). The study demonstrated high classification accuracy and highlighted the effectiveness of end-to-end feature learning compared to handcrafted feature-based methods. Similarly, Ammar Oad et al. introduced an ensemble learning strategy combined with Explainable Artificial Intelligence (XAI) [2]. By integrating multiple CNN models and visualization techniques such as class activation mapping, the proposed approach improved both classification robustness and interpretability. Traditional machine learning approaches were explored in [3], where Sunil S. Harakannanavar et al. utilized feature extraction techniques along with classifiers like Support Vector Machines (SVM) and K-Nearest Neighbor (KNN). While satisfactory accuracy was achieved, the reliance on handcrafted features limited generalization under varying field conditions.

A comprehensive review of CNN-based plant disease detection systems was presented in [4] by Tanko Daniel Salka et al., emphasizing transfer learning, dataset challenges, and real-time deployment issues. Beyond plant disease detection, CNN-based image classification frameworks have been extensively studied. In [5], Zhaoyu Li explored image classification using PyTorch-based CNN models, demonstrating the adaptability of deep learning frameworks. Yu Jiang and Changying Li [6], reviewed CNN applications for high-throughput plant phenotyping, highlighting scalability and automation in agricultural imaging. Additionally, Muqing Li et al. [7] investigated CNN-based image classification and semantic segmentation models, which are crucial for precise localization of disease-affected regions.

Recent research has increasingly focused on crop-specific disease detection, particularly in sugarcane. Ismail Kunduracioglu et al. evaluated EfficientNet architectures for sugarcane leaf disease detection, demonstrating improved performance with optimized deep learning models [8]. A comparative analysis of deep learning techniques for sugarcane disease detection was conducted by Khan Md Nomani et al., highlighting performance trade-offs among various CNN architectures. Their finding showed that DenseNet161 achieved the best performance with 97.41% validation accuracy and 0.0902 loss, followed closely by ResNet101 with 97.21% accuracy and 0.0971 loss [9]. MobileNetV2 showed moderate results, while AlexNet performed the worst (91.43% accuracy, 0.2505 loss). Overall, DenseNet161 and ResNet101 proved most effective for sugarcane leaf disease detection.

Furthermore, automated precision agriculture systems for sugarcane disease detection were developed in [10] by Sinchana H.U et al., emphasizing real-time deployment feasibility. Similar CNN-based frameworks were proposed in [11] by V. Sonia Devi et al. and surveyed comprehensively in [12] by G. Mahesh Reddy et al., outlining advancements, dataset limitations, and challenges in field-level implementation.

Overall, the literature indicates a clear transition from traditional machine learning techniques to deep learning and ensemble-based models for plant and sugarcane leaf disease detection. While CNN architectures and transfer learning approaches have significantly improved classification accuracy, challenges such as dataset imbalance, computational complexity, environmental variability, and real-time deployment remain open research problems.

Our research focuses on using a hybrid deep learning model that offers accurate and robust field-level validation for precision agriculture applications.

III. METHODOLOGY

A. Dataset Description

The dataset used in this study consists of sugarcane leaf images collected from local agricultural fields under natural environmental conditions. The dataset consists of 2521 colour images which were captured using a high-resolution smartphone camera to ensure practical applicability and real-world relevance. These images are collected from nearby region of Ichalkaranji in Kolhapur district, India. The dataset includes both healthy and diseased leaf samples representing common sugarcane diseases such as rust, yellow leaf, red rot symptoms on leaves, and mosaic patterns as shown in Figure No.1. To enhance model generalization, images were obtained under varying lighting conditions, backgrounds, and leaf orientations. Each image was carefully examined and labeled according to visible disease characteristics prior to model training. The collected dataset was further organized into class-specific directories and split into training, validation, and testing subsets to ensure unbiased performance evaluation. This real-field image database provides diverse visual patterns and supports the development of a robust deep learning-based disease classification system.

Figure 1. Sugarcane plant leaves with various diseases

B. Data Preprocessing

To ensure consistent input quality and improve model performance, several preprocessing steps were applied to the collected sugarcane leaf images. Initially, all images were resized to 493 x 1040 pixels to maintain uniformity across the dataset and reduce computational complexity. Pixel values were normalized to a standard range to stabilize the training process and accelerate convergence. Background noise and irrelevant regions were minimized through basic cropping and contrast enhancement techniques, allowing the model to focus primarily on disease-affected areas of the leaf.

To address dataset variability and prevent overfitting, data augmentation techniques were employed during training. Augmented samples were generated using random rotations, horizontal and vertical flipping, zoom transformations, and brightness adjustments. These transformations simulate real-world variations such as different leaf orientations, illumination conditions, and camera angles. By artificially increasing dataset diversity, augmentation improves the generalization capability of the proposed deep learning model and enhances robustness under practical field conditions.

C. Model Architecture

The proposed model architecture developed using the PyTorch is based on an ensemble learning framework that integrates three powerful deep learning models: Convolutional Neural Network (CNN), ResNet-50, and EfficientNet for robust sugarcane leaf disease detection. The overall architecture to perform multi-class classification of sugarcane leaf diseases is designed to leverage the strengths of each model to improve classification accuracy and generalization.

Initially, input sugarcane leaf images are preprocessed through resizing, normalization, and data augmentation techniques to enhance image quality and address dataset variability. The preprocessed images are then simultaneously fed into the three parallel models—CNN, ResNet-50, and EfficientNet-B0 for feature extraction and classification.

The CNN model captures fundamental spatial features such as edges, textures, and color patterns. ResNet-50, with its residual learning mechanism, enables deeper feature extraction while avoiding vanishing gradient issues. EfficientNet contributes by providing optimized performance through compound scaling, ensuring better accuracy with fewer parameters. Each model independently produces prediction probabilities for the input image. These outputs are then collected using a weighted ensemble strategy, where optimal weights are allotted to each model based on their individual performance. The final prediction is obtained through weighted averaging, resulting in improved decision reliability and reduced model bias.

This ensemble architecture enhances robustness against variations in lighting conditions, background noise, and leaf orientation. The modular design also allows scalability and easy integration into real-time agricultural applications, making it suitable for deployment in smart farming systems

D. Model Compilation and Training

Initially, the input dataset of sugarcane leaf images is preprocessed using resizing, normalization, and data augmentation techniques to enhance data diversity and reduce overfitting. The processed images are then fed into three parallel deep learning models for feature extraction and classification.

The proposed ensemble model, comprising CNN, ResNet- 50, and EfficientNet-B0, is compiled and trained using a structured and optimized approach to ensure high performance and generalization. Each model is initialized with pre-trained weights (transfer learning) to accelerate convergence and improve feature extraction capability. During compilation, categorical cross-entropy is used as the loss function due to the multi-class nature of sugarcane leaf disease classification. The Adam optimizer is employed with an appropriate learning rate to achieve efficient gradient updates. Evaluation metrics such as accuracy, precision, recall, and F1-score are used to monitor model performance.

The dataset is divided into training, validation, and testing sets to ensure unbiased evaluation. Each model is trained independently over multiple epochs with early stopping and learning rate reduction strategies to prevent overfitting.

After individual training, the outputs of CNN, ResNet-50, and EfficientNet-B0 are combined using a weighted averaging ensemble method. The weights are assigned based on validation performance of each model, ensuring that more accurate models contribute more to the final prediction. This training strategy results in a well-optimized ensemble model that achieves improved accuracy, stability, and generalization compared to standalone models, making it suitable for real-time sugarcane disease detection applications.

The CNN model extracts low- and mid-level features such as edges, textures, and color variations. ResNet-50 and EfficientNet are used for deeper and more optimized feature extraction. The core idea of ResNet-50 is the residual mapping, mathematically expressed as:

$$H(x) = F(x) + x \text{ ....(1)}$$

The residual unit computes F(x) by passing the input x through two weighted layers. It then adds the original input x to this result to produce H(x). If H(x) represents the ideal output that matches the ground truth, then achieving this depends on accurately learning F(x). EfficientNet-B0 improves the performance using compound scaling, which adjusts network depth, width, and resolution uniformly as per the following equations:

$$Depth = d = \alpha^{\emptyset} \cdots\cdots\cdots \quad (2)$$

$$width\ w = \beta^{\emptyset} \cdots\cdots\cdots \quad (3)$$

$$Resolution\ r = = \gamma^{\emptyset} \ \ldots\ldots\ldots \quad (4)$$

Where, α.β2.γ2 =2 and Φ is a user-specified scaling coefficient controlling available resources. Each model produces a probability vector for disease classes:

$$P_{CNN} = \sum_{l=1} (k_l^2 * C_{l-1} * C_l) \ldots\ldots\ldots (5)$$

These outputs are combined using a weighted ensemble strategy:

$$P_{\text{final}} = \text{w1}.\, P_{\text{CNN}} + \text{w2}.\, P_{ResNet} + \text{w3}.\, P_{\text{EfficientNet}} \quad (6)$$

Where, (w1, w2, w3) are weights assigned based on validation performance, satisfying: w1 + w2 + w3 = 1.The final class label is determined by selecting the class with the highest probability from Pfinal .

Figure 2 illustrates the hybrid deep learning ensemble architecture designed to improve prediction accuracy by combining the strengths of multiple models.

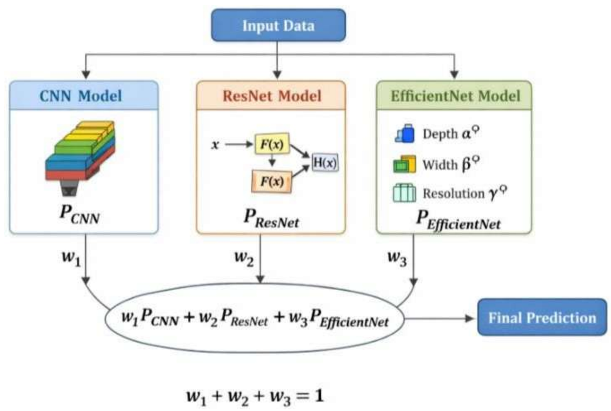

Figure 2: Proposed Weighted Ensemble Model

The input data is simultaneously fed into three parallel branches: a Convolutional Neural Network (CNN), a Residual Network (ResNet), and an EfficientNet model. The final trained model represents an optimized mapping between input leaf images and disease categories, making it suitable for automated sugarcane disease diagnosis under practical agricultural conditions.

IV. Results and Discussion

A. Training and Validation Performance

The performance of the model was evaluated using accuracy, precision, recall, and F1-score matrices providing a comprehensive view of their classification ability. Training progress on both training and validation sets was monitored. The Adam optimizer was used to train the proposed model with a batch size of 32 and a learning rate of 0.001. Figure 3 illustrates the training and validation accuracy trends across epochs, while Figure 4 shows the corresponding loss curves.

- Training Accuracy: The model's training accuracy increased steadily from 10.02% at epoch 1 to 99.49% at epoch 30, showing that the model learned effectively from the training data.
- Validation Accuracy: Validation accuracy also improved overall, reaching a peak of 98.15% at epoch 25. This indicates good generalization.
- Loss Values: Both training and validation losses decreased consistently, suggesting effective learning and no immediate signs of overfitting within the 10 epochs.

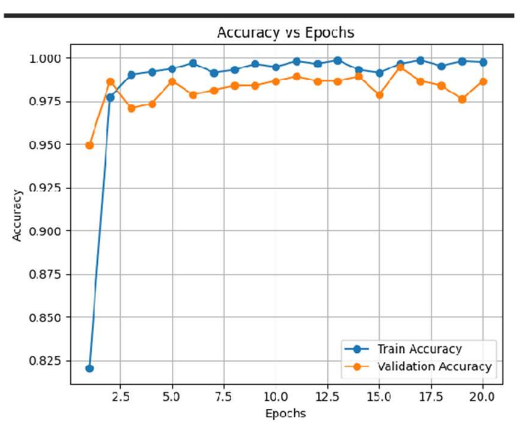

Figure 3: Training and Validation Accuracy over 30 epochs

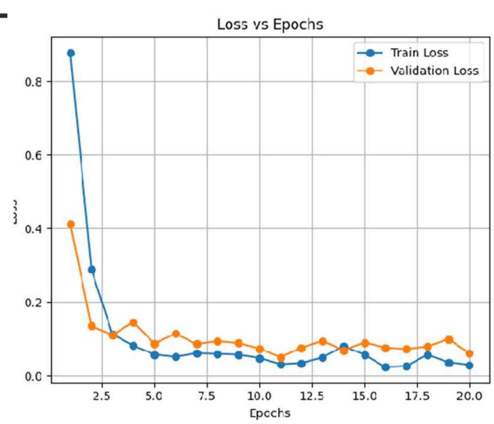

Figure 4: Training and Validation Loss over 30 epochs

TABLE I. PERFORMANCE METRICS FOR PROPOSED ENSEMBLE MODEL

Model	Accuracy	Precision	Recall	F1 Score
Proposed Ensemble Model	0.9815	0.9810	0.9819	0.9810
EfficientNet Model	0.9423	0.9355	0.9431	0.9427
ResNet Model	0.8628	0.8727	0.8628	0.8612

B. Confusion Matrix Analysis

A confusion matrix was generated to analyze misclassifications (Figure 5). The matrix indicates that the model correctly classified a majority of samples in respective classes, such as Healthy, Mosaic, Reddot, Rust and Yellow with perfect or near-perfect accuracy. Some misclassifications could arise due to similarities in leaf texture and color variations caused by environmental factors or image quality.

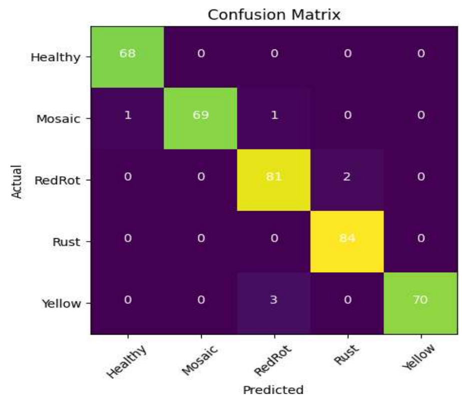

Figure 5: Confusion matrix by Ensemble learning

C. Comparison of Different Models

To evaluate the effectiveness of the proposed approach, multiple deep learning models were trained and compared based on training and validation accuracy as depicted in Table No. 2. The ensemble model demonstrates superior performance compared to individual models.

TABLE II. COMPARISON OF PROPOSED MODEL WITH BASIC MODELS

Model Name	Training Accuracy	Validation Accuracy
CNN	0.9473	0.9144
ResNet-50	0.8830	0.8628
EfficientNet	0.9615	0.9322
Proposed Ensemble Model	0.9983	0.9815

V. CONCLUSION AND FUTURE WORK

Future research direction: Although the proposed ensemble model demonstrates high accuracy and robustness in sugarcane leaf disease detection using real-field images, several directions can further enhance its effectiveness and real-world applicability. Since real-field data includes challenges such as varying illumination, complex backgrounds, occlusions, and noise, future work can focus on collecting larger and more diverse datasets across different regions, seasons, and environmental conditions to improve model generalization.

Advanced techniques such as Vision Transformers (ViT) or hybrid CNN-transformer models can be explored to better capture both local and global features from complex field images. Additionally, integrating explainable AI (XAI) methods can provide visual insights into model decisions, increasing trust and usability for farmers and agricultural experts. Further improvements can be achieved by implementing adaptive or dynamic ensemble weighting instead of fixed weights, allowing the model to adjust based on input conditions. Deployment of the system on mobile or edge devices is another important direction, enabling real-time, on-field disease detection with minimal latency.

Moreover, future research can extend this approach to multi- crop disease detection systems and integrate it with IoT- based smart agriculture platforms for continuous crop monitoring. Lightweight model optimization techniques can also be explored to reduce computational requirements while maintaining high accuracy. These advancements will strengthen the proposed system's capability to operate effectively in real-world agricultural environments and support sustainable, technology-driven farming practices.

REFERENCES

[1] A. Bhargava, A. Shukla, O. P. Goswami, M. H. Alsharif, P. Uthansakul, and M. Uthansakul, “Plant leaf disease detection, classification and diagnosis using computer vision and artificial intelligence,” IEEE Access, vol. 12, pp. 37443–37469, 2024, doi: 10.1109/ACCESS.2024.3373001.

[2] A. Oad, S. S. Abbas, A. Zafar, B. A. Akram, F. Dong, M. S. H. Talpur, and M. Uddin, “Plant leaf disease detection using ensemble learning and explainable AI,” IEEE Access, vol. 12, pp. 156038–156049, 2024, doi: 10.1109/ACCESS.2024.3484574.

[3] S. S. Harakannanavar, J. M. Rudagi, V. I. Puranikmath, A. Siddiqua, and R. Pramodhini, “Plant leaf disease detection using computer vision and machine learning algorithms,” Global Transitions Proceedings, vol. 3, no. 1, pp. 305–310, 2022, doi: 10.1016/j.gltp.2022.03.016.

[4] Salka, Tanko Daniel et al. “Plant leaf disease detection and classification using convolution neural networks model: a review.” Artificial Intelligence Review, 58,2025

[5] Z. . Li, “Application Research of Image Classification Based on Pytorch and Convolutional Neural Network”, CAI, vol. 1, no. 1, pp. 28–39, Oct. 2024,

[6] Y. Jiang and C. Li, “Convolutional neural networks for image-based high-throughput plant phenotyping: A review,” Plant Phenomics, vol. 2020, pp. 4152816:1–4152816:14, 2020.

[7] M. Li, Z. Zhu, R. Xu, Y. Feng, and L. Xiao, “Research on image classification and semantic segmentation model based on convolutional neural network,” J. Comput. Electron. Inf. Manag., vol. 12, no. 3, pp. 94–100, 2024.

[8] İsmail Kunduracıoğlu and İshak Paçal, “Deep Learning-Based Disease Detection in Sugarcane Leaves: Evaluating EfficientNet Models”, J. Oper. Intell., vol. 2, no. 1, pp. 321–335, Aug. 2024

[9] K. M. Nomani, M. Nuruzzaman, A. Nadia, and M. M. Billal, “Sugarcane leaf disease detection: A comparative analysis using deep learning,” in Proc. 2nd Int. Conf. Computing and Communication Applications (ICCA2), 2024, pp. 139–144.

[10] Sinchana H U, Shreyas N Kanakuppe, Dr. M V Sudhamani, “Sugarcane Disease Detection using Deep Learning Techniques for Automated Precision Agriculture”, IJERT ,Vol.14, Issue 11 , pp-223-237 ,Nov 2025.

[11] V. S. Devi, G. Kiran, V. V. Sagar, Y. M. P., and Y. H. M., “Sugarcane disease detection using deep learning,” Int. J. Creat. Res. Thoughts (IJCRT), vol. 12, no. 5, pp. 2739–2744, May 2024.

[12] G. M. . Reddy, P. H. V. . Ramana, P. . Anusha, B. K. . Chakravarthy, A. . Kasukurthi, and V. S. . Lakshmi, “A Survey on Sugarcane Leaf Disease Identification Using Deep Learning Technique(CNN)”, IJRITCC, vol. 11, no. 5, pp.248–254, May 2023.