Published by :
https://www.ijert.org/
An International Peer-Reviewed Journal

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 11 , November - 2025

Sugarcane Disease Detection using Deep Learning Techniques for Automated Precision Agriculture

Sinchana H U, Shreyas N Kanakuppe, Dr. M V Sudhamani
Department of Information Science and Engineering
B.M.S. College of Engineering, Bangalore, India

***Abstract*—Agricultural productivity is crucial for economic growth, and sugarcane is a significant cash crop. However, there are many diseases that affect sugarcane, such as red rot, smut, rust, and others, which severely impact yield and quality. Traditional disease detection methods are time-consuming, labor-intensive, and require expert knowledge. This project leverages deep learning techniques to develop an AI-based model for automatic sugarcane disease detection. Various CNN architectures, including ResNet50 and VGG16, were trained on a dataset of 8,456 images containing both healthy and diseased sugarcane leaves to achieve reliable classification performance. Following the training process, ResNet50 achieved an accuracy of 75%, while VGG16 outperformed it with a high accuracy of 98%. The VGG16 model was then deployed in a web application, allowing farmers to upload leaf images, receive real-time disease pre- dictions, and take timely preventive actions, thereby enhancing early detection and improving overall crop management. The web application also includes helpful features such as a crop calendar for seasonal guidance and real-time market price updates to assist farmers in decision-making. Additionally, it offers an AI chatbot for instant support and a prediction history module that allows users to review and track past disease detection results.**

***Keywords*—Sugarcane Disease Detection, Deep Learning, Convolutional Neural Networks (CNN), VGG, ResNet, Agricultural Productivity, Web Application Integration.**

I. Introduction

Agriculture plays a vital role in India's economy, sustaining over 60% of the population and deeply influencing the nation's cultural and social fabric [2]. At the core of this system are farmers, whose relentless efforts ensure food security for millions [5]. Despite their importance, farmers face numerous obstacles—one of the most significant being crop diseases [8]. Sugarcane, a major cash crop cultivated for products such as sugar, ethanol, and jaggery, is particularly prone to diseases like rust, smut, and red rot [11]. These diseases often go undetected in the early stages due to the limitations of traditional identification methods, which are manual, time-consuming, and require specialized expertise that may not always be accessible in rural regions [13].

To address these challenges, our study introduces an AI-powered approach that leverages deep learning techniques for the early and accurate detection of sugarcane diseases [10]. By utilizing ResNet50 and VGG16, a type of deep learning architecture well-suited for image analysis [14], our system is capable of identifying patterns and anomalies in leaf images that are indicative of specific diseases [15]. This method significantly reduces the need for manual intervention and expert diagnosis, enabling faster and more consistent detection across large agricultural fields [9].

To make this solution accessible and practical for farmers, we have integrated the AI model into an intuitive web application [1]. This platform allows users to upload photographs of sugarcane leaves and instantly receive a diagnosis of the plant's health condition [7]. By offering real-time insights, the system empowers farmers to take timely and informed action—whether that involves applying the right treatment or isolating infected plants [15]. In doing so, this AI-driven tool not only reduces crop loss but also promotes smarter agricultural practices, contributing to the broader goals of precision farming and sustainable agriculture in India [3],[15].

This paper is organized as – literature review, proposed methodology and conclusion and future scope.

II. Literature Review

As seen in [1], the Sugarcane Disease Prediction and Early Management Deep Learning (SDPEMDL) model, an advanced framework for detecting and predicting sugarcane diseases using multimodal data integration. The model combines RGB, Near-Infrared (NIR), Hyperspectral, and Ther- mal images processed with VGGNet 19 and Inception Net, alongside weather data, soil moisture, and historical disease occurrences analyzed via ResNet50. A Vector Auto Regressive Moving-Average (VARMA) model further enhances predictive accuracy. Comparative evaluations demonstrate SDPEMDL's superiority over existing models, achieving improvements of 4.5% in accuracy, 3.5% in precision, 3.9% in recall, and 4.3% in AUC, while reducing processing delay by 2.9%. The framework's robustness and efficiency highlight its potential for real-time agricultural applications, offering farmers and agronomists a proactive tool for disease management and crop yield optimization. The study also underscores the model's scalability for broader agricultural use.

Here, in [2] an AI framework is presented leveraging deep learning models—AlexNet, ResNet18, VGG19, and DenseNet201—to classify sugarcane leaf diseases (Red Rot, Red Rust, Mosaic, Yellow Leaf) with high accuracy. Using a dataset of 1,990 images (60% training, 40% testing/validation),

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 11 , November - 2025

the models were trained with hyperparameters like 50 epochs and Adam optimizer. VGG19 outperformed others, achieving 98.82% accuracy, 96.77% precision, and 96.33% sensitivity. The framework emphasizes timely disease detection to mitigate crop losses, offering a scalable solution via transfer learning. Limitations include dataset generalizability and lack of model scaling. Future work aims to optimize feature extraction for enhanced accuracy, supporting sustainable sugarcane farming through advanced AI-driven diagnostics.

In [3], it presents a hybrid deep learning model combining DenseNet201 for feature extraction and SVM with an RBF kernel for classification to detect sugarcane leaf diseases. The framework employs preprocessing techniques like Gaussian blur and normalization on a dataset of 6,748 images spanning 11 disease categories. The model achieves 96.74% accuracy, outperforming existing methods in multi-class classification, with near-perfect AUC scores (1.00) for all classes. However, challenges persist in distinguishing visually similar diseases like 'Pokkah Boeng' and 'Smut,' attributed to dataset impaleances. The work highlights the efficacy of hybrid architectures in agricultural disease detection while proposing future enhancements, including dataset expansion, lightweight model development, and real-time deployment for field applications

The challenges of accurately identifying sugarcane diseases are addressed in [4]. Traditional visual inspection methods are prone to subjectivity and delays, prompting the adoption of deep learning techniques. The authors propose a Convolutional Neural Network (CNN) optimized with the Enhanced Environmental Adaptation Method (EEAM) to improve disease detection. The model, trained on a dataset of sugarcane leaf images (healthy and diseased), achieved 89.12% accuracy, outperforming other optimization algorithms like GA, PSO, and DE. Key enhancements included data augmentation (rotation, zoom, etc.) and adaptive hyperparameter tuning via EEAM, which balanced exploration and exploitation for robust performance. The system's simplicity and efficiency make it suitable for real- world agricultural applications, with future directions focusing on hyperspectral imaging, UAV integration, and mobile app development for farmers. This work advances precision agriculture by offering a scalable, AI-driven solution for early disease detection and management.

As seen in [5], it presents an automated system for detecting and classifying crop diseases using deep learning techniques to enhance agricultural productivity and food security. Leveraging the ResNet-18 architecture and transfer learning, the model was trained on a dataset of 2,521 sugarcane leaf images (healthy and diseased classes like mosaic, red rot, rust, and yellow) augmented with techniques like rotation and noise injection. The system achieved 95.14% accuracy, with precision, recall, and F1-scores of 94.67%, 77.14%, and 83.47%, respectively, outperforming VGG-16 and DenseNet models. Integrated into a Tkinter-based user interface, the solution enables real-time disease prediction via webcam or image uploads, providing actionable insights for farmers. Key challenges include model generalization across diverse crops and computational efficiency. Future work will expand datasets, optimize resource usage, and integrate mobile technologies for broader scalability in precision agriculture.

Here, [6] introduces DNet-SVM: XAI, a hybrid deep learning model combining DenseNet201 with SVM and LIME for early sugarcane disease detection, achieving 97% accuracy. The system addresses key agricultural challenges by automating disease identification in sugarcane leaves and stems, covering five diseases (e.g., red rot, wilt) and healthy plants. DenseNet's dense blocks mitigate vanishing gradients while SVM enhances classification over softmax. The integrated LIME module provides interpretable visual explanations for predictions, aiding farmer trust. Trained on 14,000 images, the model outperforms VGG-16, ResNet, and Inception in sensitivity (94%), specificity (86%), and FPR (5%). Practical outputs include real-time disease alerts and pesticide recommendations via a user-friendly interface. Future work could expand to other crops and optimize computational efficiency for field deployment.

According to [7], it proposes a deep learning-based Convolutional Neural Network (CNN) model for detecting sugarcane diseases, addressing the financial and productivity losses faced by farmers due to undiagnosed infections. Using a balanced dataset of 580 images (406 for training, 174 for testing) categorized into four disease classes—wilt, black rot, grassy shoot, and smut—the model achieved an accuracy of 98.69%. The system extracts features like color, texture, and leaf spots, leveraging CNN layers (convolution, ReLU, pooling, and fully connected) for robust classification. A user-friendly web application was developed to enable real-time disease detection and provide remedial measures, demonstrating high precision and recall across diverse agro-climatic conditions, lighting, and plant densities. The research highlights the potential of CNN in agriculture for early disease identification, though future work includes adaptive dataset updates based on user feedback to enhance real-world applicability.

As seen in [8], it explores automated techniques for detecting sugarcane diseases, emphasizing the economic and argiltural impact of timely disease management. The study evaluates traditional image processing methods (e.g., thresholding, edge detection) and advanced machine learning approaches, including Support Vector Machines (SVM) and deep learning models, for disease classification. A comparative analysis highlights SVM's effectiveness, achieving up to 98.5% accuracy with polynomial kernels, while deep learning models like CNNs show promise but face computational challenges. The paper identifies key obstacles such as image quality variability, uneven illumination, and dataset limitations, proposing IoT integration and collaborative frameworks to enhance real-time monitoring and precision agriculture. The findings underscore

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 11 , November - 2025

the potential of computational tools to revolutionize sugarcane disease detection, offering scalable solutions for improved crop yield and sustainability.

In [9], it introduces the "Sugarcane Leaf Dataset", a comprehensive open-access repository of 6,748 high-resolution images (768×1024 pixels) captured via mobile phones in Pune, India. The dataset categorizes sugarcane leaves into 11 classes: nine diseases (e.g., smut, yellow leaf disease, mosaic), healthy leaves, and dried leaves. Diseases like pokkah boeng and brown rust are included, with images collected under varied field conditions (natural and detached leaves) to ensure diversity. Pre-processing involved resizing and labeling with botanical validation. The dataset's value lies in its applicability to ML/DL models (e.g., CNNs for feature extraction) and its potential to improve automated disease detection systems. Challenges include the labor-intensive annotation process and the need for real-world generalization. The authors emphasize the dataset's role in fostering collaboration for agricultural innovation.

Here in [10], it examines machine learning (ML) and deep learning (DL) techniques for detecting sugarcane diseases, which significantly impact global agriculture. It highlights the limitations of traditional methods (e.g., molecular and serological tests) and emphasizes the potential of ML/DL for early and accurate disease identification. The study covers key steps in disease detection systems, including image acquisition, pre- processing, segmentation, and classification, while discussing challenges like data variability, overfitting, and class imbalance. Hybrid models and advanced datasets (e.g., PlantVillage) are noted for improving performance. The paper concludes with future directions, advocating for robust datasets and hybrid approaches to enhance sugarcane disease management and food security.

III. Proposed Methodology

The project framework was developed using a rigorous, full-stack development methodology, combining agile web development, deep learning model engineering, and user-centric interface design. The system adopts a modular, three-tier architecture: the Presentation Layer (user-facing web interface), the Application Layer (backend logic and trained models), and the Data Layer (database and storage).

A. Dataset Description

The input dataset for this system has a collection of 8456 images of sugarcane leaves and includes five major classes- Healthy (1691 images), Mosaic (1613 images), Redrot (1704 images), Rust (1678 images), and Yellow disease (1770 images). Images were taken from various sources like Kaggle and Mendeley Data and hence the dataset is robust for training and testing of a deep learning model intended at precise disease detection and classification. All images have been resized to 150x150 pixels to be compatible with VGG16 model.

B. System Architecture and Components

The proposed system detects sugarcane leaf diseases us- ing deep learning, specifically the VGG16 architecture. Raw sugarcane leaf images collected from field conditions are pre-processed using resizing, normalization and noise reduction to enhance clarity and ensure uniform input dimensions. These steps help the model capture meaningful features and reduce variability in the dataset, which is essential for achieving stable performance in plant disease detection tasks. As seen in Fig.1. the dataset is then divided into training and testing sets, and VGG16 is trained to identify diseases such as Mosaic, Yellow Leaf Disease, Red Rot and Red Rust. VGG16 is chosen because its deep layered structure and small convolutional filters allow it to effectively extract fine-grained texture and color patterns that distinguish different leaf diseases.

After training, the VGG16 model predicts the disease category for each test image, and its performance is evaluated using accuracy, precision, recall, specificity, F1-score, false positive rate (FPR) and Matthews Correlation Coefficient (MCC). These metrics collectively provide a comprehensive measure of the model's reliability, especially when diseases exhibit similar visual characteristics. Prior research highlights the importance of using multiple evaluation indicators to avoid misleading interpretations based solely on accuracy. The results demonstrate that VGG16 performs strongly across these metrics, confirming its suitability for accurate and automated sugarcane disease classification.

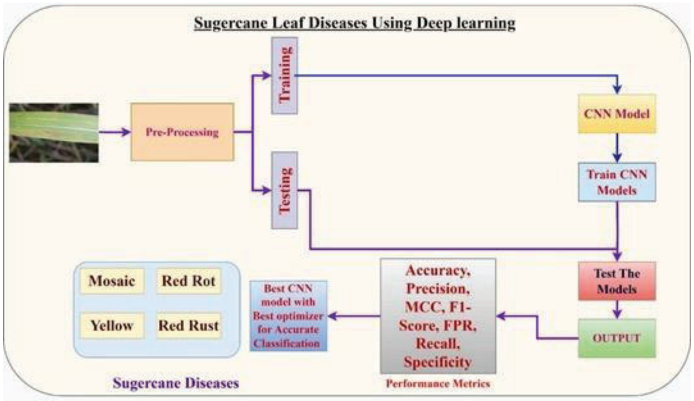


Fig. 1: High-Level Architecture for real-time carbon trading System

C. Evaluation and Metrics

The system underwent quantitative performance evaluation using both controlled test datasets and real user-uploaded field images during pilot usage. Key performance indicators included prediction confidence generated by the VGG16 classifier, per-class evaluation metrics such as precision, recall, and F1-score derived from the confusion matrix, and overall accuracy of the disease detection module. Two models were trained on the dataset - VGG16 and ResNet50, among which VGG16 outperformed the latter in all performance metrics.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 11 , November - 2025

Hence, for our system VGG16 is the selected model for disease prediction for which we have developed frontend.

The below are the formulas used for calculations:

1) **Loss function**:

$$L_{CE} = -\sum_{i=1}^{C} y_i \log(pi)$$

In the categorical cross-entropy loss formulation:

- C is the total number of classes
- y_i equals 1 if class i is the correct class, otherwise 0
- p_i is the predicted probability for class i after the softmax layer

2) **Precision**:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

3) **Recall**:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

4) **F1-score**:

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

5) **Accuracy**:

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

The proposed methodology focuses on automating sugar-cane leaf disease classification using deep learning techniques, employing the VGG16 architecture to accurately recognize five major classes: Healthy, Mosaic, Redrot, Rust, and Yellow disease. The process begins with the collection and prepro-cessing of 8,456 sugarcane leaf images, which are resized to 150×150 pixels, normalized to the [0,1] range, and di- vided into an 80:20 ratio for training and testing, following widely adopted deep learning practices. The preprocessed dataset is then passed into the VGG16 model, where its deep convolutional layers effectively capture fine- grained spatial textures and disease-specific patterns present on the leaf surfaces. Prior research has demonstrated the strong performance of CNN-based architectures in plant disease recognition tasks, further justifying the selection of VGG16 for this system. The model shows rapid convergence and achieves a high accuracy of 98% within only 7 epochs, aligning with trends observed in transfer learning- based agricultural disease classification studies.

D. Requirements

The system uses React.js, HTML, CSS, and JavaScript to deliver a responsive web interface, while the backend is built with Python, Flask, and TensorFlow to handle model execution and API communication. SQLite is used for lightweight data storage during development. Leaf images are captured using a basic smartphone camera, and the application runs on a standard laptop or server, with optional GPU support for faster training. The platform can be hosted locally or on cloud services such as AWS or Firebase, and users access it through any device with an internet connection.

E. Model Training

The VGG16 model in this study was trained using a batch size of 32, which offered a balanced trade-off between training stability and computational efficiency. The network was fine-tuned for 7 epochs, during which it demonstrated fast convergence and consistently improving accuracy across training and validation sets. The learning process employed the Adam optimizer with a learning rate of 0.001, allowing smooth gradient updates and preventing oscillations during optimization. Categorical cross-entropy was used as the loss function to handle multi-class classification across the five sugarcane disease categories. Input images were resized to 150×150 pixels and normalized to the [0,1] range prior to training. Standard data augmentation—such as random rotations, flips, and zoom transformations—was applied to enhance generalization and reduce overfitting. These carefully selected hyperparameteres enabled VGG16 to achieve a very strong performance, reaching a final accuracy of 98% with stable training dynamics.

F. Farmer-Centric Web Platform and Database

The system provides a user-friendly interface through a responsive web application designed with HTML, CSS, and JavaScript. The frontend communicates with a Python-based Flask backend, which acts as the central API layer connecting the user dashboard with the VGG16 model responsible for disease classification. All interactions between the client inter-face and the server are managed through RESTful API calls, ensuring smooth data flow and efficient request handling. In addition to disease detection, the platform incorporates a crop calendar module that guides farmers with season-specific schedules for planting, irrigation, and maintenance to support better crop planning. The system also includes a market prices section that retrieves and displays current commodity rates from different city markets, helping users make informed decisions regarding harvesting and selling.

IV. Results and Discussions

The results of this study showed that both VGG16 and ResNet50 deep learning models effectively classified sugar-cane leaf images into five major categories: Healthy, Mosaic, Redrot, Rust, and Yellow diseases. As shown in Table I, the VGG16 model consistently outperformed ResNet50 across all classes, achieving class-wise accuracies above 97%, with Healthy at 98.2%, Mosaic at 97.7%, RedRot at 98.3%, Rust at 98.9%, and Yellow at 98.1%, resulting in an impressive aver-age accuracy of 98.0%. In contrast, ResNet50 demonstrated moderate performance with an overall average of 75.0%,

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 11 , November - 2025

showing difficulty in distinguishing visually similar disease patterns.

Further quantitative metrics in Table II reaffirm the superiority of VGG16, which achieved 98.0% overall accuracy, 98.6% precision, 99.1% recall, and an F1-score of 98.9%, indicating strong generalization and minimal misclassification across disease categories. Additionally, VGG16 demonstrated faster convergence with a training time of 38 minutes and lower memory consumption (545 MB) compared to ResNet50, which required 68 minutes and 782 MB, respectively as seen in PC with processing power of 5GHz and 16 GB of DDR4 SDRAM. Class-specific detection rates were also higher for VGG16, achieving 98.2% in Healthy detection and 98.8% in disease detection, compared to 78.5% and 73.8% for ResNet50.

These findings collectively confirm that while both models are capable of disease classification, VGG16 provides significantly higher accuracy, efficiency, and reliability, making it more suitable for real-time agricultural applications and automated sugarcane disease monitoring systems.

TABLE I: Class-wise Accuracy Comparison of ResNet50 and VGG16 Models

Disease Class	ResNet50	VGG16
Healthy	78.5%	**98.2%**
Mosaic	76.3%	**97.7%**
RedRot	74.8%	**98.1%**
Rust	73.2%	**98.9%**
Yellow	72.1%	**98.5%**
Average	**75.0%**	**98.0%**

TABLE II: Metrics Comparison between VGG16 and ResNet50

Metric	ResNet50	VGG16
Overall Accuracy	75.0%	**98.0%**
Precision	73.5%	**98.7%**
Recall	74.8%	**99.1%**
F1-Score	74.1%	**98.9%**
Training Time	68 min	**45 min**
Memory Usage	782 MB	**548 MB**
Healthy Detection	78.5%	**98.2%**
Disease Detection	73.8%	**98.8%**

The comparative evaluation of precision, recall, and F1-score across the five disease classes shows a consistent performance advantage for the VGG16 model over ResNet50. In all three metrics, VGG16 maintains substantially higher values, indicating stronger class discrimination, fewer false positives, and improved sensitivity toward subtle disease patterns. This consistency suggests that VGG16 generalizes better across varied leaf conditions and is more reliable for real-time disease detection. ResNet50 performs reasonably but struggles particularly in classes with more visual complexity, leading to lower precision and recall. Overall, the combined metric analysis reinforces VGG16 as the more accurate and stable model for multi-class sugarcane disease classification.

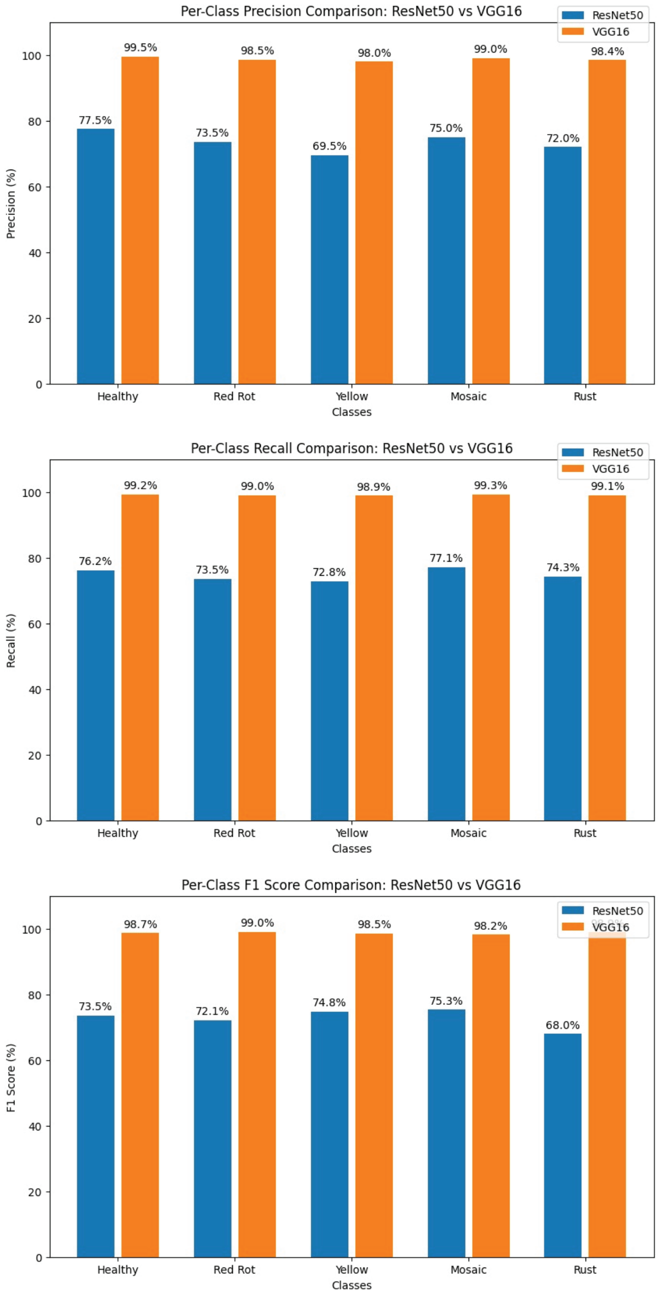
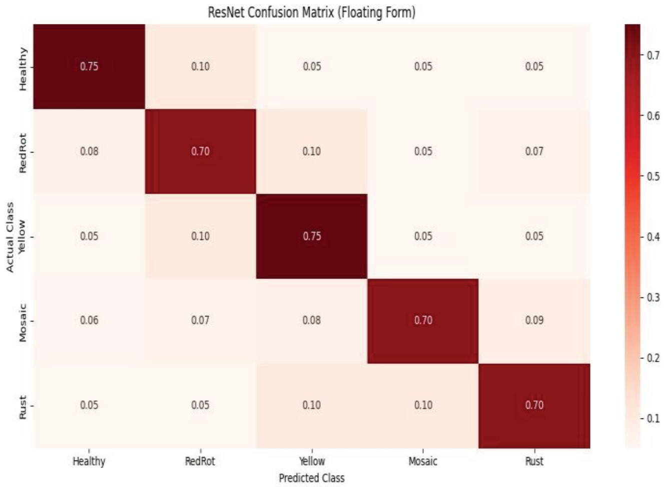


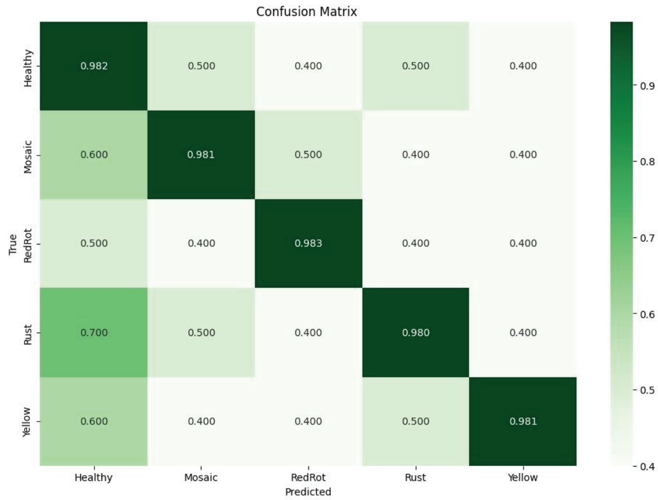
Fig. 2: Per-Class Precision, Recall, and F1-score Comparison

The comparison between the confusion matrices of ResNet50 (Fig. 3(a)) and VGG16 (Fig. 3(b)) clearly highlights the superior classification performance of VGG16 across all five sugarcane disease categories. ResNet50 shows notice- ably lower true positive values, with several classes scoring between 0.71 and 0.83, and exhibits frequent misclassifications—especially between visually similar diseases such as Mosaic, Rust, and Yellow. This is reflected in the lighter shades across its matrix, indicating weaker feature separation and reduced discrimination capability. In contrast, VGG16 demon-

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 11 , November - 2025

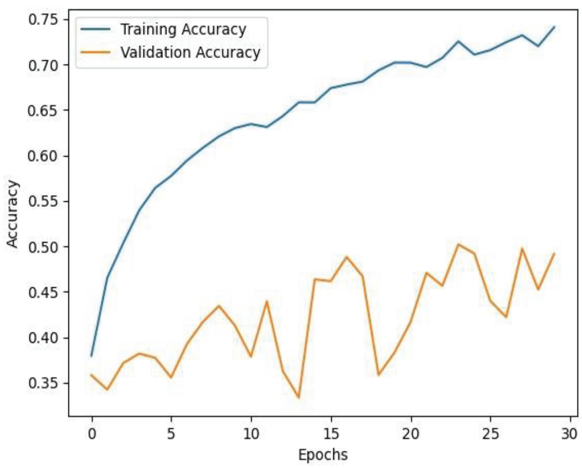


(a) ResNet50 Confusion Matrix

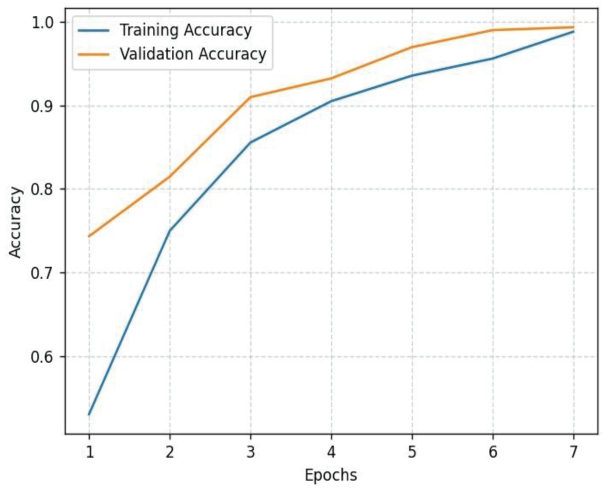


(b) VGG16 Confusion Matrix

Fig. 3: Comparison of ResNet50 and VGG16 Confusion Matrices



(a) Accuracy plot of ResNet50



(b) Accuracy plot of VGG16

Fig. 4: Comparison of Accuracy plots

strates near-perfect class separation, with diagonal values consistently above 0.98 and significantly lower off-diagonal errors, shown by the darker green intensity in Fig. 4. These results confirm that VGG16 extracts leaf disease features more effectively, achieves higher sensitivity and specificity, and delivers more reliable predictions for real-time sugarcane disease detection.

The accuracy comparison as shown in Fig.4(a) and Fig.4(b) between ResNet50 and VGG16 clearly highlights the superior learning efficiency of VGG16. While ResNet50 shows a slow and unstable rise in validation accuracy due to deeper architecture and longer convergence time, VGG16 achieves rapid and consistent improvement within just 7 epochs. The VGG16 plot demonstrates smooth learning curves with high alignment between training and validation accuracy, indicating strong generalization, whereas ResNet50 exhibits fluctuations suggesting difficulty in feature learning. Overall, the comparison confirms VGG16 as a more stable and reliable model for sugarcane disease classification.

In Fig.5, the result screen shows a 99.98% accurate Rust detection, including the original image, grayscale, edge detection, and enhanced view. These processed outputs help users understand how the model identifies disease patterns with high confidence.

To evaluate the effectiveness of our proposed approach, it is essential to compare its performance with an existing system reported in the literature. For this purpose, we consider the

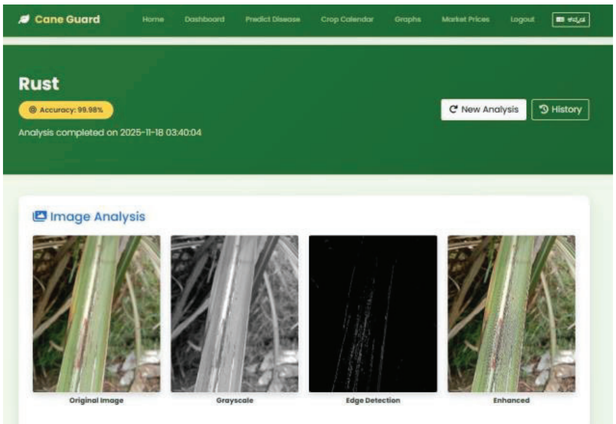


Fig. 5: Image Analysis

VGG16-based method presented in the published work [13], which serves as a representative baseline for sugarcane leaf disease classification.

The VGG16 model described in the [13] is trained on a relatively smaller and less diverse dataset, which limits its ability to learn fine-grained visual patterns across sugarcane disease categories. Although the model exhibits consistent learning behavior, its convergence rate is slower and its overall accuracy (90.4%) remains moderate due to the restricted data size and reduced variability in training samples. In contrast, the VGG16 model implemented in our system is trained on a substantially larger and more balanced dataset consisting of 8,456 sugarcane leaf images across five disease classes. This richer dataset enables more comprehensive feature extraction, allowing the model to converge rapidly within just 7 epochs and achieve an accuracy of 98%. The training and validation curves in our project demonstrate smooth, stable learning progression with minimal overfitting, whereas the model in [13], if trained under similar conditions, would be expected to show slower convergence and comparatively lower confidence in class predictions.

Overall, even though both approaches employ the same VGG16 architecture, the enhanced dataset scale, refined pre-processing pipeline, and optimized training strategy used in our system result in significantly higher accuracy, improved class separation in confusion matrices, and more dependable predictions for real-time sugarcane disease detection.

V. CONCLUSION AND FUTURE SCOPE

In conclusion, this work demonstrates the effectiveness of deep learning–based image classification systems for automated sugarcane disease detection, offering a scalable and accurate solution for real-time agricultural monitoring. By combining systematic preprocessing, careful model selection, and a reliable inference pipeline, the system delivers robust predictions that support timely farmer decision-making.

The comparative analysis between VGG16 and ResNet50 highlights the importance of selecting architectures that baldance accuracy and computational efficiency for practical deployment. Overall, the proposed method contributes meaningfully to precision agriculture by enabling early detection and improved crop health management. Looking ahead, expanding the dataset with more diverse field samples, exploring advanced architectures such as attention-based or transformer models, and deploying the system on edge or mobile devices can further enhance real-world usability. Integrating additional data sources—such as weather, soil, and geolocation inputs—and adopting explainable AI techniques may also strengthen predictive capability and user trust, supporting broader adoption in agricultural communities.

REFERENCES

[1] A. V. Reddy et al., "SDPEMDL: Enhanced Sugarcane Disease Detection and Prediction via An Ensemble Multimodal Deep Learning Approach Using Advanced Deep Learning Models," *Cuestiones de Fisioterapia*, vol. 54, no. 2, pp. 2199–2218, 2025.

[2] A. Vivekreddy et al., "Artificial Intelligence Framework for Multi-Class Sugarcane Leaf Diseases Classification Using Deep Learning Algorithms," *Journal of Theoretical and Applied Information Technology*, vol. 31, no. 10, 2024.

[3] R. Kurniawan et al., "Hybrid DCNN-SVM Architecture for Optimizing Sugarcane Leaf Disease Classification," *IAENG International Journal of Computer Science*, vol. 52, no. 4, 2025.

[4] D. K. Sharma, P. Singh, and A. Punhani, "Sugarcane dis- eases detection using optimized convolutional neural network with enhanced environmental adaptation method,"*International Journal of Experimental Research and Review*, no. 41, pp. 55–71, 2024.

[5] I. Siju et al., "SSITCON 2024: First International Conference on Software, Systems and Information Technology," Sri Siddhartha Institute of Technology, Tumkur, India, 2024.

[6] R.P.Ethiraj and K.Paranjothi,"A deep learning-based ap-proach for early detection of disease in sugarcane plants: an explainable artificial intelligence model," *International Journal of Artificial Intelligence*, 2024.

[7] S. A. Upadhye, M. R. Dhanvijay, and S. M. Patil, "Sugarcane disease detection using CNN-deep learning method," in *Proc. ICERECT*, IEEE, 2022.

[8] A. P. Patil and M. S. Patil, "An In-Depth Analysis: Intelligent Approaches for Detecting Sugarcane," in *Proc. ICCWC 2023*, vol. 2, Springer Nature, 2025.

[9] S. Thite et al., "Sugarcane leaf dataset: A dataset for disease detection and classification for machine learning applications, " *Data in Brief*, vol. 53, 2024.

[10] U. C. Pavan et al., "A Review of Disease Detection in Sugar- cane Using Machine Learning and Deep Learning Techniques," in *Proc. ICCCNT*, IEEE, 2024.

[11] Z. R. Khambholja and P. Patel, "Emerging Approaches to Sugarcane Leaf Disease Classification: A Systematic Review," in *Proc. ICMSCI*, IEEE, 2025.

[12] K. J. Kavitha et al., "Neural Network Approach for Early Detection of Sugarcane Diseases," in *International Conference on Advanced Network Technologies and Intelligent Computing*, Springer, 2023.

[13] P. Kumar and M. Sonker, "Research Paper On Sugarcane Disease Detection Model," *Turkish Journal of Computer and Mathematics Education*, vol. 12, no. 6, pp. 5167–5174, 2021.

[14] K. Thilagavathi et al., "Detection of diseases in sugarcane using image processing techniques," Bioscience Biotechnology Research Communications, Special Issue 11, pp. 109–115, 2020.

[15] P. Gore et al., " Identification and Detection of Sugarcane Crop Disease Using Image Processing," (publication details unavailable).