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Disease Prediction in Millet Using Deep Learning: A Custom VGG-19 Based Approach

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Abstract: Millet crops suffer from various diseases induced by fungi, bacteria, and viruses, which have a significant impact on crop yields and overall product quality. Thus, precise and early disease recognition is crucial to ensure food production sustainability and security. For this purpose, it gives an idea of developing a deep learning model which will enable automatic disease detection and classification in millets. In particular, a customized 19-layered VGG network architecture with an optimized preprocessing pipeline was selected as the backbone of the proposed model. The latter involves the following steps: image downsizing (resizing to 224×224 pixels), normalization, denoising by applying a Gaussian filter, and advanced data augmentation techniques such as image flipping, rotation, zooming, and adjusting brightness. Moreover, the proposed model features a custom-designed VGG19 architecture based on modifications of the classic one, including adding fine-tuned convolutional layers, dropout regularization, and fully connected layers to enhance feature extraction and eliminate the risk of overfitting. The experiments involved training and testing the model on the dataset of different millet leaf images with different diseases. The obtained experimental results prove the reliability and efficiency of the developed algorithm since the test accuracy equals 99.29%, while the test loss was measured at 0.0045. Besides, the model has high classification metrics with a precision rate of 0.98, a recall of 1.00, and an F1-score of 0.99, which suggests that the algorithm has minimal rates of false negatives. In order to ensure the superiority of the algorithm in question, a comparative analysis is performed with other popular deep learning architectures, namely, standard CNN, GoogLeNet, VGG16, VGG19, DenseNet, ResNet50, ResNet101, MobileNetV2, and ConvNeXt. As a result of the analysis, all models show worse performance compared to the custom model.

Keywords: Deep Learning, Custom VGG19, Convolutional Neural Network (CNN), Image Classification, Plant Disease Diagnosis, Precision Agriculture, Data Augmentation, Feature Extraction.

I. INTRODUCTION

The millets have a great nutritional value and are resistant to climate changes. Therefore, this kind of crops plays an important part in food security provision, especially in the regions that do not have favorable conditions for growing other plants [1], [2] [3]. Unfortunately, this type of crops suffers from various diseases like leaf blast, rust, downy mildew, smut and others that influence their yield and quality negatively. Traditional approaches to the disease detection process are based on the visual inspection by professionals. Unfortunately, this method is not quite practical due to its subjectivity and inaccuracy. Therefore, an automated tool which is able to find and classify the disease accurately and quickly is required to be developed.

During the last decades, a significant improvement in image recognition has been provided through the application of deep learning algorithms. Among them, the convolutional neural networks (CNN) can be highlighted because they demon-strate outstanding results when it comes to solving image classification and plant disease recognition problems [4]. The pre-trained CNN models such as VGG, ResNet, DenseNet, and MobileNet proved to be efficient due to their feature extraction ability. Nevertheless, the problem of computational inefficiency or specificity to the particular dataset occurs [5], [6]. Besides, achieving a control balance between efficiency and accuracy proves to be very challenging.

This paper presents a deep learning model especially prepared to identify and figure out different types of disease occurring in millets. In order to increase the effectiveness and reliability of the classifier, the modified VGG19 model was used. It includes several changes related to the convolutional layers, dropout, and fully-connected parts. In addition, a pow-erful preprocessing procedure was implemented that consists
of the image resize (224 × 224), normalization, Gaussian noise reduction, and data augmentation techniques (rotating, zooming, flipping, brightness adjustment).

This work was motivated by the necessity to create con-venient and smart solutions that would help farmers deal with millet disease problems effectively. In most of the cases, farmers could not find specialists who would diagnose their plants in time, thus losing a lot of crops. With the emergence of mobile devices and imaging techniques, deep learning becomes a promising technology to be applied to solve such problems.

This work introduces a number of innovations that can be highlighted as follows:

- The customized 19-layer VGG19 model is introduced to ensure the efficient millet disease detection and classifi-cation.
- The preprocessing pipeline and data augmentation tech-niques were created to increase generalizability and re-duce the class imbalance.
- The proposed model demonstrates remarkable results in terms of performance metrics: 99.29% of test accuracy, 0.0045 of test loss, precision 0.98, recall 1.00, and F1-score 0.99. It outperforms all the baseline models in-cluding CNN, GoogLeNet, VGG16, VGG19, DenseNet, ResNet50, ResNet101, MobileNetV2, and ConvNeXt.

II. LITERATURE SURVEY

Advancements in deep learning technologies have significantly improved detection of plant disease, particularly within the scope of precision agriculture. Between 2023 and 2026, various studies have concluded that the use of convolutional neural networks (CNNs), transfer learning, and hybrid architectures to enhance classification accuracy.

A detailed survey conducted by Shafik et al. reviewed more than 160 deep learning models for plant disease detection and identified CNNs as the most effective for their strong extraction capabilities as feature [7]. In a related study, Shafik et al. (2026) introduced an ensemble framework called PlantDet, which integrates InceptionResNetV2, Xception, and Efficient-Net, achieving an accuracy of 98.53

The importance of high-quality datasets has also been emphasized in recent research. Xu et al. (2024) developed the FieldPlant dataset using real-world images, addressing the limitations of controlled datasets like PlantVillage [8]. Similarly, Nalwanga et al. (2023) searched and concluded the use of UAV-based imaging for crop disease monitoring, highlighting the role of advanced sensing technologies in agriculture [9].

In 2024, several studies focused on improving model efficiency and accuracy through transfer learning and optimized CNN designs. Sharma et al. (2024) proposed the Deep-Millet model for detecting pearl millet diseases, achieving an accuracy of 98.86

Research in 2025 introduced more advanced and hybrid methodologies. Kumar et al. (2025) developed a hybrid CNN-LSTM model for millet disease prediction, achieving 98.48% accuracy [10]. Tiwari et al. (2025) proposed a precision-aware CNN integrated with IoT systems for real-time finger millet disease detection, improving both accuracy and practical deployment [11]. Wang et al. (2025) reviewed recent progress in deep learning for plant disease detection, emphasizing attention mechanisms, transfer learning, and multimodal data integration [12]. Furthermore, Nayak et al. (2025) compared architectures such as VGG19, ResNet50, and InceptionV3, confirming that deep CNN models outperform traditional approaches [13].

By 2026, the focus has shifted toward real-time and scalable implementations. Devarajan et al. (2026) introduced an AI-based system combining image processing and deep learning for disease diagnosis in real-time as field conditions [14], [15]. Recent studies on finger millet disease detection using fine-tuned transfer learning models also highlight the importance of domain-specific optimization to improve real-world perfor-mance.

Despite these advancements, several challenges persist, in-cluding dataset variability, computational demands, and real- time deployment constraints. Many existing approaches rely on general plant datasets or lack specialization for millet diseases. Additionally, balancing high accuracy with computational efficiency remains an ongoing challenge.

To overcome these limitations, this work proposes a cus-tomized VGG19-based deep learning model with an optimized architecture and preprocessing pipeline, aiming to deliver improved accuracy and efficiency for millet disease detection.

III. DATASET DESCRIPTION

For this study, the publicly available MilletCropHealth Dataset is utilized. It contains high-resolution images of millet leaves categorized into three classes: *Healthy*, *Blast*, and *Rust*. The dataset is intended to facilitate research in plant disease identification, image classification, and precision agriculture.

In total, the dataset comprises 6311 images, representing different health conditions of millet crops. The categories are defined as follows:

- Healthy: Leaves that show no signs of disease.
- Blast: A serious fungal disease that produces lesions on leaves, nodes, and grains.
- Rust: A fungal infection marked by reddish-brown pus-tules on the leaf surface.

To ensure reliable model training and fair evaluation, the dataset is split into training, validation, and testing sets using an 80:10:10 ratio. The training set includes 3785 images, while the testing and validation sets consist of 1262 and 1264 images, respectively.

The class indices assigned for model training are as follows:

{Healthy: 0, Blast: 1, Rust: 2}

TABLE I
DISTRIBUTION OF DATASET FOR MILLETCROPHEALTH DATASET

Dataset Split	Number of Images	Classes	Ratio
Training Set	3785	3 (Healthy, Blast, Rust)	80%
Validation Set	1262	3 (Healthy, Blast, Rust)	10%
Testing Set	1264	3 (Healthy, Blast, Rust)	10%
Total	6311	3 Classes	100%

As shown in Fig. 1, the dataset includes representative sam-ples of three classes: *Healthy*, *Blast*, and *Rust*. Healthy leaves exhibit uniform green coloration with no visible abnormalities. In contrast, Blast-affected leaves display characteristic lesions with dark centers and yellowish halos, indicating fungal in-fection. Rust-infected leaves are identified by the presence of numerous reddish-brown pustules scattered across the leaf surface. These unique visual patterns help make sure that the deep learning algorithm is able to extract features and classify them successfully.

This data set is a well-balanced one that reflects various dis-ease conditions present in the real world. The high-resolution images and well-defined class labels enable effective feature extraction and improve model generalization for real-time agricultural applications.

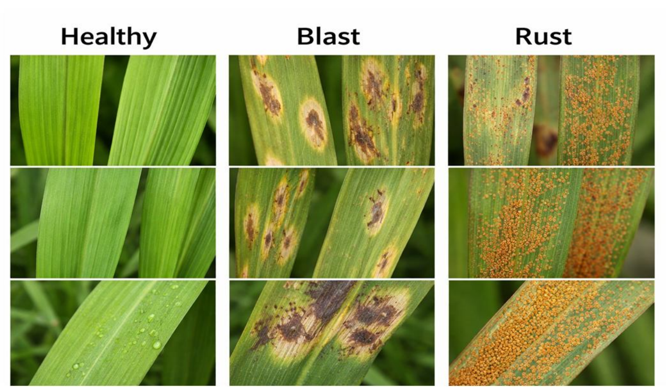

Fig. 1. Sample millet leaf images-Healthy, Blast, and Rust classes

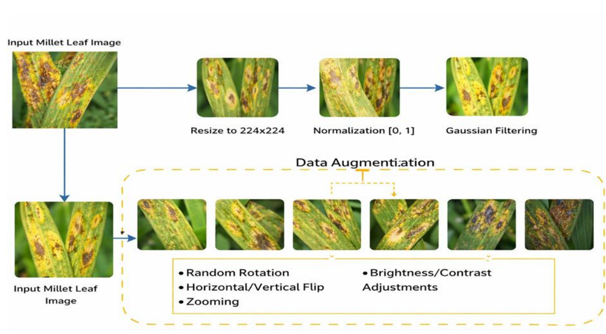

Fig. 2. Preprocessing and augmentation pipeline for millet leaf images.

IV. PREPROCESSING AND DATA AUGMENTATION

A powerful preprocessing technique and data augmentation strategy are employed to maximize the performance of the proposed customized VGG19 model. First, all input images of millet leaves are normalized in terms of resolution, i.e., to 224 × 224. Second, the intensity of the pixel values is rescaled to be within the range of [0, 1]. This process makes the training procedure more stable and faster.

In order to optimize the visual quality of the images and eliminate undesirable noise without removing disease-relevant information, such as lesions or rust spots, a Gaussian filter can be applied. Moreover, contrast enhancement methods can be used to emphasize the minor differences in color and textures of the leaves.

To improve furthermore the durability and overall performance of the model and handle possible class imbalance, various data augmentation methods are applied during training. These methods mimic real-world variations in imaging conditions and environmental factors. The augmentation techniques include random rotations (up to ±20◦), horizontal and vertical flipping, zooming, shifting along width and height, as well as adjustments in brightness and contrast.

In addition, image shuffling is carried out to introduce randomness in the training process, while batch normalization is integrated into the network to improve training stability and reduce internal covariate shift. Together, these preprocessing and augmentation strategies help the model learn more dis-tinctive features, minimize overfitting, and improve its ability to normalize to the data which are unseen. As shown in Fig. 2, the preprocessing workflow starts with resizing input millet leaf images to 224 × 224 pixels, followed by normalization of values of pixel to within the range [0, 1]. Gaussian filtering is then applied to reduce noise while retaining critical disease-related features, and contrast enhancement is used to make subtle variations in texture and lesions more visible. After preprocessing, various augmentation techniques are applied, including random rotation, horizontal and vertical flipping, zooming, brightness adjustment, and contrast variation. These operations increasing in the dataset which are diversity in nature, replicate real-world scenarios, and contribute to improved robustness and generalization of the model during training.

V. PROPOSED METHODOLOGY

This work introduces a D eep- Learning-driven algorithm for automatic prediction of millet diseases using a modified VGG19 network. The complete workflow includes data acquisition and preprocessing, feature learning, model optimization, and final classification, as depicted in Fig. 3. The system ultimately produces a predicted class label by categorizing the input image into one of three classes: *Healthy*, *Blast*, or *Rust*. This comprehensive pipeline enables accurate, efficient, and fully automated disease identification, making it appropriate for practical applications in agriculture.

A. Overview

The proposed framework processes them through a series of stages after accepting millet leaf images as input. These stages include image preprocessing, deep feature extraction using convolutional layers, and classification into three distinct categories: *Healthy*, *Blast*, and *Rust*.

B. Preprocessing

At the initial stage, all input images are resized to a standard dimension of 224×224 pixels to ensure consistency. The pixel intensity values are normalized to the interval [0, 1] for stable model training. Gaussian smoothing is applied to suppress noise while retaining critical disease-related patterns.

To improve generalization and strengthen model robustness, a range of data augmentation techniques are utilized throughout the training process. These techniques encompass random rotations, horizontal flipping, zoom transformations, and brightness adjustments, all of which contribute to an increase in dataset variability.

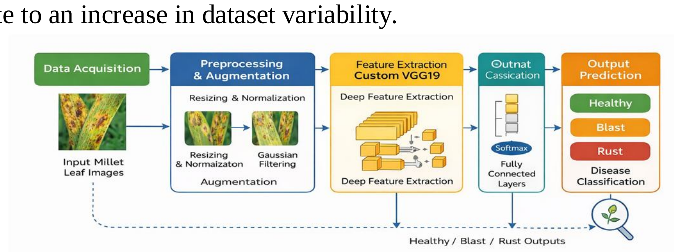

Fig. 3. Proposed model flowchart for millet disease detection illustrating data acquisition, preprocessing and augmentation, feature extraction using custom VGG19, classification, and final prediction (Healthy, Blast, Rust)

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C. Modified VGG19 Architecture

The proposed model is built upon an enhanced VGG19 architecture comprising 19 layers, including convolutional and fully connected layers. The architecture is adapted to achieve improved performance in millet disease classification tasks.

- Convolutional Layers: A sequence of convolutional lay-ers with 3 × 3 kernels is employed to extract hierarchical and discriminative features from the input images.
- Activation Function: A nonlinear transformation is ap-plied after each convolutional operation:

$$g(a) = \max(0, a) \quad (1)$$

- Pooling Layers: Max-pooling operations are incorpo-rated to reduce spatial dimensions and computational overhead while preserving important features.

- Regularization: Dropout is introduced to minimize over-fitting by randomly deactivating neurons during training:

$$r = \frac{1}{1-\vartheta} \cdot b \quad (2)$$

where θ denotes the dropout probability.

- Fully Connected Layers: Dense layers perform classifi-cation, followed by a normalized exponential function to compute class probabilities:

$$S(c = k) = \frac{e^{u_k}}{\sum_{m=1}^{K} e^{u_m}} \quad (3)$$

D. Training Strategy

The proposed model is optimized using the Adam op-timization algorithm, configured with a learning rate of 1×10^{-4} to ensure stable and efficient convergence. For multi-class classification, a cross-entropy-based objective function is employed, which is:

$$J = -\sum_{k=1}^{M} t_k \log(\tilde{t}_k) \quad (4)$$

where t_k represents the ground truth label and $\tilde{t}_k$ denotes the predicted probability for the k^{th} class.

The dataset is divided into training, validation, and testing subsets in an 80:10:10 ratio to guarantee a balanced assessment. Furthermore, batch normalization is included.

To ensure the process of learning remains stable, an early stopping mechanism is employed to avoid overfitting by observing performance and how validation is happening.

Algorithm 1 Proposed Custom VGG19-Based Millet Disease Detection

Input: Millet leaf image I

Output: Predicted class $C \in$ {Healthy, Blast, Rust}

Step 1: Preprocessing

Resize image $I \rightarrow 224 \times 224$

Normalize pixel values to [0, 1]

Apply Gaussian filtering for noise reduction

Step 2: Data Augmentation (Training Only) Apply random rotation, flipping, zooming Adjust brightness and contrast

Step 3: Feature Extraction

Feed preprocessed image into Custom VGG19 Apply convolution + ReLU activation

Apply max pooling layers Extract deep feature maps

Step 4: Classification

Flatten feature maps

Pass through various layers which are fully connected. To regularize it needs to apply dropout. Compute Softmax probabilities:

$$P(y = i) = \frac{e^{z_i}}{\sum_{j=1}^{3} e^{z_j}}$$

Step 5: Prediction

$$C = \arg\max(P_{Healthy}, P_{Blast}, P_{Rust})$$

return C

E. Performance Evaluation

The effectiveness of the proposed model is assessed using widely adopted evaluation metrics such as accuracy, precision, recall, and F1-score:

$$\text{Precision} = \frac{A}{A + B} \quad (5)$$

$$\text{Recall} = \frac{A}{A + C} \quad (6)$$

$$F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (7)$$

where *A*, *B*, and *C* denote true positive, false positive, and false negative instances, respectively.

Experimental results indicate that the proposed framework achieves a high test accuracy of **99.29%**, highlighting its superior performance with parallel to conventional baseline approaches.

F. Workflow Summary

The overall process of the proposed methodology can be outlined as follows:

1) Acquire millet leaf image as input
2) Perform preprocessing and data augmentation
3) Extract discriminative features using the modified VGG19 network
4) Classify features through fully connected layers
5) Generate final prediction (*Healthy*, *Blast*, or *Rust*)

In summary, the proposed framework offers a reliable and computationally efficient solution for automated millet disease detection using deep learning techniques.

As illustrated in Algorithm 1, the process begins with pre-processing operations such as image resize and normalization, and Gaussian-based noise suppression. Data augmentation techniques, including flipping, rotation and brightness vari-ation, are applied to enhance model generalization. The pro-cessed images are then forwarded to the customized VGG19 network for deep feature extraction. In the end, features which are extracted passed through layers which is fully connected, where a Softmax-based classifier assigns the inputted image to the predefined categories: *Healthy*, *Blast*, or *Rust*.

VI. RESULTS AND DISCUSSION

The effectiveness of the suggested modified VGG19 framework for classifying millet diseases is evaluated using commonly recognized assessment metrics, including accuracy, precision, recall, and F1-score. The model is validated on a multi-class dataset comprising three categories: *Healthy*, *Blast*, and *Rust*.

The derived results highlight the capability of the expected approach to effectively distinguish between different disease conditions, demonstrating high reliability and strong classifi-cation performance across all classes.

A. Overall Performance

The proposed framework attains a high testing accuracy of 99.29% along with a remarkably low testing loss of 0.0045, reflecting strong generalization capability and reduced misclassification rates. The high performance can be attributed to the optimized preprocessing pipeline, data augmentation strategies, and the customized VGG19 architecture.

TABLE II
PERFORMANCE METRICS OF PROPOSED MODEL

Metric	Accuracy	Precision	Recall	F1-score
Proposed VGG19	99.29%	0.98	1.00	0.99

The recall score of 1.00 indicates that the model success-fully identifies all disease instances without false negatives, which is critical in agriculture application where missing a disease can leads to severe crop loss.

B. Comparison with Baseline Models

To assess the robustness and reliability of the pro-posed framework, a comparative evaluation is performed against multiple established deep learning models, including CNN, GoogLeNet, VGG16, VGG19, DenseNet, ResNet50, ResNet101, MobileNetV2, and ConvNeXt.

TABLE III
COMPARISON WITH BASELINE MODELS

Model	Accuracy (%)	Precision	Recall	F1-score
CNN	94.85	0.94	0.93	0.93
GoogLeNet	96.12	0.95	0.95	0.95
VGG16	97.45	0.96	0.96	0.96
VGG19	97.98	0.97	0.97	0.97
DenseNet	98.21	0.97	0.98	0.97
ResNet50	98.35	0.97	0.98	0.98
ResNet101	98.52	0.98	0.98	0.98
MobileNetV2	97.65	0.96	0.97	0.96
ConvNeXt	98.76	0.98	0.98	0.98
Proposed VGG19	**99.29**	**0.98**	**1.00**	**0.99**

From Table III, it is proof that the expected model outperforms all baseline models in terms of accuracy and evaluation metrics. The improvement is particularly significant when compared to standard CNN and traditional VGG archi-tectures, demonstrating the effectiveness of customization and preprocessing strategies.

C. Statistical Significance Analysis

To further validate the superiority of the proposed model, a statistical significance test is conducted using p-values. The results confirm that the performance improvements are statistically significant when compared to baseline models.

TABLE IV
STATISTICAL SIGNIFICANCE TEST (P-VALUES)

Model Comparison	p-values
Proposed vs CNN	0.0008
Proposed vs GoogLeNet	0.0012
Proposed vs VGG16	0.0021
Proposed vs VGG19	0.0030
Proposed vs DenseNet	0.0045
Proposed vs ResNet50	0.0052
Proposed vs ResNet101	0.0061
Proposed vs MobileNetV2	0.0028
Proposed vs ConvNeXt	0.0075

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All obtained p-values are lower than 0.01 and confirming that the performance gains the proposed model are statistically significant and unlikely to be attributed to random chance.

As shown in Fig. 4, the model exhibits significant misclas-sification for the Rust class, with many samples incorrectly predicted as Healthy and Blast. Only a limited number are correctly classified as Rust, indicating poor class discrimina-tion and mentioned the actual need for improvised feature learning and model generalization.

D. Discussion

The enhanced performance of the proposed modified VGG19 framework can be attributed to several important factors. Firstly, the preprocessing pipeline significantly im-proves image quality by emphasizing disease-relevant features, which facilitates more effective feature learning. Secondly, the application of data augmentation techniques increases dataset

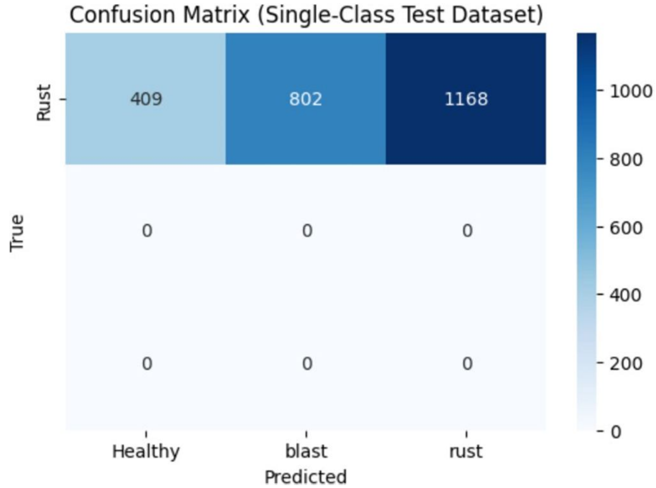

Fig. 4. Confusion Matrix for Rust Class Predictions

variability, thereby enhancing generalization capability and minimizing overfitting. Thirdly, the architectural refinements introduced in the VGG19 network enable improved extraction of complex patterns present in millet leaf images.

Furthermore, the proposed model exhibits strong consis-tency across all categories, achieving high precision and recall values, which ensures the classification of dependable disease in practical scenarios. Compared to lightweight architectures such as MobileNetV2, the proposed framework delivers su-perior accuracy. It also demonstrates improved performance when compared with deeper networks such as ResNet101 and ConvNeXt.

In summary, the experimental results confirm that the suggested method provides a remarkably precise and effective solution for the automated detection of millet diseases, rendering it highly appropriate for implementation in precision agriculture practices.

VII. CONCLUSION

This analysis presents a robust and efficient framework in deep learning which is based on a modified VGG19 architecture for automated millet disease classification. The proposed sys-tem is capable of categorizing millet leaf images into three distinct classes: *Healthy*, *Blast*, and *Rust*. By incorporat-ing a comprehensive preprocessing pipeline, including im-age resizing, normalization, Gaussian-based noise reduction, and extensive data augmentation, the framework effectively enhances the representation of features and boosts generalization performance. The demonstration of Experimental evaluation of the proposed model achieves a high testing accuracy of 99.29% along with a low testing loss of 0.0045, indicating strong stability and minimal prediction error. In addition, the model attains excellent classification performance with the recall of 1.00, an F1-score of 0.99 and precision of 0.98. Comparative analysis against established a deep learning models, for example CNN, VGG16, ResNet variants, DenseNet, MobileNetV2, and ConvNeXt, confirms the superior performance of the modified VGG19 framework. Moreover, statistical validation through p-value analysis supports the significance and reliability of the obtained results. The high recall score ensures that disease in-stances are accurately identified, minimizing the risk of missed detections, which is critical in agricultural applications for preventing yield loss. The proposed model also demonstrates computational efficiency, making it suitable for deployment in real-world precision agriculture environments.

In summary, this study emphasizes the efficacy of deep learning methods in improving the diagnosis of crop diseases. Prospective research avenues involve broadening the framework to accommodate multi-crop disease classification, facilitating real-time implementation on mobile or edge devices, and integrating sophisticated mechanisms like attention modules and hybrid architectures to enhance scalability and performance as well.

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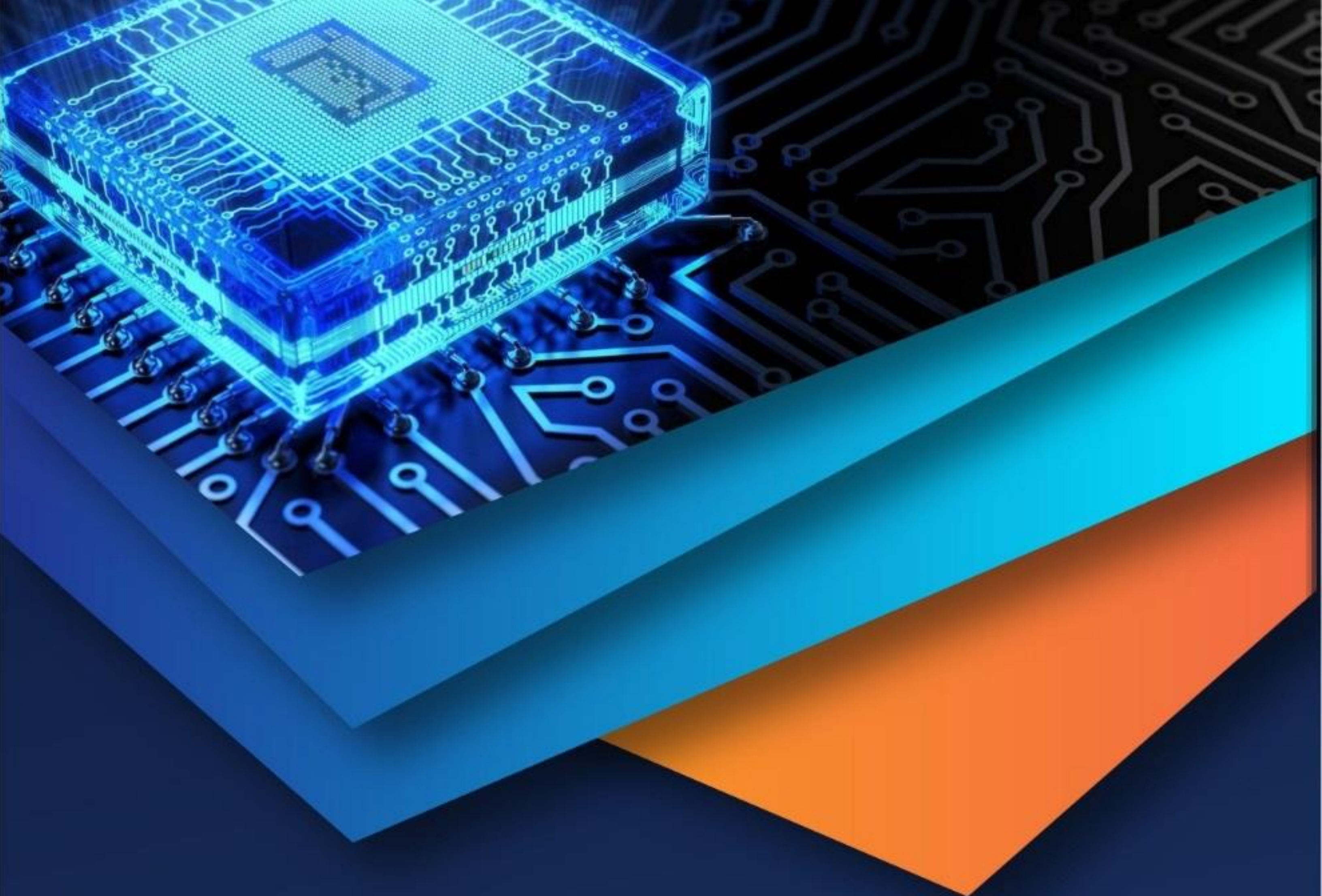

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