The Academic
International Journal of Multidisciplinary Research

An Online Peer Reviewed / Refereed Journal
Volume 2 | Issue 10 | October 2024
ISSN: 2583-973X (Online)
Website: www.theacademic.in

AI-Powered Insights for Early Detection and of Sugarcane Leaf Diseases Using VGG16 Deep Learning Model

Ubaidulla S
Research Scholar, PG & Research Department of Computer Science,
Presidency College (Autonomous) Chennai.

Dr. Mary Vennila S
Associate Professor & Head, PG & Research Department of Computer Science,
Presidency College (Autonomous), Chennai.

ARTICLE DETAILS

Research Paper

Keywords:
Sugarcane leaf disease, Deep Learning, VGG16, Data Augmentation, Regularization

DOI:
10.5281/zenodo.14106421

ABSTRACT

The early detection of diseases in sugarcane crops is critical for ensuring optimal yields and mitigating economic losses [1]. This study presents a deep learning-based approach for the early identification of sugarcane leaf diseases using the VGG16 convolutional neural network model. A comprehensive dataset of sugarcane leaf images was collected and subjected to preprocessing, including normalization and various data augmentation techniques, such as rotation, shifting, and zooming, to enhance the model's resilience against dataset variability.

By implementing transfer learning with VGG16, the model was refined to effectively extract features pertinent to sugarcane leaf diseases, with specific layers frozen to retain pre-trained knowledge. The model's performance was meticulously assessed through metrics of accuracy and loss, supplemented by classification reports that elucidated its diagnostic capabilities. The results indicate substantial test accuracy, underscoring the efficacy of this AI-driven methodology in the realm of agricultural disease management. Visualizations, including confusion matrices, were utilized to illustrate the model's classification performance across different disease categories, affirming its applicability in real-world

agricultural practices.

Introduction

Sugarcane (Saccharum officinarum) is one of the most economically significant crops globally, serving as a vital source of sugar, biofuel, and various by-products. However, its productivity is severely hampered by numerous leaf diseases, which can lead to substantial yield losses and adversely affect the agricultural economy. Traditional methods of disease detection, primarily reliant on visual inspection by farmers, often result in late diagnosis, contributing to ineffective management strategies and increased economic losses [2]. Consequently, there is an urgent need for innovative solutions that enable early and accurate detection of sugarcane leaf diseases.

Recent advancements in deep learning, particularly in computer vision, offer promising avenues for automating the identification and classification of plant diseases [3]. Convolutional Neural Networks (CNNs), with their ability to learn hierarchical features from images, have shown remarkable success in image classification tasks across various domains, including agriculture. Among these architectures, the VGG16 model, known for its depth and efficacy in feature extraction, presents an excellent opportunity for transfer learning applications in plant disease detection.

This research aims to leverage the VGG16 architecture for the early detection of sugarcane leaf diseases. By employing techniques such as data augmentation and regularization, the study seeks to enhance model performance, thereby achieving high accuracy in disease classification. The proposed approach not only promises to improve the accuracy of disease identification but also aims to facilitate timely intervention strategies, ultimately contributing to sustainable sugarcane farming practices [18].

Related Works

Santhrupth B.C. et al. [4] reported that a Convolutional Neural Network (CNN) achieved a 61% accuracy in classifying sugarcane leaf diseases. While CNNs are effective in feature extraction, the limited accuracy could stem from dataset constraints or model complexity. They suggested that tuning hyperparameters or applying data augmentation may enhance performance.

Ms. V. Sonia Devi et al. [5] applied deep learning techniques for the detection and classification of sugarcane diseases using Convolutional Neural Networks (CNNs). Their approach demonstrates the effectiveness of CNN architectures, such as AlexNetV2, in achieving high accuracy for the diagnosis of various sugarcane leaf diseases, thus providing a valuable tool for disease management and improving crop yield.

Latha D et al. [6] presents a deep learning-based system for detecting leaf diseases, using the MobileNet model to classify diseases in crops like maize, sugarcane, wheat, and grape. The approach includes steps for image preprocessing, green pixel masking, segmentation, and classification using CNN. It achieves a 78% accuracy, and a drone prototype is proposed for large-scale field monitoring. This automated solution provides early detection and actionable remedies to farmers via SMS.

Archana Saini et al. [7] focuses on categorizing sugarcane leaf diseases to improve diagnosis and management, essential for sustainable production. A small VGG model was employed, with Epoch 20 yielding the best performance: training loss of 0.6984 and accuracy of 0.7421, alongside testing loss of 0.8423 and accuracy of 0.6731. The findings aim to bolster sustainable practices, ensuring the stability of the global sugarcane industry.

Pathak L. et al. [8] presents a technique for accurately identifying agricultural leaf diseases using deep learning algorithms and transfer learning with pre-trained models such as VGG19, MobileNet, InceptionV3, EfficientNetB0, and Simple CNN. The study evaluates model performance through metrics like accuracy, precision, recall, and F1 score, highlighting the effectiveness of artificial intelligence in automated disease detection. The findings contribute to developing reliable disease prevention systems in agriculture, promoting precision agriculture and sustainable farming practices, with future research focusing on dataset balance and model interpretability.

Feng L. et al. [9] investigates the use of hyperspectral imaging and deep transfer learning for the rapid and accurate detection of rice diseases across different rice varieties. Fine-tuning demonstrated the best performance with over 83% accuracy, while the multi-task transfer strategy showed promising results, highlighting the effectiveness of deep transfer learning methods in rice disease detection. The findings suggest that combining hyperspectral imaging with deep transfer learning offers a cost-effective solution for field detection of rice diseases.

Agarwal V et al. [10] analyzes and classifies five types of bacterial and fungal diseases affecting Oryza Sativa, with the goal of reducing the 37% quantitative loss in rice plantations through early detection. A smart mobile app leverages a Deep Learning model (GoogLeNet) for timely disease classification and recommends the ideal pesticide quantity, overcoming the limitations of manual inspection. By utilizing transfer learning and the Grad-CAM technique, the system achieved an overall test accuracy of 80%, significantly improving upon traditional image processing methods.

Gong X et al. [11] highlight that apple leaf diseases significantly impact sustainable apple fruit production, making early infection monitoring and timely disease control essential for growth and economic efficiency. To address the limitations of traditional detection methods, an improved Faster R-CNN method utilizing Res2Net and feature pyramid network architecture was developed for reliable feature extraction, achieving 63.1% average precision. This method enhances apple leaf disease recognition, demonstrating its effectiveness for practical agricultural applications.

Paleti L et al. [12] presents a novel plant disease recognition model focused on sugarcane leaf image classification using deep convolutional networks, achieving an accuracy of 83%. The approach explores the effectiveness of k-NN and SVM in pre-training with ANN, followed by CNN-based methods for automatic recognition of sugarcane leaf diseases.

Methodology

Methodology

Methodology

The proposed methodology for classifying images of sugarcane plant diseases involved several key steps. Initially, a dataset consisting of images of four plant diseases—Mosaic, RedRot, Rust, Yellow and Healthy leaves—was collected and organized into training and testing datasets, with a total of 175 training images and 75 testing images, resized to a uniform dimension of 150x150 pixels.

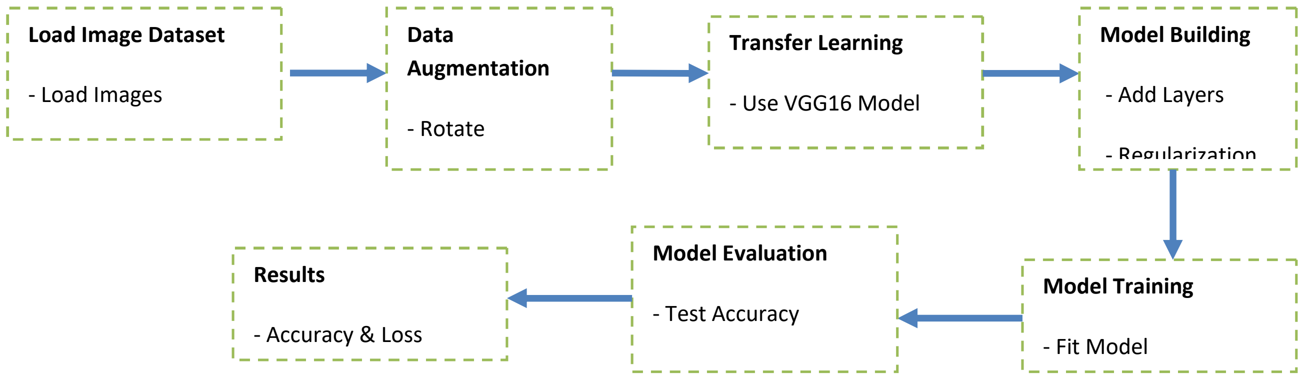

Figure 1: Methodology for detecting diseases in sugarcane leaves

Figure 1 illustrates the proposed methodology for detecting diseases in sugarcane leaves using a deep learning approach. The process involves loading and augmenting the dataset, applying transfer learning with a pre-trained VGG16 model, and evaluating the model's performance through comprehensive metrics.

Preprocessing included normalizing pixel values and converting labels to categorical format. Data augmentation techniques such as rotation, shifting, shear transformations, zooming, and horizontal flipping were applied to enhance model generalization. Table 1 presents the key model parameters used in the VGG16-based classification for sugarcane leaf disease detection. These parameters include layer configurations, regularization techniques, and optimization settings, which collectively contribute to the model's performance and accuracy.

Parameter	**Value**
Model	VGG16
Image Size	(150, 150)
Normalization	Pixel values scaled to [0, 1]
Label Encoding	Categorical (one-hot encoding)

Data Augmentation Techniques	Rotation, Width Shift, Height Shift, Shear, Zoom, Horizontal Flip
Dropout Rate	0.5
L2 Regularization	$\lambda = 0.001$
Optimizer	Adam (learning rate = 0.00005)
Loss Function	Categorical Crossentropy
Training Epochs	100
Batch Size	32
Early Stopping Patience	10
Learning Rate Reduction Factor	0.5
Minimum Learning Rate	0.00001

Table 1: Model Parameters for VGG16-Based Classification

The model utilized in this study is based on the VGG16 architecture, a well-established convolutional neural network known for its deep structure and effective feature extraction capabilities [13]. VGG16 comprises 16 layers with learnable weights, including 13 convolutional layers and three fully connected layers. It employs small receptive fields (3x3 convolutions) and a consistent architecture that allows for deeper networks while maintaining manageable parameters. The model leverages pre-trained weights from ImageNet, enabling it to benefit from prior learning and significantly reduce training time. For this implementation, some layers of the VGG16 model were frozen to serve as a feature extractor, while others were fine-tuned to adapt to the specific characteristics of the plant disease dataset. The architecture was complemented by additional layers, including a flattening layer, a dense layer with 512 units featuring L2 regularization, batch normalization to improve convergence, and dropout to mitigate overfitting. The final output layer employed softmax activation to classify the input images into multiple categories, making the model highly suitable for the complex task of plant disease classification.

Results and Discussion

The findings of this study are highly encouraging, demonstrating the effectiveness of the deep learning model in accurately classifying sugarcane leaf diseases [14]. The substantial improvements in training and validation accuracy over 40 epochs indicate that the model successfully learned to identify the nuanced features associated with each disease class [15].

The model's ability to reach a training accuracy of 90.11% underscores its capacity to effectively generalize learned features from the training dataset. Furthermore, the validation accuracy of 70.67% suggests that the model is not only memorizing the training data but is also capable of recognizing and classifying unseen data. The Figure 2 compares the Accuracy and Loss during the training and validation process.

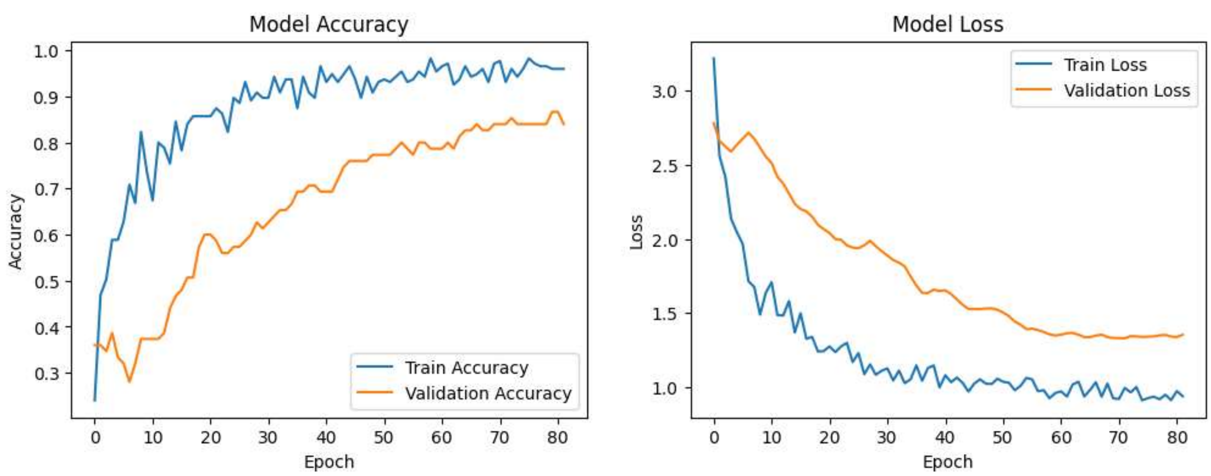

Figure 2: Model Accuracy and Loss

The results of the model trained are summarized in Figure 3. Figure 3 illustrates the performance metrics of the model across different training epochs, highlighting the accuracy and loss trends.

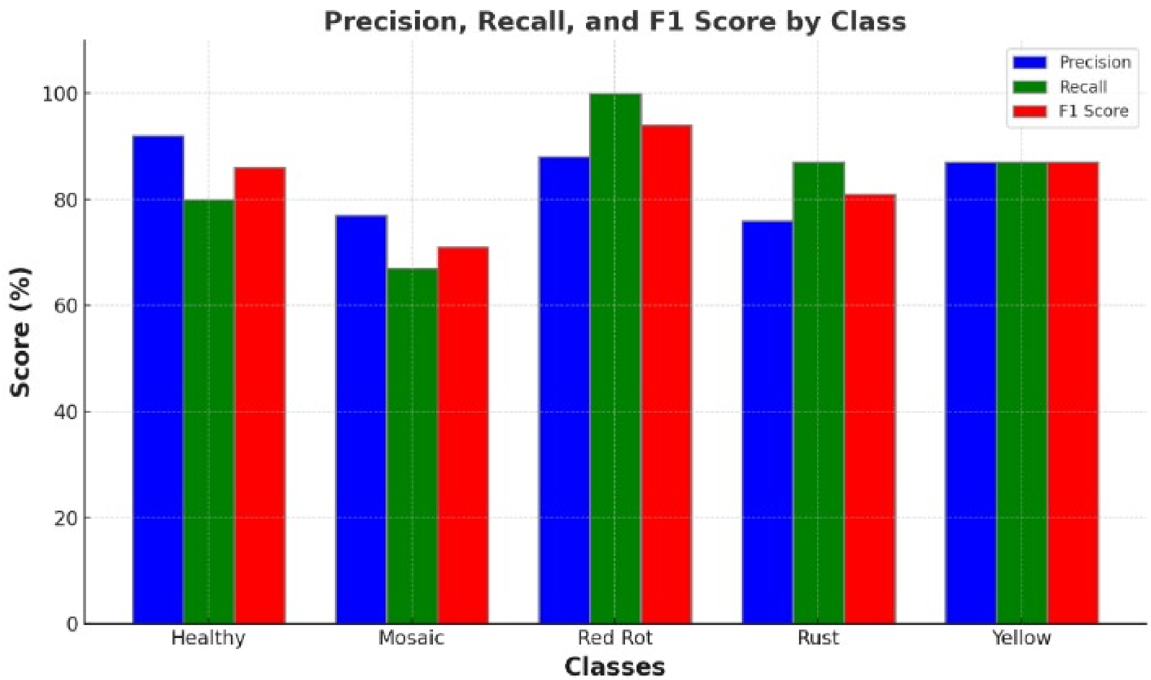

Figure 3: Comparison of Precision, Recall and F1 Score

Figure 4 presents the confusion matrix, which provides a visual representation of the model's classification performance across the different classes. The matrix highlights the true positives, false positives, true negatives, and false negatives, allowing for an assessment of where the model may be misclassifying instances.

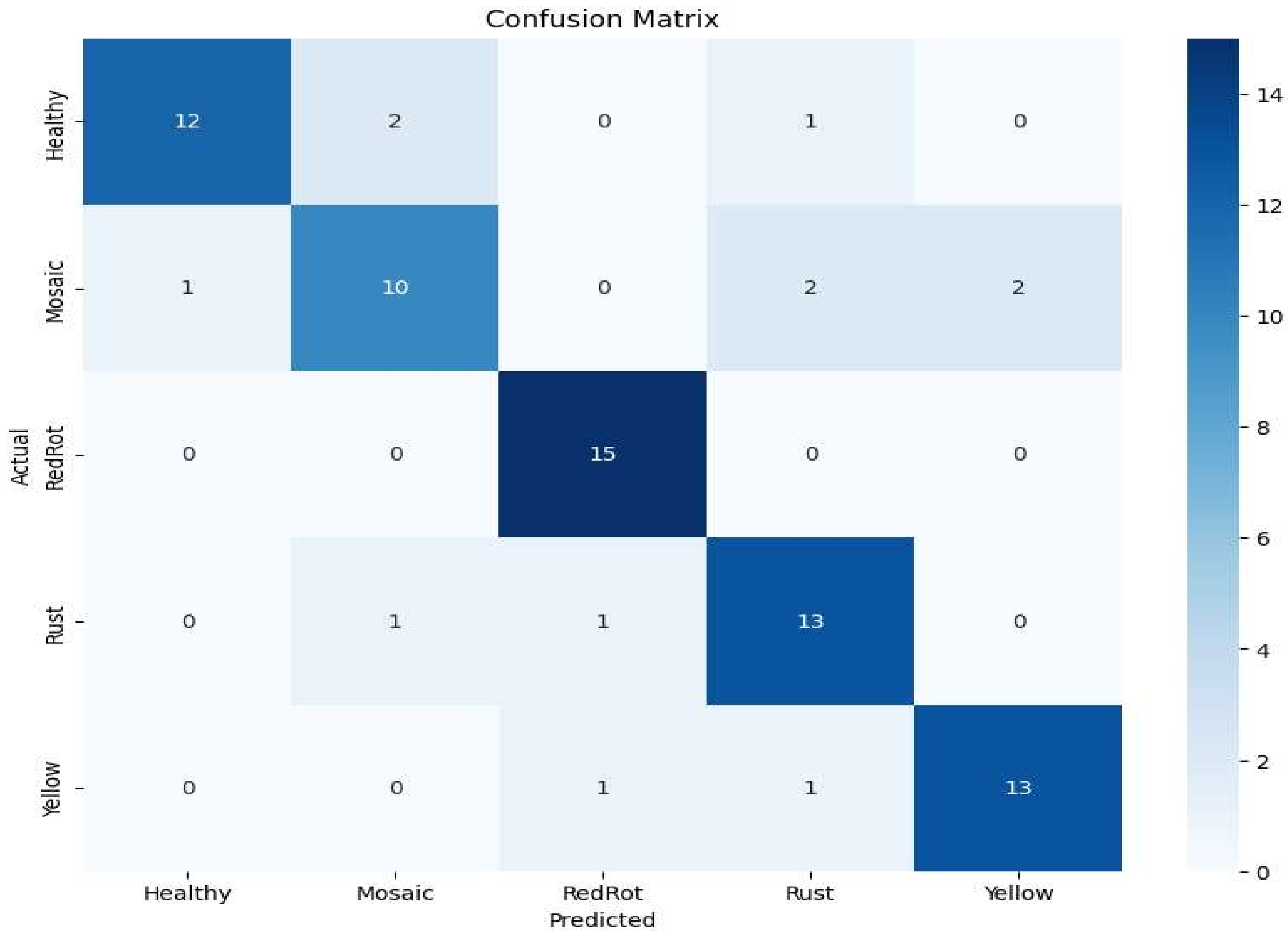

Figure 4: Confusion Matrix for Sugarcane Leaf Disease Classification

The VGG16 model was employed for the classification task. The results demonstrate an overall accuracy of 84%. This performance reflects the model's effectiveness in distinguishing between the various classes. Figure 5 illustrates the performance differences between the existing model and the proposed model, highlighting significant improvements in accuracy. The proposed model demonstrates enhanced capability in classifying sugarcane leaf diseases, showcasing its effectiveness over other approaches.

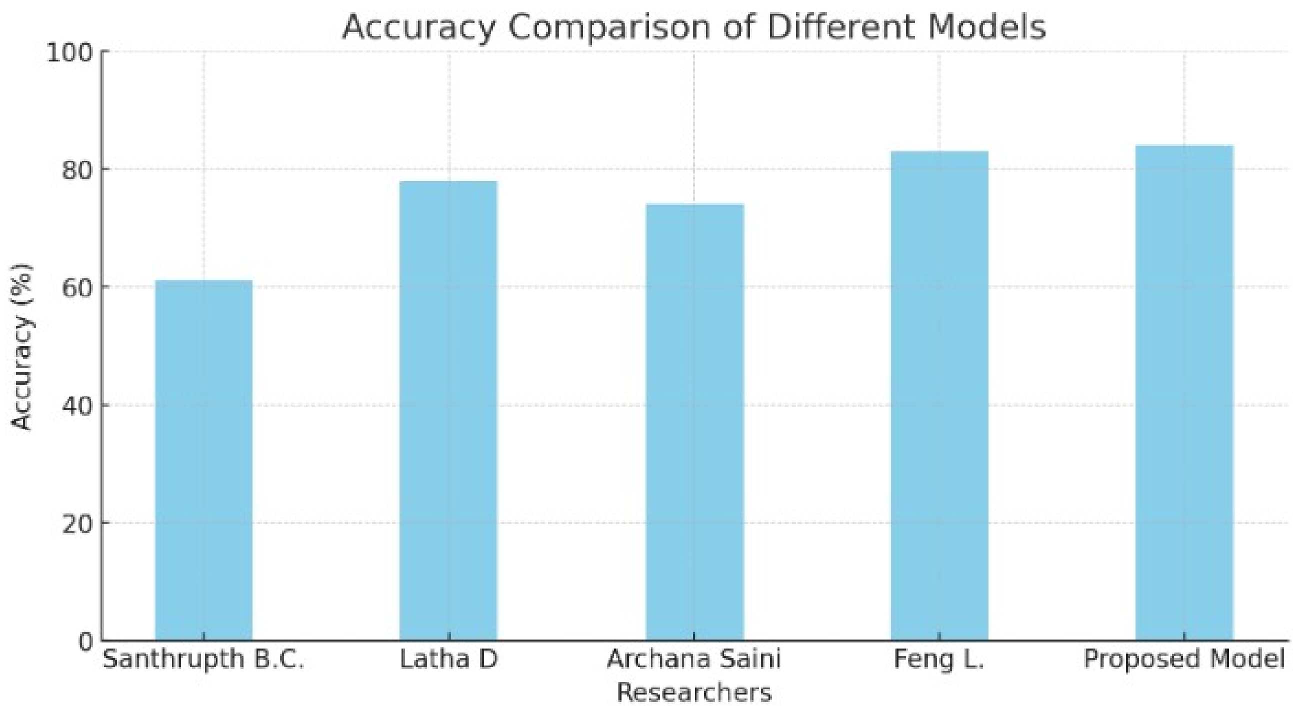

Figure 5: Comparison of Existing Model with Proposed Model

These results hold significant implications for agricultural practices, as accurate disease classification can lead to timely interventions, enhancing crop yield and sustainability [16]. The positive outcomes of this study lay the groundwork for future enhancements, such as the incorporation of advanced data augmentation techniques, hyperparameter tuning, and potentially exploring larger and more diverse datasets to further improve model performance.

This study highlights the transformative potential of deep learning in the field of plant disease classification. With continued refinement and application, these models can significantly contribute to precision agriculture, helping farmers make informed decisions that promote plant health and productivity [17].

Conclusion and Suggestions

The implementation of a deep learning model for classifying images of sugarcane plant diseases using transfer learning with VGG16 has shown promising results, achieving a test accuracy of 84%. By leveraging pre-trained weights and fine-tuning the model on a specific dataset, this accuracy demonstrates the model's effectiveness in distinguishing between different classes of plant diseases. The use of data augmentation techniques such as rotation, shifting, and flipping further enhanced the model's ability to generalize to unseen data by artificially expanding the training dataset.

The classification report and confusion matrix indicate that the model not only performs well overall but also provides insights into specific classes where performance excels or struggles, allowing for targeted improvements in future iterations. The incorporation of L2 regularization and dropout mitigated the risk of overfitting, maintaining a balance between training and validation performance.

Future work may involve exploring more advanced architectures, such as EfficientNet or ResNet, to improve classification performance further. Additional experimentation with hyperparameter tuning and regularization techniques could enhance model robustness and generalization. Expanding the dataset with more diverse plant disease images will also be beneficial for training more accurate models.

References:

Upadhye, S.A., Dhanvijay, M.R., & Patil, S.M. (2022). Sugarcane Disease Detection Using CNN-Deep Learning Method. 2022 Fourth International Conference on Emerging Research in Electronics, Computer Science and Technology (ICERECT), 1-8.

T, R., J, U., R, R., P, R., A, A.R., & A, M.H. (2024). Deep Learning for Enhancing Sugarcane Disease Detection Using DenseNet Architecture. 2024 International Conference on Science Technology Engineering and Management (ICSTEM), 1-6.

Dhawan, N., Kukreja, V., Sharma, R., Vats, S., & Verma, A. (2023). Deep Learning Based Sugarcane Downy Mildew Disease Detection Using CNN-LSTM Ensemble Model for Severity Level Classification. 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), 1-5.

B. C., S. ., & Verma C., D. . (2023). Intelligent Disease Detection in Sugarcane Plants: A Comparative Analysis of Machine Learning Models for Classification and Diagnosis. International Journal of Intelligent Systems and Applications in Engineering, 12(8s), 299–306.

Devi, M.V., KiranV, G., Vidya, V., & Sagar, A. Sugarcane Disease Detection Using Deep Learning.

Latha, D.H., & Mubeen, A. (2022). LEAF DISEASE DETECTION USING DEEP LEARNING MODELS. International Journal of Engineering Applied Sciences and Technology.

Saini, A., Guleria, K., & Sharma, S. (2024, July). An Efficient TinyVGG Model for Sugarcane Leaf Disease Classification in Precision Agriculture. In *2024 2nd World Conference on Communication & Computing (WCONF)* (pp. 1-6). IEEE.

Pathak, L., Virani, M., & Kansara, D. (2024). Classifying Crop Leaf Diseases using Different Deep Learning Models with Transfer Learning. *International Journal of Innovative Science and Research Technology (IJISRT)*.

Feng, L., Wu, B., He, Y., & Zhang, C. (2021). Hyperspectral Imaging Combined With Deep Transfer Learning for Rice Disease Detection. *Frontiers in Plant Science, 12*.

Agarwal, V., Kshirsagar, M., Jain, R., & Jain, S. (2022). Smart Mobile System for Detection and Classification of the (Oryza Sativa) Rice Plant Disease Using Deep Learning and Transfer Learning. International Journal for Research in Applied Science and Engineering Technology.

Gong, X., & Zhang, S. (2023). A High-Precision Detection Method of Apple Leaf Diseases Using Improved Faster R-CNN. *Agriculture*.

PALETI, L., NAGASRI, A., SUNITHA, P., SANDYA, V., SUMALLIKA, T., KANDUKURI, P., & KUMAR, K. K. (2023). SUGAR CANE LEAF DISEASE CLASSIFICATION AND IDENTIFICATION USING DEEP MACHINE LEARNING ALGORITHMS. Journal of Theoretical and Applied Information Technology, 101(20).

Hernandez, A.A., Bombasi, J.L., & Lagman, A.C. (2022). Classification of Sugarcane Leaf Disease using Deep Learning Algorithms. 2022 IEEE 13th Control and System Graduate Research Colloquium (ICSGRC), 47-50.

Srivastava, S., Kumar, P., Mohd, N.B., Singh, A.K., & Gill, F.S. (2020). A Novel Deep Learning Framework Approach for Sugarcane Disease Detection. SN Computer Science, 1.

Kunduracioglu, I., & Paçal, I. (2024). Deep Learning-Based Disease Detection in Sugarcane Leaves: Evaluating EfficientNet Models. *Journal of Operations Intelligence*.

Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. Computers and electronics in agriculture, 145, 311-318.

Hemalatha, N. K., Brunda, R. N., Prakruthi, G. S., Prabhu, B. B., Shukla, A., & Narasipura, O. S. J. (2022). Sugarcane leaf disease detection through deep learning. In *Deep Learning for Sustainable Agriculture* (pp. 297-323). Academic Press.

Chauhan, Y., Negi, N., & Sharma, S. (2024, August). Artificial Intelligence Based Sugarcane Leaf Disease Prediction System for Smart Farming. In 2024 7th International Conference on Circuit Power and Computing Technologies (ICCPCT) (Vol. 1, pp. 106-111). IEEE.