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CompSci & AI Advances

ISSN: xxxx-xxxx https://aristonpubs.com/computers-ai-advances https://doi.org/10.69626/cai.2024.0123

RESEARCH ARTICLE

Deep Learning Based Detection and Classification of Tobacco Leaf Diseases Using Convolutional neural networks

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ABSTRACT: Deep learning, a powerful subset of artificial intelligence, has emerged as a transformative tool in various domains, including agriculture, due to its ability to autonomously analyze complex data. This study focuses on the application of Convolutional Neural Networks (CNNs) for detecting and classifying diseases affecting tobacco leaves, a major concern in countries like India, one of the largest producers of tobacco. India produces an estimated 804 million kg of tobacco annually, with cultivation spanning half of its states. Traditional methods relying on manual inspection by farmers are time-consuming, subjective, and often inaccurate, leading to crop losses and reduced productivity. To overcome these challenges, this research developed a deep learning-based model leveraging real-time images of diseased tobacco leaves provided by farmers from the Prakasam district of Andhra Pradesh. A dataset comprising over 1000 annotated images depicting three distinct tobacco leaf diseases was curated for training and validation. The CNN model achieved an impressive accuracy of 95%, demonstrating its ability to accurately detect and classify diseases, enabling targeted interventions. The study not only underscores the efficiency of CNNs in revolutionizing disease detection but also highlights their role in reducing crop losses, improving yield, and supporting farmers with timely and unbiased disease diagnosis. By incorporating advanced image processing techniques and deep learning, this research provides a scalable, automated, and cost-effective solution to a pressing agricultural challenge, paving the way for improved crop management and sustainable farming practices.

Keywords: Deep Learning, Convolutional Neural Networks (CNNs), Tobacco Leaf Diseases, Image Processing in Agriculture.

Received: 17 March 2024; Revised: 28 April 2024; Accepted: 25 May 2024; Published Online: 13 June 2024

1. INTRODUCTION

India stands as one of the largest tobacco producers in the world, contributing significantly to both global tobacco production and the Indian economy. The cultivation, processing, and trade of tobacco collectively provide employment to approximately 50 million people across the country, making it a vital source of livelihood for millions [1]. Economically, tobacco production contributes a staggering annual revenue of around 12,00,000 crores rupees, further cementing its role as an integral part of India's agricultural sector. Despite its economic importance, tobacco cultivation faces substantial challenges due to plant diseases, which pose a persistent threat to crop yield, quality, and economic returns [2]. Tobacco leaves, in particular, are highly susceptible to diseases compared to other crops. These diseases not only reduce the quality of the tobacco produced but also result in severe economic losses for farmers and the broader industry. In a country where agriculture remains a cornerstone of the economy, plant diseases have far-reaching consequences, impacting food security, economic stability, and farmer livelihoods [3]. If left untreated or undetected, plant infections can spread rapidly, leading to significant reductions in agricultural productivity. Such reductions can exacerbate food shortages, further threatening the stability of

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rural economies that rely heavily on agriculture for survival [4].

The traditional methods of identifying plant diseases primarily rely on manual inspections performed by farmers or agricultural experts. These methods are labor-intensive, time-consuming, and prone to human error, particularly in large-scale farming operations [5]. Moreover, disease symptoms in plants often appear similar at early stages, making it challenging for farmers to accurately diagnose the problem without technical expertise. This limitation necessitates the development of automated and reliable systems for plant disease detection that are both efficient and scalable [6].

In recent years, image-based plant disease detection has emerged as a promising solution to address these challenges. By leveraging advancements in computer vision and machine learning (CVML) techniques, researchers have developed systems capable of identifying and diagnosing plant diseases by analyzing images of affected leaves [7]. This approach utilizes high-quality photographs, which are processed using deep learning algorithms to extract features and detect patterns associated with specific diseases. The advent of Convolutional Neural Networks (CNNs), a type of deep learning architecture, has further revolutionized this area of research. CNNs can automatically extract hierarchical features from images, enabling accurate classification and detection of plant diseases with minimal human intervention [8].

In the context of tobacco cultivation, three primary diseases are known to affect crop health and yield: Brown Spot, Granville Wilt, and Frogeye Leaf Spot [9]. These diseases recur frequently, causing substantial damage to tobacco leaves and reducing overall productivity. Brown Spot, caused by the fungus *Alternaria alternata*, results in brown lesions on leaves, while Granville Wilt, a bacterial disease, leads to wilting and premature plant death. Frogeye Leaf Spot, caused by the fungus *Cercospora nicotianae*, creates circular spots with gray centers, leading to leaf discoloration and reduced quality [10].

This research addresses these critical challenges by utilizing CNNs to detect and classify tobacco leaf diseases with high accuracy. A dataset comprising real-time images of diseased tobacco leaves was collected and annotated with the help of farmers from the Prakasam district of Andhra Pradesh. The CNN-based model developed in this study achieved an impressive accuracy rate of 95%, outperforming previous approaches, which reported an accuracy of 93%. The significance of this research lies in its ability to provide an automated, unbiased, and scalable solution for disease detection in tobacco leaves. By leveraging deep learning and computer vision, the proposed system offers a practical tool for farmers to monitor plant health, mitigate crop losses, and improve agricultural productivity. This study highlights the transformative potential of deep learning in advancing precision agriculture and underscores its role in addressing critical challenges in crop management.

2. LITERATURE REVIEW

In developing nations such as India, where ensuring access to sufficient food is a pressing problem and crop losses are caused by factors such as insufficient storage, transportation challenges, and plant diseases, there is a pressing need for cutting-edge solutions [1]. Deep learning provides benefits such as automated learning and feature extraction, which allow for more objective extraction of plant disease features and improve research productivity [2].Timely and precise identification of plant leaf diseases is essential for mitigating additional damage to plant species. This paper presents a novel method, the ACO-CNN, for the identification and categorization of diseases. The suggested system utilizes deep learning techniques, notably ACO for feature extraction and CNN for classification, to evaluate leaf photos. It identifies illnesses by examining color, texture, and leaf arrangement geometries. The study investigates the efficacy of illness detection using ACO and showcases enhanced precision in comparison to current methodologies [3]. The effective management of potato diseases is crucial in agriculture to prevent significant crop losses. This article addresses the need for timely recognition and classification of potato leaf diseases through an accurate automated technique [4].

This paper focuses on utilizing machine vision and convolutional neural network (CNN) methods for identifying and classifying surface defects in potatoes. The study addresses five classes of potato diseases, including Healthy, Black Scurf, Common Scab, Black Leg, and Pink Rot, using a database of 5000 potato images [5]. Agricultural production in India sustains a significant portion of the rural population and holds crucial economic importance. Cotton, a key export, contributes substantially to the country's economy. However, various crops, particularly cotton plants, face severe challenges such as pests, climate variations, and nutrient deficiencies [6].This project aims to use deep learning with novel ensemble architectures for the early identification of 9 tomato plant leaf illnesses, including healthy ones. The study utilizes a dataset consisting of 18,160 pictures. In addition to two newly developed convolutional neural network (CNN) models, four well-established CNNs models (MobileNetV3Small, EfficientNetV2L, InceptionV3, and MobileNetV2) are applied [7]. The aim of this research is to tackle the difficulties associated with the detection of illnesses in guava plants. The suggested system employs deep learning methodologies to accurately and efficiently identify several kinds of viruses from a single guava leaf in real-time [8].

This paper presents a novel approach that combines deep learning techniques to create a system capable of accurately and quickly identifying several illnesses from a single guava leaf in real-time. The framework utilizes deep learning approaches to specifically target the difficulties related to detecting diseases in guava plants. The suggested technique aims to enhance the efficiency and precision of disease detection, enabling prompt intervention and management strategies to reduce crop losses [9].Tobacco ring

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spot disease, Cucumber mosaic disease, and Tobacco leaf curl disease.The methodology involves the utilization of CLIPS and Delphi languages for the expert system's design and implementation. Noteworthy is the system's emphasis on user-friendliness, requiring minimal training for physicians to navigate effectively [10].Agriculture, a vital source of livelihood, employs a significant portion of the population in developing countries like India. With nearly 70% of India's population dependent on agriculture, it plays a crucial role in the country's economy. However, a lack of technical knowledge often leads to manual cultivation practices, hindering optimal crop selection and growth [11].

This research introduces a software application designed to detect early damage in tobacco leaves caused by the blue mold fungus (Peronospora tabacina Adam), a critical factor for ensuring agricultural sustainability. The application employs pattern recognition techniques based on Artificial Neural Network (ANN) to analyze images of tobacco leaves [12]. This study explores the possibility of identifying tobacco illness before symptoms appear using hyperspectral imaging. The research employs variable selection methods and machine-learning classifiers. The research used a hyperspectral reflectance imaging technology to acquire pictures of both healthy and Tobacco Mosaic Virus (TMV)-infected leaves at 2, 4, and 6 days after infection [13]. The research heralds the advent of CoffeeNet, an avant-garde deep learning (DL) model meticulously crafted for the precise identification and categorization of an array of anomalies afflicting coffee plant leaves [14]. In the agricultural domain, the expeditious identification of plant diseases is paramount for mitigating crop losses, ensuring premium yields, and promoting the adoption of sustainable farming practices. Recent agricultural trends underscore a disconcerting downturn in incomes, primarily stemming from the ubiquitous onslaught of bacterial, viral, and fungal infections [15].

3. PROPOSED WORK

The proposed work focuses on developing an efficient deep learning model to detect and categorize tobacco leaf diseases. This section elaborates on the methodology, data collection process, and the various stages involved in leaf disease detection and classification. The methodology involves systematic steps, starting with data acquisition and preparation, followed by model design, training, testing, and performance evaluation. A comprehensive visual representation of these steps is provided in Figure 1, offering a clear understanding of the sequential process.

The data collection process is fundamental to the success of the deep learning model. Real-time images of diseased tobacco leaves were collected with the help of farmers in the Prakasam district of Andhra Pradesh, where tobacco cultivation is prevalent. The images were carefully annotated and categorized into three major disease types: Brown Spot, Granville Wilt, and Frogeye Leaf Spot. In addition to real-time images, datasets from previously published studies were incorporated to increase data diversity and improve the robustness of the model. Overall, the dataset consisted of over 1,000 annotated images, ensuring adequate representation of each disease type.

Once collected, the data underwent preparation to ensure quality and compatibility with the deep learning algorithms. This step included noise removal, resizing images to consistent dimensions, and converting data into formats suitable for model training. Image normalization was performed to scale pixel values, and data augmentation techniques, such as rotation, flipping, and zooming, were applied to introduce variability in the dataset. Augmenting the data helps reduce overfitting, ensuring the model generalizes well to unseen data. The dataset was subsequently split into training, validation, and test sets, where 70-75% of the images were used for training, 15-20% for validation, and 10-15% for testing. This partitioning allows the model to learn patterns effectively while maintaining a separate set of images to evaluate its performance on previously unseen data.

In the model architecture design, a Convolutional Neural Network (CNN) was implemented due to its superior performance in image-based tasks. CNNs excel in extracting features from input images, making them ideal for identifying complex patterns, such as disease-specific textures in tobacco leaves. The input layer of the CNN receives the leaf images, resized to standardized dimensions, ensuring uniformity across the dataset. Convolutional layers follow, where filters (also called kernels) extract features such as edges, shapes, and textures. The initial layers detect basic features, while deeper layers capture more intricate and abstract patterns that are essential for distinguishing between different diseases. Between convolutional layers, activation functions like Rectified Linear Unit (ReLU) introduce non-linearity into the model, enabling it to learn complex relationships. Pooling layers, such as max-pooling, reduce the dimensions of the feature maps, retaining critical information while lowering computational complexity.

The flattened feature maps from the convolutional and pooling layers are passed into fully connected layers. These layers combine the extracted features to predict the disease category for each image. The output layer, using a softmax activation function, provides probabilities for each disease class, categorizing the input into the most probable disease type among Brown Spot, Granville Wilt, and Frogeye Leaf Spot. Once the model is trained, it undergoes rigorous evaluation to assess its performance. The evaluation process involves calculating metrics such as accuracy, precision, recall, and F1-score, which provide a comprehensive understanding of the model's strengths and limitations. A confusion matrix is used to analyze the model’s predictions, offering insights into misclassifications. Additionally, ROC-AUC curves demonstrate the model’s ability to discriminate between different disease classes at varying thresholds. Cross-validation techniques are also employed to ensure the reliability and robustness of the model by repeatedly testing it on different subsets of the dataset.

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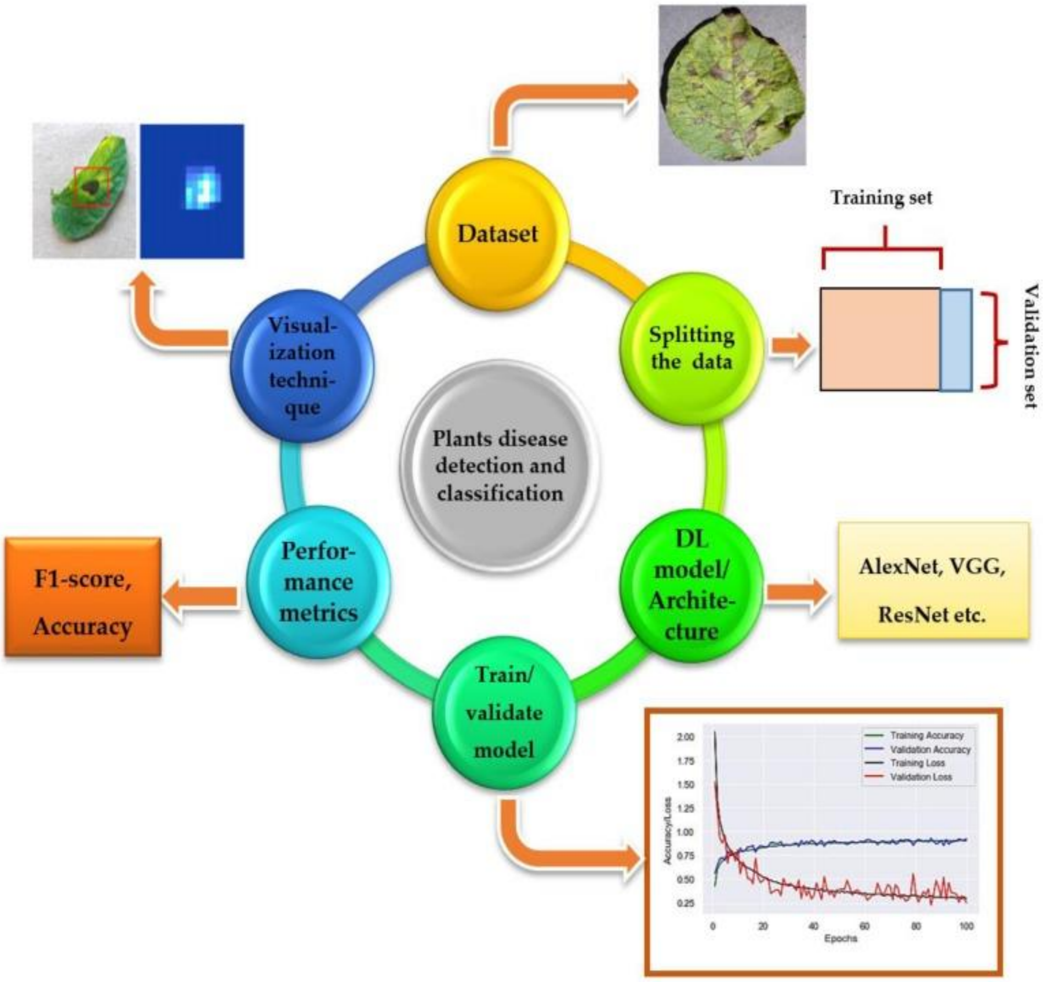

Fig. 1. Summarizes the proposed methodology, outlining each phase from data collection to model evaluation, providing a clear roadmap for achieving accurate tobacco leaf disease detection.

By conducting a thorough evaluation, the proposed approach highlights the efficiency of CNNs in detecting tobacco leaf diseases with high accuracy. The results provide confidence in the model's ability to generalize well to real-world scenarios, enabling stakeholders to adopt this technology for agricultural disease diagnosis. Figure 1 illustrates the overall methodology, capturing the flow from data collection to model evaluation and showcasing the key stages of the process. This systematic approach ensures the development of a reliable and accurate deep learning-based disease detection framework.

4. RESULTS AND DISCUSSION

4.1. Results

The experimental results, as shown in Figure 2, present a batch of images depicting healthy leaves, leaves affected by Granville Wilt, and those exhibiting symptoms of Brown Spot. These images, accompanied by their corresponding labels, serve as the foundation for the training dataset. By using these labeled images, the model can learn the distinct features that differentiate a healthy leaf from one suffering from these specific diseases. The inclusion of clear, well-labeled images in the dataset is essential for the model's ability to generalize across various plant health conditions.

Figure 3 shows the progress of the model's training over several epochs. The graph includes key performance metrics: accuracy, loss, validation accuracy, and validation loss. As the number of epochs increases, the model undergoes repeated learning cycles using the training data. The accuracy curve tracks the percentage of correct predictions made by the model, while the loss curve illustrates how much the model's predictions deviate from the actual labels. Similarly, the validation accuracy and validation loss curves provide insights into how well the model performs on unseen data. The validation accuracy curve generally increases over time, indicating that the model is effectively learning to classify leaf diseases, while the validation loss curve generally decreases, showing that the model is improving in its predictions.

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Fig. 2. Pictures of Healthy Leaf, Granville Wilt, and Brown Spot.

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Epoch 1/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 45s 2s/step - accuracy: 0.4465 - loss: 1.0459 - val_accuracy: 0.5667 - val_loss: 0.8800
Epoch 2/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 32s 2s/step - accuracy: 0.5801 - loss: 0.9451 - val_accuracy: 0.7333 - val_loss: 0.7413
Epoch 3/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 23s 1s/step - accuracy: 0.7450 - loss: 0.6472 - val_accuracy: 0.7333 - val_loss: 0.5516
Epoch 4/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 26s 1s/step - accuracy: 0.7479 - loss: 0.6259 - val_accuracy: 0.8000 - val_loss: 0.4756
Epoch 5/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 25s 1s/step - accuracy: 0.7562 - loss: 0.5727 - val_accuracy: 0.8167 - val_loss: 0.5327
Epoch 6/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 30s 2s/step - accuracy: 0.7494 - loss: 0.5995 - val_accuracy: 0.7667 - val_loss: 0.4744
Epoch 7/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 22s 1s/step - accuracy: 0.8177 - loss: 0.4919 - val_accuracy: 0.8667 - val_loss: 0.4550
Epoch 8/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 22s 1s/step - accuracy: 0.8232 - loss: 0.4506 - val_accuracy: 0.9000 - val_loss: 0.3278
Epoch 9/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 23s 1s/step - accuracy: 0.8228 - loss: 0.4726 - val_accuracy: 0.8833 - val_loss: 0.4494
Epoch 10/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 24s 1s/step - accuracy: 0.7249 - loss: 0.6393 - val_accuracy: 0.8833 - val_loss: 0.4111
Epoch 11/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 23s 1s/step - accuracy: 0.7351 - loss: 0.6145 - val_accuracy: 0.7833 - val_loss: 0.5686
Epoch 12/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 23s 1s/step - accuracy: 0.7593 - loss: 0.5464 - val_accuracy: 0.9167 - val_loss: 0.3307
Epoch 13/50
...
Epoch 49/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 22s 1s/step - accuracy: 0.9436 - loss: 0.2125 - val_accuracy: 0.9500 - val_loss: 0.2658
Epoch 50/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 22s 1s/step - accuracy: 0.9365 - loss: 0.1961 - val_accuracy: 0.9667 - val_loss: 0.1564
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Fig. 3. Accuracy, Loss, val_accuracy and val_loss.

Figure 4 visualizes the training and validation accuracy, as well as the corresponding loss over multiple epochs. The training accuracy curve generally exhibits a steady increase, reflecting the model's learning progress. However, the validation accuracy may not increase as smoothly, and this discrepancy can indicate the model's tendency to over fit or under fit, which should be monitored for potential improvements. The validation loss curve is expected to

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decrease consistently, signaling that the model's predictions are becoming more accurate and aligned with the actual labels. The comparison between the training and validation accuracy curves and the training and validation loss curves provides valuable insights into the model's overall performance and its ability to generalize to unseen data.

Figure 5 presents a visualization of the test dataset, showcasing the actual leaf images, the predicted labels, and the corresponding confidence scores. The confidence score reflects the model's certainty in its prediction, with a higher score indicating stronger confidence in the classification. This visual output helps evaluate how well the model has generalized to new data and whether it can accurately identify leaf diseases based on the learned patterns from the training set.

4.2. Discussion

The results demonstrate the effectiveness of the deep learning-based approach for identifying leaf diseases. The methodology employed relies on a systematic process involving data collection, preparation, model design, and performance evaluation. Each step in the procedure contributes to ensuring that the model can effectively recognize various leaf diseases, thus providing valuable support in agricultural practices. Data collection is a critical initial step in the model's development. The use of pre-existing datasets obtained from prior research ensures that the model has access to a rich variety of images, representative of the diseases it aims to detect. In this study, the dataset includes images of healthy leaves as well as those affected by Granville Wilt and Brown Spot, which enables the model to learn how to distinguish between healthy and diseased plants. Proper data preparation is equally important. The images are preprocessed to enhance data integrity, ensuring that the quality of the images is suitable for training the deep learning model. Furthermore, the dataset is split into training, validation, and test subsets, with each subset playing a distinct role in ensuring the model's performance can be accurately assessed.

The model architecture, based on Convolutional Neural Networks (CNNs), is highly suitable for image recognition tasks. CNNs are known for their ability to automatically extract relevant features from images, which makes them effective for classifying complex visual patterns such as those found in plant leaves. The use of CNNs allows the model to learn spatial hierarchies of features, starting from simple edges and textures in early layers to more complex structures in deeper layers, which is crucial for distinguishing between various leaf diseases. The performance evaluation metrics, including accuracy, precision, recall, F1 score, and AUC, play an essential role in assessing the effectiveness of the model. Accuracy measures the percentage of correct predictions, while precision and recall focus on the model's ability to identify diseased leaves (precision) and correctly classify them as diseased (recall). The F1 score provides a balance between precision and recall, and the AUC (Area Under the Curve) helps evaluate the model's ability to discriminate between the different classes, especially when dealing with imbalanced datasets. The training and validation curves, shown in Figures 3 and 4, provide further insights into the model's learning behavior. The training accuracy consistently increases, indicating that the model is learning from the dataset. However, the validation accuracy may exhibit fluctuations, signaling potential issues like overfitting or underfitting.

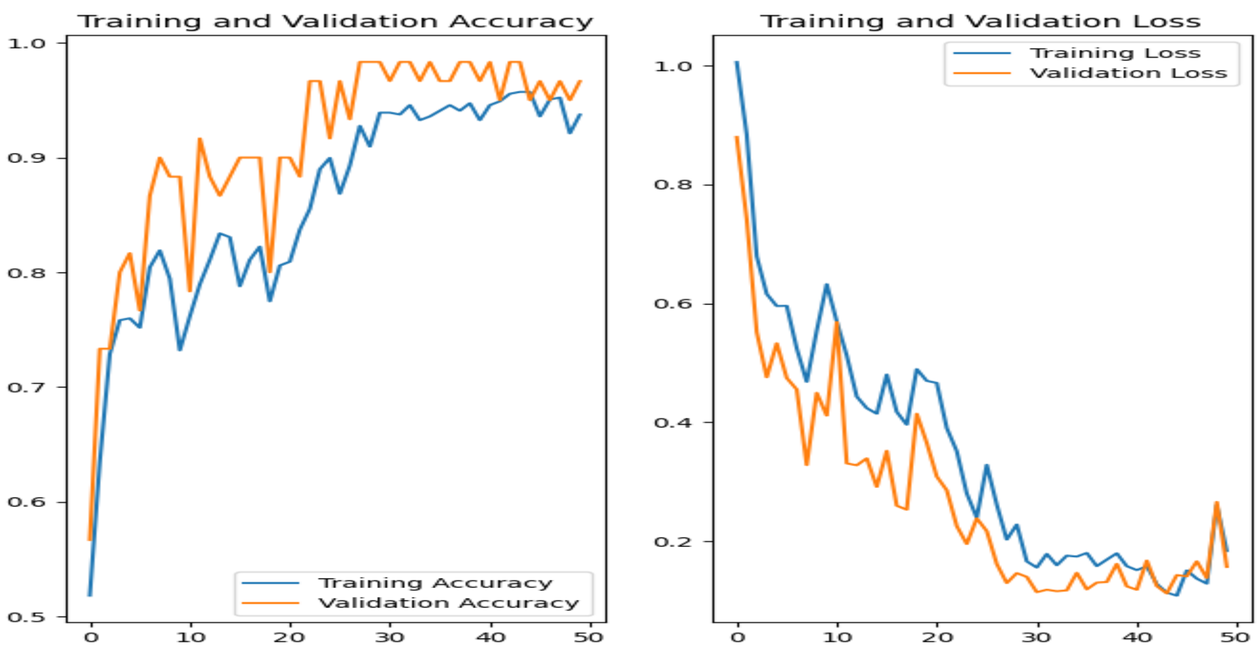

Fig. 4. Accuracy and Loss.

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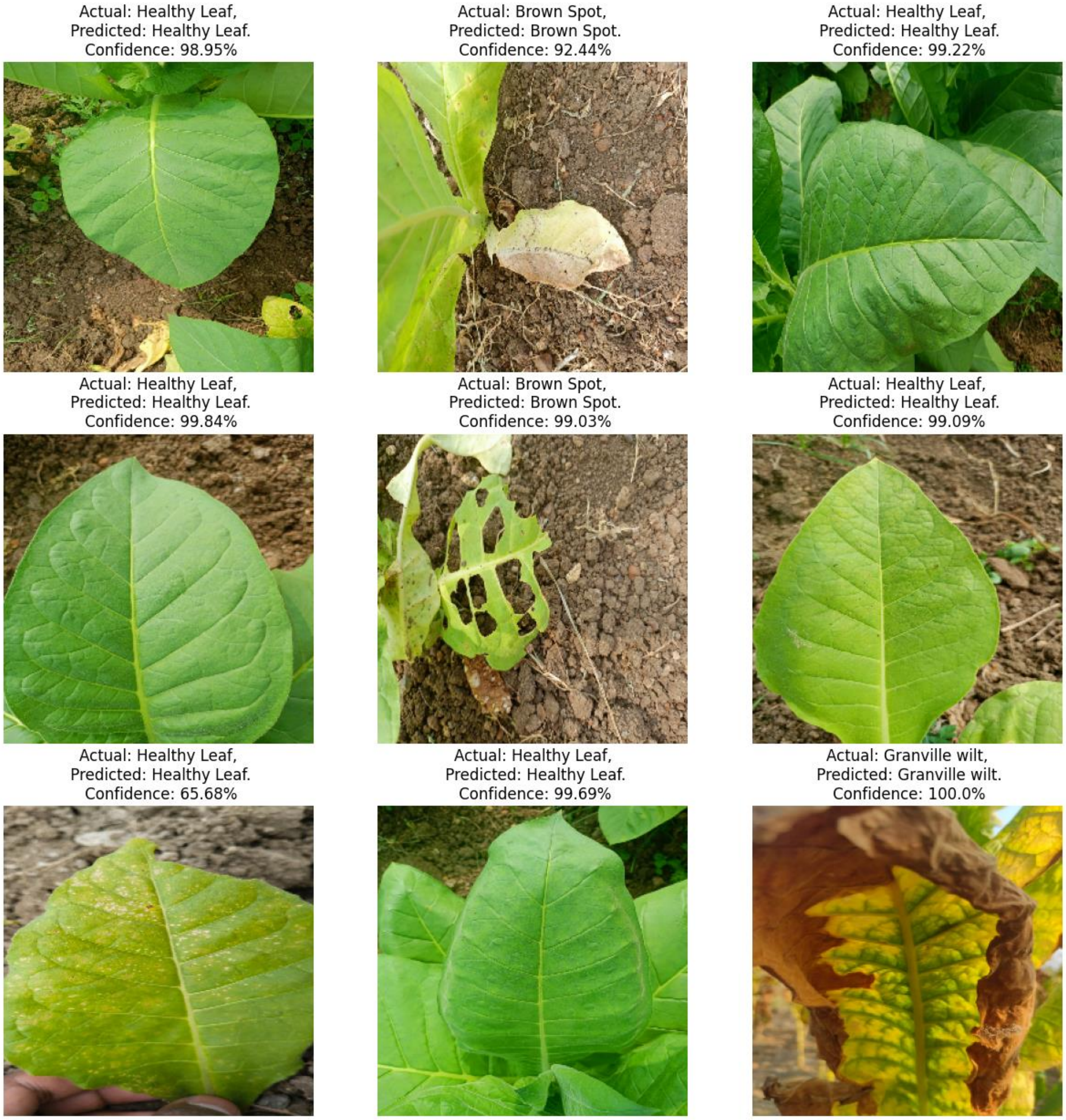

Fig. 5. Actual Leaf, Predicted Leaf and Confidence of the Leaf.

Overfitting occurs when the model learns to perform well on the training data but fails to generalize to new, unseen data. This is typically evident when there is a large gap between the training and validation accuracy. On the other hand, underfitting may occur when the model is too simple or not trained for enough epochs to capture the complexity of the data. By carefully monitoring both the accuracy and loss curves, strategies can be developed to fine-tune the model, such as adjusting hyperparameters, employing regularization techniques, or increasing the dataset size.

Figure 5 visualizes the test dataset with predicted labels and confidence scores. These predictions demonstrate the model's ability to generalize to new, unseen data, which is critical for real-world applications. High confidence scores suggest that the model is confident in its classifications, which is a positive indicator of its performance. However, misclassifications may occur, especially in cases where the leaf diseases share similar visual characteristics. In such instances, further improvements can be made by augmenting the dataset with more diverse examples or refining the model's architecture to better handle such cases.

Despite the promising results, there are several limitations that need to be addressed. One potential issue is dataset bias, where certain classes of diseases may be underrepresented, leading to suboptimal performance for those classes. Addressing this could involve augmenting the

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dataset with additional images or applying techniques like class weighting during training. Overfitting is another concern that can occur when the model learns to memorize the training data rather than generalize to new data. To mitigate this, techniques like dropout, data augmentation, and early stopping can be employed. Future studies may explore the use of more advanced deep learning architectures, such as Transfer Learning or Generative Adversarial Networks (GANs), to improve performance. Additionally, integrating supplementary data sources, such as environmental factors or disease progression information, could enhance the model's robustness and accuracy.

This deep learning-based approach to identifying leaf diseases demonstrates significant potential for improving agricultural practices. By automating the detection process, this model can aid farmers in timely disease identification, leading to better disease management and crop health outcomes. However, continuous refinement and testing will be necessary to overcome current limitations and ensure the model's effectiveness in diverse real-world settings.

5. CONCLUSION

This study presents a robust and automated approach for the detection and classification of diseases in tobacco leaves using Convolutional Neural Networks (CNNs), a deep learning architecture renowned for its ability to extract and analyze complex features from images. Traditional methods of identifying leaf diseases, which rely on manual examination by farmers, often prove inefficient, labor-intensive, and prone to subjective inaccuracies. These limitations are particularly significant in regions like India, where tobacco cultivation plays a vital economic role, contributing 804 million kg annually to global production. A dataset consisting of over 1000 annotated real-time images, depicting three common types of tobacco leaf diseases, was developed with the contribution of farmers from the Prakasam district of Andhra Pradesh. The CNN-based model trained on this dataset achieved a remarkable accuracy of 95%, showcasing its effectiveness in accurately identifying and classifying tobacco diseases. The high performance of this model highlights its potential to transform agricultural practices by providing farmers with reliable and timely disease diagnostics, thus enabling early intervention and mitigation strategies. The results of this research emphasize the importance of adopting AI-based solutions for precision agriculture, as these technologies can enhance productivity, reduce crop losses, and improve food security. Furthermore, this approach is scalable and adaptable, making it suitable for other crops and agricultural challenges beyond tobacco. Future research should focus on expanding the dataset to include more disease types, optimizing models for real-time implementation on edge devices, and integrating the system with mobile applications for widespread farmer accessibility. To summarize, the proposed deep learning framework addresses key challenges in agricultural disease detection, offering a cost-effective, scalable, and accurate solution for enhancing crop management. This research paves the way for intelligent, data-driven farming practices that benefit both farmers and the agricultural sector at large.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interests.

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