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RESEARCH ARTICLE

Multi-Step Preprocessing With UNet Segmentation and Transfer Learning Model for Pepper Bell Leaf Disease Detection

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ABSTRACT Agricultural production is a cornerstone of national economies, and the prevalence of plant diseases poses a significant threat to crop yields. Timely disease detection is essential to mitigate these risks. However, manual plant observation methods are labor-intensive and time-consuming, necessitating a shift toward automated solutions. This study addresses the pressing problem of plant disease identification by leveraging advanced image processing techniques. This research begins with a comprehensive analysis of the pepper bell leaf disease dataset. Through a series of meticulously designed image processing steps, the dataset is normalized, enhancing its quality and consistency. Building upon this preprocessing, the UNET segmentation technique in conjunction with the InceptionV3 transfer learning model is employed. This novel approach yields exceptional results, with 99.48% accuracy, 99.97% precision, 99.99% recall, and 99.98% F1 scores. To objectively assess the significance of the proposed model, the performance is benchmarked against existing state-of-the-art models. The findings demonstrate the superiority of the proposed approach in the domain of plant disease identification. By automating the detection process, this research not only enhances efficiency but also enables early disease detection, thereby potentially contributing to the agricultural sector to identify crop disease and manage it efficiently.

INDEX TERMS Pepper bell leaf disease, image processing, transfer learning, InceptionV3.

I. INTRODUCTION

Farmers face a significant challenge in accurately predicting plant leaf disease. The decision to choose the relevant pesticide to get rid of a particular plant leaf disease heavily relies on the accurate diagnosis of the disease. Plant pathology or phytopathology is related specifically to the study of plant disease, to explore the effects and causes of plant diseases. Pathogens including bacteria, fungi, viruses, viroids, and parasitic plants are the fundamental cause of such diseases and infections. Pathogens are defined as infectious organisms. Apart from pathogens, pests like mites, insects, vertebrates, and other organisms feeding on plants are the contributing factors affecting the plants. Most bacteria are benign and saprotrophic; some bacterial species are harming plants by causing diseases. Phytoplasmas and Spiroplasmas are known bacterial types to induce diseases in plants.

The global economy heavily relies on agriculture for it is the food production method as well as a great source of industrial raw material [1]. Agriculture and plantation are not only essential for our survival but also for oxygen and food as well. Effective strategies are being implemented to improve crop production and their ability to combat diseases and pests. Disease-affected plants impact all the living creatures

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dependent upon them directly or indirectly in numerous ways [2]. Plant diseases can affect any part of the plant including branches, leaves, stems, and roots. Additionally, plant diseases vary from the perspective of causing agents. They can either be bacterial disease, fungal, or viral diseases [3]. Climate change is one of the contributing factors to the severity of crop disease. Crop yield is negatively affected by the wrong identification of the disease. Plant disease can either be abiotic or biotic [4], [5]. The diseases caused by the non-living factors of the ecosystem like weather, temperature, humidity, and particular chemicals are called abiotic diseases while those caused by the living component of the ecosystem like fungi, bacteria, and viruses are termed biotic diseases. Visual observation to accurately identify a plant leaf disease is a daunting task, so a scientific approach aided by computer systems, and machine learning-based applications is a need of the hour to precisely detect the plant disease and implement the fix accordingly [6], [7].

The production of pepper bell is greatly reduced due to the challenging plant leaf diseases causing crop destruction [8]. The key problem in this scenario for the farmers is the accurate detection and classification of the disease because the visual observation technique of disease detection has proved to be ineffective, unreliable, costly, and time-consuming with low accuracy in disease detection. This causes a significant loss of the agricultural yield [9]. Usually, the disease appears first in the leaves before spreading to other parts of the plant, significantly affecting plant life, quality, and quantity of the yield [10]. Now, the latest developments in deep learning have benefited the crop sciences as well by introducing numerous plant disease classification and identification methods by deploying infected plant images [11]. Prompt plant disease identification plays a decisive role in achieving ideal crop yields [12]. Agricultural productivity is greatly affected by plant diseases [13].

Agricultural experts and farmers alike are significantly challenged by the identification of plant diseases [14]. But recent developments in the digital image processing method have presented a viable solution for the identification and accordingly grouping the plant disease resulting in a better yield [15]. By leveraging artificial intelligence (AI)-based methods, crop yields can be enhanced through timely recognition of plant leaf diseases, inhibiting their spread to nearby crops [16]. Computerized image processing approaches can identify the disease at the initial stage and hence minimize its impact in harming the entire crop. This method is highly beneficial to the regions like sub-continent where 70% of the population is directly or indirectly linked to the farming [17]. By adopting these methods, the agricultural sector can proliferate exponentially making the lives of people dependent upon it better and the global community at large. Agricultural businesses can be promoted by using deep learning methods.

This study hypothesizes that the framework combining advanced image processing techniques with deep learning using a segmentation technique and transfer learning will achieve superior accuracy and efficiency in plant leaf disease detection. This novel approach is expected to significantly improve disease identification in agriculture, ultimately reducing crop losses and more sustainable farming practices.

Challenges faced by farmers regarding diseased plant leaves are eased by automated identification to yield better and increased crops. This research aims to develop a reliable and accessible system for early disease detection using advanced deep learning and artificial intelligence technologies motivated by the pressing need to accurately identify and manage plant leaf diseases. It can help to avoid significant crop losses and improve crop yield. The proposed system will empower farmers to promote sustainable farming practices by reducing the environmental impact of excessive pesticide use. Ultimately, this research aims to enhance crop resilience and contribute to a more secure global food supply. The PlantVillage, a benchmarked dataset, is used in this study which comprises leaf images taken from the fields. In this research, an optimized convolutional neural network (CNN) model is developed and trained, incorporating image preprocessing techniques. The fundamental purpose of this study is to devise a system to automatically classify the leaves as diseased or healthy. To put it in a nutshell, the following contributions made by this study

- A novel transfer learning-based model InceptionV3 is utilized demonstrating high accuracy in classifying between bacterial-infected and healthy pepper bell plants using leaf images.
- The proposed approach incorporates multi-step image preprocessing techniques, enhancing edge detection and accurately resizing the infected areas. These preprocessing steps significantly contribute to the improved accuracy of the model. Pre-processed data is further analyzed with the UNet segmentation technique.
- To evaluate the performance of the proposed model, an open PlantVillage dataset consisting of plant leaves is utilized. The proposed model is rigorously compared with state-of-the-art approaches from previous literature, successfully demonstrating its superiority over the existing methods.

The organization of this study is as follows. Section II provides an overview of previously conducted research in this domain. The proposed approach, pre-processing steps, and a description of the models are presented in Section III. Section IV shows the evaluation of the proposed approach concerning experimental results and corresponding discussions. Finally, this study is concluded in Section V.

II. RELATED WORK

This section provides an overview of the diverse advanced methodologies used in the past for detecting leaf diseases in pepper bell plants. In recent years, several pre-processing techniques have been applied to plant leaf images, ensuring accurate identification of various types of plant diseases. Previous studies predominantly utilized image processing techniques, including smoothing and sharpening filters, to enhance the images. Additionally, different filters were employed to eliminate any additive noise present in the images.

A. CNN-BASED APPROACHES

Prabavathi et al. [18] introduced an optimized CNN-based system for plant leaf disease classification and detection. The approach incorporated image processing and feature extraction techniques to define the cropped image. The optimized CNN achieved an impressive accuracy score of 93.19% for classifying three different types of plants. For the identification of maize leaf diseases, Darwish et al. [19] proposed a deep learning system. The authors utilized various CNN models including VGG16, VGG19, InceptionV3, and Xception. The results demonstrated that the proposed VGG16 model achieved a remarkable accuracy value of 99.8%. This performance outperformed the other learning models employed in the study.

Sachdeva et al. [20] proposed a deep CNN with Bayesian learning for automatic plant leaf disease detection. The study utilized a dataset containing images from pepper bell, tomato, and potato plants. The projected CNN prototype employed various hierarchies within a Bayesian framework, resulting in an impressive accuracy of 98.9%. In another study focused on bell pepper leaf disease classification, Bhagat et al. [21] introduced an optimized CNN model. The authors collected a dataset from their garden and evaluated the model using the collected images. The results of the study revealed that the proposed optimized CNN achieved an accuracy of 96.78% for the classification of bell pepper leaf diseases.

The authors introduced a system in [28] that focused on identifying diseases in sweet pepper leaves and employed a Faster R-CNN (Region-based Convolutional Neural Network) for disease detection based on leaf images. The study utilized the R-CNN model to classify different types of leaf diseases. Notably, the authors trained the model on a relatively small dataset consisting of only 150 images. Despite the limited dataset, the system achieved commendable accuracy, reaching 97.9%. However, a notable drawback of the study is the constrained dataset size, which could potentially impact the model's generalizability and robustness.

The study [21] centered around the application of CNN for feature extraction, image recognition, and detection, with the specific aim of identifying bacterial spots on bell pepper leaves attributed to bacterial infection. Utilizing CNN, the research sought to differentiate between two categories of pepper leaves: those that are healthy and those that are afflicted with bacterial infection. Impressively, the experiment yielded a test accuracy of 96.8%, demonstrating the system's effectiveness. The evaluation encompassed a dataset consisting of twenty leaves for screening, successfully distinguishing between healthy and diseased leaves. Nevertheless, it is important to note that the study has limitations, such as the examination of only two classes and the utilization of a relatively small dataset.

B. TRANSFER LEARNING MODEL

The authors introduced a transfer learning model in [24] for classifying pepper leaf diseases. They employed the MobileNetV2 model as the sole model for disease classification. Experimental results demonstrated that the transfer learning model MobileNetV2 achieved an accuracy of 99.55%. The study [25] proposed a machine learning-based automatic classification system for bell pepper plant leaf diseases. The authors utilized multiple machine learning models and proposed HistGradientBoosting (HGB) in combination with different feature extraction techniques. The results indicate that HGB when combined with the fused histogram of oriented gradients (HoG) and local binary patterns (LBP) features, achieved an accuracy of 89.11% for bell pepper leaf disease classification.

The study [23] improved the classification of tomato leaf diseases using an enhanced VGG-InceptionV3 prototype. The authors also employed multiple linear models for comparison. The results demonstrated an impressive accuracy of 99.27% for grouping leaf diseases in tomato plants. Similarly, [29] demonstrated the effectiveness of a deep learning algorithm in categorizing different growth stages of chili plants. The authors employed several deep learning techniques Inception V3, ResNet50, and VGG16, and the outcomes indicate that these methods exhibit strong performance in terms of both accuracy and consistency. These evaluations were conducted on a dataset comprising 2320 images of capsicum plants captured under various growth stages and imaging conditions. Specifically, the pre-trained models, including VGG16, ResNet50, and InceptionV3, achieved good results.

C. ENSEMBLE LEARNING MODEL

The study [22] proposed a hybrid deep learning model for identifying tomato leaf diseases. The new model merged dense and deep residual networks, utilizing dense-connected convolution layers to extract image features within the primary Res-DenseBlock (RDBs). Aggregated input images were fed into an RDB, batch normalized, and then added after convolution within the RDB. A LeakyReLU activation function was incorporated. Furthermore, the input layer was combined with the residual layer using a concatenation of tensors to enhance the RDB block. The experiments were performed on a tomato leaf dataset containing 13,185 images from the AI challenger dataset. The recommended technique achieved an accuracy of 95% for disease detection and classification for tomato leaves, outperforming other CNN models such as DenseNet121, ResNet50, and Deep CNN, which achieved an accuracy of 91.96%, 88.49%, and 93.21%, respectively.

Fenu and Malloci [26] proposed a deep ensemble model for classifying pear leaf diseases. They individually utilized transfer learning models, namely EfficientNetB0, InceptionV3, MobileNetV2, and VGG19. Subsequently, they combined these deep-learning models into an ensemble.

TABLE 1. A comparative summary of discussed works.

Ref	Classifiers used	Dataset used	Achieved accuracy
[18]	Optimized CNN	Self (20,600 images) three different kind	93.19%
[19]	VGG16 and VGG16, VGG19, InceptionV3 and Xception	Maiz leaf	99.8% using VGG16
[20]	Optimized CNN	tomato, potato and pepper bell leaves. (plant village)	98.9%
[21]	Optimized CNN	Self collected Pepper bell	96.78 %
[22]	CNN, DenseNet121, ResNET50 and proposed deep ensemble approach	Tomato leaf	95%
[23]	CNN, VGG16, InceptionV3, DenseNet121, MobileNetV2, ResNET50 and proposed modified VGG-InceptionV3	Tomato leaf	99.27%
[24]	MobileNetV2	Pepper bell	99.55%
[25]	LR, SVM linear, SVM- RBF, NB, DT and HGB	Plant village	89.11% HGB
[26]	EfficientNetB0, InceptionV3, MobileNetV2 and VGG19, ensemble of CNNs	DiaMOS (Pear leaf)	91.14% EfficientNetB0 + InceptionV3
[27]	AlexNet, GoogleNet	Plant village	99.34% GoogleNet

The results of their study revealed that the ensemble of the EfficientNetB0 and InceptionV3 models achieved the highest accuracy of 91.14% for pear leaf disease detection. Mohanty et al. [27] employed transfer learning models for classifying leaf diseases in different plants. They utilized AlexNet and GoogleNet models with various train-test splits. The results demonstrated that GoogleNet, with an 80:20 train-test split, achieved an impressive accuracy of 99.34%. Table 1 shows a comparative analysis of the discussed works.

This study incorporates multi-step image preprocessing techniques to enhance edge detection and accurately resize infected areas. This approach addresses the need for improved accuracy, especially in scenarios with limited dataset sizes and diverse growth conditions.

III. MATERIALS AND METHODS

This section of the study elaborates on the dataset used in this study, data pre-processing steps, deep learning and machine learning models employed for detecting pepper bell leaf diseases, as well as, the proposed methodology and parameters to evaluate the performance of models.

A. DATASET

The dataset used for plant leaf diseases was obtained from Kaggle, which is a popular source of research datasets. This particular dataset focuses on pepper bell leaves and consists of 2475 images [30]. These images are categorized into two types: bacteria-infected leaves and healthy leaves, which serve as the true labels. The dataset contains comparatively a high number of healthy leaf images, i.e. 1478 while the infected leaf images are only 979. Figures 1 and 2, a few examples of infected and healthy leaves from the dataset are shown to provide an overview that manual classification may be difficult due to the similar look of leaves. Figure 1 showcases completely healthy pepper bell leaves, illustrating their appearance. On the other hand, Figure 2 illustrates numerous pepper bell plant leaves suffering from diseases.

B. PREPROCESSING STEPS

Deep learning models are composed of several layers of neural networks that incorporate numerous neurons, making it necessary to train on a substantial amount of data to obtain a better performance. To address this requirement, image augmentation is a viable technique that is often employed in the research of available images. This technique increases the number of images by generating more images from the original dataset. The original dataset is red-green-blue (RGB) color-coded, and may contain noisy values within the images [31]. Disease-affected regions are precisely extracted to enhance clarity for the model's classification and training efficiency. Four color conversion phases are carried out on original images, as depicted in Figure 3. Precisely, before being fed into the models, the following preprocessing steps are carried out

- The images in the original dataset have different sizes, so image resizing is necessary. All leaf images are firstly resized to a consistent dimension of 120×120 before being fed into the model. This transformation can be seen in Figure 3a.
- Edge detection is carried out using the resized images. Figure 3b illustrates the results with the detected leaf edges.
- In the third step, RGB leaf images are converted into the YUV color space, with a focus on preserving the luminance component (Y) at full resolution. The transformed images are presented in Figure 3c.
- Images are equalized concerning the intensity values to obtain better results. Results of image intensity equalizations are shown in Figure 3d.
- Finally, the YUV leaf images are converted to RGB format. The resulting RGB leaf images after the conversion are shown in Figure 3e.

C. UNet IMAGE SEGMENTATION

UNet is a CNN architecture often used for image segmentation tasks in the computer vision domain. It was introduced

FIGURE 1. Samples of healthy leaves from the dataset. The leaves indicate the color and shape of healthy leaves.

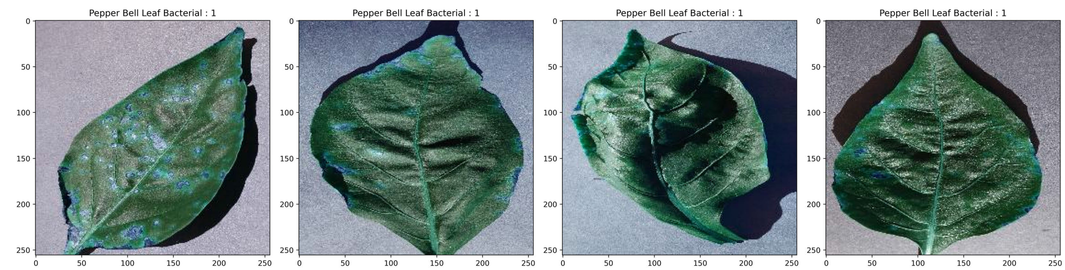


FIGURE 2. Samples of bacterial leaves from the dataset showing the change in color and shape of the leaves compared to health leaves.

by Olaf Ronneberger, Philipp Fischer, and Thomas Brox in 2015 [32]. Image segmentation is the division of a single image into numerous regions or segments to facilitate a better understanding and analysis of its content. UNet was initially designed for neuronal structure segmentation under an electron microscope. However, it has since been adapted and applied to various other segmentation tasks, such as segmenting cells, organs, or objects in diverse types of images. The key characteristic of UNet is its U-shaped architecture, which consists of two main parts

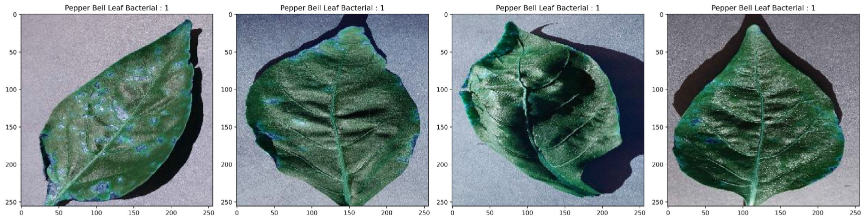
1) Contracting Path: The upper part of the U-shaped network is a traditional convolutional network that performs a series of convolutional and pooling operations, known as downsampling or contracting operations. This path uses input images for high-level feature capturing.
2) Expanding Path: The lower part of the U-shaped network is an expanding path that performs a series of upsampling and concatenation operations, known as upsampling or expanding operations. This path is responsible for recovering spatial information lost during the contracting path and refining the segmentation map.

The novelty of UNet lies in its skip connections, which connect the contracting path's feature maps to the expanding path, allowing it to merge high-resolution information with high-level feature representations. This enables the network to produce accurate segmentation maps even at the pixel level. UNet has been widely adopted due to its effectiveness, particularly in scenarios where the dataset size is limited, and the subject matter is relatively small compared to the whole image. Its architecture has become a basis for several advanced segmentation networks and has had a significant impact in the medical image analysis arena and other computer vision applications.

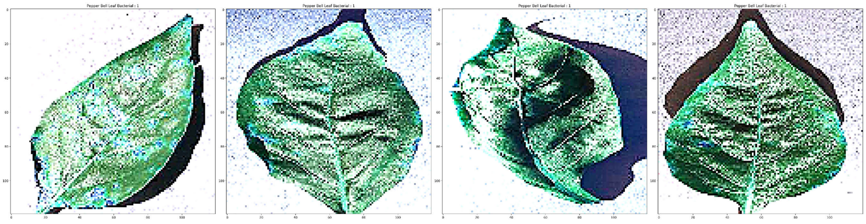
D. PROPOSED APPROACH

Leaf diseases have a significant and devastating impact on agriculture worldwide. These diseases gradually spread to other locations affecting neighboring leaves and ultimately the entire crop over time. Farmers require extensive practical exposure and expertise to accurately predict the disease type and provide appropriate medicinal treatments. The recommended method aims to assist farmers and plants by enabling the early detection of bacterial infections. This allows farmers to administer timely and accurate treatments. Figure 4 presents the proposed methodology for classifying bacterial and healthy leaves. In this study, an experimental investigation is carried out to analyze the feasibility and efficacy of the proposed approach. It involves classifying plants based on visual images using deep learning models, specifically an InceptionV3 model. The plant leaf visual images dataset contains nearly 2475 images. Image augmentation is used to increase the number of images to 20,000 for better training.

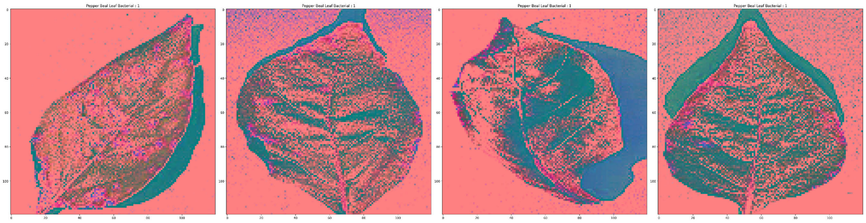
Although several works utilize automated disease detection methods, they primarily rely on machine learning models. To avoid the limitations faced by previous researchers, we employed the InceptionV3 model for this study. Unlike existing approaches, which often rely on manual feature extraction or segmentation, this study eliminates the need for such manual interventions. Segmentation, although commonly used, showed limitations in previous studies. It performed well when the background was black but



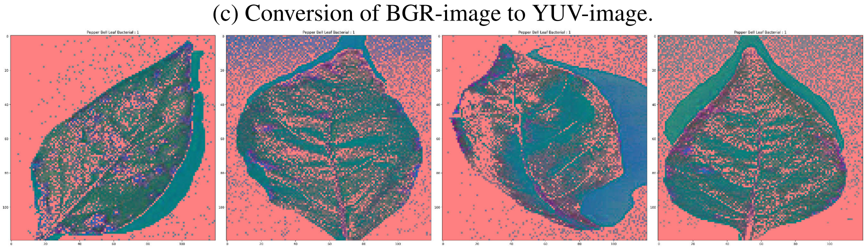
(a) Images of pepper bell leaf without preprocessing.



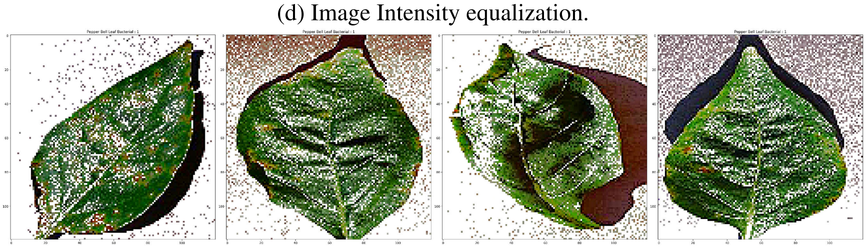
(b) Edges detection.



(c) Conversion of BGR-image to YUV-image.



(d) Image Intensity equalization.



(e) Conversion of YUV-image to BGR-image.

FIGURE 3. Four steps of pepper bell leaf image preprocessing. Images shows the output of various tasks carried out during preprocessing phase.

struggled with other backgrounds, resulting in subpar results. Additionally, some disease symptoms did not exhibit well-defined edges and became indistinguishable from healthy leaf tissues. Manual feature extraction techniques, such as analyzing histograms, shapes, and textures of leaves, relied heavily on expert knowledge and proved expensive and impractical when working with large amounts of data. We implemented edge-extracting preprocessing steps from the leaf images to overcome these challenges. Subsequently, the InceptionV3 model was applied after image preprocessing. In order to capture the required regions of interest, we utilized varied filter sizes. By employing a 5-layered InceptionV3 model, we successfully categorized diseased and healthy pepper bell leaves effectively. This approach serves as an efficient tool for diagnosing bacterial diseases in pepper bell leaves. The Scikit-learn library in Python offers a variety of machine learning classifiers. This open-source library has a large user community and significantly contributes to the research community. In this study, SVM, LR, RF, and ETC algorithms are implemented using the Scikit-learn library while transfer learning models are implemented using the Keras framework. Table 2 shows all the hyperparameters utilized for the models employed in this study.

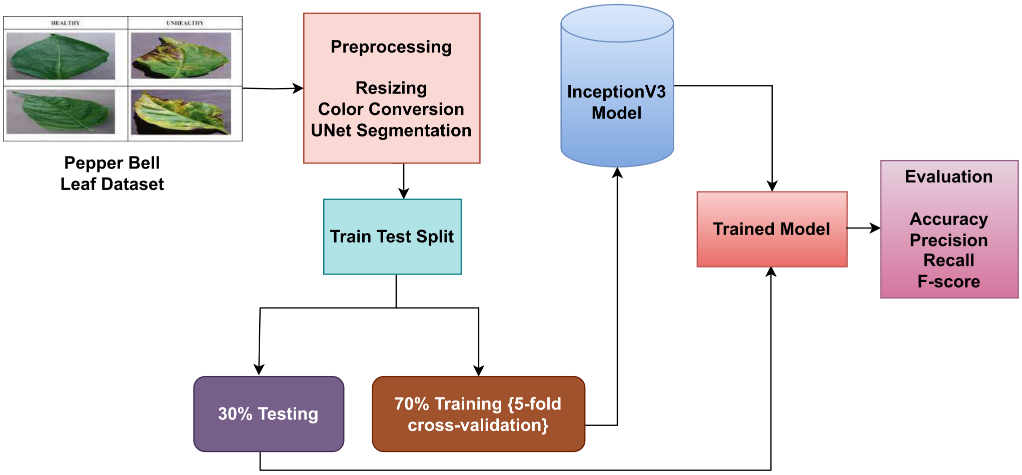


FIGURE 4. Proposed methodology for the pepper bell leaf disease classification. Boxes shows various modules of the approach while arrows indicate the flow.

TABLE 2. Hyperparameter details of all classifiers.

Classifier	Hyperparameter
LR	C = 10, class_weight='balanced', l1_ratio = 0.7, max_iter = 3000, penalty = 'elasticnet', solver = 'saga'
SVM	C = 300, class_weight = 'balanced'
RF	n_estimators = 300, criterion='entropy', max_depth = 30,
ETC	n_estimators = 300, max_depth = 30, criterion='entropy'
VGG19	Stride = (1 × 1), pool size= (@ 2), kernel= (@ 3) filter= (@ 256), Dense neuron (60), activation ='Relu', optimizer='adam', loss='categorical_crossentropy', Dropout=0.5
EfficientNetB4	Stride = (1 × 1), pool size= (@ 2), kernel= (@ 3) filter= (@ 256), Dense neuron (60), activation ='Relu', optimizer='adam', loss='categorical_crossentropy', , Dropout=0.5
InceptionV3	Stride = (1 × 1), pool size= (@ 2), kernel= (@ 3) filter= (@ 256), Dense neuron (60), activation ='Relu', optimizer='adam', loss='categorical_crossentropy', , Dropout=0.5
MobileNet	Stride = (1 × 1), pool size= (@ 2), alpha=0.75, Dense neuron (60), activation ='Relu', optimizer='adam', loss='categorical_crossentropy', , Dropout=0.5
ResNET	Stride = (1 × 1), pool size= (@ 2), kernel= (@ 3) filter= (@ 256), Dense neuron (60), activation ='Relu', optimizer='adam', loss='categorical_crossentropy', , Dropout=0.5

E. MACHINE LEARNING MODELS FOR PEPPER BELL LEAF DISEASE CLASSIFICATION

In the field of machine learning, numerous models can effectively address classification problems. The availability of open-source libraries such as sci-kit provides researchers with convenient tools to solve classification problems using machine learning and ensemble learning techniques. For this particular research work, the machine learning classifiers employed are Logistic Regression (LR), Random Forest (RF) [33], support vector machine (SVM) [34], and Extra Tree Classifier (ETC) [35]. These classifiers are commonly utilized in classification tasks and offer different strengths and capabilities. Each classifier has its own unique approach to decision-making and provides varying levels of accuracy and interpretability.

F. DEEP LEARNING AND TRANSFER LEARNING MODELS

Apart from machine learning models, the investigation of pepper bell leaf disease classification integrated transfer learning and deep learning models. Notably, a deep CNN architecture was employed, alongside transfer learning models like VGG16, ResNet, EfficientNet, and MobileNet.

In one of the interdisciplinary domains within artificial intelligence, deep learning, CNNs are regarded as advanced architectures for various computer vision tasks. When compared to other networks, CNN has demonstrated superior performance in computer vision. CNN mode possesses a distinctive characteristic known as invariance, enabling it to perceive images in a comprehensive manner [36], [37]. Even when presented with images containing dispersed attributes, CNN can still recognize them. CNN involves convolution which can extract features using a kernel of specific dimensions. The kernel is applied with predetermined strides, determining the steps taken during the architecture's implementation to obtain a feature map. Subsequently, a pooling procedure is employed to reduce feature map size. Eventually, the image is flattened and transformed into a fully or partially connected layer. Subsequently, a classification layer is utilized to categorize the image, determining its likelihood of belonging to one of several predefined classes.

G. TRANSFER LEARNING

Transfer learning is a method that allows utilization of a pre-trained model for a completely new task. Transfer learning can be advantageous as it leverages knowledge gained from a previous assignment to enhance predictions in a new task. This technique is attractive due to its ability to effectively train deep networks with limited input data. For transfer learning, the input data provided to the model must have the same dimensions as during its original training. In such cases, a resizing operation is necessary to adjust the input data to the required size before it is fed into the network.

1) EFFICIENT NET

EfficientNet represents a set of CNNs renowned for their exceptional performance compared to other models. The collection comprises eight distinct models, labeled from B0 to B7. As the model number increases, so does the number of parameters and the accuracy of predictions [38]. One notable advantage of EfficientNet is its ability to achieve outstanding results while conserving time and computational resources, surpassing many existing models. This efficiency is achieved through a clever approach known as intelligent scaling, which encompasses adjustments in depth, width, and resolution. An important aspect of EfficientNet is its backing of EDGE-enabled devices and mobile phones for deep learning methods. A compound scaling technique is used to scale the networks' resolution, depth, and width evenly by means of a compound coefficient (ϕ) in a well-founded manner. This approach enables the efficient and effective deployment of deep learning models across a wide range of devices.

2) VGG19

VGG16 is a CNN architecture that has gained significant recognition for its exceptional performance in image-processing tasks. It was created at Oxford University by VGG (Visual Geometry Group). VGG19 consists of a total of 19 layers, which encompass 3 fully connected layers and 16 convolutional layers [39]. The architectural design of VGG19 follows a consistent pattern, involving the stacking of multiple 3×3 convolutional layers with a stride of 1. This is followed by a max pooling layer with a window size of 2×2 and a stride of 2. Such a pattern enables VGG19 to effectively capture increasingly intricate patterns and features within an image. During training, VGG19 is commonly trained using the cross-entropy loss function and optimized through techniques like stochastic gradient descent. VGG19's strength lies in its simplicity and uniformity, which facilitates easier interpretation and transfer of learning. However, due to its deep architecture, VGG19 requires significant computational resources and memory capacity.

3) ResNET50

ResNet50 is a CNN architecture that has gained significant popularity for its utilization of deep residual learning. Developed by Microsoft Research for image classification, ResNet50 is composed of a total of 50 layers [40]. The primary breakthrough in ResNet50 lies in its implementation of skip connections (residual connections). Residual functions are learned by the network aided by residual connections highlighting the inconsistencies between the current and the desired layer outputs. By disseminating this residual information throughout the network, ResNet50 effectively overcomes the issue of vanishing gradients, enabling the training of much deeper networks. The architecture of ResNet50 consists of multiple residual blocks, each containing several convolutional layers. These blocks incorporate skip connections that bypass one or more layers, facilitating the direct flow of information. The core of ResNet50 comprises convolutional layers utilizing filters of size 1×1, 3×3, and 1×1, followed by ReLU activations and batch normalization. The architecture also includes fully connected layers, average pooling, and a softmax output layer for classification. ResNet50 has achieved exceptional performance across various computer vision tasks, including object recognition, detection, and segmentation. Its ability to effectively train deep networks has greatly influenced the development of subsequent CNN architectures. As a result, ResNet50 remains a widely utilized and influential model in the deep learning arena.

4) MobileNet

MobileNet is another dedicated CNN design developed precisely for embedded devices and mobile phones having limited computational resources. It fundamentally balances accuracy and prototype size [41]. The key innovation in MobileNet is the utilization of depthwise separable convolutions, dividing standard convolutional operations into pointwise and depthwise convolutions. The depthwise convolution is characterized by the application of a single filter to each input channel autonomously, followed by pointwise convolution, performing a 1×1 convolution to merge depthwise convolution outputs. By separating these operations, MobileNet significantly reduces computational costs and model size compared to traditional convolutions. This approach allows MobileNet to achieve a highly efficient architecture while maintaining a reasonable level of accuracy. MobileNet comes in various configurations, including MobileNetV1, MobileNetV2, and MobileNetV3, each introducing improvements and optimizations over its predecessor. These iterations enhance the performance and efficiency of the architecture. MobileNet has gained popularity in a range of computer vision applications on mobile and embedded devices, such as object detection, image classification, and semantic segmentation. Its lightweight design and efficiency make it well-suited for real-time inference on devices with limited computational power or bandwidth constraints.

5) InceptionV3

InceptionV3 is a CNN model that is extensively used for image recognition tasks. It has been trained on the ImageNet dataset and achieves high accuracy on various benchmarks [42]. The model architecture consists of multiple layers of convolutional, pooling, and activation functions. It also includes inception modules, which allow the network to learn different feature maps at multiple scales. InceptionV3 also uses batch normalization and factorized 1×1 convolutions to limit parameter size and improve training efficiency. The model is also designed to be transferable to other tasks and datasets, making it useful for transfer learning. However, it can be computationally expensive and requires a large amount of memory to train and deploy.

H. EVALUATION PARAMETERS

In this research, various assessment criteria are employed including accuracy, F1 score, recall, and precision. These evaluation measures serve to assess the efficiency of deep learning and machine learning models. Additionally, this study employed confusion matrices to evaluate the algorithms' performance. A confusion matrix, often referred to as an error matrix, is a tabular representation commonly utilized to depict how well a classifier performs on test data. It provides a visual representation of an algorithm's performance.

True positive (TP) indicates the cases where the model correctly predicted the positive class and true negative (TN) indicates the the cases where the model correctly predicted the negative class. On the other hand, false positive (FP) shows the cases where the model incorrectly predicted the positive class when the true class was negative. Similarly, false negative (FN) indicates those cases where the model incorrectly predicted the negative class when the true class was positive.

The overall correctness of the model's predictions is measured using accuracy. It calculates the ratio of correctly predicted to the total number of instances in the dataset. It can be calculated using

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Precision is a metric that measures the ratio of correctly predicted positive instances to all instances predicted as positive. Its primary objective is to minimize false positives, thus reflecting the model's ability to accurately identify positive instances. Precision is calculated using

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Recall, also known as the true positive rate or sensitivity, assesses the ratio of correctly predicted positive instances to all actual positive instances in the dataset. It quantifies the model's capability to capture positive cases accurately. The recall is calculated using

$$Recall/Sensitivity/TPR = \frac{TP}{TP + FN} \tag{3}$$

F1 score is the harmonic mean of precision and recall, providing a balanced measure of the model's overall performance by considering both precision and recall simultaneously. It can be calculated using

$$F1score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

An AUC-ROC plot is a graphical representation used to assess the performance of binary classification models. The ROC curve is a graphical representation that illustrates the performance of a binary classification model across different thresholds for classifying positive and negative instances. It plots the true positive rate (TPR), also known as sensitivity, on the y-axis and the false positive rate (FPR), which is equal to 1 - specificity, on the x-axis.

$$FPR = \frac{FP}{FP + TN} \tag{5}$$

The AUC is a numerical metric that summarizes the overall discriminative power of the model. A higher AUC indicates better model performance, with 1 representing a perfect classifier, 0.5 representing random guessing, and values above 0.5 indicating better-than-random performance. AUC-ROC plots are useful for comparing and evaluating different models, helping you choose the most appropriate one for your task.

IV. EXPERIMENTAL RESULTS

A. EXPERIMENTAL SETUP

In this study, open-source TensorFlow and Keras libraries were used for implementing machine learning and deep learning models, including pre-trained models. The implementation of deep learning methods on the plant leaf image dataset was carried out using the Python programming language within the Anaconda platform. To meet the dataset requirements, a Dell Poweredge T430 server with GPU was utilized, boasting 8 cores, 16 logical processors, and 32GB of RAM. To address the classification task of detecting bacteria presence in plant leaf visual images, the study proposed the adoption of the InceptionV3 deep learning approach along with image augmentation techniques. The effectiveness and significance of this proposed approach will be assessed through various scientific methods.

This study focuses on the classification of plant leaf diseases using a dataset containing 2475 images of pepper bell leaves. To achieve this, the researchers employed the InceptionV3 model combined with the image augmentation technique. Through image augmentation, the number of available images is increased to up to 20,000, which significantly improved the InceptionV3 model's effectiveness, resulting in the highest prediction accuracy

B. PERFORMANCE OF MACHINE LEARNING MODELS USING ORIGINAL DATASET

For the paper bell plant leaf disease classification, four machine learning models are used. These machine learning models are used on the original dataset without using UNet segmentation. Table 3 shows experimental results for machine learning models.

TABLE 3. Results of machine learning models using original dataset.

Models	Accuracy	Precision	Recall	F1 score
RF	75.48	81.55	82.34	82.07
LR	76.29	83.67	84.49	84.19
ETC	80.34	85.69	85.69	85.69
SVM	72.49	79.39	80.46	79.69

Supervised machine learning models have been comparatively analyzed for their performance on the original features set of the pepper bell leaf dataset. As per the results given in Table 3, the ETC classifier has achieved good results with 85.69% precision, 80.34% accuracy, 85.69% F1 score, and 85.69% recall. LR has proven to be the second-best classifier with 84.19% F1 Score and 76.29% accuracy. RF, a tree-based classifier, obtained a 75.48% accuracy score. The worst performance is observed by the SVM with 72.49% accuracy, 79.39% precision, 80.46% recall, and 79.69% F1 Score. The performance of ETC is better while other models exhibit below-par performance. Plant leaf diseases are predicted using statistical, tree, and regression-based models in this study. A statistical-based model like SVM shows poor performance in this regard. Tree-based ensemble models including ETC and RF show better performance. Similarly, the regression-based LR model is also better than SVM.

C. PERFORMANCE OF TRANSFER LEARNING MODELS USING ORIGINAL DATASET

For the image data, transfer learning models produced promising results. This study makes use of five transfer learning models. Table 4 displays the results for transfer learning classifiers with the original dataset. From the results, it is clear that transfer learning classifiers show significantly improved results concerning all evaluation matrices compared to machine learning models. InceptionV3 achieved a 84.25% accuracy, 88.89% recall, 89.91% precision and 89.49% F1 score. This shows that the transfer learning model shows 3.91% better accuracy compared to the best performer model ETC which achieved 80.34% accuracy.

TABLE 4. Results of transfer learning models without UNet segmentation.

Models	Accuracy	Precision	Recall	F1 score
MobileNet	79.69	81.34	83.91	82.48
VGG19	79.99	82.63	83.67	82.19
ResNET	77.34	80.25	83.19	82.67
EfficientNetB4	82.65	87.69	89.32	88.55
InceptionV3	84.25	88.89	89.91	89.49

D. PERFORMANCE OF MACHINE LEARNING MODELS USING UNet SEGMENTATION

Image segmentation makes use of the UNet model. Machine learning models are used on the dataset once the UNet segmentation has been carried out. The performance of machine learning models using UNet segmentation is shown in Table 5. Results show that the SVM model outperforms other learning models and achieved an accuracy of 92.22%, precision of 79.39%, recall of 80.46%, and F1 score of 79.69%. Regression-based model LR is the lowest performer with an accuracy of 87.49%. Results of the machine learning models on the UNet segmentation show that the models got improved performance when using UNet segmentation. It indicates that the UNet segmentation features are more appropriate than the original features from the dataset.

TABLE 5. Results of machine learning models with UNet segmentation.

Models	Accuracy	Precision	Recall	F1 score
RF	89.38	91.37	82.34	82.07
LR	87.49	83.67	84.49	84.19
ETC	91.82	85.69	85.69	85.69
SVM	92.22	79.39	80.46	79.69

E. PERFORMANCE OF TRANSFER LEARNING MODELS USING UNet SEGMENTATION

Transfer learning models are applied to the data after the UNet image segmentation is applied. The performance of transfer learning models using UNet image segmentation data is presented in Table 6. Results of the transfer learning model depict that InceptionV3 has outperformed other transfer learning models in terms of all evaluation parameters. InceptioV3 achieved an accuracy of 99.48%, precision of 99.97%, recall of 99.99%, and 99.98% F1 score. It is followed by the ResNet which achieves an accuracy of 97.27%. Transfer learning model MobileNet is the lowest performer and it achieves an accuracy of 89.17%. These results show that the transfer learning model InceptionV3 has a 7.26% improvement in results than the machine learning model results using the UNet image segmentation.

TABLE 6. Results of transfer learning models with UNet segmentation.

Models	Accuracy	Precision	Recall	F1 score
MobileNet	89.17	81.34	83.91	82.48
VGG19	92.37	82.63	83.67	82.19
ResNET	97.27	80.25	83.19	82.67
EfficientNetB4	92.67	87.69	89.32	88.55
InceptionV3	99.48	99.97	99.99	99.98

F. RESULTS OF THE K-FOLD CROSS-VALIDATION

We used K-fold cross-validation for added performance analysis for the proposed method. The results of 5-fold cross-validation are given in Table 7, which demonstrate how well the proposed technique performs regarding precision, F1 score, accuracy, and recall when compared to other models. Furthermore, it shows a low standard deviation, indicating stable performance throughout different folds. These outcomes provide us with more assurance that the proposed technique is trustworthy and reliable.

TABLE 7. Results of k-fold cross-validation with UNet segmentation.

InceptionV3	Acc.	Prec.	Recall	F-score
Fold-1	98.83	99.73	98.43	99.16
Fold-2	97.94	99.76	98.94	99.64
Fold-3	98.82	99.96	99.96	99.96
Fold-4	99.22	99.93	99.94	99.93
Fold-5	99.17	99.94	99.91	99.92
AVG.	**98.79**	**99.83**	**99.26**	**99.47**

G. RESULTS OF MODELS ON PLANT VILLAGE DATASET

This study also carried out validation using an additional dataset. For this purpose, we used images of pepper bells

TABLE 8. Results of models on the additional dataset with and without UNet segmentation.

Models	Acc.	Prec.	Recall	F-score
SVM	91.96	94.28	96.28	95.47
ResNET	93.66	92.38	94.57	93.82
Inception	95.49	97.38	98.42	97.38
Without UNET segmentation				
SVM	83.58	85.17	86.37	85.91
ResNET	85.22	88.38	88.75	88.46
Inception	87.31	90.11	91.24	90.91

from the plant village data. The dataset consists of various plant diseases like tomatoes, potatoes, etc. We tested the proposed approach on the whole plant village dataset. For this purpose, we used the top performer from machine learning models, i.e., SVM, and two top-performer transfer learning models InceptionV3 and ResNET. Experiments are performed without UNet segmentation and with UNet segmentation. Results of all models are presented in Table 8, indicating the superior performance of models when used with UNet segmentation.

The outcomes of the learning models using UNet segmentation indicate that InceptionV3 performed notably better than other models in terms of accuracy, achieving an impressive 95.49% accuracy on the plant village dataset. On the same dataset, the ResNet transfer learning model obtained an accuracy of 93.66%, which is also commendable. However, the machine learning model SVM showed the lowest performance among the three, achieving an accuracy of 91.96%. When considering the evaluation without UNet segmentation, the InceptionV3 model once again displayed superior performance, achieving an accuracy of 87.31%, surpassing all other learning models.

H. COMPARISON WITH STATE-OF-THE-ART MODELS

Table 9 summarizes the performance of various methods, including the proposed approach, in the task of classifying bacterial infections in pepper bell leaves. The optimized CNN approach achieves an accuracy of 98.9% on the Plant Village dataset, which includes tomato, potato, and pepper bell leaves. Whereas, the MobileNetV2 approach achieves an accuracy of 99.55% on the Pepper bell dataset. The HGB approach achieves an accuracy of 89.11% on the Plant Village dataset. The proposed approach, InceptionV3 with UNET segmentation, achieves an accuracy of 99.48% on the Pepperbell dataset. This suggests that the proposed model is highly accurate in identifying plant diseases, and it performs competitively when compared to existing state-of-the-art approaches.

I. TIME COMPLEXITY OF MODELS

Time complexity in learning models often revolves around the training phase. It measures the time required to adjust the model's parameters based on the input data. The complexity depends on factors like the model's architecture, the size of the training dataset, and the optimization algorithm. Table 10 shows the training and testing time of all learning models. The computational time for the proposed model is 205s which is less than all other transfer learning models utilized in this study. However, the accuracy that it offers is substantially better than individual models.

J. DISCUSSION

The hypothesis for this study centered on the notion that the proposed model, combining advanced image processing techniques with deep learning using the segmentation technique and transfer learning, would yield superior accuracy and efficiency in plant leaf disease detection. The results obtained in this research provide compelling support for the validity of this hypothesis. The current study has demonstrated not only the feasibility but also the substantial advantage of this novel approach. The achieved accuracy, precision, recall, and F1 scores are indicative of the model's exceptional performance in distinguishing between healthy and disease-affected plant leaves. Figure 5 presents the AUC-ROC curve of the proposed model. A high AUC-ROC score suggests that the proposed model is effective at distinguishing between the two classes (positive and negative) across different decision thresholds. It implies that the model's predictions tend to assign higher probabilities to true positive cases compared to true negative cases, leading to better separation between the classes. These results exceed those reported in existing literature, underscoring the theoretical and practical soundness of our chosen methodology.

The incorporation of multi-step image preprocessing techniques serves as a foundational step in the proposed methodology. This decision was motivated by the need to normalize the dataset, enhance image quality, and reduce noise. The quality and consistency of input data are fundamental to the success of any deep learning model. The UNET segmentation technique was chosen for its ability to accurately delineate disease-affected regions within plant leaves. This method aligns with our goal of precise disease localization, as it excels in identifying and segmenting specific areas of interest within images. The selection of the InceptionV3 transfer learning model was predicated on its proven efficacy in image classification tasks. Its deep architecture and pre-trained weights on a large dataset were considered advantageous for our problem. The model's ability to capture intricate features within images, including those relevant to disease identification, resonated with our research objectives. This methodology has not only advanced the field of plant leaf disease detection but has also laid a solid theoretical foundation for future research in agricultural image analysis.

K. REAL-WORLD APPLICATIONS OF THE PROPOSED MODEL

The proposed model has wide-ranging real-life use cases, spanning precision agriculture, research, education, insurance, and global food security. The theoretical foundation of our model, rooted in advanced image processing and deep

TABLE 9. Comparison with existing state-of-the-art approaches.

Ref	Method	Dataset used	Achieved accuracy
[20]	Optimized CNN	tomato, potato and pepper bell leaves. (plant village)	98.9%
[24]	MobileNetV2	Pepper bell	99.55%
[25]	HGB	Plant village	89.11%
Proposed Approach	InceptionV3 with UNET	Pepper bell	99.48%

TABLE 10. Time comparison of learning models (in seconds).

Model	Training Time	Testing Time
LR	92s	34s
RF	113s	41s
ETC	98s	37s
SVM	190s	64s
EfficientNetB4	298s	62s
MobileNet	239s	43s
ResNET	210s	34s
VGG19	223s	38s
InceptionV3	205s	30s

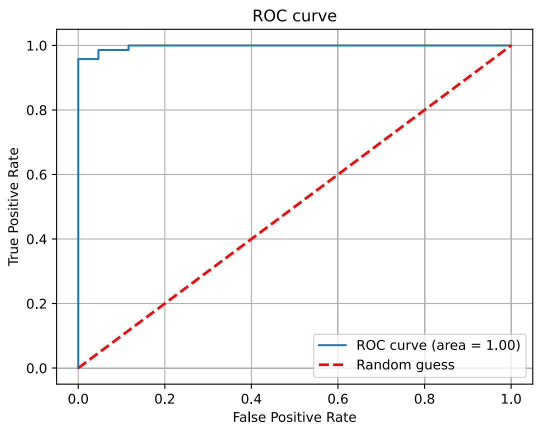


FIGURE 5. ROC-AUC of the proposed model.

learning, provides the flexibility and adaptability needed for its successful application across these diverse scenarios.

- By identifying diseases at an early stage, farmers can implement targeted interventions, such as precise pesticide or fungicide application, reducing the need for excessive chemical usage and promoting sustainable farming practices.
- It can be used to track disease progression over time, enabling farmers to make informed decisions about when to harvest or cull affected plants, optimizing crop yields.
- By accurately assessing the extent of disease damage through automated disease detection, insurers can expedite claim settlements for farmers, enhancing the efficiency of the insurance industry in the agricultural sector.
- It can be used to study disease patterns, conduct experiments on disease management strategies, and provide hands-on training in disease identification and mitigation techniques.
- In situations where physical inspections are challenging, such as large-scale farms or remote agricultural areas, the proposed model can be deployed for remote monitoring.
- By preventing disease-related crop losses, it contributes to a more reliable and sustainable food supply, which is crucial for addressing food security challenges around the world.
- The model's deep learning architecture allows for continuous learning and adaptation to evolving disease patterns, ensuring its relevance over time.
- In future applications, the proposed model can be integrated with Internet of Things (IoT) sensors and devices to enable real-time data collection and disease monitoring, further enhancing its practical utility.

V. CONCLUSION

Detecting plant leaf diseases poses a significant challenge for both farmers and automated systems during the early stages of identification. This study addresses the critical issue of plant disease identification in agriculture by utilizing the power of advanced image-processing techniques and deep learning methodologies. The study begins with a thorough analysis and preprocessing of the pepper bell leaf disease dataset, ensuring data quality and consistency. Subsequently, a novel approach combining the UNET segmentation technique with the InceptionV3 transfer learning model is employed, yielding outstanding results with remarkable accuracy. Additionally, the incorporation of multi-step image preprocessing techniques enhances edge detection and accurately resizes infected areas, significantly improving the model's accuracy. The significance of this research is underscored by the benchmarking of the proposed model against existing state-of-the-art methods, clearly establishing its superiority in the domain of plant disease identification. By automating the detection process, this study not only enhances operational efficiency but also enables early disease detection, potentially revolutionizing disease management in the agricultural sector. This research offers a promising solution to the challenges faced by farmers in identifying and managing plant diseases, potentially revolutionizing agriculture and promoting sustainable farming practices on a global scale.

REFERENCES

[1] A. Das, C. Mallick, and S. Dutta, "Deep learning-based automated feature engineering for Rice leaf disease prediction," in *Computational Intelligence in Pattern Recognition: Proceedings of CIPR 2020*. Cham, Switzerland: Springer, 2020, pp. 133–141.

[2] S. K. Tichkule and D. H. Gawali, "Plant diseases detection using image processing techniques," in *Proc. Online Int. Conf. Green Eng. Technol. (IC-GET)*, Nov. 2016, pp. 1–6.

[3] P. Bharali, C. Bhuyan, and A. Boruah, "Plant disease detection by leaf image classification using convolutional neural network," in *Proc. Int. Conf. Inf., Commun. Comput. Technol.* Cham, Switzerland: Springer, 2019, pp. 194–205.

[4] Z. B. Husin, A. Y. B. M. Shakaff, A. H. B. A. Aziz, and R. B. S. M. Farook, "Feasibility study on plant chili disease detection using image processing techniques," in *Proc. 3rd Int. Conf. Intell. Syst. Model. Simul.*, Feb. 2012, pp. 291–296.

[5] G. Balakrishna and N. R. Moparthi, "Study report on Indian agriculture with IoT," *Int. J. Electr. Comput. Eng. (IJECE)*, vol. 10, no. 3, p. 2322, Jun. 2020.

[6] J. G. A. Barbedo, "A review on the main challenges in automatic plant disease identification based on visible range images," *Biosystems Eng.*, vol. 144, pp. 52–60, Apr. 2016.

[7] K. Mannepalli, P. N. Sastry, and M. Suman, "Accent recognition system using deep belief networks for Telugu speech signals," in *Proc. 5th Int. Conf. Frontiers Intell. Comput. Theory Appl. (FICTA)*, vol. 1. Cham, Switzerland: Springer, 2017, pp. 99–105.

[8] S. Mathulaprangsan, K. Lanthong, D. Jetpipattanapong, S. Sateanpattanakul, and S. Patarapuwadol, "Rice diseases recognition using effective deep learning models," in *Proc. Joint Int. Conf. Digit. Arts, Media Technol. ECTI Northern Sect. Conf. Electr., Electron., Comput. Telecommun. Eng. (ECTI DAMT NCON)*, Mar. 2020, pp. 386–389.

[9] H. Genitha, C. E. Dhinesh, and A. Jagan, "Detection of leaf disease using principal component analysis and linear support vector machine," in *Proc. 11th Int. Conf. Adv. Comput. (ICoAC)*, Dec. 2019, pp. 350–355.

[10] P. Sharma, P. Hans, and S. C. Gupta, "Classification of plant leaf diseases using machine learning and image preprocessing techniques," in *Proc. 10th Int. Conf. Cloud Comput., Data Sci. Eng. (Confluence)*, Jan. 2020, pp. 480–484.

[11] S. V. Militante, B. D. Gerardo, and N. V. Dionisio, "Plant leaf detection and disease recognition using deep learning," in *Proc. IEEE Eurasia Conf. IoT, Commun. Eng. (ECICE)*, Oct. 2019, pp. 579–582.

[12] M. Sardogan, A. Tuncer, and Y. Ozen, "Plant leaf disease detection and classification based on CNN with LVQ algorithm," in *Proc. 3rd Int. Conf. Comput. Sci. Eng. (UBMK)*, Sep. 2018, pp. 382–385.

[13] D. Sharath, S. A. Kumar, M. Rohan, and C. Prathap, "Image based plant disease detection in pomegranate plant for bacterial blight," in *Proc. Int. Conf. Commun. Signal Process. (ICCSP)*, Apr. 2019, pp. 0645–0649.

[14] S. S. Kumar and B. K. Raghavendra, "Diseases detection of various plant leaf using image processing techniques: A review," in *Proc. 5th Int. Conf. Adv. Comput. Commun. Syst. (ICACCS)*, Mar. 2019, pp. 313–316.

[15] A. Devaraj, K. Rathan, S. Jaahnavi, and K. Indira, "Identification of plant disease using image processing technique," in *Proc. Int. Conf. Commun. Signal Process. (ICCSP)*, Apr. 2019, pp. 0749–0753.

[16] C. Rajasekaran, S. Arul, S. Devi, G. Gowtham, and S. Jeyaram, "Turmeric plant diseases detection and classification using artificial intelligence," in *Proc. Int. Conf. Commun. Signal Process. (ICCSP)*, 2020, pp. 1335–1339.

[17] L. Saxena and L. Armstrong, "A survey of image processing techniques for agriculture," in *Proc. Asian Federation Inf. Technol. Agricult.* Perth, WA, USA: Australian Society of Information and Communication Technologies in Agriculture, 2014, pp. 401–413. [Online]. Available: https://ro.ecu.edu.au/ecuworkspost2013/854

[18] S. Ashwinkumar, S. Rajagopal, V. Manimaran, and B. Jegajothi, "Automated plant leaf disease detection and classification using optimal MobileNet based convolutional neural networks," *Mater. Today, Proc.*, vol. 51, pp. 480–487, 2022.

[19] A. Darwish, D. Ezzat, and A. E. Hassanien, "An optimized model based on convolutional neural networks and orthogonal learning particle swarm optimization algorithm for plant diseases diagnosis," *Swarm Evol. Comput.*, vol. 52, Feb. 2020, Art. no. 100616.

[20] G. Sachdeva, P. Singh, and P. Kaur, "Plant leaf disease classification using deep convolutional neural network with Bayesian learning," *Mater. Today, Proc.*, vol. 45, pp. 5584–5590, Oct. 2021.

[21] M. Bhagat, D. Kumar, R. Mahmood, B. Pati, and M. Kumar, "Bell pepper leaf disease classification using CNN," in *Proc. 2nd Int. Conf. Data, Eng. Appl. (IDEA)*, Feb. 2020, pp. 1–5.

[22] C. Zhou, S. Zhou, J. Xing, and J. Song, "Tomato leaf disease identification by restructured deep residual dense network," *IEEE Access*, vol. 9, pp. 28822–28831, 2021.

[23] J. Thomkaew and S. Intakosum, "Improvement classification approach in tomato leaf disease using modified visual geometry group (VGG)-InceptionV3," *Int. J. Adv. Comput. Sci. Appl.*, vol. 13, no. 12, 2022, doi: 10.14569/IJACSA.2022.0131244.

[24] Y. Zeng, Y. Zhao, Y. Yu, Y. Tang, and Y. Tang, "Pepper disease detection model based on convolutional neural network and transfer learning," *IOP Conf. Ser., Earth Environ. Sci.*, vol. 792, no. 1, 2021, Art. no. 012001.

[25] M. B. Devi and K. Amarendra, "Machine learning-based application to detect pepper leaf diseases using histgradientboosting classifier with fused HOG and LBP features," in *Technologies in Data Science and Communication: Proceedings of SMART-DSC 2021*. Singapore: Springer, 2021, pp. 359–369.

[26] G. Fenu and F. M. Malloci, "Classification of pear leaf diseases based on ensemble convolutional neural networks," *AgriEngineering*, vol. 5, no. 1, pp. 141–152, Jan. 2023.

[27] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Frontiers Plant Sci.*, vol. 7, p. 1419, Sep. 2016.

[28] T.-L. Lin, H.-Y. Chang, and K.-H. Chen, "Pest and disease identification in the growth of sweet peppers using faster R-CNN," in *Proc. IEEE Int. Conf. Consum. Electron. Taiwan (ICCE-TW)*, May 2019, pp. 1–2.

[29] D. M. M. Rozilan, M. Hanafi, R. Ali, M. A. Razak, and C. Hairu, "Efficacy of deep learning algorithm in classifying chilli plant growth stages," *Adv. Agricult. Food Res. J.*, vol. 2, no. 2, Sep. 2021.

[30] A. Tejaswi. (Nov. 2019). *Plant Village Dataset*. [Online]. Available: https://www.kaggle.com/datasets/arjuntejaswi/plant-village

[31] M. Umer, S. Sadiq, R. M. Alhebshi, S. Alsubai, A. Al Hejaili, A. A. Eshmawi, M. Nappi, and I. Ashraf, "Face mask detection using deep convolutional neural network and multi-stage image processing," *Image Vis. Comput.*, vol. 133, May 2023, Art. no. 104657.

[32] X. Zhao, Y. Yuan, M. Song, Y. Ding, F. Lin, D. Liang, and D. Zhang, "Use of unmanned aerial vehicle imagery and deep learning UNet to extract Rice lodging," *Sensors*, vol. 19, no. 18, p. 3859, 2019.

[33] L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001.

[34] W. S. Noble, "What is a support vector machine?" *Nature Biotechnol.*, vol. 24, no. 12, pp. 1565–1567, Dec. 2006.

[35] P. Geurts, D. Ernst, and L. Wehenkel, "Extremely randomized trees," *Mach. Learn.*, vol. 63, no. 1, pp. 3–42, Apr. 2006.

[36] H. Mustafa, M. Umer, U. Hafeez, A. Hameed, A. Sohaib, S. Ullah, and H. A. Madni, "Pepper bell leaf disease detection and classification using optimized convolutional neural network," *Multimedia Tools Appl.*, vol. 82, no. 8, pp. 12065–12080, Mar. 2023.

[37] U. Hafeez, M. Umer, A. Hameed, H. Mustafa, A. Sohaib, M. Nappi, and H. A. Madni, "A CNN based coronavirus disease prediction system for chest X-rays," *J. Ambient Intell. Humanized Comput.*, vol. 14, no. 10, pp. 13179–13193, Oct. 2023.

[38] J. Wang, Q. Liu, H. Xie, Z. Yang, and H. Zhou, "Boosted EfficientNet: Detection of lymph node metastases in breast cancer using convolutional neural networks," *Cancers*, vol. 13, no. 4, p. 661, Feb. 2021.

[39] A. Younis, L. Qiang, C. O. Nyatega, M. J. Adamu, and H. B. Kawuwa, "Brain tumor analysis using deep learning and VGG-16 ensembling learning approaches," *Appl. Sci.*, vol. 12, no. 14, p. 7282, Jul. 2022.

[40] L. Fulton, D. Dolezel, J. Harrop, Y. Yan, and C. Fulton, "Classification of Alzheimer's disease with and without imagery using gradient boosted machines and ResNet-50," *Brain Sci.*, vol. 9, no. 9, p. 212, Aug. 2019.

[41] M. M. Ahsan, R. Nazim, Z. Siddique, and P. Huebner, "Detection of COVID-19 patients from CT scan and chest X-ray data using modified MobileNetV2 and LIME," *Healthcare*, vol. 9, no. 9, p. 1099, Aug. 2021.

[42] M. Mujahid, F. Rustam, R. Álvarez, J. L. V. Mazón, I. D. L. T. Díez, and I. Ashraf, "Pneumonia classification from X-ray images with inception-V3 and convolutional neural network," *Diagnostics*, vol. 12, no. 5, p. 1280, May 2022.

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