# Experimental Evaluation of Deep Learning Based Plant Leaf Disease Detection System Using Computer Assisted Image Processing Techniques

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Abstract: One of the most important contemporary agricultural techniques, plant disease detection aids in the early diagnosis of crop illnesses, which allows for more effective management and the prevention of substantial losses. Color changes, spots, lesions, or structural malformations are common visible indicators of plants damaged by diseases. Handheld, drone-mounted, or integrated into smart agricultural automation systems, high-resolution cameras or sensors record these symptoms. Computer Vision and Deep Learning (ML) algorithms examine the gathered data for patterns in form, texture, and color to determine the presence of illnesses. To achieve accurate disease identification in plant leaves, this paper proposes a novel deep learning model which is Enhanced Neural Classification Network (ENCN). So, the performance of the model can be tested by cross-validating it with a conventional learning scheme Support Vector Machine (SVM). An accurate diagnosis enables farmers to implement timely countermeasures against diseases such as blast, bacterial blight or powdery mildew. The system in many cases will recommend the use of pesticides, changes to that amount of water or fertilizer that is applied to crops or quarantining sick plants to stop disease from spreading, she said. The technology improves productivity, ensures accuracy, reduces costs, and promotes sustainable farming practices by utilizing the resources that are already there more effectively. Recent advancements in plant disease detection including integration of the internet of things and drone monitoring result into crop management, high yield and sustainable agriculture environment. Beyond aiding early diagnosis and management, predictive analysis from plant disease detection systems, based on patterns in historical and environmental data, enables farmers to prepare for future crop disease outbreaks. For all, these systems make it possible to monitor a vast area, which saves time and effort when evaluating the health of enormous farmlands.

## 1 1 INTRODUCTION

Plant disease detection is an essentially significant field of study using Deep Learning for the detection and diagnosis of plant diseases (Wubetu Barud Demilie,2024). Since they may seriously affect agricultural production, it is very important to diagnose these diseases in time and to take precautions against them to guarantee food security and healthy crops. (Payal Trivedi, et al.,2024) Firstly, the process would have required a lot of time and money from the specialists who had to work out, on a laborious and error-prone way, the identification of plant diseases. The following figure, Figure 1 represents the dataset image samples.

However, with the advent of AI and ML, one can now automate the identification of plant diseases with high accuracy and speed in modern agriculture, which is very promising (3. Manjunatha Shetti gere Krishna, et al.,2025).

One of the common techniques that many researchers employ is using supervised learning to build machine learning models for plant disease diagnosis. The algorithms are trained over labeled datasets, wherein the plant images are divided into either healthy or diseased types of images (Priyanka Pradhan, et al., 2024). The model learns to discriminate between healthy and diseased plants by analysis of millions of images and considered variables such as color, texture, shape and some presence of unique patterns characteristic to several diseases.



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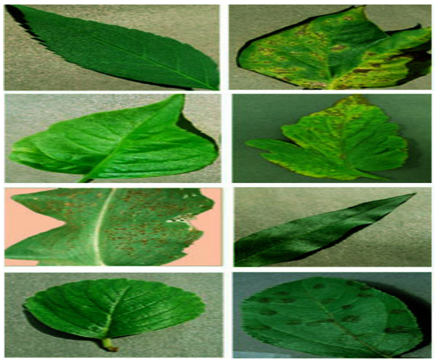

Figure 1: Dataset Image Samples.

The advantage of proposed model ENCN lies in their ability to process complex visual information with the built-in automatic extraction of relevant features from images. That is exactly why they are used to mark subtler signs of plant diseases in situations where conventional methods might not work very well. The performance of the detection system relies chiefly upon the quality of the dataset on which the machine-learning models are trained. The datasets contain both healthy and diseased plants, including quality images of plants grown under managed conditions. Datasets also have labels to indicate the presence or absence of diseases. Several of such datasets contain examples of three highly frequent agricultural diseases: leaf rust, powdery mildew, and blight; in training models to detect signs of disease, these diseases are of outstanding importance in biological and agricultural research. (B.V. Nikith, et al., 2023). A robust model would require a large, diverse and balanced dataset, which is not very easy to establish (Cemal Ihsan SOFUOGLU, et al., 2024). This dataset should include a range of plant species and diseases.

As research progresses and various datasets become more widely available, this will become a useful tool for farmers to safeguard crops and, therefore, increase global food security by providing enhancements in the speed, accuracy, and scalability of machine-learning algorithms to identify instances of plant diseases (Alwan Fauzi, et al.,2023). First, one has to collect a large number of datasets containing images of good and poor conditions of plants as a step-in kernel research of machine learning for plant disease detection. Images of plants collected to be labeled to show the absence or presence of certain diseases have been captured by devices like mobile phones, drones, or digital cameras. Next, these images undergo preprocessing to enhanced form features for appearance. This includes resizing, normalization, and augmentation (such as rotating, flipping, or scaling) in order to achieve data heterogeneity, thus preventing overfitting. Image preprocessing permits the machine learning model to concentrate on the main features such as shape, color, and texture, which are critical in the detection of disease (Rashmi Ashtagi, et al.,2025). An important aspect of autonomous feature extraction is deep learning models such as CNNs, which enable the system to internally learn complex patterns of input images (Ashutosh Kumar Singh, et al.,2022). After training on a labeled dataset, a model's performance is evaluated using various metrics such as accuracy, precision, and recall. In this case, a validation set is used for this purpose. The model is capable of being adjusted as necessary, in order to improve its performance. Once the model is accurate enough, it will be used in real-time applications, just like online platforms or mobile applications, so that farmers can identify disharmony in his/her crops by uploading pictures. In order to help guide farmers toward the rapid detection of possible illnesses, the software analyses these images and provides predictions. In addition, the system may improve itself over time in terms of different plant species and climatic conditions, since it learns from new data. There is great potential for machine-learning-powered plant disease detection to revolutionize the existing agricultural sector by reducing losses on crops and increasing food security.

The process of automating and improving the accurate and timely diagnosis of plant disease can be achieved through machine learning, especially via convolution neural networks. Convolutional neural networks, unlike any other machine learning algorithm, learn salient features from raw image data, such as pattern, texture, and shape specific to the plant disease. Training on a large dataset of labeled images allows convolutional neural networks to detect some early signs of diseases that might not be perceivable by the human eye. This allows prompt diagnosis, enabling farmers to take corrective or preventive measures before the disease spreads and causes large crop losses (Kamaldeep Kaur, et al.,2024).

Wzw the ultimate goal is to implement an easy-to-use living system to allow real-time diseases identification in crops using different platforms such as mobile application; this will allow farmers better management of crop health and hence increased agricultural yield.

(i) To enrich the model and avoid overfitting, image synthesis is used to create additional images of infested plants and hence augment the dataset.

(ii) In general, such approaches produce artificial images of sick plants by training their convolutional

neural networks with the data definitions provided through GANs. Where there is the absence of adequate labeled datasets, this can prove useful.
(iii) Early prediction and curing of plant diseases and minimizing losses to crops are made easier through the use of synthetic images produced by image synthesis, which increases the accuracy of disease detection models.
(iv) Synthetic images of infected plants can be used to fine-tune pre-trained CNN models. This allows efficient transfer learning and more accurate disease diagnosis.

# 2 RELATED WORKS

Plants form the basis of the world's food supply; nonetheless, plant diseases cause considerable losses in the output of crops, related to many environmental conditions (Muhammad Shoaib, et al.,2025). Nevertheless, Tropical plant disease identification undertaken by people becomes a long and tedious task. It is not always very reliable as a tool in Plant Disease detection and control. One way to tackle these difficulties is by implementing modern technologies like Deep Learning (DL) and Machine Learning (ML). These will allow for the early detection of plant illnesses. This study delves into the latest developments in plant disease diagnosis using ML and DL approaches. The trials included in this paper show that these methods can improve the efficiency and accuracy of plant disease detection, and the research focuses on publications from 2015 to 2022. Besides plant disease recognition, this paper also covers the challenges and constraints of ML and DL for plant diseases, such as lack of data, poor images, healthy versus sick plant distinction, etc. The survey provides a comprehensive review of the state-of-the-art work on the detection of plant diseases, along with their pros and cons, and recommendations to overcome the challenges faced while employing them. As a result, it is valuable for researchers, practitioners, and industry professionals in this field.

Scientists are now adopting intelligent agriculture-a means of greatly enhancing production with the incorporation of the use of Artificial Intelligence (AI)-to deal with various problems within agricultural fields (Sherihan Aboelenin, et al.,2025). There are a lot of illnesses that harm crop yields, and there are a lot of plants in the globe, thus finding and classifying plant diseases isn't an easy task. Any AI-based system aims to accurately classify plant illnesses and detect them early. In order to greatly enhance the accuracy of plant leaf disease categorization, this research suggests a hybrid architecture. The power of Convolutional Neural Networks (CNNs) and Vision Transformers (ViT) is utilized in this suggested model. Robust global features are extracted using an ensemble model that includes the popular CNN designs VGG16, Inception-V3, and DenseNet20. The next step in plant disease detection with high accuracy is applying a ViT model for local feature extraction. Under testing in the apple and corn public datasets, there are four classes per each dataset. The apple dataset has an accuracy of 99.24% while the corn dataset has 98%. This hybrid model will efficiently ascertain and classify multi-class plant leaf diseases in reference to other similar published models.

To protect agricultural crop output and guarantee food security, early and precise identification of plant leaf diseases is of the utmost importance (Sasikala Vallabhajosyula, et al.,2024). Bacteria, fungus, weather, and other environmental variables are among the many causes of leaf diseases that plants experience during their life cycles. By combining the best features of the enhanced Vision Transformer with ResNet9, the authors of this study provide a new hierarchical residual vision transformer that can help with the early diagnosis of leaf illnesses. By lowering the number of trainable parameters and using fewer calculations, the suggested model is able to extract more relevant and discriminating features. Tests using 13, 38, and 51 distinct leaf disease classes are conducted on the Local Crop dataset, the Plant Village dataset, and the Extended Plant Village Dataset, respectively, to assess the efficacy of the suggested approach. Using ResNet 9 for feature classification and the optimal trail parameters from Improved Vision Transformer, the suggested model is trained. When tested on the aforementioned datasets, the suggested model beat competitors like InceptionV3, MobileNetV2, and ResNet50 across a variety of metrics.

Agriculture is an essential need and their primary source of domestic income for many countries (Anuja Bhargava, et al.,2024). Plant diseases effected by more than one pathogen (as in bacteria, fungus and viruses) are so common that agricultural corporations lose big bucks worldwide. It is critical to monitor plant diseases in order to ensure the quantity and quality of harvests. This highlights the critical nature of plant disease detection. Symptoms of the plant disease syndrome manifest in certain plant tissues. Still, individual plant leaves are usually the first to show signs of infection. Several researchers have used computer vision, deep learning, few-shot learning, and soft computing approaches to automatically detect plant diseases from leaf images. Quick and suitable efforts to prevent a decrease in crop quality and quantity can also be achieved by farmers using these strategies. By using these methods to illness recognition, we may speed up technology and research while avoiding the drawbacks of origin by avoiding factious feature selection and extraction. Additionally, specific molecular methods have been developed to forestall or lessen the impact of the infectious danger. Thus, this research assists the researcher in designing automated plant disease identification systems using deep learning, machine learning, and few shots of learning. It also gives specific diagnostic methods to prevent disease. We also discuss some of the next steps in illness categorization.

Reducing economic repercussions and optimizing agricultural output require precise and timely detection of plant leaf diseases (Eman Abdullah Aldakheel, et al.,2024). The problem with precisely identifying certain illnesses is that farmers rely on traditional manual approaches, which makes it difficult. Applying the YOLOv4 algorithm to the problem of plant leaf disease detection and identification is the focus of this study. The big Plant Village Dataset is composed of more than 50,000 pictures of healthy and diseased plant leaves from fourteen different species; the study prepares the very general advanced systems for prediction of agricultural diseases. To enhance the dataset and fortify the model's durability, data augmentation techniques such horizontal flip and histogram equalization were employed. We compared the YOLOv4 algorithm's performance against that of other well-known target recognition methods, such as Densenet, Alexanet, and neural networks, as part of our thorough evaluation. An astounding 99.99% accuracy was attained by YOLOv4 when applied to the Plant Village dataset. The proposed method was verified based on consistently very high values, with 0.99 scores for all the following metrics: accuracy, precision, recall, and F1-score. The findings of this study highlight the remarkable progress made in plant disease detection and highlight the potential of YOLOv4 as an advanced tool for precise disease prediction. Because they increase our ability to manage diseases and safeguard crops, these innovations are incredibly important for researchers, farmers, and everyone else working in the agricultural sector. After the model is developed, it has to be trained using a large number of pictures that have the necessary objects tagged. Keep in mind that the EfficientNetV2B1model can only learn to differentiate between the classes if the input is balanced. After that, you need to feed the data into the EfficientNetV2B1 model. Dataset size determines whether this is best done in batches or in one continuous run. Next, a suitable optimizer, such as Adam or SGD, has to be used to train the model. In order for the model to learn to identify different objects in the images, its weights are modified continually during the training phase. After then, the testing set may be used to assess the model's correctness. The model's performance may be evaluated using a variety of measures, including recall, precision, and F1 score. We may measure the model's performance by keeping track of how many images are appropriately classified.

# 3 METHODOLOGY

Deep learning for the recognition of diseases in plants employs deep learning and some old techniques. In general, visual-based plant disease classification has leveraged conventional deep learning techniques, such as Random Forest, Naive Bayes, Support Vector Machines, and K-Nearest Neighbors. On the other hand, deep learning such as convolutional neural networks has exhibited exceedingly effective performance in identifying plant diseases present in photos. Transfer learning employing pre-trained ENCN models is yet another application for the identification of plant diseases. Hybrid techniques, combining methods such as SVM with ENCN, have also been developed to capture the best of both worlds. Other methods that help prepare the dataset and enhance it are data augmentation, image processing, and feature extraction techniques. Upon using popular datasets such as Plant Village and IPM Images for training and testing these models, deep learning shows a promising technique for reliable and quick plant disease identification. Here are some drawbacks of the procedure.

- Inadequate or biased training data might cause plant disease detection algorithms to incorrectly diagnose illnesses.
- Models for plant disease detection based on deep learning are difficult to implement on low-power devices due to the high memory and processing requirements of these models.
- High-quality images are crucial to conventional plant disease detection models, but these images are susceptible to errors caused by things like lighting, camera quality, and image processing.

The first phase of collecting data for the system would involve collecting a large dataset of healthy and diseased plants images from different sources. After this, images should be normalized to a certain size, their pixel values normalized, and data should be enhanced and diversified through data augmentation techniques for use in analysis. To be able to accomplish this, a ENCN that consists of convolutional layers, pooling layers, and fully connected layers is trained. By using k-fold cross-validation, taking precision, recall, and F1 score along with accuracy matrixes for the evaluation comes the next part on the addition of images from the users for diagnosis of the specific plant species or diseases via transfer learning which can allow fine-tuning. Certainly, asked for diagnosis, this web or mobile application is also usable for resolvable fine-tuning through transfer learning for a specific plant species or diseases. Indeed, easy usage interface in the system provides sufficient support for specialists in agriculture and farmers to utilize it for disease diagnosis and treatment suggestions. The system, therefore, can combine and work together with various technologies, like satellite imaging or drones, allowing small and large-scale infection detection and monitoring. The following figures, Figure 2 and Figure 3 show the flow diagram and system architecture of the proposed approach.

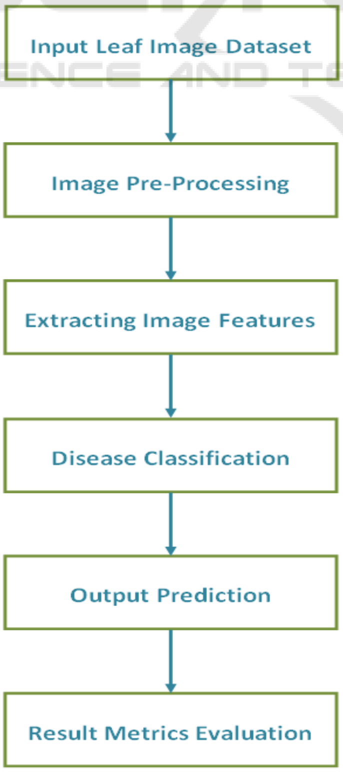


Figure 2: System Flow Diagram.

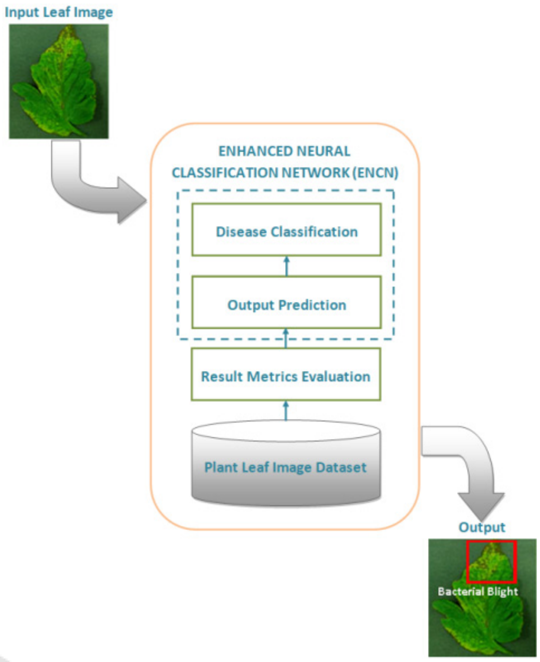


Figure 3: System Architecture.

The process of plant disease detection starts with acquiring a large dataset of images from healthy and diseased plants and working on them to standardize diversity. This is followed by designing a ENCN architecture and training using the preprocessed dataset, resorting to methods like data augmentation and transfer learning to facilitate better learning. Subsequent to this step, accuracy and F1-score metrics should be used to assess the model and deploy it through a web or mobile application so that farmers and agricultural specialists can upload images for disease detection. Eventually the model continues to get new updates from data again to learn and improve its performance in providing proper diagnosis with the required treatment suggestions. Below are the advantages:

- The use of deep learning in the ENCN algorithms for plant disease recognition can have several benefits; it, first and foremost, removes the long, tedious, and error-prone human examination and diagnosis of plant diseases. Such detection, therefore, becomes more efficient and more accurate.
- ENCN models train actually to recognize diseases early by noticing features and patterns within the images that are difficult for a human to perceive. In addition, deep learning systems can learn through huge datasets and continuously improve their performances in detecting some diseases.

- With precise insights and treatment recommendations from the ENCN algorithm that can be performed by the agricultural experts and farmers, preemptive measures will, thus, be taken to control the outbreak of the diseases.

## 3.1 Data Collection

It is challenging to guarantee the efficacy of transfer learning because the initial MobileNet pre-trained model was trained on the ImageNet dataset, which does not only include the pictures that are required. So, in order to train the model, we require a dataset that includes trash photos. There is currently no fixed dataset that is universally used for trash categorization jobs. The TrashNet dataset is used for rubbish classification; however it doesn't adequately reflect the real situation of residential waste categorization in India since it contains too few categories. Consequently, this article builds a dataset specifically for visual trash sorting using network retrieval and real-world scene imaging in the lab, covering both single-object and multiple-scene scenarios.

## 3.2 Image Processing

To augment and normalize images of plants so that accuracy in identification of plant disease is improved, an Image Preprocessing obtains images. Depending on the kind of input image it is processing, it resizes images into fixed resolution, normalizes pixel values, incorporates some augmentation techniques, removes noise or other irrelevant qualities, and enhances image quality with brightening, contrast, and saturation enhancing. The whole model is thus reinforced, has less influence from external variables, and improves the accuracy in diagnosis. The current discussion revolves around whether a new medium can replace or precedes existing media, particularly when the new channel offers similar functionality as the old one. To perceive the impact of a novel media on a preexisting one, it is crucial to analyze customer perspectives about the Modern channel and its potential to substitute the current one.

## 3.3 User Interface

Dataset was divided into three subsets: validation, training, and testing. User Explanation provides a user-friendly interface for farmers and agricultural experts to receive disease diagnosis and recommendations for treatment. It explains the detected disease, its symptoms, causes, and prevention methods, enabling users to take informed decisions about crop management and disease control. Also, the process will provide users with personal advice on pesticide application, fertilizer application, and irrigation management, allowing users to optimize their farm management systems. It also provides information on how the disease may potentially affect crop yield and quality, enabling users to plan accordingly. Likewise, a feature on the process will track the disease's history and give alerts for possible outbreaks of the disease, allowing users to implement some of their proactive measures to avoid the spread of any disease.

## 3.4 ENCN Architecture

Following preprocessing, we select an ENCN architecture that works best for trash picture classification. Our classification model of choice is EfficientNetV2B1. We loaded the model weights from a source similar to EfficientNetV2B1. The models can be found within deep learning tools, namely, TensorFlow or PyTorch. The pretrained EfficientNetV2B1 model has been modified by removing the previous classification head (fully-connected layers) and inserting a new classification head corresponding to the number of garbage categories in our dataset. We used ENCN layers as feature extractors to educate the model in such a way as to extract hierarchical and discriminative qualities from the garbage images. It is thereby necessary to use an optimizer, such as AdamorSGD, to work to adjust model weights through back propagation, as well as a suitable categorical cross-entropy loss function for multi-class classification.

## 3.5 Model Training

Following model creation, it is necessary to train the model using a large number of photographs annotated with the necessary items. If you want the EfficientNetV2B1model to learn to differentiate between the different classes accurately, you must ensure that the data is balanced. Once the data is available, it has to be loaded into the EfficientNetV2B1 model. Depending on the dataset size, this can be done in batches or all at once. Then we proceed to model training, using an appropriate optimizer (Adam or SGD). During training, the model adjusts its weights to recognize objects within the images. In the next step, the model could be tested with the testing set to check its performance. Recall, accuracy, and F1 score are all some ways we can evaluate the model. A common way to evaluate model performance is by quantifying how many photos it can correctly label. It can be used on unseen data to further test the generalizability of the model. This will demonstrate how well the model can predict using unobserved data.

## 4 RESULTS AND DISCUSSION

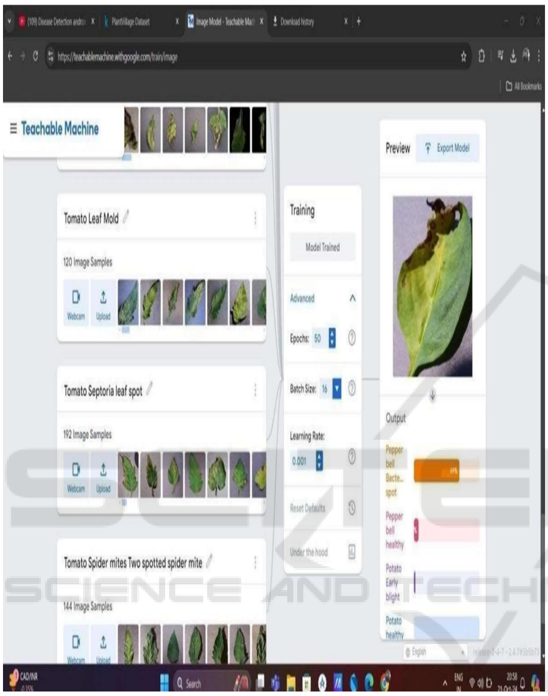


Figure 4: Dataset Uploading Port.

Using deep learning techniques to plant leaf disease detection systems has improved agricultural diagnostics extensively. The proposed representations are fed into different deep learning architecture such as Enhanced Neural Classification Network (ENCN) to identify and categorize the diseases based on leaf images. Consequently, they facilitate early intervention and improved crop management. Applications of deep learning models like the ENCN in Android apps make real-time detection and classification of maize and other cereal problems fast and efficient. Precision farming undergoes a paradigm shift with the implementation of deep learning for the identification of plant leaf maladies. The high accuracy and efficacy of these models suggest that they may be widely accepted in a variety of agricultural settings.

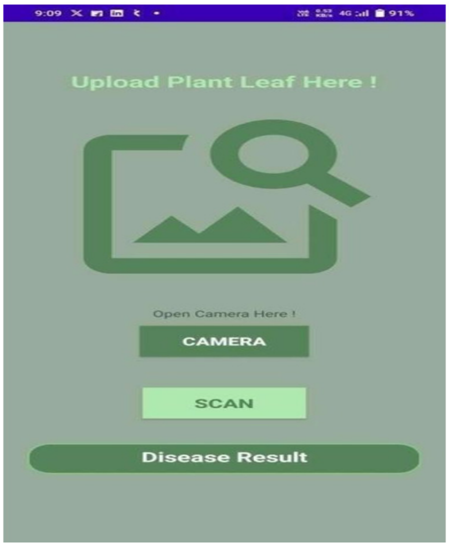


Figure 5: Validation Image Uploading Port.

Future research should focus on the inclusion of these systems in readily accessible platforms for farmers and other experts, the enhancement of model resilience under diverse environmental conditions, and the expansion of the diversity of plant species and illnesses that are addressed. Figure 5 clearly shows the testing image uploading portal that was created using an Android application; Figure 4 shows the dataset uploading site of the suggested method. Image pre-processing and leaf disease prediction results of the suggested approach are shown in Figures 6 and 7, respectively.


Figure 6: Image Pre-Processing.


Figure 7: Disease Prediction.

Figure 8 shows the results of a cross-validation test between the suggested model ENCN and a traditional learning model known as SVM, which was used to determine the model's prediction accuracy. Table-1 provides a descriptive representation of the same.

Table 1: Prediction Accuracy Comparison between SVM and ENCN.

| Epochs | SVM (%) | ENCN (%) |
|---|---|---|
| 100 | 88.62 | 96.27 |
| 125 | 86.61 | 97.63 |
| 150 | 84.43 | 95.87 |
| 200 | 85.71 | 97.31 |
| 250 | 86.62 | 97.11 |
| 300 | 87.62 | 97.35 |
| 350 | 87.63 | 97.58 |
| 400 | 88.62 | 97.82 |
| 450 | 89.73 | 96.79 |
| 500 | 88.92 | 97.29 |

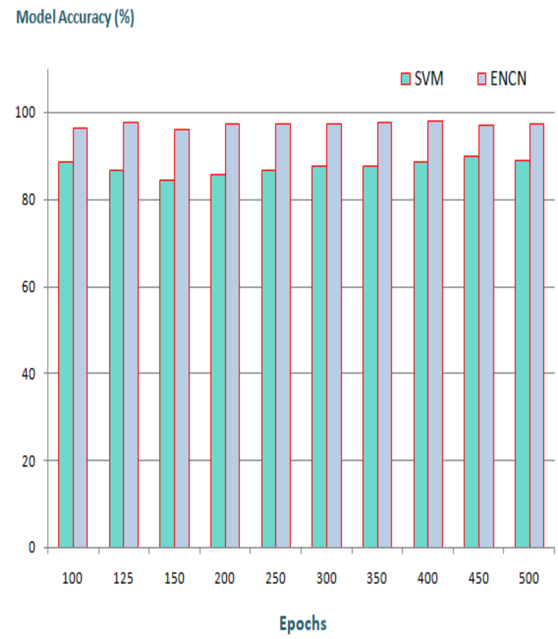


Figure 8: Model Prediction Accuracy.

The proposed ENCN loss ratio assessment is presented in the following figure, Figure 9. In this assessment, we will cross-validate the previous scheme's proposed scheme with a classical learning model referred to as SVM to find the proposed scheme's loss ratio. The same is described in the next table called Table 2.



Table 1: Comparison of Loss Ratio Between Svm and Encn.

| Epochs | SVM | ENCN |
|---|---|---|
| 100 | 6.34 | 1.19 |
| 125 | 6.62 | 1.26 |
| 150 | 4.79 | 1.34 |
| 200 | 6.27 | 1.82 |
| 250 | 6.36 | 1.94 |
| 300 | 5.29 | 2.65 |
| 350 | 4.73 | 2.72 |
| 400 | 4.50 | 2.66 |
| 450 | 6.69 | 2.67 |
| 500 | 6.47 | 2.88 |


Figure 9: Loss Ratio.

## 5 CONCLUSIONS

Plant disease detection detected plant sickness using ENCN deep learning and computer vision approach have proven highly effective in accurately identifying and tackling plant disease. By automating the process of disease detection, this approach reduces manual labor, enhances productivity, and allows for early diagnosis of diseases, minimizing damage to crops and losses. Moreover, the disease diagnosis accuracy of the system is high, thereby minimizing the chances of treating wrong disease. It has the potential to develop further in the future through transfer learning, more disease detection and IoT sensors integration. In summary, the Plant Disease Detection system is a powerful tool that aids farmers and researchers alike in maintaining optimal crop health and productivity, playing a crucial role in ensuring global food security and sustainability. The Plant Disease Detection system has far-reaching implications for global food security and sustainability. With unparalleled disease diagnosis accuracy, it ensures that researchers and producers have a reliable tool to prevent misdiagnosed and mismanaged. Potential for integration with IoT sensors, multi-disease detection, and transfer learning provides a wide avenue for further enhancement of this system which in turn will help for having more sustainable and resilient agricultural systems.

In addition, the system can be adapted to detect several illnesses at once, which decreases the need for separate models and increases overall efficiency. The application of transfer learning will also enable the system to adjust to new, previously unseen ailments while alleviating the need for significant retraining. An app will make the system easy to use which will promote the wide use of the system between farmers and researchers. By incorporating explain ability and interpretability methods, users will be able to understand how and why the system came to a particular decision, leading to increased trust and understanding amongst users. Transfer learning: The system must be able to adapt with the new unknown diseases, without retaining from scratch. The development of explainable/ interpretable techniques will provide insights into how the system makes decisions, while a future mobile application will act as a bridge between farmers and researchers.

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