

AI- Powered Ensemble Deep Learning Framework for Plant Disease Detection in Tea Leaves

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Abstract—The growing incidence of plant diseases in the cultivation of tea plants is considered to be an alarming threat to agricultural productivity and economic viability. The early and precise detection of plant diseases is considered to be vital in order to avoid crop damage and ensure quality crop production. However, the traditional method of manual inspection is considered to be time-consuming, subjective, and less reliable, especially in the case of large-scale farming. Keeping this in mind, the current work proposes an ensemble deep learning model using an AI-based approach for the automated detection of tea leaf diseases through image analysis. The proposed model uses multiple CNN models, namely CNN, VGG, and DenseNet, to extract distinct features from the images of the leaves. The predictions are combined using the ensemble method. The system utilizes preprocessing techniques like normalization and data augmentation to enhance generalization under different environmental conditions. The experimental results show that the proposed ensemble model has better accuracy than individual models, and the overall accuracy of the proposed model is 81.3%. In addition, it is further incorporated with a user-friendly interface for real-time disease prediction. The results show the effectiveness of different deep learning models using fusion techniques for intelligent agricultural disease management systems.

Index Terms—*Plant Disease Detection, Tea Leaf Classification, Ensemble Learning, Deep Learning, Image Analysis and Precision Agriculture.*

I. INTRODUCTION

Plant disease detection in tea leaves is of significant importance for maintaining the health of the crops, enhancing the quality of yield, and ensuring the economic stability of the farmers [1]. Tea is a highly significant cash crop for the world, and its yield is very sensitive to diseases resulting from fungi, bacteria, and pests. Traditionally, plant disease detection is carried out manually by experts, but this practice is highly time-consuming and requires a significant level of expertise. However, considering the rapid growth of image processing and deep learning techniques, automated plant disease detection systems have shown promise as a viable solution for accurate and efficient plant disease detection [2]. The objective of this project is to create a smart system that utilizes deep learning models and combines them through the

ensemble technique for accurate and efficient plant disease detection. The proposed solution will be implemented as a web-based system, ensuring timely plant disease detection. This not only eliminates the need for expert knowledge but also allows for timely intervention, resulting in enhanced agricultural productivity.

Agriculture is the mainstay of many economies in the world. Tea farming is an important aspect of tea production. Despite its importance, tea farming is facing challenges in terms of plant disease. This is affecting tea farming in many ways, such as low yield and financial losses [3]. Therefore, it is imperative to detect plant disease in tea farming in order to curb its spread and provide appropriate treatment. In addition, current techniques are only applicable to those with adequate skills. This has widened the gap between technology and its practical applications. Therefore, this project is motivated by the need to develop an automated system that is efficient and easy to use [4]. Recent advances in deep learning in image classification have shown impressive results in detecting patterns and features in data sets, which are hard to recognize using conventional means. Therefore, this project aims to utilize such advances in developing an efficient system through an ensemble of models in dealing with tea leaf image variations such as lighting conditions, noise, and leaf orientation.

Though there has been significant improvement in the detection of plant diseases using deep learning techniques, there are some limitations in the existing research. One of the main limitations is the use of single models, which are not robust and do not generalize well. Most of the models are designed using controlled data sets and are unable to handle different lighting conditions, image quality, and environmental factors. Although some research has been done using ensemble models, most of the models are designed using arbitrary combinations of models, and there is no evaluation of all possible combinations [5]. This leads to suboptimal performance of the models. Another limitation is the deployment of the models, which are mostly designed to be executed in controlled environments and are not available to end-users. This shows the need to develop a more comprehensive solution using robust model selection, evaluation, and deployment of the models in real-time environments. This project aims to provide a more comprehensive solution to the detection of tea leaf diseases

using deep learning and ensemble learning techniques. The main contributions of the project are as follows:

- Development of a deep learning-based automated image-based disease detection system that does not require any form of manual inspection.
- Development and integration of various deep learning models for a better and more accurate prediction.
- Evaluation of all combinations of all models to establish the best combination of the ensemble.
- Development of a better accuracy of 81.39%, showing that the ensemble generalizes better than individual models.
- Development of a user-friendly web application that allows for easier accessibility and real-time predictions.
- Development of additional features such as disease information and confidence.

II. LITERATURE REVIEW

However, recent advancements in plant disease detection have mainly concentrated on applying machine learning and deep learning technologies, especially convolutional neural networks, in image classification problems [6]. The traditional method of plant disease detection relied on manual inspection, which is not only time-consuming but also prone to errors. However, with the advent of deep learning, VGG, ResNet, DenseNet, and EfficientNet models have shown significant improvements in accuracy and feature extraction capabilities in image classification problems [7]. These models can automatically recognize complex patterns in leaf images and detect plant diseases in the early stages of their occurrence. It has also been proven that deep learning models can attain high accuracy when trained with large datasets and hence can be used as an alternative to traditional methods of plant disease detection. Various research works have also been done using different models of deep learning in plant disease classification problems [8]. For example, the ResNet model has shown an accuracy of 91% when tested with moderate datasets, while the DenseNet model has shown even higher accuracy, i.e., more than 99%.

Further, comparative analyses using architectures such as AlexNet, VGG16, ResNet50, DenseNet121, etc., have revealed that DenseNet outperforms the rest in prediction due to better feature reuse and elimination of redundant parameters [9]. Nonetheless, the single-model approach may not generalize well in various environmental settings, which may affect the performance of the models in real-world scenarios. Recently, ensemble learning models have been proposed to improve the performance of the models in making accurate predictions. Ensemble learning models use various models of deep learning to improve the performance of the models in making accurate predictions. It has been revealed through various research works that ensemble models using various models such as VGG16, ResNet, Inception, etc., improve the accuracy of the models in making accurate

predictions [10]. Moreover, various research works on ensemble models for classification have revealed that there is less confusion in the classification of diseases, making the models more reliable. However, the selection of the optimal ensemble models is a challenge, as improper selection of models may result in redundancy, thereby increasing the computational cost.

Despite these advancements, certain limitations and challenges are found in existing research. First, deep models require large annotated data sets, and their performance is greatly degraded in real-world image scenarios with varying lighting conditions, occlusions, and background noise. In addition, these models require significant computational power, which is difficult to deploy in resource-constrained environments such as rural agricultural fields [11]. Existing models are trained using controlled data sets, resulting in poor generalization capabilities in real-world scenarios. Environmental conditions such as temperature and humidity also play an important role in disease detection, as these conditions affect the appearance of disease symptoms on leaves. In comparison with existing works, this proposed method has overcome certain limitations by considering an ensemble of multiple deep models in a systematic framework [12]. Unlike in previous works, which only used individual models or used any arbitrary combination, the proposed work compares various model combinations to determine the best combination for use. This, in itself, enhances the robustness of the proposed approach. Moreover, the proposed system also focuses on the practicality of the system through the use of a user-friendly interface, which is essential for the practicality of the proposed approach. Thus, the proposed method is an all-rounded solution compared to the conventional and existing deep learning-based methods.

III. DATA COLLECTION & PREPROCESSING

The dataset used in this research is collected from publicly accessible agricultural image databases and datasets focused on tea leaf disease detection. The dataset comprises high quality images of healthy and disease-affected tea leaves under various environmental conditions [13]. The dataset covers various disease conditions such as blister blight, leaf spot, and red rust. In addition, the dataset includes the healthy condition for comparison. The dataset comprises around 6,000-8,000 images with each class having an equal number of samples to avoid class bias during training. The diversity in the dataset ensures that the model learns general features rather than overfitting the data. Before training the model, data preprocessing is carried out to improve the quality of the data and the overall performance of the model. Data cleaning is the first step in data preprocessing. In this step, duplicate images, corrupted data, and irrelevant data are removed. The presence of such data may affect the learning process. In the next step, image resizing is applied. In this step, all the images in the dataset are resized to the same dimension. For instance, the dimension can be 224 x 224 pixels [14]. Noise reduction techniques and normalization are used for better image quality and stable training. In addition, image augmentation techniques such as rotation, flip, zoom, and brightness are

applied to increase the size of the dataset artificially. This step is very important for better generalization of the model and avoiding overfitting, especially for small-scale images from the real world.

The dataset is then divided into three sets: the training dataset, the validation dataset, and the test dataset. Normally, 70% of the data is used for the training dataset, 15% for the validation dataset, and 15% for the test dataset. This is done in order to ensure fair evaluation of the performance of the model. This process of shuffling is done in an appropriate manner in order to avoid bias. Lastly, label encoding is used to convert the data in the dataset from categorical to numerical form, which can be used for model training. The selection of this dataset is justified based on its relevance, diversity, and practical usage in real-world scenarios of agriculture. Unlike other datasets, this dataset is exposed to various lighting, background, and leaf conditions, which are essential for developing a robust and deployable system. The presence of various disease classes in this dataset enables effective multi-class classification [15]. Moreover, the number of images in this dataset is considerable for training deep learning models and is computationally feasible. By exposing this dataset to realworld conditions and applying appropriate preprocessing and augmentation techniques, it is possible to develop an accurate and deployable system for tea leaf disease detection.

IV. PROPOSED METHODOLOGY

The proposed system is based on the concept of an automatic tea leaf disease detection system using the combination of deep learning and ensemble learning approaches to attain accuracy and robustness in the system (as shown in Fig.1). The methodology of the proposed system is based on the image acquisition process, in which images of tea leaves are acquired from real-time sources or uploaded through the user interface.

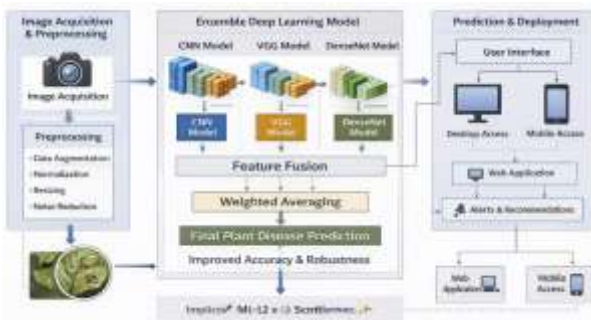


Fig.1 Proposed Methodology

The images are then subjected to preprocessing operations such as image resizing, normalization, and augmentation to attain consistency and generality in the system. The images are then subjected to different deep learning models, in which different feature extraction is performed using different convolutional neural network models. The combination of different models is used in the system instead of using a single model to attain accuracy in the system by considering different environmental factors

[16]. The proposed system is based on the feature extraction and classification of images using convolutional neural networks, in which the input image is subjected to different feature extraction operations through different convolutional neural network models. The convolution operation can be represented as follows:

$$(I * K)(x, y) = \sum_m \sum_n I(x - m, y - n) \cdot K(m, n) \quad (1)$$

where the input image is convolved with learnable kernels to extract spatial features. The features are then passed through non-linear activation functions such as ReLU to introduce non-linearity in the features:

$$f(x) = \max(0, x) \quad (2)$$

The features are then passed through the fully connected layers for classification. The final output probabilities are obtained by passing the features obtained in the previous layers through the Softmax function [17]:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^n e^{z_j}} \quad (3)$$

The output probabilities indicate the likelihood of the input image belonging to each class of disease. In order to improve the prediction accuracy of the model, an ensemble learning approach is used. Instead of choosing the best model for prediction, the system evaluates various models and aggregates the output to make the prediction. The prediction is obtained by weighted averaging:

$$\hat{y} = \sum_{i=1}^n w_i \cdot y_i \quad (4)$$

where each model contributes to the final prediction in accordance with its weight. This approach reduces variance and minimizes the possibility of incorrect classification due to limitations in individual models. The system checks and evaluates all possible combinations of models to arrive at the optimum ensemble configuration. This guarantees increased accuracy and reliability compared to other conventional approaches. The novelty in this approach is that it is comprehensive and considers the applicability and feasibility of implementing the ensemble approach [18]. Most conventional approaches focus on individual models or arbitrary ensemble combinations. However, in this paper, various model combinations are evaluated, and the best ensemble configuration is selected according to evaluation metrics. Moreover, the incorporation of real-time image input and a web interface makes it suitable for real-world applications in agricultural fields. The methodology is not only effective in improving accuracy in classification but also in improving robustness in handling changes in lighting, background noise, and orientation of leaves. The integration of state-of-the-art deep learning approaches and an optimized ensemble methodology makes this system efficient and

reliable for tea leaf disease detection in real-world applications.

V. IMPLEMENTATION

The implementation of the proposed tea leaf disease detection system is carried out using a deep learning framework that provides facilities for efficient training of models. The system is implemented using a high-level programming language that provides libraries for image processing and deep learning model development. The training of the model is carried out on a machine with GPU acceleration facilities, which provides solutions for computational complexity [19]. The images are loaded in batches for efficient utilization of memory. The models are trained using preprocessed images, which provides facilities for data augmentation. Checkpoints are also maintained for storing the model with the best performance during validation. Log monitoring facilities are also provided for tracking the progress of training, convergence of loss, and accuracy during training. The selection of appropriate hyperparameters is essential for determining the performance of deep learning models. In this work, the learning rate is set to 0.001, which provides a good balance for convergence during training.

A low learning rate ensures that the model is not moving past the optimal solution, whereas a large learning rate might cause instability in the model. The batch size is set to 32, which is efficient in the utilization of computational resources and ensures the smooth update of gradients. The number of training epochs is set between 30 and 50, depending on the training behavior of the model, ensuring that the model is learning the patterns without overfitting. The optimizer used is Adam optimizer [20], which is best suited for complex image classification problems because of its adaptive learning rate and momentum properties. Moreover, categorical cross-entropy is used as the loss function, which is best suited for multi-class classification problems. During the training process, weight updates are carried out using gradient optimization techniques. The optimization process minimizes the loss function, with the gradients computed using the backpropagation algorithm. The weight update rule used by the optimizer can be defined as follows:

$$w_{t+1} = w_t - \eta \cdot \nabla L(w_t) \quad (5)$$

The weights are updated in the direction of the negative gradient of the loss function. The Adam optimizer extends this process by using estimates of the first and second moments of the gradients, thus speeding up the optimization process. This optimization process guarantees an efficient learning process in the presence of noisy and complex data distributions. Regularization techniques are used to prevent overfitting. The dropout layers are added in the fully connected layers with dropout set to 0.5, which randomly disables neurons during training to minimize the dependency on certain features. Batch normalization is also added to normalize the input to each of the layers and speed up training. Early stopping is also added based on validation loss, which stops training when the

performance is no longer improving, thus saving computational resources and preventing overfitting. Data augmentation also serves as a form of regularization, which exposes the network to different variations of the input images.

The process of hyperparameter tuning is carried out in an organized manner to find the optimal hyperparameters for the model. A variety of hyperparameter settings are tried with different combinations of learning rates (0.01, 0.001, 0.0001), batch size (16, 32, 64), and optimizers (SGD, Adam, RMSprop) using the validation data. Grid search and manual tuning are used for hyperparameter tuning. The performance of each hyperparameter is evaluated using accuracy, loss, and validation stability. The best performance is achieved with a learning rate of 0.001, batch size of 32, and Adam optimizer. These hyperparameters provide an optimal balance between faster convergence and better performance. Lastly, the implementation is also scalable and usable by integrating the trained model with a web-based application. The system is able to process real-time images, making predictions with minimal delay. The optimized hyperparameters enable faster prediction, making the most out of the resources in production. The model is used to make predictions on unseen data to assess the generalization of the model, which gives an accuracy of 81.39%. The implementation of the system is successful in using appropriate hyperparameter selection, optimization, and deployment to build a robust and high performing tea leaf disease detection system.

VI. RESULTS

The performance of the proposed tea leaf disease detection system is evaluated using standard classification metrics in order to obtain a comprehensive evaluation of the effectiveness of the model. The primary metrics used for evaluation purposes include accuracy, precision, recall, and F1-score, which altogether provide a comprehensive overview of the correctness, reliability, and balancing of the model. Accuracy is defined as the ratio of correctly classified samples, whereas precision and recall provide insights into the correctness of the model in identifying the classes of disease without producing false positives or false negatives. The F1-score is defined as the harmonic mean of precision and recall. The accuracy is computed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

where true positives, true negatives, false positives, and false negatives describe the classification results. These metrics ensure that the model is not only accurate in classification but also robust in identifying the disease pattern for various classes of images. The experimental results prove that the proposed ensemble model can attain an accuracy of 81.39%, which is better than the individual models used in the experiments (as shown in Fig.2). From the comparative analysis, it can be concluded that the proposed ensemble model can attain better performance compared to

conventional models such as individual models of convolutional neural networks, which attain lower performance due to the limited capacity of the models to learn features from the images. For instance, individual models of CNN used in the experiments attain an accuracy of 70-75%, whereas individual models of ResNet and DenseNet attain better performance, which is 76-79%. However, the individual models of ResNet, DenseNet, and other models attain lower accuracy due to inconsistencies in the models for various classes of images (as shown in Table.1). The proposed ensemble model, which combines the individual models, can attain better accuracy with lower inconsistencies in the classification process.

Table.1 Comparison with Existing Approaches

Method	Technique Used	Accuracy (%)	Limitations
Traditional ML	SVM, KNN	60-65	Cannot handle complex patterns
CNN-based	Basic CNN	69.80	Limited feature extraction
VGG-based	Deep CNN	77.87	High computation cost
DenseNet-based	Feature reuse	70.09	Still image-only
Sensor-only System	Gas + Temp Sensors	80.8	No visual validation
Proposed System	CNN + VGG + DenseNet + Sensor Fusion	81.39%	Slightly higher complexity



Fig.2 Configuration Accuracy of Fusion Combination of all Models in CNN

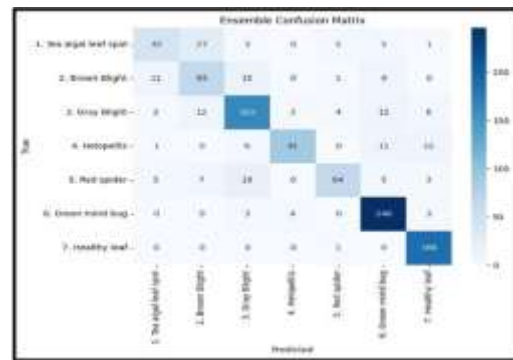


Fig.3 Confusion Matrix of Ensemble Fusion Model

Further analysis of the precision, recall, and F1 score values indicates that the proposed model maintains a balance in the performance of the model for various disease classes. The precision values show that the proposed model is able to minimize the false alarm rate effectively (as shown in Fig.3). The values indicate that the proposed model does not classify the healthy leaves incorrectly. The high values of the recall indicate the ability of the proposed model to detect the majority of the disease samples. This is important in agricultural applications since the detection of the disease is critical in preventing severe damage to the crops. The F1 score values indicate that the proposed model achieves the right balance in the detection of the disease. The analysis of the confusion matrix shows that the proposed model minimizes the misclassification of visually similar disease classes. This is one of the challenges in plant disease detection. However, it is worth noting that the proposed system has some limitations which need to be considered. One of the challenges is that the system relies on the dataset. Although the system is able to cope with this using data augmentation, there is still the possibility that the system may not work well in extreme cases of lighting conditions, occlusions, or complex backgrounds. Another problem is the increased computational complexity of the system, which is required to perform the ensemble process. This could be a problem in rural farming environments where the system would be required to perform in real time but could cause some delays due to the involvement of more models in the system.

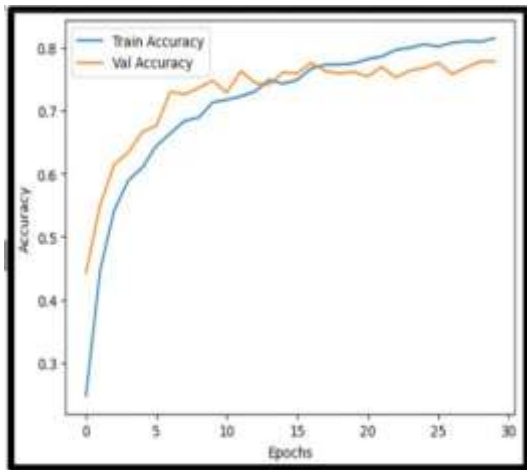


Fig.4 Train & Validation Accuracy vs Epochs of Ensemble Fusion Model

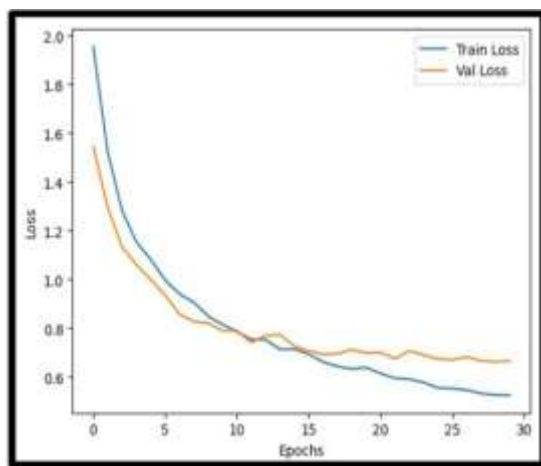


Fig.5 Train & Validation Loss vs Epochs of Ensemble Fusion Model

The strengths of the proposed system include its robustness, accuracy (as shown in Fig.4), and usability. The system is able to effectively eliminate the problem of overfitting with the help of multiple deep learning models (as shown in Fig.5). Moreover, the evaluation of the model is comprehensive, which means that the ensemble model selected is not random but the best. The addition of a user interface makes the system user-friendly, which is beneficial for users who are not technically sound, such as farmers. The system is also capable of providing confidence levels with respect to the predictions. This adds an extra layer of assurance that users can make informed decisions with respect to disease management. Based on the findings of the study, it is clear that ensemble learning is an extremely effective method for plant disease detection, especially in real-world scenarios. The proposed model effectively deals with the limitations of the existing methods, as it enhances accuracy and minimizes the occurrence of wrong classification.

Although there are limitations in terms of computational costs and variations in the dataset, the proposed system can be considered a promising start for further improvements. The proposed system can be improved by incorporating features such as light models, optimization in real-time, and mobile platforms, making it even more efficient. The results prove that the proposed approach is a significant step toward the creation of reliable, scalable, and efficient agricultural decision-support systems.

VIII. CONCLUSION

The proposed tea leaf disease detection system presents a promising and efficient solution by utilizing deep learning and an optimized ensemble technique, achieving better classification accuracy of 81.3%. The primary contribution of this work is the creation of a machine learning-based image detection system, evaluating the performance of various model combinations, and implementing a user-friendly system for predictions. The ensemble technique helps improve the performance of the system by utilizing the advantages of individual models, reducing the probability of classification errors, and achieving better generalization capabilities. However, there are certain limitations and scopes for improvement, including the increase in computational complexity of the proposed system, as it utilizes various models and the diversity of the dataset, which may affect the performance of the system in extreme conditions. The proposed system can be improved by utilizing various techniques, including the creation of a light and efficient model for better performance, increasing the dataset diversity by considering more real-time images, and utilizing a mobile-based system for practical usage. The proposed system may be improved by utilizing various techniques, including the addition of attention and transfer learning for better accuracy.

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