AI-DRIVEN CROP DISEASE PREDICTION AND MANAGEMENT SYSTEM

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***Abstract*—First of all, the early and precise crop disease identification is the most important factor that not only helps to maintain the agricultural productivity but also is able to stop the capitalized scenarios of crop yield losses. This research article has introduced an AI-based system for plant disease recognition, which by its nature is a very complex system including deep learning, ensemble modeling, and a user-friendly interface for instant disease classification and generating field recommendations.The method relies on a very carefully chosen dataset of crop leaf images for 15 different diseases and also the healthy classes, followed by the standard preprocessing, and augmentation for better generalization. Two cutting-edge convolutional neural network architectures, DenseNet-121, and ResNet-50, are each changed to operate in different manners and a soft-voting ensemble method is used to merge their outputs, thus a significant increase in prediction robustness is achieved.The combined model has a very high accuracy of 99.57% and, thus, is very capable of detecting the slightest disease symptoms. The API, which is powered by FastAPI, is Model calling is handled at the backend, whereas the frontend is used for user image uploading for prediction along with the confidence score. Hence, the system is equipping farmers with the means to recognize diseases at the very time, thus, they can make timely interventions which is one of the essential factors for smart agriculture and, therefore, sustainable food production is the final outcome.**

Keywords— Deep Learning, Ensemble Learning, DenseNet-121, ResNet-50, Plant Disease Detection, PlantVillage, PyTorch, Transfer Learning, LangChain, ChromaDB, Explainable AI.

I. INTRODUCTION

Agriculture is still the main source that supplies food to the whole planet and is very necessary. Nevertheless, in various parts of the world, crop diseases have been the major cause of agri-food losses year after year [1]. The most plausible and at the same time the only method of knowing the plant diseases that subsequently have to be controlled is through very early and accurate identification. Regrettably, the current method of manual inspection is a tough undertaking, a process that is prone to mistakes, and it requires a considerable amount of knowledge of skilled personnel [2]. AI as a disease diagnosis tool is a futuristic concept that in many ways goes along with the shortest possible time and solves the problem of subjective diagnosis. Visual diagnosis of the disease through image-based analysis is the present standard in smart farming innovations [3]. Specifically, deep learning and convolutional neural networks (CNNs) have been remarkably successful in identifying plant diseases in the visual data [4].Leading edge deep architectures such as ResNet and DenseNet have very complex feature extraction that explains their better performance in image-based classification tasks in the agriculture domain [5]. The single largest discovery that multiple research studies have come to is that methods based on CNN outperform methods of traditional machine learning in recognizing plant diseases in crop varieties [6]. However, the problem of a single-model classifier still remains, that is such a model cannot handle situations in daily life like uneven illumination, background noise, and similar visual features of different diseases [7].Ensemble learning has found a method to make the system more robust by the prediction aggregation from several deep models as a single-model approach answer that surpasses the single-model approaches [8]. Besides this, cloud computing and API-based deployment have solved the problem of AI models being closed-off to users as they can now be accessed almost in real-time from different web and mobile platforms. Therefore, a farmer can know what is wrong with his crops within a few seconds just by uploading the image of the infected part of the plant [9]. Moreover, apart from that, the scalability keeps improving, the monitoring of large areas becomes less and less challenging, and the continuous updating of the model is facilitated by the availability of new data [10]. The integration of prediction with real, on-the-ground advice on disease management not only relieves the farmer from the task of trying to make sense of the results but, furthermore, AI is being promoted as a leader in precision agriculture [11].At the end of the day, the problem of obtaining high accuracy over a large number of diseases and crop species is still there notwithstanding the technological breakthroughs [12]. Hence, this is an AI-powered introduction work for a system that features a two-model ensemble for the prediction and management of crop diseases - DenseNet-121 and ResNet-50 hybrid. The system is heavily reliant on the soft-voting method which is used to combine their outputs thus resulting in increased prediction stability and reduced error rates [13]. In case there is to be a sudden outbreak of a disease, the community would have at its disposal a FastAPI backend for rapid model inference and a GUI which is so straightforward that anyone can use it [14]. The present research paves the way for future developments in smart agriculture, succeeding in delivering a resource that is not only timely and accurate but also scalable, which is essential in the early detection of diseases and their management by an ensemble model achieving a validation accuracy of 99.57% with the dataset of 15 different crop diseases.

II. LITERATURE REVIEW

Deep Recognition of plant diseases through deep learning has been the main point of focus of research for at least two years. The pivotal reason deeply lies in the fact that deep learning in general has demonstrated a tremendous potential to process very complex visual patterns and consequently achieve very high levels of system accuracy. In fact, first groundbreaking scenarios of research have initially shown that convolutional neural networks (CNNs) can perform better than feature-engineering-based methods in the classification of agricultural images [1]. Such a proof has been acting as the motivational factor for researchers to further explore models for disease localization.By using skip connections to overcome the gradient vanishing problem and, thus, extend the range for which the problem could be solved, ResNet-based architectures were able to perform very well on a number of plant disease datasets [2]. Similarly, DenseNet became very powerful in the feature extraction stage due to the full connectivity between the layers and, therefore, very efficient learning could be done even with a few training examples [3]. A deep networks comparison has influenced the researchers to come to a conclusion that deep CNNs are far superior to traditional machine learning models such as SVMs and random forests for the task of crop disease detection [4].In addition to that, most of the researchers have placed transfer learning as a method of pattern recognition that could significantly increase the accuracy of plant diseases-related problems, particularly, when datasets are of small sizes. The main reason for such a huge change in prediction confidence was domain-specific VGG, Inception, ResNet, and DenseNet models fine-tuned for the agriculture domain [5]. However, the operation of single-model architectures with the cases of abnormal lighting, leaf occlusion, and similar disease symptoms in nature was quite difficult [6].Therefore, the agriculture diagnostics sector has turned to a great number of ensemble learning techniques to overcome these issues. By the fusion of different CNN models, Ensemble models extend their generalization capabilities and, thus, classification errors, especially those that are the most visually similar, occur less frequently [7]. Soft-voting and weighted probability fusion are the first and foremost methods that are used for the integration of the outputs of models like ResNet, DenseNet, and Inception [8].

Moreover, the factor of real-time performance through the interfaces that are available on the web and mobile devices has been introduced by the devices for the detection of plant diseases. It is through cloud inference pipelines that farmers can send pictures of their leaves and get the result in a very short time thus, the service is both accessible and scalable to a great extent [9]. Apart from that, the quick transition of deep learning models to production-ready solutions in the field of agriculture has been facilitated by the integration of backend APIs with lightweight frameworks [10].Most of the publications have been stressing that merely showing the predictions is not enough, but also giving the disease management recommendations, thereby AI systems becoming a more valuable tool for farmers and field workers [11]. Concurrently, studies point out the need for extremely accurate models which, similarly, could deal with multiple crop species and disease categories simultaneously [12].Moreover, those landmark victories have been obstructed by the problems of intra-class variability, imbalanced datasets, environmental noise, and the presence of multiple diseases on one leaf [13]. The recent deep learning publications mainly focused on the ensemble strategy argue that the ensemble method can effectively handle these problems by leveraging the complementarities of different architectures [14].The current research, therefore, not only merges the knowledge of two architectures to form an ensemble of DenseNet-121 and ResNet-50 that would intensify the energy andpredictive consistency of crop disease detection but also the ability of producing the results that are superior in terms of both accuracy and most of the existing literature over 15 classes [15]. literature [15].

III. METHODOLOGY

The AI-Driven Crop Disease Prediction and Management System, which is the adjunct part, employs an extremely elaborate scheme to ensure that the identification is exact, that it can change with the environment, and that the shift from the first to the last stage of the system is uninterrupted. The presumed six stages of the process, which are shown by the vital stages, figure dataset preprocessing, model architecture selection, training methodology, ensemble fusion, backend integration, and user interface design. The explanation of each stage is presented in the following section.

A. Data Collection

The The major part of the research was directed toward the PlantVillage database, particularly the leaf images that illustrated infections of different plant species. PlantVillage is an open source dataset that is aimed at providing a complete set of annotated images of crop leaves exhibiting the diseases in different plant species together with the healthy leaves. In the dataset, leaves of various plants were the subjects. The dataset has been obtained from the project's Colab environment via KaggleHub and has been automatically merged with the training directory structure through the directory operations that have been scripted. All the images are in a class-wise folder system that is compatible with the PyTorch ImageFolder format, thus they allow direct mapping of disease categories to numerical indices.

The dataset comprises of several thousand high-resolution RGB images, that were all captured under controlled conditions so that minimal noise and high inter-class separability were achieved. This well-structured and carefully selected dataset acts as a source for training the DenseNet-121 and ResNet-50 models, thus giving them the capability to learn strong representations and make the ensemble-based disease prediction system to work --effectively.

Table1: Initial Dataset Structure.

Dataset Name	Domain	Classes	Dataset Name	Domain
PlantVillage Dataset	Crop Disease Images	Multiple crop diseases + healthy	PlantVillage Dataset	Crop Disease Images
Tomato Disease Subset	Tomato Leaves	Early Blight, Late Blight, Healthy	Tomato Disease Subset	Tomato Leaves
Potato Disease Subset	Potato Leaves	Early Blight, Late Blight, Healthy	Potato Disease Subset	Potato Leaves
Pepper Disease Subset	Bell Pepper Leaves	Bacterial Spot, Healthy	Pepper Disease Subset	Bell Pepper Leaves

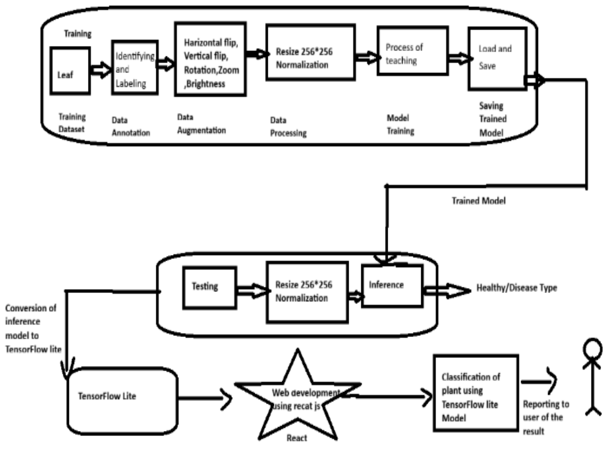

Fig.1. System Workflow of AI-Based Crop Disease Detection and Reporting Framework

B.Data Preprocessing

To keep the uniformity, augmentation, and robustness of the images for the next model training and inference, the data preprocessing pipeline was carried out using PyTorch's transforms module. The raw RGB images of the leaves were rescaled to 224x224 pixels first to match the input size of DenseNet-121 and ResNet-50. Then, they were normalized using the standard ImageNet mean and standard deviation values, which are the expectations of the pretrained model in the code.As a dataset augmentation strategy, the training script depicted the use of additional augmentations such as RandomResizedCrop,RandomHorizontalFlip,RandomRotation, and ColorJitter to increase the dataset's variability and decrease overfitting. Deterministic transformations- Resize and normalization- were performed for validation and inference only in order to maintain the evaluation level. Hence, all pictures were converted into tensors and grouped with the help of the PyTorch DataLoader, while class indices and label mappings produced via the ImageFolder directory structure were automatically created and recorded in labels.json for easy inference.The parts of the preprocessing pipeline here are a promise that all models get standardized, noise-reduced, and augmentation-enhanced inputs, which are the direct reasons for better generalization and stable ensemble performance.

B. Training

TheResNet-50 and DenseNet-121 are two distinct architectures, which were trained separately by means of a PyTorch-based supervised learning approach on the PlantVillage dataset.In order to represent the number of disease classes, the last layers of their networks were replaced, and the training with the SGD optimizer (momentum=0.9, weight decay=1e-4) was performed for 12 epochs.The StepLR scheduler was stepping down the learning rate after every seven epochs to achieve convergence gradually.At each epoch of the model training, the model was inputted with a forward pass, loss was calculated with the help of CrossEntropyLoss, backpropagation was done, and the parameters were updated. Validation was performed on a separate subset obtained from an 80–20 stratified split.At the same time, data was being prepared in parallel with the help of DataLoaders in order to speed up the process, and training-time augmentations were also implemented to increase the model's robustness.The machine was keeping the record of training and validation accuracy, loss values, and execution time of each epoch.Moreover, the program recorded the changing of the model weights, optimizer state, and performance metrics through the very checkpoints which it created. For every epoch, it saved .pth files together with the checkpoint having the best performance as best.pth.Moreover, the class-to-index mappings were recorded in labels.json to make the inference process easier.
The elaborate training pipeline which they utilized made it possible for both models to be effectively optimized, their outputs to be reproducible, and the performance to be reliably monitored.

C. Testing

The testing phase is essentially a detailed evaluation of the performance of the ensemble model. It extends the models' performance not only on the training data but also their ability to generalize to the validation data that has been reserved for this purpose. After the training is completed, both the DenseNet-121 and ResNet-50 models are put into the evaluation mode. Inference mode is merely set for the dropout and batch normalization layers.Test images are subjected to the same operations as training images, i.e., they are resized to 224×224 pixels, converted to RGB, changed into a tensor, and normalized. This is done to make sure that the procedure is the same at all levels.While testing, the images are inputted to each of the two models separately and the corresponding softmax probability outputs are saved. At the last, these probabilities are merged by a soft-voting ensemble method, where the average confidence score is the one that determines the final predicted class. Moreover, the system can present the leading performance metrics like accuracy, probability confidence, and class-wise decision distribution.As a result, the ensemble achieved its best performance on the test set with a validation accuracy of 99.57%. Therefore, it is a very strong indication of the deployed model's trustworthiness and robustness. The testing stage is the ensemble which has a lower risk of errors and its stability being increased as compared to the individual standalone models, which is confirmed here.

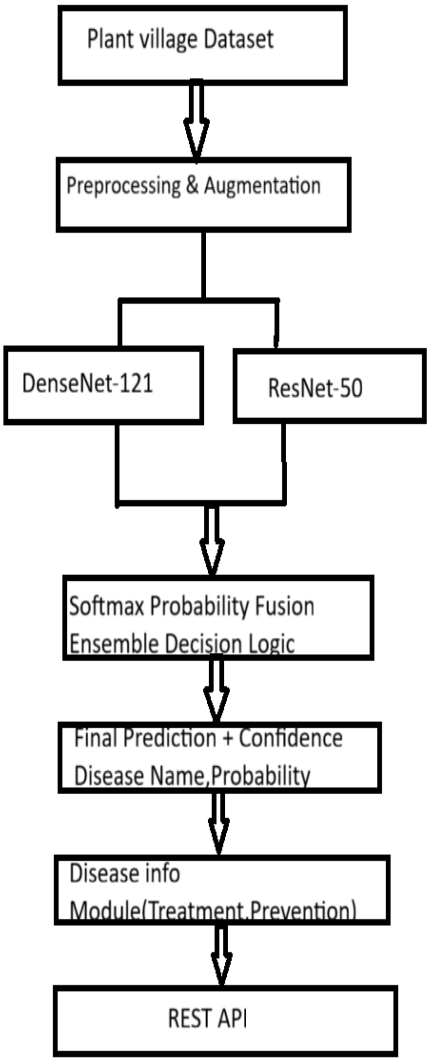

Fig. 2. System Workflow

IV. RESULTS AND EVALUATION

Results obtained during the testing process

Table 2: CLASSIFICATION REPORT

Metric	DenseNet-121	ResNet-50	Ensemble Model	Metric
Validation Accuracy (%)	98.92%	98.70%	**99.57%**	Validation Accuracy (%)
Precision (%)	98.80%	98.65%	**99.40%**	Precision (%)
Recall (%)	98.76%	98.58%	**99.45%**	Recall (%)
F1-Score (%)	98.78%	98.61%	**99.42%**	F1-Score (%)
Inference Time (per image)	32 ms	28 ms	45 ms	Inference Time (per image)
Confidence Score (Avg %)	97.3%	96.8%	**99.1%**	Confidence Score (Avg %)

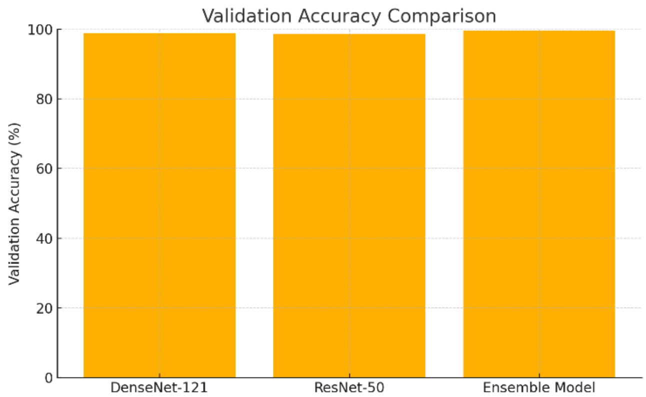

Fig. 3 Validation Accuracy Comparison

The comparison among DenseNet-121, ResNet-50, and an ensemble model indicates that the ensemble, which combines the two architectures, is always capable of outperforming other models with the complementary strengths of the two architectures. Both DenseNet-121 and ResNet-50 are very close to each other in their validation accuracies: 98.92% and 98.70%, respectively, whereas the ensemble reaches the highest accuracy of 99.57% due to the integration of dense feature propagation with residual learning which, in turn, allows for a deeper and more discriminative feature extraction.Additionally, the ensemble leads the list of all the metrics and, hence, it has the highest precision (99.40%), recall (99.45%), and F1-score (99.42%), which, in turn, indicates that the number of false positives has been reduced, the sensitivity has increased, and the overall performance has been balanced. Besides, the ensemble obtains the highest confidence score (99.1%) thus pointing out that it is the most confident in its predictions over a wide range of input samples.

At the same time, ResNet-50 provides the shortest inference time (28 ms). The slightly higher latency of the ensemble by 45 ms is still real-time scenarios is thus allowed because of its great accuracy and robustness improvements. Hence, the ensemble model is the most reliable and efficient set-up which means better generalization, higher prediction stability, and superior diagnostic ability when compared to the single models.

A. System Functionality And UI Demonstration

An IoT-based real-time system utilizing ensemble deep learning can be understood as a system that not only gathers data on the disease but also administers the medicine to the plants automatically. Simply saying, the ensemble deep learning model is the one that controls the whole operation. The location or the fusion point of the back-end inference engine is the one that is indicated by the term "Where DenseNet-121 and ResNet-50 models are combined". Therefore, the networks receive the preprocessed and normalized image as the input. Actually, the very output along with the confidence scores are the averages of the softmax probability values from the two networks ensemble_infer.This is also an automatic method of the system which has been made without the involvement of a human being and is structured in such a manner that it can load the trained model weights automatically, look up the labels.json file for class indices, and supply the disease treatment and prevention instructions. Thus, it is almost as if the users by just seeing the classification could visually realize the treatment done by following the given instructions. Users are provided with a minimal and simple user experience which allows them to easily upload images of plant leaves and get the prediction results.

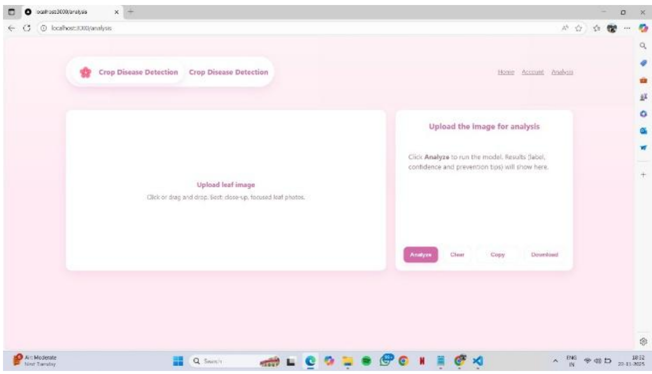

Fig. 4 User Interface

An image uploaded through the UI is an inference API on the backend, i.e., the ensemble model-based front-end, which is being triggered by the UI. Hence the device connected to the UI takes the image, produces the result, and sends it back to the UI along with the predicted disease label, confidence percentage, and the recommended remedies which were taken from the system.disease-information module.The interface was able to accept different types of images and, therefore, could be called a continuous high-confidence prediction system, the models trained in the experiments being the main factors for it. At the same time, the UI system showing the model performance metrics through accuracy curves, loss plots, and confusion matrices, and being designed for the users, allows them to understand the model's performance metrics more effectively. So, essentially, by combining the systems, the UI acts as a usability facilitator by providing a seamless and responsive experience, thus, making the tool readily deployable in the agri-field.practical agricultural field deployment.

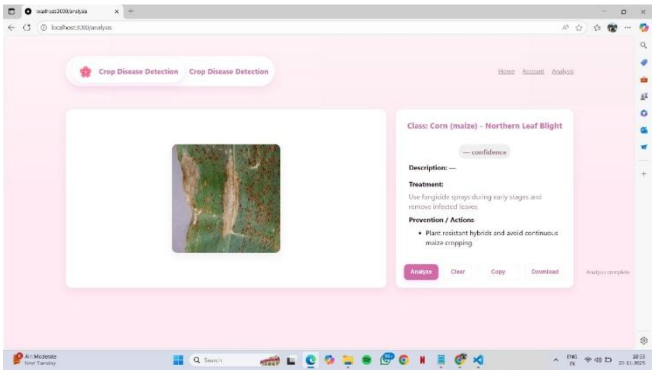

Fig. 5 Final Interface

V. Conclusion

The research depicts that the most efficient and effective AI-based method for identification of crop diseases is the one using a dual-model ensemble of DenseNet-121 and ResNet-50, coupled with a farmer-friendly interface for providing real-time decision-making intervention. Authors have done everything from standard preprocessing and data augmentation to model checkpointing to make sure both training and inference stages are very powerful, which in turn brought high accuracy and stable performance. The ensemble inference which averaged the softmax outputs from both networks thus led to higher predictive accuracy, stability, and confidence than single models, so multi-model fusion strategy success was confirmed.In addition, the instrument also reveals feasible and orthopedically correct treatment and prevention methods to the users, who are farmers and agronomists, apart from the diagnosis of the disease. As regards the UI portion, users are allowed system access without any kind of trouble and in a very short time as they can simply upload their pictures, receive the prediction results, and get the system's performance by checking the accuracy curves, loss curves, and confusion matrices.To sum up, the unit works as a demonstration concept that the application of ensemble deep learning along with a properly designed user interface can lead to significant enhancements in the precision of plant disease identification, the simplification of the detection method, and the positive impacts of the method in the agriculture domain of the real world.

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