AI-Powered Crop Disease Detection System for Sustainable Agriculture in Pakistan

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***Abstract*—Crop production in Pakistan faces significant challenges due to plant diseases leading to huge losses amounting to 40% annually. Early detection of these diseases is crucial to reduce their impact on agricultural productivity. However, traditional methods of disease detection such as inspection by trained experts can be time-consuming and inaccurate. This project outlines developing a Computer vision-based crop disease detection system that is accurate, efficient, and easy to use for farmers in the Pakistani agricultural sector. The system is trained on a large dataset of leaf images available publicly. The system can identify and classify diseases in new leaf images with high accuracy**

***Index Terms*—Crop Disease Detection, Deep Learning, Convolutional Neural Networks, Agricultural Technology, AI in Agriculture**

I. Introduction

Agriculture is the backbone of the global economy and an essential component of human survival. Crops play a crucial role in sustaining life . Nearly 66% of the world's population depends on agriculture, either directly or indirectly. [1] As there is a rapid growth in global population, agriculture is struggling to fulfill its necessity. Food insecurity, the biggest reason for crop diseases, is one of modern humanity's most serious global challenges. [2]
Plant diseases can have a significant negative influence on our lives in addition to posing a global danger to food security. So crop health is very important for the economy and food safety. Only the growth and leaf condition represent the health condition of any crop.

Crop diseases reduce both the yield and quality of food. They not only threaten global food security but also have negative effects on small-scale farmers whose livelihoods depend on healthy crops. However, there is an opportunity to mitigate the impact of crop diseases by detecting them early as they emerge on crops. With the advancements in the internet and computer vision, effective solutions to this problem have become increasingly feasible. [3]
Leaving and growth condition of a crop is an important parameter to determine its health. It enables at detection of early signs of disease, which can be monitored and mitigated through these parameters. But the conventional way to recognize a disease is mostly depends on plant pathologist inspection or laboratory tests. These approaches are labour-intensive, costly, and frequently unavailable to farmers in distant locations. An additional handicap is a world over insufficient number of expert agricultural professionals which worsens this situation since in many such scenarios there are no skilled personnel to diagnose issues with crops in a timely and precise manner.
The main purpose of this document is to provide an application that can detect disease types based on the textural similarity of leaves.To train the model we will use online available datasets. The early diagnosis of crop disease can be used to prevent further damage that can be done to the crops which is helpful for sustaining the cultivation. [3], [4]

II. Related Works

A. Deep Learning-Based Leaf Disease Detection in Crops Using Images for Agricultural Applications

In this work, the authors successfully analyzed various transfer learning models suitable for the accurate classification of 38 different classes of plant diseases. They performed standardization and evaluation of state-of-the-art convolutional neural networks (CNNs) using transfer learning techniques, evaluating the models based on classification accuracy, sensitivity, specificity, and F1 score. From the performance analysis, the proposed model achieved a classification accuracy of 82.75% and an F1-score of 88%. [5]

B. A Mobile-Based System for Detecting Plant Leaf Diseases Using Deep Learning

This paper presented the design and implementation of a machine learning (ML)-powered plant disease detector that enables farmers to diagnose the most common 38 diseases in 14 species. The authors trained a CNN model using a large imagery dataset consisting of 96,206 photos of healthy and diseased plant leaves, considering factors like crowded backgrounds, low contrast, and diverse illumination conditions in the images. They conducted several experiments to evaluate the performance and classification accuracy of the system, paying particular attention to the classification and processing time. The CNN model achieved an overall average classification accuracy of 93.6%, an F1-score of 94%, and the average prediction time was measured at 0.88 seconds. [6]

C. Crop Disease Detection Using YOLO

The detection of crop diseases using Artificial Intelligence (AI) has gained prominence due to its potential to enhance agricultural productivity. Morbekar et al. (2020) implemented the YOLO (You Only Look Once) object detection model for identifying crop diseases. Their work leverages YOLO's real-time detection capabilities and high precision to classify and localize diseased regions in crops. The paper emphasizes the use of data augmentation to improve model training and the application of grid cells for feature extraction. YOLO's lightweight architecture makes it suitable for practical deployment in agricultural settings.

Other studies have also explored deep learning models like Faster R-CNN and MobileNet for similar purposes, showing comparable success in detecting multiple crop diseases. While Morbekar et al. demonstrate YOLO's effectiveness, challenges such as dataset diversity and environmental variability remain critical. Incorporating advanced augmentation techniques and hybrid approaches could further improve detection accuracy and robustness. Their contribution establishes a solid foundation for real-time, automated crop disease detection. [7]

D. Research on Random Forest (2018)

This research utilized the Random Forest algorithm to classify plant diseases from a small dataset. Feature extraction was performed using traditional image-processing techniques, including texture analysis and shape descriptors. The lower accuracy was attributed to the dataset's size, which hindered the model's ability to generalize. Additionally, Random Forest, being a traditional ensemble learning method, lacks the capability to capture complex image patterns compared to deep learning models like CNNs. [8]

TABLE I
COMPARISON OF ACCURACY, F1 SCORE, DATASET, AND CLASSES

Paper F1 Score (%)	**Year**	**Model**	**Dataset**	**Accuracy (%)**
Paper 2.1 88	2022	VGG-16	54,305 photos	82.75
Paper 2.2 94	2021	CNN	96,206 photos	93.6
Paper 2.3 Not Reported	2020	YOLO	Custom dataset	93.6
Paper 2.4 Not Reported	2018	Random Forest	Small Image Dataset	65.30

III. METHODOLOGY

A. Data Collection

Plant Village, an open-source dataset, is utilized, containing 96,206 RGB images categorized into 38 plant disease classes. It encompasses images from 14 different plants, with each plant having at least two classes: healthy and diseased leaves, all resized to dimensions of 256×256. Since its release, numerous studies have used this dataset for plant disease identification. The dataset provides a rich diversity of images representing different crops and associated diseases.

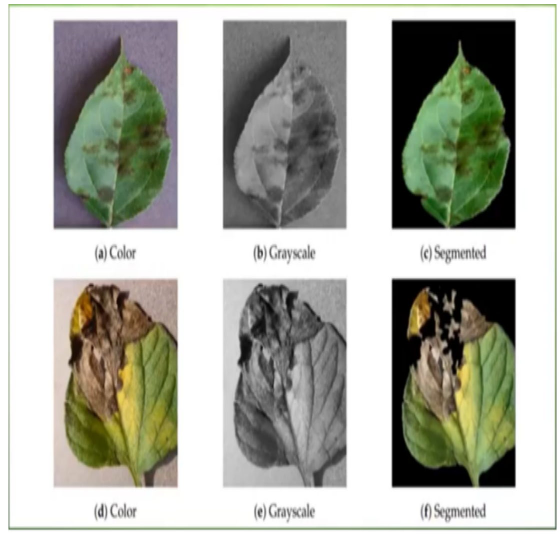

Fig. 1. Data Collection

B. Preprocessing of image

The training data undergoes preprocessing to ensure its suitability for the crop disease detection model. Using TensorFlow and Keras libraries, the images are resized to 224x224 pixels, providing uniformity and compatibility with the neural network architecture. Additionally, the data is shuffled to randomize the sample order, reducing biases and enhancing the model's ability to generalize. These steps are essential for standardizing the input and optimizing the learning process.

C. Augmentation

Data augmentation is performed offline to enhance training data diversity and improve model generalization. Techniques include rotations, flipping, zoom adjustments, and rescaling, which reduce overfitting and improve performance on unseen samples.

D. Crop Disease Detection and Classification

The VGG-16 architecture is a deep convolutional neural network (CNN) designed for image classification tasks. The VGG-16 architecture is chosen for its simplicity, efficiency, and established performance in image classification tasks.

VGG-16 comprises 16 layers, including convolutional layers for feature extraction and fully connected layers for classification. Convolutional layers capture spatial hierarchies in the image, while max-pooling layers reduce dimensionality to improve computational efficiency. Fully connected layers utilize the extracted features to classify the image into predefined disease categories.

The model is trained using a categorical cross-entropy loss function and the Adam optimizer, which ensures efficient convergence during training. Real-time data augmentation is applied to enhance model generalization and prevent overfitting. Evaluation metrics such as accuracy, precision, recall, and F1-score are used to validate the model's performance. Once trained, the system achieves high accuracy in identifying crop diseases, providing an effective and scalable solution for agricultural use.

E. Model Evaluation

The model's performance was evaluated using the accuracy metric, which measures the proportion of correct predictions. Predictions were made on both the training and testing datasets. The training accuracy assessed the model's ability to learn the data, while the testing accuracy evaluated its generalization capability. In addition to accuracy, the model was evaluated using precision, recall, and F1-score. Precision measures the proportion of true positive predictions out of all positive predictions, recall assesses the ability to identify all true positive cases, and F1- score provides a harmonic mean of precision and recall. These metrics, along with a confusion matrix analysis, revealed a high level of accuracy and balanced performance, confirming the model's reliability in predicting Parkinson's disease.

$$\text{Accuracy} = \frac{Tp + Tn}{Tp + Fp + Tn + Fn}$$

where:
Tp = True positives
Tn = True negatives
Fp = False positives
Fn = False negatives

$$\text{Precision} = \frac{Tp}{Tp + Fp}$$

$$\text{Recall} = \frac{Tp}{Tp + Fn}$$

$$\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

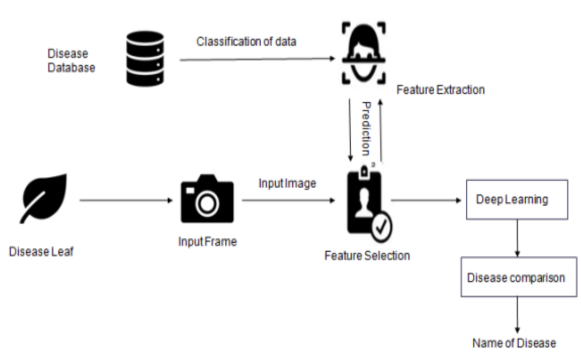

Fig. 2. System architecture

IV. Result

Trained the model on a training dataset (training set). Parameters such as the number of epochs and steps per epoch are specified to control the training process. Additionally, a validation dataset (validation set) is used to evaluate the model's performance during training. The use of the ReduceLROnPlateau callback allows for dynamic adjustment of the learning rate based on the validation loss.

A. Training and Validation Accuracy/Loss

The model's performance was evaluated during training and validation using accuracy and loss metrics. The results are as follows:

Training Accuracy: 95%
Validation Accuracy: 94%
Training Loss: 11%
Validation Loss: 20%

B. Accuracy

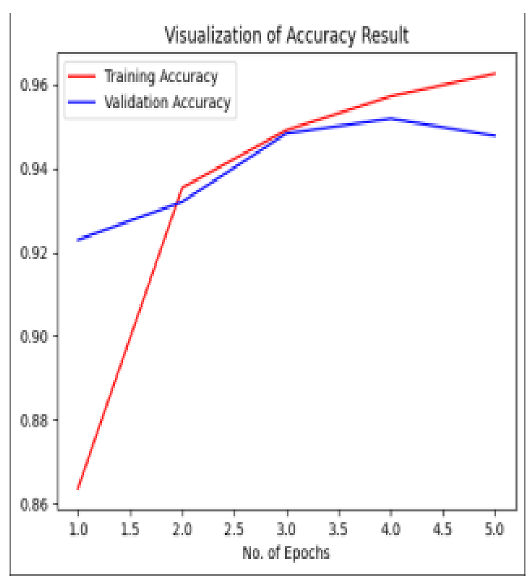

Fig. 3. Visualization of Accuracy Result

C. Loss

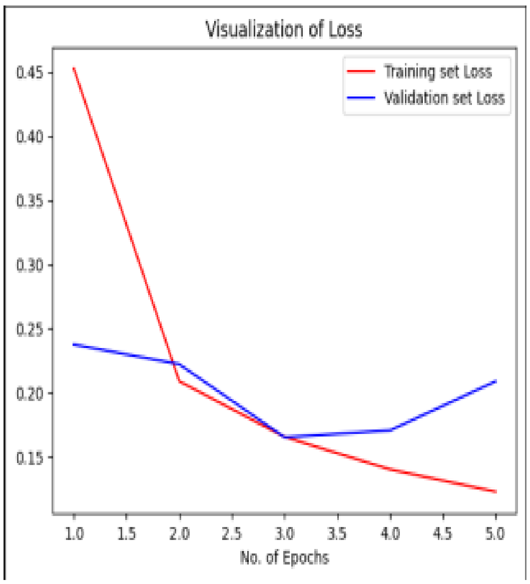

Fig. 4. Visualization of Loss

D. Confusion Matrix

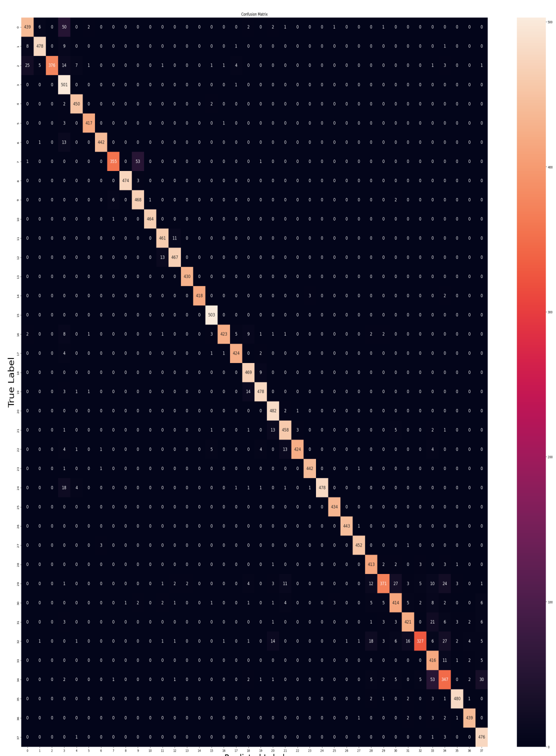

Fig. 5. confusion matrix

E. Classification Report

In this, we analyze the performance of the classification model based on various evaluation metrics, including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive understanding of the model's effectiveness in predicting plant diseases from the dataset.

Accuracy

Accuracy is one of the most fundamental evaluation metrics in classification problems. It is calculated as the ratio of the number of correctly predicted instances to the total number of instances in the dataset. The model achieved an **accuracy of 94%**, which means that 94% of the predictions made by the model were correct. This suggests that the model performs well in distinguishing between the different classes (plant diseases and healthy conditions), but there is still some room for improvement, particularly in cases where misclassifications occur.

Precision

Precision is a key metric for evaluating how accurately the model predicts the positive class. It is calculated by dividing the number of true positives by the sum of true positives and false positives.The model achieved a **precision of 95%**, which indicates that when the model predicted a positive class (such as a specific disease), it was correct 95% of the time. High precision means the model is good at avoiding false positives, ensuring that most of the instances it labels as a particular disease are truly that disease.

Recall

Recall measures the ability of the model to correctly identify all relevant instances of the positive class. It is calculated as the ratio of the number of true positives to the sum of true positives and false negatives.The model achieved a **recall of 94%**, meaning that 94% of the actual positive instances (diseased plants) were correctly identified by the model. While this is a strong recall score, the 6% of missed instances (false negatives) indicate areas where the model could be enhanced to reduce the number of missed predictions, potentially through additional training or data balancing techniques.

F1-Score

The F1-score is the harmonic mean of precision and recall, providing a single metric that balances the trade-off between precision and recall.The model achieved an **F1-score of 94%**, indicating that it maintains a good balance between precision and recall. The F1-score is particularly useful in cases of imbalanced datasets, as it provides a balanced evaluation of the model's performance without favoring precision or recall alone. The classification model demonstrated strong performance across all evaluated metrics. The **accuracy** of 94%, **precision** of 95%, **recall** of 94%, and **F1-score** of 94% all indicate that the model performs well in classifying plant diseases. While the model's precision and recall scores are high, there is still an opportunity to fine-tune it further to address any misclassifications, particularly for diseases that are less accurately predicted. Additionally, optimizing these metrics further could enhance the model's robustness, ensuring more accurate and reliable plant disease detection in real-world applications.

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Apple Apple scab	0.92	0.87	0.90	504
Apple Black rot	0.97	0.96	0.97	497
Apple Cedar apple rust	1.00	0.85	0.92	440
Apple healthy	0.79	1.00	0.88	502
Blueberry healthy	0.97	0.99	0.98	454
Cherry Powdery mildew	0.99	0.99	0.99	421
Cherry healthy	0.99	0.97	0.98	456
Corn Cercospora leaf spot	0.98	0.87	0.92	410
Corn Common rust	1.00	0.99	1.00	477
Corn Northern Leaf Blight	0.89	0.98	0.93	477
Corn healthy	1.00	1.00	1.00	465
Grape Black rot	0.96	0.98	0.97	472
Grape Esca	0.97	0.97	0.97	480
Grape Leaf blight	1.00	1.00	1.00	430
Grape healthy	1.00	0.99	0.99	423
Orange Haunglongbing	0.97	1.00	0.99	503
Peach Bacterial spot	0.99	0.92	0.95	459
Peach healthy	0.97	0.98	0.98	432
Pepper Bacterial spot	0.93	0.98	0.96	478
Pepper healthy	0.96	0.96	0.96	497
Potato Early blight	0.93	0.99	0.96	485
Potato Late blight	0.93	0.94	0.94	485
Potato healthy	0.99	0.93	0.96	456
Raspberry healthy	0.99	0.99	0.99	445
Soybean healthy	1.00	0.95	0.97	505
Squash Powdery mildew	0.99	1.00	1.00	434
Strawberry Leaf scorch	1.00	1.00	1.00	444
Strawberry healthy	0.99	0.99	0.99	456
Tomato Bacterial spot	0.90	0.97	0.94	425
Tomato Early blight	0.95	0.77	0.85	480
Tomato Late blight	0.89	0.89	0.89	463
Tomato Leaf Mold	0.94	0.90	0.92	470
Tomato Septoria leaf spot	0.96	0.75	0.84	436
Tomato Spider mites	0.79	0.96	0.86	435
Tomato Target Spot	0.80	0.76	0.78	457
Tomato Yellow Leaf Curl Virus	0.98	0.98	0.98	490
Tomato mosaic virus	0.98	0.98	0.98	448
Tomato healthy	0.90	0.99	0.94	481
Accuracy	0.95			17572
Macro Avg.	0.95	0.95	0.95	17572
Weighted Avg.	0.95	0.95	0.95	17572

TABLE II
CLASSIFICATION REPORT

CONCLUSION

Development of a computer vision-based crop disease detection system for the agricultural sector in Pakistan. With agricultural production facing significant losses of up to 40% annually due to plant diseases. Traditional methods of disease detection are time-consuming and inaccurate. By using the capabilities of Convolutional Neural Network (CNN) models, particularly the VGG-16 architecture, we created an efficient system for identifying and classifying plant diseases. The proposed system is trained on a large dataset of leaf images and achieved a high accuracy of 94diagnose diseases in their crops and reduce crop losses.

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