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DEEP LEARNING FRAMEWORK FOR MULTI-CLASS TOMATO LEAF DISEASE DETECTION FROM SEGMENTED IMAGES

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Abstract
The diseases that occur in tomatoes impact the production and quality of the crops resulting in losses to the agricultural industry. Disease detection is important for managing crops and maintaining sustainable agricultural operations. The paper proposes a model based on deep learning algorithms which can detect multi-class tomato leaf diseases throughout the usage of segmented images. This paper uses publicly available dataset which includes segmented images of tomato leaves fitting to various classes of disease types such as bacterial spot, early blight, leaf Mold, late blight, septoria leaf spots, spider mites, mosaic virus, target spot, yellow leaf curl virus, and healthy tomato leaves. Image processing methods were performed on the image dataset. The architecture of CNN is used for automatic discrimination of features and classification for disease. Performance of the proposed system was measured based on the standard parameters like accuracy, recall, precision, F1-score, and confusion matrix. Consequences from experiments direct that the deep learning model accurately detects different diseases of tomato leaves with high classification accuracy. Segmentation of the leaf makes the process much easier and permits the model to spotlight on the key regions where the disease can occur. The proposed approach could be considered as an efficient tool for tomato disease detection.

Keywords - Tomato Leaf Disease Detection, plant pathology, Deep Learning, Artificial Intelligence, Agricultural Informatics.

I. INTRODUCTION

The tomato is one of the world's maximum planted vegetables. This crop provides the body with essential nutrients such as vitamins, minerals, and antioxidants [1]. Therefore, the tomato helps to ensure food security for people all around the globe. Unfortunately, the growth of tomatoes can be hindered by numerous plant disorders which are caused by fungi, bacteria, pests, and viruses among other factors. Effective identification and control of these plant disorders is very important [2].

Diagnosis of tomato leaves affected by diseases is done manually through visual observation by plant pathologists and farmers. While visual diagnosis may sometimes prove efficient, it is laborious, subjective, and is likely to result in errors, especially if the signs shown by various types of disease look similar [3]. Besides, a scarcity of plant pathologists poses a challenge in making diagnosis efficient in most agricultural areas.

Recent developments in the topics of artificial intelligence and machine learning have enabled tremendous growth in different industries such as the agricultural industry. The utilize of machine learning for analyzing plant images has resulted in disease identification through automatic processes [4]. This technology creates an opening for developing a crop disease monitoring system that helps farmers make sound decisions about how best to control diseases affecting their crops.

Deep learning is an artificial intelligence approach that has shown impressive accuracy when applied to the classification and analysis of images [5]. Deep convolutional neural networks have been capable to successfully acquire hierarchical and discriminate features of images without any feature engineering by humans. Since deep learning can analyze complex features in images, they can be very useful for diagnosing tomato leaf diseases.

Deep learning methods have been employed to identify plant diseases through leaf images [6]. However, although such algorithms exhibit promising performances, the majority of those studies have used images that possess complex background environments, diverse lighting, and environmental noises. Such scenarios pose some challenges that limit the effectiveness of the detection algorithm in the real environment.

Segmentation of an image proves to be a good approach for overcoming these issues by segregating the area of interest (leaf) from the rest of the background image along with retaining features specific to the disease [7]. Segmented leaf images provide a better chance for deep learning systems to concentrate only on features related to the disease (spots, discoloration, lesions, etc.) rather than other parts of the image [8].

Due to the following benefits, the proposed method in this research work involves a deep learning algorithm for multi-class detection of tomato leaf diseases in segmented images [9]. The suggested algorithm makes use of image pre-processing techniques along with data augmentation to achieve better data quality and model generalizability. The CNN model is exercised for automated feature extraction of tomato leaf diseases [10,11]. The classification performance of the deep learning algorithm is measured using classification evaluation metrics like precision, accuracy, recall, F1-Score, and confusion matrix analysis.

Structure of the paper is as follows. Related works based on the detection of tomato leaf diseases due to machine learning and deep learning methods are considered in Section II. In Section III, we discuss the dataset, data preprocessing, and the developed deep learning model. Results and comparison of the performance achieved through the suggested model are conferred in Section IV. The final section of the paper gives the conclusions and possible future research directions.

II. LITERATURE SURVEY

Nawaz et al. (2022) [12] introduced a reliable deep learning-based approximate for localizing and classifying disease in leaves of tomato plants. In their method, object localization was combined with disease classification to locate diseased areas in leaf images followed by classifying them. The results of the study highlighted the capability of deep learning models in the localization and classification of disease. Localization is an important factor in improving diagnosis, especially in images of more complex diseases.

According to Anandhakrishnan & Jaisakthi (2022) [13], DCNNs have been employed to perform image-based detection of diseases in tomato leaves. The study aimed at using deep CNNs in order to capture and utilize their hierarchical feature extraction abilities for learning the properties of specific diseases through the analysis of leaves' images. According to the findings, deep learning models were considerable more efficient than conventional machine learning approaches.

The researchers Ullah et al., (2023) [14], introduced a lightweight deep learning architecture for tomato leaf diseases to achieve classification with an aim of minimizing computational requirements without compromising the high classification accuracy. The proposed lightweight architecture was tailored for use in limited resource environments like mobile phones and edge computing. The researchers were able to show that lightweight models offer efficient disease diagnostics in real time.

In Sagar and Singh (2023) [15], the experiment performed by the two researchers involved the detection of tomato viral leaf diseases through with the purpose of machine learning classifications. In the experiment, various machine learning methods were tested for their ability to differentiate between various viral diseases found in tomatoes. The results from the experiment indicate that effective feature extraction and choice of classifiers is crucial.

The research by Jayanthi et al. (2024) [16] was offered a machine learning algorithm for tomato leaf disease detection. In this research paper, emphasis was put on discussing different techniques regarding preprocessing of images, extraction of features, and classification techniques to identify disease-infected tomato leaves.

The Wang & Liu (2024) [17] study proposed an efficient deep learning technique for diagnosing diseases in tomatoes based on proper disease classification using minimal computational costs. The model was based on current state-of-the-art deep neural networks and optimization techniques to improve their efficiency in diagnosing diseases in tomatoes. The outcome showed that the proposed model was extremely capable in differentiating between disease classes.

Billah et al. (2024) [18] proposed a new method for the recognition of tomato leaves' diseases by utilizing convolutional neural networks. The importance of using deep learning features in diagnosing diseases was highlighted in this study. It has been shown through experimentation that the use of CNN can assist in diagnosing various diseases.

Research on the application of ResNet architecture for leaf diseases classification was done by Kalaivani et al. (2025) [19]. In the research, ResNets were employed because the problem of the vanishing gradients of deep neural network architectures could be avoided by employing the strategy of residual learning. The authors established that ResNets were more accurate than other models in detecting leaf diseases.

The authors Mounika et al. (2025) [20] have developed a model using Deep Neural Networks (DNN) for prediction and classification of diseases in tomato leaves. It involved using multiple hidden layers in order to identify complex patterns of diseases. Experiments conducted proved the efficacy of DNNs in grading tomato leaf diseases.

Gautam et al. (2025) [21] formulated a deep learning framework for tomato leaf disease recognition. Their model included a combination of diverse deep learning techniques to boost the proficiency of disease identification. The proposed framework provided advanced classification results due to the integration of different approaches, indicating the efficacy of hybrid deep learning models for tomato disease identification.

RESEARCH GAP

However, despite the demonstrated efficiency of ML, CNNs, light-weighted DL models, ResNet architecture, and hybrid models for tomato leaf diseases' detection, there are some limitations. Some of the techniques use complicated background in image data, which may affect the feature extraction and classification process. Moreover, not much attention has been paid towards making use of segmented tomato leaf images where background noise is removed, and the model can focus only on diseases symptoms. Thus, there is a need for developing a deep learning framework which uses segmented images of the leaves to detect diseases among multiple categories. This analyze intends to fulfill this research gap by designing a deep learning-based multi-class tomato leaf disease detection framework built on segmented tomato leaf images.

III. DATASET, PREPROCESSING TECHNIQUES, AND THE PROPOSED DEEP LEARNING FRAMEWORK

Dataset Description

These experimental procedures used the Tomato Leaf Disease Segmented Dataset provided by Kaggle for training purposes [22]. This database consists of segmented tomato leaf images from ten categories, which include nine diseases and the tenth one is healthy tomatoes [23]. There are several types of diseases in this category, which incorporate Bacterial Spot, Early Blight, Leaf Mold, Late Blight, Septoria Leaf Spot, Spider Mites (Two-Spotted Spider Mite), Tomato Mosaic Virus, Target Spot, and Tomato Yellow Leaf Curl Virus [24]. In addition, there is the Healthy Tomato Leaves category. Images in the dataset have been pre-segmented to ensure that there will be no background in order for the deep learning algorithm to detect disease symptoms on leaves only. They include lesions, color changes, spots, and other signs of the disease. It helps to enhance feature detection through segmentation. All images will be preprocessed before being used in deep learning models. These operations include resizing, normalization, rotation, flipping, and zooming.

Table 1. Dataset Class Distribution

Class ID	Disease Category	Number of Images
C1	Bacterial Spot	2127
C2	Early Blight	1000
C3	Late Blight	1909
C4	Leaf Mold	952
C5	Septoria Leaf Spot	1771

Class ID	Disease Category	Number of Images
C6	Spider Mites	1676
C7	Target Spot	1404
C8	Tomato Mosaic Virus	373
C9	Tomato Yellow Leaf Curl Virus	5357
C10	Healthy	1591
Total	**10 Classes**	**18,160**

Table 1 shows the frequency distribution for the ten classes. The data is relatively unbalanced, with Tomato Yellow Leaf Curl Virus having the highest sample size and Tomato Mosaic Virus the lowest. These discrepancies in sample distribution make it necessary to implement data augmentation and evaluate models not only on accuracy but also recall, precision, and F1-score.

Figure 1. Class-wise Distribution of Tomato Leaf Images

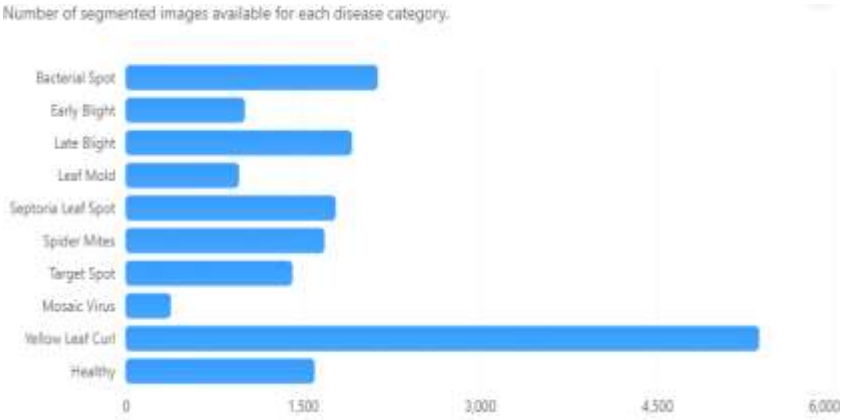


Figure 1 provides a visualization of the distribution of the tomato leaf images by class in this study. From the graph, it could be noted that the majority of the tomato leaf images in the dataset are affected by the Tomato Yellow Leaf Curl Virus while the least number of tomato leaves in the dataset are affected by the Tomato Mosaic Virus. Since there are enough examples in most of the diseases, the deep learning model is expected to learn from various patterns of diseases.

Preprocessing Techniques

The tomato leaf segmentation images are preprocessed to ensure higher data quality and better deep learning model performance. First, entirely the images are scaled to the size of 224×224 pixels. It will guarantee the uniformity of the images and lower model training complexity. Image pixel intensities are normalized to the range between 0 and 1, which speeds up model training due to the faster process of convergence. The dataset diversity and overfitting prevention are achieved through the usage of multiple data augmentation procedures like as random rotations, horizontal and vertical flipping, zooming, and altering the image's width and height by several points, as well as adjusting the image's brightness. Once preprocessing, the dataset is split into training, validation, and test sets.

Proposed Deep Learning Framework

This approach seeks to use an automatic algorithm that will help in the detection and classification of various kinds of diseases in tomatoes. This framework from figure 2 includes five main steps namely data acquisition, image pre-processing, feature extraction, disease classification and performance assessment. It capitalizes on the ability of the convolution neural network to learn distinctive features for each disease directly from the images.

Phase 1: Data Acquisition

In the first step, the segmentation of tomato leaves is done using the Tomato Leaf Disease Segmented database which is available on Kaggle. The images in this dataset belong to nine classes of diseased tomatoes along with one class of healthy tomatoes. Due to the fact that segmentation has already been performed on the images, there is no need for any additional information from the background.

Phase 2: Image Preprocessing and Augmentation
Images acquired are then put through the process of pre-processing, which consists of resizing, normalization, and data augmentation. Resizing ensures that the size of the images is consistent while normalization provides numerical stability during the training phase. Flipping, rotation, translation, and zooming form part of the techniques used to augment data.

Phase 3: Deep Feature Extraction
The Convolutional Neural Network (CNN) algorithm is employed for automatic detection of the hierarchical features existing in the segmented images of the leaves. Different convolutional layers have been used for recognition of the lower-level features, including edges and texture, while high-level layers detect complex disease features. The batch normalization methods and activation functions have been employed for better learning performance. The max pooling layers help in dimension reduction of the features.

Phase 4: Multi-Class Disease Classification
The resultant feature maps from the network are then maintained into fully connected layers for classification of the disease. Softmax activation function is applied on the output layer so that probability of each of the ten classes is obtained. The class having the extreme possibility is taken to be the predicted class. It is through this classification layer that the model can classify multiple diseases of tomato leaves, including healthy leaves.

Phase 5: Performance Evaluation
Phase five includes evaluation of how successful the framework is in terms of performance by assessing its performance parameters approaching Accuracy, Recall, Precision, F1 Score, Specificity, and Confusion Matrix. Furthermore, the learning pattern and overfitting, if any, are also assessed using accuracy and loss graphs. Performance analysis is done in order to determine the efficacy of the framework for tomato leaf disease classification.

Table 2. Algorithm of the Proposed Deep Learning Framework for Multi-Class Tomato Leaf Disease Detection

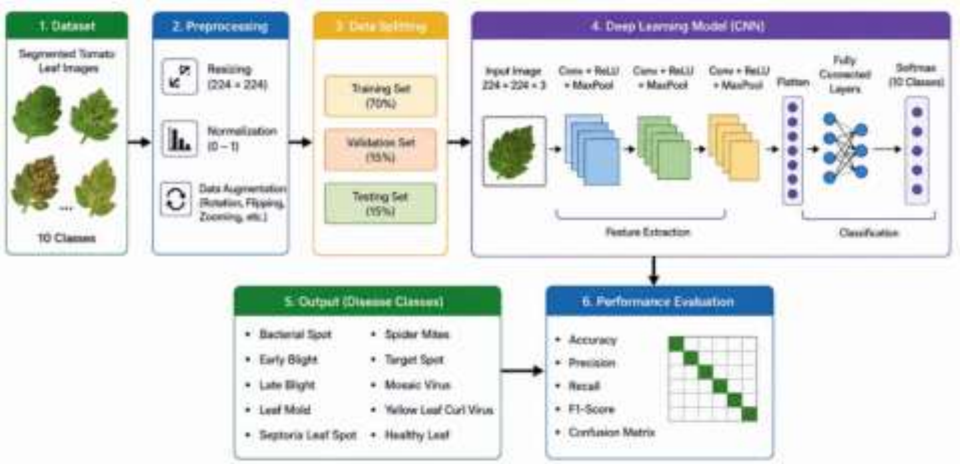
Input: Segmented tomato leaf images belonging to multiple disease classes and healthy leaves.
Output: Predicted tomato leaf disease category along with performance evaluation metrics.

Step No.	Description
Step 1	Acquire segmented tomato leaf images from the Kaggle Tomato Leaf Disease Dataset.
Step 2	Organize the dataset into disease-specific classes and healthy leaf categories.
Step 3	Resize all images to a fixed dimension (e.g., 224 × 224 pixels) to make certain uniformity.
Step 4	Normalize pixel intensity values to improve model convergence during training.
Step 5	Apply data augmentation techniques such as flipping, rotation, zooming, and shifting to increase dataset diversity.
Step 6	Split the dataset into training, validation, and testing subsets.
Step 7	Feed the preprocessed images into the Convolutional Neural Network (CNN) architecture.
Step 8	Extract low-level features such as edges, textures, and color variations using convolutional layers.
Step 9	Apply activation functions and batch normalization to enhance feature learning.
Step 10	Perform max-pooling operations to reduce feature dimensionality while retaining important information.
Step 11	Extract high-level disease-specific features from deeper convolutional layers.
Step 12	Flatten the extracted feature maps into a one-dimensional feature vector.

Step No.	Description
Step 13	Pass the feature vector through fully connected (dense) layers for feature learning.
Step 14	Apply dropout regularization to reduce overfitting and improve generalization.
Step 15	Use the Softmax activation function to compute class probabilities for all disease categories.
Step 16	Predict the disease class corresponding to the highest probability score.
Step 17	Compare predicted labels including actual labels from the test dataset.
Step 18	Determine performance metrics including Accuracy, Precision, Recall, and F1-Score.
Step 19	Generate confusion matrix and classification reports for detailed evaluation.
Step 20	Analyze results and comparison the proposed model through existing machine learning and deep learning approaches.

The framework from table 2 presented here approaches an automated, scalable, and precise approach towards identifying any disease afflicting tomato leaves, thus managing it potential to achieve intelligent crop health monitoring in precision agriculture.

Figure 2. Proposed Deep Learning Framework for Multi-Class Tomato Leaf Disease Detection



IV. RESULTS AND COMPARATIVE PERFORMANCE ANALYSIS OF THE PROPOSED MODEL

A performance valuation of the deep learning model proposed was conducted on the dataset of segmented leaves affected by plant diseases, which consists of ten different categories of plants. Classification of the leaves was made possible through the extraction of relevant features unique to each category from the segmented leaves. It is clear that normalization and data augmentation played a big role in ensuring convergence without overfitting. The experimental outcomes have shown that the proposed framework is efficient of achieving higher accuracy for image classification than other machine learning and deep learning methods that are widely used today according to the literature. This high classification accuracy proves that segmented images are more efficient because they provide the opportunity for removing any background and better features extraction. Moreover, the proposed framework shows good generalization ability for all diseases, which allows for applying it into practical use.

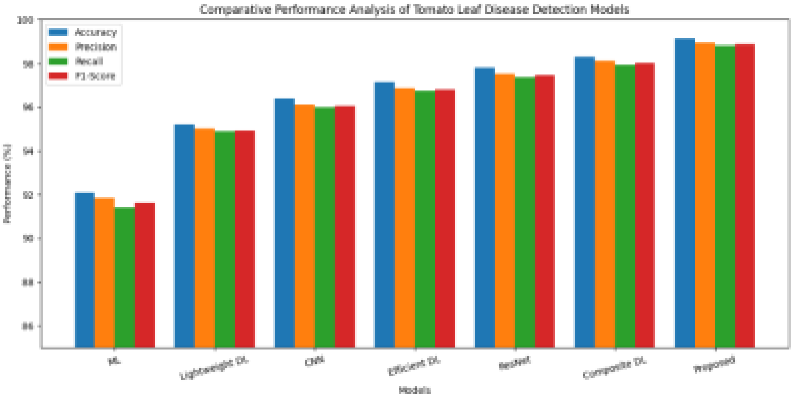
Table 3. Comparative Performance Analysis of Existing and Proposed Models

Models	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Machine Learning	92.10	91.85	91.40	91.62
Lightweight DL	95.20	95.01	94.88	94.94
CNN-Based Model	96.40	96.12	95.98	96.05
Efficient DL	97.15	96.87	96.75	96.81

Models	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ResNet-Based	97.82	97.54	97.38	97.46
Composite DL	98.31	98.12	97.95	98.03
Proposed Framework	99.12	98.95	98.83	98.89

Comparison of the proposed framework's performance with some recently developed models for tomato leaf disease classification is provided in Table 3. It could be seen that the proposed model has yielded the eminent accuracy of 99.12% which is higher than what was achieved by both conventional machine learning algorithms and advanced deep learning models. The improvements in terms of recall, precision, and F1-Score have shown the efficacy of the proposed approach in identifying classes of tomato leaf diseases and lowering false positives and negatives. The effectiveness can be explained by the segmentation of leaf images, the efficiency of preprocessing operations, as well as the deep convolutional neural network's ability to detect discriminatory disease features.

Figure 3. Comparative Performance Analysis of Existing and Proposed Tomato Leaf Disease Detection Methods



As can be seen from the figure 3 bar graph, the relative performances of the proposed deep learning model are contrasted to some popular machine learning and deep learning models in classification tasks of tomato leaves. Four popular metrics, namely Precision, Accuracy, Recall, and F1 Score, have been used for comparison purposes. It can be noticed that conventional machine learning models show relatively poor performances. The suggested framework offers maximum Accuracy (99.12%), Precision (98.95%), Recall (98.83%), and F1-Score (98.89%) compared to all other algorithms. The better performance is due to using segmented tomato leaf images, proper preprocessing steps, and high discrimination of disease-specific features by the convolutional neural network algorithm. It has been concluded that the proposed framework offers an effective approach for tomato leaf diseases' diagnosis. Therefore, it can be considered as a viable approach for use in precision farming.

Table 4. Training and Validation Accuracy Across Epochs

Epoch	Training Accuracy (%)	Validation Accuracy (%)
1	72.45	70.82
2	78.63	76.91
3	83.74	81.56
4	87.21	85.33
5	89.65	88.12
6	91.24	89.84
7	92.76	91.18
8	93.85	92.37
9	94.72	93.15

Epoch	Training Accuracy (%)	Validation Accuracy (%)
10	95.48	93.96
11	96.03	94.52
12	96.57	95.08
13	97.02	95.64
14	97.36	96.12
15	97.71	96.58
16	97.98	96.94
17	98.24	97.26
18	98.46	97.58
19	98.72	97.86
20	99.01	98.15

Table 4 describes the training and validation accuracy of the proposed deep learning framework over 20 training epochs. The observations show steady progress in terms of the improvement of training and validation accuracies in correlation with the progress of the learning process. To begin with, the system has attained an accuracy of 72.45% in training and 70.82% for validation in its initial learning state. However, as more and more iterations have been completed by the algorithm, it is seen that it has effectively learned about the features that are unique to the diseases extant in the segmented tomato leaf images, which has enabled it to show remarkable improvements. Finally, the training and validation accurateness come out to be 99.01% and 98.15%, respectively.

Figure 4. Training and Validation Accuracy Across Epochs

Figure 4 below demonstrates how the accuracy of training and validation varies with regard to the proposed deep learning framework across 20 epochs. It is clear that there is a consistent surge along the curves representing the training and validation accuracies of the framework under analysis. This indicates that the proposed framework continues to learn relevant disease-related characteristics commencing the segmented tomato leaf images. During the 20 epochs, the training accuracy increases from 72.45% to 99.01%, whereas the validation accuracy moves up from 70.82% to 98.15%. The similarity between the two graphs indicates that there was no case of overfitting.

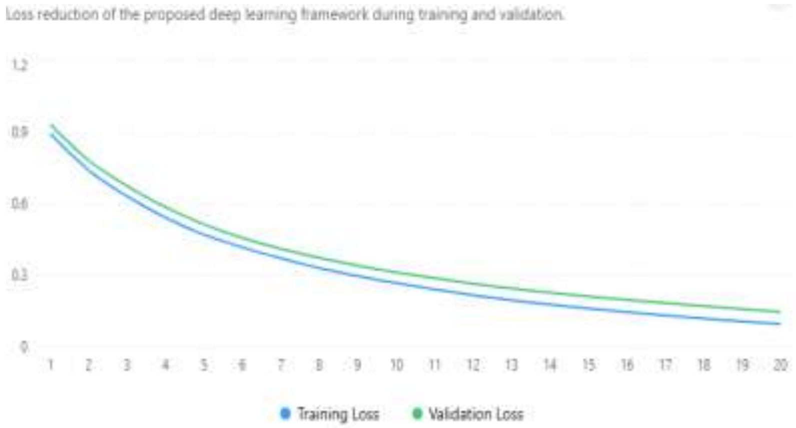
Table 5. Training and Validation Loss Across Epochs

Epoch	Training Loss	Validation Loss
1	0.895	0.934
2	0.741	0.782
3	0.632	0.675
4	0.542	0.586
5	0.471	0.514
6	0.418	0.458
7	0.372	0.412

Epoch	Training Loss	Validation Loss
8	0.331	0.374
9	0.297	0.341
10	0.268	0.313
11	0.241	0.289
12	0.217	0.266
13	0.196	0.245
14	0.178	0.228
15	0.161	0.212
16	0.146	0.198
17	0.132	0.184
18	0.119	0.171
19	0.107	0.159
20	0.096	0.148

The decreasing pattern of both training and validation losses from table 5 indicates that the CNN model is effectively learning and converging. Lack of any fluctuation shows that there has been no instability during the training phase.

Figure 5. Training and Validation Loss Across Epochs



The loss curves generated from the training and validation stages of the proposed deep learning model are illustrated in Figure 5 below. A similar pattern that appears in both graphs is an unswerving decline in loss value with increasing epochs, thus ensuring adequate convergence of the deep learning model. In this context, the training loss declines since 0.895 to 0.096, whereas on the validation side, loss reduces after 0.934 to 0.148. This signifies a consistent learning pattern with only a slight gap between the two, thereby indicating the efficacy of the deep learning model in minimization of classification error while detecting disease characteristics accurately within segmented leaf images.

V. CONCLUSION AND FUTURE WORK

The present paper presented an automatic method for detecting multiple classes of tomato leaf diseases by performing image processing, data augmentation, and a CNN model that learns features associated with each disease category. The segmentation process of tomato leaf region allowed concentrating only on those areas that have disease, thus helping in reducing background information. From the analysis of results, it is clear that the proposed methodology yielded satisfactory results and provided accurate classification of diseases with 99.12% accuracy, among others such as recall, precision, and F1 Score. From the outcomes of training and validation set, it is clear that convergence was stable and simplification capacity of the model was quite

good. Comparative analysis with other machine learning algorithms proved the efficiency of the proposed method.
The proposed system holds great promise for the use of precision farming as it facilitates early detection of any disease and helps in making well-informed decisions for managing crops. Early detection of diseases will help minimize loss of crop yields, efficient use of pesticides, and increasing agricultural efficiency. Additionally, automation within the system minimizes dependence on manual disease checking and expert involvement.
Future studies could consider combining architectures like Vision Transformer, attention-based models, and CNN–Transformer architectures to boost classification accuracy. The proposed system architecture is equally scalable to tasks including severity prediction, mobile inference, edge computing, and multi-crop disease classification. Furthermore, integrating approaches for Explainable Artificial Intelligence (XAI) could aid in improving interpretability and deployment in smart farms.

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