AI-Powered Plant Disease Identification: A Deep Learning Framework for Tomato Crops

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Abstract: A plant develops disease when enduring ongoing exposure to an underlying agent results in biological disruptions which disrupt its normal structure. All harmful agents acting upon a plant form what we term as disease complicated. This document demonstrates an approach to implement successful image classification through deep learning methodologies. The framework, uses two particular deep-learning frameworks as its principal foundation. The research collected its data from the publicly available Kaggle dataset for building the model. The detection of plant diseases uses basic neural network models as a classification solution. The network demonstrated 97.96% accuracy when operating on the dataset. We use Streamlit application in our local system. Through its updated detection system the web application recognizes and classifies tomato plants into ten specific disease groups to deliver precise disease predictions of identified conditions and indicates the appropriate safety measures that should be followed when the designated disease affects a plant.

Keywords: CNN1, CNN2, Deep learning in Agriculture, Streamlit for web application, training and validation accuracy.

1. Introduction

Since 2015 according to the Food and Agriculture Organisation there has been a purposeful growth in global starvation numbers. A total of 680 million people endure hunger at present which represents a minority of 9% in the worldwide demographic. The population reached a 10-million increase in twelve months and has grown by 120 million in ten years. Eighty percent of the worldwide population depends on agriculture as their key sustenance source. The agriculture sector together with the food sector need efficient cultivation tools. Living organisms acquire their required oxygen through photosynthesizing plants that support environmental equilibrium. The disease that affects plant leaves may cause death or decline to both plants and create barriers for agricultural fertilizer application. Plant disease causes substantial negative effects on the growth of food crops. The 1845 Irish potato famine led to the death of greater than 1.2 million people. The diagnostic procedures for plant diseases within laboratories incorporate multiple formal approaches. The detection and control and prevention of plant diseases remain vitally essential since their early stages. Plant disease detection throughout extensive fields proves difficult because it requires experienced personnel who must examine leaves manually [1]. Plant disease identification by farmers relies on their visual assessment of leaf symptoms combined with their disease identification expertise but requires intensive labour and specialised skills as well as taking up significant time. A disease identification mechanism seeks to help non-specialist users who do not understand pathology and botany [2].

Deep learning and machine learning techniques are currently prevalent in plant disease recognition because they deliver accurate digital image-based plant illness detection. Traditional machine learning adopts both feature extraction and classification techniques for studying plant illnesses in various fields [3]. The identification methods first extract visual elements from photos such as color features and shape characteristics and texture patterns before training an identification system that distinguishes between diseased and healthy plant specimens. Different identification techniques enable the detection of leaf blotches together with rust and powdery mildew disease along with environmental symptomatology caused by drought and nutrient deficits [4]. These examination methods still experience limitations in pinpointing uncommon disease indicators and disease onset. High-quality images and complex images prove to be processing challenges for such systems.

Deep belief networks (DBNs) as well as convolutional neural networks represent modern advancements of deep learning techniques that detect plant diseases [2]. Neural networks learn fundamental image features through these methods as a part of their teaching process. Regular image processing techniques lose track of minor illness indications while deep learning methods find such indications more easily [5]. Deep learning methods work proficiently with complicated large-scale pictures because of which they suit high-resolution use. Large amounts of labelled training data are needed for these methods to operate correctly yet such data could be insufficient for new disease detection. [6], [7]

The identification of plant diseases depends on recent investigations that use multiple machine learning approaches including deep learning methods. The majority of research investigations have limited themselves to working with particular disease categories alongside particular plant species. Further research needs to establish an extensive model which can recognize different diseases in multiple plant species. The model assessment process requires increased availability of datasets accessible to the public domain. Transfer learning proves to be a major breakthrough in the field since it allows pretrained models to operate efficiently across different datasets. Image-based investigations employs convolutional neural network (CNN) deep learning techniques extensively [5]. The system collects fundamental data elements through efficient operations of visual data. Training the layers of deep convolutional neural networks remains difficult because the computational expenses required to perform the process are substantial. The identification of new methodologies through transfer learning has emerged as a solution to handle these difficulties according to research findings. Transfer learning incorporates various techniques which include VGG-16, ResNet and Inception and DenseNet among others according to [4]. ImageNet provides the training data for model development as the dataset includes various classes. The computational models work well for diverse dataset training because they can detect the consistent image features which include edges as well as contours. When it comes to image classification researchers established transfer learning as a resilient approach which provides superior results. The implementation of transfer learning generates better learning achievements mainly during situations with limited dataset availability.

The main contributions of this manuscript could be outlined in the following manner:

- Development of a deep learning approach for the diagnosis of diseases within tomato plants.
- Determination of an efficient deep learning technique for attaining elevated accurate classification along with ideal recognition rates in recognizing of multi-class plant diseases [2].

The following sections that comprise the article are structured in the manner outlined below. Section 2 provides a comprehensive review of the existing literature. The methodology for this work is detailed in Section 3. Section 4 provides an analysis of the various experiments conducted. Section 5 presents the results along with discussion. Section 6 ends the paper by outlining recommendations for the future.

2. Literature review

In recent decades, there has been a notable increase in the application of machine learning along with deep learning approaches within agricultural as well as botanical investigations.[12]

Scientists demonstrate the production-enhancing capabilities of these methods along with their capabilities to detect plant lesions and optimize plant development. Approaches that use machine learning and deep learning methods surpass traditional procedures through multiple advantages which creates substantial potential for agricultural along with botanical research advancements. Agricultural and botanical research depends mainly on human evaluation and skilled expertise through traditional methods. The measures employed commonly require a workforce working at elevated physical levels that are also prone to human mistake. ML along with DL methods possess the capability to automate these processes to become more accurate at the same time minimizing human personnel requirements.

Some deep learning techniques allow researchers to identify plant and pest issues. Digital image infection detection methods have shown promising results in research studies [5]. The deep learning algorithms can independently draw valuable information from photographic images which human processing methods often disregard. Deep learning models need extensive collections of training data that has been clearly marked for their operation. Considerable processing capabilities are necessary for such methods although these demands might limit some particular applications. The application of computer vision as an AI processing method serves purposes in plant disease detection. [6], [7]

Computer vision techniques that perform object identification and semantic segmentation help visualize and mark particular areas of interest within visuals containing plant leaves alongside illness indications. The conversion of images into identifiable characteristics through these methods allows their connection to disease-diagnosing and disease-classifying algorithms based on machine or deep learning. Training computer vision models demands significant amounts of assorted picture data for labelling although the requirement exceeds what exists for newly identified medical conditions [4].

According to [5] represents unsupervised deep learning models through layers of RBMs that organize themselves into multiple networks according to their description. Images of vegetation-affected areas undergo DBN-based analysis to detect plant diseases alongside pests using the technique which extracts leaf-related image characteristics. According to research results Deep Belief Networks (DBNs) function at image classification accuracy levels between 96% and 97.5% for plant leaf pictures with pest and disease manifestations.[9], [10]

A new CNN architecture proposed by the authors enabled the identification of multiple plant diseases through transfer learning techniques [13]. The authors describe their research as the first study for multi-label CNN-based disease type recognition among 28 plant diseases. The hidden architecture component of CNN provided major advancements to the identification of plant diseases through its processes [8]. Every time benchmark datasets were used for testing the model returned ineffective results.

The field of using machine learning alongside deep learning techniques for plant disease detection shows positive results in its development [3], [14]. The strategies show successful results in proper plant disease identification and classification tasks. Multiple challenges remain in the path toward their full implementation. Research needs to continue with the goal of developing universal disease identification models while also improving public information databases for training assessment purposes. Researchers have reached current milestones within this field and this part describes this work. All research from the past ten years generated progress through a wide examination of machine learning and deep learning approaches which analysed usability and advantages and drawbacks together with potential solutions. The analysis chapter delivers vital knowledge about current research approaches to assist researchers and plant disease detection practitioners and industry experts who seek deep understanding of this field.[10], [15]

3. Material & methods:

3.1. Datasets:

Our research required us to obtain photos from the open-source Kaggle website by using its Tomato Leaf Disease Detection dataset. The plant-village dataset consisted of 10,000 training pictures but included 1,000 pictures used for testing and validation. All files within the dataset present JPEG images which maintain a dimension format of 255 pixels in width by 255 pixels in height. [11]

The dataset contains the ten primary diseases which affect tomato plants. Images were recorded with different viewpoints as well as multiple lighting conditions and backdrop settings. The pictures undergoing pre-processing operations are converted to de-noised and segmented images with dimensions of 256 × 256 pixels. The tomato leaf disease detection dataset acts as one of the principal tools for agricultural disease identification through stockpiles of publicly available datasets. Our research utilized images collected from tomato leaf disease identification datasets found inside the laboratory as part of our training process. Our methodology depends on genuine field yield photographs which requires us to develop a particular field database. We obtained the test images with a special tool camera then save them in a digital storage system. The dataset produced by the field is accessible and suitable for the proposed study. The subsequent categories of disorders will get their classification through analysis of this dataset.[16]

3.2. Methodology:

The future framework of leaf disease classification research in numerous crops appears in Figure 1. A base group of plant leaf disease photos undergoes classification into different categories during the initial process. The image-processing techniques consist of photograph filtering and grey conversion with image sharpening and scaling operations [17]. The data enhancement techniques create new image samples from existing pictures to strengthen and improve the dataset collection. The images act as inputs for the next phase of training the proposed methodology. A recently trained structural model has been used to forecast previously unknown pictures. The process ends in successful plant condition diagnosis and disease grouping.

The Convolutional Neural Network (CNN) models exist specifically for purposes of object recognition and image dataset classification. The advantages provided by CNNs are contrasted against continuing training difficulties as well as the need for abundant dataset amounts. To extract both common and sophisticated image elements deep neural network models require higher difficulty during the training process. Transfer learning strategies demonstrate effectiveness against the above-described problems. The application of parameter values derived from a specific dataset becomes possible through transfer learning due to its usage of pre-trained networks. [13]

3.3. Multi-Class Classification:

Multiple pictures show diseased and healthy plant samples in each plant illness file while a specific classification exists for each sample. All images which contain healthy or diseased tomato samples need to establish a connection with the distinct classification when focusing on the tomato plant. The target image classification depended on the information extracted from its source image. A total of ten disease classifications make up the tomato plant classification system which includes bacterial spot and healthy along with early blight and leaf mold and Late blight and leaf spot and spider mites would be significant concerns in agricultural practice. Plant health together with yield quantity receives negative effects from these several factors. Effective control demands proper identification involving necessary management strategies. These types of diseases include the Two-spotted spider mite and Yellow Leaf Curl Virus and the malware known as Target Spot and mosaic virus. During testing the trained system processes a specific illness sample together with disease samples from all ten categories of tomato diseases before identifying it among those ten disease categories. A distinction exists between multi-class classifications because its operations separate different conditions while multi-label categorization considers each distinct class category as unique category.

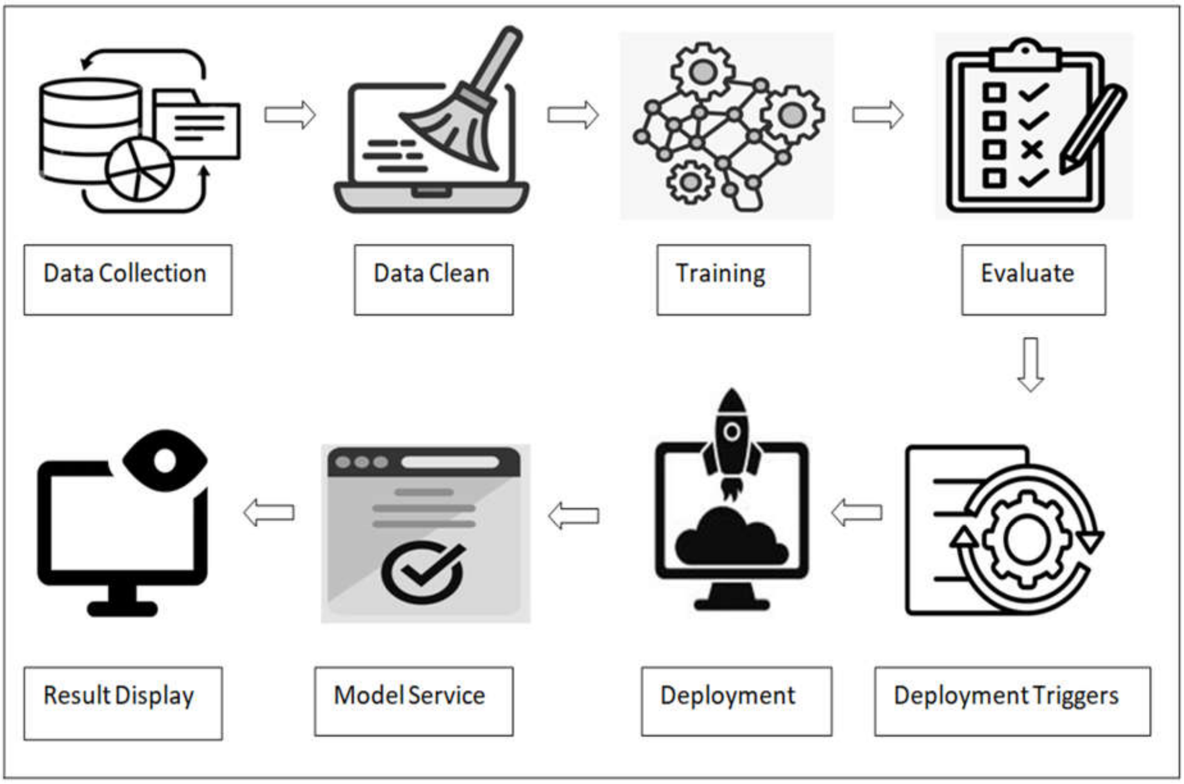

Figure 1: Pipeline of Proposed Model

3.4. Convolutional neural network:

Figure 2 explains that the Convolutional Neural Network (CNN) incorporates various layers including convolutional layers and pooling layers as well as fully connected layers and dense layers. The following provides a concise summary of the layers. Main convolutional layer operation includes identifying specific features in images followed by their extraction process. The consistent application of multiple convolutional layers facilitates the aggregation of characteristics of the input

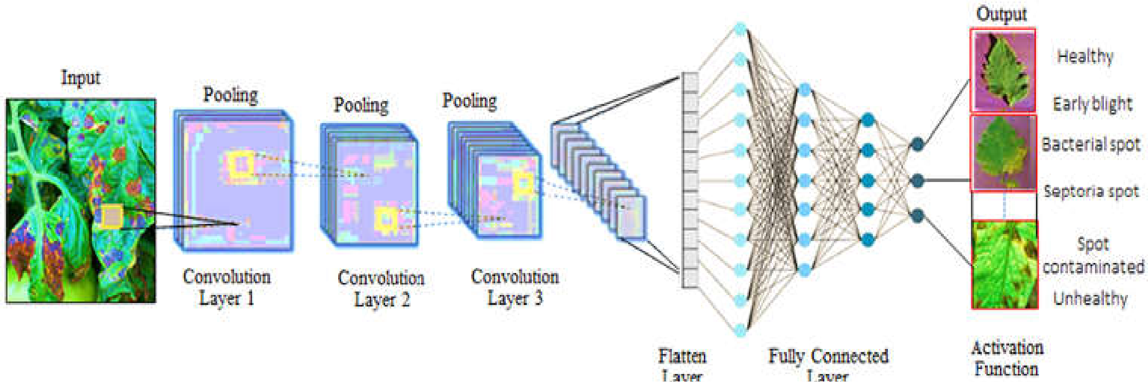

Figure 2: Proposed CNN framework

Convolutional Neural Networks (CNNs) have pooling layers that perform fundamental operations for their network function. Image processing requires lower computational resources thanks to this method which also shrinks convolved features sizes. The fundamental pooling are categorized as average and max pooling. Max pooling obtains the most dominant image pixel values but average pooling generates the average value throughout the image area section. The model performance improves because of Dropout layers. The technique provides regularization benefits as well as overfitting prevention through its ability to decrease neurone interconnections. The drop mechanism operates on each activation layer although it undergoes modification by a defined factor [8].

The process of flattening preserves the ratios of channels when it minimizes the spatial extent of pooled feature mappings. Each layer flattens the dimensional structure before the conversion into a vector takes place. The input data passes through vector-based structures to reach fully connected layers with their other names being dense layers. The categorization of image-derived features relies heavily on completely linked layers because of their specialized operational features. Softer features from several preceding layers come from the softmax algorithm. The activation method Softmax enables identification of various classes that exist in output layers.

The primary aspect of ConvNet architecture defines its thoroughness as a whole system. The achievement depended on supplemental design variables along with increasing network depth by adding more convolutional layers and employing 3x3-sized convolution filters throughout all layers. Their improvement of ConvNet architecture design has resulted in more precise models which achieve the highest performance in classification and localization tasks. The recognition datasets benefit significantly from these structures because they generate outstanding results with basic processing pipelines. The training process requires ConvNets to handle images which have been standardized to 224 × 224 RGB format. As a pre-processing step the mean RGB value serves to subtract from each pixel within the first training set. The image processing depends on 3x3 filter operations for a sequential convolutional layered approach. A different approach uses 1x1 convolution filters to transform linearly the input channels before executing a non-linear activation function. One pixel was allocated for calculating the convolution phase while the spatial padding received its value as one pixel throughout all three convolutional layers to preserve the spatial resolution between the convolution steps. Spatial pooling operations occur within five designated max-pooling layers that are defined as convolutional layers. The max-pooling operation includes a two-by-two pixel window with a 2-pixel stride.

4. Experimentation:

The system architecture integrated the Tensor Flow and OpenCV libraries together with Pillow and NumPy within the implementation along with Streamlit. Various model training parameters allow us to determine the accuracy levels of training and validation phases. We monitored training and testing accuracy metrics through all experiments of this study. Loss evaluation occurred across entire training and testing periods for all models. Training of these predictive models utilized previously described datasets to enhance the learning speed of CNN through transfer learning methods [13]. The study recorded different parameter values for learning rate and number of epochs along with dropout rate and number of images during its investigation period. Training loss accuracy and validation accuracy with loss represent the recorded values. Tests for model assessment and confirmation were carried out on the leaf surfaces of tomato plants.

The team built a deep neural network to identify healthy as well as unhealthy plant specimens. We develop multiple layered neural networks for our purpose. The training of two-layer neural network models occurred using ten classification data from tomato plant diseases obtained from Kaggle. The specialized convolutional network together with pooling solutions run on the platform that enables parameter sharing. CNN designs operate identically across all hardware platforms because of this feature which makes them accessible to all users. The implemented solution will become usable for automation purposes. A CNN model was subsequently designed per Figure 3. The divided structure operates in two layers which contain 32 filters that measure 3x3 pixels in each layer. The first layer of dense nodes has an element count of 128 while the second layer contains 10 nodes. All layers include a two-dimensional convolutional block that is followed directly by maximum pooling operations. SoftMax worked as the layer responsible for category classification. The method implements an Adam optimizer together with Binary Cross Entropy as its losses function.

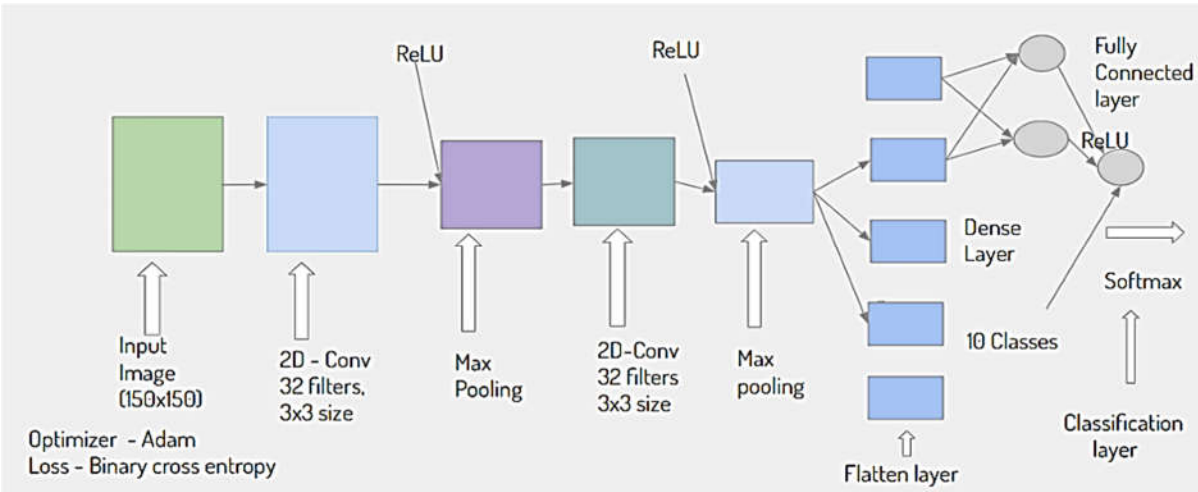

Figure 3: Proposed CNN Model-1

Training accuracy showed a different outcome than validation accuracy after implementing CNN-1. A fully connected layer now uses the default batch dimension according to the design displayed in figure 4. The updated design produces better results than the previous structure because it contains two layers with 32 filters having dimensions of 3x3 in each layer. The structures of dense layers one and two contain node configurations of 128 and 10 respectively. The network incorporates two-dimensional convolution layers that immediately follow maximum pooling layers in each of its structural layers. A SoftMax layer enabled us to achieve categorization from our model. The implementation uses Adam optimizer and Binary cross entropy loss function for its operation.

Implementation of CNN-2 led to another appearance of training accuracy divergence from validation accuracy. The last fully connected layer of CNN-2 was removed while the remaining whole layer received a batch size of 64. Current outcomes surpass those from previous designs. The network contains two compact layers with 128 and 10 nodes for each layer. Each layer contains two-dimensional convolution followed by maximum pooling operations. The Softmax layer served to perform categorization within this model. Adam functions as the optimizer together with Binary cross entropy operating as the loss function during this implementation.

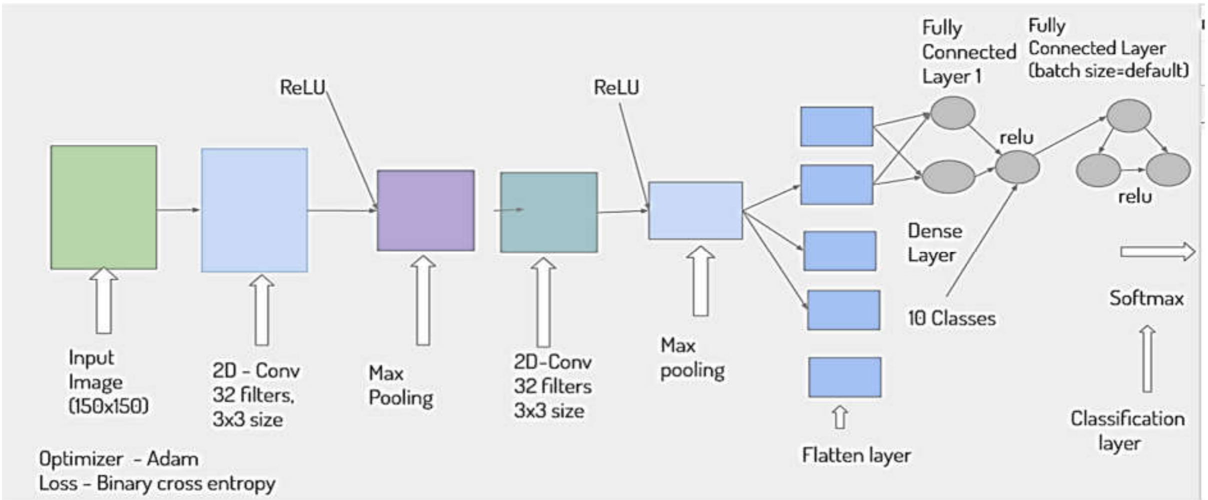

Figure 4: Proposed CNN Model-2

5. Results and Discussions:

The dataset contains numerous causal features of tomato leaves which come from multiple sources. The training dataset contains a wide selection of leaf images which serve as foundational material for model learning about leaf attributes and designs. The collection features 18,345 images which will be used for tomato leaf disease identification. The training images number 14,678 (80%) while 4,585 (20%) serve for testing purposes. The model tested its ability to generalize across unknown data through evaluations on data contained within the validation set. [19], [20]

5.1. Training and Validation accuracy:

This shows how well the model advances in its learning phase along with how many hidden patterns it managed to detect within the training dataset. The model changes its internal parameters throughout training to achieve minimal loss thus it learns to predict real target values accurately in training data. The training accuracy rises because models learn to understand aggregated input better thus leading to improved generalization abilities. The training accuracy and validation accuracy must display similar results. The model displays data overfitting when these two values differ notably from each other. The model learns the training data to an excessive extent when it picks up irrelevant noise and patterns that fail to apply to new data during overfitting.

Figures 5 and 6 represent the training and validation accuracy and loss of CNN-1 model. From the figures 5, 6, it is concluded that the Training Accuracy and loss are 99.37 and 0.0057 respectively whereas testing Accuracy and loss are 93.54 and 0.0738 respectively. Figures 7 and 8 represent the training and validation accuracy and loss of CNN-2 model. From the figures 7, 8, it is concluded that the Training Accuracy and loss are 99.35 and 0.0126 respectively whereas testing Accuracy and loss are 88.80 and 0.0102 respectively.

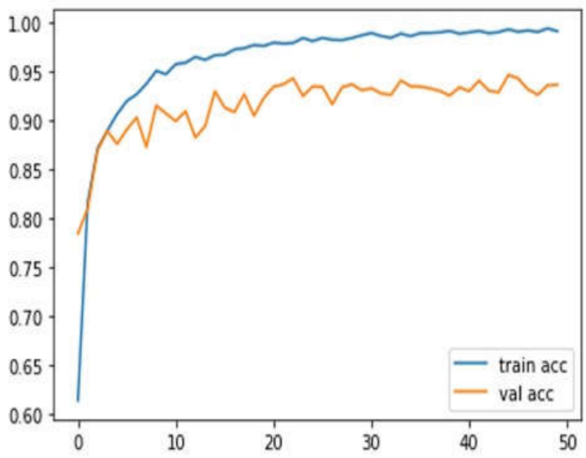

Figure 5: Training &Validation Accuracy of CNN model 1

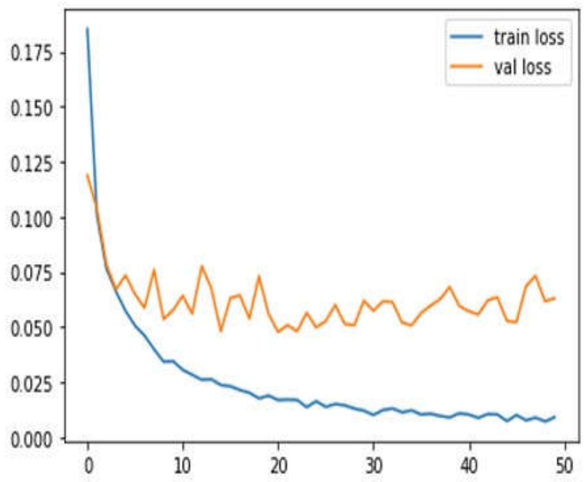

Figure 6: Training & Validation Loss of CNN model 1

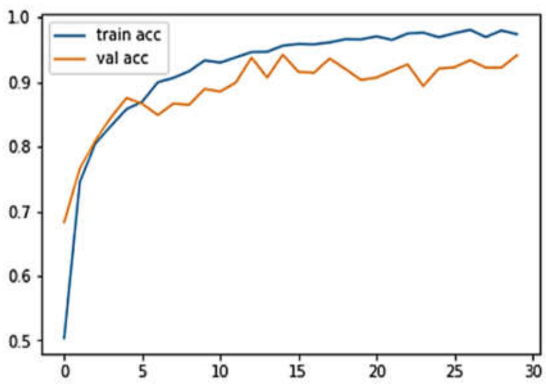

Figure 7: Training & Validation Accuracy of CNN model 2

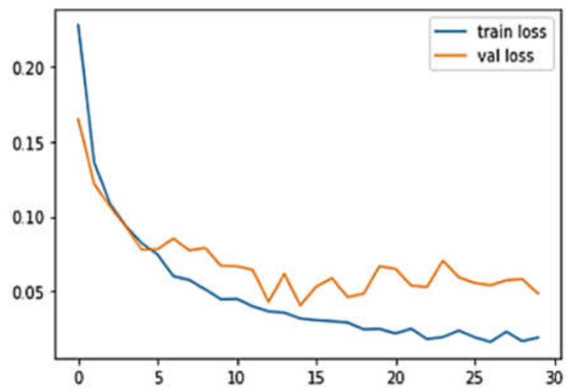

Figure 8: Training & Validation Loss of CNN model 2

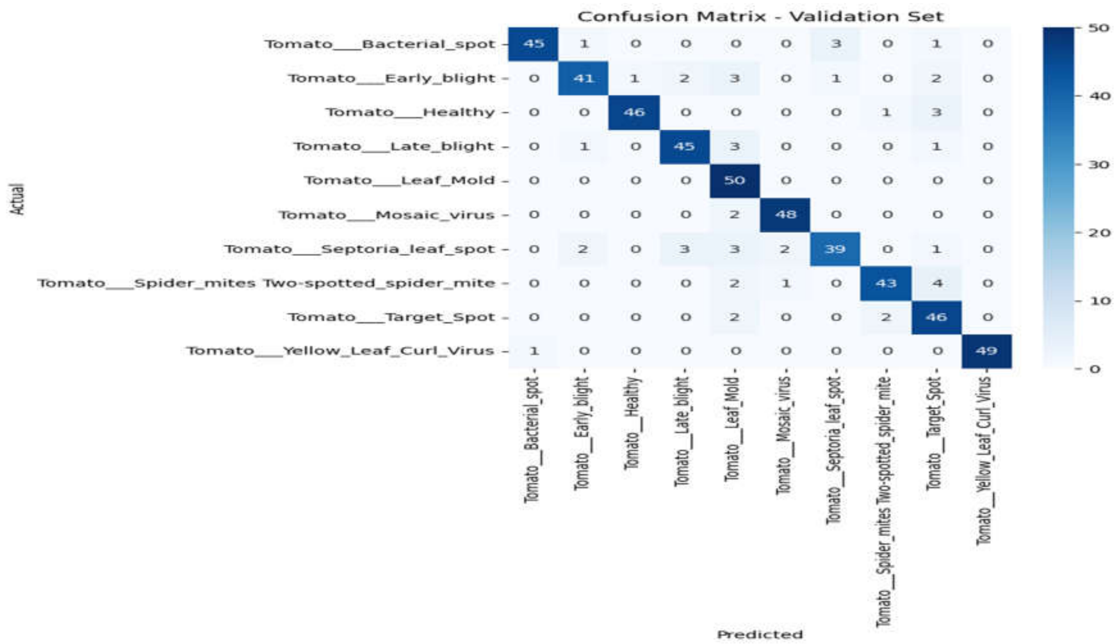

Figure 9: Confusion Matrix for CNN model-1

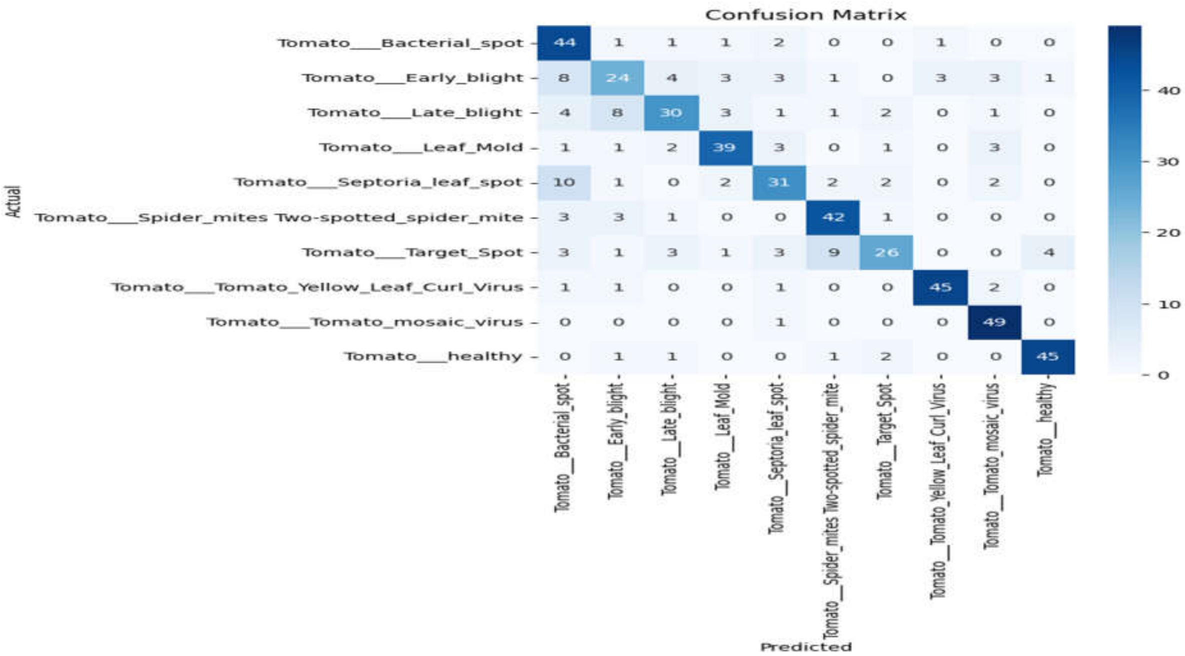

Figure 10: Confusion Matrix for CNN model-2

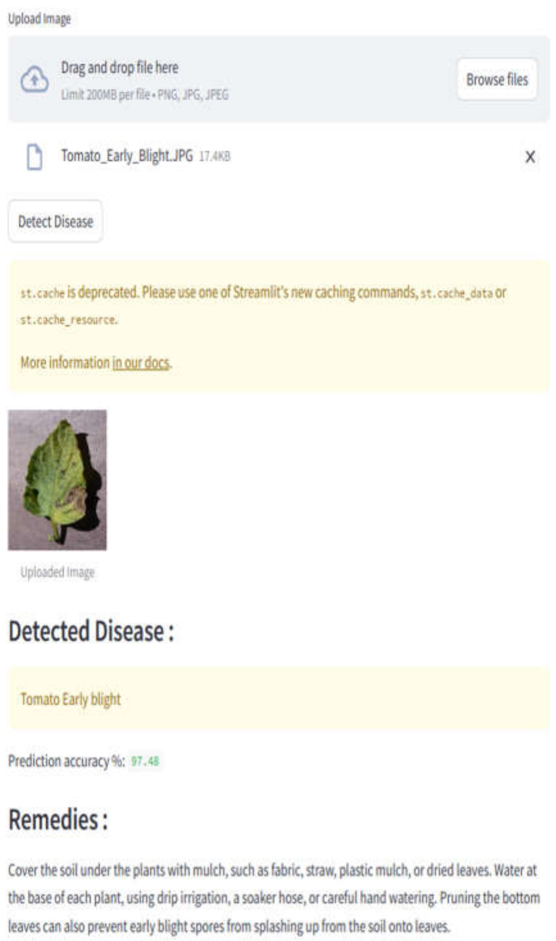

Figure 11: Screenshot of the image displaying results

6. Conclusion:

Our model development relies on public access data from Kaggle. Our research implemented two different convolutional neural networks. Testing this network on the dataset achieved 98% accuracy in results. Our application displays two key features which enable users to upload leaf images for disease detection alongside process information display. Crops are assessed through this technique which proves advantageous to farmers checking plant health.

By this proposed and developed model farmers get a better option to find out the type of disease that has affected the leaves of the tomato plant and also better recommendations will be given based on the type of disease that is affected to the tomato plant leaves.`

Conflicts of Interest:

The authors declare no conflict of interest.

Author Contributions:

The authors in this article is mainly focused on making the farming is easy by identifying the Tomato leaf disease and if once the disease is affected what kind precautions need to be consider are clearly explained by using web application instead of spraying chemicals to the entire tomato plants. The Author1 performed data collection, designed the proposed model and drafted the manuscript and Author2 conducted and supervised the research. All the authors analysed the results and approved the final results.

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