Tomato Disease Detection and Identification

A Project Report

Submitted for Minor Project - CS6490 of 6th Semester for the partial fulfillment of the requirement for the award of the degree of

Bachelors in Technology
in
Computer Science and Engineering

submitted by

Rishita Singh (1906022)
Aradhana kumari(1906033)
Lovely kumari (1906034)

Under the supervision of

Dr. Rajib Ghosh
CSE Department
NIT Patna

Department of Computer Science and Engineering

National Institute of Technology Patna Patna-800005

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राष्ट्रीय प्रौद्योगिकी संस्थान पटना

NATIONAL INSTITUTE OF TECHNOLOGY PATNA

CERTIFICATE

This is to certify that Aradhana Kumari with Roll No. 1906033, Lovely Kumari with Roll No. 1906034, Rishita Singh with Roll No. 1906022 has carried out the Minorproject (CS6490) entitled as "Tomato Disease Detection and Identification" during their 6th semester under the supervision of Dr. Rajib Ghosh , CSE Department, in partial fulfillment of the requirements for the award of Bachelor of Technology degree in the department of Computer Science & Engineering, National Institute of Technology Patna.

……………………………..

Dr. Rajib Ghosh
CSE Department
NIT Patna

राष्ट्रीय प्रौद्योगिकी संस्थान पटना

NATIONAL INSTITUTE OF TECHNOLOGY PATNA

DECLARATION

We, the students of 6th semester, hereby declare that this project entitled " Tomato Disease Detection and Identification" has been carried out by us in the Department of Computer Science and Engineering of National Institute of Technology Patna under the guidance of Dr. Rajib Ghosh. No part of this project has been submitted for the award of degree or diploma to any other Institute.

Name	**Roll no.**
Aradhana Kumari	1906033
Lovely Kumari	1906034
Rishita Singh	1906022

Place	**Date**
NIT Patna	29th April, 2022

राष्ट्रीय प्रौद्योगिकी संस्थान पटना

NATIONAL INSTITUTE OF TECHNOLOGY PATNA

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1. Aradhna Kumari
2. Lovely Kumari
3. Rishita Singh

CONTENT

ABSTRACT

The tomato crop is an important staple in the Indian market with high commercial value and is produced in large quantities. Diseases are detrimental to the plant's health which in turn affects its growth. To ensure minimal losses to the cultivated crop, it is crucial to supervise its growth. There are numerous types of tomato diseases that target the crop's leaf at an alarming rate.The application of computer vision technology has increased exponentially due to automatic and accurate disease detection capability. However, a convolutional neural network (CNN) requires high computational resources, limiting its portability. The main aim of the proposed work is to find a solution to the problem of tomato leaf disease detection using the simplest approach while making use of minimal computing resources to achieve results comparable to state of the art techniques. We have designed a lightweight convolutional neural network by incorporating different attention modules to improve the performance of the models. The models were trained, validated, and tested using tomato leaf disease datasets split into an 8:1:1 ratio. All the hyperparameters are evaluated using Bayesian optimization technique , which is a global optimization method.it keep track of past evaluation results which they use to form a probabilistic model mapping hyperparameters to a probability of a score on the objective function..optimal number of epochs are decided by using a regularization technique called EarlyStopping,which is called using call back library.it is used to reduce overfitting issueThe efficacy of the various attention modules in plant disease classification was compared in terms of the performance and computational complexity of the models. The performance of the models was evaluated using the standard classification accuracy metrics (precision, recall, and F1 score). This proposed system has achieved an average accuracy of 96-97% indicating the feasibility of the neural network approach even under unfavourable conditions.

Keywords—leaf disease detection, neural network, convolution, Bayesian optimization,EarlyStop.

1. INTRODUCTION

India is a country with a majority of the population relying heavily on the agricultural sector. Tomato is the most common vegetable used across India. The three most important antioxidants namely vitamin E, vitamin C and beta-carotene are present in tomatoes. They are also rich in potassium, a very important mineral for good health. Tomato crop cultivation area in India spans around 3,50,000 hectares approximately and the production quantities roughly sum up to 53,00,000 tons, making India the third largest tomato producer in the world. The sensitivity of crops coupled with climatic conditions have made diseases common in the tomato crop during all the stages of its growth. Disease affected plants constitute 10-30% of the total crop loss. Identification of such diseases in the plant is very important in preventing any heavy losses in yield as well as the quantity of the agricultural product. Monitoring the plant diseases manually is a difficult task due to its complex nature and is a time consuming process. Therefore, there is a need to reduce the manual effort put into this task, while making accurate predictions and ensuring that the farmers' lives are hassle free. Visually observable patterns are difficult to decipher at a single glance, leading to many farmers making inaccurate assumptions regarding the disease. As a result, prevention mechanisms taken by the farmers may be ineffective and sometimes harmful. Farmers usually come together and implement common disease prevention mechanisms, as they lack expert advice on how to deal with their crop infestation . There has been circumstances where due to inadequate knowledge or misinterpretation regarding the intensity of the disease, over-dosage or under-dosage of the pesticide has resulted in crop damage. This is the underlying motivation for the proposed methodology that aims to accurately detect and identify diseases in the tomato crop. The methodology suggested in the paper pertains to the most common diseases found in the tomato plant like, Bacterial leaf spot and Septorial leaf spot, Yellow Leaf Curl among many others. Any leaf image given as input can be classified into one of the disease classes or can be deemed healthy. The database used for evaluation is taken from kaggle, a repository that contains 18,000 images of tomato leaves infected with 9 diseases. Broadly, the proposed methodology consists of three major steps: data acquisition, model optimization and classification. Since all the images were of same size (256*256) hence,there is no need to resize or rescale before feeding it into the classification model. The final step is the classification of the input images with the use of convolutional neural network (CNN) which consists of the convolutional, activation, pooling and fully connected layers. The paper is organized as follows: Section II focuses on the prominent work done in regard to the concerned field. Section III elucidates the proposed methodology and the model used along with the steps taken to obtain the necessary results. Section IV pertains to the results and the analysis of the proposed methodology. Section V includes the conclusion of the paper and provides the scope for future work.

Related Work

1. **Automated Image Capturing System for Deep Learning-based Tomato Plant Leaf Disease Detection and Recognition**

   This paper proposes to identify the Tomato Plant Leaf disease using image processing techniques based on Image segmentation, clustering, and open-source algorithms, thus all contributing to a reliable, safe, and accurate system of leaf disease with the specialization to Tomato Plants.

2. Deep Learning for Plant Diseases: Detection and Saliency Map Visualisation

The current limitations and shortcomings of existing plant disease detection models are presented and discussed in this paper. Furthermore, a new dataset containing 79,265 images was introduced with the aim to become the largest dataset containing leaf images. Images were taken in various weather conditions, at different angles, and daylight hours with an inconsistent background mimicking practical situations. Two approaches were used to augment the number of images in the dataset: traditional augmentation methods and state-of-the-art style generative adversarial networks.

3. **A Lightweight Attention-Based Convolutional Neural Networks for Tomato Leaf Disease Classification**

This work proposed a Deep Convolutional Neural Network (DCNN) model for image-based plant leaf disease identification using data augmentation and hyperparameter optimization techniques. The DCNN model was trained on an augmented dataset of over 240,000 images of different healthy and diseased plant leaves and backgrounds. Five image augmentation techniques were used: Generative Adversarial Network, Neural Style Transfer, Principal Component Analysis, Color Augmentation, and Position Augmentation. The random search technique was used to optimize the hyperparameters of the proposed DCNN model.

4. Tomato plant disease detection using transfer learning with C-GAN synthetic images

In this work, the authors reviewed the latest CNN networks pertinent to plant leaf disease classification,summarized DL principles involved in plant disease classification. Additionally, they summarized the main problems and corresponding solutions of CNN used for plant disease classification. Furthermore, discussed the future development direction in plant disease classification.

5. Automated Image Capturing System for Deep Learning-based Tomato Plant Leaf Disease Detection and Recognition

This paper proposes to identify the Tomato Plant Leaf disease using image processing techniques based on Image segmentation, clustering, and open-source algorithms, thus all contributing to a reliable, safe, and accurate system of leaf disease with the specialization to Tomato Plants.

6. Identification of Apple Leaf Diseases Based on Deep Convolutional Neural Networks

This study review recent work where DL principles have been utilized for digital image–based plant stress phenotyping. it provide a comparative assessment of DL tools against other existing techniques, with respect to decision accuracy, data size requirement, and applicability in various scenarios. Finally, it outline several avenues of research leveraging current and future DL tools in plant science.

7. A Robust Deep-Learning-Based Detector for Real-Time Tomato Plant Diseases and Pests Recognition

In this work, specific CNN architectures were trained and assessed, to form an automated plant disease detection and diagnosis system, based on simple images of leaves of healthy and diseased plants. The available dataset contained images captured in both experimental (laboratory) setups and real cultivation conditions in the field

8. A Robust Deep-Learning-Based Detector for Real-Time Tomato Plant Diseases and Pests Recognition

In this paper, we review existing implementations and show that deep learning has been used successfully to identify species, classify animal behaviour and estimate biodiversity in large datasets like camera-trap images, audio recordings and videos. We demonstrate that deep learning can be beneficial to most ecological disciplines, including applied contexts, such as management and conservation.

9. Deep learning models for plant disease detection and diagnosis

In this paper, we present a comprehensive review of research dedicated to applications of machine learning in agricultural production systems. The works analyzed were categorized in (a) crop management, including applications on yield prediction, disease detection, weed detection crop quality, and species recognition; (b) livestock management, including applications on animal welfare and livestock production; (c) water management; and (d) soil management. The filtering and classification of the presented articles demonstrate how agriculture will benefit from machine learning technologies. By applying machine learning to sensor data, farm management systems are evolving into real time artificial intelligence enabled programs that provide rich recommendations and insights for farmer decision support and action.

10. A review on the main challenges in automatic plant disease identification based on visible range images

this paper propose a deep learning-based approach that automates the process of classifying ba- nana leaves diseases. In particular, it make use of the LeNet architecture as a convolutional neural network to classify image data sets. The preliminary results demonstrate the effectiveness of the proposed approach even under challenging conditions such as illumination, complex background, different resolution, size, pose, and orientation of real scene images.

11. **Applications of computer vision techniques in the agriculture and food industry: a review**

This paper presents a detailed overview of the comparative introduction, latest developments and applications of computer vision systems in the external quality inspection of fruits and vegetables. Additionally, the principal components, basic theories, and corresponding processing and analytical methods are also reported in this paper.

12. **Detection of gray mold disease and its severity on strawberry using deep learning networks**

In this study, a lightweight convolutional neural network was designed by incorporating different attention modules to improve the performance of the models. The models were trained, validated, and tested using tomato leaf disease datasets split into an 8:1:1 ratio. The efficacy of the various attention modules in plant disease classification was compared in terms of the performance and computational complexity of the models.

The performance of the models was evaluated using the standard classification accuracy metrics (precision, recall, and F1 score). The results showed that CNN with attention mechanism improved the interclass precision and recall, thus increasing the overall accuracy (>1.1%).

13. **Deep-plant: Plant identification with convolutional neural networks**

this paper perform a survey of 40 research efforts that employ deep learning techniques, applied to various agricultural and food production challenges. it examine the particular agricultural problems under study, the specific models and frameworks employed, the sources, nature and pre-processing of data used, and the overall performance achieved according to the metrics used at each work under study.

14. **Plant recognition via leaf shape and margin features**

In this paper, a set of features that depict leaf shape and margin are proposed to improve the performance of plant recognition. The proposed margin features utilize the area ratio to quantify the convexity/concavity of each contour point at different scales and such margin features are effective in capturing the global information and contour details. The area ratio is the ration of the disk to the inside of the contour. The proposed shape features use a combination of morphological features to characterize the global shape of the leaf, which has merits in preserving the geometric properties of leaf shape.

15. **Image-based deep learning automated sorting of date fruit**

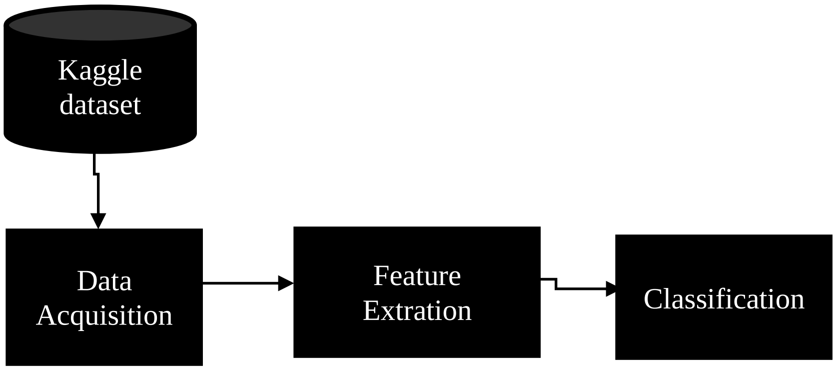
in this study, a deep learning neural network as a smart, real-time and non-destructive method was developed and applied to automate the identification of four economically important carp species namely common carp (*Cyprinus carpio*), grass carp (*Ctenopharingodon idella*), bighead carp (*Hypophtalmichthys nobilis*) and silver carp (*Hypophthalmichthys molitrix*).

16. Deep learning-based appearance features extraction for automated carp species identification

This paper focuses on applications of DL in aquaculture, including live fish identification, species classification, behavioural analysis, feeding decisions, size or biomass estimation, and water quality prediction. The technical details of DL methods applied to smart fish farming are also analysed, including data, algorithms and performance. The review results show that the most significant contribution of DL is its ability to automatically extract features. However, challenges still exist; DL is still in a weak artificial intelligence stage and requires large amounts of labelled data for training, which has become a bottleneck that restricts further DL applications in aquacultu

METHODOLOGY

The proposed approach includes the three important stages namely: Data Acquisition, getting optimized Hyperparameters and Classification. Flow diagram is shown in Fig. and current section includes the brief discussions of the same.



Data Acquistion

Data

We have used the “Tomato disease detection and identification” dataset provided by kaggle.The data contained two folders: train and val .val data contains 9000 images available for testing.Train data contains two folders :unhealthy and Healthy.Healthy contains 1000 healthy leaves images,Unhealthy contain 9 files ,each containg 1000 images of one disease type. Therefore, a total of 19,000 images.

Label information for each image is provided in train file only classifying images into two classes – Tomato__Healthy or Tomato__unhealthy.

The data contains only the training dataset. To test and compare the performance of various classification and deep learning models, we have splitted this dataset into training, testing and val dataset in ration 8:1:1. Finally, our training dataset contains 8000 images , the testing and val set each contains 1000 images.

Labelling

After dataset was extracted,we labeled all the Healthy images as 0 and all Unhealthy images as 0.After that ,since unhealthy class contains 9 subclasses containing 9 kind of defected leaves,we labeled each subclass :starting from 0 to 8.

Experimental Settings

The implementation of the proposed methodology has been carried out on the Kaggle dataset. It consists of around 19000 images belonging to 10 different classes of tomato leaf diseases. Keras, a neural network API written in Python, has been used for the model implementation. Out of the 19000 images, 9000 images were set aside for testing and 10000 images were used for training. In order to increase the dataset, automatic data augmentation techniques has been used by randomly rotating the images by a small amount of 20 degrees, horizontal flipping, vertical and horizontal shifting of images. The optimization was carried out using Bayesian optimization method of Keras Tuner with categorical cross entropy as the loss function. Batch size of 32 has been used.We used early stop method to find optimal number of epochs for model training and the model has been trained for the number of epochs given by early stop method. The initial learning rate has been set to 0.01 and it is reduced by a factor of 0.3 on plateau where the loss stops decreasing. Early stopping has been used in order to monitor the validation loss and stop the training process once it increases.

Results and Analysis

To evaluate the performance of the proposed model, a set of quantitative metrics comprising of accuracy, precision, recall and F1-score have been used. The results are reported in Table 1. They show the highest values of the quantitative metrics obtained until the corresponding epoch number.

Evaluation Metrics :

For evaluating the proposed models we used precision , recall , F1 Score , support and accuracy.We have used classification report and confusion matrix , these metrics are widely used for evaluating supervised machine learning models for classification when the dataset is multi labelled . Suppose a multi-labeled dataset consists of N number of instances, where each instance N_i is given by (x_i,y_i) , where x_i represents the set of attributes and y_i represents the set of labels . Let us say that y_i and y_i' represent the labels which are true and labels which are predicted respectively for the i^{th} instance then the metrics can be described for the ith instance which are by the following formulae.

Precision :

It is the ratio of accurately predicted authors as hate speech spreaders or not to the total number of predicted authors. It is computed as given in the equation below. The range of precision varies between 0 and 1 , where 1 is the best value and 0 is the worst value.

$$\text{Precision} = \frac{\text{Number of accurately predicted authors}}{\text{Total number of predicted authors}} = \frac{|yi \cap yi'|}{|yi'|}$$

Recall :

It is the ratio of accurately predicted authors as hate speech spreaders or not to the total number of authors. It is computed as is given in the below equation. The range of recall varies between 0 and 1 , where 1 is the best and 0 is the worst value .

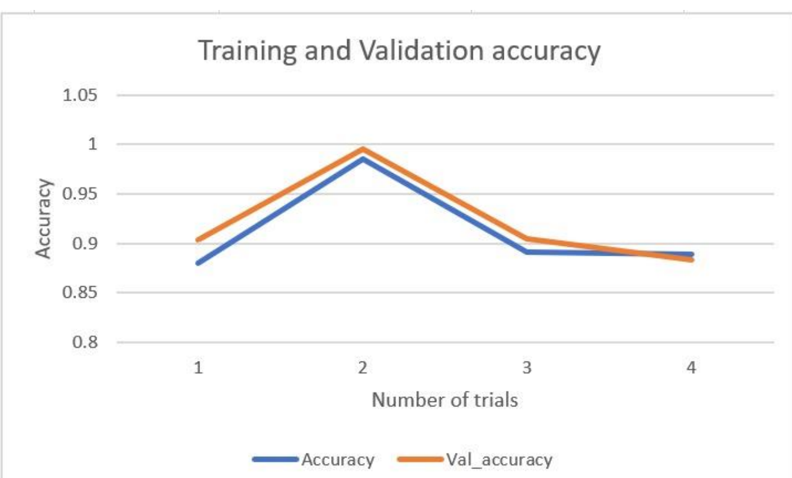
$$\text{Recall} = \frac{\text{Number of accurately predicted authors}}{\text{Total number of authors}} = \frac{|\, yi \cap yi' \,|}{|yi|}$$

F1-Score :

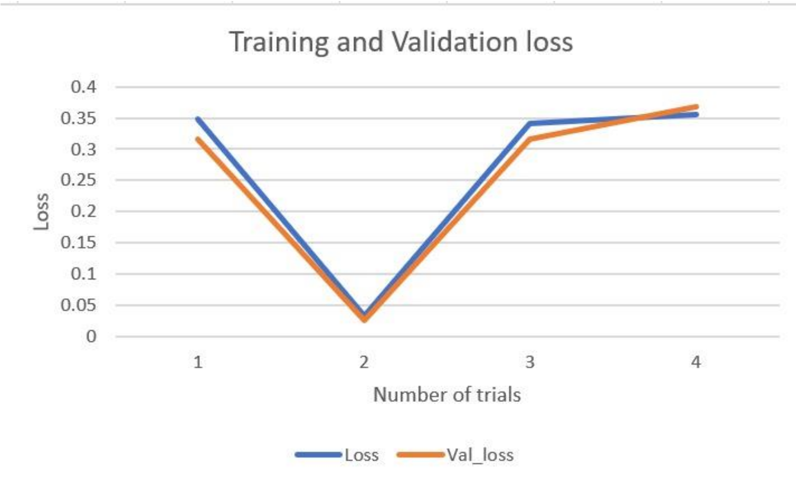
The harmonic mean between Precision and Recall is called F1-Score, which gives the balanced equation between them . It can be represented by the below equation . The range of F1-score varies between 0 and 1 , where 1 is the best and 0 is the worst value.

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

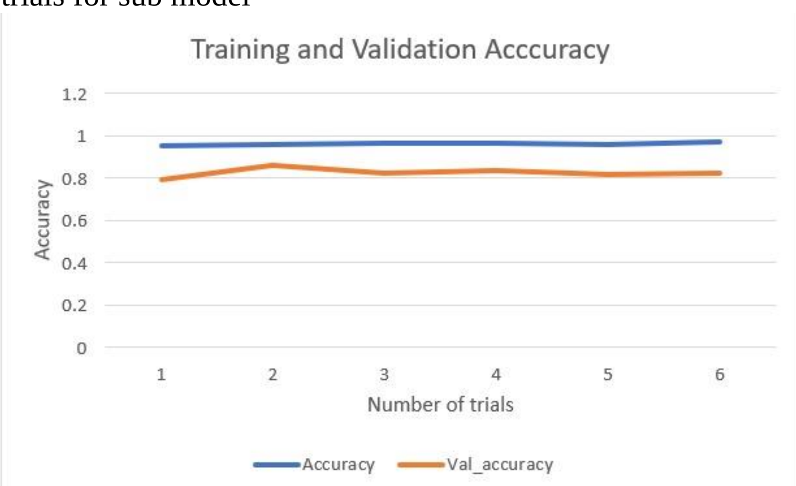
Comparing training and validation accuracy with number of trials for base model



Comparing training and validation loss with number of trials for base model



Comparing training and validation accuracy with number of trials for sub model



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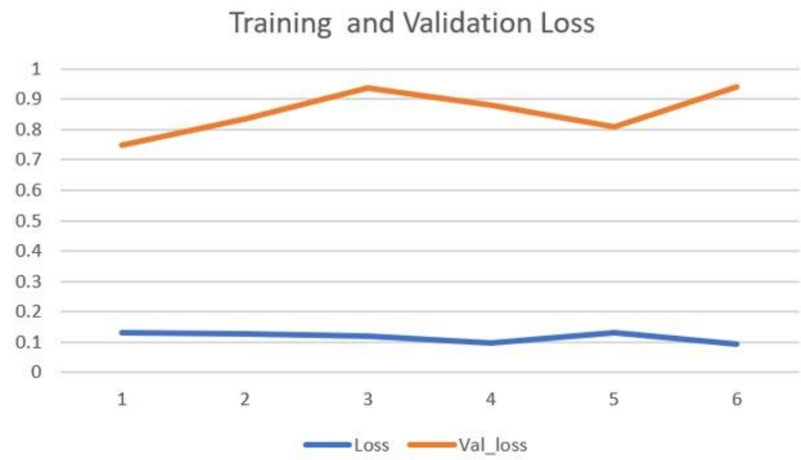

A highest validation accuracy of 98% was obtained over 13 epochs of training(for base model), and the highestvalidation accuracy of 96% was obtained over 30 epochs,so overall for healthy images accuracy of 98% was obtained and for unhealthy images accuracy of 94% is obtained. This is an effective measure of the classification made by the deep learning model. The plots of train and test accuracy and loss against the epochs in Fig. 6 provide a means of visualization and indication of the speed of model convergence. It can be seen that the model has stabilized around 20 epochs and the metrics do not show a significant improvement in the last 10 epochs. The results show that the model performs well on the dataset and can be used as a means for classification of the 10 tomato leaf diseases with minimum resource requirements.

The implementation process requires minimum hardware requirements unlike large neural networks which generally have high computational resource requirements or the use of a Graphics Processing Unit. This is due to less number of training parameters owed to the presence of fewer layers with less filter sizes and smaller train size images. Unlike other state of the art models, the model implementation can be carried out on CPU with minimum time owing to the simplicity. The model thus, provides a simple and effective way of solving the problem of tomato disease detection with results , where the authors deal with plant diseases of multiple crops. With less resource constraints and minimal data, the model gives comparative results to traditional state of the art techniques.

Description Of Hyper Parameters :

Activation function	Relu(for hidden layers),Sigmoid(for dense layers)
Loss function	Sparse Categorical Cross Entropy
Optimizer	Bayesian optimizer
Epochs	13
Batch-size	32
Metrics	Accuracy

RESULTS

Evaluation Metrics :

For evaluating the proposed models we used precision , recall , F1 Score , support and accuracy.We have used classification report and confusion matrix , these metrics are widely used for evaluating supervised machine learning models for classification when the dataset is multi labelled . Suppose a multi-labeled dataset consists of N number of instances, where each instance N_i is given by (x_i,y_i) , where x_i represents the set of attributes and y_i represents the set of labels . Let us say that y_i and y_i' represent the labels which are true and labels which are predicted respectively for the i^{th} instance then the metrics can be described for the ith instance which are by the following formulae.

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Recall :

It is the ratio of accurately predicted authors as hate speech spreaders or not to the total number of authors. It is computed as is given in the below equation. The range of recall varies between 0 and 1 , where 1 is the best and 0 is the worst value .

$$\text{Recall} = \frac{\text{Number of accurately predicted authors}}{\text{Total number of authors}} = \frac{|yi \cap yi'|}{|yi|}$$

F1-Score :

The harmonic mean between Precision and Recall is called F1-Score, which gives the balanced equation between them . It can be represented by the below equation . The range of F1-score varies between 0 and 1 , where 1 is the best and 0 is the worst value.

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

CONCLUSION

Agricultural sector is still one of the most important sector over which the majority of the Indian population relies on. Detection of diseases in these crops is hence critical to the growth of the economy. Tomato is one of the staple crops which is produced in large quantities. Hence, this paper aims at detection and identification of 9 different diseases in the tomato crop. The proposed methodology uses a convolutional neural network model to classify tomato leaf diseases obtained from the kaggle dataset. The architecture used is a simple convolutional neural network with minimum number of layers to classify the tomato leaf into 2 different classes,and then unhealthy Images into 9 classes. Different learning rates and optimizers is also used for experimenting with the proposed model as a part of the future work. It could also include experimentation with newer architectures for improving the performance of the model on the train set. Thus, the above mentioned model can be made use of as a decision tool to help and support farmers in identifying the diseases that can be found in the tomato plant. With an accuracy of 94-95% the methodology proposed can make an accurate detection of the leaf diseases with little computational effort.

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