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An Empirical Performance Analysis of Multi-Classification of Diseases of Tomato Leaf using CNN Models in the Deep Learning

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Abstract— Tomato farming in India, producing tomatoes is one of the leading productions and stands second-largest producer of tomatoes in the world. Tomato farming has been facing challenges as the crop is susceptible to tomato diseases that include Bacterial_Spot, Early_Blight, Septoria_Leaf Spot, Spider_Mites and Late_Blight, that accounts to massive decline in the crop production. The significant drop in the production raises alarm in the analysis of the leaf of tomato with adoption of state of art technologies into the farming. The analysis of tomato leaf with the intent of early prediction of particular disease, includes employment of Convolutional Neural Network (CNN) Models include LetNet5, ResNet50 and AlexNet of the Deep Learning. The proposed work employed the kaggle database tomato leaf diseases dataset that contains 10,000 images that consist of healthy leaves and disease affected leaves. Deep Learning includes Convolutional Neural Networks models: LetNet5, ResNet50, AlexNet are applied on the disease affected and healthy leaves of tomato dataset and it is performed empirical analysis of the CNN models in the prediction of diseases of leaf of tomato through metrics related to performance such as F1-Score, Accuracy, Precision, Recall. The proposed work which highlights empirical performance analysis of the CNN models: LetNet5, ResNet50, AlexNet, provided the noteworthy result that ResNet50 model is able to perform multi-classification the tomato leaf diseases with better accuracy 0.98701 and F1-score 0.98932.

Keywords- Convolutional Neural Network, Deep Learning, LetNet5, ResNet50, AlexNet, CNN, Tomato Crop, Tomato Leaf Diseases, Late Blight, Early Blight, Septoria

I. INTRODUCTION

Tomato production across the world accounts several million tons of tomatoes leading tomato crop as vital crop among other crops. Tomatoes enhance health and reduce diseases risk such as heart disease, tumour related diseases. People who eat tomatoes regularly have a risk at lower level in tumour related diseases include mouth, lung, breast [20, 21]. As crops are predominantly vulnerable to diseases, that have severe difficulty for the economy of agriculture, safeguard against diseases has been absolutely required to make sure the better amount and value of the harvest. As per study of standard organization related to food and agriculture of United Nation, the key cause of the decline in global tomato production is tomato disease [22, 23]. However, the majority tomato infectivity begins in the leaves of tomato and steadily spread throughout the whole plant. There is absolute requirement to make a note of that early monitoring is the mainly valuable approach and prevent progression of diseases. Agriculture skilled personnel regularly spot and notice diseases of tomato leaf with just a simple manual [24, 25]. Therefore, to become aware of plant diseases at an early period, techniques of deep learning and machine learning are the central research trend in the future. Management of diseases happening timely ensure vegetable, flower, fruits crop survival rate enhancement [26, 27]. As the swift development in the technology of computer, agricultural disease detection is currently widely using techniques of deep learning, machine learning, and computer vision. The improvement in this era with respect to hardware accelerated ensured the deployment of economical monitoring devices of agriculture capable of with artificial intelligence (AI) algorithms and ability of image processing. Similarities in disease characteristics make it is complex to distinguish between diverse disease types, contributing to lack of accuracy in disease detection in very complex natural environments [28, 29]. Nowadays, convolutional neural networks (CNN) outperform methods of feature extraction. The network of Deep Learning that is CNN employs architecture which is an end-to-end woks at high-level with type eliminates the complex process such as pre-processing and feature extraction processes, thereby simplifying the process of recognition match up to to its counterpart model of learning. Techniques of Deep learning have attained noteworthy authority in quite a lot of application areas in contemporary years. Deep learning, an emerging area have been mounting rapidly in the usage of majority of typical application as well as some applications of innovation, offered extra grand prospect in the various fields of imaging in medical, translation of machine, recognition of speech, vision through computer, processing through medical information, processing of natural language [30, 31, 32].

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II. RELATED WORK

Several literatures in classification of diseases of plants have been published in the process of provision of solution that is effective. The research literature established methods that aided in the identification of diseases of crop in the domain of agriculture. The section of related work highlighted the research contributions of researcher in the area of models of CNN on leaf of tomato diseases and other crops. AlexNet and VGG16 CNN models have been used on categorized illnesses and a healthy leaves of tomato [33]. It has been concluded that AlexNet yielded better precision with very short execution time than VGG16 with experiment conducted on 13,262 images [33]. A customized model of CNN was implemented with alteration in architecture of VGG16 and comapred against three different CNN models applied on diverse classes of 1400 images and it has been eventually concluded that modified CNN provided better accuracy of 98.40% [34]. The proposed disease identification model for tomato plants is an architecture based on CNN that include three layers of convolution, followed by a layer of max pooling and filter layers that are configurable with certain number [35]. Leaf of tomato data were obtained from PlantVillage source is considered as dataset. In the collected data, a layer contains only healthy images and other layers are dedicated to diverse diseases. The accuracy of average testing of the model is 91.20% [35]. Authors in the work compared InceptionV3., GoogleNet., AlexNet., ResNet50, and ResNet18, models to find 10 different tomato disease detections. All networks were trained 4,444 times with the dataset Plantvillage consists of 18,160 images [36]. The model of type GoogleNet achieved 0.9939 accuracy, however confusion matrix ensured 100% results in recognition in categorizing three out of ten leafs of tomato varieties in the dataset of test [36]. In this work authors contributed on the implementation of CNN with Learning Vector Quantization on 500 images and it has been seen better accuracy and F1- Score for each class of tomato leaf datasets [7]. Authors implemented architecture of CNN to effectively spot and categorize diseases of tomato leaf using distinct 3000 images of tomato leaves affected by diseases of 9 types and leaf of one healthy type. The accuracy of the prediction of the model classification is 0.9849 [37]. The authors evaluated four models of CNN to detect diseases of ten types on leaves of tomato [38]. Authors worked on 18,215 images of tomatoes from the dataset of PlantVillage and dataset is six times multiplied, in a way that 109,290 images are generated from the augmentation [38]. The model of Xception achieved 100.00% accuracy, but from the confusion matrix, 100% results in recognition were obtained in, one type of the tomato diseases of ten varieties in the dataset of test [38].

III. PROPOSED WORK

3.1 The Dataset Description:

The Dataset of Tomato leaves collected comprises leaves of tomato images of about10000 include one healthy and all other leaves affected by tomato leaf diseases. The collected dataset has been in JPEG format with resolution of 256X256 pixels. The following figures represent leaf in health and leaves affected tomato leaf diseases.

3.2 Dataset Augmentation

Dataset Augmentation is the method of improving the performance of classification with the generation of a large augmented dataset contains new dataset for training from the current training dataset. Augmentation of the current training dataset generates a large diversified new training dataset that helps CNN model to become generalized model. Eventually this generalized model can yield better predictions without any overfitting problems. In this work, augmented dataset, provided to each CNN model, obtained from the original dataset upon which several techniques such as flipping vertically, shift in height, flipping horizontal, rotation at random, and shift in width have been performed to improve the quality of the data.

Training Settings	Corresponding Value
Rotation at Random	[+10,-10]
Shift in Width	[0.7,1.2]
Zoom	[0.6,0.8]
Flip in Horizontal	true
Flip in Vertical	true

Table 1: Data Augmentation on the Training Dataset

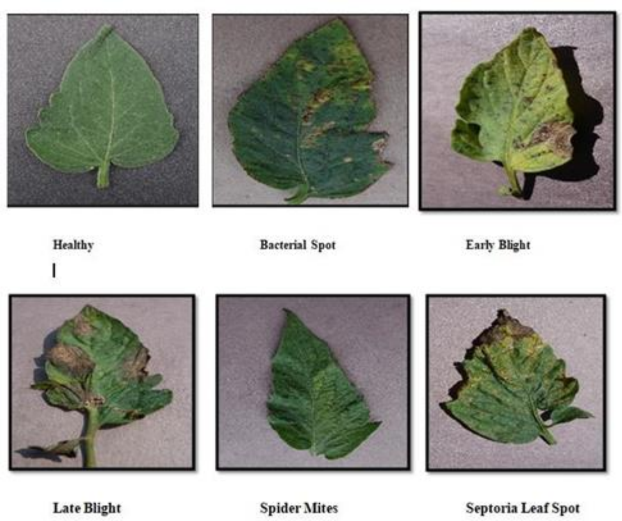

Figure 1: Healthy Leaf and Disease Affected Leaves of Tomato

3.3 Splitting of the Dataset

In this work, training validation and test set are separated after applying division on the Dataset with the ratio 90/10. The split ratio employed in this work is 90/10 which indicates dataset accounts 90% has been used for training and validation and dataset accounting 10% ensured for testing purpose. Among 90% of the dataset, there has been again one more split which divides 80% for training and 10% for validation. Training dataset which contains large new dataset that is obtained from the augmentation is used to train the various models of CNN on new data to make predictions and enhance the performance

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prediction of the model. Validation dataset determines how best the model undergone training is generalized with dataset of training and optimizes the performance trained CNN model. Test dataset in this work evaluated the CNN models performance through performance metrics.

3.4 CNN Models and their Parameters

Tomato Tomato leaf disease classification employed four Convolutional Neural Models: LetNet5, ResNet50, AlexNet with their respective parameters. Optimizer, an algorithm motive is to decrease loss function value which is known as the error function value to maximize the production. It is a mathematical function that takes weights and biases to give the error value. Optimizers adjust the weights and biases to minimize the error function value and thus leading to improvement of the model. Rate of learning determines the size of the step of the optimizer at which model is updated. Most frequently the learning rate should be as small as enough to get the model trained effectively and converge at a better solution. Epochs specifies how many times model is to get trained using dataset of training set. Batch-Size ensures total samples in number that pass through the epochs through the model to train the neural network. Loss function is an objective function ensures the error to get minimized and this error value lies in the range of predicted class and actual class in the dataset.

Training Parameters	**Corresponding Values**
Optimizer	Adam
Rate of Learning	0.0001
Epochs	50
Size of the Batch	32
Error Function	Cross_Entropy

Table 2: Training Parameters for the models of CNN

3.5 Performance Metrics

The CNN models performance in this work has undergone evaluation with the employment of the following metrics: F1-Score, Accuracy, Precision, Recall, and ROC [19]. The metrics of the evaluation are calculated by construction Confusion Matrix where it contains True_Positives, False_Positives, True_Negative, False_Negatives. Eventually, ROC is plotted to highlight the AUC which specify how effectively the models of CNN identifies the diversified class types. [19]

IV. IMPLEMENTATION AND RESULTS

4.1 Platform Specifications in the Implementation:

The three CNN Models: LetNet5, AlexNet and ResNet50 have been modeled with the training settings discussed in the sub section 4.4 and applied on the Tomato Leaf Kaggle Dataset. The experiment: CNN models trained, validated and tested on the datasets have been conducted on the GPU (Intel UHD), i7 10850H CPU with 8 GB RAM. Implementation of these models included Python 3, Keras, Tensorflow, Jupyter Notebook. Training settings to the models such as Optimizer, Learning Rate, Epochs, Batch-Size and Loss Function which were chosen appropriately to enable the models to effectively generalize validated dataset and eventually produce accurate prediction on the test data.

4.2 Accuracy/Loss of Training/Validation

The performances of the CNN models have been evaluated with training/validation accuracy, training/validation loss, recall, precision, accuracy, F1-Score, overall accuracy, and AUC. The following figures shows accuracy of training/validation and loss of training/validation of the LetNet5, AlexNet, ResNet50 CNN models for epochs upto 50.

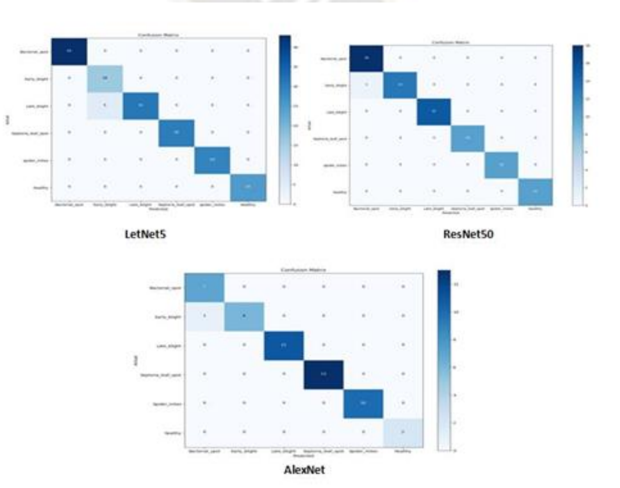

Figure 2: Graphical Analysis of Training/Validation Accuracy and Loss of CNN Models: LetNet5, ResNet50, AlexNet

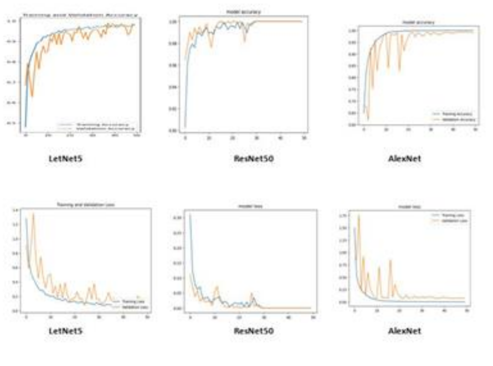

Figure 3: Confusion Matrix of CNN Models: LetNet5, ResNet50, AlexNet Models

V. EVALUATION OF THE PERFORMANCE OF CNN MODELS

The following table highlights the performance measurement results in the test set to compare the three CNN Models.

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	LetNet5	ResNet50	Alexnet
Accuracy	0.97206	0.98701	0.98
Recall	0.976851	0.988	0.97619
Precision	0.96031	0.9912	0.97916
f1-score	0.965	0.98932	0.97606

Table 3: Performance Metrics of the CNN Models: LetNet5 ResNet50, and AlexNet

The following graphs analysis performance metrics of the CNN Models employed in this work.

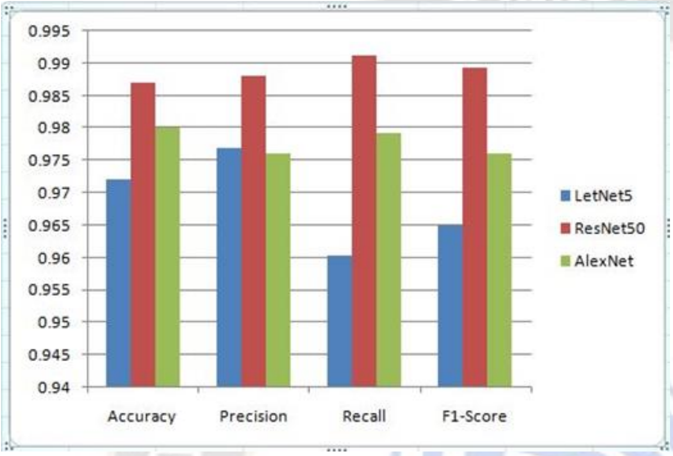

Figure 4: Bar Graphical Analysis of Performance Metrics of CNN Models: LetNet5, ResNet50, AlexNet

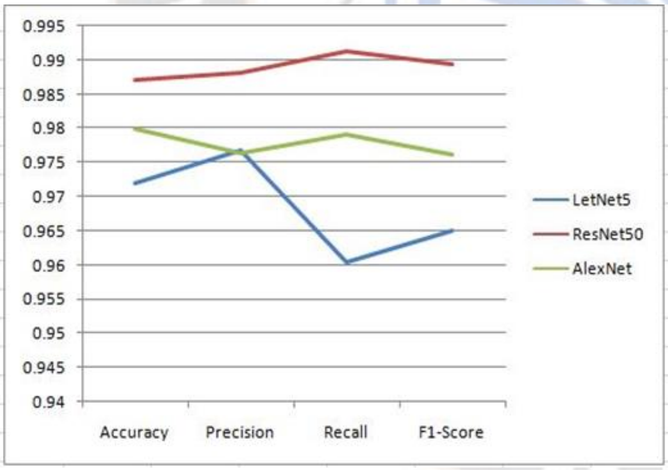

Figure 5: Line Graphical Analysis of Performance Metrics of CNN Models: LetNet5, ResNet50, AlexNet

It is evident with the empirical analysis on the models of CNN performance and analysis of performance metric values of each model through the graph states that the ResNet50 is performing better relative to the other two models LetNet5 and AlexNet on the Tomato Leaf Datasets.

CONCLUSION

Tomato Crop in India plays significant role in the production has been affected with various diseases of leaf. The prominent tomato diseases of leaf, highlighted in this work have been identified with the state of art CNN models with appropriate training parameters. In this work, LetNet5, AlexNet and ResNet50 were employed on the Disease of Tomato Leaf dataset and analyzed the accuracy of training/validation and loss training/validation function with graphical representation. It has also been constructed confusion matrix and presented calculated metrics of performance: F1-Score, Accuracy, Precision, and Recall, of the each CNN models employed in this work. The objective of this work is to perform analysis of the performance metrics which is comparatively done for each model through visual representation. The proposed work in this paper concludes that the ResNet50 yields better F1-Score and accuracy relative to other two models: LetNet5 and AlexNet used in the work.

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