International Journal of Scientific Research in Science, Engineering and Technology

Print ISSN - 2395-1990
Online ISSN : 2394-4099

OPEN ACCESS

Available Online at : www.ijsrset.com
doi : https://doi.org/10.32628/IJSRSET

Disease Detection of Plant Leaf using Image Processing and CNN

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ARTICLEINFO

Article History :

Accepted: 10 Nov 2023
Published: 30 Nov 2023

Publication Issue :
Volume 10, Issue 6
November-December-2023
Page Number :
213-222

ABSTRACT

Agriculture is a very significant field for increasing population over the world to meet the basic needs of food. Meanwhile, nutrition and the world economy depend on the growth of grains and vegetables. Many farmers are cultivating in remote areas of the world with the lack of accurate knowledge and disease detection, however, they rely on manual observation on grains and vegetables, as a result, they are suffering from a great loss. Digital farming practices can be an interesting solution for easily and quickly detecting plant diseases. To address such issues, this paper proposes plants leaf disease detection and preventive measures technique in the agricultural field using image processing and two well-known convolutional neural network (CNN) models as AlexNet and ResNet-50. Firstly, this technique is applied on Kaggle datasets of potato and tomato leaves to investigate the symptoms of unhealthy leaf. Then, the feature extraction and classification process are performed in dataset images to detect leaf diseases using AlexNet and ResNet-

50 models with applying image processing. The experimental results elicit the efficiency of the proposed approach where it achieves the overall 97% and 96.1% accuracy of ResNet- 50 and the overall 96.5% and 95.3% accuracy of AlexNet for the classification of healthy-unhealthy leaf and leaf diseases, respectively. Finally, a graphical layout is also demonstrated to provide a preventive measures technique for the detected leaf diseases and to acquire a rich awareness about plant health.

Index Terms - Disease Detection, Plant Leaf, Image Processing, CNN, AlexNet, ResNet-50, Preventive Measures

I. INTRODUCTION

The huge population of the world depends on their large economy. As well as the economy growth plays an important role in the development of any country and their GDP. The impact of this economy depends entirely on agriculture. But, different factors of cultivation affect the quality and quantity of grains and vegetables. These grains and vegetables come in contact with different diseases due to different climates and conditions in different places. As a result, cultivators in any country face severe losses because of these diseases. For leaf disease, the amount of crop production is decreasing day by day. The main challenge is to identify the leaf disease in the agricultural field and to increase the quality and quantity of the production rate. First of all it is necessary to consider two crops leaf to identify disease. Tomato and potato can be considered as two important crops that are used in our daily food items and to replenish nutrients in human body.

Any disease is naturally created which can have some serious effects on grains and vegetables, as well as it can ultimately reduce productivity, quality and quantity of products. So, proper classification and identification of leaf disease may be a key issue in agricultural erosion prevention. Different grains and vegetable leaves carry different diseases such as viral, fungal and bacterial. The most common plant diseases are Al- ternaria Alternata, Anthracnose, Bacterial Blight, Cercospora Leaf Spot, Powdery Mildew, Black mold, Downy Mildew and Rust. When the infection occurs on the plants leaf, the symptoms are exposed by the quality of texture, color, shape and size of plant leaf. Most of the symptoms are microscopic, so the identification of diseases is not possible due to the limited capabilities of human vision.

However, it is necessary to develop a very efficient technique to detect disease symptoms using scientific knowledge and experience. Initially, the captured crops leaf images of tomato and potato are collected from Kaggle datasets for this paper. The images could be captured using a regular digital camera or high resolution mobile phone camera. Then, image processing is applied on the collected leaves of the tomato and potato. Various image processing techniques such as acquisition, preprocessing, restoring, segmentation, augmentation, feature extraction, classification are performed for detecting the plant diseases. In preprocessing phase, the color conversion technique is applied on RGB images which are converted into gray images.However, several contrast enhancement algorithm are used to increase the contrast of images after removing different types of noise. These images can be changed into aligned forms according to flipping, cropping and rotating ways of image augmentation technique and various properties such as portion, color information or boundaries are traced in the image. In addition, the classification algorithm can be applied on the color image section for disease recognition. In this paper, we use convolutional neural network (CNN) models such as AlexNet and ResNet-50 which are different types of classification approach. AlexNet and ResNet-50 classify the healthy and unhealthy leaf images and recognize the various diseases of leaves. Besides, in the area of agriculture, many existing systems can detect some plant leaf diseases but provide no process of preventive measures. For this reason, this paper proposes a system that can detect diseases and also provide a preventive measure using the mechanism of graphical user interface.

The following contributions are the main synopsis of proposed
framework: Firstly, we perform image processing technique on leaf datasets for disease detection. Secondly, we classify the processed leaf images using AlexNet and ResNet-50 archi- tectures. Thirdly, this paper analyzes the overall leaf disease classification accuracy. Finally, we evaluate and develop the graphical layout for disease detection with preventive mea- sures. The rest parts of the paper are structured as follows: Section II expounds the concepts of the Related Work. The proposed methodology is presented in Section III. Section IV describes the experimental results and discuss about obtained accuracy. In Section V, the paper is concluded

II. RELATED WORK

This section denominates the different approaches of previ- ous studies which were used to identify and classify the vari- ous leaf diseases of plants. Zhou et al. proposed K-Means clustering algorithm and faster R-CNN Fusion algorithm to detect rice diseases as well as to address several complications such as blurred image edge, noise, large background interfer- ence and low detection accuracy using 3010 images which cap-tured by camera. And also faster 2D- Otsu algorithm was used to classify the rice disease images for getting output. Sharma et al.introduced the image pre-processing along with k-means clustering, segmentation and four classifiers such as logistic regression, SVM, KNN, and CNN to detect and classify leaf diseases automatically wherein logistic regression performs quite well due to classes but highest accuracy was provided by CNN due to classification and detection of diseases using 20,000 images from GitHub and Kaggle. In , it was suggested an incorporated method to create heterogeneous data from Normalized Difference Vegetation Index for achieving a rich and comprehensive knowledge of wheat's health using IoT sensors, machine learning such as SVM and NB and drone technology. Sardogan et al. presented a CNN modelalong with Learning Vector Quantization (LVQ) algorithm to identify and classify leaf diseases of 500 tomato leaf images from PlantVilliage dataset. Also, the different filters ofconvolutions were used to progress recognition level in clas- sification method. Ozguven et al. developed a modernize Faster R-CNN architecture with the changing parameters of a CNN model to detect leaf spot diseases in sugar beet by imaging-based expert systems with 155 images in order to achieve the highest accuracy as well as to reduce the spending time and human error. Lu et al. proposed CNN based innovative rice disease identification model with image pre- processing to identify and recognize the rice diseases using 500 natural images from rice empirical field. Additionally, the proposed model provided higher accuracy due to 10- fold cross-validation scheme, greater feasibility and efficiency, faster convergence rate as well as greater recognition ability than traditional model of machine learning. A novel disease detection model of viral plant based on CNN techniques with image pre- processing was presented by Kawasak et al. to diagnose diseases automatically using the 4-fold cross- validation approach with higher accuracy where 800 cucumber leaf images captured by digital cameras. Jiang et al. proposed a new model INAR-SSD which was applied in the Caffe structure of GoogLeNet Inception structure and Rainbow concatenation on the GPU platform that uses deep-CNNs to detect disease in real-time for apple leaf using Apple leaf disease dataset containing 26,377 images from the composition of laboratory and complex images of real field in order to obtain higher accuracy and feasible solution. Pallagani et al. developed a smartphone app dCrop which was Deep- Learning based approach as AlexNet, ResNet-50 and ResNet- 34 to predict of crop diseases accurately in modern agriculture exhausting a public dataset containing 54,306 captured images of plant leaves. Also, for live prediction of crop diseases, trained PyTorch model was converted into .pb file of ten- sorflow which was loaded into dCrop app by demonstrating the feasible solution. In , it was used CNN model with transfer learning method to diagnose diseases and identify pests of crops using leaf images from PlantVillage database by reducing time and human efforts which provided higher accuracy.

III. PROPOSED METHODOLOGY

The proposed framework of leaf disease detection with preventive measures is shown in Fig. 1. This framework depicts the concepts of proposed approach with leaf image collection. The leaf images of tomato and potato are taken from Kaggle dataset. Image processing techniques namely Image preprocessing, image augmentation, feature extraction, feature selection and classification are applied on leaf image dataset. Then it is designed a supervised machine learning which trains the dataset image and extracts the data from it. This paper introduces a leaf diseases detection system using two CNN architectures such as Residual Neural Network-50 (ResNet-50) and AlexNet. Besides, it has also developed a preventive measures layout of leaf diseases. The proposed method controls the following procedures step by step to identify leaf diseases.

A. Leaf Image Dataset

The role of quantitative or qualitative datasets is very essen- tial to ensure the integrity of the research, the performances of field study or data preference.

However, Leaf images for datasets can be collected by high resolution digital camera or smart camera. But, we have taken the leaf images of tomato and potato as samples from Kaggle dataset for our research performance analysis which contains healthy or unhealthy leaf images. The dataset contains over 4000 specimens of leaf images that are affected by four types of disease. These diseases are classified as Potato early blight, Potato late blight, Tomato early blight, Tomato late blight. In this dataset, there are also 2000 sample images of healthy leaf to construct the leaf disease classification and detection model.

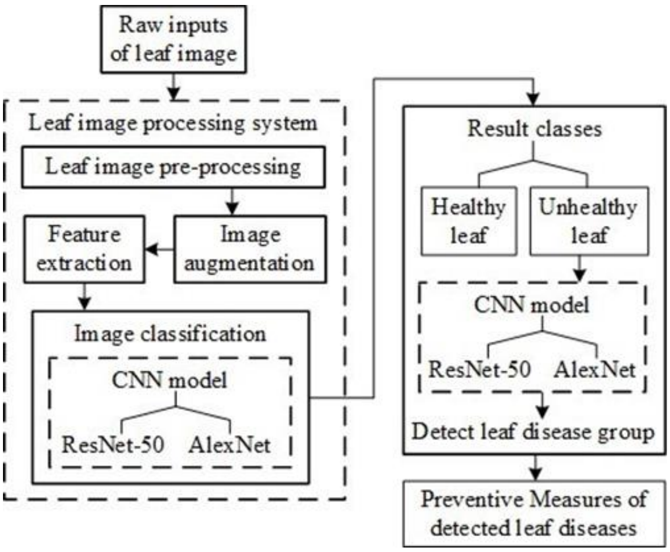

Fig. 1. Framework of Leaf disease detection with preventive measures

B. Image Preprocessing

The process of pre-processing technique transforms raw input leaf image datasets into desirable process datasets format to develop the quality of leaf images and to eliminate the undesired portions from the leaf images. These processes occur in various phases such as data cleaning, integration, reduction and transformation which are shown in Fig. 2. In the data cleaning phase, it eliminates the undesired distortion, manages the missing data and rectifies the inconsistent data. At the inte- gration stage, multiple and heterogeneous data as well as data redundancy in leaf image datasets is an ordinarily encounter situation of data retrieval strategies which resolves multiple data conflicts and arranges a unified representation of data. A large size datasets increases the storing space size and com- putational difficulty due to the different feature dimensions. In the process of data reduction, a large volume of data is reduced to increase the performances and efficiency of image processing. The operations of data transformation perform the data smoothing, aggregation, feature construction, data normalization and discretization to inhibit the dependability of the attributes in the data assessment structures and units for data images conversion. These leaf image datasets are resized and converted into 256×256 dimension for training datasets and testing datasets analysis. So, pre-processing technique can provide preparing datasets to identify leaf diseases through the leaf image datasets.

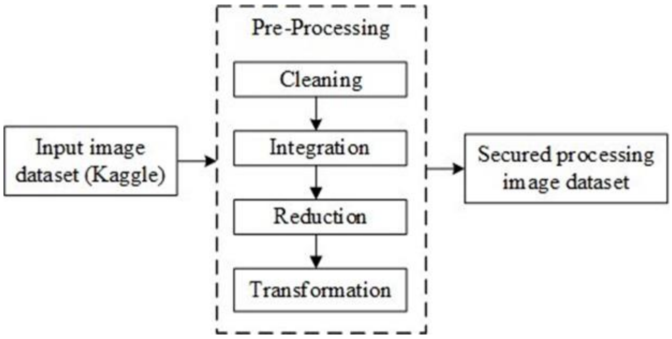

Fig. 2. Phases of leaf image pre-processing

C. Image Augmentation

Image augmentation is involved for changing and facilitat- ing of the leaf image representation to accurately identify leaf disease. Thus, the training and testing leaf image datasets are augmented to diminish the chance of over-fitting and to enrich the simplification of the model. The process of augmentation is applied to resize the original leaf image dataset using flipping, cropping and rotation techniques as well as to convert the leaf images into RGB using color transformation technique. However, the augmented leaf images are created to maintain the balanced quality and size of images in the healthy and unhealthy leaf datasets.

D. Feature Extraction

Feature extraction is the very important phase of the image processing technique to provide a suitable platform and opti- mal constraints. The feature extractor of the CNN based detection framework can extract the image feature vectors of the leaf disease. The feature extraction technique analyzes the properties of a leaf image such as color, shape and texture in a convenient way. So, this extraction technique is able to assist in proper classification of different leaf disease classes. For the leaf diseases, the feature extraction mechanism extracts the features of various lesion shapes and colors.

Fig. 3. Leaf diseases class of Potato and Tomato

Classify to separate into four different disease classes such as potato early blight, potato late blight, tomato early blight and tomato late blight. Therefore, these techniques can detect leaf disease group from the leaf images of potato and tomato plants.

E. Graphical Layout of Preventive Measures

After applying the leaf disease classification system, the user's graphical layout is designed in such a way that it can display the message of leaf disease and provide preventive measures for a rich awareness about plant health to farmer. Fig. 4 illustrates leaf disease detection and user preventive measures layout using AlexNet and ResNet-50 pre-trained network models for potato early blight, potato late blight, tomato early blight and tomato late blight.

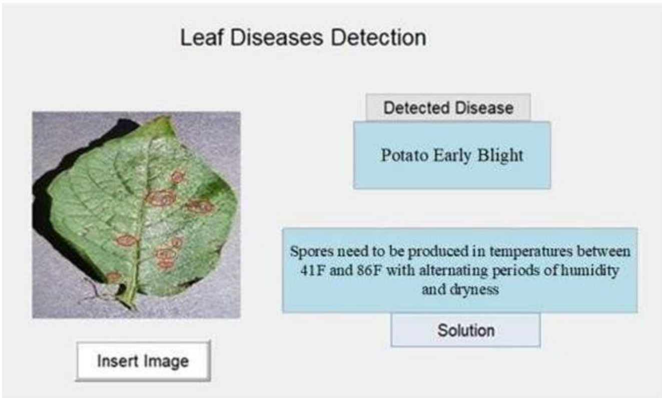

Fig. 4. Graphical layout of preventive measures

IV. EXPERIMENTAL RESULTS DISCUSSION AND OBSERVATION

In this section, it has been mentioned the classification results of tomato and potato leaf images by conducting a set of experiments on dataset which incorporates two categories as healthy and unhealthy leaf images for representing the performance of experimental results wherein 70% leaf images used for training dataset and the remaining 30% for testing dataset. Two deep learning architectures as ResNet-50 and AlexNet are applied to the collected image datasets for leaf disease classification and detection. All of these experiments and simulations have been evaluated through MATLAB2018a. This approach can notify to the farmers about the potato early blight, potato late blight, tomato early blight and tomato late blight diseases. The confusion matrix of the ResNet-50 and AlexNet architectures are analyzed in this paper to achieve overall accuracy.

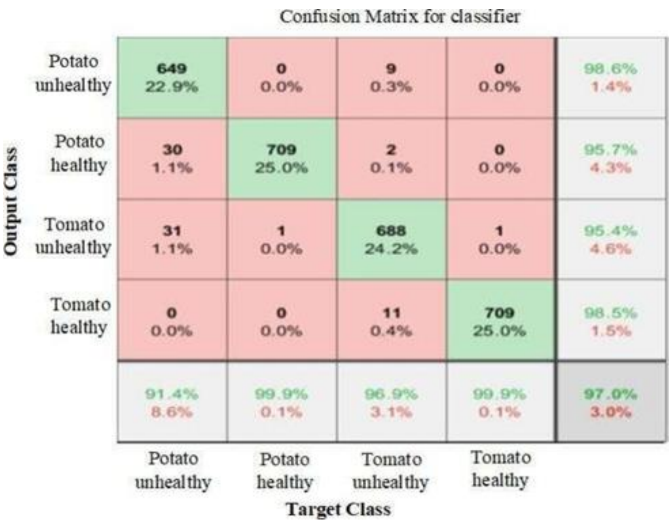

Fig. 5. Confusion Matrix for ResNet-50 (Healthy & Unhealthy leaves)

TABLE I. PERFORMANCE OF RESNET-50 MODEL FOR HEALTHY-UNHEALTHY LEAF

Classification label	Total no. of leaf image	Correctly classified images no.	Accuracy for Output class	Accuracy for Target class
Potato unhealthy	658	649	98.6%	91.4%
Potato healthy	741	709	95.7%	99.9%
Tomato unhealthy	721	688	95.4%	96.9%
Tomato healthy	720	709	98.5%	99.9%

A. Results Measures

The performance of CNN classifiers and its visualization for leaf diseases detection based on training and testing datasets are presented in a tabular form as confusion matrix. The value of confusion matrix is estimated between the output class values and target class values with different classification label. The values of diagonal line cells are correctly predicted the leaf disease images and other values of remaining cells are incorrectly predicted the leaf disease images in the confusion matrix for ResNet-50 and AlexNet architectures.

The analysis of leaves including healthy and unhealthy using confusion matrix applying ResNet-50 architecture is shown in Fig. 5 and their classification performances are listed in TABLE I. According to the results, the overall classification accuracy in this system for healthy and unhealthy leaf classes is 97.0% and the remaining 3% are misclassified.

Fig. 6 provides the diagnosis of leaf diseases from unhealthy leaves using confusion matrix applying ResNet-50 architecture and their performances of classification are listed in TABLE

II. The results of this system show that the overall classifi- cation accuracy for the leaf disease classes is 96.1% and the remaining 3.9% are misdiagnosed. The analysis of healthy and unhealthy leaves of potato and tomato plants using confusion matrix applying AlexNet model is presented in Fig. 7 and their classification evaluations are listed in TABLE III. It is seen from the results of this system, the overall classification accuracy for healthy and unhealthy leaf classes is 96.5% and the remaining 3.5% are misguided.

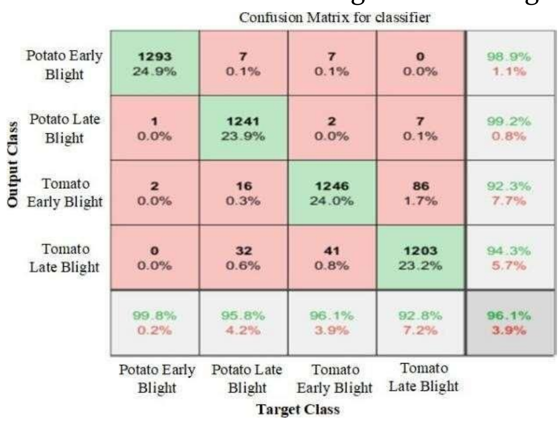

Fig. 6. Confusion Matrix for ResNet-50(Leaf diseases)

TABLE II

PERFORMANCE OF RESNET-50 MODEL FOR LEAF DISEASES

Classification label	Total no. of leaf image	Correctly classified images no.	Accuracy for Output class	Accuracy for Target class
Potato early blight	1307	1293	98.9%	99.8%
Potato late blight	1251	1241	99.2%	95.8%
Tomato early blight	1350	1246	92.3%	96.1%
Tomato late blight	1276	1203	94.3%	92.8%

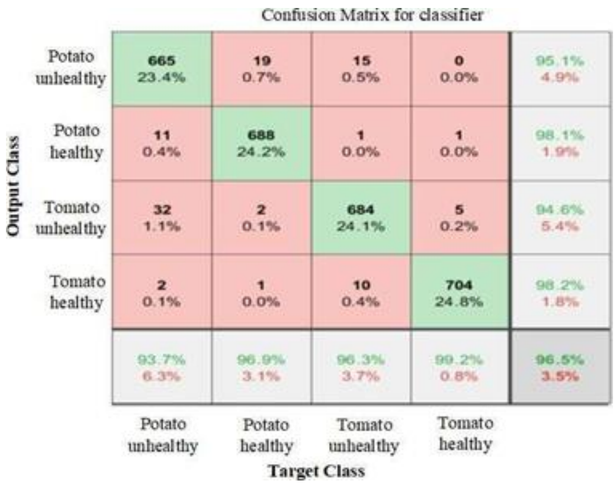

Fig. 8 shows the diagnosis of potato and tomato leaf diseases from unhealthy leaves using confusion matrix by applying AlexNet model and its evaluation of classification are recorded

TABLE III
PERFORMANCE OF ALEXNET MODEL
FOR HEALTHY-UNHEALTHY LEAF

Classification label	Total no. of leaf image	Correctly classified images no.	Accuracy for Output class	Accuracy for Target class
Potato unhealthy	658	665	95.1%	93.7%
Potato healthy	741	688	98.1%	96.9%
Tomato unhealthy	721	684	94.6%	96.3%
Tomato healthy	720	704	98.2%	99.2%

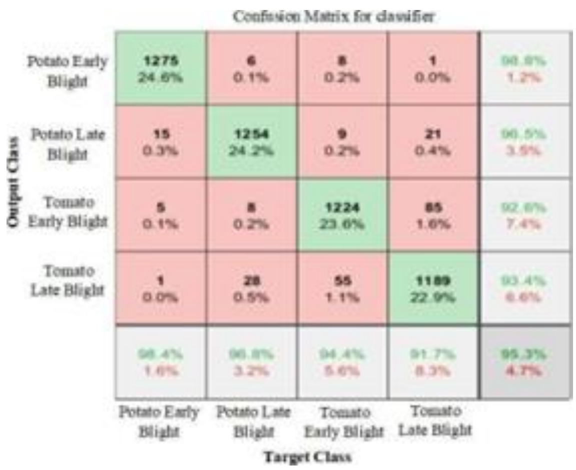

Fig. 8. Confusion Matrix for AlexNet (Leaf diseases)

in TABLE IV. It is observed from the results of this scheme that the overall recognition accuracy for the leaf disease cases is 95.3% and the misdiagnosed in some cases are 4.7%.

B. Result analysis

To investigate the best analysis results of disease detection, the comparison between the accuracy levels of two classified models in terms of leaf datasets have been drawn for differ- ent conditions. The correctly detection accuracy of healthy- unhealthy leaves on training and testing leaf datasets are determined and the comparison between the accuracy results for AlexNet and ResNet-50 models are plotted in Fig. 9(i). The comparison of the classification accuracy of four leaf diseases for target class between ResNet-50 and AlexNet model is shown in Fig. 9(ii) and the comparison of the classification accuracy of four leaf diseases for output class between ResNet-50 and AlexNet model is shown Fig. 9(iii). The comparison of the overall detection accuracy of leaf diseases from unhealthy leaves between ResNet-50 and AlexNet model is shown in Fig. 9(iv). However, for the classification of healthy and unhealthy leaves, the system provides overall accuracy as 97% through ResNet-50 whereas the system achieves the overall accuracy as 96.5% through AlexNet. On the other hand, for the leaf disease detection, the overall accuracy through ResNet-50 is 96.1% and the overall accuracy through AlexNet is 95.3%. From all the comparisons it has been analyzed that the performance of Resnet-50 is better than the performance of AlexNet.

TABLE IV. PERFORMANCE OF ALEXNET MODEL FOR LEAF DISEASES

Classification label	Total no. of leaf image	Correctly classified images no.	Accuracy for Output class	Accuracy for Target class
Potato early blight	1290	1275	98.8%	98.4%
Potato late blight	1299	1254	96.5%	96.8%
Tomato early blight	1322	1224	92.6%	94.4%
Tomato late blight	1273	1189	93.4%	91.7%

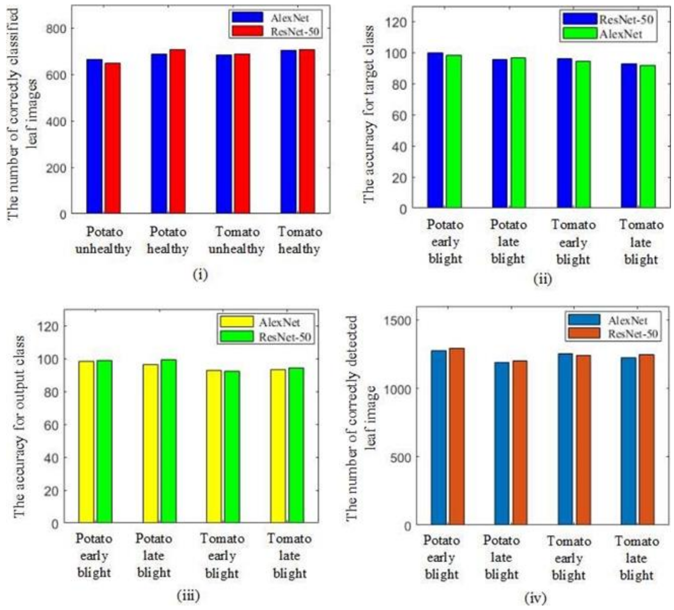

Fig. 9. Comparison between AlexNet and ResNet-50 for (i) correctly detection of healthy-unhealthy leaves, (ii) accuracy of leaf diseases Target Class, (iii) accuracy of leaf diseases Output Class, and (iv) correctly detection of leaf diseases

V. CONCLUSION

In this paper, it has been mentioned the leaf diseases problem of grains and vegetables which are harmful aspects for farmers in the agricultural sector. This paper has suggested a significant diagnostic approach of tomato and potato plant leaf diseases with graphical layout of preventive measures using image processing and CNN. Image processing technique is performed on Kaggle datasets of potato and tomato leaves through the operation of data pre-processing, augmentation and data extraction to investigate the symptoms of unhealthy leaf. Moreover, this framework classifies the processed leaf images into potato early blight, potato late blight, tomato early blight and tomato late blight using AlexNet and ResNet-50 architectures. In addition, this paper analyzes the overall clas-sification accuracy of leaf diseases. For which, this approach achieves the better accuracy of ResNet-50 model over AlexNet model. So, it is feasible to demonstrate the graphical layout for leaf disease detection with preventive measures.

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Cite this article as :

Prof. Ashish Manwatkar, Nitin Ambegave, Parth Fiske, Wasim Khan, Atharva Sable, Nitin Dhawas, "Disease Detection of Plant Leaf using Image Processing and CNN", International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Online ISSN : 2394-4099, Print ISSN : 2395-1990, Volume 10 Issue 6, pp. 213-222, November-December 2023.
Journal URL : https://ijsrset.com/IJSRSET2310614