Potato Leaf Disease Classification using Transfer Learning based Modified Xception Model

1Rajasekaran Thangaraj, 2Pandiyan P and 3Vishnu Kumar Kaliappan
1,3Department of Computer Science and Engineering
2Department of Electrical and Electronics Engineering
1,2,KPR Institute of Engineering and Technology, India
1rajasekaran30@gmail.com, 2pandyyan@gmail.com, 3vishnudms@gmail.com,

4S. Anandamurugan
Department of Information Technology
Kongu Engineering College, India
dranandamurugan@gmail.com

5Indupriya P
Kovan Labs, India
induece23@gmail.com

Abstract - Plant diseases are the essential thing which decreases the quantity as well quality in agricultural field. As a result, the identification and analysis of the diseases are important. The proper classification with least data in deep learning is the most challenging task. In addition, it is tough to label the data manually depending upon the selection criterion. Transfer learning algorithm helps in resolving this kind of problem by means of learning the previous task and then applying capabilities and knowledge to the new task. This work presents the convolution neural network-based model to predict and analysis the potato plant disease using plant village datasets with deep learning algorithms. Transfer learning with feature extraction model is employed to detect the potato plant disease. The results show that improved performance with an accuracy of 98.16%, precision of 98.18%, the recall value of 98.17% and the F1 score value of 98.169 %.

Keywords - Deep Learning, Transfer Learning, Modified-Xception, Potato leaf disease, Fine-Tuning

1. Introduction
In today’s world, agriculture with modern technologies produce enough food to meet the people demand and economy of India also depends on its productivity [1,2]. However, security of food remains challenging owing to factors such as climatic changes, the decline in pollinators, plant diseases, and other factors. Potato is the fourth foremost used world’s significant food crop after rice, wheat and corn according to the statistics of the survey done in agriculture department of USA [3]. Potato production exceeds 300 million metric tons across global and it contains a various compound including vitamins, minerals, proteins and carbohydrate which is the vital elements for assist and maintain the human health [4] in proper way. Phytophthora infestans (late blight) and Alternaria solani (early blight) are the two common disease occurs generally in potato plants [5].Detection of plant diseases play vital role in agricultural field .Moreover, plant diseases are becoming big threat to food security and small holder farmers contribute more than 80 percent of agricultural production and reports 50 percent of crop yield loss due to diseases and pets [6].

Automated classification of plant diseases based on images is a complex problem owing to inter class similarities of plant and extrinsic factors including variations in image background, illumination, color, pose and occlusion [7]. An early detection of diseases allows taking preventive measures against huge damage, curtailing the production and economic losses to the farmers. Over the last decades, plant diseases is identified by specialist by their naked eyes, but this approach results infeasible due to unavailability of specialist at farm situated in the remote locations and too much of processing time. Hence, the introduction of computer vision, machine learning, image processing and deep learning techniques turn out to be an efficient way to detect the plant disease at early stage and continuous monitoring of plant health condition.

Deep Learning (DL) is sub-field of machine learning, which is a part of artificial intelligence. In recent years, DL has achieved significant success in various field including speech recognition, natural language processing, computer vision, image analysis and recognition. This paper mainly focuses on detection and recognition of diseases from leaves of the potato plants using deep learning. The potato leaf images including late blight, early blight and healthy plant images are taken from the plant village website which are trained and tested on Modified-Xception model for classification of diseased and healthy plant.

The structure of this paper is organized as follows: section 2 gives insight about the related literature work. Materials and methodology are discussed in section 3. Section 4 provides the performance evaluation of the proposed method. Section 5 deals the experimental results and its discussion on classifying the potato plants. At last, conclusions are drawn in the section 6.

@ IJAICT India Publications 2020
M.G. Sumithra et al.(eds.), Advances in Computing, Communication, Automation and Biomedical Technology, https://doi.org/10.46532/978-81-950008-1-4_096
2. Related works
The literature related to detect and recognize the plant disease through plant image datasets with deep learning algorithms is discussed in this section. [8] proposed an automatic disease detection system based on web to identify the disease affected in pomegranate fruit. Bacterial blight is the major disease which decreases the fruit production and causes the loss for the farmers. The system proposed K-means algorithm for clustering based on extracted features including color, morphology, CCV and finally Support Vector Machine (SVM) is employed for the classification of disease infected fruits and healthy fruits with 82% of accuracy.

[9] presented machine vision based agro-medical expert system in order to assist farmer for papaya cultivation and detection of diseases. The system employs k-means clustering algorithm to segment the disease affected spot and extract the required features from the image captured through mobile or handheld devices. Then the features are used by Support Vector Machine (SVM) and achieve more than 90% of accuracy in classification of papaya diseases [10]. In [11], the author used artificial neural network (ANN) and various image processing technique for early detection of plant diseases. The proposed approach extracts the features through Gabor filter and results recognition rate up to 91% using ANN classifier. The classifier based on ANN performs classification of different plant diseases and uses the color, texture features combination to recognize plant with different diseases.

The author in [12] proposed a transfer learning approach for classification of tomato crop disease using pre-trained deep learning architecture especially AlexNet and VGG16. The architectures are trained for classifying seven different categories (six disease classes and a single healthy class) of tomato leaf images, consist of 13,262 segmented leaf images obtained from the public dataset website of PlantVillage. The architectures AlexNet and VGG16 achieve 97.49% and 97.23% of accuracy respectively in classification of diseases. The experimental results shows that VGG16 outperforms compared with AlexNet.

[13] developed a model based on convolution neural network to perform identification and diagnosis of plant diseases through deep learning methodologies using healthy and diseased plant images. The models were trained with 87,848 images, including 58 distinct classes of plant and disease. The VGG convolution neural network outperforms among all the models with success rate of 99.53 % in classification of plant diseases. [14] proposed a method for detection of rice disease using techniques, deep convolution neural networks (CNNs). The CNNs are trained on dataset, which consist of 500 rice leaf images including diseased, healthy and stems captured from the rice field. The model results 95.48% of accuracy in recognizing 10 common diseases of rice through 10-fold cross validation. Compared with other conventional methods, the proposed model outperforms in training the CNNs parameters, convergence speed and recognition rate.

3. Materials and methodology

Image Dataset
The datasets related to this study are collected from the plant village – an open access repository. This repository consists of 14 varieties of plants with 54,306 leaf images of healthy and diseased plant categories. In order to authenticate the proposed research work, the datasets of potato leaves are available in the plant village database. This database comprises of 3 different kinds of classes in which 2 classes are diseased and 1 class comes under healthy category. The disease occurs in the potato plants and its sample images with quantity of images in each class are tabulated.

Data Augmentation
Data augmentation method is applicable for increasing the data size utilized to train a model. In order to obtain the consistent identification, the deep learning algorithms frequently needs an enormous number of datasets for training that is not possible for all the times. As a result, the available datasets are augmented to create better comprehensive datasets to be needed for further processing. An over-fitting takes place in CNN algorithm when the model attains the best fit through learning the patterns available in the training datasets and fall short to recognize when the data is not available in the training datasets. From the Table 1, the images for healthy plant category is 152 and the other two disease affected images are in 1000 in quantity. In order to balance the images in all categories, data augmentation techniques like flipping and rotations are utilized. The samples after performing the data augmentation techniques are depicted in Figure 1.

Table 1: Potato Plant Classification Based on Disease

| Potato Class | Sample Image | Number of Image |
|--------------|--------------|----------------|
| Early blight | ![Early blight](image) | 1000           |
| Healthy      | ![Healthy](image) | 152            |

![Table Image](image)
Fig. 1: Sample data augmented images

Table 2: Number of training and testing datasets

| Potato Class | Number of training samples | Number of validation samples | Number of testing samples |
|--------------|----------------------------|-----------------------------|--------------------------|
| Early blight | 640                        | 160                         | 200                      |
| Healthy      | 640                        | 160                         | 200                      |
| Late blight  | 640                        | 160                         | 200                      |

Transfer Learning
The CNN models need a numerous dataset for training from the scratch data that is the most difficult task for the researchers who are working in this field. As a result, machine learning technique namely transfer learning is utilized in most of the cases. Transfer learning (TL) applies the knowledge of the CNN model trained on the large dataset to the similar smaller dataset. TL is also a very famous method used in pre-trained CNN models trained with ImageNet dataset. TL is employed for two categories namely feature extraction and fine tuning. In feature extraction process, the output layer of the pre-trained model is truncated and lower layers act as the feature extractor tool. In fine-tuning, the weights of the lower layers are frozen and newly added top layers are updated through retraining with the new images.

Modified-Xception model
The Xception model is trained on ImageNet dataset that comprises of 1.2 million image datasets of thousand varieties of group. The proposed model is the modified version of the original xception model. In the Modified-Xception model the dense output layer is replaced with the new softmax layer which is depicted in the Figure 2. The Modified-Xception model performs of three main tasks such as feature extraction, fine-tuning and disease classification.

Fig. 2: Modified -Xception Model for Potato Disease Classification
Feature extraction

The feature extraction is the most important component of CNN which involves convolution layers, pooling layers and activation functions. The activation function used in this study is Rectified Linear Unit (ReLU) which is used for activating the neurons in each convolution layer[15-16].

Convolution layer

Convolution layer is the primary layer in the CNN architecture which has filters for extracting the image features. The feature map \(FM\) from each convolution layer is achieved through sliding the filters on the input images. The convolution operations take place between input image pixels and filter pixels which produces the feature map. The feature map from each convolution layer is obtained using the Equation (1)

\[
FM=(I_h-fl_h+1) * (I_w-fl_w+1) * 1
\]

where, \(I_h\) is the height, \(I_w\) is the width, \(fl_h\) is the filter height, \(fl_w\) filter width

ReLU Function

The activation function of CNN performs the function of converting the addition of input weights of all the nodes to activate that node. The activation function enhances the computation speed and reduces the overfitting occurs in the network. The activation functions used in CNN are sigmoid, tanh and ReLU function etc. ReLU is one of the best activation functions in used in the CNN. This function returns 0 value if any negative attained in the feature map else it returns some positive value which is obtained by means of Equation (2).

\[
f(FM)=\max (0, FM)
\]

Global Average Pooling (GAP) layer

GAP obtain the feature map for every object used in the classification task from the final convolution layer. Then, GAP generates the feature vector \(FVGAP\) and forward to the softmax layer for classification. The feature vector \(FVGAP\) is obtained using the Equation (3).

\[
FVGAP = \{FM_1, FM_2, ..., FM_n\}
\]

Disease Classification

Fine tuning

Fine-tuning happens in the top most layer of CNN model which improves the performance of the model. The weights of the top layers are updated by means of retraining the layers with target datasets. The output layer weights are updated with retrained potato disease datasets. The fine tuning done in this work follows the Equation (4).

\[
FinT = ft X FVGAP
\]

Softmax Classifier

Softmax classifier uses output obtained from APL layer as input for its operation. From the input data, it estimates the probability by means of Equation (5), for each individual class. The resultant class is the class in which the maximum probability occurs.

\[
s(FinT) = \frac{e^{FVGAP}}{\sum_{j=1}^{k} e^{FVGAP_j}}
\]

for \(i=1 \ldots \ldots \ldots k\)

4. Performance Evaluation Metrics

The predictive strength of the model is evaluated using the performance evaluation metrics viz precision, accuracy, F1 score and recall. The accuracy can be calculated using Equation 6 which gives the value by number of images identified correctly among the total number of predictions done.

\[
Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions}
\]

The precision measurement is done using Equation (7) which is the ratio of exactly identified positive results (TP – True positive) to the total quantity of positive results identified by the proposed model.

\[
Precision = \frac{TP}{TP + FP}
\]

Precision value becomes less value when FP value increases. The range of precision metric is in between 0 to 1.

Recall metric is measured with correctly identified true positive predictions (TP) divided by overall positive samples (TP+FN) shown in Equation (8).

\[
Recall = \frac{TP}{TP + FN}
\]

where, FN denotes false negative

The F1 score is obtained by Equation (9) by estimating the weighted harmonic mean between recall and precision.

\[
F1score = 2 \times \frac{Recall \times Precision}{(Recall + Precision)}
\]
Advances in Computing, Communication, Automation and Biomedical Technology

The evaluation of the test results is done through confusion matrices shown in Figure 5. In this confusion matrix, row values indicate the actual class and column values denote the predicted class. From the confusion matrix, the value of TP, TN, FP, and FN are obtained as outputs. The amount of FPs and FNs varies for each class due to class and number of data samples variations. The confusion matrix for identifying the disease in potato plant by means of Adam optimizer for the proposed research work is presented in Figure 4.

### Table 3: Performance indicators of the proposed model

| Performance Evaluation metrics | Value   |
|-------------------------------|---------|
| Accuracy                      | 0.98167 |
| Precision                     | 0.9818  |
| Recall                        | 0.9817  |
| F1 score                      | 0.98169 |

### Fig. 5: Confusion matrix of Modified-Xception on test dataset

The performance evaluation of the proposed work is done by calculating the accuracy of each test dataset. The accuracy performance is obtained using the values of Top 1 and Top 2 of the model is 98.16% and 100%. The results of the performance evaluation metrics are listed in Table 3.

### 6. Conclusion

Recently, agricultural field becomes automated for cultivation. The disease prediction in plants is needed for increasing the production yield. In this work, efficient usage of transfer learning with deep convolution neural network algorithm to classify the disease occurs in the potato leaves with least datasets. The proposed work depends on transfer learning with feature extraction of a pre-trained model done in ImageNet. The performance evaluation from the simulation reveals that the accuracy of the proposed work is to be 98.16%. The outcome of this work shows that employing CNN model with transfer learning method can be used for plant disease classification with low accuracy performance scenario. This work can be extended to detect the disease in variety of crops such as cottons, crop millet etc.

### References

[1]. VijaSingh, A.K. Misra, Detection of plant leaf diseases using image segmentation and soft computing techniques, INFORMATION PROCESSING IN AGRICULTURE 4 (2017) 41–49.

[2]. Rajasekaran, T.; Anandamurugan, S. Challenges and Applications of Wireless Sensor Networks in Smart Farming—A Survey. In Advances in Big Data and Cloud Computing; Springer: Singapore, 2018; pp. 353–361. https://www.ers.usda.gov/topics/crops/vegetables-pulses/potatoes

[3]. M. Islam, AnhDinh, K. Wahid, P. Bhowmik, Detection of potato diseases using image segmentation and multiclass support vector machine, IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE), p.no:1-4.2017.

[4]. UNEP Smallholders, food security, and the environment, (2013).

[5]. K. Kavukcuoglu, P. Sermanet, Y.-L. Bouraeu, K. Gregor, M. Mathieu, Y. LeCun, Learning convolutional feature hierarchies for visual recognition, in: Advances in neural information processing systems, 2010, pp. 1090–1098.

[6]. Barbedo, J.G.A., Digital image processing techniques for detecting, quantifying and classifying plant diseases. SpringerPlus 2, 660, 2013.

[7]. Y. LeCun, Y. Bengio, and G. E. Hinton, “Deep learning,” Nature, vol. 521, no. 7553, pp. 436–444, 2015

[8]. Habib, M. T., Majumder, A., Jakarta, A. Z. M., Akter, M., Uddin, M. S., & Ahmed, F. (2020). Machine vision-based papaya disease recognition. Journal of King Saud University-Computer and Information Sciences, 32(3), 300-309.

[9]. D.P. Hughes, M. Salathe, an open access repository of images on plant health to enable the development of mobile disease diagnostics. (2015) CoRR abs/1511.08060.

[10]. O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A.C. Berg, L. Fei-Fei, ImageNet large scale visual recognition challenge, Int. J. Comput. Vis. 115 (3) (2015) 211–252.

[11]. A.K. Rangarajan, R. Purushothaman, A. Ramesh, Tomato crop disease classification using pre-trained deep learning algorithm, in: International Conference on Robotics and Smart Manufacturing (RoSMa2018), Procedia Computer Science 133 (2018) 1040–1047.

[12]. Konstantinos P. Ferentinos, Deep learning models for plant disease detection and diagnosis, Computers and Electronics in Agriculture 145 (2018) 311–318.

[13]. Yang Lu, Shujuan Yi a, Niayin Zeng, Yu orang Liu d, Yong Zhang, Identification of rice diseases using deep convolutional neural networks, Neurocomputing267 (2017) 378–384.

[14]. D.P. Hughes, M. Salathe, an open access repository of images on plant health to enable the development of mobile disease diagnostics. (2015) CoRR abs/1511.08060.

[15]. Abirami, K. R., & Sumithra, M. G. (2019). Evaluation of neighbor credit value based AODV routing algorithms for selfish node behavior detection. Cluster Computing, 22(6), 13307–13316.

[16]. Karrick, A., Kalidasa Murugavel, K., Sudalaiyandi, K., & Matu Manokar, A. (2020). Building integrated photovoltaic modules and the integration of phase change materials for equatorial applications. Building Services Engineering Research and Technology, 41(5), 634-652.