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Transfer learning based leaf disease detection model using convolution neural network

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ABSTRACT

The plants are attacked from various micro-organisms, bacterial illnesses, and pests. The signs are normally identified via leaves, stem, or fruit inspection. Illnesses that generally appeared on vegetation are from leaves and causes big harm if not managed in the early ranges. To stop this huge harm and manipulate the unfold of disorder this work implements a software system. This research work customs deep neural network to gain knowledge of probable illnesses on leaves within the early phases so it can be stopped early. Deep neural network (DNN) used for image classification. This work mainly focuses a neural network model of leaves ailment detection. The commonly available plant leaves dataset is undertaken with a dataset having special training of disease detection. In this work VGG16, ResNet50, Inception V3 and Inception ResNetV2 architectural techniques are implemented to generate and compare the results. Results are compared on the factors like precision, accuracy, recall and F1-Score. The results lead to the conclusion, that the convolution neural network (CNN) is more impactful technique to perceive and predict plant diseases.

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1. INTRODUCTION

The effective protection against disease is a problem mostly related to non-perishable farming. Green use of insecticides can lead to more time to resist pathogens specially decreasing potential to shield themselves [1], [2]. Timely and correct interpretation of plant diseases is a main pillar of good farming. It is important to accurately identify sickness of plants without wasting more capital and resources. Plant cytology can be detected by several ways. In some cases, there are no visible symptoms or the effects are noticed too late. In most of the diseases some indications are in the form of visible spectrum, so an expert person can identify the same by eye examination [3]–[5]. To have more accuracy in disease diagnosis a plant pathologist must have excellent observational skills. The characteristic symptoms can be identified with a good observational skill [6], [7]. The changes in symptoms may lead to wrong diagnostics. The system with automatic plant disease identification using appearance and visual symptoms will be of great help for disease diagnosis [8], [9].

Improvisation in computer technology is helpful for plant safety and expand precision. In this research, to perceive and classify the plant diseases digital picture processing method with color analysis is used [10], [11]. In this work, concept of transfer learning under the machine learning is mainly applied for the disease detection. In transfer learning existing models are used to solve new problems or challenges. The transfer learning is a training model used under machine learning [12]–[14]. The concepts developed in earlier training are used to perform new tasks in transfer learning. The new tasks are in sequence with the previous tasks. The high level of generalization is essential in trained model to support new data. Transfer learning is associated with problems together with multi assignment learning and idea to go with flow. Transfer learning also works more effectively in association with deep learning [15]–[17]. Hence, this implementation uses the concept of transfer learning in association with convolutional neural network (CNN).

The transfer learning is a machine learning technique in which model developed for one task is used as a starting point for another task. The knowledge gained in one task is used in subsequent task to improve performance. The few key concepts of transfer learning include pre-trained model, feature extraction, fine tuning, domain adaptation, cross-domain learning. The large datasets are used to extract features, then the parameters are adjusted to make it suitable for new task, the domain adaptation is done by making model trained for one domain suitable for another related domain. The transfer learning mainly works to apply knowledge gained from one domain to another domain. The subsequent paper is organized as follows, section 2 explores related work and methodology. Section 3 is about the result and discussion whereas section 4 leads to conclusion of the work.

2. METHOD

2.1. Literature review

This segment examines the literature in the realm of plant disease detection, mostly with the support of deep learning, CNN, image separation and soft computing technology. Transfer learning method is emerging in the market. The aim of the literature analysis is to know the benefits, limitations and state of art of this technology.

Guan [18] proposed a plant disease recognition model by integrating four CNN models. The four CNN models are Inception, DenseNet, ResNet, and Inception ResNet respectively. The author used an open source database of plant leave images categorized in ten different types and 61 classes of healthy. Use of integrated method achieves 87% accuracy as per the author's work, which is significantly more than a single CNN model. It is show that the CNN integrated model is more appropriate for advanced plant disease detection.

Prakash *et al.* [19] used an image processing method for recognition of plant leaf diseases. This work implemented image analysis and classify it for the detection of leaf disease. The authors framework includes four modules namely image preprocessing, segmentation using K-means algorithm, feature extraction, and classification. The features are extracted using gray-level co-occurrence matrix (GLCM) and organization is completed using support vector machine (SVM).

Xu *et al.* [20] proposed a transfer learning method to increase result accuracy of plant disease recognition for multiple plants. The authors used different factors for disease recognition including large scale dataset, vision transformer (ViT), transfer learning, and pre-trained ImageNet. The authors applied this method to twelve plant diseases and proved that the technique is more accurate. As per the authors claim the proposed method is more accurate for plant growth stage and for weed dataset.

Ramesh *et al.* [21] used random forest algorithm to differentiate diseased and healthy plant leaves. The authors used the phases including dataset creation, feature extraction, training the classifier, and classification. The dataset trained under random forest algorithm is used for image classification under healthy and diseased category. The histogram of oriented gradient is instrumented to feature extraction. As per the authors, machine learning makes a major impact on plant disease detection.

Singh and Misra [22] presented an algorithm for image separation which is useful for image classification and plant disease detection. The authors conducted a survey of disease classification techniques. As per the authors, image separation using inherent algorithm is a significant for disease detection. The automatic techniques of plant disease recognition are more useful as it reduces the efforts.

Harakannanavar *et al.* [23] considered disorder of tomato vegetations for investigation. The leaves of tomato are resized to 256 by 256 pixels and then histogram match is used to expand quality of sample leaves. In next step K-means clustering algorithm is used for partitioning of information in the form of cells. The borders of leaf cell extracted using tracing technique. Various parameters like co-occurrence matrix, Principal Factor Investigation, Wavelet alter are considered to extract the informative topographies of the leaf. The extracted topographies are divided using the algorithms SVM, CNN, and k-nearest neighbor (KNN). As per the claim of author accuracy of all the algorithms is more than 90%.

Eunice *et al.* [24] utilized CNN based trained method for plant disease recognition in efficient way. Author focused on fine tuning of hyperparameters such as ResNet, DenseNet, VGG, and Inception. The dataset considered encompasses more than fifty thousand sample images of different plants. The author evaluated outcome of the system through specificity, F1 score, sensitivity and classification accuracy. Author compared the state of art work with similar studies and claimed 99% accuracy.

Aravind and Raja [25] acquired images through smartphone and stored on personal computer. Applied organization in the form of ten diverse diseases using transfer learning for four dissimilar crops. The six different versions of CNN model are used and results are evaluated. In real-time images are classified and prediction accuracy is assessed for each type of disease. As per the results VGG16 lead to in greatest precision of more than 90%.

Praveen *et al.* [26] used deep CNN for image identification and classification. The work provided a perspective to develop model for leaf blight identification. The authors work distinguishes plant leaves and 13 types of diseases. The work mainly collects pictures, creates database and get is verified from external experts. The authors claim accuracy in the array of 91% to 98%.

Kusumandari *et al.* [27] projected a model to minimize spread of disease on strawberry plant. Initially the images are processed to identify status of diseases of the strawberry vegetal. The work is performed in various phases including image enhancement, color segmentation, and regional segmentation. The author claimed accuracy of 85%.

As per the literature it is understood that, the several authors have used diverse approaches of plant disease detection. Many of the researchers have applied CNN algorithm for image classification, identification. The algorithms like SVM, KNN, are also used by few of the authors. The literature reviewed in this work is summarized and presented in the Table 1.

Table 1. Summary of literature review

Sr. No.	Author	Methodology	Limitation
1	Guan [18]	CNN	Accuracy is 87% only
2	Prakash *et al.* [19]	K-means, GLCM, SVM	Accuracy of each model is limited
3	Xu *et al.* [20]	Vision transformer	Implementation process is complicated and time consuming
4	Ramesh *et al.* [21]	Random forest algorithm	Used only histogram for feature extraction
5	Singh and Misra [22]	SVM	Used only image segmentation method
6	Harakannanavar *et al.* [23]	SVM, CNN, KNN	Implementation process is complicated and time consuming
7	Eunice *et al.* [24]	CNN	Performance is dependent on hyperparameters
8	Aravind and Raja [25]	CNN	Use classification hence performance is dependent on size of dataset
9	Praveen *et al.* [26]	CNN	Accuracy is main concern
10	Kusumandari *et al.* [27]	Image processing, color segmentation	Accuracy is 85% only

As per the summary of literature review presented in Table 1 it is concluded that, in the literature many papers are either with less percentage accuracy of disease detection, implementation is very vast and time consuming, algorithms are not properly selected. In most of the implementations the accuracy is dependent on accuracy of dataset and it is size. The precise work is lagging in the literature hence, this paper proposed a transfer learning-based leaf disease recognition model using CNN.

2.2. Working

This research uses Python programming for development of the system; Python’s wide series of libraries are useful for various operations. The system used around 87K+RGB pictures in the dataset, the pictures are of healthy and affected leaves. The dataset is alienated in 38 classes. The leaves considered are of the plants like tomato, cotton, and strawberry. In the second phase the model is trained using multiple types of CNN architecture. The InceptionV3, ResNet50, InceptionResNetV2, VGG16 CNN architectures are mainly used by the system to train the system and compare the results.

As per the system architecture shown in Figure 1 the system takes leaf image as an input, then disease detection algorithm is applied, features of the image are mined with the help of trained dataset and using transfer learning techniques. The transfer learning techniques work in collaboration with CNN algorithms namely InceptionV3, ResNet50, InceptionResNetV2, and VGG16. The model is proficient to accept user input in the form of affected leaf image. The images are sent for feature extraction and classification. The mined features are used by classification algorithms. The classification algorithm generates exact prediction of the leaf disease.

The InceptionV3, ResNet50, InceptionResNetV2, and VGG16 algorithms are selected because of their certain strengths. The VGG16 has a simple and uniform architecture and it is often used as a baseline for image classification. In ResNet50 the residual connections are much deeper without degrading the quality of images for various recognition tasks. The InceptionV3 algorithm is efficient as it uses less computations while calculating results; it also allows parallel computations for different filter sizes. The InceptionResNetV2 merges Inception and ResNet models and resulting in high accuracy and improved training time.

InceptionV3 model works for enhancement in the form of label smoothing, factorization, and classification. This technique resulted into highest efficiency with less expenses. ResNet50 model helps to train deep neural system with maximum load and many layers with outstanding overall performance. InceptionResNetV2 is an example of CNN. It can use I million images to train the model from dataset. It uses 164 layers to classify images. As a result, this model gives rich features representation with very fast training model of higher accuracy. VGG16 is a 16-layer deep CNN model. This can load pre-trained version of trained system with thousand of categories of an object. It supports image size of 224 by 224.

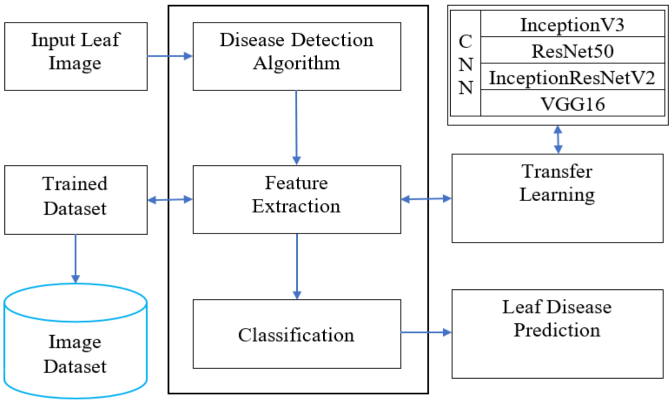

Figure 1. System architecture

The results achieved with the help of all the models are depicted with the help of Figure 2. All these outcomes show that these models give higher accuracy and lower loss. The graphs plotted in Figure 2 are mainly related to inception; for other models namely ResNet50, InceptionResNetV2, VGG16 pattern of the graphs is similar in terms of accuracy and loss. The Figure 2 is divided in two parts including Figure 2(a) training and validation CAT Accuracy as first part and Figure 2(b) training and validation loss as a second part. The actual results in the form of data values are given in the Table 2 for all four models.

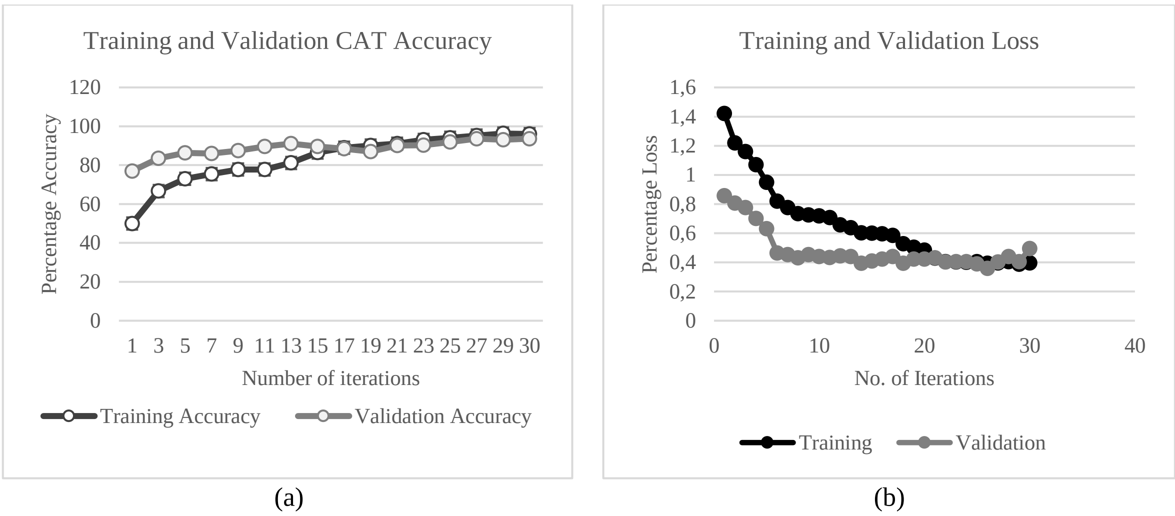

Figure 2. Sample result charts (a) training and validation CAT accuracy and (b) training and validation loss

3. RESULTS AND DISCUSSION

The results can be evaluated with various metrics, some of the significant metrics are discussed below. These metrics helps to understand generated results in easiest manner. The metrics definition and formula are explained with the help of required parameters. All these parameters are considered in the evaluation of respective metrics.

3.1. Accuracy (Ac)

Accuracy is the simplest and easiest metrics can be applied on prediction algorithms. Accuracy is measured like, total no of correct prediction out of total prediction. The evaluated results in Table 2 shows that, there is not much difference in the accuracy values.

Table 2. Results with proposed model

Metrics	InceptionV3	ResNet50	InceptionResNetV2	VGG16
Accuracy	0.8731	0.8820	0.8523	0.821
Precision	0.82	0.85	0.81	0.78
Recall	0.84	0.84	0.82	0.80
F1 Score	0.83	0.84	0.83	0.79

The maximum accuracy is obtained with ResNet50 model.

$$Ac = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \tag{1}$$

3.2. Precision (Ps)

The precision metrics is used to find total positive predictions that are true out of all the true Prediction. Precision is estimated with the below formula. The highest value of the precision is 0.85 with ResNet50 model. The results with other models are comparatively low than ResNet50 model.

$$Ps = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{2}$$

3.3. Recall (Rc)

Recall is the metrics used to find how the model is best for positives. It shows that, out of all positive predictions how many are correctly predicted as a true. Recall is evaluated with the below formula. In this research the value of the recall is 0.84 for Inception V3 and ResNet50 as shown in Table 2.

$$Recall\ Rc = \frac{True\ Positives}{True\ Positives + False\ negatives} \tag{3}$$

3.4. F1 Score

F1 Score combines the recall and precision together as there is a tradeoff between these two metrics. Here precision is called as Ps and recall is called as Rc then the F1 Score is evaluated as below. Important point to note is while calculating F1 Score if any of the value of precision or recall is zero the F1 score result will be zero.

$$F1\ Score = \frac{Ps * Rc}{Ps + Rc} \tag{4}$$

Table 2 shows the results of the anticipated model. The proposed model gets maximum precision of 0.882, highest precision of 0.85, highest recall value of 0.84 and highest F1 score of 0.84. The conclusion of results shows that the ResNet50 model is gives more accuracy as compared to other systems. The outcomes are shown in Figure 3 with the help of bar chart. The bar chart trends indicate that the ResNet50 algorithm gives highest accuracy values.

The key finding of the results are, the accuracy obtained through all the algorithms is more than 80%. The precision value obtained is more than 80% for first three algorithms and around 78% for VGG16 algorithm. The recall value is 80% and above for all the algorithms, F1 score value is 80% and above for first three algorithms and around 79% for VGG16 algorithm.

In the literature the percentage accuracy is around 80 or below. The proposed work achieved accuracy more than 80 percentage for most of the algorithms. The implementation methods used in the literature are vast and time consuming. The proposed work uses variants of CNN algorithm which are more efficient with respect to time and accuracy. The data set used in the proposed work is not limited to one crop hence accuracy is not dependent on dataset of one crop. Hence the proposed work is more precise as it uses concept of transfer learning-based leaf disease recognition using CNN.

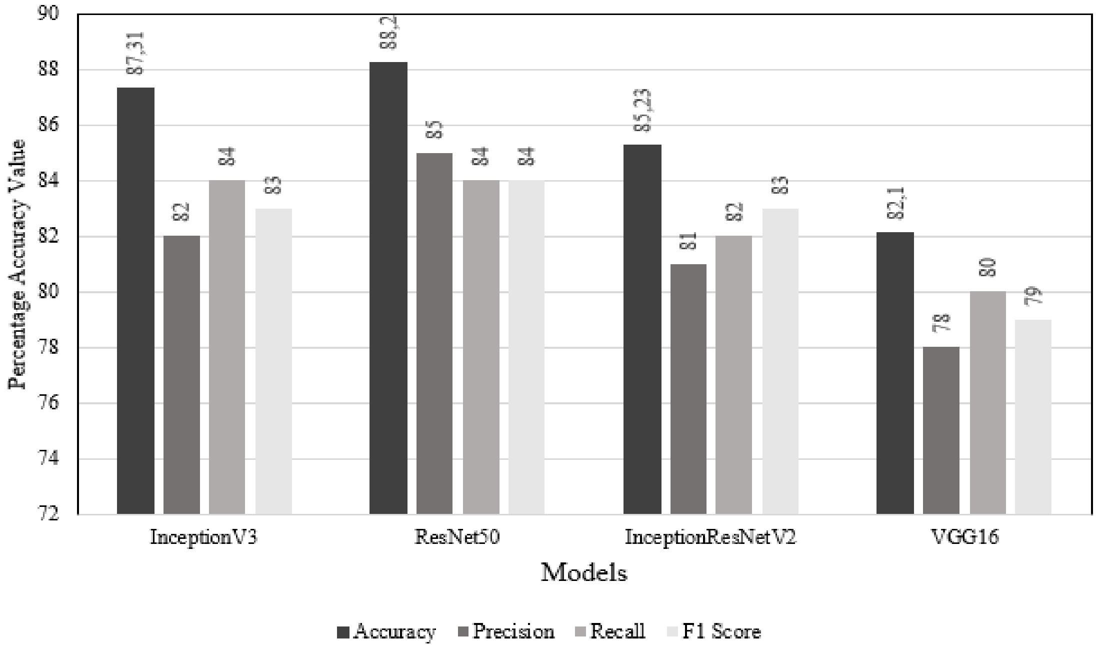

Figure 3. Bar Chart of results with proposed models

4. CONCLUSION

The plant disease is a major problem of modern faming. The work is a minor step towards the use modern technology for the benefits of farmers and society. The various architectures of CNN are applied in this work to predict diseases. The software system is supported with GUI for image uploading and to display the results. This work classifies the diseases into 38 classes and 13 different species of the plant. The model identifies various diseases of plant and categories healthy and affected leaves. It is observed that the ResNet50 gives more prominent results as compared to other CNN models. The overall accuracy achieved by this implementation is around 87.3%. In future the model can be applied to multiple plants for more diseases to validate the working and ensure better accuracy.

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