

Potato Leaf Diseases Identification using CNN

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1. Abstract

Early and accurate analysis and identification of plant diseases are very helpful in reducing plant diseases and improving the quality and quantity of the food crop. Plant disease experts are not available in remote areas thus there is a requirement of automatic low cost, approachable and reliable solutions to identify the plant diseases without the lab inspection and expert's opinion. Deep learning approaches like convolutional neural network (CNN) can be employed to identify the plant diseases. In this paper the CNN model is developed to classify potato leaves into three classes: healthy leaves, early blight and late blight diseased leaves. 1500 image dataset having 500 leaves belonging to each class is used in this paper. The CNN models automatically learn the features from the raw images and are able to classify the images with 94.4 % accuracy.

Keywords: Plant diseases, Convolutional neural network, Machine Learning

2. Introduction:

In India, the agriculture sector employed a 50% workforce and contributed 17-18% of India's GDP in 2017-18. In order to ensure the high yield agriculture sector needs to be supported by the latest technological advancements. Agriculture crops suffer heavy losses due to insect damage and plant diseases. The expected population of the world by 2050 is 9.2 billion and in order to meet the food requirements, food production should increase by about 70% [1]. Food crops suffer heavy losses due to strong winds, adverse weather conditions, drought, fungi, bacteria, viruses, etc. Worldwide out of the crop losses 70-80% losses are caused by plant diseases. Efforts should be made to reduce crop losses due to plant diseases.

Potato (*Solanum tuberosum*) is an important food crop. Worldwide more than 300 million metric tons of potato are produced in more than 100 different countries. In the year 2018-19, India produced about 53 million tones of potato. Potato is a root vegetable with more than 1000 different varieties is an essential staple food source and is a major vegetable crop based on its production and consumption worldwide. It is carbohydrate-rich and has good nutritional quality. The potato crop is a major source of income for farmers. Different diseases of potato are early blight caused by fungus *Alternaria Solani* [3], late blight fungus, Potato virus Y which is a pathogenic virus, bacterial wilt, black scurf etc [12]. Healthy plants will produce quality tuber which will benefit the farmers.

Potato blight disease can destroy food crops. Preventive measures must be taken at an early stage to stop the spread of the disease. If the disease is treated from the leaves at an early stage disease will not spread to the stem and food crop can be saved from damages. Deep learning methods can be used for the identification of the diseases by inspecting leaf images. Multi-layer artificial neural network for image classification tasks have high computational and memory requirements. Computer Vision by using digital image processing can be used for identifying plant diseases [2]. A deep learning approach employing a convolutional neural network for multi-class classification of images is used in this paper. The developed approach for the analysis and classification of plant images is able to perform the task of classification with a good accuracy.

3. Literature Review

Plant pathologists analyze different parts of the plants like root, kernel, stem and leaf for the identification of plant diseases. Ferentinos, K. P. (2018) presented paper implementing different CNN model architectures for the identification of plant diseases with high accuracy [4]. Brahim, M (2017) investigated 14828 images of tomato leaves and classified them into nine different disease classes. By using localized diseased regions of the leaf and availability of sufficient dataset, the CNN model was able to provide 99.18% of accuracy [5]. Plant pests harm crops and can cause serious losses to farmers. In a research paper used transfer learning to improve the accuracy to identify the pests and showed promising results [6]. Hasan, M (2018) used a region-based CNN model for estimating the wheat yield and achieved the average accuracy ranging from 88 to 94% [7]. The model was applied for estimating the yield production of different wheat varieties. Patil and Bodhe for plant disease detection extracted shape features of leaves of sugarcane. They used threshold segmentation and triangle segmentation for determining the leaf and lesioning area and achieved 98.6% accuracy [13].

In a presented a research paper titled “Using deep learning for image-based potato tuber disease detection” used computer vision for potato disease classification using a CNN model [8]. D. Oppenheim and G. Shani used the CNN model to classify tubers into five different classes [9].

Barbedo, Jayme et al. (2016) presented a research paper identified research requirements in the field of image processing to automatically identify the diseases in the plants. Barbedo proposed colour transformations and colour histogram approach for image classification [2].

Atole et al (2018) presented a research paper using transfer learning from an AlexNet deep network for classification of rice plants into three classes and achieved an accuracy of 91.23% [10]. Andrushia, A. and Patricia, T presented a research paper using artificial bee colony based feature selection to determine the optimal feature set required for classification of grape plant images using support vector machine classifier. The proposed algorithm achieved 92.14% accuracy [11]. It has been observed that nature inspired computing algorithms could also be used for identification of plant diseases [15 – 19].

4. Proposed Work

A computer vision-based automated method has been proposed that can be used for identifying the diseased and healthy potato plants. Three different classes of potato leaf images are used in the proposed work.

4.1 Data acquisition

A total of 100 images of potato leaves were acquired. Out of the total 1200 images were used for training and validation and 300 images were used for testing. Three different classes (early blight, late blight, healthy) of potato leaves are used in the dataset. The sample of the leaves is shown in Fig 1.

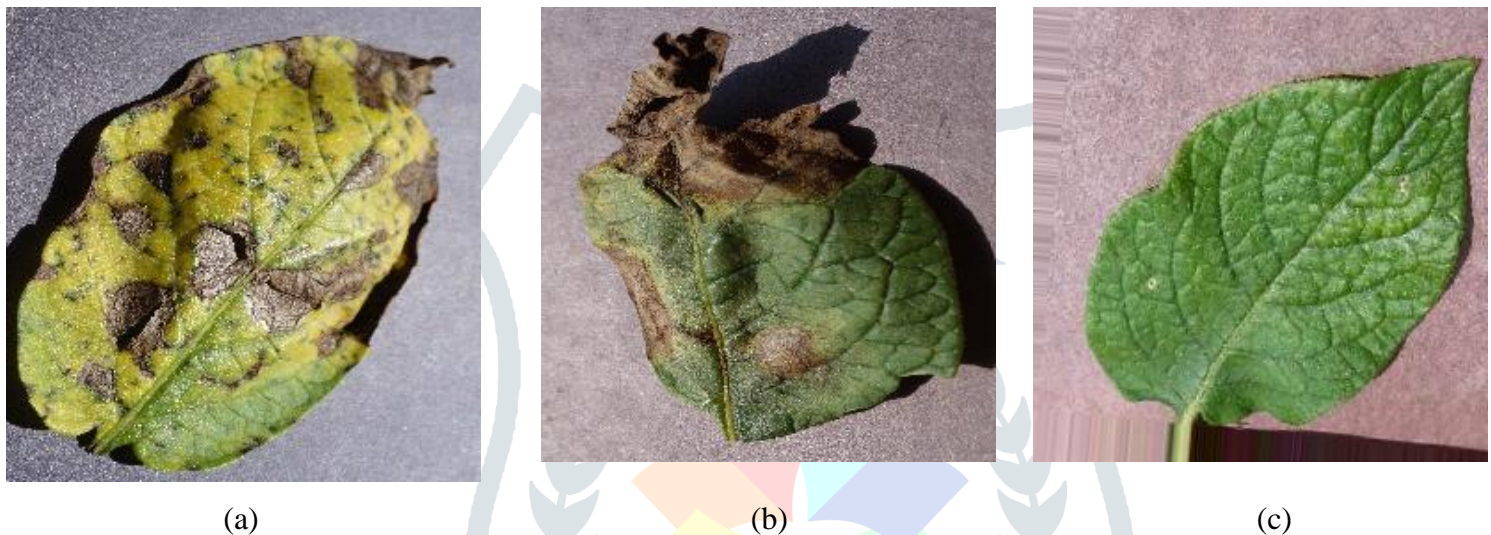


Fig. 1 Samples of collected potato leaf images: a) Early Blight b) Late Blight c) Healthy

The images are resized to 150 X 150 pixels square for every class in order to minimize time complications.

4.2 Convolutional Neural Layer Structure

Computer vision problems while handling input images can become a memory and computationally expensive as the input data can become really big. Given an image of height 128, width 128 and 3 number of channels the input feature dimension is 49152. For images of a larger size, the input data becomes even bigger. Inputting this huge data to the neural network will require high computational power. Convolutional neural network (CNN) also known as ConvNet is a powerful deep learning procedure which was designed from the biological driven models similar to how a human perceives an image into the brain using different layers. CNN captures the spatial and temporal dependencies in an image through the application of filters at different layers. CNN reduces the image into a form that requires fewer computations preserving the features needed for making the prediction. CNN model is composed of a convolutional layer, the ReLU layer, the pooling layer, the drop out layers and

fully connected layers. Convolutional layers extract high-level features by application of a set of filters that extract useful information from an image. Convolutional layers detect patterns in the input image. After the application of filters/kernels, the data is passed from the ReLU layer. ReLU sets all negative values of the convolved matrix to zero by using $\max(a, 0)$ function. The processed data is inputted into another layer called the pooling layer. The pooling layer reduces the size of the inputs and speeds up processing. Different hyperparameters at the pooling layer of the CNN model are filter size, stride, max or average pooling. There can be n number of convolutional and pooling layers in a CNN model. Fully connected layers are present at the end of a CNN model. Each node is connected to every node in the previous layer in fully connected layers. Fully connected layers are heavy data-driven layers of the CNN model. A fully connected layer performs the task of classification of the image into different classes in the output layer.

Fig. 2 Framework of designed CNN network

The structure of the CNN model developed for diseases of potato leaf images.

As you can see multiple convolutions and pooling layers are used for identifying the patterns in the input image. Before inputting the data to the fully connected layer the reduced image matrix is flattened. The fully connected layers also called dense layers of the CNN model to perform the task of image classification. The dropout layer is used to prevent the neural network from overfitting. Dropout is a powerful regularization technique for neural networks.

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 148, 148, 200)	5600
conv2d_2 (Conv2D)	(None, 146, 146, 180)	324180
max_pooling2d_1 (MaxPooling2D)	(None, 29, 29, 180)	0
conv2d_3 (Conv2D)	(None, 27, 27, 180)	291780
conv2d_4 (Conv2D)	(None, 25, 25, 140)	226940
conv2d_5 (Conv2D)	(None, 23, 23, 100)	126100
conv2d_6 (Conv2D)	(None, 21, 21, 50)	45050
max_pooling2d_2 (MaxPooling2D)	(None, 4, 4, 50)	0
flatten_1 (Flatten)	(None, 800)	0
dense_1 (Dense)	(None, 180)	144180
dense_2 (Dense)	(None, 100)	18100
dense_3 (Dense)	(None, 50)	5050
dropout_1 (Dropout)	(None, 50)	0
dense_4 (Dense)	(None, 3)	153

Total params: 1,187,133		
Trainable params: 1,187,133		
Non-trainable params: 0		

Activation function Softmax is used at the output layer which outputs a vector that represents the probability distribution of the possible output classes.

4.3 Performance measurement

The proposed CNN model is trained and validated. Adam optimizer of Keras with learning rate 0.0001, loss function= 'sparse_categorical_crossentropy' and metrics=['accuracy'] is used. The training dataset of 1200 images is split such that 70% of data is used for training and 30% is used for validation. The model is trained for 30 epochs. During the 29th epochs, the CNN model achieved 94.44% training accuracy.

4.4 Training–Progress Graphs of the Designed CNN Model

The training-progress graphs for the designed CNN modes representing model accuracy and loss are shown in Fig. 3

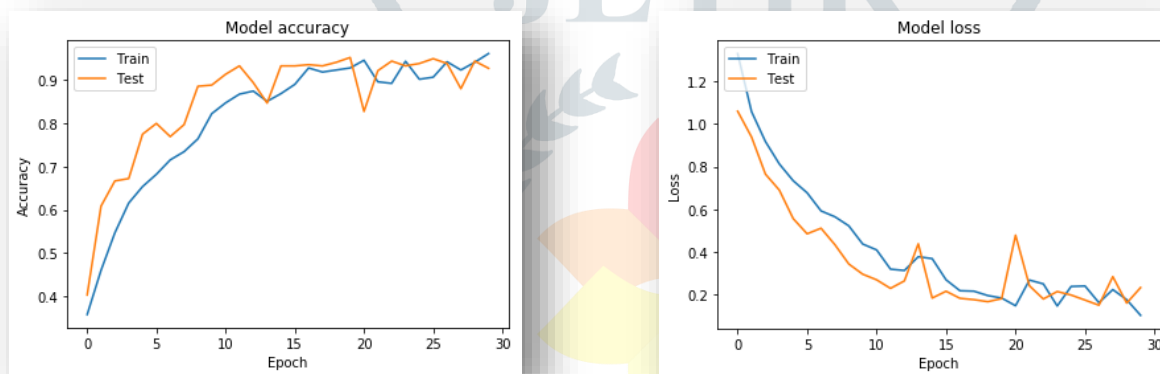
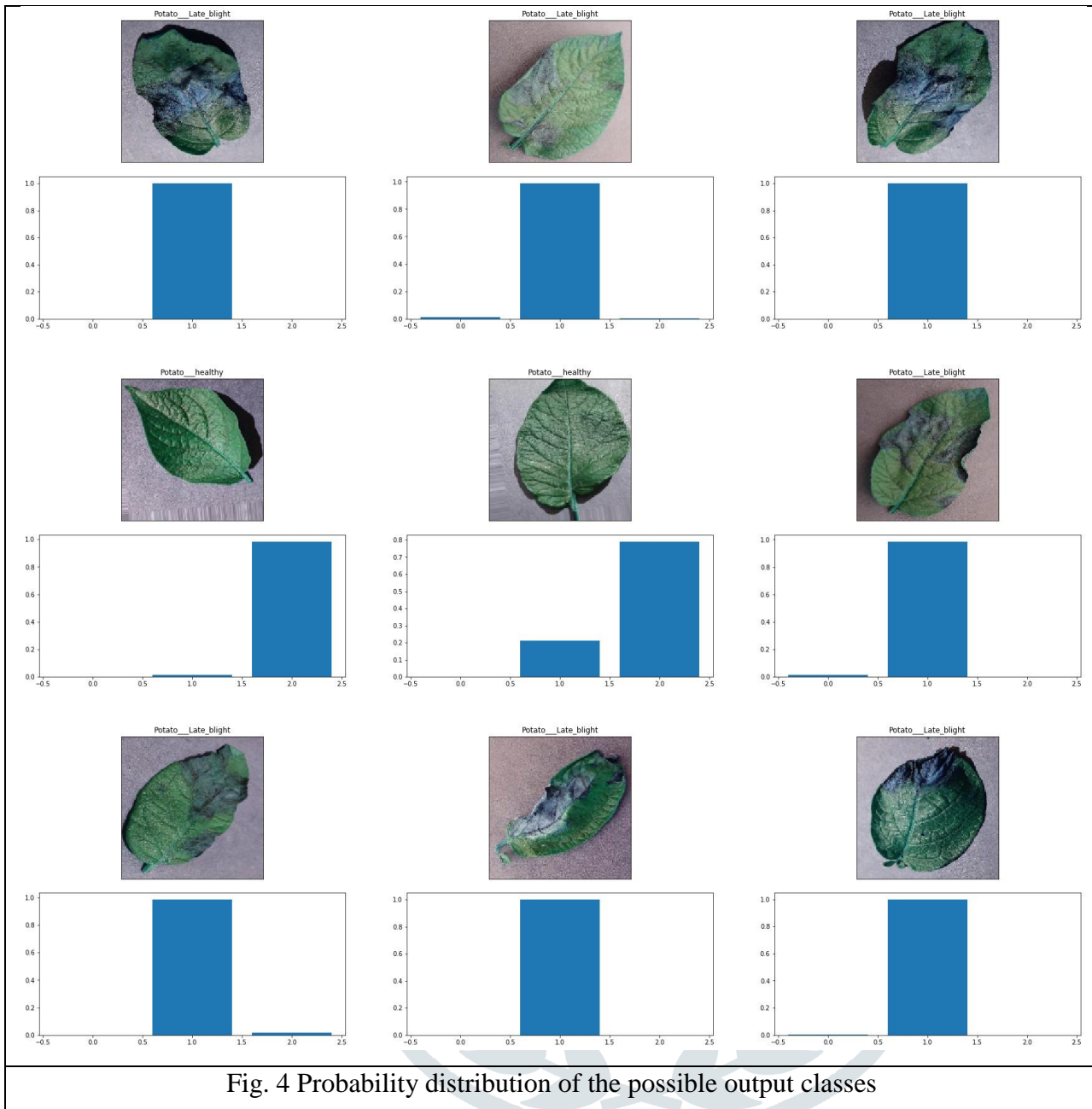


Fig. 3 Training–Progress Graphs

Graphs are shown in Fig. 3 indicate that with an increase in the number of iterations for each epoch the training accuracy increases and at the same time the model loss decreases.

A test set comprising of 300 images with 100 images per class was used for testing. Softmax function at the output layer classifies the images based on the probability distribution. Fig. 4 depicts the output of the fully connected layer of the developed CNN model.



5. Results and Discussions

A confusion matrix is a table that gives information about how the test dataset performs on the trained model. Fig. 4 shows the confusion matrix and will be used for the calculation of various performance measures like accuracy, precision, recall or sensitivity and specificity of the model [14].

A number of test examples of any class will be obtained by the sum of all items of rows corresponding to that class (TP + FN). For example for early blight i.e row 0, the total number of test images is $94+6+0=100$.

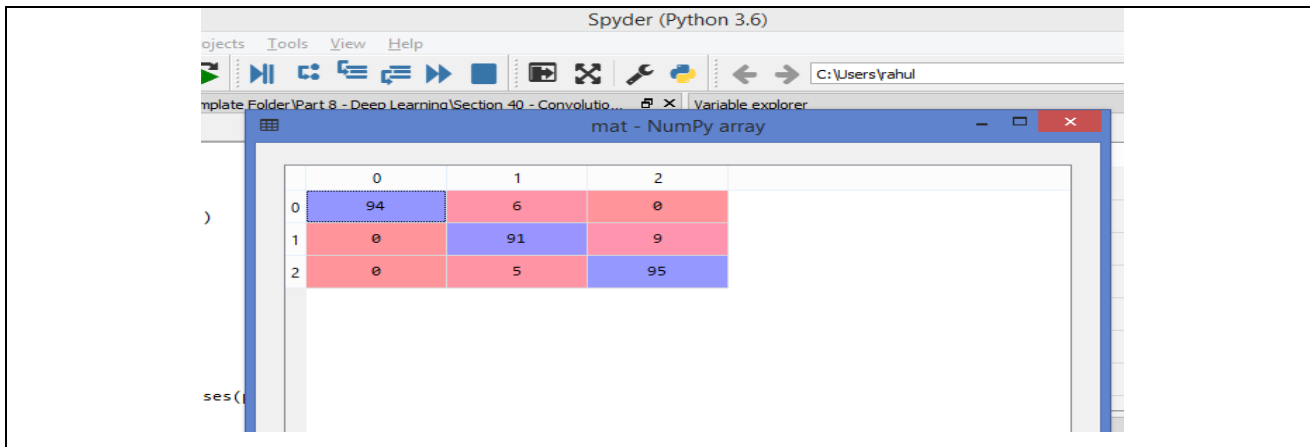


Fig.5 Confusion matrix of a CNN model trained and validated on 80% dataset and tested on a 20% dataset. Rows of the Confusion matrix represent the actual class of the CNN model and the columns represent the CNN model's class prediction. Column 0 represents early blight, column 1 represents late blight and column 2 represent healthy leaves

Similarly, the number of false positives (FP) for a class is the sum of values in the corresponding column excluding true positives TP for that class. The total number of true negative TN for a certain class will be the sum of all columns and rows values excluding that class's column and row. Accuracy is defined and the sum of correct classifications divided by the total number of classifications. Sum of all diagonal elements divided by the sum of all items in the confusion metrics. Accuracy gives the overall correctness of the predicted model. Accuracy of developed CNN model is $\text{accuracy} = (94 + 91 + 95) / 300 = 280/300 = 93.33\%$. Precision is the measure of the accuracy of the predictions of a specific class and is given by $\text{TP}/(\text{TP}+\text{FP})$. For example, the CNN model's precision of prediction of healthy leaves (column 2) leaves is $95/(95 + 9) = 95/104 = 91.3\%$.

6. Conclusions and Future Work

In this paper, the applicability of the CNN model for the identification of potato plant diseases is examined. Dataset of 1500 potato leaves of three classes was used. CNN model was trained and the developed model achieved 94.44% training accuracy when the model was trained for 29 epochs. The model performed well on the testing dataset with an overall accuracy of 93.33%. CNN model is trained with 80% images and tested with 20% images. For future work based on a different train, the test ratio split the model's performance can be analyzed. The hyperparameters of the used CNN model like the number of the epoch, batch size, number of filters in each convolution layer, size of the filters, number of convolution layers, activation function for convolution layer, pooling after each convolution layer, number of fully connected layers, etc is tuned manually. An automatic optimized selection of these hyperparameters can further increase the performance of the model.

References:

1. Friedrich, T. (2015). A new paradigm for feeding the world in 2050 the sustainable intensification of crop production. *Resource Magazine*, 22(2), 18-18.

