Detection of Plant Diseases based on Deep Convolutional Neural Network

Md. Kamrul Islam Asik
Department of Electrical and Computer Engineering
North South University
Dhaka, Bangladesh
mdkamrul.islam@northsouth.edu

Mukith Al Alim
Department of Electrical and Computer Engineering
North South University
Dhaka, Bangladesh
al.alim@northsouth.edu

Shadman Sameer
Department of Electrical and Computer Engineering
North South University
Dhaka, Bangladesh
sameer.shadman@northsouth.edu

Dr. Riasat Khan
Department of Electrical and Computer Engineering
North South University
Dhaka, Bangladesh
riasat.khan@northsouth.edu

***Abstract*—Agriculture is a very vital industry to Bangladesh, where it would bring a huge impact on the country's Prosperity. Plants have become an important source of energy and a critical piece in the puzzle of resolve the global warming problem. Convolutional neural networks have demonstrated great performance in Object recognition and image classification problem. The primary goal of the proposed work is to find a solution to the problem of detection Potato Plants diseases using the simplest approach while utilizing minimal computing resources to achieve better result than traditional models. It is investigated that by using CNN, an average classification accuracy of 99.63 percent can be achieved when performing the classification of leaf diseases. To provide a treatment handling method for the detected disease, a graphical interface for the system is also being developed. CNN can extract important features and classify plant disease from images taken in the natural environment. The accuracy results in disease identification demonstrated that the deep CNN model is promising and can have significant impact on the efficient identification of disease, as well as potential in disease detection in real-time agricultural systems.**

***Index Terms*—Plant disease detection, Potato Plant Disease, Image Processing, CNN, Color thresholding, Deep learning.**

I. Introduction

The agricultural land mass and productivity determine a country's economic progress. Agriculture is the primary source of income for the majority of the population. Farmers grow a variety of crops depending on soil fertility and resource availability. Crops can become infected by fungi, bacteria, and viruses as a result of changes in climatic factors such as rainfall, temperature, and soil fertility [1]. They use appropriate pesticides and herbicides on the plants to prevent illnesses and improve product output and quality. Plant diseases are identified and studied through visual observation patterns on the plants. Plant disease detection at an early stage is advantageous since the disease can be controlled. In a few nations, farmers have no knowledge how to contact professionals or have the means to do so. Visual examination of leaf patterns by experts is one such method for detection. However, it necessitates a huge specialist staff. An automated plant infection or disease monitoring system will come in handy in this circumstance. Automation will be cheaper by comparing the leaves of the plants in the agricultural farm area with the stored plant disease symptoms. Anthracnose, Cercospora Leaf Spot, and Bacterial Blight are the three plant diseases classified here. Anthracnose develops irregularly shaped tan or brown patches on the leaf. These spots will be close to the veins of the leaves. Leaf drop will occur if the infection is severe. Small brown flecks with a reddish border will appear on Cercospora leaf spot leaves. It has a grey center and stretches out. The leaf tissue eventually gets thin and fragile, and it falls out, leaving a hole. Bacterial A plant's trunk, branches, shoots, buds, flowers, leaves, and fruit can all be affected by blight disease. On the leaf, a little pale green spot emerges and spreads across the leaf. Later, the lesion area becomes a dry dead patch. To diagnose the infection or sickness, a sample of the leaf is given into image processing algorithms [2]. Image capture, preprocessing, segmentation, feature extraction, and classification are some of the procedures involved in Plant disease detection.

II. Literature Review

The section discusses recent trends in the use of CNN and deep learning architectures in agricultural applications. Before deep learning, image processing and machine learning techniques were used in classify various plant diseases. In general, most of these systems procced as follows: The first digital images are captured with a digital camera. Following that, image processing techniques such as image enhancement, segmentation, color space conversion, and filtering are used to prepare the images for the next steps. The image's key features are then extracted and used as input for the classifier [3]. The overall classification accuracy is thus determined by the image processing feature extraction techniques employed. However, recent research has shown that networks trained on generic data can achieve state of the art performance. CNN are multi-layer supervised networks that can learn features from datasets automatically. CNN have achieved state of the art performance in almost all-important classification tasks in recent years. Under the same architecture, it can perform both feature extraction and classification [4].

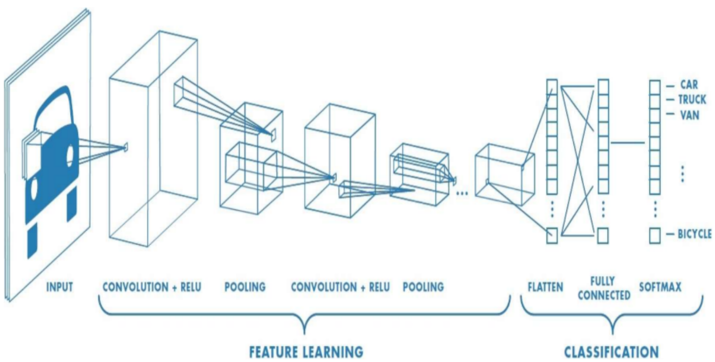

Fig. 1. CNN can perform both Feature extraction and Classification

A CNN is type of neural network that has been widely used to solve pattern recognition problems such as computer vision, speech recognition, and so on. The CNN is based on the visual system of humans. CNN use three architectural ideas to ensure shift, scale, and distortion invariance, which are Local receptive fields, shared wights, and spatial or temporal subsampling. Various CNN architectures, such as LeNet, AlexNet, and GoogleNet, have been proposed for use in object recognition [5].

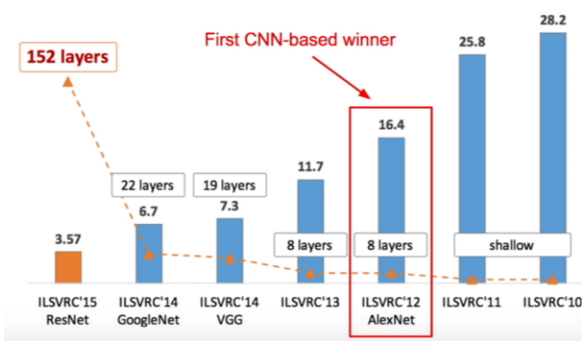

Fig. 2. ImageNet Large Scale Visual Recognition Challenge

LeNet is the first CNN architecture introduced by LeCun et at., to recognize handwritten digits [6]. It is made up of two convolutional layers, two subsampling layers, and a fully connected MLP. A few researchers proposed using CNN for leaf recognition and disease classification in plants. To identify plants based on leaf images, Ataby created a convolutional neural Network architecture. The proposed architecture is made up of five layers. After each convolutional layer, a Rectified Linear Unit (ReLu) or Exponential Linear Unit (ELU) activation function is used, and the MaxPooling approach is used for each pooling layer. The proposed system is tested on the Flavia and Swedish leaf datasets, which contain 32 plant species with 1907 samples each and 15 plant species with 1125 sample each. The dataset contains images of a single leaf taken against a uniform background. The input images are all grayscale images with dimensions of 160x160 pixels. For each dataset, the model achieved classification accuracy of 97.24 percent and 99.11 percent. The results demonstrated that the proposed architecture for CNN-based leaf classification competes with the most recent extensive approaches to developing leaf features and classifiers. Angie K. Reyes et al., used a deep learning approach to learn the entire system without hand engineered components. The system is designed with 5 convolutional layers followed by 2 fully connected layers. The CNN was trained with 1.8 million images from the ILSVRC 2012 dataset 1 and a finetuning strategy was used to transfer learned recognition capabilities from general domains to the specific challenge of Plant identification. The dataset is a collection of images of aa plant or a portion of a plant taken in both a controlled and natural environment. They achieved a precision of 0.486 on average. Sharada P. Mohanty et al. Classified plant diseases using existing deep CNN architectures such as AlexNet and GoogleNet. The CNN was trained to identify 14 crops species and 26 diseases using a public dataset of 54,306 images of diseased and healthy plant leaves collected under controlled conditions. The models were 99.35 percent accurate. When tested on images taken in a different than those used for training, the model's accuracy dropped to 31.4 percent. Overall, the results show that deep CNN can be used to classify plant diseases.

III. Methodology

To classify Potato plant disease a large collection of the plant's leaf images is required. The images are downloaded from PlantVillage dataset. In this section the methodology followed is discussed in details.

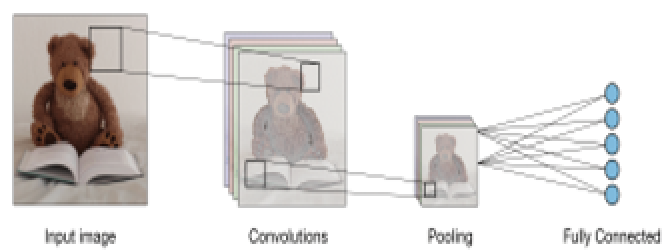

Fig. 3. Convolutional layer, pooling layer and fully connected layer.

A. Dataset

During the training and testing phases of classification research, a suitable and large dataset is required. The experiment's dataset is obtained from the PlantVillage dataset, which contains various plant leaf images and labels [7]. It is a collection of images taken in various environments. A dataset with 54,305 leaf images on healthy and infected leaves. For the potato disease detection, we select potato leaf images a total of 2,152 images of three classes, including Early blight, Late blight and healthy leaves. Table-1 summarizes the dataset's samples by class.

TABLE I
DATASET USE FOR THE CLASSIFICATION

No.	Type	Number
1	Healthy Leaf	152
2	Early Blight Leaf	1,000
3	Late Blight Leaf	1,000

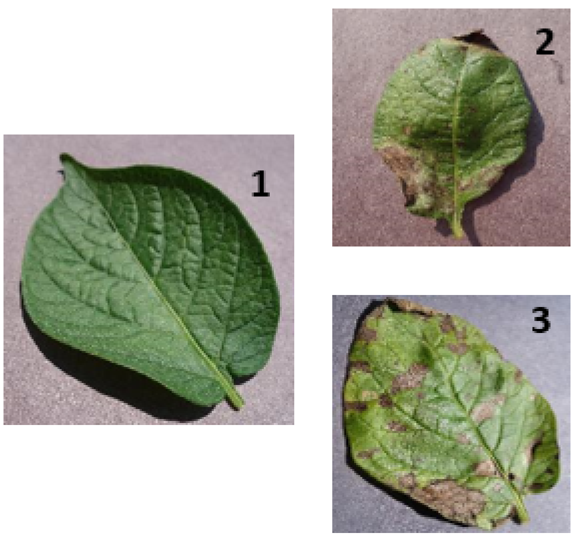

Fig. 4. Sample images from the dataset, where (1) Healthy Potato Leaf, (2) Early blight Potato Leaf, and (3) Late blight Potato leaf

Figure 4 depicts a few simples from the database. To prepare the dataset for training, images with varying resolutions are resized to 128x128 pixels. Because the images were captured in an uncontrolled environment, the differences in lighting and background in the training images may bias the neural network. The experiment was also carried out using the grayscale and segmented versions of the database to test this.

B. Design

The proposed system architecture includes data acquisition from a large dataset, processing different convolution layers, and plant disease classification, which determines whether the plant image is healthy or disease.

TABLE II
ARCHITECTURE OF THE PROPOSED MODEL.

Layer	Type	Filter Size	Stride	Output Size
L1	Conv	3 x 3	1	128 x 128 x 32
	Pool	2 x 2	2	64 x 64 x 32
L2	Conv	4 x 4	1	61 x 61 x 32
	Pool	2 x 2	2	64 x 64 x 32
L3	Conv	1 x 1	1	30 x 30 x 128
	Pool	2 x 2	2	15 x 15 x 128

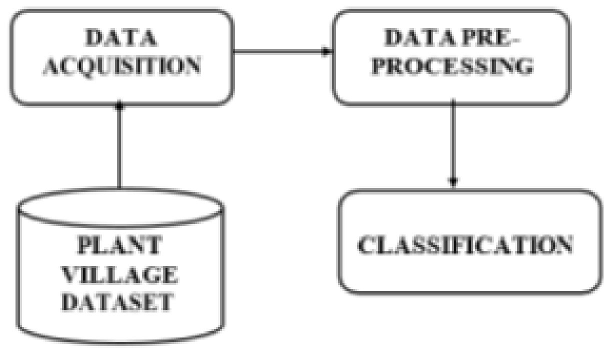

Fig. 5. System Architecture.

C. The Proposed CNN Model

CNN architectures differ depending on the problem at hand. Three convolution layers are followed by a maxpooling layer in the proposed model. The final layer is MPL that is fully connected. Every convolutional layer and fully connected layer's output receives the ReLu activation function. Here, we use Image size of 256x256. Batch size of 32 for 3 channel and 50 epochs. The first convolutional layer filters the input image using 32 kernels of size 3x3. After maxpooling, the output is used as an input for the second convolution layer, which has 64x64 kernels. The final convolutional layer has 256 kernels of size 1x1 followed by a fully connected layers of 512 neurons. This layer's output is fed into the softmax function, which generates a probability distribution of the four output classes [8]. The architecture of the proposed model is shown in Table 2. The model is trained using adaptive moment estimation (Adam) with batch size of 32 for 50 epochs.

```
input_shape = (BATCH_SIZE, IMAGE_SIZE, IMAGE_SIZE, CHANNELS)
n_classes = 3

model = models.Sequential([
    resize_and_rescale,
    data_augmentation,
    layers.Conv2D(32,(3,3),activation = 'relu', input_shape = input_shape),
    layers.MaxPooling2D(2,2),
    layers.Conv2D(64, kernel_size = (3,3), activation = 'relu'),
    layers.MaxPooling2D(2,2),
    layers.Conv2D(64, kernel_size = (3,3), activation = 'relu'),
    layers.MaxPooling2D(2,2),
    layers.Conv2D(64, (3,3), activation = 'relu'),
    layers.MaxPooling2D(2,2),
    layers.Conv2D(64, (3,3), activation = 'relu'),
    layers.MaxPooling2D(2,2),
    layers.Conv2D(64, (3,3), activation = 'relu'),
    layers.MaxPooling2D(2,2),
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(n_classes, activation='softmax'),
])

model.build(input_shape = input_shape)
```

Fig. 6. Proposed CNN Model.

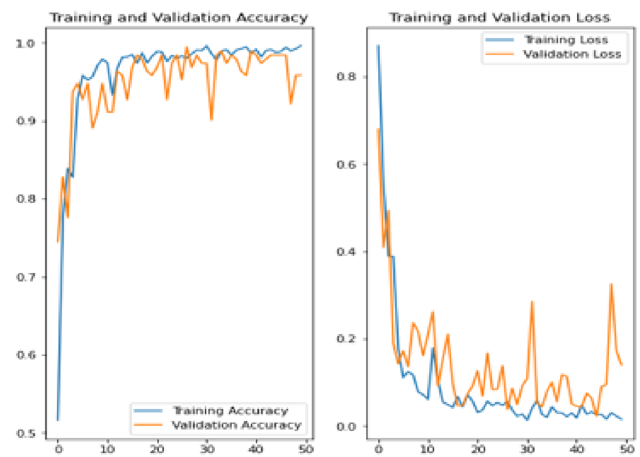

Fig. 8. Training VS Validation Accuracy and loss.

IV. Experimental Result

The dataset is divided into 80 percent for training, 10 percent for validation, and 10 percent for testing. Various models with varying architectures and learning rates are tested. The network parameters, such as kernel size, filter size and learning parameter, were chosen through trail and error. The ReLu activation function is used because studies have shown that is results in faster training.

The outcome us shown in Fig 3 below.

```
Epoch 1/50
54/54 [==============================] - 136s 2s/step - loss: 0.8704 - accuracy: 0.5162
48
Epoch 2/50
54/54 [==============================] - 133s 2s/step - loss: 0.5613 - accuracy: 0.7766
81
Epoch 3/50
54/54 [==============================] - 117s 2s/step - loss: 0.3894 - accuracy: 0.8391
60
.
.
.
Epoch 48/50
54/54 [==============================] - 119s 2s/step - loss: 0.0304 - accuracy: 0.9896
9219
Epoch 49/50
54/54 [==============================] - 118s 2s/step - loss: 0.0225 - accuracy: 0.9925
9583
Epoch 50/50
54/54 [==============================] - 118s 2s/step - loss: 0.0158 - accuracy: 0.9959
9583
```

Fig. 7. Accuracy Result.

As the results show, the classification accuracy of the first epoch is 51.62 percent and increasing to 99.59 percent on 50 epochs. Three convolution layers are followed by a max pooling layer in the model that provides good classification accuracy. For each layer, the ReLu activation function is used. Figure 4 depicts the model's training accuracy versus validation graphs. The graphs demonstrate that the model is overfitting. Overfitting occurs when the model fits the training set too well.

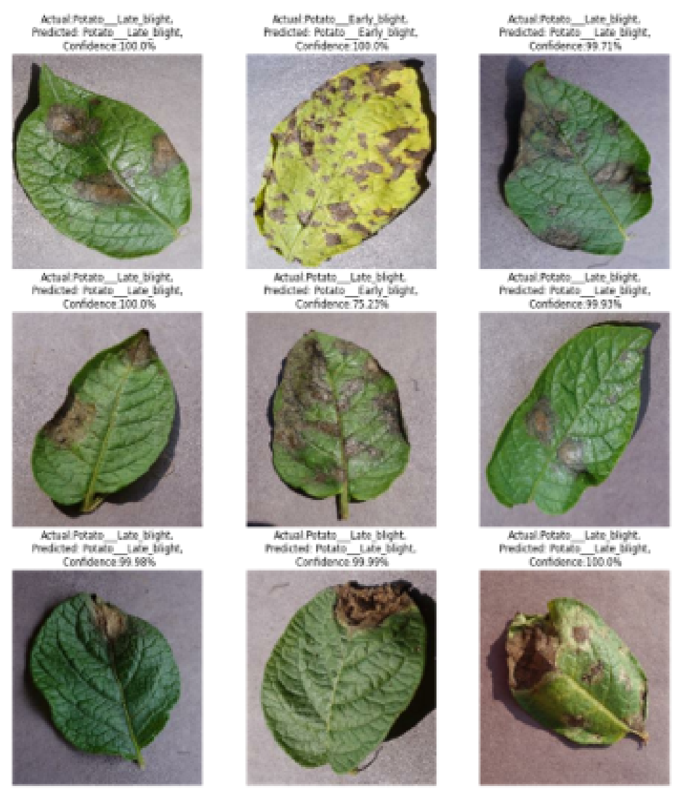

Fig. 9. Predicted Class and the Confidence.

It then becomes difficult for the model to generalize to new examples that were not in the training set.
To overcome overfitting, several techniques have been developed, including data augmentation, introducing weight penal-

ties of various types, such as regularization and dropout. Experiments were carried out to determine the impact of each technique on the model's performance. Because the dataset is too small in comparison to the total number of trainable parameters of the model, the first experience we performed was to increase the training data by rotating, flipping, and re-scaling the images. Only the training data is used for data augmentation. Data augmentation alone solves overfitting significantly. It also increases the validation accuracy. Dropout and Regularization are also applied. Both models showed a slight improvement over the model's performance.
As a result, adding a dropout layer with a probability of 0.5 after the MLP results in good classification accuracy.

V. CONCLUSIONS

A convolutional neural network is used in this study to detect and classify Potato Plant diseases. The Network was trained using images taken in the natural environment and achieved a classification ability of 99.59 percent. This demonstrates CNN's ability to extract important features in the natural environment that are required for plant disease detection.
According to our knowledge, this is the first attempt that used images taken in the wild environment and achieved remarkable results. Experiments also show that using data augmentation on the training set improves network performance when the dataset is small. Dropout and regularization were also found to be affected in overcoming overfitting. Further we can build a First API server around the model. Then we can build a website and deployment model to google cloud. Finally, we can build a app for agricultural benefits.

ACKNOWLEDGMENT

This research is carried out in Department of Computer Science and Engineering, North South University, under the guidance of Dr. Riasat Khan for providing us all the required facilities and suitable environment to successfully complete this research.

REFERENCES

[1] A. Ramcharan, K. Baranowski, P. McCloskey, B. Ahmed, J. Legg, and D. P. Hughes, "Deep learning for image-based cassava disease detection," *Frontiers in plant science*, vol. 8, p. 1852, 2017.

[2] P. K. Sethy, N. K. Barpanda, A. K. Rath, and S. K. Behera, "Deep feature based rice leaf disease identification using support vector machine," *Computers and Electronics in Agriculture*, vol. 175, p. 105527, 2020.

[3] H. M. Alexander, K. E. Mauck, A. E. Whitfield, K. A. Garrett, and C. M. Malmstrom, "Plant-virus interactions and the agro-ecological interface," *European journal of plant pathology*, vol. 138, no. 3, pp. 529–547, 2014.

[4] T. Akram, S. R. Naqvi, S. A. Haider, and M. Kamran, "Towards real-time crops surveillance for disease classification: exploiting parallelism in computer vision," *Computers & Electrical Engineering*, vol. 59, pp. 15–26, 2017.

[5] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 4700–4708, 2017.

[6] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," *Advances in neural information processing systems*, vol. 25, 2012.

[7] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Frontiers in plant science*, vol. 7, p. 1419, 2016.

[8] M. Akila and P. Deepan, "Detection and classification of plant leaf diseases by using deep learning algorithm," *International Journal of Engineering Research & Technology (IJERT)*, vol. 6, no. 7, pp. 1–5, 2018.