Detection of various crop diseases from images, A Convolution Neural Network based approach

Hasnain Iqbal
Institute of Information Technology
University of Dhaka
Dhaka, Bangladesh
bsse1106@iit.du.ac.bd

Khairul Alam
Institute of Information Technology
University of Dhaka
Dhaka, Bangladesh
bsse1118@iit.du.ac.bd

Mushfiqur Rahman Chowdhury
Institute of Information Technology
University of Dhaka
Dhaka, Bangladesh
bsse1110@iit.du.ac.bd

BM Mainul Hossain
Institute of Information Technology
University of Dhaka
Dhaka, Bangladesh
mainul@iit.du.ac.bd

Abstract: **Agricultural productivity plays a vital role in the Bangladeshi economy, with both food and cash crops significantly contributing to the well-being of the environment and human population. Unfortunately, crop diseases pose a recurring threat, as their symptoms often go undiagnosed, leading to the loss of numerous plants. This study offers valuable insights into plant disease detection and introduces a novel approach based on the Convolutional Neural Network (CNN).**

The study entails a comprehensive examination of plant disease detection, focusing on the analysis of sample images in terms of time complexity and the extent of infection. This analysis includes image processing techniques. A dataset comprising 14 cases is utilized, consisting of 10 cases of diseased plant leaves, encompassing ailments such as Rice Brown Spot, Rice leaf and neck blast, Potato Early Blight, Potato Late Blight, Corn Common Rust, Corn Gray Leaf Spot, Corn Northern Leaf Blight, Wheat Brown Rust, Wheat Yellow Rust. Additionally, four cases feature healthy leaves, including Rice Healthy, Corn Healthy, Potato and Wheat Healthy.

The experimental results reveal a validation accuracy of 89.3%. Furthermore, various performance metrics are derived from the experiment to provide a comprehensive assessment of the proposed CNN-based method's effectiveness.

Keywords: **CNN, Agriculture, Crop Disease, Image Processing**

I. Introduction

The Agriculture sector plays an important role in the overall economic development of Bangladesh. The agricultural sector (crops, animal farming, forests, and fishing) contributes 11.38 percent to the country's GDP. And Corps and Horticultures cover almost 50 percent of this contribution. [1]

Although rice and jute are the primary crops, maize and vegetables are assuming greater importance.
Because of Bangladesh's fertile soil and normally ample water supply, rice can be grown and harvested three times a year in many areas.[2] According to the report of 2021, Bangladesh is third on the list of rice-producing countries all over the world just under the huge lands of China and India. [3]

The same report says of having the seventh position held by Bangladesh in the manner of producing potatoes. Also, Bangladesh holds a steady second position in the top jute-producing countries all over the world. [4]
So, it goes without saying, that Bangladesh is very much dependent on its agriculture sector, specifically saying, in the crop production sector.
According to the report of Bangladesh Agriculture Ministry, Bangladesh has 88.29lakh hectares of land for cultivation. Including the frequency of production in an agricultural year, these lands are increased up to 160.57lakh hectares. [5]

In the 2017 report, 42.7 percent of the entire population of Bangladesh was reported to be directly involved in agriculture. [6]

So, if the productivity of crops can be elevated, the economy of Bangladesh can be boosted further. In this work, we have worked with some of the common diseases of rice, corn, potatoes, and wheat plants, to boost up productivity. We have formulated an approach to detect the diseases to give the farmers more time to act accordingly, which eventually will push the productivity rate higher.

Diseases of rice

Brown spot: Brown spot is a fungal disease that infects the coleoptile, leaves, leaf sheath, panicle branches, glumes, and spikelets.

Its most observable damage is the numerous big spots on the leaves which can kill the whole leaf. When infection occurs in the seed, unfilled grains or spotted or discolored seeds are formed. [7]

How to identify:

- Infected seedlings have small, circular, yellow-brown, or brown lesions that may girdle the coleoptile and distort primary and secondary leaves.
- Starting at the tillering stage, lesions can be observed on the leaves. They are initially small, circular, and dark brown to purple-brown.
- Fully developed lesions are circular to oval with a light brown to gray center, surrounded by a reddish brown margin caused by the toxin produced by the fungi.

Fig 1: Brown Spot

Blast: Blast is caused by the fungus *Magnaporthe oryzae*. It can affect all above-ground parts of a rice plant: leaf, collar, node, neck, parts of panicle, and sometimes leaf sheath. [8] Here we will work with the leaf and neck blast.

How to identify:

- Initial symptoms appear as white to gray-green lesions or spots, with dark green borders.
- Older lesions on the leaves are elliptical or spindle-shaped and whitish to gray centers with red to brownish or necrotic borders.

Fig 2: From left, Leaf and Neck Blast

Diseases of Potato

Early Blight: Early blight is primarily a disease of stressed or senescing plants. Symptoms appear first on the oldest foliage. Affected leaves develop circular to angular dark brown lesions 0.12 to 0.16 inch (3–4 mm) in diameter. Concentric rings often form in lesions to produce a characteristic target-board effect. Severely infected leaves turn yellow and drop. Infected tubers show a brown, corky dry rot. [9]

Fig 3: Late Blight

When plants have become infected, lesions (round or irregularly shaped areas that range in color from dark green to purplish black and resemble frost injury) appear on the leaves, petioles, and stems. A whitish growth of spore-producing structures may appear at the margin of the lesions on the underleaf surfaces.

Potato tubers develop rot up to 15 mm (0.6 inch) deep. Secondary fungi and bacteria (particularly Erwinia species) often invade potato tubers and produce rotting that results in great losses during storage, transit, and marketing. [10]

Fig 4: Early Blight

Diseases of Corn

Common Rust: Common rust produces rust-colored to dark brown, elongated pustules on both leaf surfaces. The pustules contain rust spores (urediniospores) that are cinnamon-brown in color. Pustules darken as they age. Leaves, as well as sheaths, can be infected. Under severe conditions, leaf chlorosis and death may occur. Common rust can be differentiated from Southern rust by the brown pustules occurring on both top and bottom leaf surfaces with common rust. [11]

Fig 5: Common Rust

Gray Leaf Spot: The disease first appears in the form of small, necrotic spots with halos. These usually expand to become rectangular lesions, about 1/8 inch wide by up to 2 inches to 3 inches long, and gray to brown in appearance. Mature lesions usually have distinct parallel edges and appear opaque when put up to the light, but the lesion hybrids vary widely in shape and color. Symptoms can sometimes be confused with northern corn leaf spot, although gray leaf spot lesions are usually limited on the sides by veins. [12]

Fig 6: Gray Leaf Spot

Northern Leaf Blight

Typical symptoms of northern corn leaf blight are canoe-shaped lesions 1 inch to 6 inches long. The lesions are initially bordered by gray-green margins. They eventually turn tan colored and may contain dark areas of fungal sporulation. The length or size of lesions may vary within different corn hybrid reactions with different resistance genes. Lesions begin on the lower leaves and then spread to the upper leaves. Severe symptoms can progress rapidly, resulting in blighted leaves. The disease can be confused with symptoms of Goss's leaf blight on some hybrids, and perhaps with Stewart's wilt where this disease occurs. [13]

Fig 7: Northern Leaf Blight

Wheat Diseases

Brown Rust: Orange-to-brown color pustules (about 0.5–1.0 mm in diameter) often develop in the autumn on early-sown crops. In early infections, pustules are frequently confused with yellow rust. There is greater differentiation of color later in the season. Additionally, brown rust pustules tend to be scattered at random, compared with the more striped symptoms of yellow rust. Often seen on the leaves, symptoms can occur on the stem, leaf sheaths, and ears when the infection is severe. When leaves begin to senesce, a 'green island' develops around individual pustules. Dark teliospores may be produced towards the end of the season. [14]

Fig 8: Brown Rust

Yellow Rust: Early on, the pustules are very difficult to distinguish from brown rust. However, yellow rust lesions tend to spread as a band up and down young leaves, often with a yellow band on the leaf moving ahead of the sporulating lesion. Pustules are also often scattered at random on young leaves before becoming more obvious stripes as the leaf gets older. Under hot, dry conditions – or after fungicide use – the epidemic has been checked meaning pustules may be difficult to detect.

Infected leaves can rapidly become chlorotic and then necrotic in May/June, if weather conditions are conducive. In severe attacks, yellow rust infection of the ears can occur, resulting in the formation of masses of spores between the grain and the glumes. At the end of the season, secondary black spores (teliospores or telia) are sometimes produced amongst the stripes of pustules. [15]

Fig 9: Yellow Rust

In our approach we have tuned a CNN to detect the diseases included above.

II. Literature Review

Many researchers have applied DL techniques in agriculture in the past decade, especially for crop leaf disease detection. The development of a robust automatic system that is capable of classifying a large number of classes is still a highly complex task. However, various research has been carried out using CNNs in order to classify and detect the diseases available in the plants' leaves.

In [16], the authors suggested a CNN architecture for classifying the diseased and healthy cucumber leaves using the image database. The researchers presented a CNN model, which utilizes the Caffe framework [17], comprising convolutional layers (CL), normalization layers, and pooling layers. Finally, the accuracy of approx. 95 % was achieved after applying a 4-fold cross-validation methodology.

In another research [18], a cucumber leaves disease detection model was proposed, which deployed a CNN comprised of four CL, local response normalized operations, and pooling layers. The configuration of local response normalized parameters was the same as for AlexNet model parameters. In the end, an accuracy of 82.3 % was achieved with a 4-fold cross-validation methodology.

In reference [19], the authors implemented a CNN model for plant leaf disease detection. This deployed model has the capability to classify thirteen distinct types of diseases present in leaves. Furthermore, the implementation was based on the Caffe framework. The experimentations depict a precision variation of 91–98 %, and the final classification accuracy was 96.3 % for the trained CNN model.

In [20], a CNN model was deployed to identify the northern leaf blight spots on maize crop leaf images. For training, testing, and validation, a ratio of 70:15:15 was divided, correspondingly. The proposed model attained 96.7 % accuracy for the test image dataset that was not utilized for training. Moreover [21], introduced a CNN technique for rice disease classification. Ten commonly inoculated rice diseases were identified using AlexNet. Consequently, the

architecture attained 95.48 % classification accuracy with a 10-fold cross-validation approach.
In [22], authors deployed diverse traditional DL models in order to classify plant leaf diseases using transfer learning. This study achieved a high average classification accuracy (99.34 %). In research [23], DenseNet, InceptionNet, ResNet, and VGG were deployed for leaf disease detection among 14 plant species. DenseNet outperformed all with the highest classification accuracy of 99.75 %. However, computational cost and controlled homogeneous background using only a solitary leaf are challenges for this study.
In reference [24], the authors implemented a CNN architecture to recognize rice blast disease present in the leaves and attained a better classification accuracy than feature extraction (FE) techniques, e.g., haar wavelet transformation, and histogram-based binary pattern. The implemented CNN model gave 95.83 % accuracy. Although this implementation is limited to a controlled image acquisition environment, and training dataset also needs to be expanded.
In [25], the authors deployed '2' conventional CNN schemes, namely, InceptionV3 and VGG16, for identifying rice diseases. They have also introduced a two-stage CNN architecture that is effective with devices having constant memory. Researchers determined that manual labeling of symptoms in distinct classes might give misclassified results. In another study [26], the authors used a custom-CNN architecture to train the model using both original images and segmented images. The model was deployed for classifying the 10 disease classes and attained an accuracy of 98.6 % and 42.3 % for S–CNN and F–CNN, respectively. This implementation has some challenges, such as segmentation in uneven radiances and different angles.

III. Methodology

The First Step is Exploratory Data Analysis (EDA). It helps us analyze the entire dataset and summarize its main characteristics, like class distribution, size distribution, and so on. Visual methods are often used to display the results of this analysis.

The second step is Image Pre-Processing, where the aim is to take the raw image and improve image data (also known as image features) by suppressing unwanted distortions, resizing and/or enhancing important features, making the data more suited to the model, and improving performance.
Exploratory data analysis comprises brief analyses to describe a dataset to guide the modeling process and to answer preliminary questions. For classification problems, this might include looking at the distributions of variables or checking for any meaningful patterns of predictors across different classes. The same problem holds for the classification of image data. We intend to find meaningful information.

Data Collection and Preprocessing:

Initial Dataset: The data was collected from Kaggle which is a generalized dataset consisting of 14 different classes of crop diseases, including corn, potato, rice, and wheat diseases. This dataset served as the starting point for our study.

Data Resizing: Images were resized to a uniform dimension of 200x200 pixels, denoted as $W_i \times H_i = 200 \times 200$.

Pixel Value Scaling: To ensure consistent pixel intensity values, the images were rescaled to the range of [0, 1] by dividing each pixel value by 255. This rescaling operation is defined as

$$X_{scaled} = X_{original} / 255$$

Where $X_{original}$ represents the original pixel value, and X_{scaled} represents the scaled pixel value.

Generalized CNN Model:

Model Architecture: A Convolutional Neural Network (CNN) model was designed to classify crop diseases. The model consisted of multiple layers, including convolutional and pooling layers, followed by fully connected layers.
Before we move on to building the models, we will explain the major building blocks in pretrained CV models. Every major ImageNet model has a different architecture, but each one has the common building

blocks: **Conv2D, MaxPool, and ReLU**. We will explain MaxPool and ReLU.

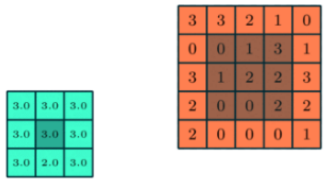

Fig 10: Max Pooling

The Pooling layer is responsible for reducing the spatial size of the Convolved Feature. This is to decrease the computational power required to process the data through dimensionality reduction. Furthermore, it is useful for extracting dominant features that are rotational and positional invariant, thus maintaining the process of effectively training the model.

There are two types of Pooling: Max Pooling and Average Pooling. Max Pooling returns the maximum value from the portion of the image covered by the Kernel. On the other hand, Average Pooling returns the average of all the values from the portion of the image covered by the Kernel. Max Pooling also performs as a Noise Suppressant. It discards the noisy activations altogether and also performs de-noising along with dimensionality reduction. On the other hand, Average Pooling simply performs dimensionality reduction as a noise-suppressing mechanism. Hence, we can say that Max Pooling performs a lot better than Average Pooling.

Convolutional layer: The main objective of convolution is to extract features such as edges, colors, and corners from the input. As we go deeper inside the network, the network starts identifying more complex features such as shapes, digits, and face parts as well.

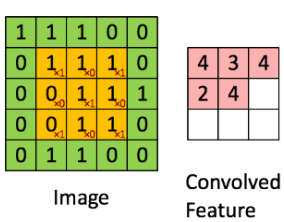

Fig 11: Convolution Filter

ReLU is the most commonly used activation function in neural networks, especially in CNNs. If you are unsure what activation function to use in your network, ReLU is usually a good first choice.

ReLU stands for rectified linear unit and is a type of activation function. Mathematically, it is defined as

$$y = max(0, x)$$

Visually, it looks like the following:

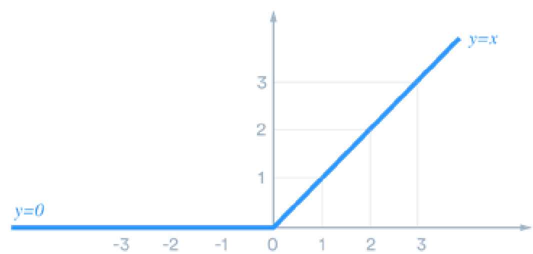

Fig 12: ReLU Activation Function

Our Model Architecture:

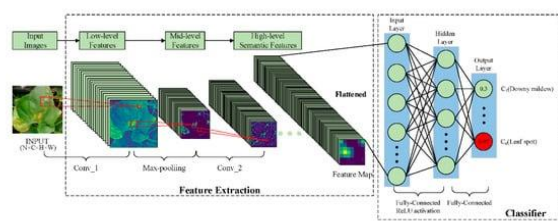

Fig 13: CNN Model

Training: The CNN model was trained on the preprocessed dataset using the stochastic gradient descent (SGD) optimization algorithm. The training process aimed to minimize the categorical cross-entropy loss function L_{CCE}.

Categorical Cross-Entropy: This loss function is applicable for multi-class classification problems.

$$L(y, \hat{y}) = -\frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{C} y_{ij} log(\hat{y}_{ij})$$

Where C represents the number of classes.

Species	Predictor Class	Frequency	Description
Corn	Corn Common Rust Corn Gray Leaf Spot Corn Healthy Corn Northern Leaf Blight	1192 images 513 images 1162 images 985 images	This is a well-structured dataset with some clear images, suitable to run an algorithm.
Potato	Potato Early Blight Potato Healthy Potato Late Blight	1000 images 152 images 1000 images	Data is clean and very well maintained.
Rice	Rice Brown Spot Rice Healthy Rice Leaf Blast Rice Neck Blast	613 images 1488 images 977 images 1000 images	Not very clean, not suitable for running algorithms. Contains shadows, which are difficult to differentiate from the features.
Wheat	Wheat Brown Rust Wheat Healthy Wheat Yellow Rust	902 images 1116 images 924 images	A well-maintained dataset.

Table: Table1

Model Output: Let y' represent the predicted class probabilities vector for a given input image of shape $(W_i,H_i,d)=(200,200,3)$, where d is the number of image channels (typically 3 for RGB images). The output of the model can be represented as:

$$y' = f(x; \theta)$$

where f is the CNN model with learnable parameters θ.

IV. Dataset

The name and description of the classes are given in Table1. The table shows that a total of 13,024 images were collected which were classified into 14 different classes. The corn and species images were collected from the PlantVillage dataset. PlantVillage is a standard and most popular leaf image dataset for plant disease detection. The rice plant images were collected from the datasets Dhan-Shomadhan which is a rice leaf disease classification dataset for Bangladeshi local rice and Rice Leafs" dataset from Kaggle. [27]

V. Results

We built a model to classify all the diseases for the different plants mentioned above. The model achieved a training accuracy of approximately 94.9%. On the validation dataset, the model attained an accuracy of 89.3%. The training loss reduced significantly from 0.5734 in the first epoch to 0.1257 in the fifth epoch. The validation loss also decreased from 0.3356 in the first epoch to 0.2055 in the final epoch.The progressive reduction in both training and validation loss signifies that the model optimized its weights and biases to minimize the prediction errors. The small gap between training and validation accuracy suggests that the model generalizes well to new, unseen data. While there is a slight drop in accuracy from training to validation (94.9% to 89.3%), the difference is relatively minor, indicating a well-trained model.

However, we expected over 98% accuracy for the quality of data and the carefully built model. When we examined the problem, we found out that the Rice disease dataset was not up to the mark. The images have flaws. The images had a very tiny area of paddy with a larger portion of the background. There were also some shadows which made the image look more confusing. It even seemed very hard to differentiate the healthy and diseased image with bear eyes. And the model gave only 35% accuracy for the Rice disease classification.

Fig 14: Brown Spot Rice

Then we formulated a different approach for the Rice dataset. We extracted the color (Yellow to Green) of the paddy leaf to filter out the irrelevant background. We applied random zoom to the image and detected the edges using Canny edge detection to find the uneven spots in the image.

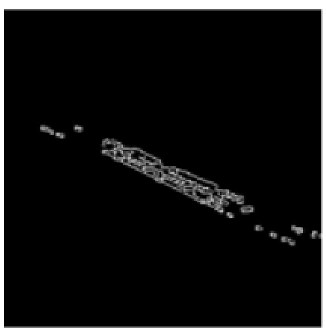

Fig 15: Rice Leaf Blast (processed)

Then we trained our model with this new set of data, and the accuracy got higher. In the end, we achieved 63.7% accuracy for the Rice disease detection. It still is a pretty low accuracy but for this time we will accept that. Increasing the accuracy of this dataset may require another study.

The following sections will show the relevant graphs and figures related to our study.

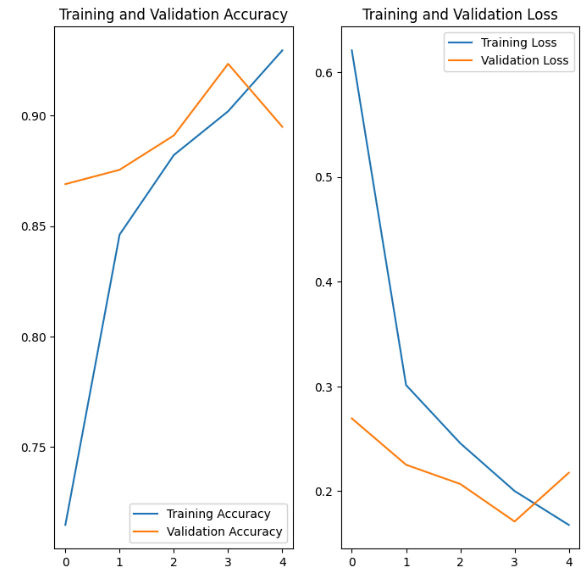

Fig 16: Accuracy and Loss function for overall detection

Fig 17: Rice Disease detection, validation, and loss

VI. Conclusion

The proposed approach is implemented successfully to train the system. The accuracy percentage on the validation set is 91.3% with no overfitting There is still room for improvement as the Rice disease detection is still not up to the mark. This present work can contribute to the agricultural domain and can be used to help people track their house plants and also enables the farmers to keep track of the harvest.

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