Deep Learning Based Zucchini Leaf Diseases Detection: A Commercial Agriculture Development in Bangladesh

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***Abstract*— The economic growth of Bangladesh is heavily dependent on agricultural production, but the several diseases have significantly impeded the growth of crops. The zucchini plant is commonly afflicted by diseases such as alternaria blight, anthracnose, and angular leaf spot. As a result, it is now crucial to detect leaf diseases at an early stage to prevent damage to the entire crop. However, farmers often lack of sufficient knowledge regarding leaf diseases and resort to manual methods for identifying disorders. The accuracy of detection is inadequate and time consuming. Therefore, it is crucial to develop an automated and precise identification system to solve this issue. This article introduces a new method for diagnosing and categorizing diseases in zucchini plants. Deep learning, which is a modern and effective approach, is suggested as a means to recognize the disorder and determine the appropriate treatment. Our primary focus was on training the raw dataset using the CNN algorithm, which resulted in an accuracy rate of 88.30 percent. Detecting and identifying diseases in the zucchini plant would contribute to the economic growth of Bangladesh by enhancing the production rate of the crop.**

Keywords*— *Deep Learning; CNN; Image Processing; Machine Learning; Computer Vision; Plant Leaf Disease; Alternaria Blight; Anthracnose; Angular Leaf Spot.

I. Introduction

The economy of Bangladesh is primarily built on the development of agricultural products and a significant number of individuals, specially people who live in rural areas mostly depend on agriculture, either directly or indirectly, as their source of income. Agriculture, which is the foundation of the Bangladeshi economy, is heavily reliant on the crops that are raised here each year during various growing seasons. Zucchini is one of them, that is also known as courgette. It is a well-known summer squash that belongs to the Cucurbitaceae family as cucumbers, pumpkins, and melons. A versatile vegetable, zucchini may be used in a number of cuisines, from salads and soups to pasta sauces and casseroles. It can be eaten directly or cooked. It is a favorite of the both adults and kids due to its mild, slightly sweet flavor and soft, crunchy texture. This vegetable is an ideal choice for a nutritious diet as it is low in calories but high in essential vitamins and minerals. It is especially rich in vitamin C, which strengthens the immune system and protects against diseases and infections. Plus, it's rich in vitamin A, which supports healthy eyes and skin, as well as potassium, a mineral that regulates blood pressure and supports heart health.

Several negative factors have a significant impact on agricultural production. One of the most significant problems in Bangladesh is leaf diseases, which significantly hinder agricultural production and reduce the quantity and quality of crops. Since our country requires a huge amount of fruits to meet the demands of our population, farmers love to use pesticides to increase crop production despite the fact that it damages the growing ecosystem. Although pesticides may sometimes be necessary to protect crops from harmful insects, improper use by farmers can lead to significant damage to the crops themselves. Using image processing methods to identify plant diseases is a potential solution to this problem.This research project's primary purpose is to determine the various of diseases that affect zucchini leaves and determine the appropriate remedy. To achieve this goal, we used a deep learning technique (specifically CNN) to train and test our model. Diseases we focused on were Alternaria Blight, Angular Leaf Spot, Anthracnose, Healthy Flowers in Zucchini and Healthy Leaves in both Zucchini and Luffa plants. While Zucchini leaf diseases may pose a difficulty for cultivators, they can be effectively managed through appropriate prevention and treatment measures. It is crucial to maintain a dry environment and minimize humidity, plant in an area that offers ample air circulation, and address pest problems that may spread disease. In cases where leaf diseases are already present, treatment can involve the use of fungicides or the removal of infected leaves. By implementing these practices, growers can take steps to promote a thriving and fruitful zucchini crop.

Our newly developed system will undoubtedly provide valuable support to farmers in the efficient and rapid identification of platimnt disorders. Identifying diseases at their initial stages, farmers can take necessary measures to eliminate them. Unfortunately, due to their limited education, many farmers in our country lack the ability to identify diseases using advanced scientific technologies such as CNN. Instead, they typically rely on hand-made measuring tools and their own visual assessments, which are not always accurate. Conversely, in several developed countries around the world, farmers are using cutting-edge scientific technologies such as artificial intelligence, CNN, image processing and deep learning to detect plant diseases and improve crop yields.

II. LITERATURE REVIEW

The agricultural sector faces the challenge of detecting leaf diseases and managing their incidence to maintain crop quality. This problem has been a concern for a long time. In the past, various research studies have been conducted to develop multiple leaf disease detection systems through the implementation of computer vision and image processing methods.

In their conference paper, Abdur Nur Tusher et. al., [1], [2] is using the CNN model to identify diseases in plant leaves, specifically those of mango, guava, corn, peach and rice leaf. From this paper highlights that farmer experience significant losses in crop production due to various plant diseases, compounded by a lack of advanced technology to accurately detect and diagnose these diseases. To solve this issue, the authors proposed the use of the CNN algorithm, which achieved an accuracy level of 95.26% using around 9547 images, with 7213 images used for training the model and 2334 images used for testing the system.

Jagtap and Hambarde [3] presented a conference paper detailing the creation of a comprehensive image processing system that can automatically detect crop diseases by examining leaf spots. The system consists of four stages of image processing, which are image enhancement, segmentation, feature extraction, and classification. In order for the system to work accurately, it must be trained on a set of images that show different faults. It has the potential to be expanded to include more diseases and detect irregularities in other plant parts.

Aakanksha et. al., [4] emphasizes the importance of automated identification of leaf diseases in the agricultural field. They propose a system that uses Euclidean distance technique and K-means clustering technique to segment the leaf image into three regions – leaf area, disease region and background region. This allows the percentage of infection in the leaf to be calculated and categorized into different grades. The system has been designed with an intuitive Interface. The system is not difficult, it is computationally efficient, making it suitable for practical use in agriculture.

Padol et. al., [5] presents a method of identification and categorization of leaf diseases in grapevine plants using SVM classification. The process involves segmenting the affected area using K-means clustering, collecting data on leaf color and texture, and using classification methods to recognize a specific type of leaf disease. The results show that the system achieved 88.89% accuracy in detecting the investigated disease and could be a valuable tool for the agricultural sector.

Tulshan and Raul [6] published a research paper and primary objective was to improve existing machine learning methods for plant leaf disease identification. The proposed algorithm was tested on five specific diseases: Early Blight, Mosaic Virus, Down Mildew, White Fly, and Leaf Miner, which had not been studied before. The results showed that the proposed algorithm, which used the KN_N classifier, outperformed the current SVM classifier with an accuracy of 98.56% compared to the existing system's 97.6%.

Kien Trang and colleagues [7], utilized a dataset called Plant Village to detect plant diseases. They concentrated primarily on image processing techniques such as contrast enhancement and transfer learning, as well as neural net-works. Their goal was to rapidly and accurately identify diseases in plant leaves, in order to help farmers, reduce their substantial production losses. The authors relied heavily on neural networks and image processing tech-niques, and their presentation demonstrated that their model attained an accu-racy of 88.46 percent, which was higher than the accuracy of the pre trained model they used. They also explored the use of a mango dataset to detect diseases in mangoes.

Sukanya S. Gaikwada and colleagues [8] they published a paper for a conference where they utilized a CNN algorithm to identify fungal diseases of guava leaves. The document highlighted that farmer who grow guava commercially face significant losses due to these diseases, which discourage further production. The authors addressed this issue by utilizing CNN algorithms and employing ap-proximately 4,000 images as source data, achieving an accuracy of 75.9 per-cent.

The key aim of this study is to precisely recognize ailments affecting zucchini plants and suggest efficient remedies for them. Our proposed model uses images of defective leaves and offers a simple and efficient method for detecting different diseases, saving a significant amount of time. Our CNN model can provide real-time results.

III. Proposed Methodology

Processing of images is an extremely effective method for analyzing an image pixel by pixel. It can be extremely difficult, if not impossible, to identify diseases in affected leaves by relying only on the human eye. By utilizing image processing, individuals can easily and efficiently identify malfunctions with accuracy. The technology is straightforward for those with knowledge of the diseases of zucchini. The method uses the images of unhealthy and nutritious leaves for input and after the analysis is done, it automatically and successfully provides the expected result.

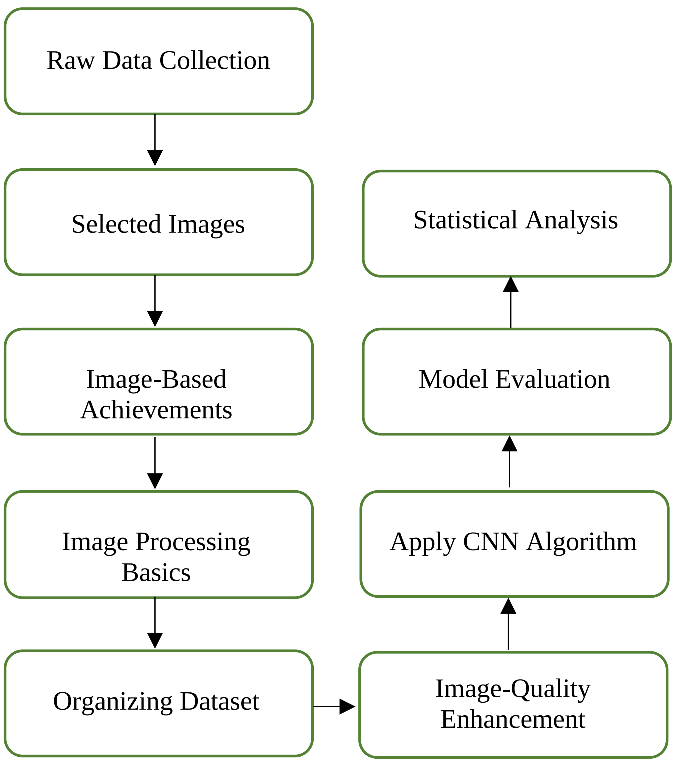

Fig.1. Proposed Methodology

***Image-Based Achievements*:**

To conduct research with accuracy and effectiveness, a fundamental requirement is having input data or a dataset. In our case, Since the image serves as our input data, resizing and enhancing the data is a crucial task at the beginning of the research. The accuracy of the research outcomes largely varies depending on the dataset's size. When the dataset is extremely large, the results will be much closer to the expected outcomes. At the beginning of our research, we collected approximately 2449 data. The majority of images coming from zucchini fields. Then we resized the collected data and saved it in different file formats like .gif, .bmp, .jpg etc. to get the desired results.

Image Processing Basics:

The collected images were initially divided into folders, and 2445 images were deemed appropriate for the model. The entire procedure was divided into two parts: testing and instruction. 80% of the data were used in the training phase, while the additional data was allocated for testing. To test the system, we chose alternaria_blight (40 images), angular_leaf_spot (123 imag-es), anthracnose (48 images), zucchini_healthy_flowers (280 images), and zucchini_luffa_healthy_leaf (229 images). During the training phase, we uti-lized alternaria_blight (88 images), angular_leaf_spot (176 images), anthrac-nose (123 images), zucchini_healthy_flowers (499 images), and zucchi-ni_luffa_healthy_leaf (839 images). Each data point was reshaped to a size of 256 by 256 pixels. Subsequently, we improved the image quality by reducing noise using image processing techniques to obtain the desired outcome. Fig-ure 2 depicts an example of the dataset used in our research.

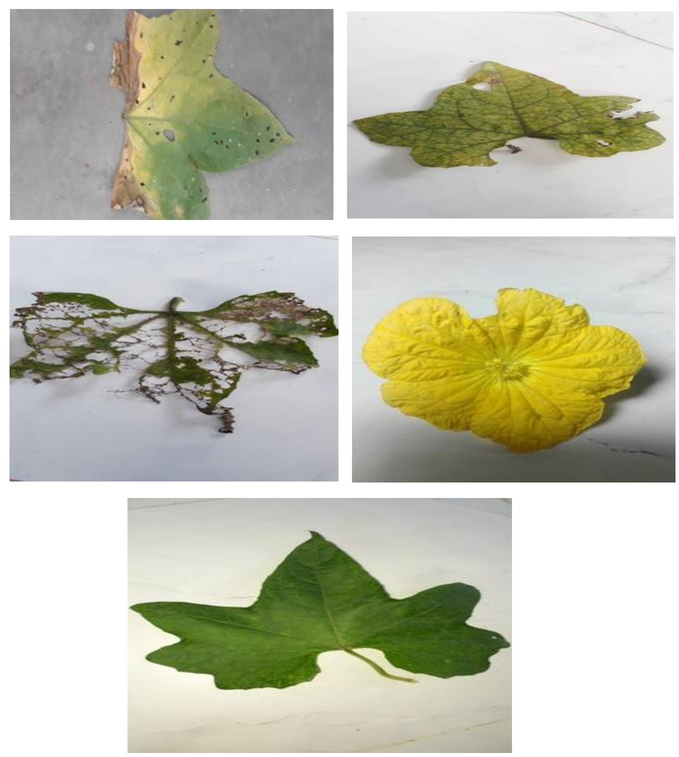

Fig.2. Collecting Dataset

Designing the System Architecture:

A single-level or multi-level CNN model can be used to build the system. A multi-level approach was used to achieve better results and a full description of the system is provided here. In the initial layer, the ReLu activation function is set to '1', The type of input is (254, 254, 3), size of the filter is '32x32 ', size of the kernel is 8x8, the padding is 'SAME' and the steps are (1x1).

$$ReLU(X) = MAX(0, X) \tag{1}$$

No any impressive distinction between first, and second layer. In the third layer, the ReLu activation function is set to '1', The type of input is (124, 124, 3), size of the filter is '64 x64', size of the kernel is 3x3, the padding is 'SAME', and the strides are (1x1). No any impressive distinction between third, fourth, and fifth layer. The activation function of SoftMAX is used to determine model's final result,

$$\sigma(Z) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \; for \; i = 1, \ldots, k \quad (2)$$

Our model's rate of learning is set at 0.001, and this value is utilized for optimizing ADAM.

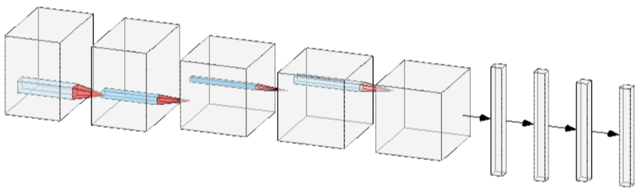

Fig.3. Proposed CNN

Optimizer and Learning Rate:
When we choose the optimization approach, it is clear that computer vision and deep learning results are significantly affected. Adam's work demonstrates the effectiveness and potential of optimization. The article describes how sub-sample data is evaluated by subfunctions, and several objective functions are combined to generate the sub-sample. The algorithm has demonstrated its efficiency and improvement in terms of gradient steps as reported in references [9], [10], [11]. Our model used a learning rate of 0.001 from the ADAM optimizer.

$$V_t = (1 - \beta_2) \sum_{i=1}^{t} \beta_2^{t-1} \cdot g_i^2 \quad (3)$$

Currently, neural networks and the Cross-Entropy algorithm have performed well for prediction and classification tasks, with the Cross-Entropy approach performing better than classification. However, due to cross-entropy error and weight changes, training may not always be successful. To solve this problem our technique introduces a new loss function, which is presented below:

$$L_i = \sum_j t_{i.j} \log(p_{i,j}) \quad (4)$$

Image Quality Enhancement:
The enhancement method involves dividing a single image into multiple partitions, and the specifications for this enhancement are outlined below: [12], [13], [14].

- To discover a simplified and contemporary image presentation model.
- To manipulate the image domain, including its shape, phase, and size, to create a large dataset.
- To rotate the image while ensuring that the maximum width and height ranges do not exceed 40 and 60 respectively. In addition, the height and zoom ranges should be limited to 1/5 and the width shift range should be limited to 1/155. Figure 4 provides more specific details regarding the appropriate range of data for this purpose.
- To control the steep angle's range with respect to the opposite direction of the clock, which results in cropping the image.
- Each image falls under the RGB category and is multiplied by a suitable numerical value to scale the data. The coefficients for each image range from 0-255. However, our proposed model cannot account for the wide range of values. So, our goal is to set a target range of values between 0 and 1, and we scale the values by dividing by 1/255 to reach that range.

Original *Rotation* *Width Shift* *Height Shift*

Fig.4. Image-Quality Enhancement

3.1 Train the Model
During the training process, multiple datasets with a batch size of roughly 32 are used. To ensure validation accuracy during processing, we mainly rely on reducing the learning rate. When the validation accuracy and learning rate reduction is supervised for 30 epochs, the workflow becomes manual.

3.2 A Layer-by-Layer Visualization:
The process involves visually representing a symbol through subtle changes in the section below contains a depiction of images and their visualization.

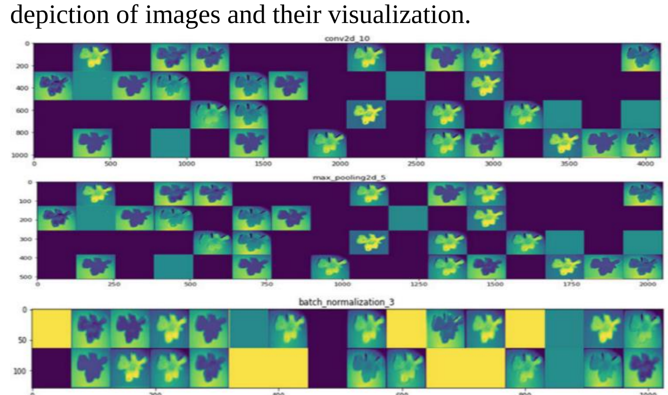

Fig.5. Layer Visualization

IV. Result & Discussion

The main objective of this section is to showcase the outcomes of various elements of the model, including training, testing, validation, and error identification. Therefore, this part of the article is of considerable importance compared to the other parts, and we have provided here a careful description of results of our recommended algorithm.

4.1 Statistical Analysis

At the outset, the model exhibited a training accuracy of 53.69% and a validation accuracy of 62.07%. However, the model's accuracy gradually increased with each subsequent run. After completing the 10th run, the accuracy of the model during training and validation increased significantly to 81.22% and 81.39%, respectively. As the model ran, its learning rate gradually decreased. After 29 successful runs, model validation increased to 86.22 percent and training accuracy to 88.30 percent. At this point the learning rate was improved.

4.2 Accuracy Graph

Accuracy graph was design to highlights four key factors: training loss, validation loss, training accuracy, and validation accuracy. We needed a clear and efficient method to express loss and precision metrics due to the size and presence of some noisy and imprecise data in our data set. The accuracy chart was an ideal tool for this purpose. The graph has been divided into two parts, upper and lower, to provide a comprehensive view of the model's performance. The upper part of the graph represents the loss function, while the lower part represents the accuracy function. The graph shows two functions, one for training (shown by the blue line) and one for validation (shown by the pink line). At the beginning of the graph, it can be seen that the validation loss is very high and the precision is very low. However, over time, the verification loss decreases and the accuracy increases. The training line chart follows the same pattern. After 10 epochs, all the lines stabilize and the loss goes down while the precision is high, and this pattern continues until the final epoch.

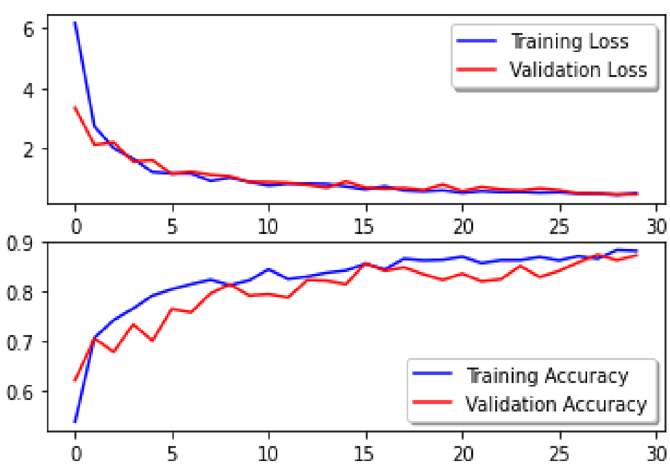

Fig.6. Accuracy and Loss Graph

4.3 Confusion Matrix

Error table, also acquainted as a confusion matrix, is an excellent tool for presenting a model's performance. It is made from both the true and false image data are assessed separately for each image. Table 1 illustrates the true and false images for each disease.

Table 1. Accurate and Error Data

Disease	True	False	Total
alternaria_blight	7	33	40
angular_leaf_spot	69	54	123
anthracnose	6	42	48
zucchini_healthy_flowers	277	3	280
zucchini_luffa_healthy_leaf	228	1	229

The confusion matrix displays the higher value along the diagonal positions, which are arranged in a 5x5 pattern. In addition, the diagonal positions are colored deeper (blue) than the remaining positions. A color that stays the same indicates that diagonal positions yield more accurate results. The confusion matrix can be seen in Figure 7, and the classification report can be found in Table 2.

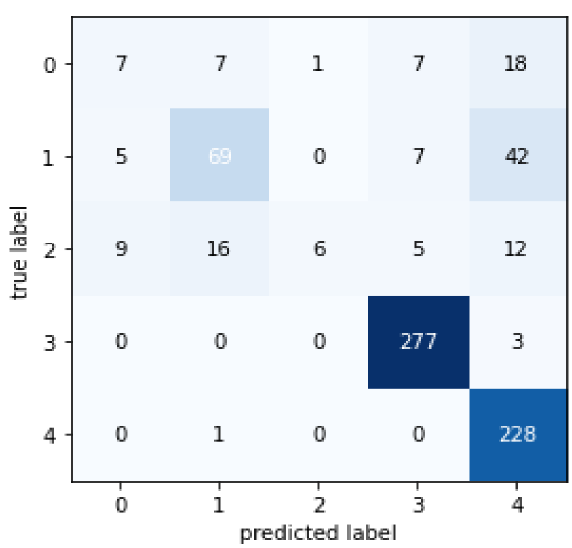

Fig.7. Confusion Matrix

Table 2. Classification Report

Disease	precision	recall	F1-score	support
alternaria_blight	0.3333	0.1750	0.2295	40
angular_leaf_spot	0.7419	0.5610	0.6389	123
anthracnose	0.8571	0.1250	0.2182	48
zucchini_healthy_flowers	0.9358	0.9893	0.9618	280
zucchini_luffa_healthy_leaf	0.7525	0.9956	0.8571	229
accuracy			0.8153	720
Macro avg	0.7241	0.5692	0.5811	720
Weighted avg	0.8057	0.8153	0.7831	720

4.4 Comparison of Result with other models

Our primary and fundamental goal was to analyze relevant findings and obtain useful insights that are directly or indirectly related to our proposed model. To achieve this, we compared our model with several other research models to better understand our proposed approach. The results of our comparison clearly showed that our proposed model provided more accurate results than the other models, which are shown in the table below,

Table 3. Comparison of the accuracy levels between various models

Work	Accuracy (%)
Gaikwada et al. [8]	75.9
Kanabur et al. [15]	79.50
Proposed model	88.30

V. CONCLUSION

Our agriculture has seen the inevitable damage that has led to a decline in fruit production. Farmers are unable to accurately and quickly detect plant leaf diseases, resulting in significant production and financial losses. To resolve this issue and accurately recognize plant infections, we developed an algorithm that can automatically detect diseases affecting plant leaves. A large proportion of the farmers in our country lack education and do not have access to cutting-edge technology. As a result, they rely on outdated and inefficient methods to identify leaf diseases, which can be both time-consuming and ineffective. Our technology allows farmers to detect crop diseases and increase their production levels. Our system uses a high-performance model using multiple CNNs to detect plant diseases. Our results are commendable, with an accuracy level of 88.30%. The main challenges of this work are to collection of data and the preparation of dataset in order to train the model perfectly. We need to go to field and discuss with farmer during data collection and it was very challenging for us as a full-time student. We overcome these challenges successfully and go acceptable results. In the future, we plan to develop an Android app that farmers can easily use. With this app, farmers will only need to take a photo of an infected leaf and the appropriate treatment for the disease will be provided by the app automatically.

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