Wheat Diseases Detection and Classification using Convolutional Neural Network (CNN)

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***Abstract*—Ever since the medieval era, the preponderance of our concentration has been concentrated upon agriculture, which is typically recognized to be one of the vital aspects of the economy in contemporary society. This focus on agriculture can be traced back to the advent of the industrial revolution. Wheat is still another type of grain that, in the same way as other types of harvests, satisfies the necessity for the essential nutrients that are required for our bodies to perform their functions correctly. On the other hand, the supply of this harvest is being limited by a variety of rather frequent ailments. This is making it difficult to meet demand. The vast majority of people who work in agriculture are illiterate, which hinders them from being able to take appropriate preventative measures whenever they are necessary to do so. As a direct consequence of this factor, there has been a reduction in the total amount of wheat that has been produced. It can be quite difficult to diagnose wheat illnesses in their early stages because there are so many various forms of environmental variables and other factors. This is because there are numerous distinct sorts of agricultural products, illiteracy of agricultural workers, and other factors. In the past, a variety of distinct models have been proposed as potential solutions for identifying illnesses in wheat harvests. This study demonstrates a two-dimensional CNN model that can identify and categorize diseases that affect wheat harvests. To identify significant aspects of the photos, the software employs models that have previously undergone training. The suggested method can then identify and categorize disease-affected wheat crops as distinct from healthy wheat crops by employing the major criteria described above. The reliability of the findings was assessed to be 98.84 percent after the collection of a total of 4800 images for this study. These images included eleven image classes of images depicting diseased crops and one image class of images depicting healthy crops. To offer the suggested model the capability to identify and classify diseases from a variety of angles, the photographs that help compensate for the collection were flipped at a variety of different perspectives. These findings provide evidence that CNN can be applied to increase the precision with which diseases in wheat crops are identified.**

Keywords*—*Wheat crop diseases; artificial intelligence; convolution neural networks; image processing; feature extraction

I. INTRODUCTION

In addition to terms of its civilization, but also terms of its cuisine, Bangladesh is a very diverse country. Bangladesh is primarily an agricultural nation, with 80% of its inhabitants dependent on the sector for their livelihood. Wheat is an excellent resource for a variety of minerals, including magnesium and selenium. Certain nutrients are essential for maintaining healthy health. Wheat leaves are particularly susceptible to damage from leaf rust. It has a high incidence of fungus illness, latent infection, and other diseases. Wheat diseases focus on leaves and can be diagnosed using Deep Learning and computer vision [1]. Wheat is the main carbohydrate source in most countries. Both wheat protein and wheat starch are readily absorbed by the body [2]. When wheat is combined with a tiny quantity of animal or legume protein, it becomes highly nutritious because it includes minerals, vitamins, and fats (lipids). One of the earliest plants that have been domesticated, wheat has long been a vital food source for many nations. The nutritional content of the wheat grain is very high. The wheat grain contains 14% protein, 14% starch, and other nutrients like fiber, vitamins, minerals, and high-quality amino acids. Wheat was previously essential to global nutrition due to its high nutritional value and excellent storage qualities. For the manufacturing of contemporary food, basic resources derived from wheat are crucial, such as wheat starch and wheat proteins. 20% of our daily caloric intake comes from bread and baked goods, which are essential to a healthy diet [3,4]. We find it fascinating that one of the oldest crops on the planet may employ modern processing techniques to offer a significant solution to fresh problems. In a variety of applications, the natural components of wheat increase quality and lower resource usage in the final product for the consumer. In the developing world, wheat accounts for more than 35% of the calories consumed from cereal, compared to 74% in the rich world and 41% globally. Almost 70% of wheat is utilized for food, whereas just 20% and 2% to 3% of it are used for industrial processing and animal feed, respectively. Between 2001/02 and 2016/17, the world's consumption of wheat increased by 25%. Two-thirds of the globe's wheat is utilized for food, 20% for animal feed, and 3% to 5% for seed, industry, and other uses. The economy grew rapidly over a shorter time as a result of the transportation of wheat. Wheat might be used to make a variety of novel foods, including muffins, cereal, and bread. The largest producer of wheat in the world, China has produced over 2.4 billion tonnes of wheat in the past 20 years or around 17% of global production. China consumed roughly 148.5 million metric tons of wheat in the marketing year 2021–2022. In that year, the United States consumed close to 31 million metric tons of wheat. Precision agriculture, often known as artificial intelligence systems, is assisting in enhancing the overall quality and accuracy of harvests. AI technology aids in the detection of pests, plant diseases, and undernutrition on farms. Artificial intelligence (AI) sensors can identify and target weeds before deciding which herbicide to use in the area. The condition of a plant can be assessed by looking at its leaves. This effort aims to create a system based on statistical analysis and blob detection that can detect and classify different diseases. Precision agriculture, often known as artificial intelligence (AI) technologies, is assisting in enhancing harvest quality and accuracy. AI technology helps identify plant illnesses, pests, inadequate plant nutrients, etc. Additionally, it enables farmers to keep an eye on the condition of the soil and crops. After rice, wheat is Bangladesh's second-most significant crop for producing staple foods. Since independence, it has become more significant as a crop for food and nutrition security. From about 0.115 million tons in 1971–1972 to 0.73 million tons in 2005–2006, wheat production climbed considerably. Several study articles discuss the various problems associated with diagnosing wheat crop diseases, such as the frequencies of disease groups, the accurateness, and the dataset; however, there are a lot of areas that may be improved. We have attempted to classify all of the different diseases that can harm wheat crops in this article. We have decided to focus on this system due to our desire to aid our farming sector by fixing these challenges so that the rate of production of wheat may be increased. This is why we have chosen to work on this system. As a result, we are concentrating on the challenge of binary image classification, in which a picture of a leaf can either be assigned to a wheat crop that is healthy or one that is infected with a disease. Here, we used 12 classes, 11 of which were for photographs of crops that were sick, and one class was for a healthy wheat crop. The 12 varieties of wheat crops that we have access to for our research are as follows: Barley yellow dwarf, Black chaff, Common root rot, Fusarium head blight, Leaf rust, Powdery mildew, Tan spot, Wheat loose smut, Wheat soil-borne mosaic, Wheat streak mosaic, Karnal bunt with Healthy wheat crops samples. Following is how the rest of the article is organized. Section II of this study's literature review provides details on the previous study. The materials and procedures utilized to assess our strategy are covered in Section III, along with a description of our system, picture pre-processing, the Keras sequential model, and the datasets that were employed. Section IV contains a report on the experimental findings and related discussion. The conclusions are presented in Section V. Limitations were discussed in Section VI, along with suggestions for further study. In this study, a disease detection system for wheat employing a dataset of 4800 pictures and CNN models is described. The Keras-sequential model served as the foundation for the CNN model.

II. Literature Review

With automated wheat disease diagnostic system is what the authors of article [5] set out to demonstrate and verify. They were able to circumvent the challenges and achieve an average output of 97.95percent by employing VGG-FCNVD16. They have made use of the 2017 Wheat Disease Database (WDD2017),. There were four distinct categories of illness. K-means clustering is proposed as an automatic and successful strategy in this study. Image segmentation was utilized by the author [6] to identify diseases on wheat leaves. They have discovered that the accuracy rates are more than 90 percent for three main disorders (powdery mildew, leaf rust, and stripe rust). In [7], author developed a Computer Vision Framework for the Identification and Classification of Wheat Diseases Using Jetson GPU Infrastructure demonstrating that manually identifying and interpreting wheat illnesses requires a significant amount of time and effort. They demonstrated that the VGG19 model was accurate in identifying wheat disease 99.38% of the time. Article [8] offered an ML-based system for automatically identifying brown- and yellow-rust wheat diseases. They provided an efficient ML-based framework for wheat disease detection and classification. The suggested scheme surpassed known ML algorithms with 99.8% accuracy. PRI and ARI at different development stages were computed as all conceivable three-band combinations across such susceptible wavelengths, and their ability to predict yellow rust disease severity was examined by the author [9]. In the article [10], the author used a better deep convolutional architecture to find and classify leaf and spike wheat diseases. The study comes up with a brand-new way to group wheat diseases. A new deep learning system has been made that can appropriately put 10 different wheat diseases into the right category. The paper [11] conducted a thorough assessment of recently published data and addressed WD prediction methods for recognizing and categorizing wheat illnesses. A machine learning-based early detection strategy based on hyperspectral images was reported in [12]. This research initially extracted the normalized difference texture indices (NDTIs) and vegetation indicators to discriminate between wheat with powdery mildew and healthy wheat (VIs). Study [13] used three common diseases and an insect of winter wheat as examples to investigate the applicability of channels' reflectance and many conventional vegetation indicators (VIs) of seven high-resolution satellite sensors. A method for diagnosing five fungal diseases that harm wheat shoots was provided by the author in this article [14]. The dataset's 2414 images of wheat fungal infections were utilized (WFD2020). They discovered a 94.2% accuracy rate. In [15], the author advocated Qt-based applications. Using image processing, the identification rate is 96.2% and the accuracy is 92.3%, approximately similar to human eyesight. This approach identifies, diagnoses, and classifies crop illnesses. It's a field-inspecting agricultural robot. According to the paper, using certain wavelength ranges, reflectance measurements may be employed for disease diagnosis and discrimination in the early stages of infection. This method has been used to identify wheat powdery mildew. Article [16] describes PCR methods for detecting wheat illnesses and DNA regions for fungal identification. PCR-based approaches for detecting wheat pathogens need additional research. For diagnosing wheat leaf illnesses and their severity, Paper[17] proposed an algorithm based on Elliptical-Maximum Margin Criterion (E-

MMC) metric learning. The highest identification accuracy of the proposed method is 94.16%. Paper [18], presented an AI-based algorithm (ANN). After analyzing 300 test photos of wheat leaves, the proposed system successfully detected illness in 97% of instances. Research [19] examined the viability of employing the newly announced Sentinel-2 Multispectral Instrument (MSI) to discern between the several phases of yellow rust infection (healthy, mild, and severe) in winter wheat. In the article [20], Continuous wavelet analysis (CWA) was compared to traditional spectral features to diagnose yellow rust on leaves. Both phases exhibited perfect R2 and RMSE of 0.81 and 0.110. In the paper [21], high, medium, and low LAI values were utilized to identify wheat leaf rust in the canopy. Four machine learning (ML) techniques were developed to measure disease severity (DS) at the canopy scale: support vector regression, boosted regression trees, random forests regression, and Gaussian process regression. Author [22] developed a kernel discriminant technique (SVIKDA) for detecting yellow rust, aphid, and powdery mildew in winter wheat at the leaf and canopy level. The author of this study [23] presented a simple convolutional neural network (CNN) model named SimpleNet for detecting wheat illnesses such as glume blotch and scab in genuine field photos [24]. This research assessed the spectro-optical, photochemical reflectance index's (PRI) precision for assessing the yellow rust disease index (DI) in wheat (Triticum aestivum L.) and its utility in detecting the sickness using hyperspectral pictures. The precision of the earlier study's use of a different model is unclear. Additionally, although it is not ideal, they have used fewer datasets to train the CNN model and other models. The CNN model is currently essential in identifying plant diseases. For greater accuracy, image pre-processing is also desirable. Therefore, a CNN model based on a Keras-sequential model is suggested in this study paper to more reliably identify and categorize wheat illnesses. The following are the article's main factors that contribute:

- The far more recent identification and classification findings from the massive dataset utilizing the Keras-sequential model are given. Compared to previous CNN models, the testing model demonstrated more accuracy.
- During the model's training and testing, samples from 12 diseases that afflicted the class were taken, demonstrating how the CNN model can be useful in identifying wheat diseases.
- To allow the CNN model to recognize and categorize diseases from various angles, images were rotated at various angles.
- A total of 4800 recorded photos were used to create a dataset, demonstrating how using more datasets can improve the training accuracy of the CNN model.

III. Methodology and Design

In this day and age of advanced technology, the early diagnosis and identification of plant diseases are of the utmost importance. If diseases can be diagnosed in their early stages, then it will be much simpler to administer the appropriate treatment. More importantly, the production of agricultural goods would not be affected in any way by any diseases. Farmers and agro-technologists would benefit more from the disease detection system if it were possible to transform it from a manual system to a machine system. The objective of this study is to create a machine-learning tool that employs a CNN model to identify and diagnose wheat illnesses early on. The proposed classification scheme was developed to identify and classify various diseases that can affect wheat. The model includes the following information:

- The various layers and the layering scheme of the model.
- The number of components for each output data dimension for every tier.
- The number of variables (strength training) for each tier.
- A list of all the design variables.

The following modules are included in the system that is being proposed: dataset collecting, image pre-processing, feature extraction, identification, and classification. These modules are currently being redesigned to be the flowchart that is seen below in Fig. 1:

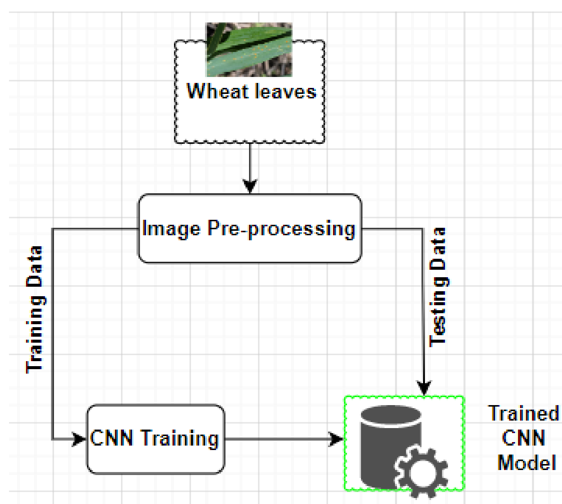

Fig. 1. Overview of the Proposed System.

The proposed system used the following algorithm:

1) Image pre-processing of the collected dataset.
2) Import the appropriate modules.
3) Load photos from the dataset.
4) Convert images to binary images and save them in a pixel array.
5) Image noise reduction
6) Define the input layer and build the model.
7) Encoded the layer as needed.
8) Train the model

TABLE I. NUMBER OF IMAGES TAKEN PER CLASS

Class Name	Number of Images
Barley yellow dwarf	400
Black chaff	400
Common root rot	400
Fusarium head blight	400
Healthy wheat	400
Leaf rust	400
Powdery mildew	400
Tan spot	400
Wheat loose smut	400
Wheat soil-borne mosaic	400
Wheat streak mosaic	400
Karnal bunt	400

9) Determine training accuracy
10) Test the model with various inputs
11) Obtain the model's testing accuracy.

The dataset utilized in the development of this suggested system was compiled using data obtained from a variety of online sources. Kaggle provided a dataset, while Github provided additional datasets, both of which were retrieved. After that, the two datasets were combined, and the result was a dataset consisting of 4,800 photos. This dataset included photographs of various areas of wheat leaves and roots that were impacted by the illness, as well as images of wheat leaves that were disease-free. These are shown in Table I below:

Pre-processing is a term used to describe activities with the lowest quality photographs. both the input and the output are intensity images at this level of abstraction. These famous pictures are of the same type as the original data that the sensor originally acquired, with a matrix of image function values typically used to depict an intensity image. (brightness). Pre-processing is intended to enhance the image. data that reduces unintentional distortions or enhances certain aspects of the image geometric changes of pictures (such as rotation, scaling, and translation) are categorized as pre-processing but are crucial for subsequent processing since similar approaches are employed here. Feature extraction tries to reduce the number of features in a dataset by extracting new ones from existing ones. This new, smaller set of features should then describe the bulk of the data included in the initial shipment of characteristics. In the object-based approach used by Feature Extraction to classify images, an object (also known as a segment) is a group of pixels with common spectral, spatial, and/or textural features. Using standard pixel-based classification approaches, the spectral data contained in each pixel is used to classify photographs. A deep learning model called CNN is used to handle data with a grid pattern, such as photographs. because of the high degree of precision it has, CNNs are utilized for picture categorization and recognition. Yann LeCun, a computer scientist, first proposed it in the late 1990s after becoming intrigued by how humans recognize objects visually. Utilizing CNNs is advantageous since they can create an internal representation of a two-dimensional image. This enables the model to pick up on location and size in different types of data structures, which is crucial when working with photos. Each plant class's diseases are taught to the CNN classifiers. The classifier, which has been trained to categorize various diseases in that plant, is called up using Level 2 results. A pre-trained CNN model called VGG16 is employed for picture classification. It has been fine-tuned to easily suit picture classification datasets after being trained on a sizable and diverse dataset. Convolutional Neural Networks have three different kinds of layers: Hidden Convolutional Layer connects each input neuron. CNN's input neurons are partially connected to the buried layer. Pooling shrinks the map. CNN has activation and pooling layers. Last is Fully Connected Tiers. The last pooling or convolutional layer output is flattened and applied. Fig. 2 shows the image classification process using CNN. The model summary for the proposed system is given in Table II.

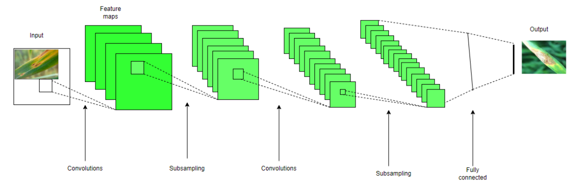

Fig. 2. Image Classification Process using CNN.

TABLE II. THE MODEL SUMMARY FOR THE PROPOSED SYSTEM

Layer (type)	Output Shape	Param #
sequential (Sequential)	(32, 256, 256, 3)	0
conv2d (Conv2D)	(32, 254, 254, 32)	896
maxpooling2d (MaxPooling2D)	(32, 127, 127, 32)	0
conv2d1 (Conv2D)	(32, 125, 125, 64)	18496
maxpooling2d1 (Max Pooling 2D)	(32, 62, 62, 64)	0
conv2d2 (Conv2D)	(32, 60, 60, 64)	36928
maxpooling2d2 (Max Pooling 2D)	(32, 30, 30, 64)	0
conv2d3 (Conv2D)	(32, 28, 28, 64)	36928
maxpooling2d3 (Max Pooling 2D)	(32, 14, 14, 64)	0
conv2d4 (Conv2D)	(32, 12, 12, 64)	36928
maxpooling2d4 (Max Pooling 2D)	(32, 6, 6, 64)	0
conv2d5 (Conv2D)	(32, 4, 4, 64)	36928
maxpooling2d5 (Max Pooling 2D)	(32, 2, 2, 64)	0
flatten (Flatten)	(32, 256)	0
dense (Dense)	(32, 64)	16448
dense1 (Dense)	(32, 12)	780

A variety of APIs is available from Keras-sequential that can be used to define neural networks. Sequential API, Functional API, and Model Sub-classing API are all different names for APIs. Layer by layer can be built up a model using a sequential API. One input layer, one hidden layer, and one output layer make up the Keras-sequential model. Two neurons are joined to form the hidden layer.

IV. EXPERIMENTAL SETUP AND RESULT ANALYSIS

The previous section showed how to use a CNN model to classify and identify wheat illnesses. In this section, the theoretical process that was described in our previous section will be converted to a computational function so that using the digital device for image processing the diseases of wheat can be identified and classified. This experimental phase will be deployed using algorithm construction, deploying the algorithm via computational machine and output evaluation. We will be able to take the necessary measures for additional research and assess a good identical system that will work more accurately and perfectly based on the results of the performance evaluation that we conduct. All of the experimental data, as well as the experimental design and the analysis of the system, are given throughout this section. There are many different

TABLE III. TRAINING AND VALIDATION ACCURACY WITH LOSS

Epoch	Total Steps Per Epoch	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
1	30	0.9555	0.1023	0.9062	0.3057
50	30	0.9778	0.0628	0.9479	0.1309
100	30	0.9862	0.0403	0.9479	0.1245
150	30	0.9873	0.0333	0.9792	0.1049
200	30	0.9882	0.0118	0.9797	0.0203
250	30	0.9901	0.0099	0.9812	0.0188
300	30	0.9979	0.0021	0.9861	0.0139
350	30	1.0000	0.0000	0.9933	0.0067
400	30	0.9912	0.0088	0.9891	0.0102
450	30	0.9812	0.0188	0.9803	0.0197
500	30	0.9801	0.0199	0.9791	0.0209

forms of accuracy in the methods used to evaluate systems, and they are all covered here in that they can be of great use in one's subsequent academic endeavors. This research project was performed in the rainy season but this is not the production season of wheat. For this reason, the dataset for this research project was collected from a variety of online resources. Then, 4800 photos of wheat crops with 11 diseases and healthy wheat crop images were mixed. 3840 photos were utilized for preparing the model, 480 for validation, and 480 for testing the system. 32-batches were used. The following graphic in Fig. 3 shows training, validating, and testing dataset ratios:

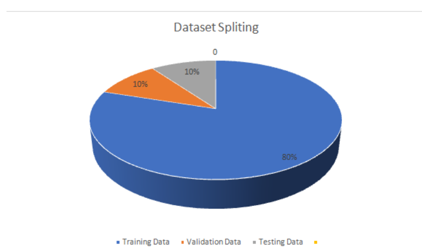

Fig. 3. Dataset Splitting Ratio for the Proposed System.

After pre-processing all the images, the feature vector was created using feature extraction. Then this feature vector was used for training the CNN model. A total number of 500 epochs were moved to the dataset for training and validation testing. There was a total of 30 steps per epoch. Using these feature vectors the model was trained and a validation test was performed for checking the validity of the dataset (Fig. 4to 7). The measurement shows in Table III.

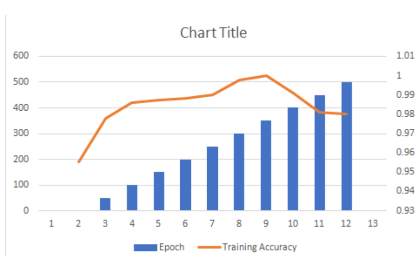

Fig. 4. Comparison between Epoch vs Training Accuracy.

Fig. 5. Comparison between Epoch vs Training Loss.

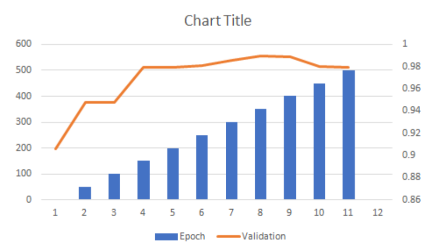

Fig. 6. Comparison between Epoch vs Validation Accuracy.

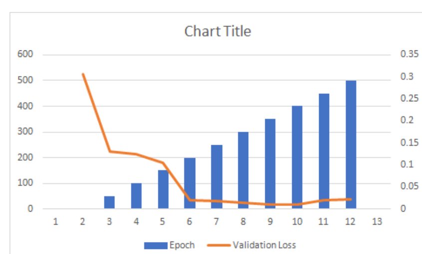

Fig. 7. Comparison between Epoch vs Validation Loss.

After completing training and validation testing on the dataset using the proposed model these scores were stored for prediction and testing of the system. Following the testing had been completed on the dataset, the F-1 score and recall value were then determined. After performing all the processes it was found that the training accuracy was 100%, the validation accuracy is 99.33%, and the testing accuracy is 98.84%. A comparison between training and validation accuracy is shown below in Fig. 8:

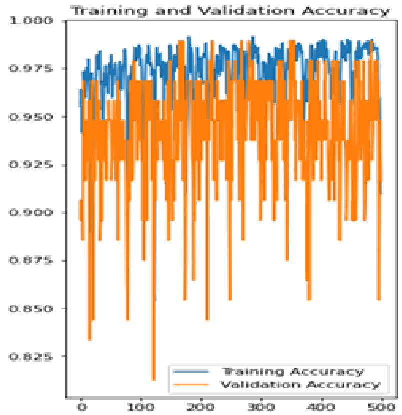

Fig. 8. Training vs. Validation Accuracy.

Comparison of training and validation loss is given below in Fig. 9:

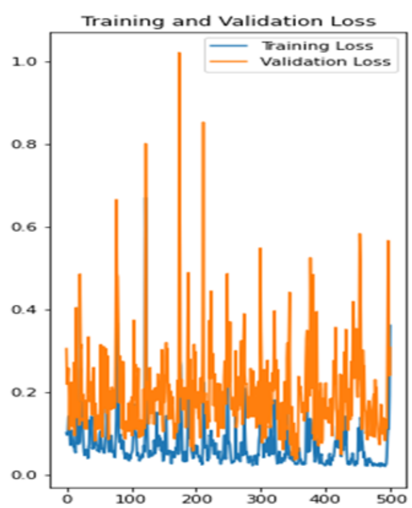

Fig. 9. Comparison of Training and Validation Loss.

Finally, some samples were tested for checking the confidence and testing accuracy of this proposed system. Average confidence for identifying and classifying varied from 93%-100%. The average F-1 score for all classes was 99%. The average recall value and precision value were 0.99 and 0.99. The following Fig. 10 is showing these prediction results based on the proposed system:

TABLE IV. Recall Value, F1-Score, Precision Value per Class

Class	Recall	F-1 Score	Precision
0	1.0	0.99	0.98
1	1.0	1.0	0.99
2	0.99	1.0	1.0
3	0.98	1.0	0.99
4	1.0	1.0	1.0
5	0.97	0.97	1.0
6	1.0	0.99	1.0
7	1.0	0.98	1.0
8	0.99	1.0	0.97
9	0.97	0.98	0.97
10	1.0	1.0	1.0
11	0.98	0.99	0.98
Avarage	0.99	0.99	0.99

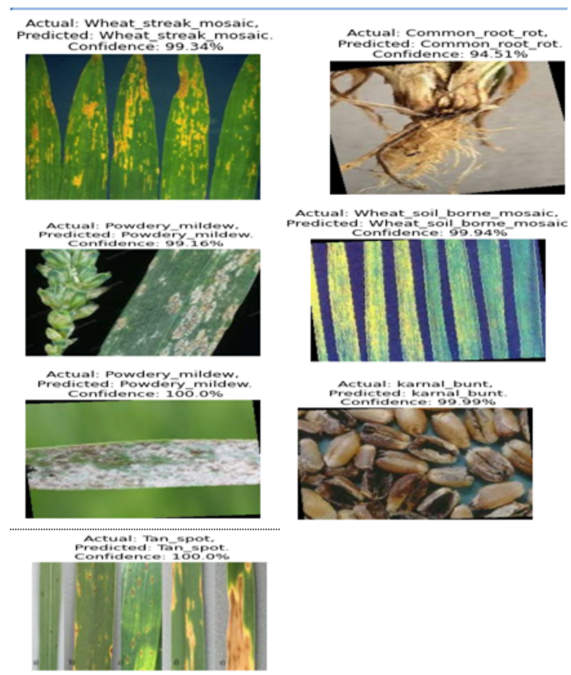

Fig. 10. Prediction Result based on Samples.

Following the Recall value, the F-1 Score, and Precision values were obtained after calculating the confusion matrix shown in Table IV.

When compared to the accuracy of the other proposed systems, the accuracy of this system is adequate to be considered satisfactory. Even though the accuracy of the research [24] was measured at 99.8 percent, the authors chose to concentrate their attention on two disease categories, namely, brown and yellow rust disease. The following Table V provides a comparison of the following:

V. Conclusion

This study presents a CNN-based paradigm for wheat illnesses. We gathered high-quality images of wheat leaf diseases such as barley yellow dwarf, black chaff, common root rot, fusarium head blight, leaf rust, powdery mildew, tan spot, wheat loose smut, wheat soil-borne mosaic, wheat streak mosaic, and karnal bunt from Bangladeshi agricultural websites to evaluate the proposed system. We also gathered samples

TABLE V. COMPARISON BETWEEN THE PROPOSED METHOD AND OTHER PROPOSED METHODS BY OTHER AUTHORS

Model Proposed	Number Of Classes	Dataset	Accuracy
K-Mean Clustering [25]	Three classes including powdery mildew, leaf rust, stripe rust		90%
MTMF + NDVI	Two classes including powdery mildew and leaf rust	Onfield Experiment	88.6%
Machine Learning [26]	Two classes brown- and yellow-rusted disease	1050 samples	99.8%
Photo chemical Reflectance Index + Anthocyanin Reflectance Index [27]	One class including Yellow rust	Onfield Experiment	93.2%
Deep Convolutional neural network [28]	One class including Yellow rust	Onfield Research	85%
Proposed System	Twelve classes include Barley yellow dwarf, Black chaff, Common root rot, Fusarium head blight, Healthy wheat, Leaf rust, Powdery mildew, Tan spot, Wheat loose smut, Wheat soil-borne mosaic, Wheat streak mosaic, and karnal bunt	4800 samples	98.84%

of healthy wheat crops. Techniques such as segmentation and resizing are utilized so that the pre-processing can be precise. The use of distinct feature descriptors allows for the extraction and combination of a wide variety of features, including shape, color, and texture features. Following the completion of the comparative study, the proposed CNN model was found to have higher levels of accuracy. Accuracy, precision, recall, and F1-score were used to evaluate the suggested methodology on unseen data. A comparison between our method and the other methods already in use is carried out as part of the ongoing evaluation process. As a consequence of this, it has been determined that our approach is superior to other methods in terms of the accuracy with which it recognizes and categorizes wheat diseases.

VI. FUTURE WORK

Based on the experiments, the approach has the potential to help farmers and agri-technologists measure wheat disease. As a consequence of this, they would be able to implement necessary precautions for the control and prevention of disease. A software program will also be investigated in greater depth to assist farmers in discovering wheat diseases as quickly as is practically possible. This will help agricultural workers quickly identify wheat illnesses. In addition, the suggested system will be capable to manage additional disease classes, which will allow it to manage a greater number of illness types. Farmers would benefit more from this approach if there were a greater variety of crop diseases included in it. In addition, it was observed that adopting multidimensional CNN could provide more accuracy for detecting disease. Multidimensional CNN can recognize output from a variety of inputs. Furthermore, it would be preferable if such a model could be created to acquire numerous photos and diagnose disease in each of them at the same time.

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