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Detecting Three Different Diseases of Plants by Using CNN Model and Image Processing

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Abstract: - Agricultural output is critical to Pakistan's economy, and plant disease detection is critical for both the environment and human health. This work presents a CNN-based approach for detecting plant diseases, which is evaluated on sample photos to assess the temporal complexity and infected area. The model was given three disease cases: corn common rust, tomato bacterial spot, and potato early blight. Using the CNN algorithm, the CNN model attained an accuracy of 95.55% for tomato bacterial spot, 96.72% for Corn Common Rust, and 97.63% for Potato Early Blight. This method may aid in the diagnosis and treatment of plant diseases.

Keywords: CNN (Convolutional Neural Network), Plant Disease, Tomato Bacterial Spot, Deep learning

I. INTRODUCTION

Early diagnosis of plant diseases is critical for agricultural output efficiency and economic development. agricultural operations sometimes entail the use of costly pesticides and laborious disease diagnosis, both of which may harm plants and the environment [1]. Advancements in technology have enabled the automated diagnosis of plant diseases from raw photos. Using image processing tools, this research studies plant illnesses and insect infestations that influence plant leaves. CNN are frequently employed in image processing, and studies have shown that they are good in detecting and classifying leaf properties [2]. The approach is divided into three stages: data collection, pre- processing, and picture categorization. The Plant village dataset was employed in the research, which comprises plant types such as apple, maize, grapes, potato, sugarcane, and tomato. Overweight is a treatable medical disease caused by an excess of calorie consumption, which may lead to diabetes, cholesterol, and heart attacks. These challenges are often addressed using computer approaches [3]. This work used transfer learning algorithms like ResNet50 to recognize food categories, check labels, and provide nutrients to construct a system to detect and diagnose food allergies using food photos [4]. The system was taught to attain 95% accuracy and the greatest mean average accuracy. Using a transform learning strategy, the researchers also investigated CNN to distinguish three types of cotton leaf disease [5]. The feature extractor-trained Inception-VGG-16 model had the greatest mean average accuracy and differentiated between healthy and unhealthy leaf types. The use of the DL technique to properly diagnose cotton leaf disease may aid in preventing the negative impacts of dietary management difficulties. The trained model detected and classified the four-leaf kinds on pictures of cotton leaves, with an overall CNN accuracy of 98% [6]. This paper's major issue is as follows. Even for agricultural

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professionals, predicting plant diseases may be a difficult process, and if you are new to utilizing field guides, it can be hard to figure out where to even begin looking among the hundreds of pages. Plant type, disease kind, leaf form, and leaf color may all be classed differently. We can anticipate plant disease by utilizing CNN.

This paper's contribution is as follows. 1) To identify the bird species by examining a photograph. Some professionals, such as ornithologists, were unable to accurately identify bird species based on images. 2) Although domain specialists can do bird categorization manually, with increasing volumes of data, this becomes a laborious and time-consuming procedure. As a result of this approach, we can properly and quickly identify the species of birds.

II. LITERATURE REVIEW

The global hunger rate has been rising since 2014, with about 690 million people being hungry. More than 90% of the world's plant diseases and pests are responsible for more than half of agricultural production losses [7]. Accurately detecting and diagnosing plant diseases is critical, since erroneous identification may result in large losses in the agriculture industry [8]. The goal of this study is to create a novel method for modeling plant disease diagnosis utilizing massive convolution networks based on leaf image categorization. The growing global population necessitates the development of technologies for identifying and controlling plant diseases, which are critical for enhancing food output and lowering pesticide usage [9]. Manual exams by farmers or professionals are used in traditional procedures, which may be time-consuming and expensive. The advancement of computer vision models, on the other hand, has resulted in an exponential increase in automated methods for identifying plant illnesses using observable signs on leaves [10]. Deep learning models have been used to overcome the problem of defining symptoms for computer identification. These models obtain varying degrees of accuracy on laboratory/field photos, but suffer when evaluated on diverse data. In this work, a CNN model was constructed that obtained more than 93% accuracy for 15 distinct plant kinds [11]. The scale of the filters and outputs vary as the input moves through the network, allowing for training and detection of comparable characteristics with varied scaling [12]. Convolution filters used to whole pictures for training data make CNNs insensitive to feature modifications such as rotation and translation. Food security is jeopardized when agricultural productivity declines, notably in Pakistan. A common pest, the whitefly, may infect cotton fields and surrounding crops, limiting plant development by up to 50% [13]. This presents a serious danger to both domestic and international food crops. Advances in technology, such as spatial drones and automated disease detection algorithms, have increased the automation of field inspection. Identifying plant diseases, on the other hand, remains time-consuming and labor-intensive [14]. Using Convolutional Neural Network (ConvNet/CNN), this study provides an automated, precise, and cost-effective technique for diagnosing plant illnesses. The program makes use of a dataset of afflicted and healthy plants gathered from different sources and by hand. When tested in the field, the model obtains good accuracy [15]. This approach is used to analyze sick leaf symptoms using Kaggle datasets of potato and tomato leaves. Crop loss due to illnesses has a huge impact on the Indian economy and concerns food supply [16]. A real-time technique for detecting maize leaf disease based on a deep convolutional neural network is given. The model is designed for real-time inference and may be operated on standalone smart devices such as the Raspberry Pi, smartphones, and drones. This strategy has the potential to reduce crop losses and increase global food security [17]. Over time, deep learning architectures have developed and been used to picture identification and classification in a variety of agricultural applications. For example, with a CA of 97.3%, leaf classification was done using author-modified CNN and Random Forest classifier [18]. Plant identification, crop/weed distinction, and disease detection have all benefited from DL methods. This study focuses on the application of DL methods to these tasks, emphasizing the need for additional visualization tools and research gaps in order to get a better perspective of plant disease symptoms [19]. The work is divided into parts on well-known and customized DL architectures, visualization mapping approaches, Hyperspectral Imaging with DL models, and future suggestions for developments in plant disease visualization, detection, and classification [20].

A computerized approach for identifying and diagnosing plant diseases might be useful for agronomists and farmers in places with limited infrastructure. Deep learning, a novel branch of artificial intelligence, has transformed industries such as image identification, speech recognition, and machine translation and interpretation [21]. Convolutional Neural Networks (CNNs) are a useful tool for modeling complicated processes and pattern detection in data-intensive applications. This research offers an effective method for identifying numerous diseases in a variety of plant kinds, including apple, maize, grapes, potato, sugarcane, and tomato. The system was trained using 35,000 photos of healthy and diseased plant leaves, and it achieved an accuracy rate of 96.5% and up to 100% in identifying and distinguishing the plant variety and the kind of disease the plant was afflicted [22]. Deep learning methods have just recently been used into agriculture, notably in the area of plant disease diagnostics. The device can identify several forms of plant illnesses and is controlled by a suitable, simple, and user-friendly smartphone application. This research presents a technique for detecting and diagnosing illnesses in tomato leaves by using LeNet, a variant of the convolutional neural network model. The goal is to attain an average accuracy of 94-95%, demonstrating the neural network approach's viability even under adverse situations. The study's goal is to solve the problem of early diagnosis of plant diseases, which reduce agricultural output and net profit for farmers.

III. MATERIAL AND METHOD

This section contains the methodology of the study

A. Proposed System

The CNN is a multilayer perceptron developed to recognize two-dimensional image data. There are four layers in it: an input layer, a convolution layer, a sample layer, and an output layer. CNN is not restricted to the Boltzmann machine, and it does not need each neuron to see the whole picture. Each neuron parameter is set to the same value, which allows for weight sharing. To extract features and decrease training parameters, the core era of CNN focuses on local receptive field, weight sharing, and subsampling by time or space. To save complexity, the CNN algorithm skips explicit feature extraction and instead learns intuitively from training data. It has significant advantages in image processing.

B. Architecture Of CNN

Convolutional Neural Networks (CNNs) are Deep Learning techniques that give relevance to different parts of an image while needing less pre-processing than other categorization methods. ConvNets may learn filters and capture spatial and temporal correlations with adequate training. ConvNets perform better on picture datasets with fewer parameters and reusability of weights, maintaining crucial aspects for reliable predictions. Figure 1 depicts the CNN architecture.

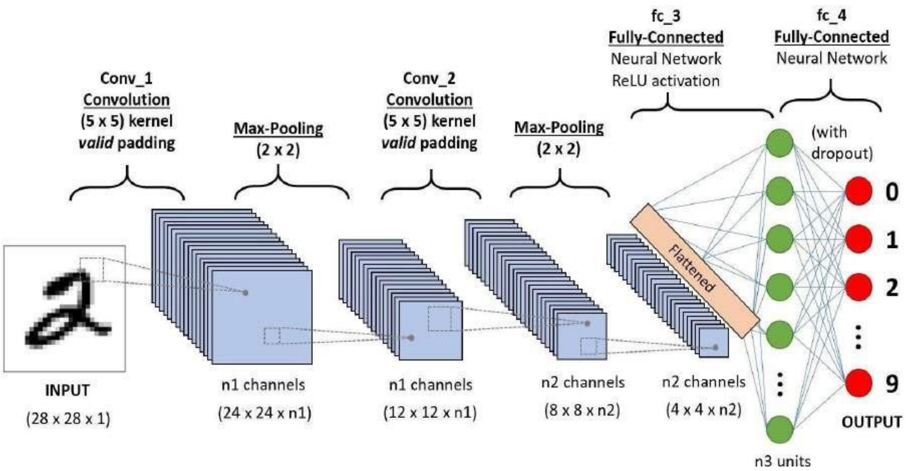

Figure 1. Architecture of CNN

C. Dataset Description

Create a folder in which you will place the photographs that you need. For example, if you had a folder containing Corn photographs and another containing Tomato images, you would combine the two files into a single folder and call it datasets. If you access the datasets folder, you should notice a folder called corn and tomato. First, provide the path to the folder containing both of your dataset files, as well as the picture size. We used 900 photos of our plants from three distinct categories for this thesis. This dataset has been tagged and grouped into three separate folders, with each folder containing 300 photos. Each picture includes a visible leaf section, binary characteristics, and bounding boxes that enclose the leaves. Figure 2 depicts the dataset.

Three types of plant disease discuss in this paper.

- Corn Common Rust
- Potato Early Blight

- Tomato Bacterial Spot

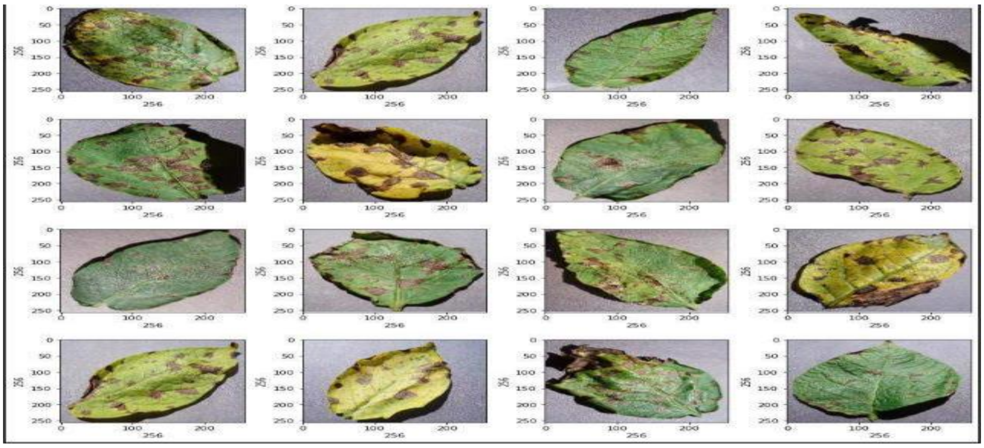

Figure 2. Dataset

D. Corn Common Rust

Figure 3 depicts prevalent rust corn is the most prevalent corn rust infection in the US, generating little productivity losses in Ohio field corn. However, it may cause major damage in the state's southern half when weather conditions promote the development and spread of the rust fungus. Sweet corn is especially susceptible, with output losses happening during cool summers when leaves get diseased prior to grain load. Dark, reddish-brown pustules develop throughout corn leaves, and symptoms generally occur after tasseling. These pustules are oval to elongate in shape, less than a quarter-inch long, and may appear in bands over the surface as the leaf expands in size.

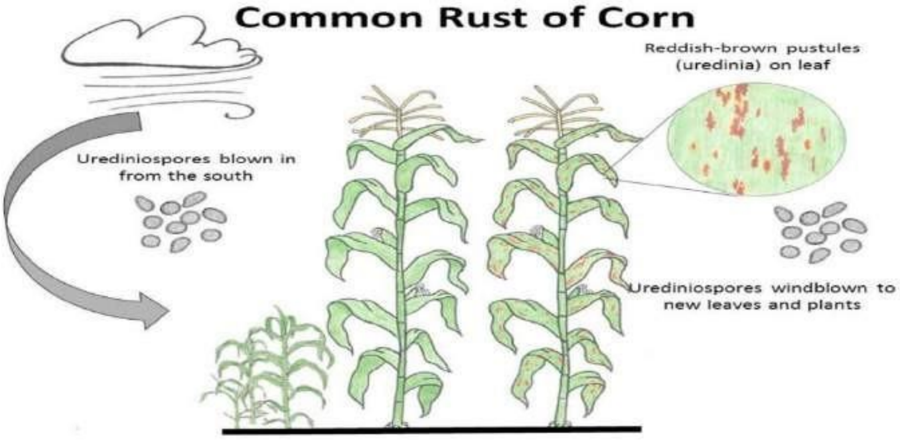

Figure 3. Common rust of Corm

E. Potato Early Blight

Figure 4 depicts potato early blight, an endemic disease. If not addressed, it might result in yield losses. Infected leaf tissue decreases the crop's photosynthetic capacity, which affects output on its own, but it also erodes the crop's ability to bulk up its tubers, resulting in worse grade and market quality. The fungus that causes early blight thrives mostly on crop leftovers, but also in soil, tubers, and other potato-related plants. Airborne spores and leaf wounds transmit the illness, which generally begins around blooming time or under most circumstances - either from weather or dew. Once infected, however, Early blight loves warm, dry environments. Early blight is often more severe when plants are subjected to mid-summer stressors (e.g., nutritional deficits or disease infection) and during alternating wet (dew) and dry periods.

Figure 4. Potato Early Blight

F. Tomato Bacterial Spot

Figure 5 depicts Tomato Bacterial Spot, often known as tomato bacterial spot, is a potentially deadly disease that, in extreme instances, may result in unmarketable fruit and even plant death. In Wisconsin, the illness is often a problem. Bacterial spot may infect all portions of a tomato plant above ground, including the leaves, stems, and fruit. Bacterial spot occurs on leaves as tiny (less than 18 inch) circular spots that are occasionally water-soaked (i.e., wet-looking). Spots may seem yellow-green at first, then deepen to brownish-red as they mature. Spots on green fruit are often tiny, elevated, and blister-like, with a yellowish halo. As the fruit matures, the spots increase (to a maximum size of 14 inch) and become dark, scabby, and scratchy. Mature patches might be elevated or depressed with elevated margins. Bacterial spot symptoms are readily mistaken with those of a different tomato disease known as bacterial speck.

Figure 5. Tomato Bacterial Spot

The research focuses on three forms of plant diseases: corn common rust, potato early blight, and tomato bacterial spot. To identify these disorders, 300 samples of varied sizes are utilized, with Table 1 detailing the dataset. The study's goal is to get a better knowledge of these illnesses and their influence on agriculture.

Table 1. Dataset Details

S No.	**Plant Disease Name**	**Samples Count**	**Dimensions of the Image**
1.	Corn Common Rust	300	Any Size
2.	Potato Early Blight	300	Any Size
3.	Tomato Bacterial Spot	300	Any Size

IV. RESULT AND DISCUSSION

With a test size of 0.2, the three planned illness datasets will be separated into testing and training data. The dataset will be adjusted using pixel values ranging from 0 to 255. Layers such as Conv_2d, max_pooling2d, flatten, and Dense will be used to build a network architecture. The model will be trained during 18 epochs with 128 batches. Because the model has already achieved high accuracy, it does not need to be run again. Viewing the training and validation accuracy throughout each epoch allows you to track the model's performance. Figure 6 depicts the model's accuracy and loss for the training history, enabling assessment of the model's correctness. The model's performance will be assessed by charting the model's accuracy and loss throughout the training history.

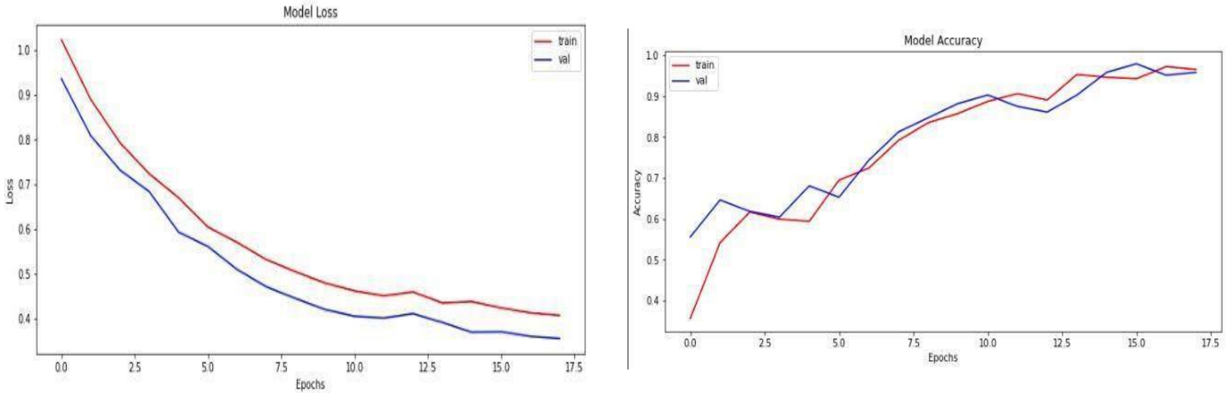

Figure 6. Model loss and Accuracy Plot

A. Discussion

At each epoch, the model is fitted and evaluated using validation and training data from the dataset. The model is trained during 18 epochs with a batch size of 128. Because the model has already reached excellent accuracy, more epochs are not required. During each epoch, the training and validation accuracy are measured. The results of all three-plan disease accuracy utilizing the CNN algorithm are shown in Table 2, suggesting that the CNN algorithm is superior at forecasting potato early blight.

Table 2. Result

SR #	Algorithm	Disease	Precision	Recall	F1-Score	Accuracy
1	CNN	Tomato Bacterial Spot	0.85	0.86	0.85	0.9555
2	CNN	Corn Common Rust	0.88	0.87	0.89	0.9672
3	CNN	Potato Early Blight	0.91	0.89	0.90	0.9763

V. CONCLUSION AND FUTURE WORK

Google Colab was used to load the dataset, and Google Drive was used to normalize it. Using the photos provided, a CNN model was developed to forecast plant illnesses. This methodology may help agricultural enterprises and farmers enhance productivity and reduce crop waste due to illness. The primary goal of this thesis is to diagnose plant diseases using photographs provided by the reader. CNN is appropriate for complex algorithms and has high numerical precise accuracy. The model was 95.55% accurate for tomato bacterial spots, 96.72% accurate for corn common rust, and 97.63% accurate for potato early blight.

In future work explores the potential of smartphones to increase food production by 70% by 2050, potentially aiding in disease diagnosis through machine learning and big data.

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