2023 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES) | 979-8-3503-2391-7/23/$31.00 ©2023 IEEE | DOI: 10.1109/CISES58720.2023.10183413

Automatic Leaf Disease Detection Using Convolution Neural Network

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***Abstract*— Pests damage plants and crops, which have an impact on the nation's agricultural output. Usually, farmers or professionals used their own eyes to examine the plants to look for disease and identify it. However, this approach could be costly, time taking and erroneous. To reduce the time and error, in the proposed method we used deep convolution neural network to classifying leaf images in order to recognize plant diseases. The technique of precise plant protection has the potential to grow and improve, and computer vision advancements have the potential to boost the market for applications in precision agriculture. The developed model's innovation and advancement lie in its simplicity; healthy leaves and background images are consistent with those of other classes, enabling the model to utilize CNN to distinguish between damaged and healthy leaves or from the surroundings. Accuracy, Precision, and Recall are taken into consideration as evaluation parameters in the proposed method and three standard datasets are used to assess performance.**

Keywords—Plant Disease, Machine Learning, CNN;

I. INTRODUCTION

The productivity of the agricultural sector is crucial to the Indian economy [1]. Therefore, both the environment and people greatly benefit from the contribution that food and cash crops make. Numerous diseases claim the lives of crops every year [2-3]. Numerous plants perish as a result of poor diagnosis of these diseases and lack of awareness of the symptoms and cure. This paper offers details on an overview of the various algorithms used to detect plant diseases. Here, a strategy for detecting plant diseases using CNN has been suggested [4]. On sample photos, simulation research and analysis are carried out in terms of time complexity and the size of the infected area [5]. It is carried out using image processing methods. Many studies have reported a number of methods for the monitoring and detection of plant diseases. To extract characteristics from tomato leaves, researchers introduced Gabor wavelet transform methods [6]. In the past, professionals used chemical techniques or visual inspection of the leaves to identify plant diseases. This requires a sizable team of experts and ongoing plant monitoring, both of which are expensive when done with large farms [7-8]. The suggested method is effective in these conditions for monitoring huge crop fields. It is easier and less expensive to automatically identify illnesses by simply seeing the signs on plant leaves [9-10]. Although in drastically different methods than that already in use, the agronomic requirements have given rise to numerous new opportunities for service. Therefore, they ought to be checked using non-destructive methods. The classification of agricultural harvests is evaluated dynamically, and leaves are a fragile element of plants. The leaf's color and texture are its most significant visual characteristics [11-13]. Therefore, classifying leaf disease is essential for evaluating agricultural output, raising market value, and maintaining standards of quality. Identifying the infections and taking additional measures to prevent their spread is also beneficial [14-15]. If the identification and categorization are done using physical approaches, the procedure will be excessively sluggish, necessitating the assistance of experts, who may not always be readily available. Farmers group crops according to color, size, etc. The endeavor will be speedier and error-free if these quality methods are implemented into an automated system utilizing the proper software design language [16-18]. The use of technology in agriculture has significantly improved crop yields and productivity in recent years. With the help of computer vision and machine learning algorithms, plant diseases can be detected at an early stage, allowing farmers to take corrective action before it spreads and reduces the overall crop yield.

In addition, these technologies can assist in reducing the use of harmful pesticides, reducing costs and improving the environment. Various algorithms have been developed for plant disease detection, such as image processing, deep learning, and convolutional neural networks (CNNs)[36]. CNNs are particularly effective in identifying patterns in images and have been used extensively in image recognition tasks. By analyzing images of plant leaves, CNNs can detect visual cues associated with plant diseases, such as discoloration, spots, and deformities. Several studies have focused on the use of machine learning techniques for plant disease detection, including the use of Gabor wavelets, decision trees, and support vector machines [37]. These methods have shown promising results, but the use of deep learning techniques, such as CNNs, has demonstrated superior performance in detecting plant diseases [38].

The motivation behind research on plant disease detection using learning techniques is to address the growing challenge of food security and sustainable agriculture. With the global population projected to reach 9.7 billion by 2050, the demand for food is expected to increase significantly. At the same time, factors such as climate change, land degradation, and pests and diseases are putting pressure on food production systems, making it more challenging to meet this demand.

The paper is structured into four sections: introduction, related work, proposed methodology, and results. The related work section discusses existing methods and their limitations. The proposed methodology section describes the use of CNNs and image processing techniques for plant disease detection, while the results section presents the findings of the study. The last section concludes the paper and outlines future work.

II. Literature Survey

A plant pathologist needs to have outstanding observational abilities to recognize distinctive symptoms and diagnose plant diseases accurately. Variations in the symptoms displayed by ill plants could result in a wrong diagnosis since amateur gardeners and hobbyists could find it more challenging to make the diagnosis than a trained plant pathologist. Both inexperienced gardeners and qualified specialists could benefit greatly from an automated system created to diagnose plant illnesses by the appearance of the plants and visual symptoms as a verification mechanism in disease diagnosis. The technique of precise plant protection has the potential to grow and improve, and computer vision advancements have the potential to boost the market for applications in precision agriculture. A strategy for crop disease identification for rural region economic growth is described by Yashpal Sen et al. in their article [1]. This paper presented an emerging topic of research in precision agriculture, an automated system for diagnosing and categorizing various diseases of the contaminated plants. The method for preventing the crop from suffering severe losses is discussed in this study. Because most diseases only affect the leaf region, it is where the internet is located. When an image has low contrast, histogram equalization is used to enhance the contrast before the K-mean clustering technique, which identifies items. Image processing techniques are utilized to properly detect illness in crop leaves and to assess the disease for the benefit of farmers. K. Elangoran and S. Nalini proposed a method for categorising plant diseases using photo segmentation and SVM algorithms [2]. This study presents a color image analysis method for detecting the visual signs of plant illnesses. The method uses software to analyze colored photographs and identify the color and shape of leaves. The plant RGB color model image was captured using Lab View software, and MATLAB software is utilized to enable a recognition procedure to identify the plant illness from the photos of the leaves. The color model was utilized to effectively distinguish between leaf colors and eliminate the effect of illumination. The generated color pixels were then grouped to create groupings of color in the photos. Karthik Ingale and Sandesh Raut [9] suggested a quick and precise method for identifying and categorizing plant diseases. Early scorch, Cottony mould, Ashen mould, Late scorch, and Tiny whiteness are the main five plant diseases that the proposed algorithm was tested for. A color transformation structure is first established for the RGB leaf image that has been acquired, after which the RGB image is captured. The RGB colour value was then converted to the area that the colour transformation structure had specified in the following phase. After masking the predominantly green pixels, segmentation is carried out using the K-means clustering algorithm in the following phase. A trained neural network was then used to recognize the feature that had been retrieved. The outcome demonstrates that the suggested approach can accurately identify and categories the diseases with a detection rate of 83 to 94 %. Anjali Chandavale and Sagar Patil [10] the primary focus of this study is the disease identification of dicot plants. To acquire images, RGB picture patterns are employed as input, which are then converted into HSI forms. CCM and SGDM are then applied for texture analysis. Rice farming is essential in agricultural fields. But numerous disorders have an impact on their growths. If the infections are not discovered at an early stage, production will decline. This work's major objective is to create an image processing system that can recognize and categories the several rice plant illnesses that influence rice farming. The detection of rice plant illnesses and the diagnosis of rice plant diseases can be divided into two portions in this study. Using KNN and a clustering classifier, the diseased area of the rice plant is first recognized in the disease detection process. After that, KNN and SVM classifiers are used to identify the type of disease affecting rice plants.

III. Proposed Methodology

The primary goal of the proposed system, which is depicted in Fig. 1, is to identify plant leaf diseases using feature extraction techniques that take form, color, and texture into account. Plant leaves are classified as healthy or diseased using the convolution neural network (CNN), a machine learning approach. If the plant leaf is diseased, CNN will identify the ailment. It is made to suggest treatments for certain diseases that will aid in the growth of healthy plants and increase output. To get better outcomes and efficiency, high resolution camera is first used to capture photographs of diverse leaves. The essential features needed for further investigation are then extracted from these images using image processing techniques. The basic operations of the system can be summed up as follows:

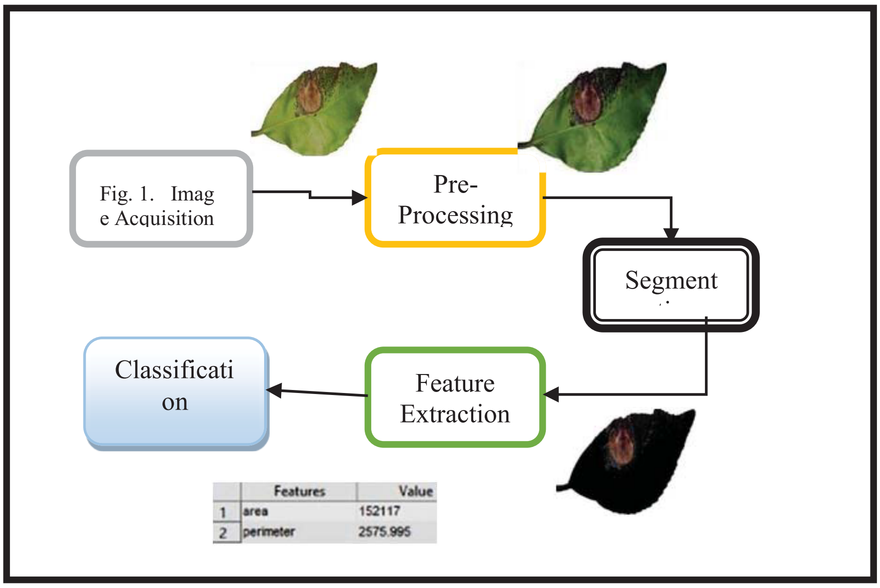

Fig. 1. Flow chart of Proposed System

A. Image Acquisition

The first step in the procedure is gathering data from the public repository. For further processing, it accepts the image as input. We chose the most well-liked image domains so that our algorithm may accept input in any format, including.bmp, .jpg, and .gif. The image is taken, scanned, and then transformed into a controllable object. Image acquisition is the method in question. In a test phase, we use a digital scanner to collect a number of color photos to create a single image of a leaf.

B. Image Preprocessing

Pre-primary processing's goals are to suppress undesirable image data and improve a few key image attributes. Image resizing, median filtering and RGB to Gray conversion are all included. In this case, a color image is turned into a grayscale image to make it device independent. The image is then downsized to 256*256 pixels. The image is then subjected to median filtering to get rid of the noise. About 30% of the decaying leaf sample's digital representation is made up of leaves, with the remaining 70% being the background. As a result, the redundant background uses a lot of disc storage space and consumes CPU time during segmentation. The digital image of the leaf sample is reduced in size to 16x20 square cm in order to maximise disc storage and process data quickly. Consequently, the pre-processing stage that was included decreases disc storage capacity by about 30% and increases CPU processing by 1.4 times. The region of interest, or the chosen leaf sample, is unaffected by the cropping process. After preprocessing, the sample leaf image's digital counterpart has around 70% of the leaf area and the remaining 30% is the backdrop.

C. Classification

In machine learning, CNN approaches regularization in a variety of ways. Compared to standard regularization models, it is simpler. We used CNN for feature extraction and classification. Fig. 2 depicts the CNN organizational structure. Different hyper parameters are used to train CNN. Table I contains a summary of the model as a result.

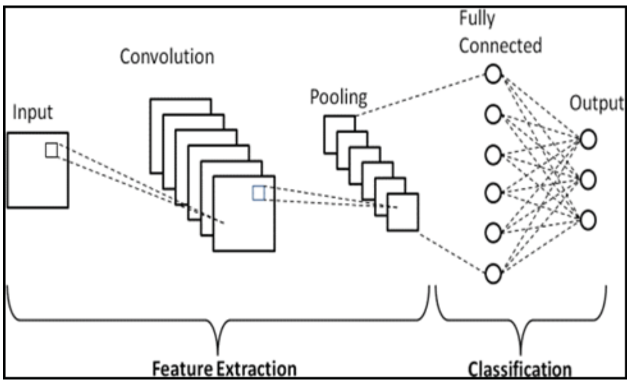

Fig. 2. CNN Architecture [5]

IV. Results Analysis

The Plant Village dataset's 54303 pictures of both healthy and unhealthy leaves are divided into 38 classes based on species and disease. We attempted to predict the class of diseases by analyzing more than 50,000 photos of plant leaves with scattered labels from 38 classes. We reduce the image's size to 256 pixels before optimizing and making model predictions on it. The size of the stride, the number and size of the kernels in each convolution layer, and the size of the kernels in the pooling layer are among the main parameters that make up the CNN structure. The hyper parameters details of CNN are shown in the TABLE I.

TABLE I. Hyperparameters of CNN

Parameter name	values
Epoch	25
Learning Rate	0.001
Batch Size	32
Dropout	0.2-0.8
Final Conv2D filters	128
Kernel window size	3*3
Max Pooling size	2*2

A. Model Accuracy

The accuracy of a model is frequently evaluated after the model's input parameters, and the results are typically represented as a percentage. It determines the degree to which your model's forecast coincides with the actual data. Our model's test accuracy is displayed in Fig. 3.

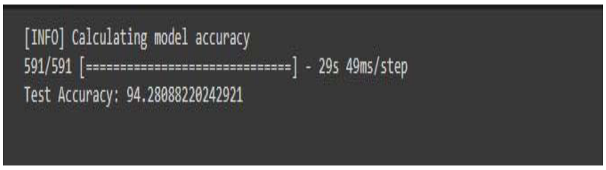

Fig. 3. Test Accuracy of the Model

B. Accuracy and Loss Graphs

Only 400 pictures from each folder were chosen. An array is created from each image. The input file was also scaled from [0, 255] (the image's least and most common RGB values) to the range [0, 1]. The dataset was then divided into 30 percent for testing and 70 percent for training images. Objects that conduct random rotations, motions, inversions, civilizations, and sections of our image set are formed as image generators. We built backend switches that support "first channel" in addition to the "last channel" design we utilised in the conventional model. Next, we perform Conv => Relu => Pool. Our Conv layer consists of 36 filters, each of which has a 3 x 3 core and is activated by Relu. Batch normalization, maximal aggregation, and a 27% decrease are the techniques that are applied here (0.26).

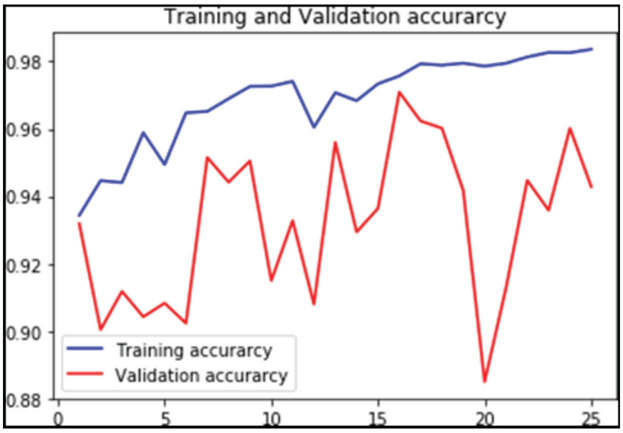

Fig. 4. Training and Validation Accuracy on Plant Village Dataset

Dropout is a control technique that prevents the correction of complex collaborative data used for training, hence lowering the amount of readjustment necessary for neural networks. After then, Relu is just a collection of layers that are all connected. The training and validation accuracy are shown in Fig. 4 as a graph, and the training and validation loss are shown in Fig. 5. For our model, we employ Adam's Hard Optimizer. In order to get our network up and running, we first execute model.fit generator.

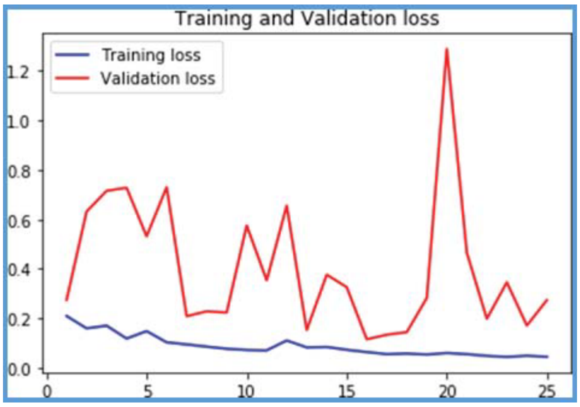

Fig. 5. Training and Validation Loss Plant Village Datase

Our objective is to increase the amount of data, as well as the train-test data and the number of training epochs. For this particular endeavour, the epoch value that we utilized was 25.

C. Quantitative Analysis

Understanding behaviour can be accomplished by a technique known as quantitative analysis (QA), which involves the application of mathematical, and statistical modelling, measurement, and research. TABLE II lists all the authors who utilized the same database as the suggested approach and obtained various degrees of accuracy for their models. For all models over the years, it has been referred to as the performance matrix. Fig. 6 provides a graphic illustration of the same. Many authors have already used novel technologies to identify leaf diseases, and each of them has a special feature to boost accuracy and computing efficiency. A few of these authors' works are contrasted with the suggested system in TABLE. III shows the same graphic as Fig. 7 in more detail.

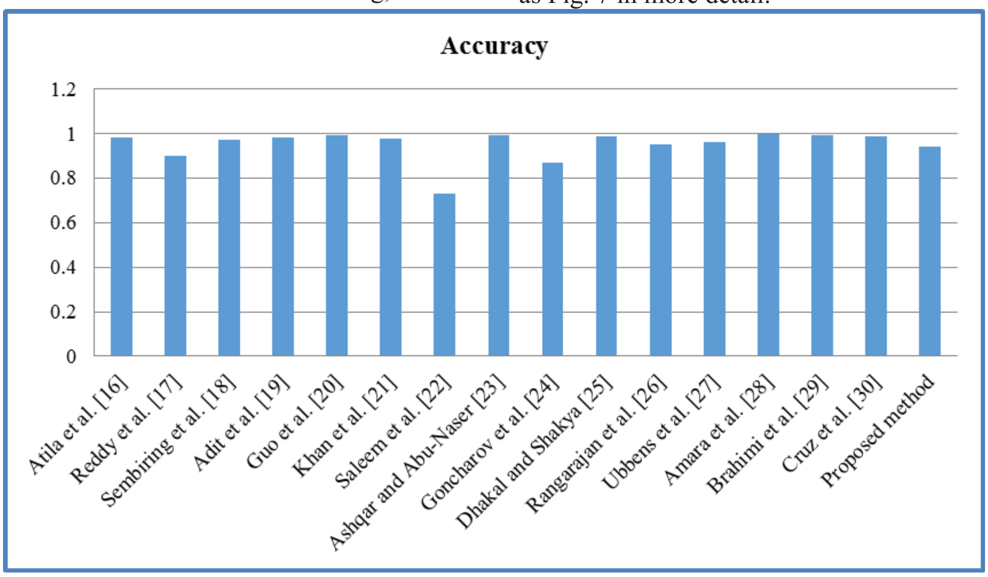

Fig. 6. Test Accuracy of the Model

TABLE II. COMPARATIVE ANALYSIS WITH DIFFERENT MODELS

Authors	Year	Database used	Images used	Accuracy
Atila et al. [16]	2021	PlantVillage	61,486	0.984
Reddy et al. [17]	2021	PlantVillage	54,305	0.900
Sembiring et al. [18]	2021	PlantVillage	17,641	0.972
Adit et al. [19]	2020	PlantVillage	76,000	0.980
Guo et al. [20]	2020	PlantVillage	61,486	0.992
Khan et al. [21]	2020	PlantVillage	7,733	0.978
Saleem et al. [22]	2020	PlantVillage	61,486	0.730
Ashqar and Abu-Naser [23]	2019	PlantVillage	9,000	0.994
Goncharov et al. [24]	2019	PlantVillage	54,306	0.870
Dhakal and Shakya [25]	2018	PlantVillage	54,000	0.985
Rangarajan et al. [26]	2018	PlantVillage	13,262	0.950
Ubbens et al. [27]	2018	PlantVillage	18,160	0.962
Amara et al. [28]	2017	PlantVillage	3700	0.997
Brahimi et al. [29]	2017	PlantVillage	14,828	0.992
Cruz et al. [30]	2017	PlantVillage	299	0.986
Proposed method	**2022**	**PlantVillage**	**54,305**	**0.942**

TABLE III. COMPARATIVE ANALYSIS OF PROPOSED WORK WITH EXISTING SYSTEMS

Author	**S. Khirade et al.[31]**	**S. Madiwalar et al.[32]**	**Peyman Moghadam et al. [33]**	**Sharath D. M. et al. [34]**	**G. Shrestha et al.[35]**	**Proposed Method**
Algorithm	Digital image processing and BPNN	Digital Image processing and SVM	Hyper spectral imaging and SVM	Digital image processing	CNN	CNN
Accuracy	87%	83.34%	93%	-	88.80%	94%
Computationally efficient	✘	✔	✘	✔	✔	✔
Specialized hardware requirement	✘	✘	✔	✘	✘	✘

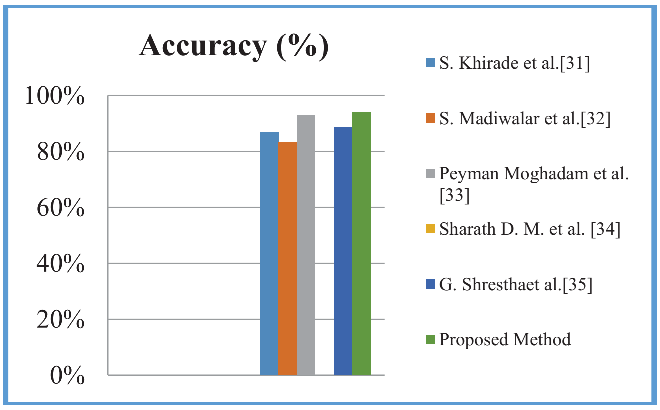

Fig. 7. Graphical representation of comparative analysis

V. CONCLUSION & FUTURE SCOPE

The system is successfully trained using the suggested algorithm. With no over fitting, the accuracy rate for the test set is 94.28%. Even though the remaining 5.72% is covered, there is still opportunity for development. This work can help people track their indoor plants and give farmers a way to maintain tabs on the crop while also advancing the field of agriculture. This research can be worked upon to create an app that would allow one to learn the treatment for a plant illness. An expansion of this work will concentrate on automatically calculating the disease's severity once it has been detected.

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