CROPS DISEASE CLASSIFICATION USING MACHINE LEARNING ALGORITHMS

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Abstract:

This Research highlights the issues, kinds of the illness and investigations performed to tackle the challenges linked to the diseases utilising different deep learning algorithms. Generally, we can recognise the plants that are damaged by specific illnesses, but away from our vision, it is challenging to detect. Without supplying the proper treatment and early activities, the complete cultivated ground might change into a disease afflicted region; otherwise all plants which are a neighbour to one another can be impacted by means of spreading. So, to identify the plant illnesses in advance and to detect the diseases with the use of contemporary computer technology, a model is developed to effectively discriminate plant diseases. The dataset utilised here comprises of different species of plants of both damaged and healthy, and all these photos are acquired from various publicly accessible sources. An accuracy of 97% in plant classification and over 96% in disease classification utilising VGG and ResNet architecture is obtained. To identify apple, grape, and potato leaf diseases, a graphical user interface (GUI) was devised. The technology identifies leaf problems as well as cures for such diseases, which is valuable to farmers.

Keywords:VGG16, ResNet, Adam, SGD, RMSprop

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I INTRODUCTION

Crop diseases are a huge danger to food security, but due to a lack of infrastructure in many regions of the world, timely detection is challenging. As a result, plant disease detection is an important aspect. Without proper identification of the disease and the disease-causing agent, disease control measures can be a waste of time and money. This can lead to further plant losses. As a result, accurate plant disease diagnosis is critical.

The agriculture industry in India has been performing an extremely important function for the country's overall economy. Agriculture was responsible for around 17-18% of India's Gross Domestic Product in 2018 [1]. In the agricultural industry, plants are susceptible to a wide variety of illnesses. This results in a significant economic loss. The manual examination of crop diseases is a laborious procedure that may be simplified by the use of automated approaches. A method for the categorization of plant diseases based on deep learning has been developed. In this location, the illnesses that affect grape, potato, and apple plants are identified.

It's possible that portion of the crop is suffering from a deficiency of water or nutrients in some areas. In addition, there are a lot of fungi that are disappearing from the grain fields. As a result of this, it is susceptible to a wide variety of diseases, including scab, black rot, cedar rust, esc, early leaf blight, and late leaf blight, amongst others. The spread of these diseases has a significant negative effect on the development and quality of the plants they infect. The price of the plants has a one-to-one correspondence with their level of excellence. The yield of the crop is of the biggest importance, as it determines the livelihood of many farmers in rural areas. Therefore, the quality of the crop should be the primary focus.

CNN has been the subject of a number of studies that have been conducted to investigate the detection of plant diseases. Standard computational architectures, such as VGG-Net, GoogleNet, ResNet, and others, may be used in the process of illness prediction. [4] Suggested a smart mobile application that uses convolutional neural networks to identify tomato leaf illnesses. The programme has an accuracy of 90.3%. In instance, CNN has shown strong performance on many picture classification tasks. On the image-net dataset, the standard architectures underwent their training. Transfer learning may be utilised to do a variety of classification tasks, and this trained model can be used as the starting point for such tasks. Within the scope of this study, a CNN-based categorization system for plant leaf diseases was presented.

The identification of plant diseases is very important since it enables farmers to identify plant diseases at an earlier stage. It is possible to identify plant illnesses at an early stage, which enables the necessary procedures to be taken in order to increase agricultural productivity. Apple, grape, and potato are the three crops that have been harvested from their respective plants. The CNN model was used in the development of a system that first identifies the plant leaf and then determines whether or not the plant is infected. Training and testing were done on the VGG-16 and ResNet models. A graphical user interface, sometimes known as a GUI, was developed in order to identify leaf diseases in apple, grape, and potato plants. The fact that the system can identify leaf illnesses and provide farmers with information on how to treat such diseases is a significant benefit to the farmers.

A solution based on a Neural Network was suggested to be implemented. A method known as deep learning is utilised in order to appropriately categorise plant diseases. A comparison was made between the CNN models VGG-16 and ResNet in terms of their performance when used as pre-trained models using a dataset. It is required that apples, grapes, and potato leaves be included in the dataset. The CNN model was used in the development of a system that first identifies the plant leaf and then determines whether or not the plant is infected. A graphical user interface, sometimes known as a GUI, was developed in order to diagnose leaf diseases in apple, grape, and potato plants. The fact that this technology can identify leaf problems and also potential treatments for such diseases is very valuable to farmers.

The following is an outline of the pre-planned sections of the paper: section 2 examines the related work of the detects leaf illnesses in addition to cures for these ailments. In Section 3, we provided a detailed explanation of the technique that was recommended. In section 4, you will see a presentation of the results obtained using the suggested methods. Section 5 of the paper is where the conclusion of the article is delivered.

II. LITERATURE SURVEY

Plant diseases diminish the amount of food that is accessible to people because they cause crop yields to suffer. Many researchers have focused a great amount of their efforts on identifying plant diseases because of the significant danger that it poses to the development of plants and the output of crops. The accurate identification of illnesses is a duty that is essential to the growth and development of the economy of the nation. The infections that affect the plants are the root of the problem that has led to a decline in both the quality and quantity of the agricultural output [4]. Over the last several years, there has been an increase in the use of deep learning in agriculture, which has helped to boost agricultural productivity. This idea has been used by the authors in the process of illness categorization of mango leaves that were affected with anthracnose disease by employing Multilayer Convolution Neural Network [5]. A real-time detection approach that is based on upgraded convolutional neural networks has been established for apple leaf diseases. This method was developed specifically for the apple industry. Using a dataset consisting of 26,377 photos of damaged apple leaves and a convolution neural network model [6, INAR-SSD was trained to detect apple leaf illnesses. [6] This training was carried out using INAR-SSD.

Several writers have put image processing methods to use in their work in order to get findings that are reliable, accurate, and quick. Methods such as clustering, colour-based image analysis and classifiers are used in the process of diagnosing plant diseases. Image Recognition Technology (IRT) was used on 35 different grape samples, and the results showed that it was accurate 92.9% of the time [7]. In order to categorise the four distinct forms of leaf diseases, a number of machinelearning strategies, including Support Vector Machine (SVM), Random Forest tree, and ad boost, were used. We were able to attain 93% accuracy by using SVM [8][9] The researchers trained the system to distinguish the differences between healthy sugarcane leaves and those that were infected by the yellow spot illness using a support vector machine (SVM). An Android-powered mobile phone-based diagnostic method for wheat scab has been developed. The CARS-RS-SVM model was able to obtain an accuracy of 92.7% [10]. In order to develop a method for identifying plant diseases, a segment of the afflicted section of the leaf was extracted, and then the k-mean clustering algorithm was used to analyse the data. A smartphone application was used to analyse the photographs to diagnose the illnesses that were affecting the leaves. The method of feature extraction is helpful in the process of removing diseased leaves from the plant as well as in the categorization of different types of plant diseases. The accuracy of the SVM was between 94-96%, while the accuracy of the KNN ranged between 83-85% [11].

A technique based on neural networks and a set of criteria derived from swarm optimization were used in order to optimise the agricultural land's suitability for cultivation. Image processing and machine learning techniques were used, and the results were analysed so that they may be used to the diagnosis of diseases that affect a variety of plants [12]. This allowed for enhanced optimization. A SVM classifier was used to differentiate the many illnesses that might affect rice plants and identify their characteristics. It was discovered that the SVM technique successfully recognised rice diseases with an accuracy of 97.2% [13]. [Citation needed] An artificial neural network method was used to detect watermelon leaf diseases such as downy mildews and anthracnose. This method had a class result of 79% accuracy and was based entirely on the extraction of colour functions from RGB colour versions that were received from recognised images from the region of interest [14]. Image Recognition Technology (IRT) was utilised to identify illnesses that affect alfalfa leaf by using a validation method that included five passes and was repeated fifty times. In order to determine the most frequent findings, the K-means classification technique was used. Neural networks were used only for segmentation on plant data sources such as apples and cucumbers, while scale invariant feature transforms were used for classification (SIFT). When compared to the SIFT and IRT methods, the greatest reputation rate that neural networks may achieve is 84, which is considered to be a high reputation rate [15].

In order to evaluate nutritional shortages in different plant species, an image analysis approach was used. Calculating colour indices required using the fundamental components of colour characteristics, which are tied to the mathematical processes known as RGB. They came to the conclusion that a segmentation approach based on thresholding produced an empirically better outcome with a more probable edge value. In addition, the procedure that was suggested required a great deal of time. The diagnosis of disease in rice plants with uneven mineral compositions and the creation of spots across infected regions, which are the primary reasons of a decline in rice production, were adopted as a method of reducing the amount of rice produced. Back Propagation Neural Network (BPNN) was used in the development of a prototype system that was intended to locate rice's inherent flaws. As a consequence of this, the selection of an appropriate grouping strategy plays a significant influence in the determination of the outcome of the first-class classification [16]. The author used DCNN in order to categorise the three different fungal infections that were discovered in wheat plants. The photos used in the proposed work were taken in a real-time environment at two distinct places over the course of three years [17]. The Goog-LeNet and Cifar10 networks were proven as tools for the diagnosis of illnesses based on photographs of maize leaf lesions. The suggested models demonstrate improved accuracy when categorising nine distinct types of maize leaves when compared with other networks such as VGG and AlexNet [18].

III. PROPOSED ARCHITECTURE

Both the quality and quantity of agricultural products are seeing a decline as a direct result of plant diseases. The leaves, fruits, stems, vegetables, and flowers all suffer a decline in quality as a result of this. Productivity and profitability are both significantly impacted as a result of this [2]. There are many different factors that might affect the productivity of a plant. Alterations in the climate are another factor that contributes to the proliferation of plant diseases. The exponential expansion in human population is one of the factors that contribute to climate change, which has led to a reduction in the amount of food that can be produced by crops [5]. Because these diseases are impossible to prevent, early diagnosis is essential because they may spread over the field, resulting in severe losses for both the farmer and the economy of India. The identification of sick leaves, the provision of therapy, and the consultation of professionals may be challenging for farmers. It might be time-consuming and expensive, leading to the use of pesticides and fertilisers that aren't necessary, which would be harmful to the environment and contaminate the soil and water [6].

Farmers spend billions of dollars on disease management, yet they often do not get enough technical help, which results in ineffective disease control, pollution, and other unfavourable effects. Plant diseases may also be harmful to natural ecosystems, contributing to a greater number of environmental problems such as the loss of biodiversity and improper land management.

The combination of shifting weather patterns and increased pollution may cause a rise in the number of unwanted insect populations, which in turn reduces agricultural yields for essential foods. Aside from our vision, it is difficult to detect whether or not a plant is infected with a particular illness. However, people are often able to determine which plants are afflicted. It is possible for disease management efforts to be a waste of time and money, and they may even result in the death of more plants if the illness and the agent that causes the disease are not properly identified. As a result, in order to identify plant illnesses in a timely manner and to identify diseases with the use of contemporary computer technology, a model that differentiates plant diseases in an effective manner was presented. The dataset that was utilised in this study includes a number of different types of plants, including those that were afflicted as well as others that seemed to be healthy. All of the photos used in this study were gathered by hand and from a variety of publicly accessible sources.

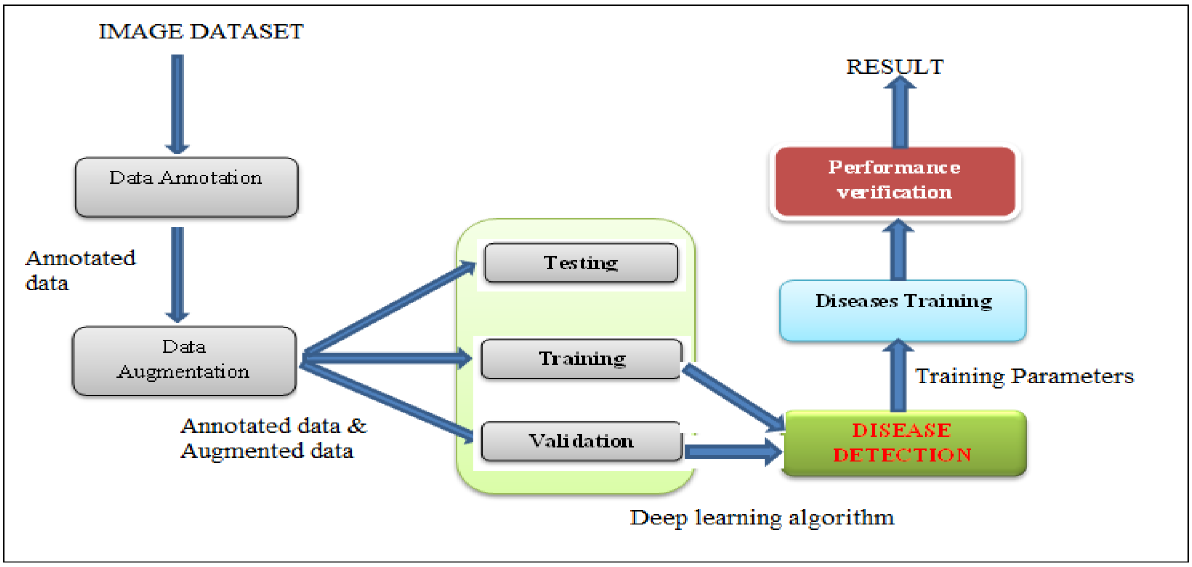

Figure 1: System design

The following provides a full discussion of each block shown in Figure 1:

1. Dataset, an aggregation of other datasets used for the model.
2. Training and Testing: In order to achieve the level of accuracy that is needed, the model must first be trained and then evaluated using the dataset.
3. Optimization entails looking for the optimizer that works best with our

model so that it may operate more effectively.

4. The final model that has the least amount of loss and the highest accuracy is chosen for the deep learning model.
5. The implementation of the model Capturing device: In order to collect visual data for the categorization of plant leaf diseases
6. Server: Deep learning model on server.
7. The deep learning model is the final model that has the highest accuracy and the least amount of loss.
8. Determine the plant's classification by looking at the picture of the potato, grape, or apple plant.
9. The categorization of illnesses: the categorization of plant leaf diseases
10. Treatments: If there are any treatments available for the ailment, please recommend the most effective ones.

Architecture of VGG-Net:

The kernel size of 3x3 remains the same throughout the whole network; the only variable that changes is the depth between layers 5. The proportions are kept consistent throughout all of the layers thanks to the provision of suitable cushioning. Even while the number of parameters in this network seems to be somewhat huge, it would have been an order of magnitude greater if we had opted instead for a network that was completely Fully-Connected.

Architecture of ResNet

1. Every two levels in the ResNet, we combine the input that was supplied to the first layer with the output that was received at the second layer and send this combination forward.

a. Input: x1, b. Output: x2 = f(x1) + x1, c. Output after two layers: x3 = f(x2) + x2

2. Because of this, the gradients were able to flow back more smoothly, which improved the training.

3. It is known as a Residual Network owing to the fact that at each step, there remains a remnant of the input that is carried along once again with the output.

4. They were able to train very deep neural networks using this approach, reaching as much as 151 layers in depth.

Stochastic Gradient Descent:

Instead of selecting all of the samples from the data set at random for each iteration of stochastic gradient descent, just a few samples are picked at random. In the event that your dataset contains one million samples, you will be required to make use of each and every one of them in order to finish one iteration of the Gradient Descent, and you will be required to continue doing this for each iteration until the minima are reached in the event that you make use of a traditional Gradient Descent optimization strategy.

Adam:

According to the guidelines for the Adam update, the most current update is given greater weight than the one that came before it. It is a method of changing the value of learning rate that belongs to the category of adaptive learning rate techniques. One way to think of Adam is as a mix of RMSprop and Stochastic Gradient Descent that also takes momentum into account. It scales the learning rate by utilizing the squared gradients, much as RMSprop does, but it also takes use of momentum by using the moving average of the gradient, just like SGD with momentum does, rather than the gradient itself.

IV. RESULT ANALYSIS

As can be shown in table 1, when it came to the classification of apple diseases, the RES-net model with 0.05 as its learning rate and Adam as its optimizer produced better results than VGG. In figure 2, we see a graphical depiction of the accuracy of the apple leaf disease classifier both during training and during testing.

Table1: AppleDiseaseresults

Model	Optimizer	Learningrate	Batchsize	Epochs	TrainingAccuracy	TestingAccuracy
VGG	SGD	0.001	32	3	96.875	90.625
VGG	Adam	0.05	32	3	93.75	90.62
ResNet	SGD	0.05	32	3	96.875	96.475
ResNet	Adam	0.001	32	3	98.325	96.857

Figure2: AccuracyofAppleclassifier

As shown in table 2, for grapesleaf disease classifier, Resnet model with learning rate 0.001 performs well in training as well as testing. A graphical representation of training and testing accuracy of potato leaf disease classifier is shown in fig. 3.

Table2: GrapesDiseaseresults

Model	Optimizer	Learning Rate	Batch Size	Epochs	Training Accuracy (%)	Testing Accuracy (%)
VGG	SGD	0.01	32	3	93.75	96.88
VGG	Adam	0.05	32	3	96.875	96.875

ResNet	SGD	0.001	32	3	100	90.62
ResNet	Adam	0.01	32	3	93.75	93.75

Figure 3: Accuracy of Grapesclassifier

V. CONCLUSION

In this study, a number of different deep learning strategies that are capable of accurately classifying plant diseases were used. We evaluated the efficacy of various state-of-the-art CNN models, such as VGG16 and ResNet, as a pre-trained model by using a dataset that included images of three distinct plant species. The identification of plant diseases is an essential feature since it assists farmers in the detection of the diseases.

Diseases that affect plants may be discovered at an early stage, at which point appropriate measures can be implemented to improve agricultural output. In order to get correct findings, it is necessary for the dataset to have both healthy and sick examples of leaf tissue. CNN has been of use in the diagnosis of plant diseases. In order to properly diagnose the ailment affecting the plant, the feature extraction layers were fine-tuned to extract certain characteristics from the picture. We are able to improve the recognition rate of the classification process by working on more effective strategies for segmentation, as well as by choosing and using more effective algorithms for feature extraction and classification. We have high hopes that the suggested method would be of significant assistance in the field of agricultural research.

In our further investigations, we want to broaden the scope of our investigation into these baffling illnesses and use a variety of methods to enhance the precision of our findings. In addition to this, we are going to develop a simple application that will be able to take a picture of a leaf and quickly provide the farmer with information on the kind of disease, as well as treatments and the location of the store closest to them that sells fungicides.

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