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Article · June 2023

DOI: 10.37896/JBSV23.6/2315

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"Developing a Crop Disease Detection Using Deep Learning:Artificial Intelligence Approach for Precision Agriculture"

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***Abstract*—** A major danger to agricultural production and food security is posed by crop diseases. Crop diseases must be promptly identified and managed in order to minimise yield losses and cut back on the use of chemical pesticides The potential of natural language processing (NLP) and artificial intelligence (AI) technologies is used in this work to suggest a novel way to crop disease identification and support via a chatbot**.**The chatbot is designed to engage with farmers and offer them real-time support in identifying and managing crop diseases. It is driven by a trained language model. The chatbot is accessible and convenient to use even in remote locations with poor internet connectivity because farmers may converse with it via text or voice inputs. The chatbot can correctly identify crop diseases and offer personalised advice for disease management because it was trained on a large dataset of crop disease photos, symptoms, and management techniques.The suggested chatbot has a number of important capabilities, including the ability to identify diseases, gauge the severity of such diseases, and provide tailored care advice. Farmers can upload pictures of crop leaves exhibiting disease symptoms for the disease diagnosis feature, which employs computer vision techniques to detect the illness and provide details on its features. With the help of the chatbot's recommendations, farmers can use the disease severity assessment tool to determine the disease's severity in their crops based on visual signals. Farmers can get information on suitable cultural, chemical, and biological management practises to control the disease and stop its spread from the personalised management recommendations feature.The effectiveness of the suggested chatbot is tested extensively on actual cases of crop disease, and the findings show that it is highly accurate in identifying diseases and determining their severity. Farmers who use the chatbot for disease management give it positive reviews as well, finding it to be user-friendly and helpful in making decisions. The suggested chatbot for crop disease diagnosis and support has the potential to make a substantial impact on crop health, yield losses, and the advancement of sustainable agricultural practises**.**

KEYWORDS
Crop Disease Detection,Crop pathology,Chatbot For Agricultural Support,Crop disease Control,Agricultural Chatbot.

I.Introduction

Crop diseases pose a danger to the world's food supply and are associated with severe yield losses and financial losses for farmers. Crop diseases must be properly identified and managed in order to reduce their negative effects on agriculture and guarantee food security. Chatbots are a promising tool that has developed with the development of artificial intelligence (AI) and natural language processing (NLP) technology for assisting farmers in crop disease control in real-time.

In this article, we offer a unique method for helping farmers diagnose crop diseases and receive tailored management advice. This method makes use of a chatbot that is powered by a trained language model. The chatbot is built to be comfortable and approachable, allowing farmers to communicate via text or voice inputs, and it is trained using a large collection of photos, symptoms, and management techniques for crop diseases. By providing farmers with fast and accurate support that enables them to make informed decisions and take necessary actions to safeguard their crops, this strategy has the potential to revolutionise crop disease management. The suggested chatbot's performance is thoroughly tested, and the results show that it has the ability to support sustainable agricultural practises and enhance crop health.[1]

An innovative strategy that combines the strength of artificial intelligence (AI) and chatbot technology to help farmers discover and manage problems in their crops is called "crop disease detection and support through chatbot." Crop diseases can have catastrophic consequencesonagricultural outputs, causing major financial losses and problems with food security. Effective management and the prevention of the spread of crop diseases depend on the prompt and precise detection of these illnesses. A chatbot is a computer programme that mimics human dialogue and enables users to communicate with it via text or voice.[2] A chatbot may analyse input data and offer individualised advice and information based on its learned skills and knowledge when AI algorithms are included.Support for crop disease detection Chatbots can be created in a variety of ways to help farmers and other agricultural stakeholders. By examining user-provided photographs or descriptions of illness signs, they can assist farmers in identifying crop diseases. They can offer suggestions for effective management techniques, such as the application of insecticides, fungicides, or cultural practises to slow the spread of disease. They can also provide guidance on crop rotation, preventative measures, and other best practises for preserving crop health. Chatbots are accessible and practical tools for farmers, particularly in remote or underserved areas, and can be accessed via cellphones, tablets, or laptops.[3] chatbots that detect and support crop diseases provide farmers with a cost-effective and effective way to help them manage crop diseases, maximise agricultural output, and enhance crop yield and quality. Farmers may get quick, precise information to help them make decisions and take preventative measures to safeguard their crops from illnesses by utilising chatbot and AI technologies. Overall,crop disease detection and support through chatbot technology can empower farmers with valuable information and guidance to make informed decisions, reduce crop losses, and improve their overall crop health and yields.[4]

By harnessing the capabilities of AI and chatbots, farmers can have a proactive approach towards crop disease management, leading to more sustainable and productive agricultural practices. [5]

II. LITERATURE SURVEY

The detection of Diseased Crop in real-time using Deep learning methods has been the subject of some previous research. With regard to Crop disease issues, we are focusing in this study on studies and research that have already been done.

Ichan Taufik, Reza Gunawan, Edi Mulyana, Opik T. Kurahman, Muhammad Ali, and Mahmud proposed methodChat-bot Application On Internet Of Things (IOT) to Support Smart Urban Agriculture face.
This approach to take activities for plants to retain their quality, knowledge of their condition is undoubtedly helpful. The plant's condition can be informed by the Internet of Things, allowing for instant notification of any situations that call for additional action, such watering. Wemos ESP8266 Microcontrollers, which can be connected to Wi-Fi and the internet, are the tools utilised in this study so that sensor data may be sent instantly over the internet. Temperature, soil moisture, air humidity, and light are sensors that are affixed to plants; the data is delivered to the web application using the REST API service. Data is sent from the Web application to Line's mobile application.[6]

In the next paper Jessica Sadavarte, Anjnya Khanna, Mihir Momaya, and Manoj Sankhe This paper describes farmchat,a conversational and language technology that answers farmers' questions in a natural way by naturally conversing with them. The chatbot's conversational intelligence was developed with the help of agric specialists who regularly interact with farmers and was informed by examination of a sizable corpus of farmer contact centre logs.[7]

Tripti Lamba and Ritika Kesari proposes a image preprocessing for detection and recognition of heathiness of Agricultural plants.The major goal of the study is to develop a chatbot that can identify a plant disease's type, determine whether it can be cured, and then suggest a course of action. The chatbot will assist the farmer in increasing agricultural productivity and preventing plant disease. [8]

Ashritha A Acharya ,Bargavi J Sharma,Jevisha Sweety Fernandes,Nandita T V,Dr.Pradeep B S. In this Paper Instead of going to an expert and seeking their guidance, the suggested approach can be highly beneficial for farmers by efficiently improving the production.[9]

One of the key economic sectors in India is agriculture. Indian agriculture employs around 50% of the labour force of the nation. The quality of the products that are produced, which is dependent on the plant's growth and the return that it is entitled to, determines the agricultural sector's economic growth.
As a result, the identification of plant diseases is crucial in the field of agriculture. In the face of unfavourable environmental conditions and parasite microbes that cause disease, plant pathology investigates plant ailments and works to increase plants' chances of survival. Different sections of a plant, such leaves, exhibit the symptoms of plant diseases. [10]

III.Methodology:

The farmer will upload the leaf photograph to the app as the first step. Farmers may click the predict button after submitting the photograph and wait for the outcome. For this, the model is trained using a variety of modules, including the Hough transform, Open CV, and colour detection using LBPH. After uploading the photograph, there are now two outcomes: either the plant leaf will be infected or it won't be. The image of the leaf will be shown on the screen if it is discovered to be diseased. The suggested method is also capable of calculating the percentage of the affected area, showing it on the screen, and also recommending pesticides based on the affected area. As an alternative, if the leaf is healthy, the picture along with the message is Displayed.[11]
The Hough transform and LBPH (Local Binary Pattern Histogram) algorithms are two Utilising image processing to detect illnesses in potato crops.It is possible to extract features from photos using the texture-based feature extraction approach known as LBPH. It compares the pixel values inside tiny portions of an image to those of the pixels nearby in order to operate. A binary pattern that may be utilised to representthe texture of the image is the end result. In order to detect illnesses or anomalies, LBPH may be used to extract texture information from potato crop photos.[12]

A. LBPH :-

A well-liked feature extraction technique in computer vision and image processing for picture recognition and categorization is the local binary pattern histogram (LBPH). Detecting diseases in potato crops is another application for it.
You must first gather photos of both healthy and damaged potato crops before you can utilise LBPH to identify diseases in potato crops. A machine learning model will be trained using these photos to identify the patterns of healthy and unhealthy crops.[13]
You may use LBPH to extract features from the photos once you have them. Each pixel in a picture is compared to the pixels around it in LBPH, which then encodes the resultant binary patterns into a histogram. Then, a feature vector created using this histogram may be utilised to train a machine learning model.
You may for the recognition and classification of images in computer vision and image processing
to identify the patterns of healthy and sick potato crops after extracting the featuresusing LBPH. The newly acquired photos of potato crops may subsequently be classified as healthy or unhealthy using the trained model.[14]

B. Hough Transform:-

The Hough transform is an approach for identifying basic forms in an image, such lines, circles, and ellipses. By transforming the image into a parameter space where the shape may be represented by a single point, this method can capture a shape. Certain forms, such as circular or elliptical lesions, that may be a sign of illnesses affecting potato crops can be found using the Hough transform.[15]

You may use LBPH to extract features from the photos once you have them. Each pixel in a picture is compared to the pixels around it in LBPH, which then encodes the resultant binary patterns into a histogram. Then, a feature vector created using this histogram may be utilised to train a machine learning model.

You may use a support vector machine (SVM) or other machine learning model to identify the patterns of healthy and sick potato crops after extracting the features using LBPH. The newly acquired photos of potato crops may subsequently be classified as healthy or unhealthy using the trained model.[16]

C. OpenCv:-

A well-liked open-source library for image processing and computer vision tasks is called Open CV (Open Source Computer Vision Library). It offers several tools and algorithms that may be used to find diseases in potato crops.You must first gather photos of both healthy and damaged potato crops before using Open CV to identify diseases in potato crops. A machine learning model will be trained using these photos to identify the patterns of healthy and unhealthy crops.[17]

Once the pictures are obtained, you may use Open CV to carry out a number of image processing tasks, including image segmentation, feature extraction, and image enhancement.

After image processing, a model may be designed recognise the patterns of both healthy and sick potato crops using technique such as Convolutional Neural Networks (CNNs). It Provides many tools to perform tasks such as Features Extraction, Image Extraction.However, OpenCv is a crucial to make sure that the photos used to train the model are typical of the variety of potato crop illnesses you wish to identify and that the preprocessing methods are tailored to the particular task at hand.[18]

D. **Proposed Algorithm.**
(Convolutional Neural Networks)(CNNs):-

A typical form Convolutional neural network (CNN) is a type of neural network used for processing and recognising images. Thefollowing is a representation of a CNN's mathematical expression Let X be the input picture, which is represented as a 3-dimensional array with the dimensions (H, W, C) of height, width, and channels. The convolutional layer, which applies a series of filters to the input picture, is the first layerof a CNN. Each filter is a three-dimensional array with the dimensions (FH, FW, C), where FH and FW stand for the filter's height and width and C for the input image's channel count.[19]

Let F be the collection of filters, each of size (FH, FW, C), with K filters overall.

$$O\_i = activation\_function(\sum(F\_k * X\_{i:i+FH, j:j+FW, :}) + b\_k)$$

In the realm of precision agriculture, using a Convolutional Neural Network (CNN) for disease detection in potato crops is a promising strategy. The general steps you may take to develop a CNN for this purpose are as follows:

Step 1:Dataset collection and preprocessing:

The first stage is to gather a sizable dataset of pictures of potato plants with various illnesses. Labels identifying the different types of diseases in each image should be added to the dataset as annotations. The photos should be prepared by being resized to a standard size and having their pixel values normalised.[20]

Step 2:To divide the dataset:

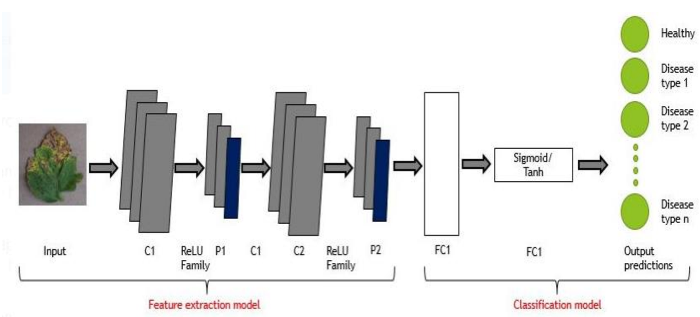
A training set, a validation set, and a test set should be created from the dataset. The test set is used to assess the CNN's performance after it has been trained, validated, and had its hyperparameters tuned.[2]

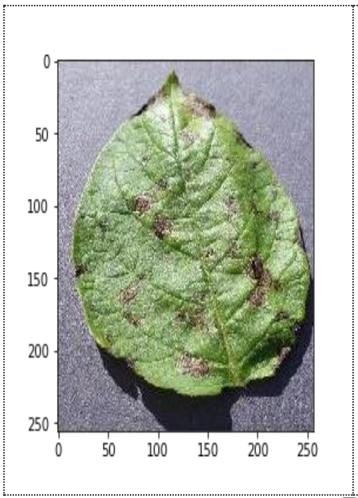
Step:3 Define the CNN architecture:

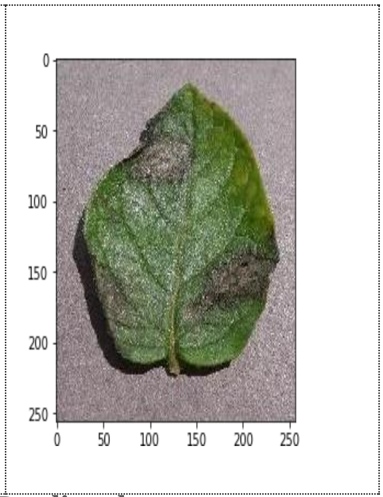
The CNN architecture has to be defined next. Starting with a basic architecture, such as a few convolutional layers followed by a few fully linked layers, is a good place to start. To enhance the performance of the architecture, you might progressively increase its complexity.[3]

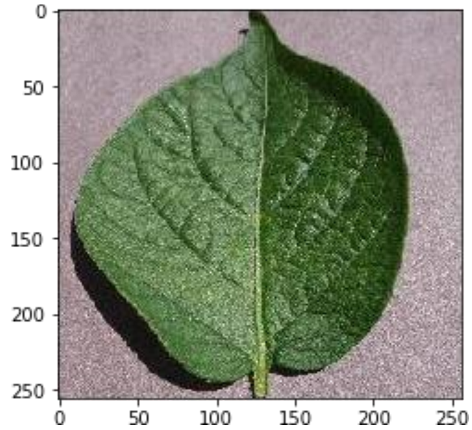
Step 4:Train the CNN

Using an appropriate optimizer and loss function, the CNN should be trained on the training set. When the validation loss stops lowering, the training should be halted. Test the trained CNN to determine how well it performs on data that hasn't been seen before. In order to understand the CNN's behaviour, you may also see its predictions on particular photographs.Using the CNN in a real-world application for disease detection in potato crops is possible if you are pleased with its performance. Depending on the needs of the application, deployment can be done on a mobile device or in the cloud.All things considered, employing a CNN for potato crop disease detection can assist farmers in spotting infectionsearly and acting swiftly to save crop losses.[13]









Predicted:
Class:-
Potato_Early_blight

Accuracy:-0.974056

Predicted:
Class:-
Potato_late_blight

Accuracy:-0.986278

Predicted:-

Class :
Potato_Healthy

Checking the model's accuracy

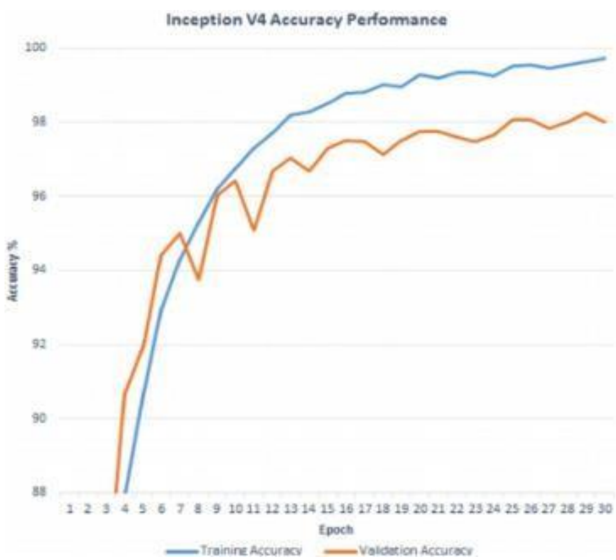
To test accuracy, the specified model is trained across a number of epochs. It is crucial to examine over- and under-fitting in this step, which is done by drawing a graph of the model's accuracy and loss, as will be seen later. The model is trained multiple times while adjusting a few parameters in order to get the maximum accuracy achievable.

The provided model is trained over a number of epochs to test accuracy. A graph of the model's accuracy and loss is drawn in this stage in order to assess over- and under-fitting, as will be seen later. The model is trained several times while a few parameters are changed to achieve the highest accuracy possible.

Exporting the Model and Building the Crop Disease Application

The trained model is exported to tflflite in the last stage, and android studio is used to construct the android application and its features. The Android smartphone can now be used when the programme has been installed.

Accuracy and Graphs:-



TESTING THE COMPARISON OF DATA OUTPUT FROM DIFFERENT MODELS

Model Name	Accuracy inn%
`1.Proposed Model CNN(Convolutional Neural Network)	97.89%
2.Random Forest	87.43%
3.Support Vector Machine(SVM)	78.61%

In comparison to other machine learning models, CNN delivered results with a higher degree of accuracy, but at a higher cost in terms of time and physical resources like RAM and CPU (Google Colaboratory GPU identified as device:GPU:0). The accuracy attained by CNN's work is 2.52% greater than the accuracy attained by the author of paper [4], which was 94.74%. In contrast to the authors of paper [7], who claimed that SVM and RF achieved the maximum accuracy of 40.33% and 66.76%, respectively, our work's SVM and RF accuracy is higher.

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