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EMPOWERING FARMERS WITH MACHINE LEARNING FOR PLANT DISEASE DETECTION AND PREDICTION

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ABSTRACT

A serious issue that endangers farmers, consumers, the environment, and the world economy is plant disease. Farmers in India lose 35 percent of their harvest when field crops fail owing to diseases and pests alone. As many pesticides are extremely toxic and can be exacerbated by living things, they pose a major risk to human health. With appropriate disease identification, crop monitoring, and customized treatment approaches, these outcomes can be avoided. Generally, specialists in agriculture would initially look for outward signs of an illness. Farmers, meanwhile, seldom have access to specialists. We have created the first comprehensive, collaborative platform for autonomously diagnosing, tracking, and forecasting illnesses. By snapping images of the afflicted plant sections, farmers may quickly and effectively identify illnesses using a smartphone app. Thanks to advanced artificial intelligence algorithms for cloud-based image processing, real-time diagnosis is now feasible. The AI model uses information from user-uploaded photos and professional reviews to continuously improve its performance. Farmers can use the platform to communicate with local specialists. For the purpose of prevention, illness density maps with spread projections are created using a cloud-stored database of geotagged images and microclimate factors. Specialists may do geographically-based sickness assessments using an online interface. In this study, we trained an artificial intelligence model for convolutional neural networks (CNNs) utilizing massive disease datasets that were generated from plant photos that were gathered over a period of seven months from different farms in a decentralized manner. Plant pathologists verified and approved the results after the automatic CNN model was used to diagnose test photos. The accuracy rate for sickness diagnosis was over 95%. We have created a unique, adaptable, and user-friendly tool to assist farmers and agricultural specialists in managing diseases in a variety of crop plants so as to harvest their crops in a sustainable manner.

Keywords: neural network, CNN, and machine learning. Computational Intelligence

1. INTRODUCTION

An integral component of human existence is agriculture. It is crucial to increase agricultural, fruit, and vegetable yield in emerging nations with dense populations, like India. Both the number and quality of the items provided affect the general public's health. Issues include the spread of diseases that may have been stopped with early identification hinder production and food quality. A number of these illnesses spread widely, completely eradicating agricultural production. Human-assisted disease detection is ineffective and unable to meet the enormous demand due to the dispersed nature of agricultural areas, the low educational levels of farmers, the shortage of relevant knowledge, and the difficulty in acquiring access to plant pathologists. It is necessary to automate crop disease diagnosis with technology and introduce low-cost, accurate machine-aided diagnostics that are readily available to farmers in order to address the shortcomings of human helped disease detection. Robotics and computer vision technologies have developed to the point where they may be applied to address a variety of issues facing the agriculture sector. The application of image processing may be advantageous for precision agriculture techniques, weed and pesticide technology, monitoring plant development, and nutrient control [1][2]. Although many plant diseases can be identified by plant pathologists through visual inspection of physical symptoms like detectable colour change, wilting, the appearance of spots and lesions, etc., in addition to soil and climatic conditions, progress on automating plant disease diagnosis is still in its infancy. On the overall, commercial investments in agricultural technology integration are still less significant than those made in more lucrative industries like human health and education. Due to obstacles like access and links for farmers to plant pathologists, significant implementation costs, and scalability of solutions, promising research ideas have not been able to materialise. Recent advances in mobile, cloud, and artificial intelligence (AI) technologies provide a scalable, affordable solution that might be widely used to fight agricultural diseases. Mobile devices with internet capabilities are used far more often in nations with poorer standards of living, such as India. Geolocated photographs may be readily shared by individuals utilising widely accessible, affordable mobile phones. They may interact with more advanced Cloud-based backend services that handle computationally challenging operations, centralise data storage, and perform data analytics over open mobile networks. The ability of the human eye to recognise and categorise images properly has recently been surpassed by artificial intelligence (AI) based image analysis. Neural networks (NN) with a connection structure based on the visual cortex are used in the underlying AI algorithms. To achieve high accuracy in image classification on new, unseen images, these networks are "trained" using a huge volume of previously categorised, "labelled," photographs. Deep convolutional neural networks (CNNs) have taken over the field of computer vision and image processing since "AlexNet" won the ImageNet competition in 2012 [3]. The development of NN algorithms, the rise in processing power, and the availability of big data sets are all thought to be responsible for the breakthrough in CNN capabilities. Open source platforms like TensorFlow have made it feasible to develop improved AI that is more inexpensive and accessible [4].

2. SYSTEM ANALYSIS

EXISTING SYSTEM:

In India, pathogens and pests are responsible for the failure of 35% of field crops, resulting in financial losses for farmers. Pesticides represent a serious threat to human health since many of them are highly toxic and can be amplified by living organisms. Avoiding these consequences is possible with proper disease detection, crop monitoring, and individualised treatment plans. Typically, agricultural experts would first seek for visible symptoms of a disease. Meanwhile, farmers have little access to experts[5].

DISADVANTAGE:

Pesticides pose a serious threat to human health since many of them are highly toxic and can have a multiplied effect when used carelessly [6].

PROPOSED SYSTEM:

In this study, we use all of the plant disease photos to train a convolution neural network (CNN), which then detects the presence of plant diseases in newly submitted images. The CNN train model and accompanying photographs are stored in the author's cloud account. Thus, information on plant diseases is predicted by the author and kept in the cloud[7].

To submit photographs, we use a smart phone, but developing an Android app would be too costly and time-consuming for our project, so instead we developed a Python online app.This online tool is used to train a convolutional neural network (CNN), which is then used to analyse uploaded photos for disease prediction[8].

ADVANTAGES OF PROPOSED SYSTEM:

Use a smartphone app to take images of diseased plant parts for a precise diagnosis.

3. SYSTEM DESIGN

SYSTEM ARCHITECTURE DIAGRAM:

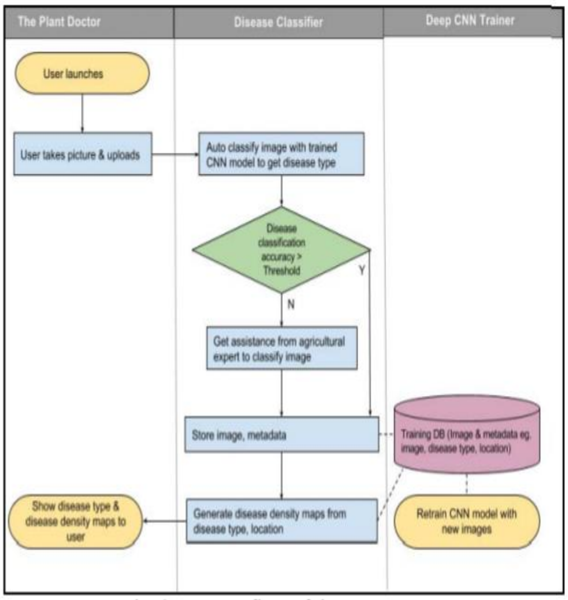

Fig 1: Machine Learning Techniques for Disease Identification:

Discussion of various machine learning algorithms used for plant disease identification

Mention of image recognition techniques, including convolutional neural networks (CNNs), and their role in analyzing leaf images for disease symptoms.

Case studies and examples of successful disease identification systems[2].

Tracking and Monitoring Plant Diseases:

Explanation of how machine learning can be used to track and monitor the spread of diseases.

Utilization of sensor data, satellite imagery, and IOT devices for real-time disease tracking

Illustration of how data-driven insights can aid in early disease detection and control[3].

Forecasting Disease Outbreaks:

Elaboration on the predictive capabilities of machine learning models in forecasting disease outbreaks[4].

Discussing the integration of historical data, weather patterns, and environmental factors to predict disease occurrences Importance of accurate forecasting in enabling farmers to implement preventive measures[5].

Challenges and Considerations:

- Addressing challenges such as data quality, model robustness, and interpretability.
- Ethical considerations in data collection and sharing, especially when involving farmers' data
- Discussion on the digital divide and ensuring accessibility to technology in different agricultural regions

Benefits and Impact:

- Outlining the potential benefits of implementing machine learning in disease management
- Improved crop yield, reduced pesticide usage, and minimized economic losses.
- Positive ecological impact through targeted treatments

Case Studies and Applications:

Highlighting real-world applications and success stories from different regions

Examples of collaborations between researchers, farmers, and technology developers

Demonstrating the scalability and adaptability of machine learning solutions

Future Directions:

- Speculating on the future developments in this field
- Advancements in AI and data collection techniques
- Integration of other technologies such as blockchain and edge computing

4. ALGORITHM MODEL

Many studies have discussed utilising transfer learning to identify common CNN models for plant disease diagnosis, and they have found extremely high classification accuracy. However, these untrained models need a lot of storage space and laborious training since they have a significant number of nodes in the flattening layers and convolution layers. This chapter aims to demonstrate that even with simple CNN models, extremely high classification accuracies may be achieved[8]. The method has been demonstrated through the categorization of diseases in tomato and grape crops. The outcomes have also been contrasted with what can be learned using conventional machine learning techniques. The plant village dataset that is utilised for case studies is described after the chapter first explains the light versions of CNN models. Then, using the light versions, tests on tomato and grape crops are conducted[9].

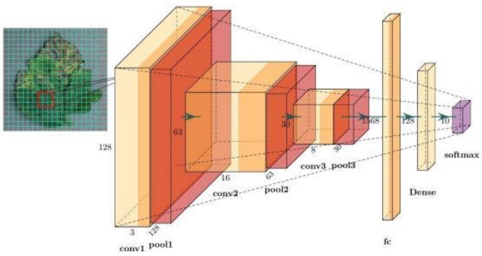

Fig 2: CNN model

5. RESULTS

Register page:

Login page:

Main page:

Cotton crop disease:


```
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 126, 126, 32)      896
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 63, 63, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 61, 61, 32)        9248
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 30, 30, 32)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 28800)             0
_________________________________________________________________
dense_1 (Dense)              (None, 256)               7373056
_________________________________________________________________
dense_2 (Dense)              (None, 5)                 1285
=================================================================
Total params: 7,384,485
Trainable params: 7,384,485
Non-trainable params: 0
```

6. CONCLUSION

Accurately, quickly, and early detection of agricultural illnesses and early detection of disease outbreaks present a major issue for farmers. Our project provides an easy-to-use, low-cost end-to-end solution for this problem. As a result, farmers would be in a better position to decide how to curb the spread of illness. This proposal builds on earlier work by employing deep Convolutional Neural Networks (CNNs) for disease classification, a social collaborative platform to gradually increase accuracy, geocoded imagery for disease density maps, and an expert interface for analytics. The powerful deep CNN model "Inception" provides real-time disease classification in the Cloud via a user-facing mobile app. The collaborative technique allows continuous improvement in the sickness categorization accuracy by automatically expanding the cloud-based training dataset with user-added photos for retraining the CNN network. User-uploaded photos in the Cloud repository allow the generation of disease density maps based on the availability of aggregate sickness categorization data and geolocation information within the images. The proposal has a great deal of potential for practical implementation, according to our experimental results, for a variety of reasons, including its highly scalable Cloud-based infrastructure, the accuracy of the underlying algorithm even when dealing with a large number of disease categories, its improved performance when using high-fidelity real-world training data, its improved accuracy when the training dataset is increased, and its ability to detect multiple diseases at once.

Future work:

More research is required in the area of extending the model to incorporate additional factors that might reinforce the link between the sickness and the variable. To increase the precision of our model and allow disease predictions, we may add to the picture database additional information from the farmer on the soil, prior fertiliser and pesticide treatment, and publically accessible weather factors like temperature, humidity, and rainfall. Our goals also include a decrease in professional intervention as a whole and an increase in the number of agricultural illnesses that are covered. It may be feasible to automatically accept user-uploaded photos into the Training Database for increased classification accuracy with minimal human involvement utilising a simple method of setting the threshold based on the average of all classification results. The results of this work might be used to construct time-based automated monitoring of illness density maps, which would allow for the prompt issuance of alerts and the tracking of disease outbreaks. Users may receive notifications about potential illness outbreaks in their area by using predictive analytics.

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