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AI-driven Cloud Server for Disease Classification of Chilli Plants: An Enhanced Crop Management System

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Abstract

Agriculture plays a vital role in feeding the ever-growing global population and providing essential resources. However, it faces numerous challenges, and one of the most significant issues for farmers is dealing with plant diseases. These diseases can wreak havoc on crop yields and overall agricultural productivity. Therefore, it becomes crucial to identify, track, and forecast these diseases effectively to manage them and prevent widespread losses. The main problem lies in the difficulty faced by farmers in accurately identifying plant diseases in their crops. Traditionally, farmers have relied on manual observation and experience to detect and identify plant diseases. However, this approach is time-consuming, subjective, and prone to errors. It heavily relies on the farmer's knowledge, experience, and ability to recognize disease symptoms accurately. While some farmers may seek advice from agricultural experts or extension workers, this is often not a scalable solution due to the limited availability of experts and the associated costs. To overcome the limitations of traditional methods, there is a critical need for an innovative AI-driven and cloud-based platform tailored specifically for farmers. This platform would harness the power of artificial intelligence, cloud computing, and data analysis to enable more precise, efficient, and easily accessible plant disease identification, tracking, and forecasting. By empowering farmers with cutting-edge technology, knowledge, and real-time insights, this platform can significantly improve crop yields, reduce losses, and ultimately contribute to enhancing global food security.

Keywords: Smart agriculture, crop management, disease classification, artificial intelligence, cloud server.

1. Introduction

Agriculture is fundamental to human survival. For populated developing countries like India, it is even more imperative to increase the productivity of crops, fruits, and vegetables. Not only productivity, but the quality of produce also needs to stay high for better public health. However, both productivity and quality of food gets hampered by factors such as spread of diseases that could have been prevented with early diagnosis. Many of these diseases are infectious leading to total loss of crop yield. Given the vast geographical spread of agricultural lands, low education levels of farmers coupled with limited awareness and lack of access to plant pathologists, human assisted disease diagnosis is not effective and cannot keep up with the exorbitant requirements. To overcome the shortfall of human assisted disease diagnosis, it is imperative to build automation around crop disease diagnosis with technology and introduce low cost and accurate machine assisted diagnosis easily accessible to farmers. Some strides have been made in applying technologies such as robotics and computer vision systems to solve myriad problems in the agricultural domain. The potential of image processing has been explored to assist with precision agriculture practices, weed and herbicide technologies, monitoring plant growth and plant nutrition management [1][2]. However, progress on automating plant disease diagnosis is still rudimentary although many plant diseases can be identified by plant pathologists by visual inspection of physical symptoms such as detectable change in color, wilting, appearance of spots and lesions etc. along with soil and climatic conditions. Overall, the commercial level of investment in bridging agriculture and technology remains lower as compared to investments done in more lucrative fields such as human health and education. Promising research efforts have not been able to productize due to challenges such as access and linkage for farmers to plant pathologists, high cost of deployment and scalability of solution.

Recent developments in the fields of Mobile technology, Cloud computing and Artificial Intelligence (AI) create a perfect opportunity for creating a scalable low-cost solution for crop diseases that can be widely deployed. In developing countries such as India, mobile phones with internet connectivity have become ubiquitous. Camera and GPS enabled low-cost mobile phones are widely available that can be leveraged by individuals to upload images with geolocation. Over widely available mobile networks, they can communicate with more sophisticated Cloud based backend services which can perform the compute heavy tasks, maintain a centralized database, and perform data analytics. Another leap of technology in recent years is AI based image analysis which has surpassed human eye capabilities and can accurately identify and classify images. The underlying AI algorithms use Neural Networks (NN) which have layers of neurons with a connectivity pattern inspired by the visual cortex. These networks get “trained” on a large set of pre-classifieds “labeled” images to achieve high accuracy of image classification on new unseen images. Since 2012 with “AlexNet” winning the ImageNet competition, deep Convolutional Neural Networks (CNNs) have consistently been the winning architecture for computer vision and image analysis [3]. The breakthrough in the capabilities of CNNs have come with a combination of improved compute capabilities, large data sets of images available and improved NN algorithms. Besides accuracy, AI has evolved and become more affordable and accessible with open-source platforms such as TensorFlow [4].

Prior art related to our project includes initiatives to gather healthy and diseased crop images [5], image analysis using feature extraction, RGB images, spectral patterns and fluorescence imaging spectroscopy. Neural Networks have been used in the past for plant disease identification, but the approach was to identify texture features. Our proposal takes advantage of the evolution of Mobile, Cloud and AI to develop an end-to-end crop diagnosis solution that simulates the expertise (“intelligence”) of plant pathologists and brings it to farmers. It also enables a collaborative approach towards continually increasing the disease database and seeking expert advice when needed for improved NN classification accuracy and tracking for outbreaks.

2. Literature survey

Sardogan [6] et al. presented a Convolutional Neural Network (CNN) model and Learning Vector Quantization (LVQ) algorithm-based method for tomato leaf disease detection and classification. The dataset contains 500 images of tomato leaves with four symptoms of diseases. We have modelled a CNN for automatic feature extraction and classification. Color information is actively used for plant leaf disease research. In this model, the filters are applied to three channels based on RGB components. The LVQ has been fed with the output feature vector of convolution part for training the network. The experimental results validated that the proposed method effectively recognizes four different types of tomato leaf diseases. Hossain [7] et al. proposed a technique for plant leaf disease detection and classification using K-nearest neighbor (KNN) classifier. The texture features are extracted from the leaf disease images for the classification. In this work, KNN classifier will classify the diseases like alternaria alternata, anthracnose, bacterial blight, leaf spot, and canker of various plant species. The proposed approach can successfully detect and recognize the selected diseases with 96.76 % accuracy.

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Saleem [8] et al. review provided a comprehensive explanation of DL models used to visualize various plant diseases. In addition, some research gaps are identified from which to obtain greater transparency for detecting diseases in plants, even before their symptoms appear clearly. Wang et al. [9] conducted a performance comparison test and ablation test between the optimized model and other mainstream models. The results showed that the operation time and accuracy of the optimized model are 11.8% and 3.98% higher than the original model, respectively, while F1 score reaches 92.65%, which highlight statistical metrics better than the current mainstream models. Moreover, the classification accuracy rate on the self-made dataset reaches 92.57%, indicating the effectiveness of the plant disease classification model proposed in this paper, and the transfer learning ability of the model can be used to expand the application scope in the future.

Francis [10] et al. created and developed a Convolutional Neural Network model is to perform plant disease detection and classification using apple and tomato leaf images of healthy and diseased plants. The model consists of four convolutional layers each followed by pooling layers. Two fully connected dense layers and sigmoid function is used to detect the probability of presence of disease or not. Training of the model was done on apple and tomato leaf image dataset containing 3663 images achieving an accuracy of 87%. The overfitting problem is identified and removed setting the dropout value to 0.2. As the model allows parallel processing, it is also run on GPU Tesla to evaluate its speed of performance and accuracy. Hence the paper provides an insight of creativeness to the researchers to develop an integrated plant disease identification system that gives successful results in real time. Shruthi [11] et al. presented the stages of general plant diseases detection system and comparative study on machine learning classification techniques for plant disease detection. In this survey it observed that Convolutional Neural Network gives high accuracy and detects a greater number of diseases of multiple crops.

Dhingra [12] et al. addressed a comprehensive study on disease recognition and classification of plant leaves using image processing methods. The traditional manual visual quality inspection cannot be defined systematically as this method is unpredictable and inconsistent. Moreover, it involves a remarkable amount of expertise in the field of plant disease diagnostics (phytopathology) in addition to the disproportionate processing times. Hence, image processing has been applied for the recognition of plant diseases. The paper has been divided into two main categories viz. detection and classification of leaves. A comprehensive discussion on the diseases detection and classification performance is presented based on analysis of previously proposed state of art techniques particularly from 1997 to 2016. Finally, discussed and classify the challenges and some prospects for future improvements in this space. Elangovan [13] et al. produced serious effects on plants and due to which respective product quality or productivity is affected. Disease classification on plant is very critical for supportable agriculture. It is very difficult to monitor or treat the plant diseases manually. It requires huge amount of work, and need the excessive processing time, therefore image processing is used for the detection of plant diseases. Plant disease classification involved the steps like Load image, pre-processing, segmentation, feature extraction, svmClassifer

Ozguven [14] et al. developed an Updated Faster R-CNN architecture by changing the parameters of a CNN model and a Faster R-CNN architecture for automatic detection of leaf spot disease (Cercospora beticola Sacc.) in sugar beet were proposed. The method, proposed for the detection of disease severity by imaging-based expert systems, was trained and tested with 155 images and according to the test results, the overall correct classification rate was found to be 95.48%. In addition, the proposed approach showed that changes in CNN parameters according to the image and regions to be detected could increase the success of Faster R-CNN architecture. The proposed approach yielded better

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outcomes for relevant parameters than the modern methods specified in previous literature. Therefore, it is believed that the method will reduce the time spent in diagnosis of sugar beet leaf spot disease in the large production areas as well as reducing the human error and time to identify the severity and course of the disease.

Ead [15] et al. reduced the checking of massive field by individuals. In sickness affirmation from picture, the key is to remove the brand name feature of the infected locale. As specified by the infection the features may change. The features that are isolated from the image are shading, shape surface and so on. Now and again for identification of the ailment more features are removed, and these isolated features would construct the equipment similarly as programming cost. This further causes increase in the eccentricism and the calculation time. Subsequently it is essential to reduce the element data.

3. Proposed model

The process flows in the system are captured in the activity diagram. Similar to a state diagram, an activity diagram also consists of activities, actions, transitions, initial and final states, and guard conditions as shown in Figure 1. According to the facts, training and testing of proposed model involves in allowing every source image via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from [0,1]. Convolution layer as is the primary layer to extract the features from a source image and maintains the relationship between pixels by learning the features of image by employing tiny blocks of source data. It's a mathematical function which considers two inputs like source image $I(x, y, d)$ where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an image (here $d = 3$, since the source image is RGB) and a filter or kernel with similar size of input image and can be denoted as $F\left(k_x, k_y, d\right)$.

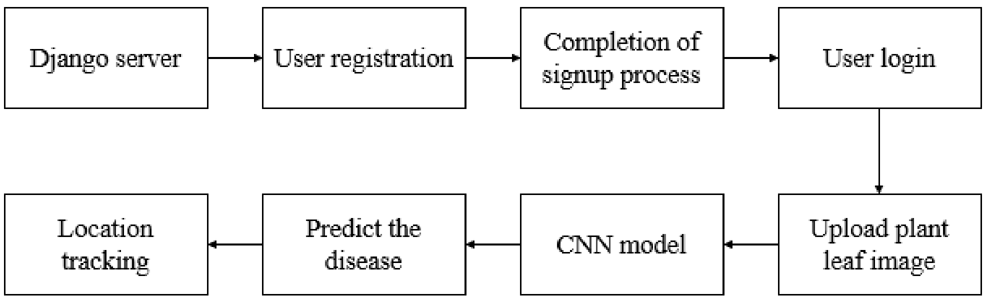

Figure 1: Block diagram of proposed system.

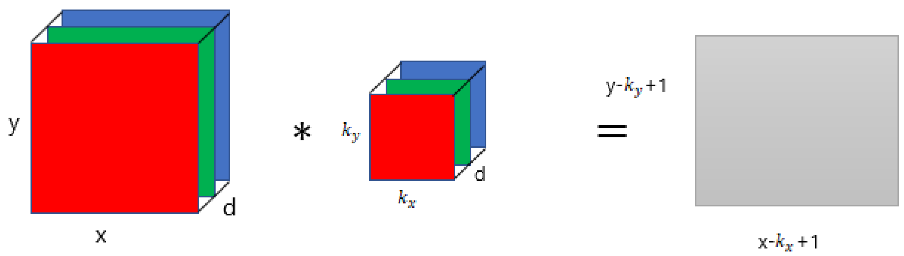

Fig. 2: Representation of convolution layer process.

The output obtained from convolution process of input image and filter has a size of $C\left((x - k_x + 1), \left(y - k_y + 1\right), 1\right)$, which is referred as feature map. Let us assume an input image with a size of 5×5 and the filter having the size of 3×3. The feature map of input image is obtained by multiplying the input image values with the filter values.

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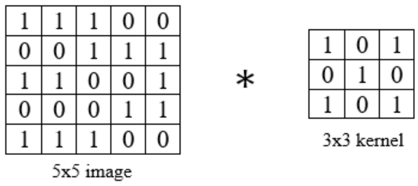
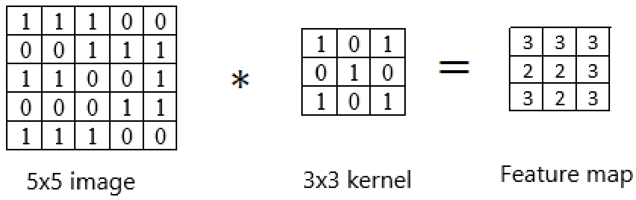
ReLU layer: Networks those utilizes the rectifier operation for the hidden layers are cited as rectified linear unit (ReLU). This ReLU function $\mathcal{G}(\cdot)$ is a simple computation that returns the value given as input directly if the value of input is greater than zero else returns zero. This can be represented as mathematically using the function $max(\cdot)$ over the set of 0 and the input x as follows:

$$\mathcal{G}(x) = \max\{0, x\}$$



(a)



(b)

Fig. 3: Example of convolution layer process (a) an image with size $\mathbf{5 \times 5}$ is convolving with $\mathbf{3 \times 3}$ kernel (b) Convolved feature map.

Max pooing layer: This layer mitigates the number of parameters when there are larger size images. This can be called as subsampling or down sampling that mitigates the dimensionality of every feature map by preserving the important information. Max pooling considers the maximum element form the rectified feature map.

Softmax classifier: Generally, as seen in the above picture softmax function is added at the end of the output since it is the place where the nodes are meet finally and thus, they can be classified. Here, X is the input of all the models and the layers between X and Y are the hidden layers and the data is passed from X to all the layers and Received by Y. Suppose, we have 10 classes, and we predict for which class the given input belongs to. So, for this what we do is allot each class with a particular predicted output. Which means that we have 10 outputs corresponding to 10 different class and predict the class by the highest probability it has.

4. Results and discussion

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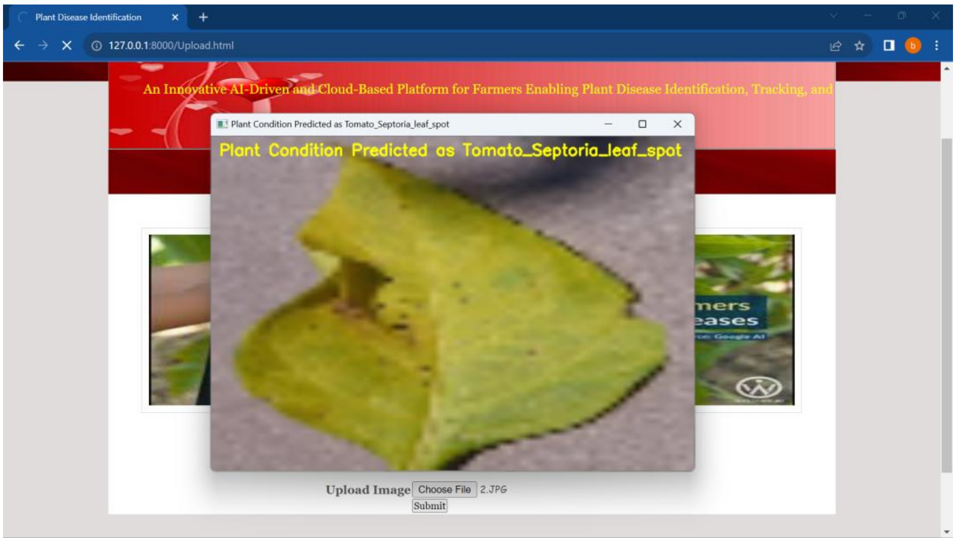
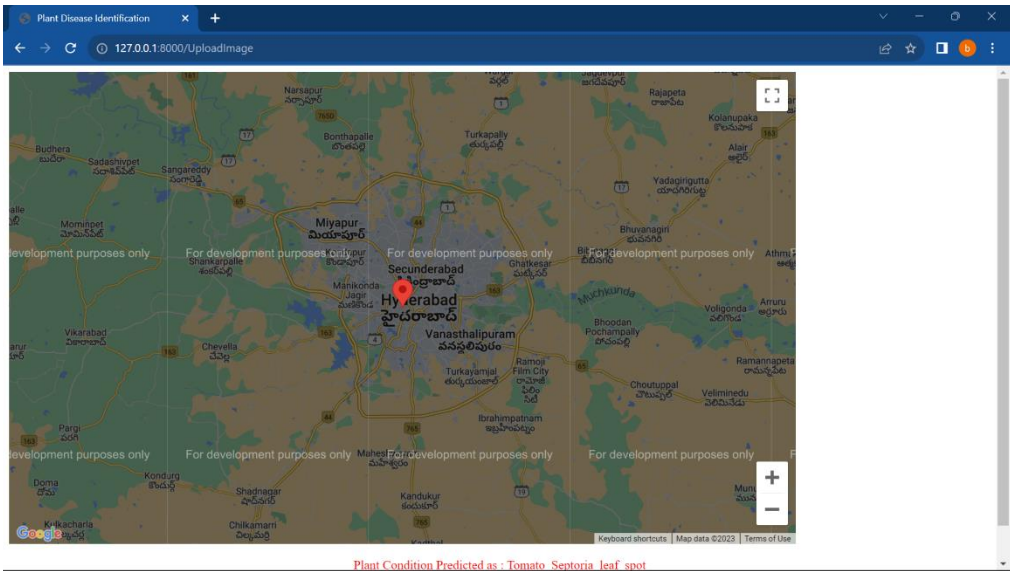
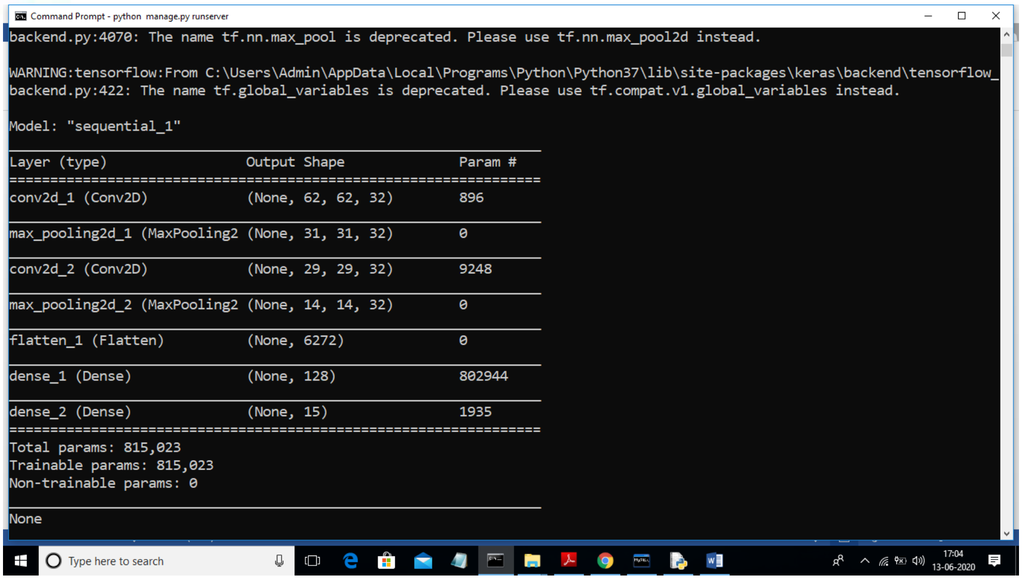


In above screen we will get image with predicted disease name printed on image and now close that image to get locations in map



In above screen in map we can get location of uploaded image mark with marker and below map we can see predicted disease name in red colour. Similarly you can upload any image from ‘uploadimages’ folder. In below screen we can see CNN layers created to build plant disease model



In above screen we can see CNN multi layers filter created where first filter created with image size 62 X 62 and second filter with size 31 X 31 and goes on.

5. Conclusion

This work presents an automated, low cost and easy to use end-to-end solution to one of the biggest challenges in the agricultural domain for farmers – precise, instant, and early diagnosis of crop diseases and knowledge of disease outbreaks - which would be helpful in quick decision making for measures to be adopted for disease control. This proposal innovates on known prior art with the application of deep Convolutional Neural Networks (CNNs) for disease classification, introduction of social collaborative platform for progressively improved accuracy, usage of geocoded images for disease density maps and expert interface for analytics. High performing deep CNN model “Inception” enables real time classification of diseases in the Cloud platform via a user facing mobile app. Collaborative model enables continuous improvement in disease classification accuracy by automatically growing the Cloud based training dataset with user added images for retraining the CNN model. User added images in the Cloud repository also enable rendering of disease density maps based on collective disease classification data and availability of geolocation information within the images. Overall, the results of our experiments demonstrate that the proposal has significant potential for practical deployment due to multiple dimensions – the Cloud based infrastructure is highly scalable and the underlying algorithm works accurately even with large number of disease categories, performs better with high fidelity real-life training data, improves accuracy with increase in the training dataset, is capable of detecting early symptoms of diseases and is able to successfully differentiate between diseases of the same family

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