AN INTEGRATED NEURAL AND CLOUD-BASED TECHNIQUE FOR DETECTING, CLASSIFYING, AND TRACKING PLANT DISEASES

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ABSTRACT
A significant threat to farmers, consumers, the environment, and the world economy is posed by plant diseases. Pathogens and pests alone in India cause the loss of 35% of field crops, costing farmers money. Because many pesticides are poisonous and bio magnified, indiscriminate use of them poses a major health risk. Early disease identification, crop surveillance, and tailored treatments can prevent these negative impacts. Agricultural specialists typically detect illnesses by looking at their outward signs. Farmers, meanwhile, have little access to professionals. Our initiative is the first collaborative, comprehensive platform for automatically diagnosing, tracking, and forecasting diseases. Farmers can instantly and accurately identify diseases and get solutions with a mobile app by photographing affected plant parts. Real-time diagnosis is enabled using the latest Artificial Intelligence (AI) algorithms for Cloud-based image processing. The AI model continuously learns from user uploaded images and expert suggestions to enhance its accuracy. Farmers can also interact with local experts through the platform. For preventive measures, disease density maps with spread forecasting are rendered from a Cloud based repository of geo-tagged images and micro-climactic factors. A web interface allows experts to perform disease analytics with geographical visualizations. In our experiments, the AI model (CNN) was trained with large disease datasets, created with plant images self-collected from many farms over
7 months. Test images were diagnosed using the automated CNN model and the results were validated by plant pathologists. Over 95% disease identification accuracy was achieved. Our solution is a novel, scalable and accessible tool for disease management of diverse agricultural crop plants and can be deployed as a Cloud based service for farmers and experts for ecologically sustainable crop production.
Keywords: Plant diseases, Artificial Intelligence (AI), Cloud based services.

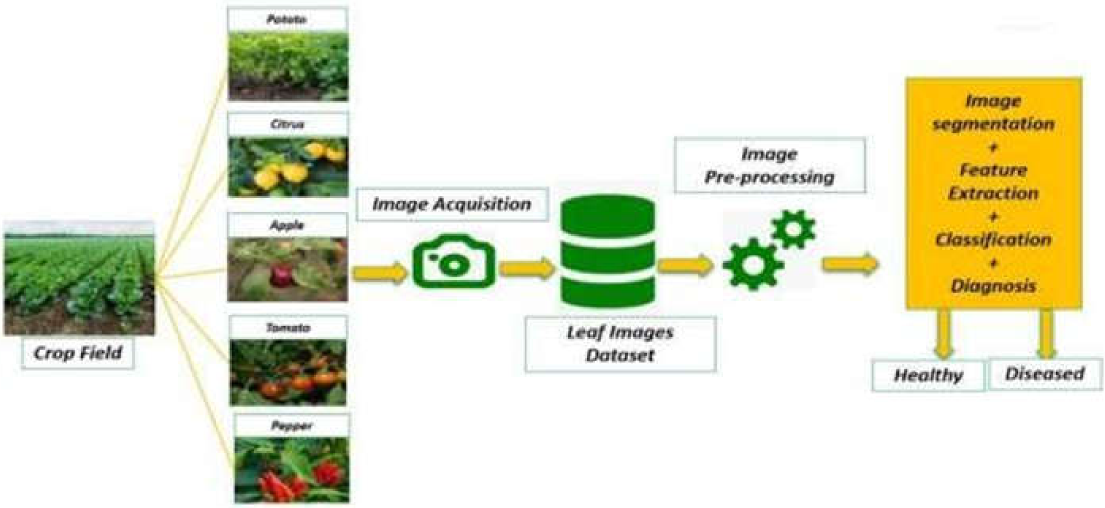
INTRODUCTION

A vital component of human life is agriculture. It is much more crucial to boost agricultural, fruit, and vegetable yield in densely populated emerging nations like India. For improved public health, produce quality as well as productivity must remain high. Yet, problems like the spread of infections that could have been stopped with early detection hinder both production and food quality. Several of these illnesses are contagious, which causes a complete loss of agricultural productivity. Human aided disease diagnosis is ineffective and unable to keep up with the astronomical demand because to the extensive geographic distribution of agricultural areas, low education levels of farmers, limited knowledge, and lack of access to plant pathologists.

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 in spite of the fact that 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 relocation. 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 eyecapabilities 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-classified "labelled" 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 has come with a combination of improved compute capabilities, large data sets of images available and improved NN algorithms. Besides accuracy, AIhas evolved and become more affordable and accessible with open-source platforms such as TensorFlow [4].

Fig. 1: AI and cloud-based platform for disease detection and classification in plants.



Prior art related to our project includes initiatives to gather healthy and diseased crop images [5], image analysis using feature extraction [6], RGB images [7], spectral patterns [8] and fluorescence imaging spectroscopy [9]. 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

PROPOSED SYSTEM

Disease Classifier

The Classifier is a standalone application running in the Cloud platform that receives the images uploaded via the mobile app and uses a trained deep Convolutional Neural Network (CNN) model to classify the disease type. The CNN model is computed by the Deep CNN Trainer and is used by the Classifier to automatically classify the uploaded images into the correct disease type. The Classifier also performs post-processing such as making a decision on whether the uploaded images should be added to the Training Database based on the classification score or sent to an agricultural expert registered on the platform for further analysis. When the classification score is greater than a preconfigured threshold, the images along with their metadata such as disease type and location of the images get added to the Training Database. In case of low classification score, the system forwards the case and seeks assistance from agricultural expert teams for manual classification which are then sent to the farmer and stored in the Training Database. Low accuracy typically occurs if the user uploads an image with an underlying disease that is so far not known to the trained CNN model, orthe image quality is poor. Expert intervention in case of low classification score allows addition ofnew disease types which can be stored for future training runs. After the Training Database has sufficiently large number of images of the new disease category and high classification accuracy is achieved, the Classifier can start recognizing the new disease automatically. Over time as more farmers collaborate and contribute images, it enables us to improve the accuracy for automated response to covered diseases, while using the limited expert resources to expand coverage for new diseases. x Deep CNN Trainer - This Cloud application is responsible for the more intensive work of training the neural network and builds the deep CNN model that is used by the Classifier to classify images into the correct disease types. This application is run asynchronously (without any interferenceto the Classifier) whenever he number of new images added to the Training Database goes beyond a pre-configured threshold. Each subsequent run of this training application works on a larger training dataset, and hence continually improves the deep CNN model used by the Classifier for more accuratedisease classification. AWS was used to build the entire Cloud platform. The Disease Classifier and the Deep CNN Trainer are applications developed in Python. To make these Python applications accessible over mobile internet, they were developed using a web framework called FLASK and deployed behind an Apache Web Server running on an AWS EC2 machine (Ubuntu 16.04.2 LTS, 2 GiB memory, 8 GiB EBS volume). Disease Classifier and Deep CNN Trainer are built with TensorFlow [4], which is an open source library for Artificial Intelligence by Google. x Training Database - This is a Cloud based database that stores all images used to train the deep CNN model. In addition to the images, it stores the metadata such as disease type, location of the images and time stamps. This database grows with wider use of the mobile app and as farmers uploads more images taken from their fields. Growth of the Training Database allows continual retraining of the deep CNN model with larger datasets. Data in this database is also used to compute disease density relative to theuser‟s location from collective metadata, such as disease types and image geo locations, and the generated disease density maps are rendered in the mobile app. AWS S3 was used to implement the image database and MySQL running on AWS EC2 was used to store disease metadata such as classification, treatment, and location. Expert Interface – A web-based expert interface has been developed that allows agricultural experts to manually classify images that get low classificationscore. After the expert manually classifies the image, an SMS alert is sent to the user to check the mobile app history to receive the updated classification and remedial suggestions. Another feature of this interface is that it leverages the disease metadata stored by the Cloud platform to allow the experts to render time based and geographical visualizations of disease data for analytics and monitoring purposes.

Convolutional Neural Network (CNN):

- A convolutional neural network, or CNN, is a deep learning neural network sketched forprocessing structured arrays of data such as portrayals.
- CNN are very satisfactory at picking up on design in the input image, such as lines, gradients,circles, or even eyes and faces.
- This characteristic that makes convolutional neural network so robust for computer vision.
- CNN can run directly on a underdone image and do not need any preprocessing.
- A convolutional neural network is a feed forward neural network, seldom with up to 20.
- The strength of a convolutional neural network comes from a particular kind of layer called theconvolutional layer.
- CNN contains many convolutional layers assembled on top of each other, each one competent of recognizing more sophisticated shapes.
- With three or four convolutional layers it is viable to recognize handwritten digits and with 25 layers it is possible to differentiate human faces.

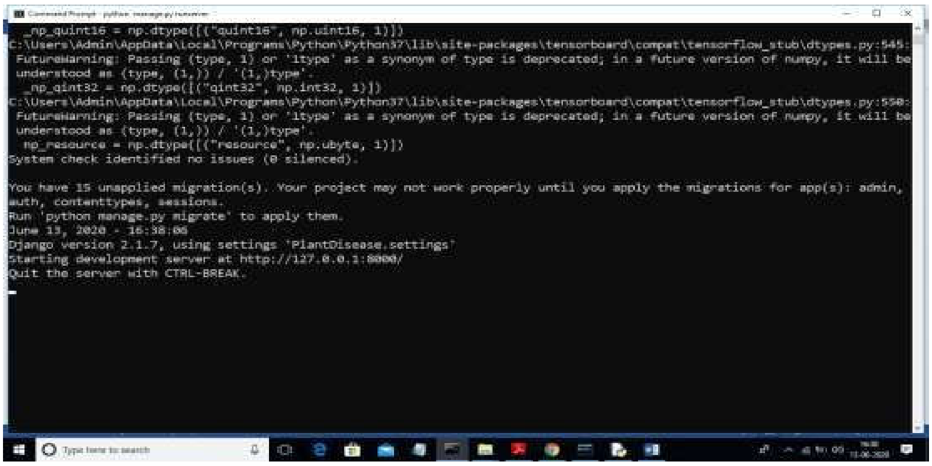
- The agenda for this sphere is to activate machines to view the world as humans do, perceive it in a alike fashion and even use the knowledge for a multitude of duty such as image and video recognition, image inspection and classification, media recreation, recommendation systems, natural language processing, etc.

Convolutional Neural Network Design:

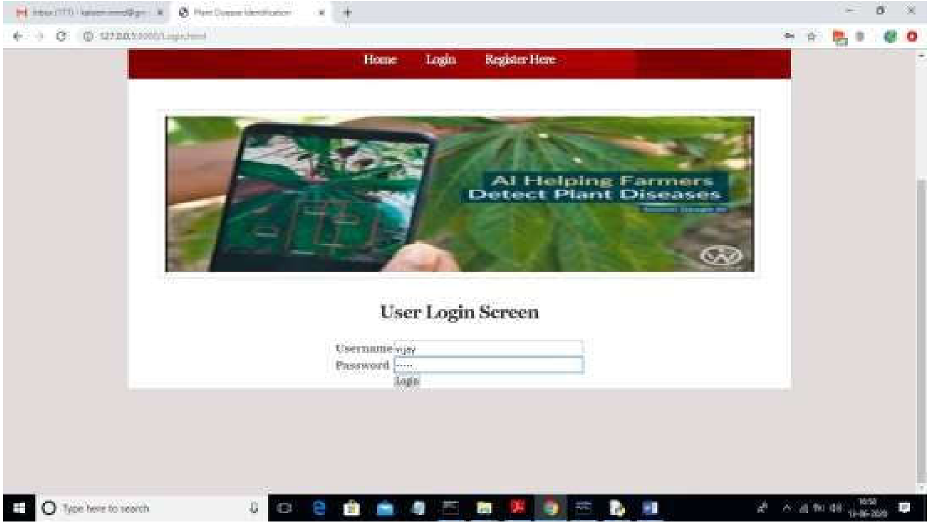
- The construction of a convolutional neural network is a multi-layered feed-forward neural network, made by assembling many unseen layers on top of each other in a particular order.
- It is the sequential design that gives permission to CNN to learn hierarchical attributes.
- In CNN, some of them followed by grouping layers and hidden layers are typically convolutional layers followed by activation layers.
- The pre-processing needed in a ConvNet is kindred to that of the related pattern of neurons in the human brain and was motivated by the organization of the Visual Cortex.23.4 Case Study of CNN for Diabetic retinopathy
- Diabetic retinopathy also known as diabetic eye disease, is a medical state in which destructionoccurs to the retina due to diabetes mellitus, It is a major cause of blindness in advance countries.
- Diabetic retinopathy influence up to 80 percent of those who have had diabetes for 20 years or more.
- The overlong a person has diabetes, the higher his or her chances of growing diabetic retinopathy.
- It is also the main cause of blindness in people of age group 20-64.
- Diabetic retinopathy is the outcome of destruction to the small blood vessels and neurons ofthe retina.

RESULTS

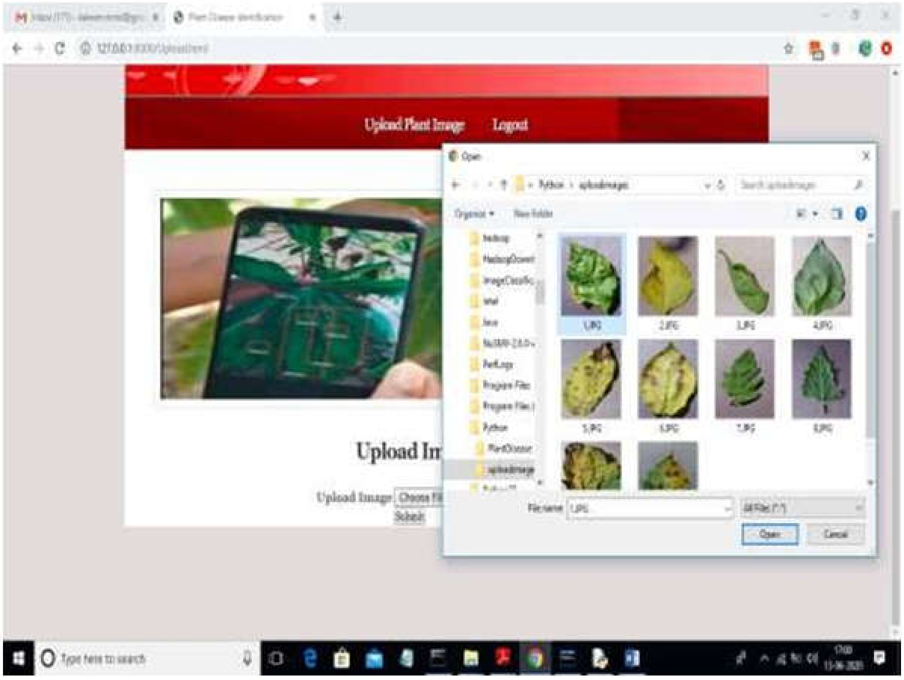
In below screen python server started and running on IP‟. Now open browser and enter URL as „http://127.0.0.1:8000/index.html‟ to get below screen



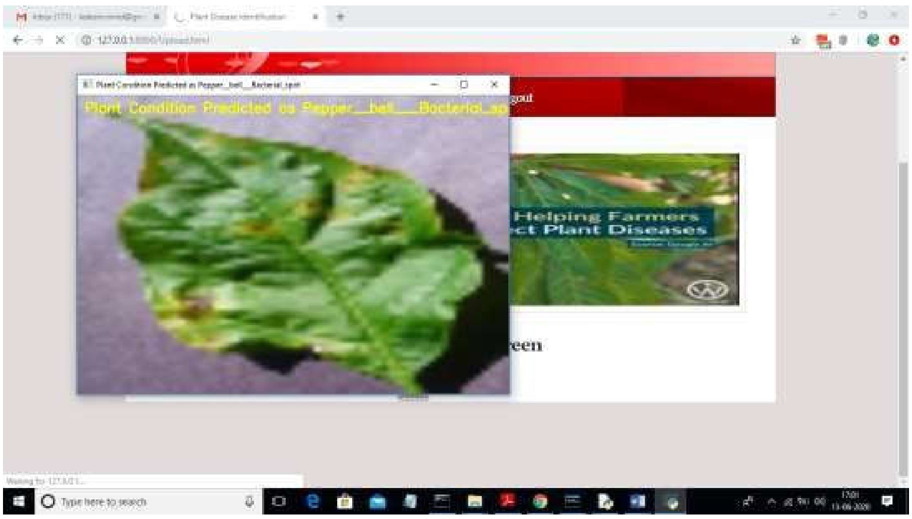
In above screen click on „Register here" link to allow user to register with the application



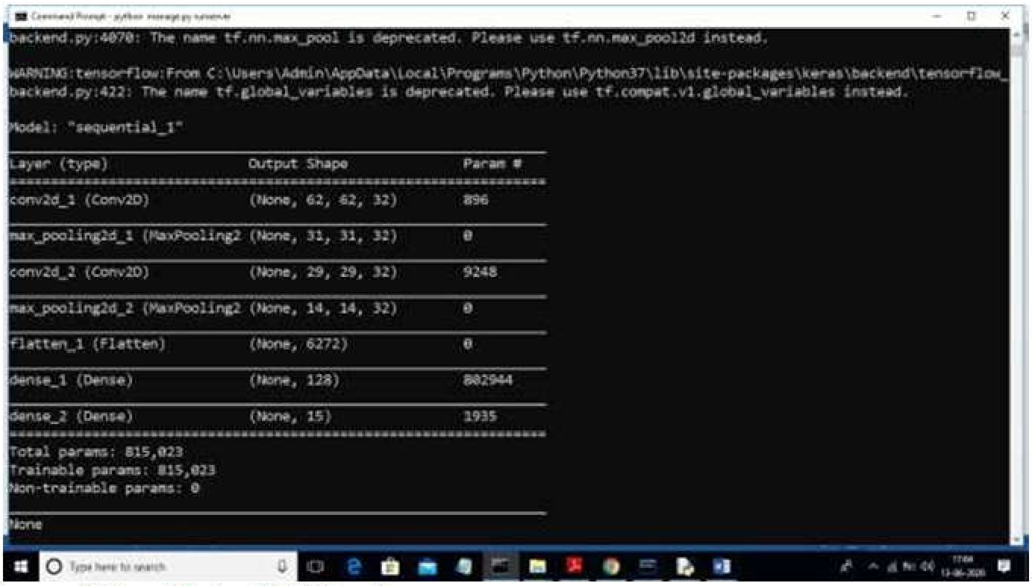
After login will get below screen



In above screen uploading 1.JPG image and now click on „Open" button to upload image



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 we can see CNN multi layers filter created where first filter created with image size62 X 62 and second filter with size 31 X 31 and goes on.

CONCLUSION

This paper 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 detectingearly symptoms of diseases and is able to successfully differentiate between diseases of the same family

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