

AN AI AND CLOUD BASED COLLABORATIVE PLATFORM FOR PLANT DISEASE IDENTIFICATION, TRACKING AND FORECASTING FOR FARMERS

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ABSTRACT

Plant diseases are a major threat to farmers, consumers, environment, and the global economy. In India alone, 35% of field crops are lost to pathogens and pests causing losses to farmers. Indiscriminate use of pesticides is also a serious health concern as many are toxic and biomagnified. These adverse effects can be avoided by early disease detection, crop surveillance and targeted treatments. Most diseases are diagnosed by agricultural experts by examining external symptoms. However, farmers have limited access to experts. Our project is the first integrated and collaborative platform for automated disease diagnosis, tracking and forecasting. Farmers can instantly and accurately identify diseases and get solutions with a mobile app by photographing affected plant parts. Realtime 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-climatic 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 disease detection, Artificial Intelligence, CNN.

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-classified “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.

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, svmClassifier

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 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 SYSTEM

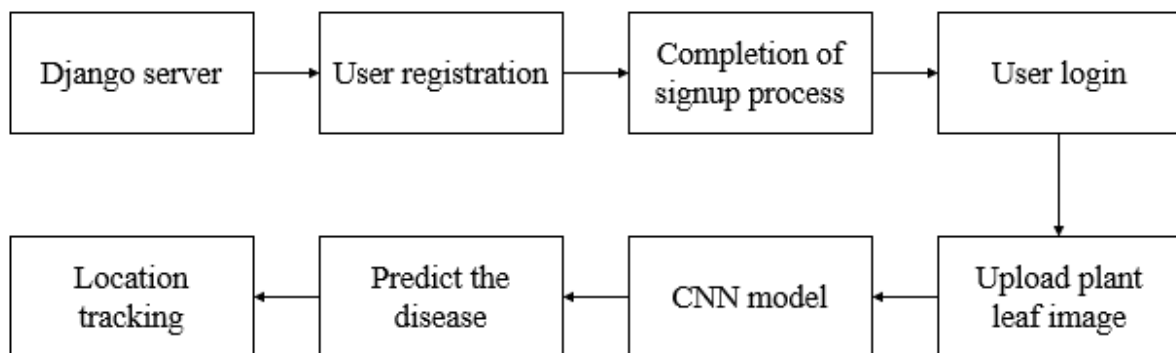


Fig. 1: Block diagram of proposed system.

3.1 Registration

This module is used for user registration. Here, user must fill up the following modules

- Username
- Password
- Contact number
- Email ID
- Address

Then, click on the register button to add new user.

3.2 User login

After completion of signup process user have to login to their account by entering the username and password. In this module user has to upload the plant leaf images.

3.3 Training and testing using CNN

According to the facts, training and testing of DL-CNN 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]. Figure 1 discloses the architecture of DL-CNN that is utilized

in proposed methodology for CBIR system for enhanced feature representation of word image over conventional retrieval systems.

Convolution layer as depicted in Figure 3.2 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 $F(k_x, k_y, d)$.

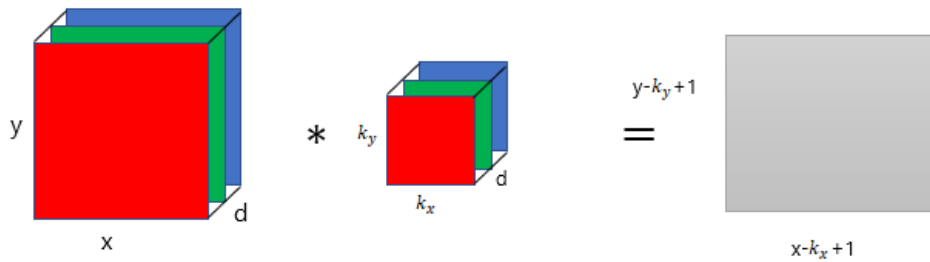
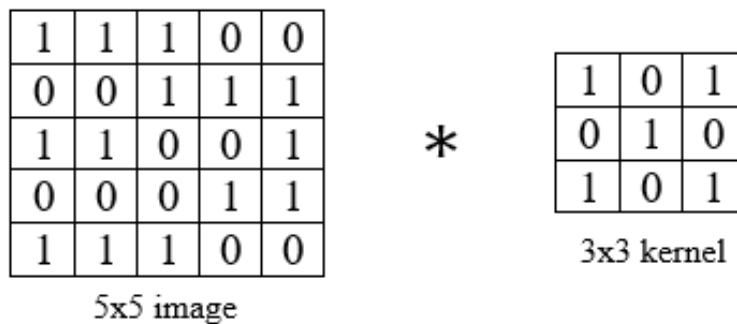
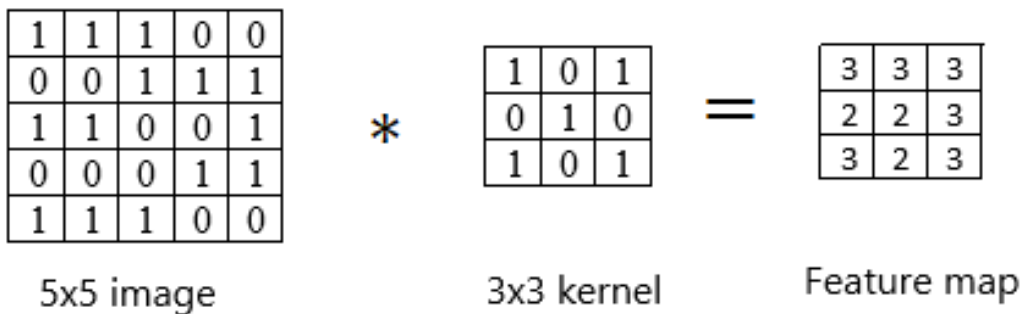


Fig. 2: Representation of convolution layer process.

The output obtained from convolution process of input image and filter has a size of $C((x - k_x + 1), (y - k_y + 1), 1)$, which is referred as feature map. An example of convolution procedure is demonstrated in Figure 3.2. 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 as given in Figure 3.



(a)



(b)

Fig. 3: Example of convolution layer process (a) an image with size 5×5 is convolving with 3×3 kernel (b) Convolved feature map.

3.3.1 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:

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

3.3.2 Max pooling 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.

3.3.3 Principal component analysis

Principal component analysis is an approach of machine learning which is utilized to reduce the dimensionality. It utilizes simple operations of matrices from statistics and linear algebra to compute a projection of source data into the similar count or lesser dimensions. PCA can be thought of a projection approach where data with m -columns or features are projected into a subspace by m or even lesser columns while preserving the most vital part of source data. Let I be a source image matrix with a size of $n * m$ and results in J which is a projection of I . The primary step is to compute the value of mean for every column. Next, the values in every column are centered by subtracting the value of mean column. Now, covariance of the centered matrix is computed. At last, compute the eigenvalue decomposition of every covariance matrix, which gives the list of eigenvalues or eigenvectors. These eigenvectors constitute the directions or components for the reduced subspace of J , whereas the peak amplitudes for the directions are represented by these eigenvectors. Now, these vectors can be sorted by the eigenvalues in descending order to render a ranking of elements or axes of the new subspace for I . Generally, k eigenvectors will be selected which are referred principal components or features

3.3.4 Euclidean distance

To evaluate distances between query word image I_q and retrieved word images I_r , a metric must be defined. We need a measurement method to tell how the query and retrieved word images are similar (bit per bit). Therefore, we want a similarity measure where the distance value will be the number of similar bits in the considered images.

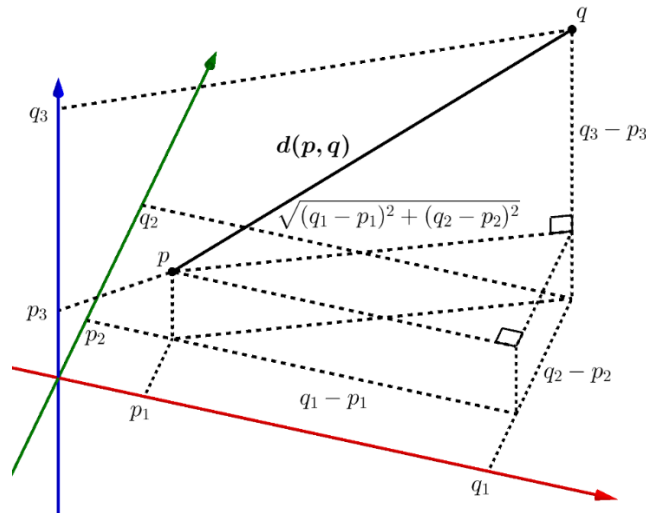


Fig. 4: Illustration of Euclidean distance.

3.4 Prediction

This module will predict the disease of the uploaded plant leaf image with disease name using CNN.

3.5 Location tracking

By using this button, we will track the location from the google maps of uploaded image mark with marker.

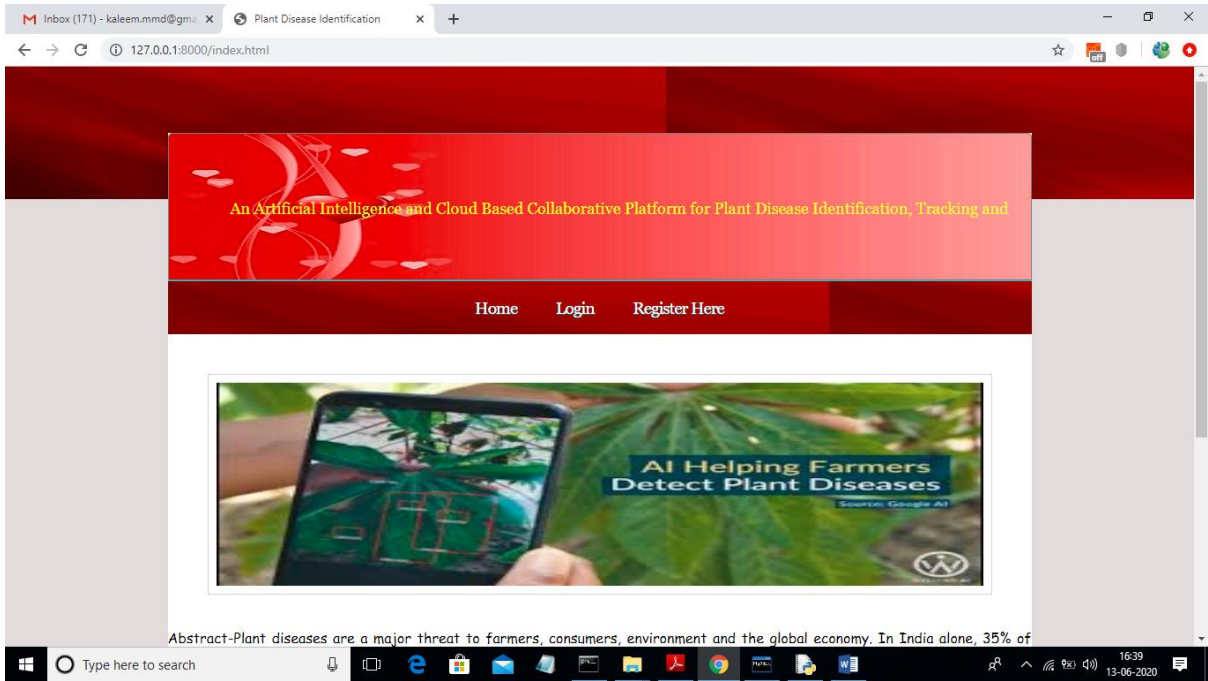
5. RESULTS

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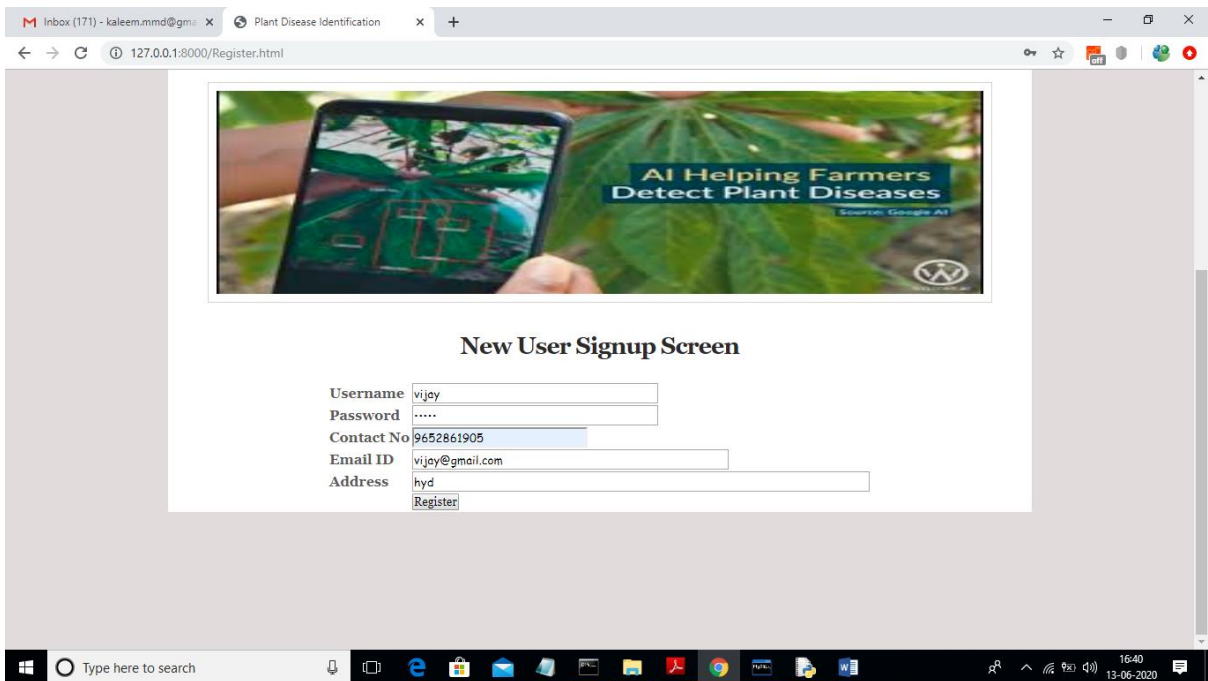
Command Prompt - python manage.py runserver
_ np_quint16 = np.dtype([('quint16', np.uint16, 1)])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:545:
FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be
understood as (type, (1,)) / '(1,)type'.
_ np_qint32 = np.dtype([('qint32', np.int32, 1)])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:550:
FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be
understood as (type, (1,)) / '(1,)type'.
_ np_resource = np.dtype([('resource', np.ubyte, 1)])
System check identified no issues (0 silenced).

You have 15 unapplied migration(s). Your project may not work properly until you apply the migrations for app(s): admin,
auth, contenttypes, sessions.
Run 'python manage.py migrate' to apply them.
June 13, 2020 - 16:38:06
Django version 2.1.7, using settings 'PlantDisease.settings'
Starting development server at http://127.0.0.1:8000/
Quit the server with CTRL-BREAK.
    
```

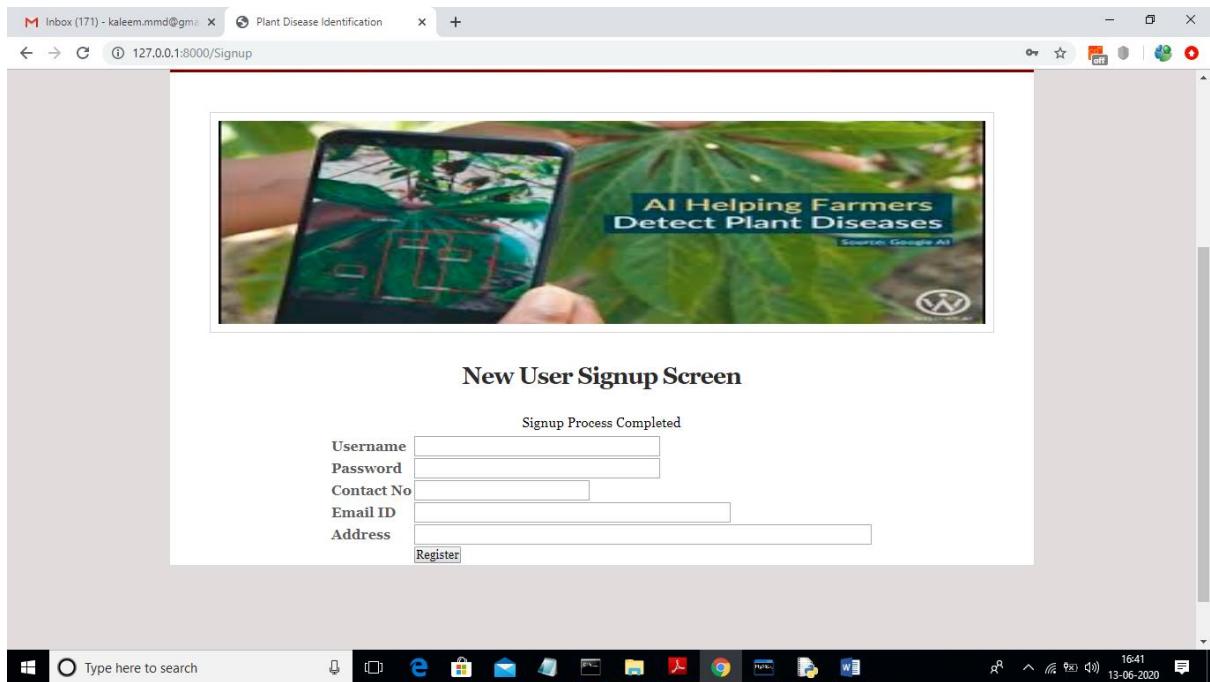
In above screen python server started and running on IP <http://127.0.0.1:8000/>. Now open browser and enter URL as ['http://127.0.0.1:8000/index.html'](http://127.0.0.1:8000/index.html) to get below screen



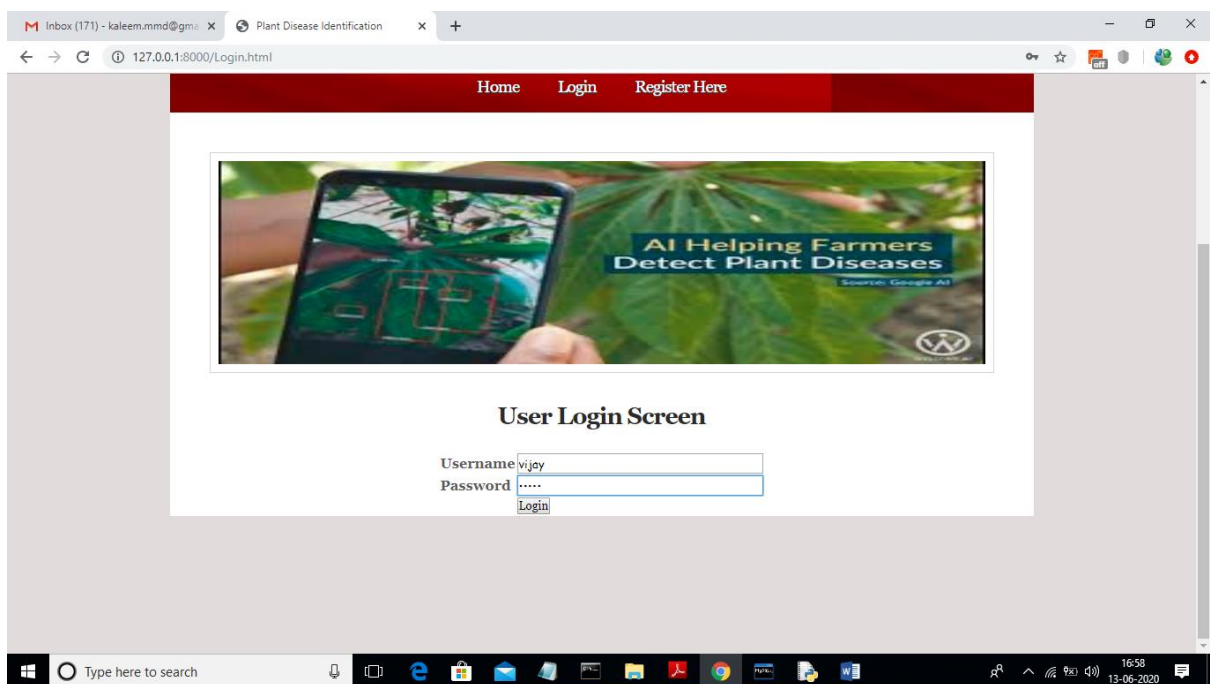
In above screen click on 'Register Here' link to allow user to register with the application



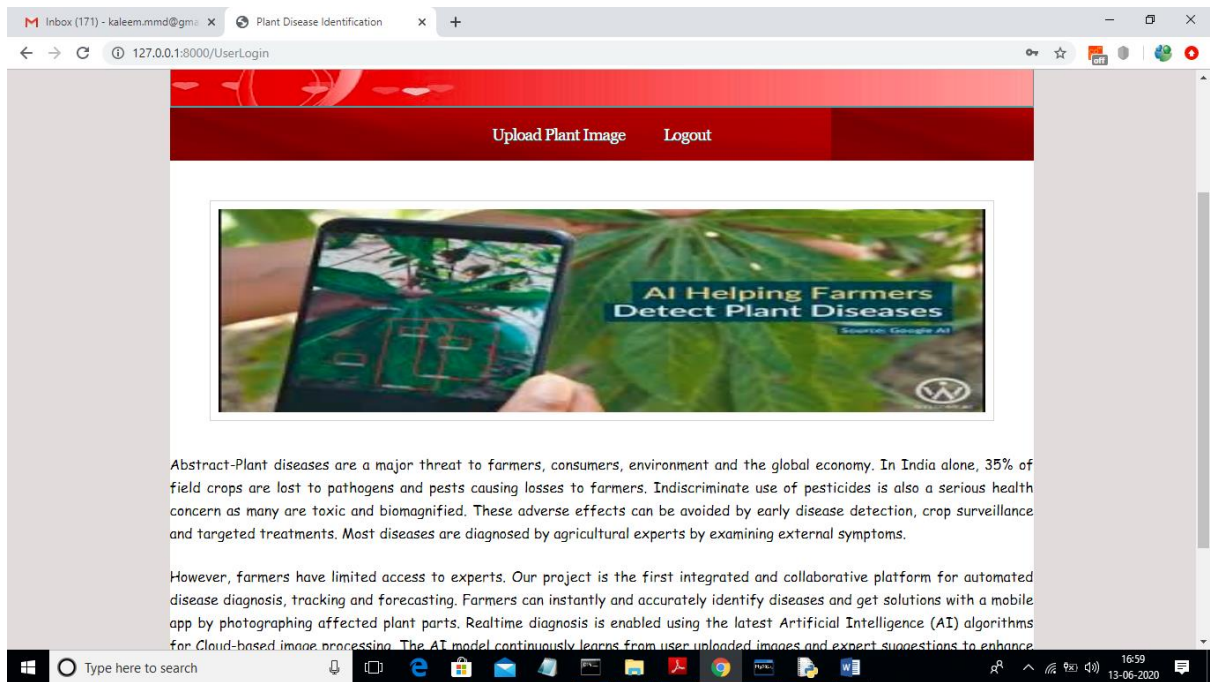
In above screen click on 'Register' button to add new user



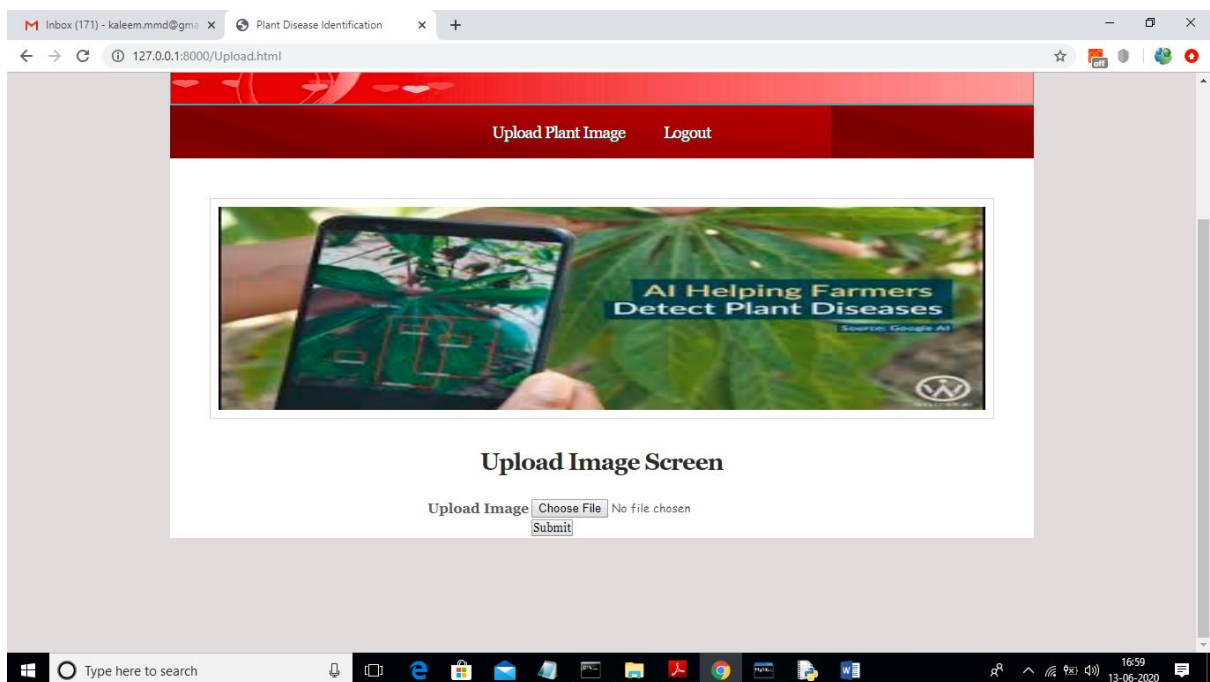
In above screen user signup process completed. Now user can click on 'Login' link to login to application



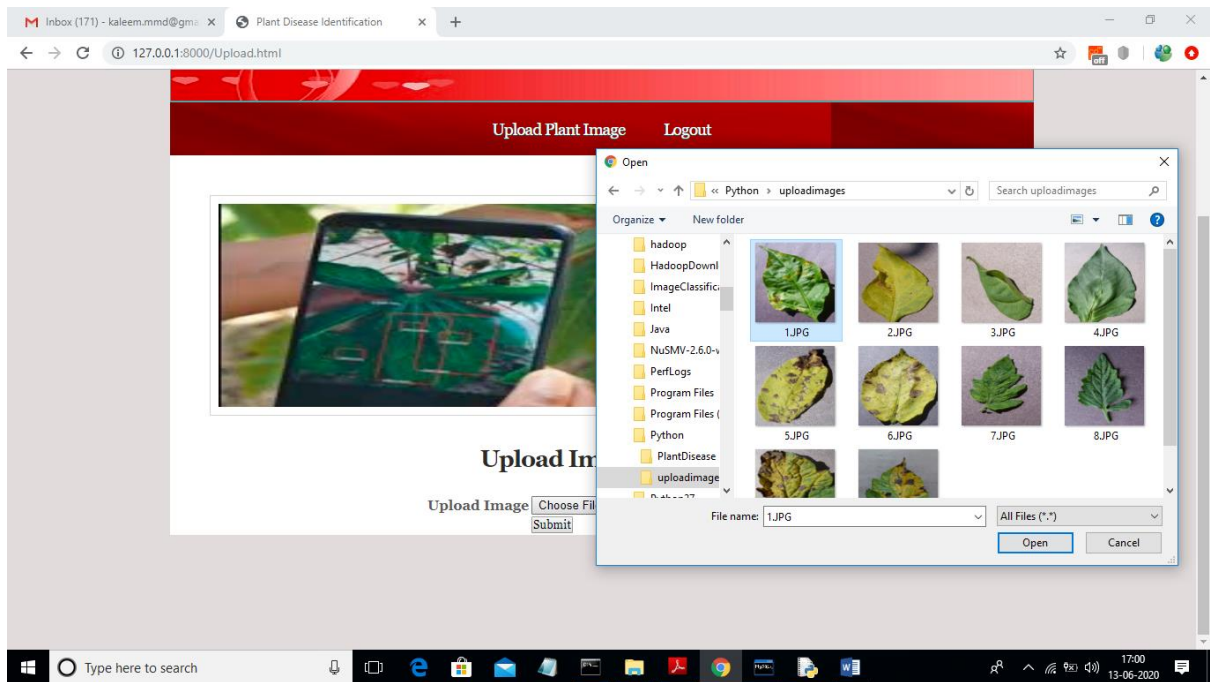
After login will get below screen



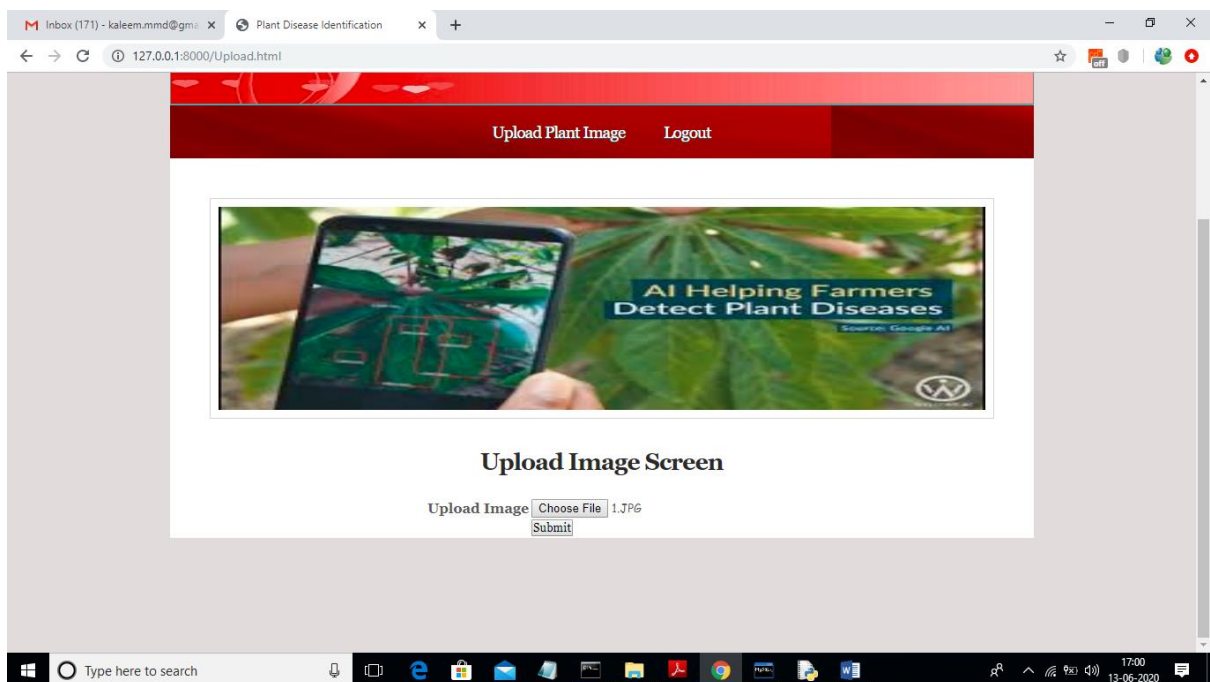
In above screen click on 'Upload Plant Image' link to get below screen



In above screen user can upload image of his crop to predict disease using CNN



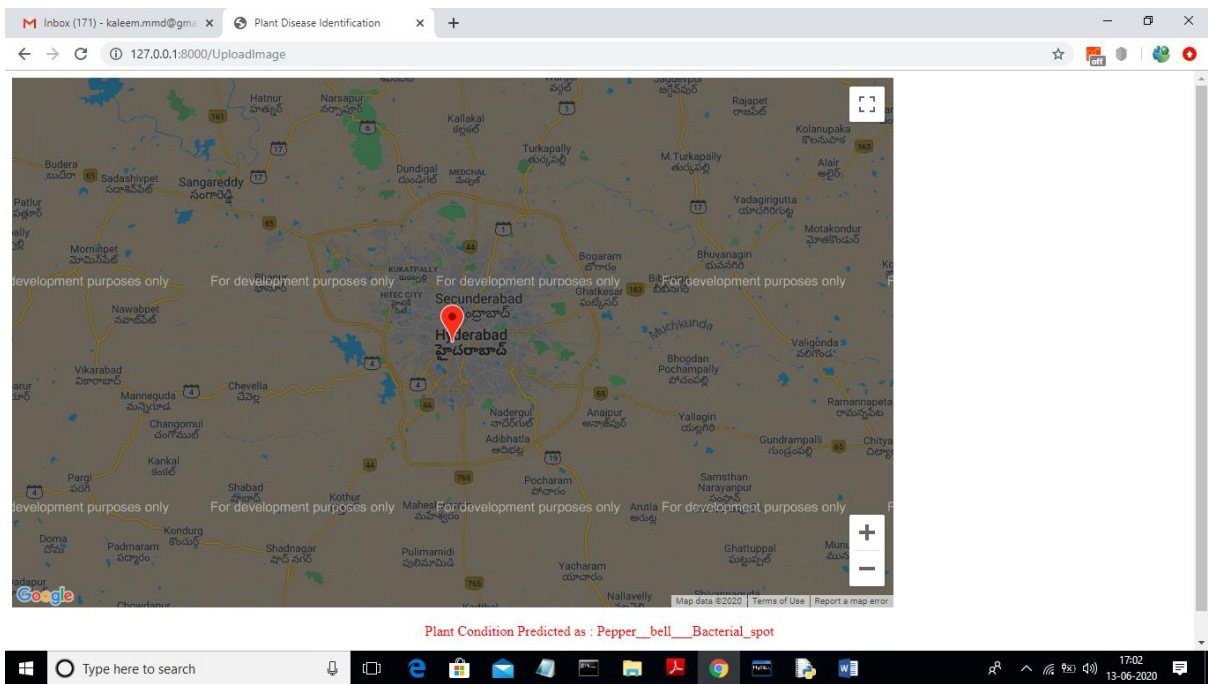
In above screen uploading 1.JPG image and now click on 'Open' button to upload image



In above screen click on 'Submit' button to predict disease



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

```

Command Prompt - python manage.py runserver
backend.py:4070: The name tf.nn.max_pool is deprecated. Please use tf.nn.max_pool2d instead.

WARNING:tensorflow:From C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\keras\backend\tensorflow_
backend.py:422: The name tf.global_variables is deprecated. Please use tf.compat.v1.global_variables instead.

Model: "sequential_1"
-----
Layer (type)                Output Shape              Param #
-----
conv2d_1 (Conv2D)           (None, 62, 62, 32)       896
max_pooling2d_1 (MaxPooling2 (None, 31, 31, 32)       0
conv2d_2 (Conv2D)           (None, 29, 29, 32)       9248
max_pooling2d_2 (MaxPooling2 (None, 14, 14, 32)       0
flatten_1 (Flatten)         (None, 6272)             0
dense_1 (Dense)             (None, 128)              802944
dense_2 (Dense)             (None, 15)               1935
-----
Total params: 815,023
Trainable params: 815,023
Non-trainable params: 0
None
    
```

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 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 detecting early symptoms of diseases and is able to successfully differentiate between diseases of the same family

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