FARMER-CENTRIC AI AND CLOUD PLATFORM FOR PLANT DISEASE SURVEILLANCE AND FORECASTING

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ABSTRACT

Farmers, consumers, the environment, and the global economy are all jeopardized by plant diseases. Viruses and pests inflict significant financial losses on farmers, obliterating 35% of India's agricultural harvests. The biomagnification and toxicity of pesticides make their indiscriminate use a significant hazard to human health. Precise interventions, agricultural surveillance, and prompt disease identification might mitigate these adverse impacts. Agricultural experts can detect the majority of illnesses only by observing symptoms. Nevertheless, farmers possess little access to specialists. Our project is the first initiative to provide a centralized platform for the automated identification, monitoring, and forecasting of health issues. Farmers may quickly and correctly diagnose illnesses and get medicines by capturing images of the afflicted plant sections using a web application. Cutting-edge AI techniques for cloud-based image processing facilitate real-time diagnosis. To enhance its precision, the AI model integrates data from user-uploaded images and recommendations from specialists. The portal facilitates connections between farmers and local professionals. Creating disease density maps that include spread projections using a cloud-based aggregation of geo-tagged photos and microclimatic variables is one approach to disease prevention. Experts may do disease analytics with the use of geographical visualizations on an internet platform. The artificial intelligence model (CNN) used in our studies was trained using large disease datasets made up of plant pictures that were gathered over the course of seven months from many farms. Plant pathologists confirmed the results of the automated CNN model's diagnosis of test photographs. An sickness identification accuracy of more than 95% was achieved. To help farmers and experts practice ecologically responsible crop production, we have developed a new, scalable, and easily deployable technology for disease management in a variety of agricultural crops. This technology may be used as a cloud service.

Index Terms:- Plant disease detection, Artificial intelligence, Cloud computing, Convolutional Neural Network (CNN), Precision agriculture, Real-time diagnosis, Smart farming, Sustainable agriculture, Expert collaboration, Agricultural technology.

1.INTRODUCTION

People can't survive without agricultural. It is crucial to increase food yields, especially for heavily populated emerging countries like India. Raising product quality is just as important as increasing production when it comes to improving public health. However, factors like the spread of diseases that may have been prevented via early identification have a negative impact on both productivity and food quality. Due to the highly infectious nature of many of these ailments, agricultural production has been decimated. Ineffective and unable to satisfy the large needs, human-assisted disease detection is a result of the dispersed nature of agricultural regions, the low educational attainment of farmers, and their lack of expertise and access to plant pathologists. Automated crop disease detection systems using technology and the availability of low-cost, accurate machine-assisted diagnostic tools for farmers are crucial in resolving the gap in human-assisted disease diagnosis. Robots and computer vision systems have helped advance technological solutions to many problems in farming. Researchers have looked at how image processing may improve precision agriculture, weed and pesticide technologies, plant growth monitoring, and nutrition management [1][2]. Despite plant pathologists' ability to visually examine physical symptoms, such as noticeable color changes, wilting, and the emergence of spots and lesions, in conjunction with soil and climatic conditions, they have only made basic advancements in automating plant disease diagnosis. Investment in agricultural technology integration is relatively low compared to more lucrative areas like healthcare and education. Problems with farmers' access to plant pathologists, high implementation costs, and solutions' inability to scale have prevented promising research endeavors from reaching the commercialization stage. There has never been a better opportunity to develop a widely applicable, cost-effective remedy for agricultural illnesses than the current state of mobile technology, cloud computing, and artificial intelligence (AI). The use of mobile phones that can connect to the internet has become widespread in developing countries such as India. Anyone may now share photos with geolocation data thanks to the widespread availability of inexpensive mobile phones with cameras and GPS. Through generally available mobile networks, they may communicate with sophisticated backend services in the cloud that administer a central database, do data analytics, and carry out computationally heavy tasks. The ability to accurately identify and classify images is one of the most recent technological achievements, and it is based on artificial intelligence (AI). Neural Networks (NN) including layers of neurons organized in a connection pattern similar to the visual cortex are used by the primary AI algorithms. In order for these networks to achieve high accuracy in identifying new, unseen photos, they conduct "training" on a large collection of pre-classified "labeled" photographs. Deep Convolutional Neural Networks (CNNs) have been the go-to architecture for computer vision and image analysis ever since "AlexNet" won the ImageNet competition in 2012. The availability of large image datasets, improvements in neural network methodologies, and increased processing power have all contributed to CNNs' growing capabilities. Thanks to open-source systems like TensorFlow, AI has not only gotten more accurate, but also cheaper and more accessible [4]. Searches for images of healthy and diseased crops [5], feature extraction for image analysis [6], RGB imaging [7], spectral analysis [8], and fluorescence imaging spectroscopy [9] are all relevant to the current body of work on the subject. One area where neural networks have shown promise is in the identification of plant diseases; specifically, in the area of textural cue recognition. In order to provide farmers access to information similar to that of plant pathologists, our solution takes use of developments in mobile, cloud, and AI technology to build a comprehensive crop diagnostic system. It allows for a team approach to continuously improving the disease database and, when needed, to seek expert advice to increase the accuracy of neural network classification and outbreak monitoring.

2.RELATED WORK

The computer technology proposed by Lalit P. Saxena and Leisa J. Armstrong may enhance agricultural productivity in several ways. Image processing is rapidly becoming as a valued asset. This article offers a succinct review of the research about the potential advantages of image processing techniques for academics and farmers in enhancing agricultural practices. Image processing has enhanced technologies for weed and pesticide management, plant nutrition optimization, plant growth monitoring, and precision agriculture. This research examines several agricultural economic situations in which image processing may be beneficial in the future.

In the ImageNet LSVRC-2010 competition, A. Krizhevsky, I. Sutskever, and G. E. Hinton trained a large deep convolutional neural network to divide 1.2 million high-resolution images into 1,000 unique categories. We had a top-1 error rate of 37.5% and a top-5 error rate of 17.0% on the test data, in comparison to the previous state-of-the-art. There are three fully connected layers, five convolutional layers, and a 1000-class softmax function in the neural network. Six hundred fifty thousand neurons and sixty million parameters make it up. After a few convolutional layers, max-pooling layers come next. To speed up the training process, we used non-saturating neurons and an efficient GPU convolution approach. A novel regularization technique called "dropout" was used to drastically reduce overrides in the fully-connected layers. We entered a variant of this model into the ILSVRC-2012 competition, and it had a top-5 test error rate of 15.3%, significantly outperforming the second-best entry.

P. Ramos-Quintana, J. Guerrero, and D. L. Hernández-Rabadán In order to overcome the major obstacles presented by unregulated lighting and background in greenhouses and similar environments, Juk suggests a technique for diseased plant segmentation that merges supervised learning with unsupervised learning. This technique is called a self-organizing map (SOM). The training process makes use of two SVMs, or support vector machines. The first support vector machine (SVM) uses K-means and specified criteria to create picture color clusters, which are subsequently classified as either "vegetation" or "non-vegetation" using the same set of rules. If the first SOM makes a mistake with its classification, the second SVM will fix it. The Bayesian classifier's conditional probabilities are evaluated by creating two-color histograms from the two color classes. In order to identify hazardous areas that were incorrectly classified as non-vegetation, the Bayesian classifier must first segment the input image, transform it to a binary representation, and then extract and evaluate contours. The proposed method outperformed two of the most popular color index methods in the investigation.

According to the research conducted by S. Sankaran, A. Mishra, J. M. Maja, and R.

Ehsani, visible-near infrared spectroscopy may be used to identify Huanglongbing (HLB) in citrus orchards. Using a visible-near infrared spectroradiometer, researchers measured the reflectance of 110 healthy citrus trees and 93 HLB-affected plants throughout a range of 350 to 2500 nm, capturing 989 spectral features. Normalization and averaging of spectral data in 25 nm increments throughout processing lowered the spectral characteristics from 989 to 86. Using the preprocessed raw data, a composite dataset was created along with first and second derivatives. Three derivatives were created from the initial data after it was further cleaned up. Using principle component analysis (PCA), the preprocessed datasets were examined with the goal of reducing the number of features used as inputs to the classification system. A training set with 75% of the data and a testing set with 25% of the data were randomly created from the main components dataset. Because of this, we were able to evaluate the classification techniques using a reduced dataset. There were 145 samples in the training set and 48 samples in the testing set. Four different classification methods were considered: k-nearest neighbor, SIMCA, linear discriminant analysis (LDA), and quadratic discriminant analysis (QDA). Three independent runs were used to get the given algorithmic classification accuracies. With an average overall accuracy of 95% and HLB-class accuracies of 98%, the QDA-based technique provided the best results among the classification methods evaluated on the second derivatives dataset. In the combined dataset, algorithms that used SIMCA produced overall classification accuracies higher than 92% while achieving very low false negative rates (around 3%).

The speakers, including Wojna, Szeledy, Ioffe, Vanhoucke, and Shlens, express Convolutional networks are the backbone of most advanced computer vision systems. Very deep convolutional networks have been all the rage since 2014, when they began to demonstrate remarkable performance on a number of benchmarks. With sufficient labelled training data available, larger models with higher processing costs may quickly improve performance. Mobile vision and big data are two examples of applications where computer speed and a small number of parameters are crucial. We take a look at network scaling strategies that improve processing performance using rigorous regularization and suitably factorized convolutions. When tested on the validation set of the ILSVRC 2012 classification challenge, our methods outperform the state-of-the-art. Using a network with less than 25 million parameters and 5 billion multiply-add operations per inference, we were able to obtain a top-1 error rate of 21.2% and a top-5 error rate of 5.6% for single frame evaluation. Employing a four-model ensemble with multi-crop assessment yielded an error rate of 3.5% for the validation set, 3.6% for the test set, and 17.3% for the top-1.

3.PROBLEM STATEMENT:

The indiscriminate use of pesticides poses a significant health risk due to their toxicity and biomagnification. These detrimental impacts may be mitigated by early disease identification, crop monitoring, and specific interventions. The majority of illnesses are identified by agricultural specialists via the assessment of outward signs. Nevertheless, farmers possess restricted access to specialists.

DRAWBACKS

- Due to their toxicity and biomagnification potential, pesticides provide a substantial health risk when used carelessly.

4.PROPOSED MODEL:

Using images of different plant diseases, the author trains an artificial intelligence tool called a convolutional neural network in this research. Afterwards, once new photographs are submitted, the CNN will identify any plant illnesses that may be present. The author stores the CNN training model and images on the cloud. The prediction of plant diseases is aided by artificial intelligence, while data storage is accomplished via the use of cloud technologies.Since creating an Android app would be more time-consuming and expensive, we are building it as a Python web app instead. The author used a smartphone to contribute photographs for this project.Users may upload images to help train a convolutional neural network (CNN) model that can then utilize those images to make disease predictions. When run on a real web server, this app will display the user's position on a map by extracting it from the request object.

ADVANTAGES

Utilize a web-based application to accurately identify plant diseases and choose remedies by capturing images of the affected regions.

5.SYSTEM MODEL:

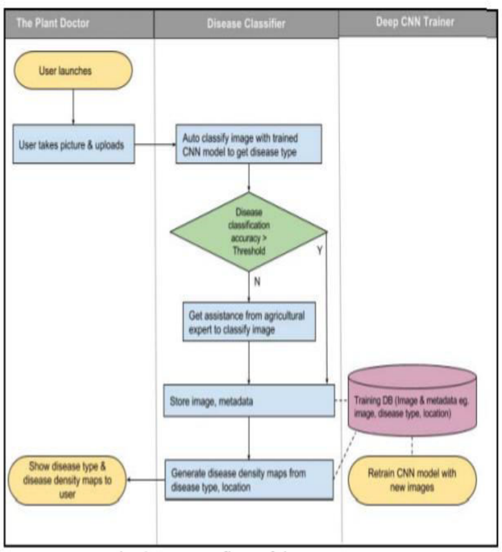


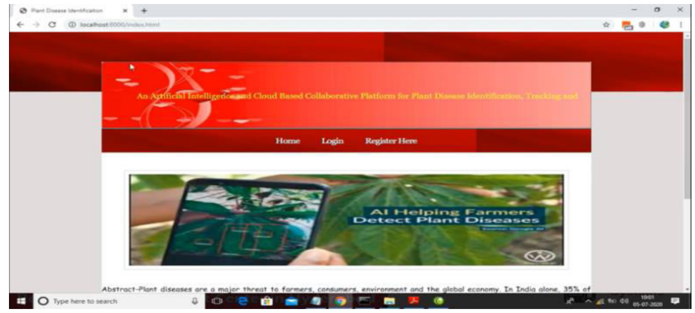
Fig.1 System Model

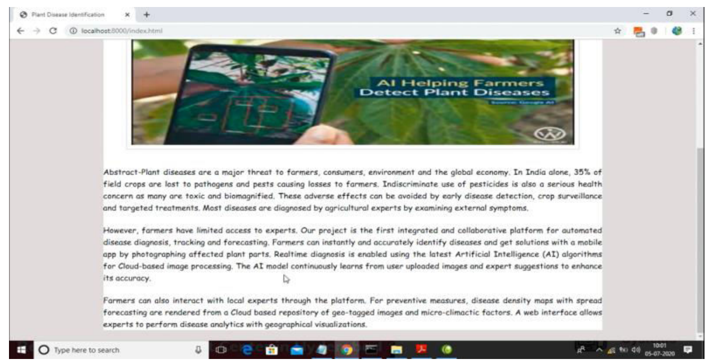
6.IMPLEMENTATION:

- **Register:**
  Create an account on the platform.
- **Login:**
  Enables registered users to securely access their accounts.
- **Upload Plant Image:**
  Users can upload images of diseased or affected plant parts for AI-based diagnosis, tracking, and forecasting.
- **Logout:**
  Safely ends the user's session and logs them out of the platform.

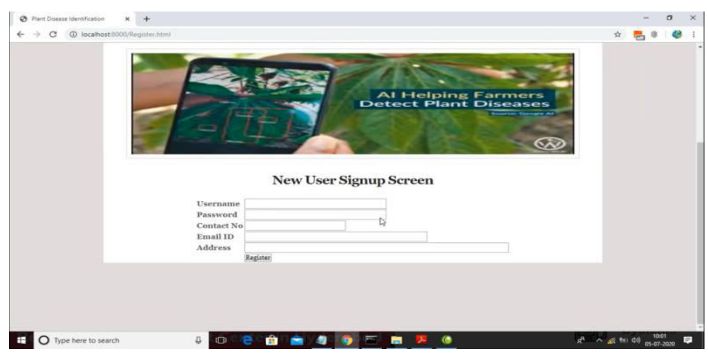
7.RESULT

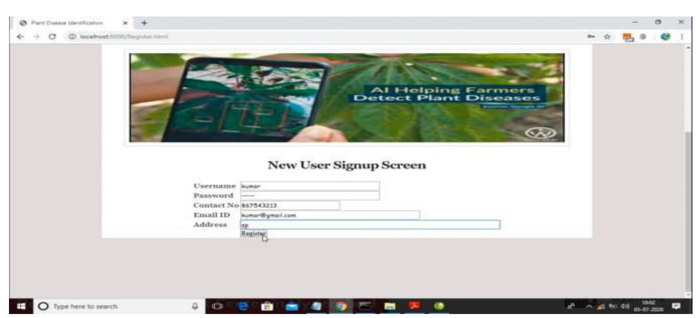
Index.html



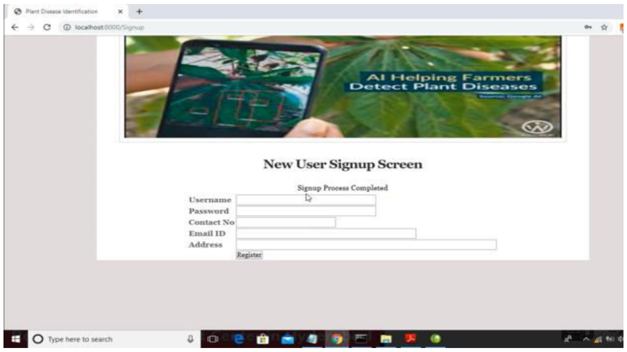


Register.html

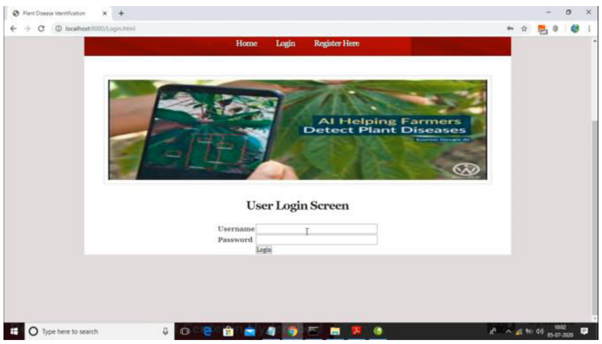


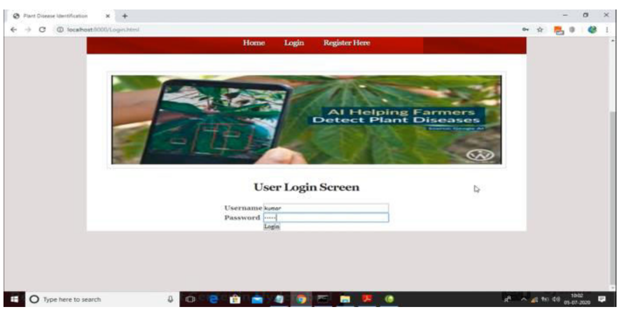


Signup



Login.html





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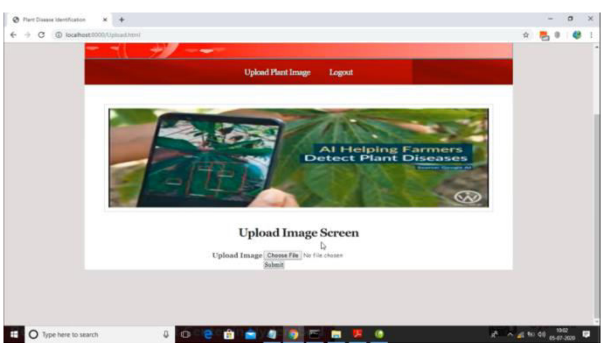
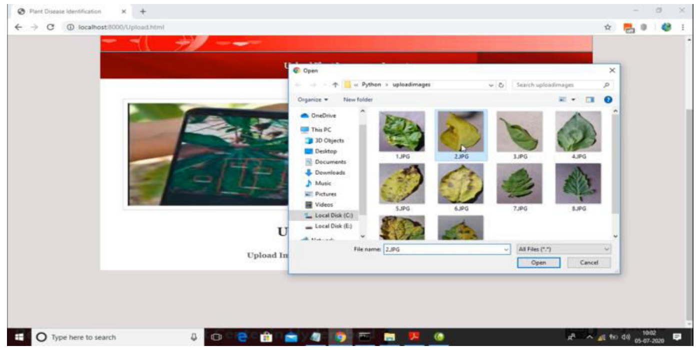
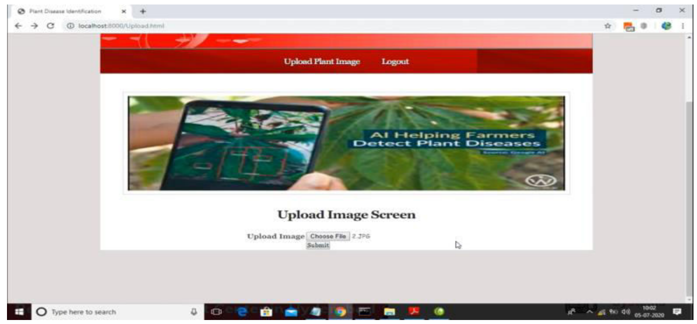
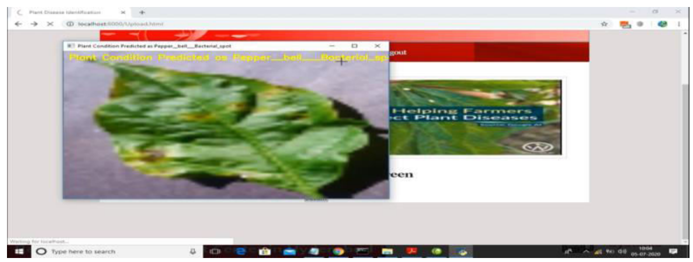
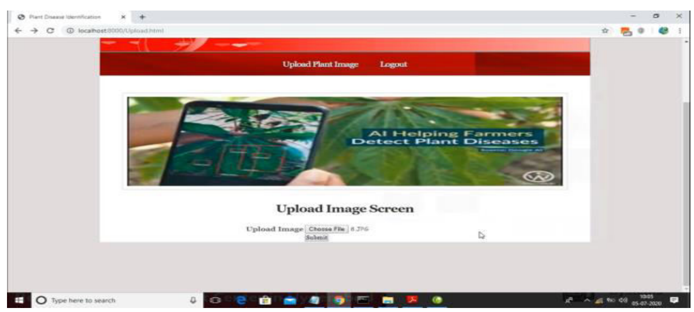


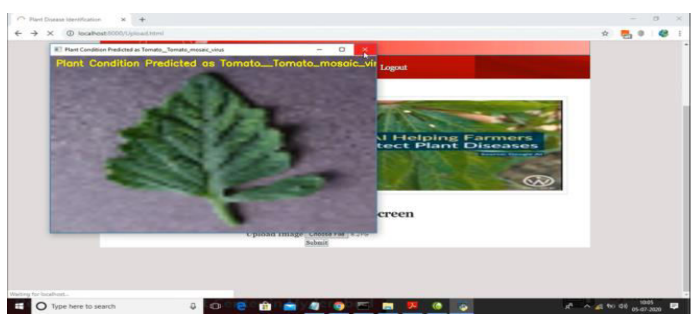








Prediction Result



8.CONCLUSION

More accurate, quick, and timely identification of crop diseases and awareness of outbreaks, enabling prompt decision-making for disease control strategies, is a critical concern in agriculture. This research presents an automated, cost-effective, and accessible comprehensive answer to this issue. This proposal enhances current methodologies by employing deep Convolutional Neural Networks (CNNs) for disease classification, incorporating geocoded images for disease density mapping, creating a social collaborative platform for incremental accuracy improvement, and developing an expert interface for analytics. An intuitive smartphone application may categorize illnesses in real-time on a cloud platform using the effective "Inception" model of a deep convolutional neural network. This collaborative method enhances sickness classification accuracy by automatically including user-submitted pictures into the cloud-based training dataset, therefore retraining the CNN model for ongoing development. By combining aggregated data on illness categorization with the geolocation parameters provided in the photographs, the pictures kept in the cloud repository make it easier to create disease density maps. The experimental results demonstrate that the proposal has substantial real-world applicability across multiple domains, including high scalability of the cloud-based infrastructure, effective performance of the underlying algorithm with various disease types, enhanced efficacy with larger training datasets, facilitation of early symptom detection, and differentiation between diseases within the same family.

9.FUTURE WORK AND EXTENSIONS

Improving the model's correlation with the disease will be the primary goal of future efforts. We can improve the picture database by adding more farmer-provided data on soil conditions, past pesticide and fertilizer applications, and publicly available weather variables like temperature, humidity, and precipitation. This will help with disease forecasting and make the model more accurate. We want to broaden the scope of agricultural diseases treated while reducing the need for specialized help, with the exception of new types of diseases. A simple way to determine the threshold is to take the average of all classification scores. This will allow user-uploaded photographs to be automatically added to the Training

Database, improving classification accuracy with little human intervention. This method has the potential to make automated tracking of disease development and alert activation much easier by allowing for the temporal monitoring of sickness density maps. It is possible to employ predictive analytics to alert customers to possible disease outbreaks close to their current location.

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