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Plant Health Diagnosis: AI-Based Classification on Plant Health Issues for Agricultural Optimization

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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. Different diseases often exhibit similar symptoms, making it challenging, especially for those farmers with limited expertise, to differentiate between them accurately. As a result, misdiagnosis can occur, leading to inappropriate or ineffective treatments that waste valuable resources and worsen the problem. Additionally, once a disease outbreak is confirmed, there's a pressing need for effective tracking and forecasting to implement timely preventive measures and stop its rapid spread. 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, CNN 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: Convolutional Neural Network, Artificial Intelligence, Plant Diseases, CloudComputing, Agriculture Productivity

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 visualcortex. These networks get "trained" on large set of pre-class fields "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 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 leafdiseases.

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 alternariaalternata, 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, 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 (CercosporabeticolaSacc.) 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 eccentrics and the calculation time. Subsequently it is essential to reduce the element data.

3.PROPOSEDMETHODOLOGY

To overcome the limitations of existing methods, this study proposes a deep learning-based plant health diagnosis system utilizing convolutional neural networks (CNN). The system is designed to analyze images of plants to classify their health status accurately. By incorporating advanced preprocessing techniques such as image normalization, resizing, and data augmentation, the proposed system enhances the quality and diversity of the training data, leading to improved model performance. This automated approach allows for real-time detection and classification of plant health issues, enabling timely and targeted interventions that optimize crop management.

Module Splitting

- **Dataset**: A diverse dataset comprising images of plants displaying various health conditions will be compiled to train the CNN model effectively.
- **Dataset Preprocessing**: This module involves enhancing image quality through normalization, resizing, and data augmentation techniques to improve model robustness and accuracy.
- **Train-Test Splitting**: The dataset will be divided into training and testing sets, ensuring the model's performance can be evaluated on unseen data for reliability.
- **CNN Classification Model**: A convolutional neural network (CNN) will be employed for the classification of plant health issues, leveraging its capability to learn complex patterns from image data.
- **Performance Estimation**: The model's performance will be assessed using various metrics, including accuracy, precision, recall, and F1-score, to evaluate its effectiveness in diagnosing plant health issues.

Advantages

- **Enhanced Accuracy**: The use of CNNs allows for precise identification and classification of plant health issues, minimizing human error associated with manual diagnosis.
- **Real-Time Monitoring**: The automated system facilitates immediate diagnosis, enabling timely interventions and effective pest management strategies.
- **Cost Efficiency**: By optimizing treatment applications, the system can reduce unnecessary expenditures on pesticides and fertilizers, improving overall cost-effectiveness.
- **Scalability**: The proposed system can be easily scaled to accommodate diverse crops and agricultural practices, making it suitable for various farming environments.
- **Sustainable Practices**: The emphasis on accurate diagnosis promotes eco-friendly practices by reducing reliance on chemical treatments and enhancing crop health.

Applications

- **Precision Agriculture**: The system can be integrated into precision agriculture practices, enabling farmers to monitor crop health and optimize resource use effectively.
- **Agricultural Research**: Researchers can utilize the system to study plant health trends and disease progression, contributing to the development of more resilient crop varieties
- **Extension Services**: Agricultural extension services can employ the system to provide farmers with accurate diagnoses and tailored recommendations for pest management.

- **Urban Farming**: The system can assist urban farmers in maintaining plant health in limited spaces, promoting sustainable food production in urban environments.
- **Education and Training**: The system can be used as an educational tool in agricultural training programs, helping students and practitioners learn about plant health management techniques.

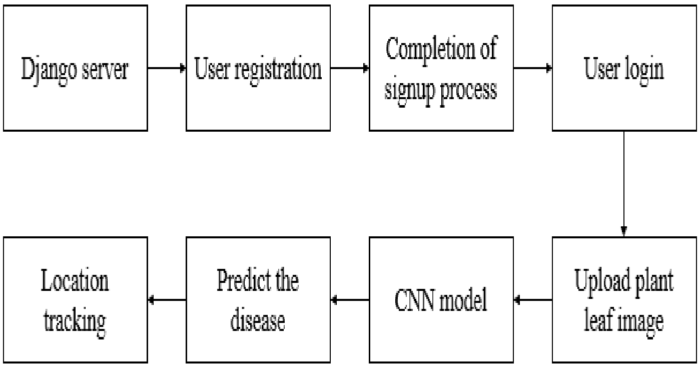

Fig 3.1.: Block diagram of proposed system

4.EXPERIMENTAL ANALYSIS

Fig:1 This figure showcases the home screen of the Plant Disease application. The home screen serves as the primary interface for users to navigate through the application's features and functionalities. It typically presents a user-friendly layout with intuitive design elements, such as menus, buttons, and navigation bars, to guide users in accessing different sections of the application.

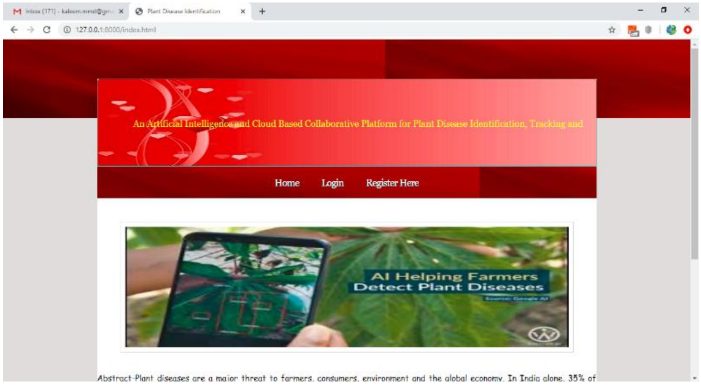

Figure 1: Presents the Home Screen of Plant Disease.

Fig:2 In this figure, users are presented with the sign-up screen of the Plant Disease application. The sign-up screen prompts new users to create an account by entering their personal information, such as username, password, contact details, email address, and address. This information is essential for creating a unique user profile within the application's database. Users are required to fill out the sign-up form accurately, providing valid information to ensure the integrity and security of their accounts. Once all required fields are filled out, users can proceed to submit their registration details, thus completing the sign-up process and gaining access to the full range of features offered bythe application.

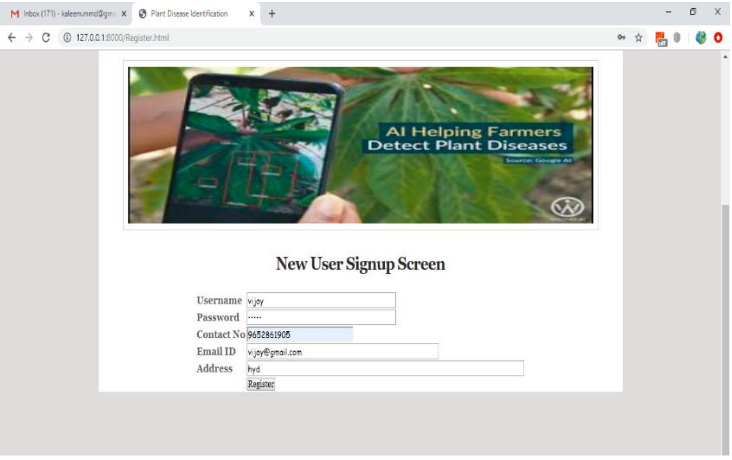

Figure 2: Presents the user SignUp Screen and the Credential to enter.

Fig:3 Upon completion of the sign-up process, users can proceed to log in to their newly created accounts and begin exploring the various functionalities offered by the Plant Disease application. The confirmation message also includes additional instructions or prompts to guide users on how to get started with using the application effectively.

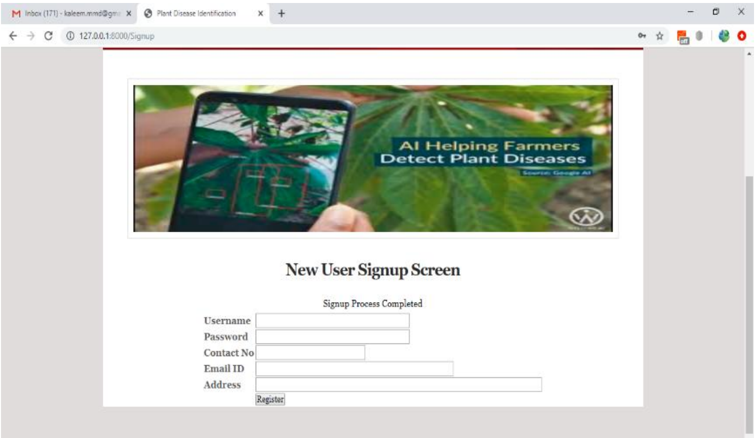

Figure 3: Signup process completed.

Fig:4 In this figure, users are presented with the option to upload a plant image for disease detection using the Plant Disease application. This feature allows users to capture or select an image of a plant exhibiting symptoms of disease and upload it to the application for analysis.

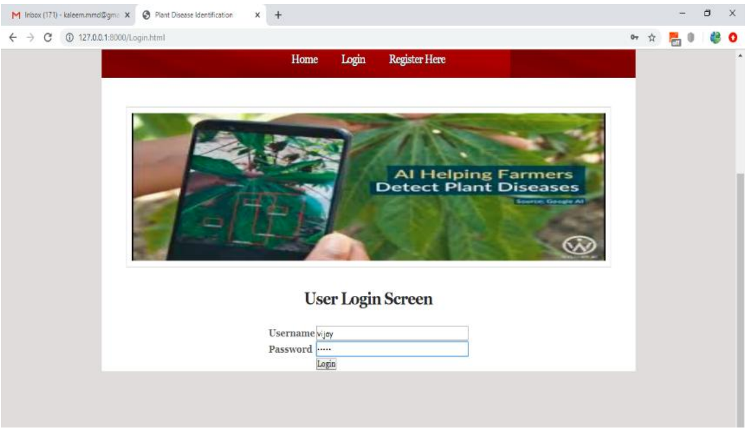

Figure 4: Logging in with login Credentials.

Fig:5 In this figure, users are presented with the option to upload a plant image for disease detection using the Plant Disease application. This feature allows users to capture or select an image of a plant exhibiting symptoms of disease and upload it to the application for analysis.

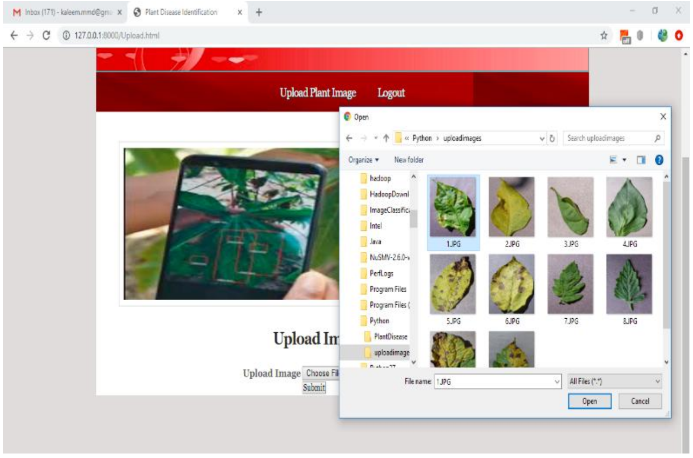

Figure 5: Upload Plant Image to detect the disease by the Proposed Model.

Fig:6 In this figure, users are presented with the model prediction generated by the Plant Disease application based on the uploaded plant image. The application's machine learning model analyzes the uploaded image and generates a prediction regarding the presence of any diseases or abnormalities in the plant along withany recommended actions or treatments to address the issue.

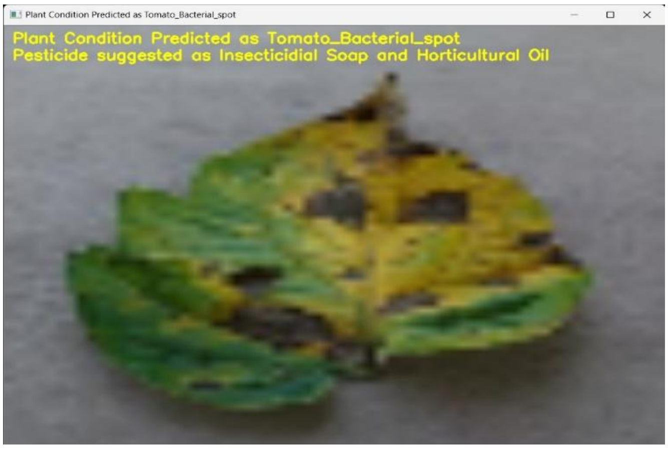

Figure 6: Shows the model Prediction on uploaded Image

Fig:7 In this figure 7, users are presented with a map displaying the location where the uploaded plant image was captured or uploaded. This feature utilizes geolocation data associated with the uploaded image to pinpoint the exact location of the plant in question on a map interface.

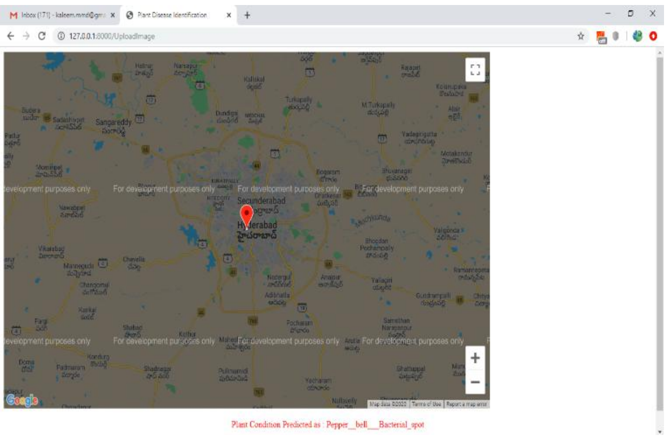

Figure 7: Displays the Uploaded image location on the map.

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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