AGROEYE – A PLANT DISEASE DETECTION APPLICATION

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Abstract - AgroEye is a mobile application developed for the purpose of accurately detecting and diagnosing plant diseases based on images of leaves. The main objective of this project is to provide a user-friendly solution that enables early disease identification, contributing to improved crop management and early intervention strategies. The implementation of AgroEye involves leveraging the powerful EfficientNet B7 machine learning model, which was trained on a public dataset consisting of significant amount of plant diseases. By harnessing advanced image recognition techniques, the application is highly accurate in identifying and categorizing several types of plant diseases. The development process incorporates the utilization of popular frameworks such as React Native and Flask, ensuring a seamless and intuitive user experience. Through training and rigorous validation, the machine learning model has demonstrated its exceptional effectiveness in disease detection. While numerous research studies have addressed plant disease detection, there remains a notable scarcity of practical applications in this area. AgroEye stands out by providing an accessible and user-friendly solution that caters to the needs of farmers, researchers, and agricultural enthusiasts. AgroEye represents an innovative approach to plant disease detection, utilizing image analysis to provide accurate and accessible insights. Its high level of accuracy, user-friendliness, and potential for future development position it as a valuable tool in promoting sustainable agriculture and mitigating crop losses associated with plant diseases.

Keywords - Plant disease detection, EfficientNet B7, React-Native, Flask.
Index terms – Amazon Elastic Compute Cloud (EC2)

I. INTRODUCTION

Leaf or plant disease detection is an essential element of agriculture. Early detection and identity of plant diseases can assist prevent the spread of the disease, reduce crop losses, and boom yields. Traditional techniques of disorder detection involve visible inspection by using farmers or agricultural specialists. However, these methods can be time-eating and subjective, main to capability misdiagnosis and useless remedy. With advancements in generation, there now are several progressive and green strategies of plant disease detection which can be turning into increasingly famous in the agricultural enterprise. One such approach is using faraway sensing technologies, is using drones. Drones geared up with the sensors can be speedy and as it should be surveying massive regions of crops, allowing for early detection and focused remedies. Another effective method is the usage of artificial intelligence and machine learning algorithms to examine plant records and identify patterns that can imply diseases. These methods have the capability to revolutionize plant disorder detection and significantly enhance crop yields.

In this paper, we propose a novel approach that uses infected or diseased plant images for the early detection of respective disease and provide proper solution to control it.

II. METHODOLOGY

The methodology employed in the AgroEye project encompasses a systematic approach to develop a robust plant disease detection system. The mobile application frontend was developed using React Native, a cross-platform framework known for its capability to create intuitive user interfaces. The EfficientNet model, a cutting-edge deep learning architecture, was utilized for accurate disease detection. Training of the EfficientNet model involved a comprehensive dataset consisting of images depicting healthy leaves and leaves affected by various diseases. The model was fine-tuned to optimize its parameters and achieve superior performance in disease identification. The backend of the application was implemented using Flask, a lightweight Python web framework that facilitated the creation of efficient APIs for handling requests. The deployed application was hosted on Amazon EC2, a scalable cloud-based infrastructure, ensuring reliable performance and efficient handling of user requests. The integration of React Native, EfficientNet, Flask, and EC2 facilitated seamless communication between the frontend, backend, and machine learning model, enabling the capture of leaf images, their preprocessing, and subsequent disease prediction. This comprehensive methodology ensures the development of a sophisticated and user-friendly mobile application capable of accurately detecting plant diseases, thereby providing farmers and researchers with a valuable tool for effective disease management in the field of agriculture.

In this study, we analyzed plants with different diseased leaves and healthy leaves to identify patterns and features that could distinguish diverse types of plant diseases. We used a public dataset that contains diseased and healthy leaves of various plants, including Black Rot, Early blight, Late blight, and healthy leaves. The dataset includes 62,979 images of leaves of size 256x256 pixels which have eleven healthy plant classes and 23 diseased classes. The above number of images are achieved after the data augmentation process.

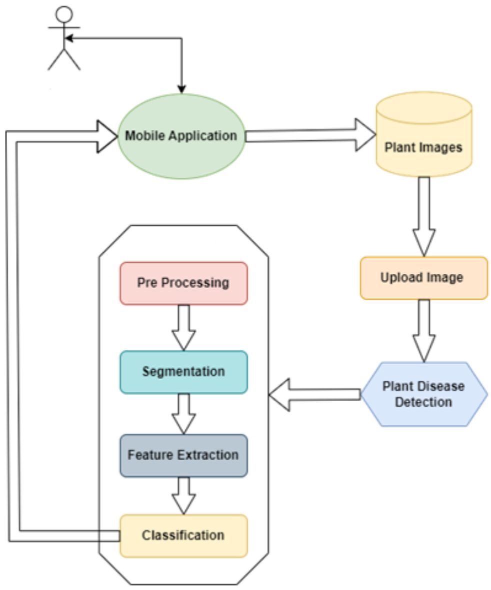

Fig.1 Architecture of the proposed system

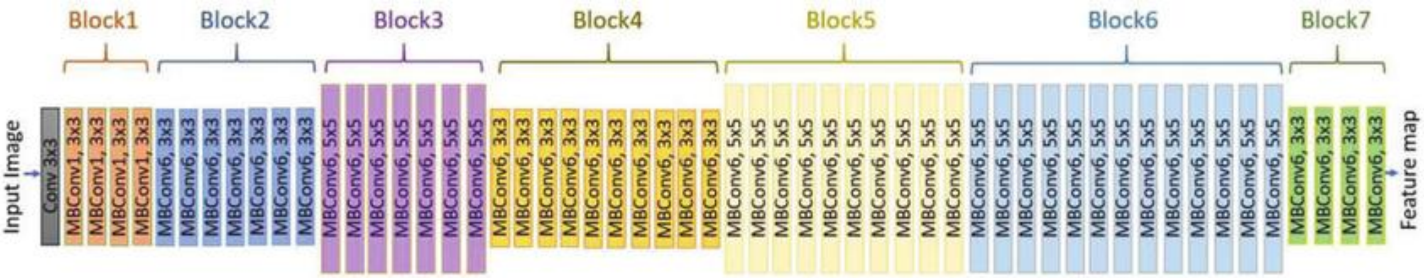

Fig.2 Architecture of EfficientNet B7

III. IMPLEMENTATION

The implementation of the AgroEye project consists of significant steps which lead to a highly accurate in detecting diseases of plants. It began with the use of New Plant Diseases dataset from Kaggle which has pictures of healthy leaves and leaves suffering from various plant diseases. Preprocessing steps had been then implemented to the dataset, such as resizing, normalization, and data augmentation techniques, to prepare the dataset for training. The EfficientNet B7 version, recognized for its super overall performance in image type tasks, lightweight architecture, is selected for mobile application. The obtained dataset breaks up into training, validation, and testing sets. The model underwent training using the preprocessed dataset. The training procedure involved high-quality tuning and optimizing the model's parameters to acquire excessive accuracy and generalization. To facilitate user interaction, the frontend of the AgroEye React Native was used, ensuring compatibility across a couple of structures. The person interface changed into a design to be intuitive and person-pleasant, permitting users to seize images of plant leaves the use of their smartphone cameras. The captured leaf photographs were then handed to the backend applied with Flask, a light-weight Python web framework. Flask facilitated the development of APIs that processed the photos and sent them to the trained model for disease prediction. Deployment of the AgroEye utility performed on Amazon EC2, a scalable cloud infrastructure, ensuring dependable overall performance and efficient handling of person requests. Rigorous checking out and iterative refinements had been carried out to validate the functionality and accuracy.

S. no.	Name of the Test Case	Description of Test Case	Process	Given Input	Output	Status of the Test Case P/F
TC01	Preprocessing	Checking whether the dataset is balanced and fit for training	Analyzing Correlation plot and confusion matrix	Dataset	Normalized Dataset	Passed

TC02	Validation of model with test data	Trained model will be assessed with test data and data from internet	Checking the performance and accuracy of the results	Image of a diseased plant leaf	Name of the diseased plant leaf	Passed
TC03	Working of android application	We check whether the app is providing the required information	a. Open the application. b. Take a picture through the camera.	Image of a diseased plant leaf	Name of the disease, methods to counter the disease.	Passed
TC04	Multi Language support	Checking if user can use the app in different languages	Open the application and select the required language.	Hindi	Hindi language is used in the application.	Passed

IV. RESULTS

Our results showed that our model could accurately identify distinct types of plant diseases using plant leaves. We achieved an overall accuracy of 95% in the classification of detecting diseases of various images of leaves. We also identified features that the application, which was proposed are user friendly, gives appropriate recommendations to the user of the diseased plant. The application also supports multiple languages, which adds much more advantage to the users. The mobile application has also undergone unit testing and other tests to ensure maximum throughput. The proposed approach was evaluated on different images from the internet. Images from the internet consist of various plant diseases of diverse levels of severity, which helps in real world scenarios. The performance of the approach was evaluated based on the results demonstrated. The overall accuracy of the approach was 95% ranging from 85% to 100% for each plant disease class or category.

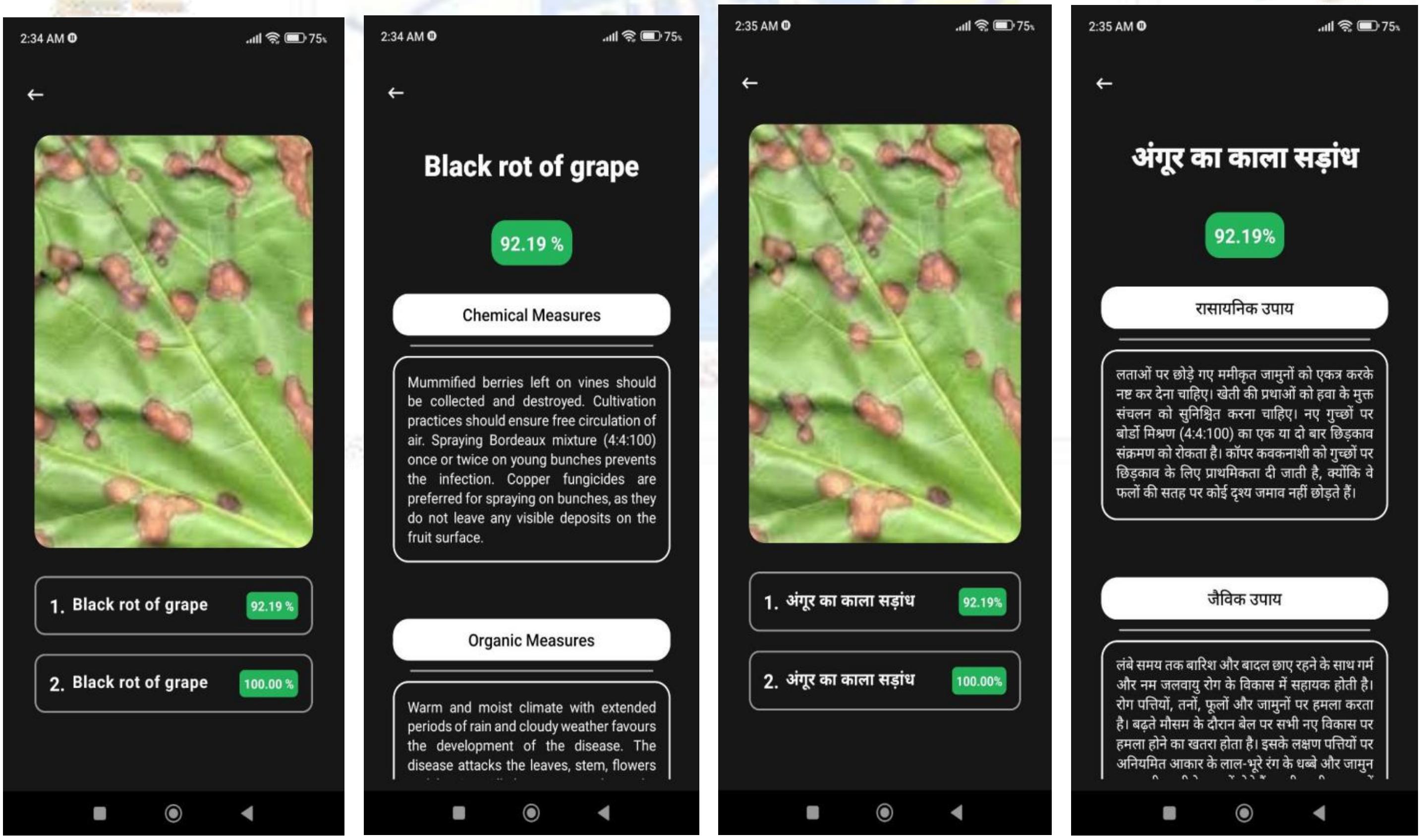

Fig.3 Mobile application screenshots

V. FUTURE SCOPE

The AgroEye project holds gigantic capability for future improvement and growth. Several regions may be explored to enhance the utility's capabilities and deal within the subject of plant disease detection. The following are a few key points of future scope:

- **Dataset Expansion**: To further enhance the accuracy and robustness of the system getting to know model, expanding the dataset is crucial. Incorporating a bigger variety of plant illnesses, together with uncommon and area-unique ones, will help the version generalize better and enhance its diagnostic competencies. Collaborations with research institutes, agricultural agencies, and farmers can help the collection of diverse and consultant datasets.
- **Model Fine-tuning**: Continuous version refinement via tuning techniques can optimize its overall performance. By fine-tuning the pre-skilled EfficientNet B7 model the use of transfer learning, the model may be tailored to plant disease detection duties. Fine-tuning lets in for improved accuracy, decreased overfitting, and elevated performance.
- **Integration of Advanced Techniques**: Exploring and integrating superior strategies along with deep getting to know architectures (e.g., convolutional neural networks), ensemble mastering, and data augmentation techniques can in addition beautify the version's performance. These techniques can be used in extracting more problematic capabilities from leaf photos and improve the model's ability to discriminate between one-of-a-kind sorts of plant diseases appropriately.
- **Real-time Disease Monitoring**: Implementing actual-time disorder monitoring competencies within the AgroEye application can provide farmers with updated facts on the progression of plant diseases in their plants. By incorporating photo analysis algorithms which could examine live or frequent picture updates, farmers can get hold of well-timed alerts and take immediate movements to save crops from the spread of diseases and limit crop losses.
- **User Feedback and Validation**: Encouraging consumer remarks and integrating a validation mechanism inside the software can contribute to ongoing improvements. By allowing customers to offer remarks on disease predictions and incorporating validation procedures, the model's performance may be constantly assessed and delicate based on actual-global statistics and user stories.
- **Integration of Additional Agricultural Parameters**: Expanding the software program past disorder detection to embody other agricultural parameters can offer entire insights to farmers. Integration of functions which includes nutrient deficiency identity, pest detection, and weather-based predictive methods can empower farmers with a holistic preference-making device for crop control.
- **Collaboration with Agricultural Experts**: Collaborating with agricultural specialists, researchers, and agronomists can offer valuable regional information and steering for in addition enhancing the application. Expert input can help refine illness identity algorithms, confirm outcomes, and ensure the practicality and accuracy of the application in actual-global situations.

VI. CONCLUSION

In conclusion, the AgroEye undertaking makes a substantial contribution to the field of plant disease detection with its improvement of sturdy and correct mobile software. By using EfficientNet B7 version for disease category and using React Native for frontend improvement, the challenge has successfully addressed the need for an intuitive and person-friendly interface for capturing leaf pictures. The integration of Flask because the backend framework and deployment on Amazon EC2 ensured green processing and reliable overall performance of the utility, making it suitable for rea world scenarios. Testing and iterative refinements performed during the project's lifecycle have performed a crucial function in improving the application's usability, accuracy, and common performance. In summary, the AgroEye challenge represents a considerable advancement in plant disease detection, presenting a complete answer that combines innovative technology with person-centric layout. The successful development of the mobile application, at the side of its sturdy overall performance and practical implications, positions it as a promising device for farmers, researchers, and stakeholders inside the agricultural area.

VII. REFERENCES

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