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A Mobile Application for Crop Optmisation using Satellite Imagery and Disease Detection using AI

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Abstract: Despite being crucial to the world's food supply, small-scale farmers do not have access to resources or contemporary technologies. This makes it more difficult to make educated decisions, which lowers yields and causes financial hardship. To help farmers overcome this obstacle, our research uses satellite data to provide them with useful insights that will enable them to increase production and make wise decisions. We suggest a smartphone app that uses image-based disease diagnosis and artificial intelligence (AI) to transform precision agriculture. Using real-time data on plant disease, water use, and soil health, the app helps farmers reduce risks, maximize resource use, and eventually increase yields. Our approach helps small-scale farmers close the technology gap by converting their customary techniques into a more effective and sustainable model. We think there is a lot of potential for this technology to improve socioeconomic conditions and the standard of living for farmers throughout the world.
Keywords: Small Scale Farmers; Satellite data; Mobile Application; Precision Agriculture; Artificial Intelligence;

I. INTRODUCTION

Significant changes in the global agricultural environment are being driven by developing diseases and pests, technology advancements, and climate change [1].

The population of the world is predicted to rise quickly, surpassing 9 billion people by the year 2050. [2] Small-scale farmers, who still make up a sizable share of the agricultural labour, frequently lack access to precision agriculture instruments, even as large-scale farms are increasingly using similar practices [3]. This discrepancy may result in less-than-ideal crop management techniques, lower yields, and unstable finances [4].

Mobile applications have the ability to close the technology divide in agriculture, according to recent research [5]. In order to provide small-scale farmers with practical insights, this article suggests creating an intuitive smartphone application that makes use of satellite data and artificial intelligence (AI). The app will provide functionalities such as:

A. Precision Agricultural Recommendations

Utilizing AI algorithms, the app will analyse satellite imagery and local weather data to provide farmers with site-specific recommendations for the crop, such as health of the crop and what action to take [1].

B. Image based Plant Disease Detection

Farmers will be able to recognize any plant illnesses by using real-time image capture and analysis with the app thanks to its integration of image recognition technologies [5]. Early discovery can direct suitable treatment and help reduce crop losses.

The developed smartphone application aims to enhance agricultural yields by giving small-scale farmers access to these technologies. Research has shown that precision agriculture methods can optimize resource allocation, leading to considerable increases in crop yields [3].

Enhance Decision-Making: Farmers will be better equipped to choose their crops thanks to real-time data access and AI-powered insights. Boost Socio-Economic Well-Being: Small-scale farmers may earn more money and have a more stable living if crop yields are raised and farm management techniques are strengthened [2].

II. LITERATURE REVIEW

This section discusses methodologies that have existed to handle the difficulties of detecting diseases and crop monitoring, with an emphasis on existing mobile apps.

A. Plant Disease Detection Methodologies

Experienced farmers, known for their expertise in agriculture, are often relied upon to diagnose pests and plant diseases on-site. However, this traditional method is arduous, time-consuming, and subjective, often resulting in limited success. Furthermore, inexperienced farmers may resort to indiscriminate pesticide use and erroneous judgments during the identification process, leading to compromised output, reduced quality, environmental damage, and financial losses. To address these challenges, leveraging images for disease identification has emerged as a promising solution [10].

The application of deep learning algorithms for plant disease identification represents a significant advancement in agricultural technology [7]. Initially, researchers focused on utilizing leaf vein patterns in plant photos for identification purposes. Dubey and Jalal, employed an enhanced support vector machine (SVM) combined with K-means clustering to successfully identify three types of apple diseases, achieving an impressive classification accuracy of 93% [6].

According to current research, Convolutional Neural Networks (CNNs) stand out as the most widely utilized classifiers for image recognition, demonstrating exceptional performance in image processing and classification [8]. CNNs leverage large datasets for training, enabling them to provide accurate results. A CNN-trained model using the Plant Village Dataset has been made accessible to mobile applications through platforms like Kaggle. This accessibility democratizes advanced disease identification technology, making it available to a wider audience [9].

B. Satellite image processing techniques

The advent of Earth observation satellites has opened up new avenues in agriculture, such as crop mapping using satellite imagery. Many applications for crop monitoring emphasize the use of machine learning classification algorithms with publicly available image sources like MODIS, Landsat, and Sentinel. With just a single photograph, it's now possible to obtain yearly crop maps or crop cycle maps, revolutionizing agricultural decision-making [11]. SVM and Random Forest classifications from the Sentinel satellite were used by R. Saini and S. K. Ghosh to classify crop kinds with an overall accuracy of 82% to 91% utilizing a single picture [12]Afterwards, to estimate and offer insights, a crop cycle's worth of photos is taken into consideration. The yearly crop maps used to build the multi-year cropping patterns were created by Martínez et al using a sequence of photos. A seven-year time-series (1993, 1994, 1996, 1997, 1998, 1999, and 2000) of crop maps made from Landsat 5 TM and Landsat 7 ETM+ images was used. [13]

To process crop indices with ease, the mobile application makes use of Agromonitoring API, a sentinel satellite agricultural insight provider. [14]

III.PROPOSED SYSTEM

The mobile application is the end-user experience , the app works with dual functionality mainly focusing to retrieve satellite data from crop monitoring API and local image processing for plant disease detection.

The mobile app segregated into individual modules to deliver scalable usage. Each module provides a use case to the farmer to get insights and suggestions.

A. Authentication - Firebase

To securely personalize data, farmers can use the authentication function offered by the application. We immediately register the user in Firebase (a cloud storage and database hosted by Google) using their Google Account.

B. Cloud Data Storage

For an improved user experience Personal information including the user's name, phone number, and crop map coordinates for location are kept in a different cloud cluster in Mongo DB. The application connects to the database via a node.js server. This allows scalability and reduces server load for authentication.

C. Agro Monitoring API

The geographic coordinates are the input to the Agro Monitoring API to obtain crop data. It creates a polygon with the selected co-ordinates. The interface's design presents the user with a Google Maps screen where they may choose four coordinates and form a polygon. This polygon is later analysed and produces fair results of various vegetation indexes, a custom algorithm is used to convert these indexes into actionable results for farmers.

D. Disease Detection

A flask API is developed to integrate with mobile application. When user inputs an image with the plant disease the Api communicates with a pre-trained model and provides insights and solutions to the user.

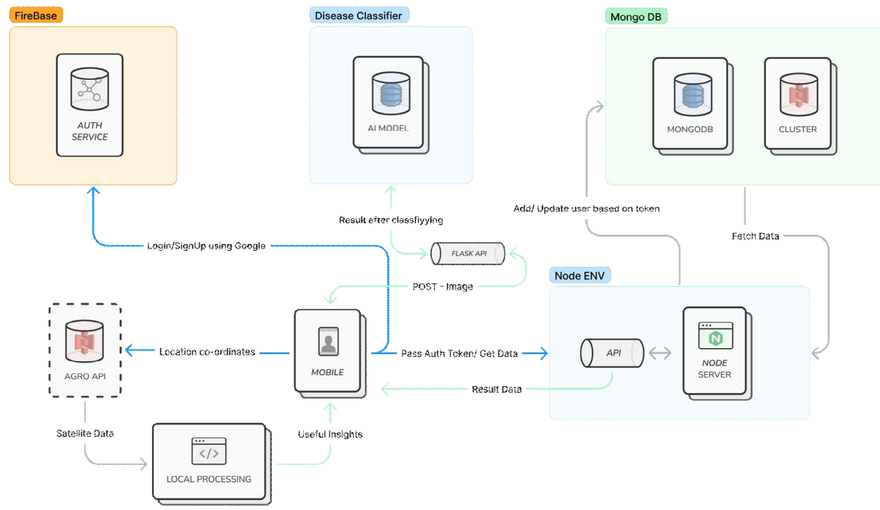

Fig. 1.Overall System Design

IV. DATA FLOW

A. Use Case Diagram

The main interaction component in this application is to upload location and images to process and view suggestions to impact farmers' yield. The user can use the authentication service, location mapping for crop monitoring and also the disease detector parallelly. Fig 2 depicts the various interactions a user can have with the application.

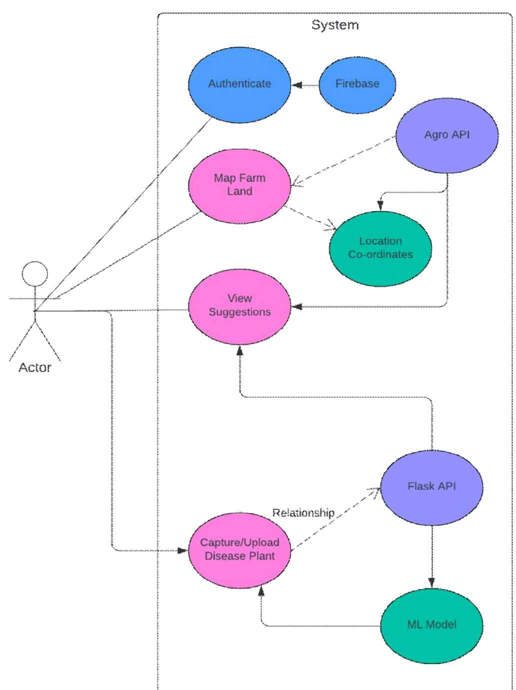

Fig. 2.Use Case Diagram

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B. Sequence Diagram

The sequence diagram in Fig 3 visualizes the workflow within the application. The application then functions with two processes. The satellite data from Agro API provides into factors like weather patterns or soil conditions. The ML model, on the other hand, analyses the image itself to identify the specific disease.

By combining these two data streams, the app can potentially provide the user with a more comprehensive analysis. The user receives the final results, which include the diagnosed plant disease and any relevant insights gleaned from the satellite data.

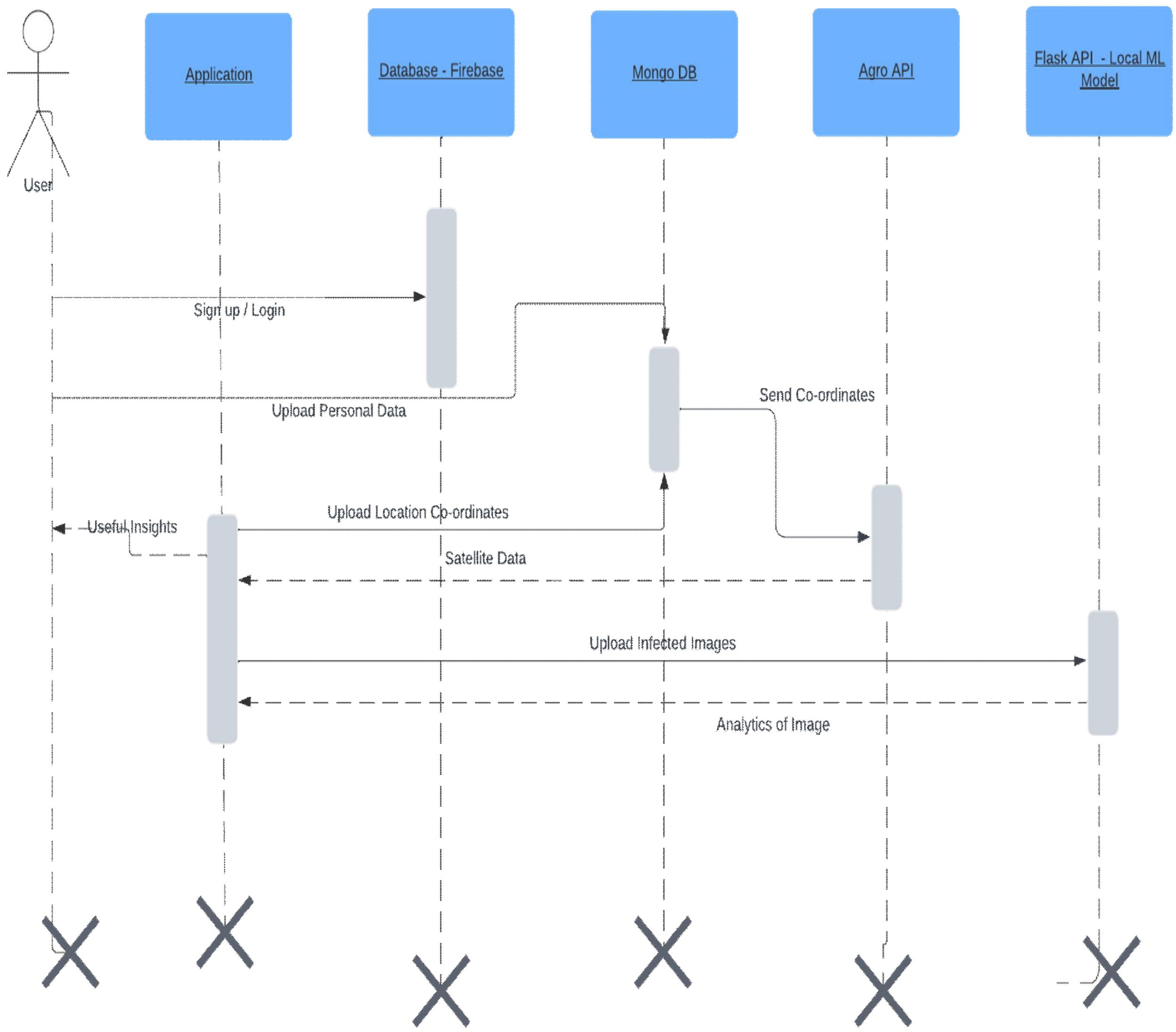

Fig. 3.Sequence Diagram

V. SYSTEM REQUIREMENTS

A. Usage Requirements

1) Device: Smartphone or tablet with
   - Android (minimum version - 9)
   - iOS (minimum version - 16)

2) Camera: A built-in camera with autofocus is required to capture images of Leaves.

3) Internet Connection: An internet connection (Wi-Fi or cellular data)

B. Development Requirements

1) Hardware Requirements

a) System: Windows/Linux with min version 10
b) Hard Disk: 200 GB.
c) Monitor: 15’’ LED
d) Input Devices: Keyboard, Mouse
e) Ram: 8GB.
f) GPU: Processor equivalent to GTX 1080 or AMD Radeon 560 MX

2) Software Requirements

a) Programming languages: DART, PYTHON-3.8, JAVASCRIPT.
b) Package and Libraries:

- Flutter: Mobile Application Interface for Client side
- MongoDB: User data storage and Fast access processing
- Firebase: User authorization and token generation
- Flask: Simple API Framework for AI model requests
- AgroAPI: Satellite Image inventory service
- Nodejs: Server-Side Scripting for MongoDB

VI. IMPLEMENTATION

A variety of frameworks are used to implement the mobile application. The program can be separated into front-end and back-end sections.

A. Front-end – User Interface

The front end is client side application user interface, it is developed entirely using Flutter Framework (A cross platform application framework). The front end is divided into sections focusing on functionalities.

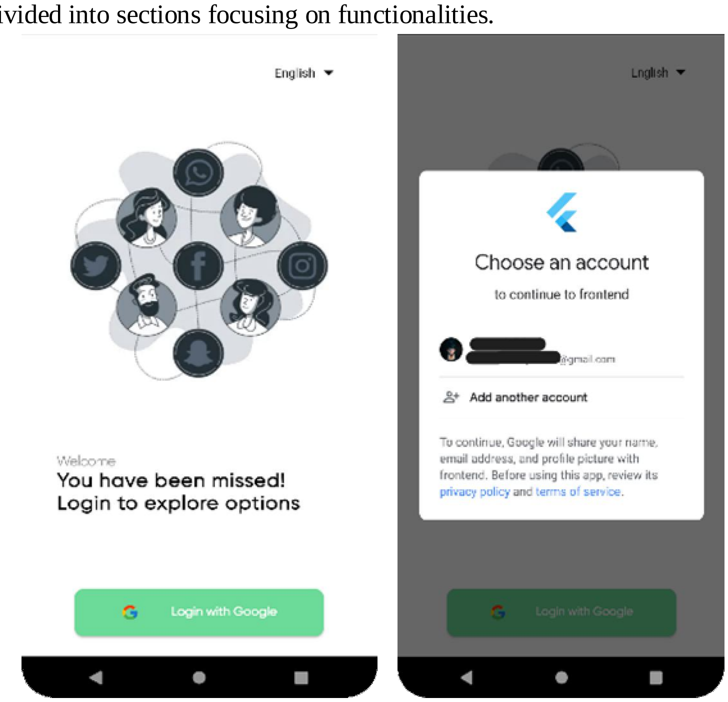

Fig. 4. Authorisation Screens

Fig 4 is the first screen the user comes across and will be able to register with the application or login into his existing account.

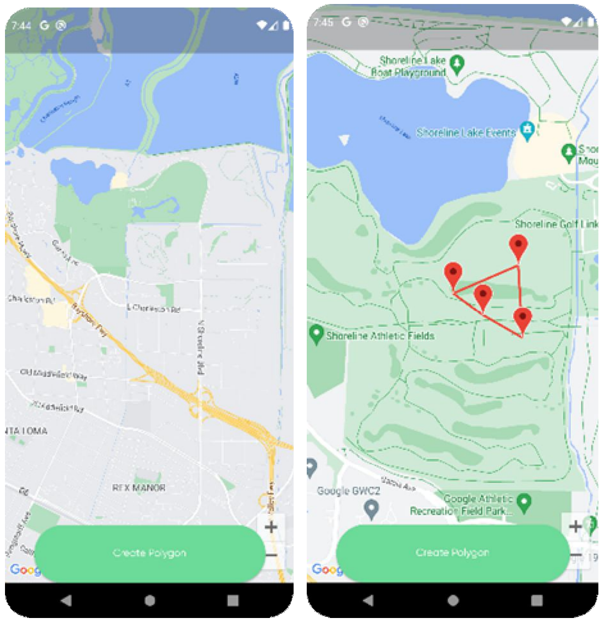

Fig. 5.Location selection Screens

Fig 5 depicts the selection of the farm land – a user can select 4 location co-ordinates and they are mapped to the crop. This date is later used for crop monitoring results.

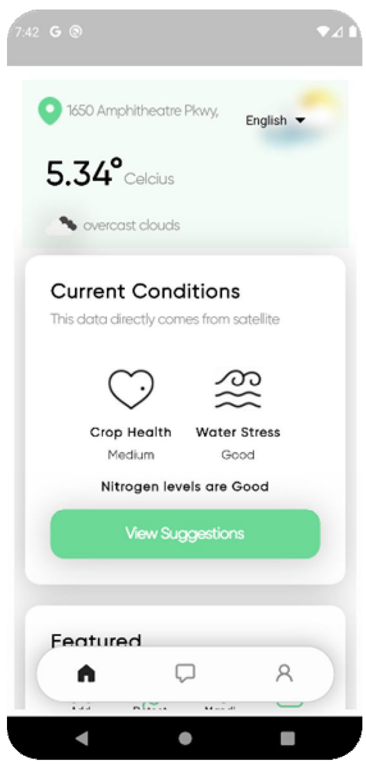

Fig. 6.Home Screen

Fig 6 is the home screen of the application, it provides all necessary data from satellite with insights, it is also the start of navigation to other screens for more functionality.

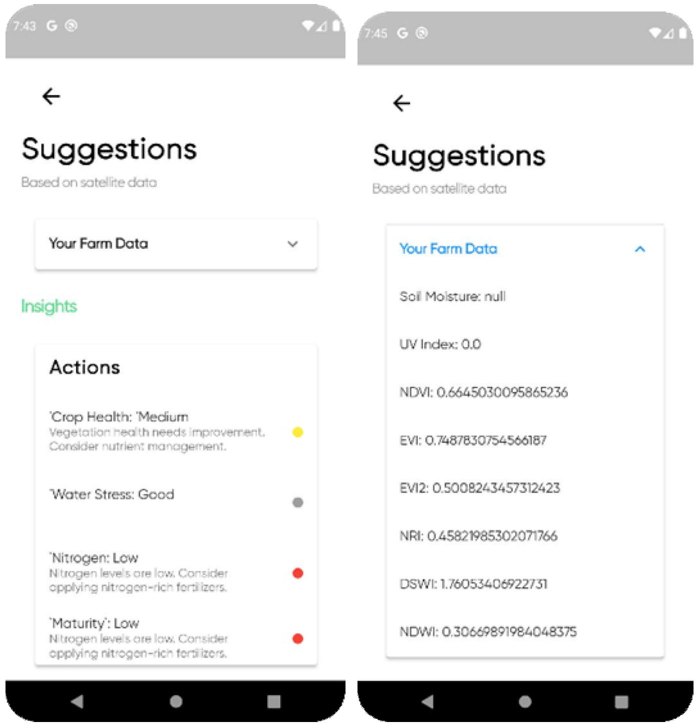

Fig. 7.Suggestion Screens

Fig 7 represents the end results of the satellite data, these are insights and actions that a farmer can perform to produce good yield. Similarly Fig 8 represents the plant disease detection results with an option to upload images locally these images can be captured by the smartphone camera.

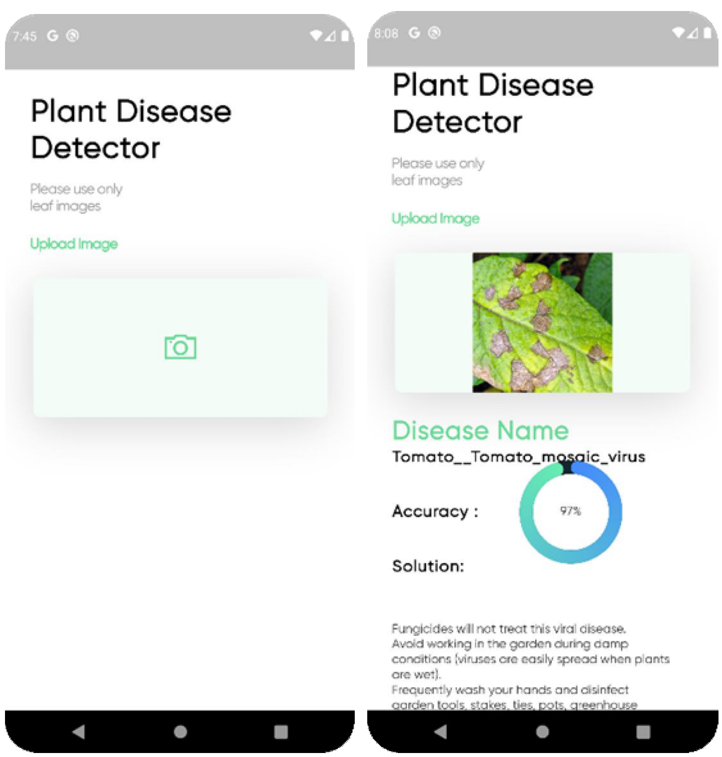

Fig. 8.Plant Disease Detector Screens

B. Front-end – Server Programs

The Back-End of the application contains various processes to run and accommodate for functionality. This section primarily involves the CNN model for Plant Disease Detection and Processing of satellite data from Agro API.

1) CNN model for Plant Disease Detection :

As part of the preprocessing stage, the input images are first resized. Following this, a NumPy array is created for the data. Following the conversion of the images to grayscale, image augmentation is done to ensure that the images are positioned accurately. As a result, the framework identifies the supplied leaf image and proceeds to preprocess it in order to derive a prediction

a) Input Layer

- The model receives input in this layer. The number of neurons and characteristics in the neural network are equal at this early stage. When looking at an image, the total number of features is equal to the number of pixels in the image.
- The model is trained and tested using two different portions of the input data distributing 20% of the data set to testing and 80% for training.

b) Three Hidden Layers

- The output from the input layer is received by this layer. It depends on the model as well as the volume of data. The quantity of neurons in every hidden layer differs.

c) Output Layer

- The algorithm converts each class's output into an equivalent probability score. This score can be the key result of classifying data into the correct category.

Layer	Output Shape	Parameters
sequential	(32, 256, 256, 3)	0
sequential_1	(32, 256, 256, 3)	0
conv2d	(32, 254, 254, 32)	896
max_pooling2d	(32, 127, 127, 32)	0
conv2d_1	(32, 125, 125, 64)	18,496
max_pooling2d_1	(32, 62, 62, 64)	0
conv2d_2	(32, 60, 60, 64)	36,928
max_pooling2d_2	(32, 30, 30, 64)	0
conv2d_3	(32, 28, 28, 64)	36,928
max_pooling2d_3	(32, 14, 14, 64)	0
conv2d_4	(32, 12, 12, 128)	73,856
max_pooling2d_4	(32, 6, 6, 128)	0
conv2d_5	(32, 4, 4, 128)	147,584
max_pooling2d_5	(32, 2, 2, 128)	0
flatten	(32, 512)	0
dense	(32, 256)	131,328
dense_1	(32, 15)	3,855

TABLE I. MODEL SUMMARY

Parameter Type	Count
Total params	449,871
Trainable params	449,871
Non-trainable params	0

TABLE II. PARAMETER COUNT

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2) AGRO API Result Processing :

The Agro API is a pivotal component in modern agriculture, offering a suite of tools for precision farming. At its core, the API harnesses satellite imagery, vegetation indices, and weather data to provide actionable insights into crop health and environmental conditions. Through a sophisticated processing pipeline, the API returns NDVI classes, which serve as a key indicator of crop condition. These classes are derived from vegetation indices such as NDVI, EVI, and others, computed from multi-spectral satellite imagery. Table III represents various parameters returned by the Agro API when a farm co-ordinates from mobile application are inputted.

Parameter Type	Response
dt	Acquisition date (Unix time, UTC)
type	Satellite name (Landsat 8, Sentinel 2)
dc	Approximate percent of valid data coverage
cl	Approximate percent of cloud coverage
sun	Sun zenith and azimuth angles at scene acquisition time
image, stats, data, tile	API calls to get image for a polygon in PNG format Parameters truecolor falsecolor Ndvi Evi Evi2 Nri dswi ndwi

TABLE III. PARAMETERS OF RESPONSE FROM AGRO API [14]

Satellite imagery forms the foundation of the Agro API, offering high-resolution views of agricultural landscapes. Updated every 2-4 days, this imagery provides real-time monitoring of crop growth and land conditions. Additionally, historical archives dating back to 2018 enable trend analysis and long-term monitoring of vegetation dynamics. By integrating satellite data with vegetation indices, the API enables users to accurately assess crop health and vigour.

Vegetation indices, particularly NDVI, play a crucial role in crop monitoring and management. NDVI values reflect the photosynthetic activity and biomass production of vegetation, providing valuable insights into crop health. Hence is the main indicator for result computation. We determine three main crop health metrics.

VII. AGRO API RESULT ESTIMATION

A. Overall Crop Health

Overall crop health is primarily based on NDVI Values and hence provides more insight into how to improve the health of the crop

NDVI Value Range	Vegetation/ Health
0 – 0.2	Low
0.2 – 0.4	Medium
0.4 – 0.6	High

TABLE IV. NDVI VEGETATION CLASSIFICATION

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B. Water Stress

To calculate water stress, we take into factor NDWI, DSWI and Soil moisture level. A formula is constructed to briefly estimate water stress in the crop.

$$a = S\,(NDWI + DSWI\square) / 2 \qquad \square\square\square$$

The result from equation (1) provides the base for classifying water stress.

$$b = a \,\square\, (\text{Soil Moisture} / 10) \qquad \square 2 \square$$

Beta Value	Stress Level
<0.2	Good
0.2 – 0.5	Medium
>0.5	High

TABLE V. WATER STRESS CLASSIFICATION

C. Nitrogen Level

The NRI index provides accurate information about nitrogen level in a crop. Can be used to estimate yield potential. NRI values less than 0.2 indicate very less nitrogen content in the crop. Values greater than 0.2 represented crops have decent nitrogen value.
In addition to satellite imagery and vegetation indices, the Agro API integrates weather data to provide a comprehensive view of agricultural conditions improving the sustainability of the crop.

VIII. RESULTS

The CNN model has shown very accurate results on training achieving an accuracy of 98.86%. This high level of accuracy empowers farmers with a reliable tool for early detection of crop health issues. By promptly identifying potential diseases, farmers can take timely action through targeted interventions like fungicides or adjustments to irrigation practices. Early intervention can significantly improve crop yields and minimize economic losses due to disease outbreaks.

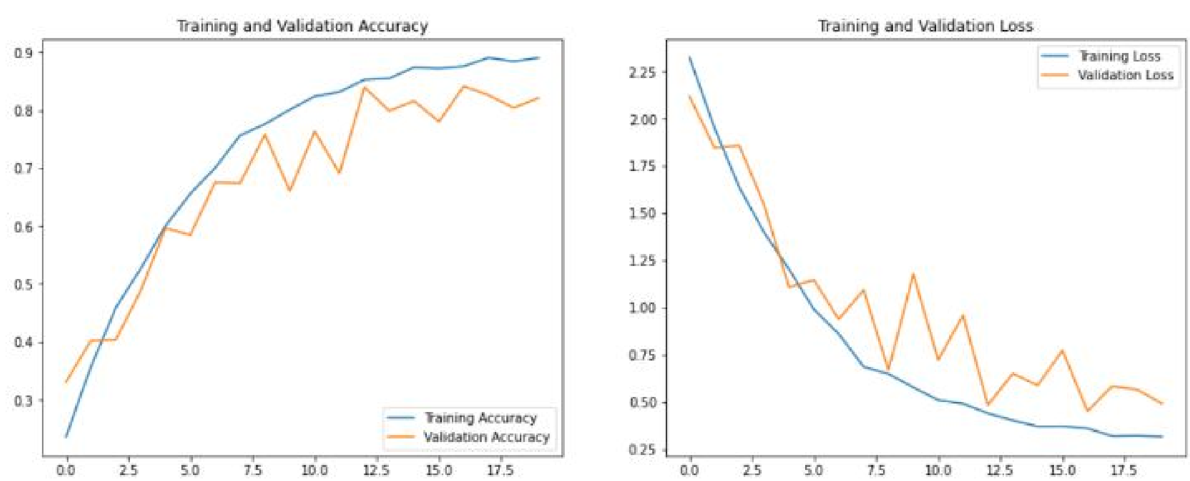

Fig. 9.Training and Validation Loss

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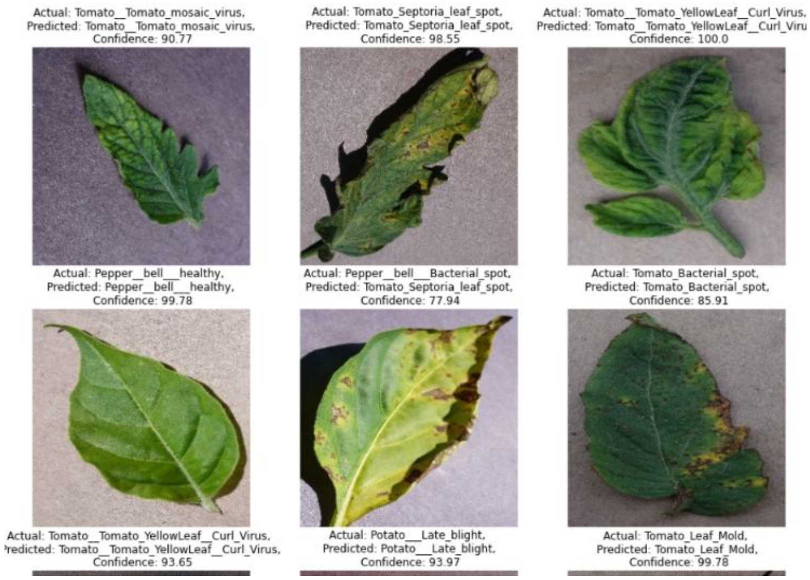

Fig. 10. Pla Actual vs Predicted Results

IX. CONCLUSION

The mobile application discussed in this research paper serves as a pivotal bridge between traditional farming practices and modern technological solutions, particularly in the realm of precision agriculture. By seamlessly integrating features for precision farming and plant disease identification, coupled with actionable suggestions, it empowers farmers to make informed decisions to enhance their crop yield. This innovative tool not only addresses existing challenges in agriculture but also exemplifies the transformative potential of technology in facilitating sustainable and efficient farming practices.

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