

Disease Detection In Wheat Crop (DDWC)



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In the name of ALLAH, the Most benevolent, the Most Courteous

CERTIFICATE OF CORRECTNESS AND APPROVAL

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DECLARATION OF ORIGINALITY

We hereby declare that no portion of work presented in this thesis has been submitted in support of another award or qualification in either this institute or anywhere else.

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Allah Subhan'Wa'Tala is the sole guidance in all domains.

Our parents, colleagues and most of all supervisor, _____ without your guidance.

The group members, who through all adversities worked steadfastly.

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ABSTRACT

Disease Detection in Wheat Crops

Our project aims to address the challenges faced by Pakistani farmers in identifying plant diseases quickly, leading to reduced crop quality and productivity. To achieve this, we propose the development of a cutting-edge smart phone app utilizing deep learning technology to accurately diagnose plant disease. The focus will be on wheat crops, and we will create our dataset of images to train a convolutional neural network. Our approach involves using transfer learning with the VGG16 architecture to achieve high accuracy and performance in disease identification. Through the implementation of our solution, we hope to empower farmers and increase agricultural productivity, contributing to a more sustainable and prosperous future for Pakistan. The project aims to revolutionize the agricultural industry in Pakistan by leveraging technology to improve plant disease diagnosis and management.

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Chapter 1:

1.1 Background:

Infectious illnesses as well as pests have been impacting agricultural crops in recent years, resulting in production losses and financial losses for the agricultural business around the world. Agricultural production is severely impacted by crop diseases, which have unpredictable effects on agricultural produce both in terms of quantity and quality. According to the Food and Agricultural Organization (FAO), weeds, insects, and illnesses account for around 25% of crop losses internationally [1]. Typically, crops are farmed on a big scale. Agricultural output and growth are significant factors that have an impact on peasants' economic, social, and other elements of their lives. Yet, a number of issues that could be caused by numerous environmental elements and unforeseen changes in the climate and atmosphere have significantly impacted the world's tropical and temperate regions and could easily attack the crops to a big amount. Thus, careful observation at various phases of crop growth is required in order to detect illnesses early. According to the Food and Agriculture Organization (FAO), an estimated \$220 billion USD, or 14.1% of crop loss globally, occurs as a result of plant disease each year. Smallholder farmers contribute significantly to the world's food production in the majority of developing nations, but they are unable to use standard methods of plant disease detection since they are costly and time-consuming. Thus, careful observation at various phases of crop growth is required in order to detect illnesses early. Yet, showing humans in their natural state might not be enough, and sometimes false assumptions might be made.

In this regard, accurate identification depends on the automatic recognition and classification of various illnesses affecting a certain crop. The illiteracy of Pakistani farmers is one of the major factors contributing to the rise of pests and diseases. It is challenging for farmers to identify the true cause of diseases once a crop has become afflicted with one or more diseases. Crop, plant, and fruit diseases can significantly reduce the quantity and quality of produce, leading to lower production levels. Visual examination is a structural issue of the majority of traditional plant disease monitoring and identification systems. Molecular microscopic inspection can sometimes help with illness detection. These methods typically yield accurate results, but their applicability is spatially constrained, and the visual inspector's prior experiences may bias the outcomes [3]. These techniques are also expensive and ineffective for the overwhelming majority of farmers. According to the Food and Agriculture Organization of the United Nations, plants contribute to 80% of the average person's diet and play a significant role in ensuring global food security [4]. Plant pests and diseases, which harm crops and result in food shortages by lowering the amount of food available and access to food, pose a danger to plants' crucial role in ensuring food security. So, the costs of food rise as a result of plant pest and disease damage, which may also reduce how tasty the food is. The harmful and destructive organisms known as pests have been detrimental to people, crops, and livestock, and some of these invasive pest species (such as aphids, wheat weevils, and wheat midges) have been found to cause serious, life-threatening

diseases on crop production that recurrently lead to crop failures. Developed nations use complex and time-consuming ground investigations and controlling activities to detect and monitor plant health and other field conditions [5]. For instance, the US Forest Health Monitoring Program's detection and monitoring component, which gathers information on the current state of the forest ecosystem, is carried out once a year [6].

The ability to give early warning and forecasting for effective plant disease prevention and management will be a crucial factor in agriculture in the ensuing decades. The early diagnosis of plant diseases could be a key component of this effort because it would reduce the likelihood of severe economic losses and boost the resilience of smallholder agriculture. This makes the creation of reliable and economical plant disease diagnosis technologies a top concern. Image processing and neural networks can be used as one of the helpful approaches for detecting plant diseases. Recent studies have demonstrated the effectiveness of neural networks and deep learning for completing these classification tasks quickly. Unmanned aerial vehicles (UAVs), public satellites, and private satellites are widely used today, making it possible to image nearly every site on Earth at high temporal, spectral, and geographic resolutions at a low cost. High-resolution multispectral aerial imaging makes it possible to continuously monitor agricultural diseases and plant health globally for a lot less money than it would cost to use the more expensive conventional methods. In this section, we provide the background and driving forces underlying our project, as well as our contributions to the field and the framework for more precise and straightforward identification of pests and illnesses that affect plants, which will be helpful when creating a treatment approach while minimizing revenue losses significantly. Our project's objective is to identify a deep learning framework that is appropriate for the task at hand. Our diseased and healthy plant dataset, which includes diverse images of plants infected by pests and diseases and several variables, such as infection status and treatment of the infected part in the plant, is used to train and test our systems end-to-end. Our system will be able to recognize various types of crops affected by diseases and pests, regardless of the plant's surroundings because of our system's capacity to handle complex scenarios, according to testing of our framework on a mobile device using an application that accepts random sample crop images, including both diseased and healthy.

1.2 Problem statement:

The wheat crop is the subject of the planned research. Detection of pests in wheat crop is a major challenge for farmers and researchers. Pests can cause significant damage to crop, resulting in huge economic losses. Early detection and effective control of pests are crucial to prevent such losses.

The Pakistani wheat crisis began in November 2019 and grew worse starting in the middle of January 2020. Presently, Pakistan is experiencing one of its biggest food crises. According to reports, there is a shortage of wheat grain in several sections of the nation. There has been a

severe lack of wheat in a number of areas, including the provinces of Khyber Pakhtunkhwa, Sindh, and Baluchistan. The crop productivity in our nation can be increased by improving treatment and automating the disease detection system.

Developing an accurate and efficient system for early detection of pests in wheat crops, which can help farmers to take timely remedial measures to prevent crop damage and minimize economic losses.

The system should be able to identify different types of pests such as *Puccinia striiformis*, *Zymoseptoria tritici*. The solution should also be easy to use, cost effective and scalable to meet the needs of both small and large scale farmers.

1.3 Proposed Solution:

With the help of deep learning algorithms, it is possible to train models that can detect the presence of pests in wheat crops. These models can be trained on large datasets of image to recognize patterns associated with pest damage. Once trained the model can be applied to new images or data to automatically detect pests in real time.

1.4 Objectives:

1. Our goal is to create a mobile application that uses advanced technologies like machine learning and artificial intelligence to identify wheat diseases with high accuracy.
2. We are using deep learning techniques, specifically the VGG16 architecture, to train the disease detection model in our Agrona project.
3. We aim to create a user-friendly interface for farmers to easily use the Agrona system for crop disease monitoring and prevention.

1.5 Working Principle:

Transfer learning is a technique that allows us to make use of existing data when we don't have access to high-performance computing resources or a large dataset. Essentially, it enables us to pre-train a model from a related domain to give it a "head start" before training it on a new dataset. The aim is to retrain the last layers of a previously learned model with randomly initialized parameters and then train it on a new dataset of interest, which is also known as the target model. A pretrained model is one that has already been trained on a

very large dataset, such as millions of photos, over the course of several days or weeks. This is an efficient and useful method for achieving high accuracy quickly by building on the knowledge of others' experiences. Common features can be directly employed as the model's weight parameter to reduce training cost as well as model errors. These features are the top-level feature of the model that can be derived from the low-dimensional representation and can be shared across related tasks. However, it's important to note that transfer learning can lose some of its efficiency if the training target differs significantly from the pretrained model. Recent studies have shown that transfer learning can enhance generalization and that transferred parameters from remote tasks can perform better than randomly initialized parameters.

The Agrona project is aimed at assisting farmers in identifying crop diseases quickly and accurately using a mobile application-based system powered by machine learning and artificial intelligence. The system works by analyzing images of crop leaves and detecting any signs of disease using deep learning techniques. To begin the process, the machine learning model is trained using a curation dataset of crop images. In our Agrona project, we are using the VGG16 architecture, a convolutional neural network model, to detect diseases. After training the model, the farmer can take a photo of a crop leaf using their mobile phone and upload it to the Agrona project. The app then analyzes the image and compares it to the trained model to identify any signs of disease. To enhance the accuracy and efficiency of disease detection, transfer learning techniques are utilized, which enables the system to learn from new data and adapt over time. The Agrona project provides farmers with an easy-to-understand interface that displays the results of the disease detection analysis. Farmers can take appropriate action to prevent or treat the disease based on the results. In summary, the Agrona project aims to provide farmers with a mobile application-based system that utilizes machine learning and artificial intelligence to quickly and accurately detect crop diseases. By offering farmers with early detection and prevention tools, we hope to increase crop yields and minimize the economic impact of crop diseases.

1.6 Deliverables:

The Agrona project includes various deliverables aimed at improving wheat crop disease detection. One of the primary deliverables is a mobile application that allows users to create an account by entering their personal information and a working email address. Users can also log in using their existing account by entering their registered email address and password. In the event that a user forgets their password, they can easily reset it and access their account again. Another important aspect of the project is the model training process. To accurately detect wheat crop diseases, we will train our machine learning model using a combination of pre-trained architectures or models for disease diagnosis. We will fine-tune the model's hyperparameters to improve its accuracy, and incorporate new feature extraction methods such as texture-based features can be used, including LBP, GLCM, and Gabor

filter. Alternatively, pre-trained CNNs like VGG-16 can be employed for deep learning-based feature extraction which would enhance its performance. To gather data for training the model, we will employ a cell phone camera to capture images of crop leaves in the real world. We will categorize these images based on various ailments and enhance the dataset to broaden its range and improve the model's precision. By improving the dataset and training the model effectively, we hope to provide farmers with a reliable tool for detecting crop diseases and improving their crop yields.

1.7 SDG's:

The Agrona project aligns with the United Nations' Sustainable Development Goals (SDGs), particularly SDG 8, which focuses on decent work and economic growth. SDG 8 aims to encourage policies that promote productive endeavors and create respectable jobs, stimulate entrepreneurship, innovation, and the formalization and expansion of micro, small, and medium-sized enterprises (MSMEs), including access to services. The SDGs promote stable economic development, higher productivity, and technological advancement, and aim to put an end to forced labor, slavery, and human trafficking, while supporting job creation. The ultimate goal is to achieve decent employment for all men and women by 2030, along with full and productive employment. The Agrona project has the potential to contribute to the achievement of SDG 8 by providing innovative solutions to farmers, which can enhance their ability to detect and prevent crop diseases. This can result in increased productivity and higher crop yields, leading to job creation in agriculture and related sectors. By incorporating machine learning and artificial intelligence, the Agrona project can help farmers access information and solutions in a more efficient and effective way, which can lead to improved economic growth and development. Moreover, the Agrona project can also contribute to the exploration of unexplored farm and non-farm job potential in agriculture and related sectors. By improving the efficiency of disease detection and prevention, the project can promote sustainable agriculture, agri-business development, and related support services, thereby creating job opportunities for people in these sectors. In summary, the Agrona project is not only focused on disease detection and prevention but also aligns with the United Nations' Sustainable Development Goals. By enhancing agricultural productivity and promoting job creation in agriculture and related sectors, the project can contribute to the achievement of SDG 8, which aims to promote decent work and economic growth.

1.8 Thesis Structure:

SR	Tasks	Deliverables
1	Literature Review	Literature Survey
2	Project Development	Overall Description
3	Machine Learning	Training Model
4	Operation Of Project	Hardware/Software
5	Design and Development	System Architecture
6	Project Test and Evaluation	Test Strategy

Chapter 2:

2.1 Literature Review:

Crop diseases have been a significant threat to food security, especially in developing countries like Pakistan, where agriculture is a crucial sector of the economy. According to the Food and Agriculture Organization of the United Nations (FAO), crop diseases can lead to yield losses of up to 40% globally (FAO, 2020). In Pakistan, crop diseases such as wheat rust and bacterial blight have caused significant yield losses, leading to food insecurity and economic losses for farmers (Mehmood et al., 2018).

Traditionally, farmers rely on visual inspection to detect crop diseases, which is not always reliable and can result in delays in treatment and significant yield losses. The use of machine learning techniques for crop disease detection has the potential to overcome these challenges by providing early and accurate disease detection. In recent years, there has been a significant increase in the use of machine learning techniques for crop disease detection. Several studies have explored the use of machine learning models for disease detection in crops such as rice (Singh et al., 2019), tomato (Huang et al., 2018), and apple (Liu et al., 2018). These studies have demonstrated the potential of machine learning techniques for crop disease detection, with promising results in terms of accuracy and efficiency. However, most of these studies have focused on crops and diseases found in developed countries, and there is limited research on crop disease detection in developing countries like Pakistan.

Additionally, most of these studies have used pre-existing datasets, which may not be suitable for detecting diseases in crops in developing countries due to variations in environmental and geographical conditions. Therefore, there is a need for research on the use of machine learning techniques for crop disease detection in developing countries, especially in crops such as wheat, which is a vital crop for Pakistan's economy. In this study, we propose the development of a mobile application named Agrona that uses machine learning techniques to detect diseases in wheat crops in Pakistan. We use transfer learning with VGG 16 as the primary model due to its accuracy and better performance compared to other trained models.

Previous Research:

Several studies have explored the use of machine learning techniques for crop disease detection. For instance, Singh et al. (2019) proposed a deep learning-based approach for the detection of rice diseases using a convolutional neural network (CNN) model. The authors used a dataset of 3,000 images of rice leaves infected with six different diseases and achieved an accuracy of 97.75% using a ResNet-50 model.

Similarly, Huang et al. (2018) proposed a tomato disease detection system using a CNN model. The authors used a dataset of 15,000 tomato leaf images infected with six different diseases and achieved an accuracy of 98.03% using a VGG-16 model. Liu et al. (2018) proposed a deep

learning-based approach for the detection of apple diseases using a CNN model. The authors used a dataset of 7,000 images of apple leaves infected with five different diseases and achieved an accuracy of 98.4% using a VGG-16 model.

In another study, Chollet et al. (2017) used transfer learning with VGG-16 to detect melanoma skin cancer. The authors achieved an accuracy of 95% using the pre-trained VGG-16 model. In Pakistan, several studies have been conducted on crop disease detection. For instance, Mehmood et al. (2018) proposed a model for the detection of bacterial blight in rice using hyperspectral imaging. The authors achieved an accuracy of 95% using a support vector machine (SVM) classifier.

Similarly, Aslam et al. (2019) proposed a system for the detection of potato diseases using a CNN model. In addition to these efforts, there has been recent advances in the application of machine learning for crop disease detection. Machine learning is a branch of artificial intelligence that uses algorithms and statistical models to enable computers to learn from and make predictions based on data. With the increasing availability of large datasets and advancements in computing power, machine learning has become a powerful tool for disease detection and diagnosis in various fields, including agriculture.

Previous research has demonstrated the potential of machine learning in crop disease detection. For instance, researchers have used convolutional neural networks (CNNs), a type of deep learning algorithm, to classify and detect plant diseases using leaf images. In one study, a CNN was trained to detect six different types of diseases in tomato plants, achieving an accuracy of 99.7% (Mohanty et al., 2016).

Similarly, another study applied a CNN to detect and classify four types of diseases in apple trees, achieving an accuracy of 98.21% (Fuentes et al., 2017). Other researchers have used machine learning to detect crop diseases in rice, maize, and other crops. In one study, researchers used a support vector machine (SVM) algorithm to detect rice leaf diseases, achieving an accuracy of 95.56% (Chen et al., 2018). In another study, a CNN was used to detect and classify three types of diseases in maize plants, achieving an accuracy of 92.16% (Kaggle, 2019).

While these studies demonstrate the potential of machine learning in crop disease detection, there are also challenges and limitations to this approach. One challenge is the need for large and diverse datasets for training and testing the models. Collecting and labeling images of diseased and healthy plants can be time-consuming and labor-intensive. Moreover, different regions and seasons may present different challenges to disease detection, and models trained on one dataset may not perform well on another. Another challenge is the potential for misclassification or false positives, where the model may identify a healthy plant as diseased or misidentify the type of disease present. This could lead to unnecessary treatments or incorrect management decisions, which could be costly for farmers.

Despite these challenges, the potential benefits of machine learning in crop disease detection are significant. By enabling early and accurate detection of diseases, farmers can take timely action to manage the disease and prevent its spread. This could lead to improved crop yields, reduced losses, and more sustainable agricultural practices.

In this context, our project Agrona aims to contribute to the field of crop disease detection using machine learning. By developing a mobile application that can detect diseases in wheat crops in Pakistan, we aim to provide a useful tool for farmers in the region. Our approach utilizes transfer learning with the VGG 16 model, which has shown promising results in previous studies. We have collected our own dataset of wheat images from various regions of Pakistan, and our model has shown an accuracy of approximately 90% on certain training sets.

In summary, crop diseases pose a significant threat to food security, particularly in developing countries like Pakistan. The development of machine learning models and applications for crop disease detection has the potential to improve agricultural practices and increase crop yields. While there are challenges and limitations to this approach, recent research has demonstrated promising results, and our project Agrona aims to contribute to this field by developing a mobile application for wheat disease detection in Pakistan.

In addition to the use of machine learning in crop disease detection, there have been some efforts to develop mobile applications for the same purpose. For example, the Plantix app developed by a German startup, allows farmers to take pictures of their crops, which are then analyzed using machine learning algorithms to detect diseases, pests, and nutrient deficiencies. The app provides recommendations on how to address the problem and even offers a marketplace for agricultural products. Similarly, the Crop Disease Diagnosis System (CDDS) developed by researchers at the University of Agriculture in Faisalabad, Pakistan, uses machine learning algorithms to analyze images of crops for the detection of diseases. The app provides an interface for farmers to input their crop images and get recommendations on disease control measures. Although these apps are useful tools for farmers, they have limitations in terms of accuracy and availability of data. Most of the existing apps are not specific to certain crops and can have difficulty distinguishing between different types of diseases.

The Agrona project aims to address these limitations by focusing specifically on wheat crops in Pakistan and using a dataset that has been collected locally, resulting in a more accurate diagnosis. In terms of machine learning models, the VGG-16 model has been widely used for image classification tasks and has shown superior performance compared to other models in various studies. For instance, a study by Simonyan and Zisserman showed that the VGG-16 model achieved state-of-the-art performance in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2014, which is a benchmark for image classification tasks.

Therefore, it is not surprising that the Agrona project uses the VGG-16 model for disease detection. One of the challenges in using machine learning models for crop disease detection is the availability of high-quality datasets. Many studies have used publicly available datasets such

as the PlantVillage dataset, which contains images of several crops affected by various diseases. However, such datasets may not be representative of the local conditions and may not capture the diversity of diseases that are prevalent in a particular region.

To overcome this challenge, the Agrona project collects its own dataset of images of wheat crops affected by various diseases in Pakistan, resulting in a more accurate diagnosis. Overall, the Agrona project represents an important step in using machine learning for crop disease detection in Pakistan. By focusing on wheat crops and using a locally collected dataset, the app offers a more accurate diagnosis of diseases, which can help farmers to take appropriate measures to protect their crops and improve their agricultural practices. Future work can focus on expanding the app to other crops and diseases in Pakistan and refining the machine learning model to improve its accuracy further.

2.2 Machine Learning In Disease Detection:

2.2.1 Introduction

Crop disease detection is an important task that can significantly impact crop yield and production. Machine learning algorithms have been extensively utilized to detect and classify crop diseases accurately and efficiently. These algorithms can be broadly classified into three categories: traditional machine learning algorithms, deep learning algorithms, and hybrid algorithms.

2.2.2 Traditional Machine Learning Algorithms

Traditional machine learning algorithms, such as SVM, decision trees, and KNN, have been used in crop disease detection. These algorithms work well in cases where the input data is well-defined and the feature extraction process is straightforward. SVM has been used to classify tomato diseases[19], while decision trees have been used to classify apple and wheat diseases. KNN has been utilized for the detection of maize and soybean diseases [25].

2.2.3 Deep Learning Algorithms

Deep learning algorithms, such as CNN, have been used in crop disease detection due to their ability to learn and extract high-level features from images. CNNs have been used in the detection of rice, tomato, and potato diseases. They have also been used to classify diseases in fruit trees, including apple and peach trees. The use of CNNs has shown promising results in crop disease detection, with high accuracy and fewer false positives.

2.2.4 Hybrid Algorithms

Hybrid algorithms, which combine traditional machine learning algorithms with deep learning algorithms, have also been utilized in crop disease detection. The combination of CNNs and SVMs has been used in the detection of banana diseases [27], while the combination of KNN and CNNs has been used in the detection of tomato diseases [32]. Hybrid algorithms have shown improved performance compared to using traditional machine learning algorithms or deep learning algorithms alone.

2.2.5 Previous Work

Various research studies have been carried out to evaluate the effectiveness of different machine learning algorithms in crop disease detection. One notable investigation involved comparing the performance of Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and decision trees in identifying cotton leaf curl disease. The results indicated that SVM exhibited superior performance compared to the other algorithms tested. Another study focused on the detection of rice diseases and compared the performance of Convolutional Neural Networks (CNNs) and SVMs. The findings demonstrated that CNNs surpassed SVMs in terms of accuracy, suggesting their efficacy in detecting rice diseases.

In our own project, we recognized the significance of transfer learning in crop disease detection. Transfer learning involves leveraging pre-trained models that have been trained on large datasets, such as ImageNet, to solve similar problems in a different domain. By utilizing transfer learning, we were able to benefit from the knowledge and features learned by these models, significantly reducing the training time and improving the performance of our own crop disease detection system.

Through transfer learning, we incorporated a pre-trained CNN model as the backbone of our detection system. This pre-trained model had been trained on vast amounts of diverse image data, enabling it to learn general features that are valuable for image recognition tasks. We then fine-tuned this pre-trained model using our specific crop disease dataset, allowing it to adapt and specialize in detecting diseases in crops accurately.

By employing transfer learning, we harnessed the power of a well-established model's knowledge, which was built upon extensive training on diverse visual data. This approach not only expedited the development of our crop disease detection system but also improved its accuracy and robustness.

2.2.6 Conclusion

In conclusion, machine learning algorithms have shown great potential in crop disease detection, with promising results reported using traditional machine learning algorithms, deep learning algorithms, and hybrid algorithms. The choice of the algorithm to be used depends on various factors such as the size of the dataset, the complexity of the problem, and the computational resources available. Future research in this field should focus on developing more efficient and accurate algorithms and expanding the datasets to improve the generalization of the models.

Chapter 3:

3.1 Introduction:

For our wheat crop disease detection app, the manual is crucial as it defines the app's capabilities, including its ability to detect diseases in live images or uploaded images from the gallery. Additionally, it outlines the app's performance requirements and quality standards, ensuring it meets the desired objectives. The manual facilitates effective communication between the development team and stakeholders, promoting a shared understanding of the project's goals, objectives, and constraints. This understanding is necessary to ensure that all stakeholders are aligned and working towards the same goals, leading to a successful project outcome. In summary, the manual serves as a guide for the entire development process, from planning to testing and deployment. It outlines the requirements for the wheat crop disease detection app, ensuring that the development team meets the desired functionalities, performance, and quality standards. Effective communication between the development team and stakeholders is promoted through the manual, resulting in a successful project outcome. This is an essential tool for any project's success, as it sets the foundation for a comprehensive and aligned development process.

3.2 Purpose:

This document outlines the requirements for our project, Agrona, which aims to assist wheat farmers in detecting diseases on their crops. The idea behind Agrona is to use image recognition technology to analyze pictures of wheat crops taken by any image capturing device, and notify users of potential diseases through an Android application. This will not only reduce the need for manual labor, but also enable early detection of diseases, ultimately reducing the number of crops affected. With Agrona, farmers can expect more accurate results and timely notifications of crop diseases, allowing them to address the issue promptly and without the need for time-consuming inspections. This document serves as a guide for developers and a software validation tool for prospective clients, outlining the key features and requirements of Agrona.

3.3 Overall Description

3.3.1 Project Perspective:

The main goal of the Agrona project is to reduce the workload on farms and improve disease detection accuracy. Diseases that begin in the middle of a crop can spread quickly, causing significant damage before they become visible. Unfortunately, it is not always possible for

humans to inspect crops regularly and accurately, especially on large-scale farms. The Agrona project aims to minimize the losses caused by disease and reduce the need for manual labor in monitoring the fields. This will ultimately help farmers save time, money, and reduce overall risks.

3.3.2 Project Function:

Agrona is a project designed to assist wheat farmers in detecting diseases on their crops. Its main features include:

- **Image Acquisition:** Agrona allows users to capture images of their wheat crops using any image capturing device such as a smartphone camera. The process of collecting crop images has been automated through the Agrona app. In the past, farmers and researchers had to manually examine crops for indications of disease and capture photographs to analyze later. This was a demanding and time-consuming job, especially when dealing with extensive farmlands or research fields. Agrona's image acquisition feature has made this task easier as users can simply take pictures of their crops using their smartphone cameras.
- **Image Processing:** The Agrona app uses machine learning algorithms to analyze and compare patterns. Specifically, it employs deep learning algorithms like Convolutional Neural Networks (CNNs) to extract high-level features from images and differentiate healthy crops from those infected with diseases. The app has been trained on a vast dataset of crop images that includes both healthy and diseased crops. The deep learning model in the app has learned to recognize patterns and features that indicate diseases and distinguish them from healthy crops. By using this model, the app can accurately identify the presence of a disease in crops and provide information about its causes, symptoms, and recommended treatments.
- **Disease Detection:** With Agrona, farmers can detect potential diseases affecting their wheat crops early on. Early detection can help reduce the number of crops affected and ultimately minimize losses.
- **Uploading to Firebase:** Agrona allows users to upload the detected disease images to Firebase cloud storage. This feature enables users to access their data from anywhere at any time.
- **Login Using Google Account:** Users can log in to the Agrona system using their Google account. This feature makes it easy for farmers to access the system without the need to remember additional login credentials.
- **Temperature and Humidity Sensor:** Agrona has a built-in temperature and humidity sensor. This feature allows farmers to monitor the environmental conditions of their crops, which can help them take appropriate actions to maintain crop health.








Overall, Agrona is a system that is designed to reduce the workload on farmers and help them detect potential diseases early on. The system provides farmers with accurate and timely information, enabling them to take appropriate actions to protect their crops and minimize losses.

3.3.3 User Classes and Characteristics

- **Farmers (Regular User):** Farmers are the primary users of Agrona. They will use the Android application to take images of their wheat crops using any image capturing device. The application will then use image recognition technology to detect any potential diseases on their crops, and notify them of the same. This will help farmers in early detection of diseases, allowing them to take corrective measures before the disease spreads, ultimately reducing the number of crops affected.
- **Land Tenants (Regular User):** Land tenants, like farmers, will use Agrona to acquire images of their farms and check for wheat disease. They can use the application to monitor their crops regularly and identify any signs of disease early, thereby taking appropriate action to prevent the disease from spreading.
- **Project Supervisor (Occasional User):** The project supervisor will use Agrona to evaluate the project's accuracy and performance. They will review the system to ensure it meets the project requirements and objectives. In addition, they will provide guidance and feedback to the development team based on their findings.
- **Testers (Occasional User):** Testers will use Agrona to identify and report any issues or bugs in the system. They will ensure that the application is in compliance with the software requirements specification document. Testers will also provide feedback to the development team on the usability and user experience of the application.

3.4 Dataset and annotations:

The Agrona project is focused on detecting three main categories of crop diseases, which include septoria, stripe rust, and healthy crops. We have collected a dataset of almost 8000 images of plant leaves to train our machine learning model to identify these diseases accurately. This dataset comprises images of plant leaves affected by each of the three target diseases and images of healthy plant leaves for comparison. The collection of this dataset is a critical aspect of our project because it enables us to train our model to recognize and distinguish between the target diseases and healthy crops. The more images we have in our dataset, the more accurate our model will be in detecting these diseases in new images.

-  Brown Rust
-  Healthy
-  Nitrogen Deficient
-  Septoria
-  Stripe Rust
-  Wheat Leaf Rust
-  Yellow Rust

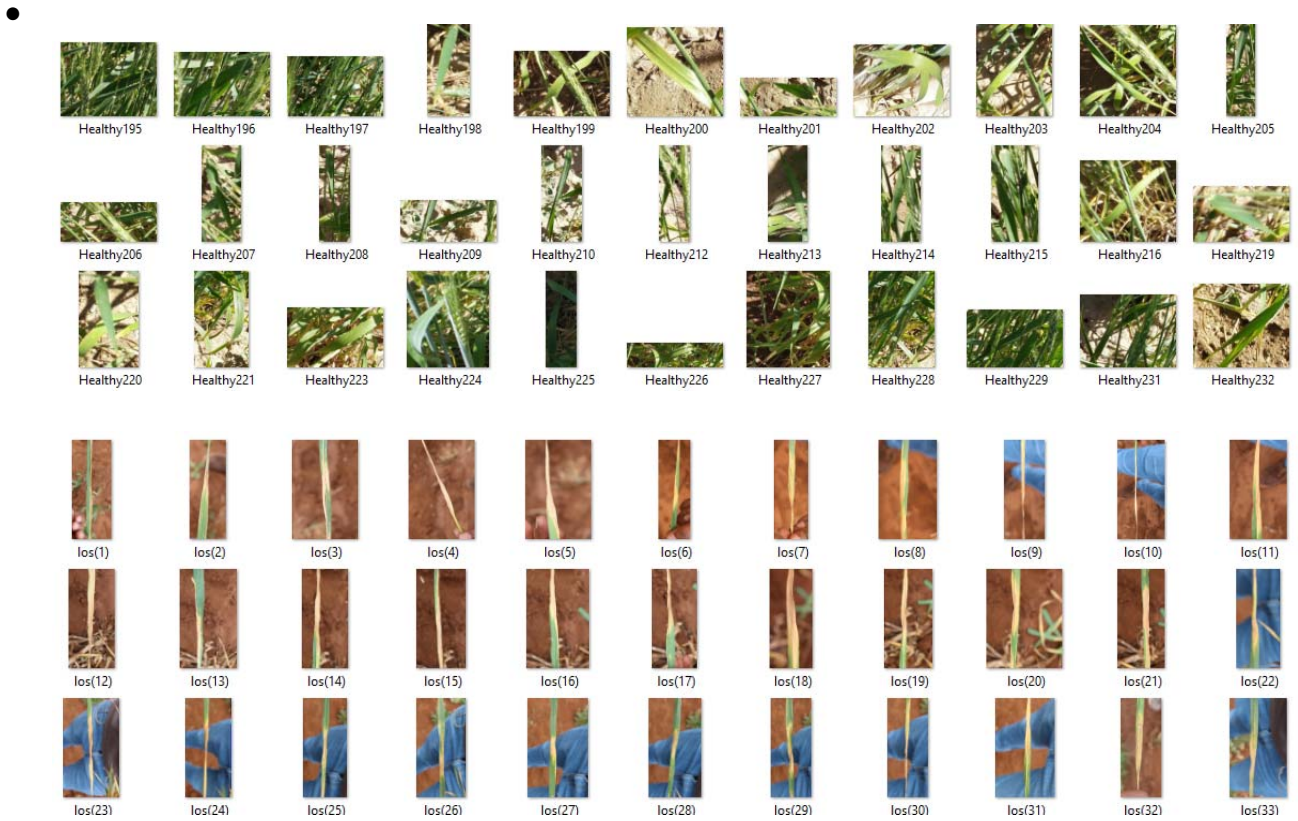


Figure Dataset of The Categories

3.4.1 Healthy Wheat Leaf:

Healthy wheat crops are an essential component of the agricultural industry in Pakistan. These crops are characterized by their lush green color, upright stems, and strong root systems. Healthy wheat crops are free from diseases and pests and have a high yield potential. Farmers in Pakistan take various measures to ensure the health of their wheat crops, including the use of fertilizers, pesticides, and other agricultural practices. In addition to its economic importance, wheat is a staple food in Pakistan, and the quality and health of the wheat crops directly impact the food security of the country. Therefore, ensuring the health of wheat crops is of utmost importance to the agricultural sector and the country's population.



Figure 3-1 Healthy Leaf [12]

3.4.2 Septoria Wheat leaf Disease:

Septoria leaf spot is a common fungal disease that affects wheat crops in Pakistan. It is caused by the fungus *Septoria tritici* and is characterized by small, circular spots on the leaves that are dark brown in the center and surrounded by a yellow halo. As the disease progresses, the spots coalesce and cause the leaves to turn yellow and die prematurely, ultimately reducing the yield of the crop. Septoria leaf spot is typically managed through a combination of cultural practices, fungicides.



Figure 3-2 Septoria leaf [12]

3.4.3 Stripe Rust Wheat leaf:

Stripe Rust is a fungal disease that affects wheat crops in Pakistan and other countries around the world. It is caused by the *Puccinia striiformis* fungus and can lead to significant yield losses if not managed properly. The disease is characterized by the appearance of yellow or orange stripes on the leaves, which can turn into pustules containing spores. One of the most effective ways to manage Stripe Rust is through the use of resistant wheat varieties. Plant breeders have developed a number of resistant wheat varieties that can help minimize the impact of the disease. However, due to the high genetic variability of the *Puccinia striiformis* fungus, new strains of the disease can emerge that are able to overcome the resistance of existing wheat varieties. In addition to resistant wheat varieties, other management strategies for Stripe Rust include timely planting, crop rotation, and the use of fungicides. Timely planting can help to avoid periods of high

disease pressure, while crop rotation can help to reduce the buildup of the fungus in the soil. Fungicides can be effective in controlling the disease, but they can also be costly and may have negative impacts on the environment. Overall, the management of Stripe Rust in wheat crops requires a combination of different strategies, including the use of resistant wheat varieties, timely planting, crop rotation, and the judicious use of fungicides. By implementing these strategies, farmers in Pakistan and other countries can help to minimize the impact of this devastating disease on their wheat crops and ensure a more sustainable and secure food supply.



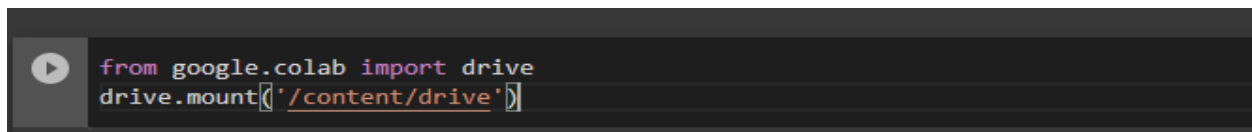
Figure 3-3 Stripe Rust [12]

Chapter 4: Training the Machine Learning Model Using VGG16 Transfer Learning on Google Colab

Introduction: The process of building a machine learning model requires a lot of resources, time, and expertise. However, with the use of transfer learning, we can leverage pre-trained models to build highly accurate models in less time and with fewer resources. In this chapter, we will be using the VGG16 pre-trained model to build a wheat leaf disease detection model. We will be using Google Colab to execute our code, and Google Drive to store our dataset. By the end of this chapter, you will be able to build a highly accurate machine learning model using transfer learning.

4.1 Setting up Google Drive and Google Colab

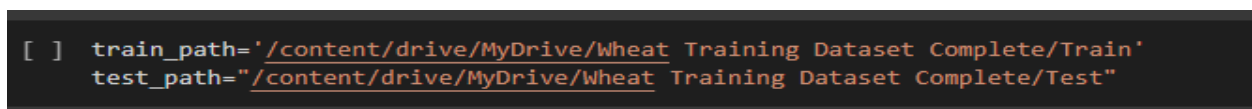
Before we begin training our machine learning model, we need to set up our Google Drive and Google Colab. First, we will create a new folder in our Google Drive called "Wheat Leaf Disease Detection." Next, we will upload our dataset, which contains two folders: "train" and "test." These folders contain images of wheat leaves, with each image labeled according to the disease it represents. Once our dataset is uploaded, we will open Google Colab and connect it to our Google Drive by running the following code.



```
from google.colab import drive
drive.mount('/content/drive')
```

Figure4-1 [mounting drive]

This code will prompt us to authenticate our Google Drive account and provide us with a link. After following the link and authenticating, we will be able to access our Google Drive in our Google Colab notebook.



```
[ ] train_path='/content/drive/MyDrive/Wheat Training Dataset Complete/Train'
test_path="/content/drive/MyDrive/Wheat Training Dataset Complete/Test"
```

Figure4-2 [Giving the paths]

This code will provide the training and testing folder paths which we have uploaded on our google drive.

4.2 Loading the VGG16 Model and Freezing Layers

Next, we will load the VGG16 pre-trained model using Keras. We will freeze all layers in the model except for the last fully connected layer. This allows us to use the pre-trained model's features to train our model without modifying the pre-trained model's weights. We will also add

a new fully connected layer with the same number of output neurons as the number of classes in our dataset. This new layer will be trained to classify the wheat leaf images into their respective disease classes.

```
import tensorflow as tf
from tensorflow.keras.layers import Input, Lambda, Dense, Flatten
from tensorflow.keras.models import Model
from tensorflow.keras.applications.vgg19 import VGG19
from tensorflow.keras.preprocessing import image
from tensorflow.keras.preprocessing.image import ImageDataGenerator, load_img
from keras.optimizers import RMSprop
from tensorflow.keras.models import Sequential
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.models import load_model
import numpy as np
import matplotlib.pyplot as plt
from glob import glob
```

Figure4-3 [Importing Libraries]

```
[ ] IMAGE_SIZE=[224,224]
```

Figure 4-4 [Pixilation]

```
[ ] folders=glob('/content/drive/MyDrive/Wheat Training Dataset Complete/Train/*')
folders

['/content/drive/MyDrive/Wheat Training Dataset Complete/Train/Healthy',
 '/content/drive/MyDrive/Wheat Training Dataset Complete/Train/Brown Rust',
 '/content/drive/MyDrive/Wheat Training Dataset Complete/Train/Wheat Leaf Rust',
 '/content/drive/MyDrive/Wheat Training Dataset Complete/Train/Stripe Rust',
 '/content/drive/MyDrive/Wheat Training Dataset Complete/Train/Yellow Rust',
 '/content/drive/MyDrive/Wheat Training Dataset Complete/Train/Septoria',
 '/content/drive/MyDrive/Wheat Training Dataset Complete/Train/Nitrogen Deficient']
```

Figure4-5 [Providing Paths]

```
[ ] len(folders)

7

[ ] folder=glob("//content/drive/MyDrive/Wheat Training Dataset Complete/Test/*")
folder

['//content/drive/MyDrive/Wheat Training Dataset Complete/Test/Stripe Rust',
 '//content/drive/MyDrive/Wheat Training Dataset Complete/Test/Yellow Rust',
 '//content/drive/MyDrive/Wheat Training Dataset Complete/Test/Wheat Leaf Rust',
 '//content/drive/MyDrive/Wheat Training Dataset Complete/Test/Brown Rust',
 '//content/drive/MyDrive/Wheat Training Dataset Complete/Test/Nitrogen Deficient',
 '//content/drive/MyDrive/Wheat Training Dataset Complete/Test/Septoria',
 '//content/drive/MyDrive/Wheat Training Dataset Complete/Test/Healthy']
```

Figure 4-6 [Checking Directory]

```
[ ] vgg19=VGG19(input_shape=IMAGE_SIZE+[3],weights='imagenet',include_top=False)
Download data from https://storage.googleapis.com/tensorflow/keras-applications/vgg19/vgg19\_weights\_tf\_dim\_ordering\_tf\_kernels\_notop.h5
80134624/80134624 [=====] - 4s 0us/step

[ ] for layer in vgg19.layers:
    layer.trainable=False

[ ]
# our layers - you can add more if you want
x = Flatten()(vgg19.output)
```

Figure4-7 [Downloading the model]

```
[ ] prediction = Dense(len(folders), activation='softmax')(x)

# create a model object
model = Model(inputs=vgg19.input, outputs=prediction)
```

Figure 4-8 [Creating the model]

```
[ ] model.summary()

Model: "model"
-----
Layer (type)                Output Shape                Param #
-----
input_1 (InputLayer)        [(None, 224, 224, 3)]      0
block1_conv1 (Conv2D)        (None, 224, 224, 64)       1792
block1_conv2 (Conv2D)        (None, 224, 224, 64)       36928
block1_pool (MaxPooling2D)   (None, 112, 112, 64)       0
block2_conv1 (Conv2D)        (None, 112, 112, 128)      73856
block2_conv2 (Conv2D)        (None, 112, 112, 128)      147584
block2_pool (MaxPooling2D)   (None, 56, 56, 128)        0
block3_conv1 (Conv2D)        (None, 56, 56, 256)        295168
block3_conv2 (Conv2D)        (None, 56, 56, 256)        590080
block3_conv3 (Conv2D)        (None, 56, 56, 256)        590080
block3_conv4 (Conv2D)        (None, 56, 56, 256)        590080
```

Figure 4-9 [Layers of model]


```
[ ] block4_conv1 (Conv2D)      (None, 28, 28, 512)      1180160
    block4_conv2 (Conv2D)      (None, 28, 28, 512)      2359808
    block4_conv3 (Conv2D)      (None, 28, 28, 512)      2359808
    block4_conv4 (Conv2D)      (None, 28, 28, 512)      2359808
    block4_pool (MaxPooling2D) (None, 14, 14, 512)      0
    block5_conv1 (Conv2D)      (None, 14, 14, 512)      2359808
    block5_conv2 (Conv2D)      (None, 14, 14, 512)      2359808
    block5_conv3 (Conv2D)      (None, 14, 14, 512)      2359808
    block5_conv4 (Conv2D)      (None, 14, 14, 512)      2359808
    block5_pool (MaxPooling2D) (None, 7, 7, 512)       0
    flatten (Flatten)          (None, 25088)            0
    dense (Dense)              (None, 7)                175623

=====
Total params: 20,200,007
Trainable params: 175,623
Non-trainable params: 20,024,384
```

Figure 4-10 [Showing the layers when we train the model]

4.3 Compiling and Training the Model

After creating our model, we need to compile it with the appropriate loss function, optimizer, and evaluation metric. We will be using the categorical cross-entropy loss function, the Adam optimizer, and the accuracy metric.

```
[ ] optimizer=RMSprop(0.001)
    model.compile(loss='categorical_crossentropy',optimizer=optimizer,metrics=['accuracy'])
```

Figure4-11 [The optimizer and loss function being used]

4.4 Data Augmentation

In order to improve the performance and generalization of our model, data augmentation techniques are often employed. Data augmentation is the process of generating new training data by applying various random transformations to the existing training data, such as rotating, flipping, or shearing the images. To implement data augmentation in our model training process, we have used the ImageDataGenerator class from the tensorflow.keras.preprocessing.image module.

The `test_datagen` object is created using `ImageDataGenerator` with `rescale=1./255` parameter to rescale the pixel values of the images to a range of 0 to 1. This object is used for the test set. The `train_datagen` object is created with various parameters including `shear_range`, `zoom_range`, `rotation_range`, and `horizontal_flip` to apply different random transformations to the images in the training set. The `rescale` parameter is also set to normalize the pixel values of the images. Next, we use the `flow_from_directory` method of the `ImageDataGenerator` class to generate batches of augmented image data for training and testing. We pass the path of our training and testing datasets, target image size and batch size as parameters to this method. We also set `class_mode='categorical'` to indicate that our dataset has multiple classes.

By using data augmentation, we can generate a large number of diverse training samples from a relatively small number of original images. This can help in reducing overfitting and improving the performance of our model on new, unseen images.

```
#Data augmentation
test_datagen=ImageDataGenerator(rescale=1./255)
train_datagen=ImageDataGenerator(rescale=1./255,
                                shear_range=0.2,
                                zoom_range=0.2,
                                rotation_range=40,
                                horizontal_flip=True)

training_set=train_datagen.flow_from_directory(
    "/content/drive/MyDrive/Wheat Training Dataset Complete/Train",
    class_mode="categorical",
    target_size=IMAGE_SIZE,
    batch_size=32
)

test_set=test_datagen.flow_from_directory(
    "/content/drive/MyDrive/Wheat Training Dataset Complete/Test",
    class_mode='categorical',
    target_size=IMAGE_SIZE,
    batch_size=32
)

Found 4160 images belonging to 7 classes.
Found 992 images belonging to 7 classes.
```

Figure-12 [Checking the data]

The code below is using the `EarlyStopping` callback from Keras to stop the training process of our model when it starts to overfit or does not improve anymore. We set the `patience` parameter to 20, which means that the training will stop if there is no improvement for 20 epochs. The `restore_best_weights` parameter is set to `True`, which means that the weights of the best epoch will be restored when the training process is stopped. This will ensure that we get the best possible model with the highest validation accuracy. We then use the `fit_generator` method to train our model using the augmented training data and validate it using the testing data. We set the number of epochs to 20, `steps_per_epoch` to the length of the training set and `validation_steps` to the length of the test set. Finally, we pass the `EarlyStopping` callback to the

callbacks parameter to use it during the training process. The 'r' variable stores the history of the training process, which we can use to plot the training and validation accuracy and loss over the epochs to visualize the performance of our model.

```
es = EarlyStopping(patience=20, restore_best_weights=True)

r = model.fit_generator(
    training_set,
    validation_data=test_set,
    epochs=20,
    steps_per_epoch=len(training_set),
    validation_steps=len(test_set),
    callbacks=es
```

Figure 4-13 [compiling model]

```
Epoch 6/20
130/130 [=====] - 297s 2s/step - loss: 0.4634 - accuracy: 0.8678 - val_loss: 0.4889 - val_accuracy: 0.8538
Epoch 7/20
130/130 [=====] - 291s 2s/step - loss: 0.4521 - accuracy: 0.8745 - val_loss: 0.4458 - val_accuracy: 0.8931
Epoch 8/20
130/130 [=====] - 293s 2s/step - loss: 0.4158 - accuracy: 0.8822 - val_loss: 0.5961 - val_accuracy: 0.8528
Epoch 9/20
130/130 [=====] - 294s 2s/step - loss: 0.4070 - accuracy: 0.8873 - val_loss: 0.9694 - val_accuracy: 0.7923
Epoch 10/20
130/130 [=====] - 290s 2s/step - loss: 0.3569 - accuracy: 0.8988 - val_loss: 1.3098 - val_accuracy: 0.7490
Epoch 11/20
130/130 [=====] - 288s 2s/step - loss: 0.3700 - accuracy: 0.8950 - val_loss: 0.4996 - val_accuracy: 0.8790
Epoch 12/20
130/130 [=====] - 294s 2s/step - loss: 0.3346 - accuracy: 0.9079 - val_loss: 0.6426 - val_accuracy: 0.8296
Epoch 13/20
130/130 [=====] - 295s 2s/step - loss: 0.3481 - accuracy: 0.9058 - val_loss: 0.4832 - val_accuracy: 0.8800
Epoch 14/20
130/130 [=====] - 297s 2s/step - loss: 0.3199 - accuracy: 0.9062 - val_loss: 0.5227 - val_accuracy: 0.8810
Epoch 15/20
130/130 [=====] - 301s 2s/step - loss: 0.3602 - accuracy: 0.9055 - val_loss: 0.5711 - val_accuracy: 0.8770
Epoch 16/20
130/130 [=====] - 298s 2s/step - loss: 0.2754 - accuracy: 0.9171 - val_loss: 0.4926 - val_accuracy: 0.8800
Epoch 17/20
130/130 [=====] - 301s 2s/step - loss: 0.3086 - accuracy: 0.9163 - val_loss: 0.6406 - val_accuracy: 0.8569
Epoch 18/20
130/130 [=====] - 296s 2s/step - loss: 0.2876 - accuracy: 0.9233 - val_loss: 0.4084 - val_accuracy: 0.8992
Epoch 19/20
130/130 [=====] - 304s 2s/step - loss: 0.2895 - accuracy: 0.9212 - val_loss: 0.4580 - val_accuracy: 0.9042
Epoch 20/20
130/130 [=====] - 304s 2s/step - loss: 0.2903 - accuracy: 0.9219 - val_loss: 0.3865 - val_accuracy: 0.9032
```

Figure 4-14 [Epochs]

```
valid_loss, valid_acc = model.evaluate_generator(test_set, steps=len(test_set))
print(f"Final validation accuracy: {valid_acc*100:.2f}%")

<ipython-input-15-efb5effc6a0e>:1: UserWarning: `Model.evaluate_generator` is deprecated and will be removed in a future version.
valid_loss, valid_acc = model.evaluate_generator(test_set, steps=len(test_set))
Final validation accuracy: 90.32%
```

Figure 4-15 [Showing the final validation accuracy after model training completion]

4.5 Training and Accuracy

When training a machine learning model, it is important to analyze its performance over time. To do so, we can plot the training and validation loss and accuracy to identify any potential overfitting or underfitting issues. The first plot generated using the code above displays the training and validation loss of our model over the specified number of epochs. The plot shows the trend of decreasing loss over time for both training and validation sets. The plot can help in identifying if the model is overfitting or underfitting the training data. If the validation loss starts to increase while the training loss keeps decreasing, it could indicate overfitting.

On the other hand, if both the training and validation loss are high, it could indicate underfitting. The second plot displays the training and validation accuracy of our model over the specified number of epochs. The plot shows an increase in accuracy over time for both training and validation sets. This plot can help in identifying if the model is accurately classifying the data or if it is simply memorizing the training data. Overfitting can also be detected by this plot if the validation accuracy starts to plateau or decrease while the training accuracy keeps increasing.

By analyzing the loss and accuracy plots, we can make decisions on fine-tuning the model hyperparameters, adjusting the dataset, or adding more data. These plots serve as a valuable tool to evaluate the performance of our machine learning model.

```
# plot the loss
plt.plot(r.history['loss'], label='train loss')
plt.plot(r.history['val_loss'], label='val loss')
plt.legend()
plt.show()
plt.savefig('LossVal_loss')

# plot the accuracy
plt.plot(r.history['accuracy'], label='train acc')
plt.plot(r.history['val_accuracy'], label='val acc')
plt.legend()
plt.show()
plt.savefig('Acc-Val_acc')
```

Figure 4-16 [Plotting results]

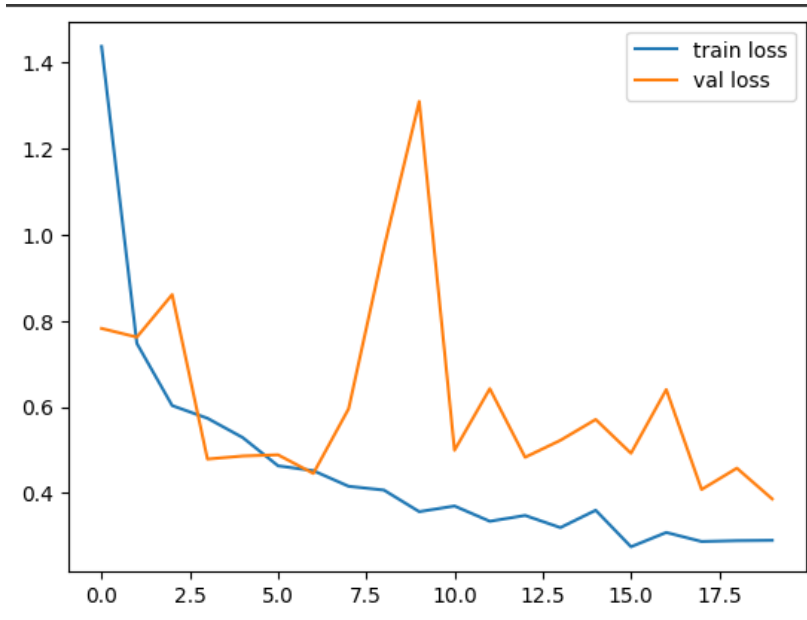


Figure4-17[Comparison of train and validation loss]
x-axis=Number of epochs y-axis=Loss on epoch

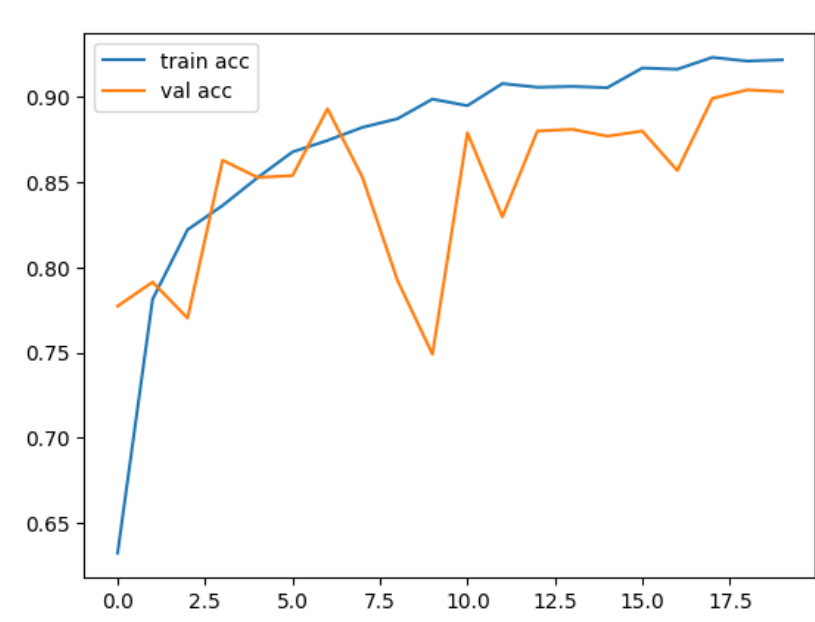


Figure4-18 [Comparison of train and validation accuracy]
x-axis=Number of epochs y-axis=Loss on epoch

4.6 Saving the Tensorflow lite model for application

After training the model, the next step is to save and optimize it for inference. In this code block, we save the model using TensorFlow's `saved_model` function and specify the export directory. Next, we optimize the model for either size or speed by setting the optimization variable. If mode is set to "Storage," we optimize the model for size. If it is set to "Speed," we optimize the model for latency. Otherwise, we use the default optimization.

We then convert the saved model into a TensorFlow Lite model using `TFLiteConverter` from the TensorFlow Lite library. We set the optimizations to the optimization variable specified earlier. Finally, we save the converted model as a `.tflite` file. We also define a list of class names for the different categories of wheat leaf diseases detected by our model.

We save this list in a text file called "Final_Disease_Detector_labels.txt". Lastly, we use the `ls` command to list the files in the current directory, which should include the saved TensorFlow Lite model file and the labels file.

```
[ ] loss, accuracy = model.evaluate(test_set)

31/31 [=====] - 46s 1s/step - loss: 0.3865 - accuracy: 0.9032

[ ] #save the tflite model
export_dir = 'Complete_Trained2020/saved_model/'
tf.saved_model.save(model, export_dir)

WARNING:absl:Found untraced functions such as _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_co

[ ] #optimize the model for inference
mode = "Storage"

if mode == 'Storage':
    optimization = tf.lite.Optimize.OPTIMIZE_FOR_SIZE
elif mode == 'Speed':
    optimization = tf.lite.Optimize.OPTIMIZE_FOR_LATENCY
else:
    optimization = tf.lite.Optimize.DEFAULT

optimization

<Optimize.OPTIMIZE_FOR_SIZE: 'OPTIMIZE_FOR_SIZE'>
```

Figure 4-19 [Optimizing model]

```
[ ] #convert the model
converter = tf.lite.TFLiteConverter.from_saved_model(export_dir)
converter.optimizations = [optimization]
tflite_model = converter.convert()

WARNING:absl:Optimization option OPTIMIZE_FOR_SIZE is deprecated, please use optimizations=[Optimize.DEFAULT] instead.
WARNING:absl:Optimization option OPTIMIZE_FOR_SIZE is deprecated, please use optimizations=[Optimize.DEFAULT] instead.
WARNING:absl:Optimization option OPTIMIZE_FOR_SIZE is deprecated, please use optimizations=[Optimize.DEFAULT] instead.

▶ #Save the converted model tflite file
tflite_model_file = 'Final_Disease_Detector.tflite'

with open(tflite_model_file, 'wb') as f:
    f.write(tflite_model)

▶ CLASS_NAMES = ['Stripe Rust',
'Yellow Rust',
'Wheat Leaf Rust',
'Test/Brown Rust',
'Nitrogen Deficient',
'Septoria',
'Healthy']
```

Figure 4-20 [Creating tflite]

```
[ ] with open('Final_Disease_Detector_labels.txt', 'w') as f:
    f.write('\n'.join(CLASS_NAMES))

!ls

Acc-Val_acc.png      Final_Disease_Detector_labels.txt  sample_data
Complete_Trained2020 Final_Disease_Detector.tflite
drive                LossVal_loss.png
```

Figure 4-21 [Checking files]

Chapter5: Operation Of The Project

5.1 Operating environment

Hardware Requirements:

- **Camera:**A camera is essential to use the Agrona app. The device must have a front or back-facing camera with a minimum resolution of 720p. The camera's quality is crucial to enable high-quality image acquisition, which is necessary for the accurate detection of diseases in crops.
- **Internet Connection:**To upload captured images and data to the cloud, a stable internet connection is required. It is recommended to use a 4G or Wi-Fi connection for faster and more reliable data transfer. With a stable internet connection, users can upload data in real-time and access their data from anywhere.
- **Storage Capacity:**Sufficient storage capacity is crucial to store the Agrona app and all captured images and data. Users should ensure that their device has enough storage space before using the app to prevent issues related to insufficient storage.
- **RAM:**To ensure that the Agrona app runs smoothly and without any lags or crashes, the device should have at least 2GB of RAM. This is important to ensure that the app can handle large amounts of data and run efficiently.

Software Requirements:

1. Flutter framework
2. GoogleColab
3. Python programming language
4. iAndroid Studio
5. TensorFlow and OpenCV libraries
6. Firebase cloud infrastructure

5.2 Design and Implementation Constraints

- **Hardware Limitations:**The app must be designed to work on a variety of devices with different hardware capabilities. This includes devices with varying screen sizes, resolutions, and processing power.
- **Internet Connection:**Agrona app requires a stable internet connection to upload images and data to the cloud. This can be a limitation in areas with poor network coverage or slow internet speed.
- **Image Processing:**The Agrona app heavily relies on image processing algorithms to detect diseases accurately. Therefore, the app needs to be optimized to handle image processing efficiently while maintaining accuracy.

- **User Experience:**The app should be designed to provide a user-friendly experience. The user interface should be easy to use and navigate, and the app should provide clear and concise instructions.
- **Time Constraints:**The Agrona app is designed to be completed within a specific timeframe. Therefore, the development team must work within this constraint to ensure the app is delivered on time.
- **Compatibility:**The Agrona app must be compatible with different operating systems such as Android and iOS. The app should be designed to work seamlessly on different devices regardless of the operating system they are running on.

These constraints must be taken into consideration during the design and implementation of the Agrona app to ensure that it meets the needs of its users and performs effectively.

5.3 User Documentation

The users of Agrona app will receive a comprehensive user manual that includes specific instructions tailored to their roles, such as regular user, admin, developer, or tester. The manual will provide details about the system's functionalities and how to use them effectively. In addition to the user manual, the app will have help documents available to provide further assistance. Furthermore, a detailed project report will also be available for users, which will highlight the system's features, working, and procedures. The report will provide users with a better understanding of the app's development and how it functions.

5.4 Assumptions and Dependencies

1. To use the Agrona app effectively, users are expected to have basic knowledge of operating a smartphone and using mobile applications.
2. The app is designed to function with a stable internet connection for uploading images and data to the cloud.
3. The device's camera is a critical component of the app, as it is used for image acquisition, and sufficient storage capacity is needed to store captured images and data.
4. While the Agrona app's disease detection is highly accurate, various factors such as lighting conditions, camera quality, and image resolution may affect its accuracy.
5. Additionally, the app relies on third-party tools and technologies like Google Colab, Flutter, Android Studio, and Python, which may impact the app's performance and compatibility.
6. The Agrona app is also dependent on the availability and accessibility of the Firebase database and its APIs.
7. To ensure that the app is used ethically and legally, users are expected to use it exclusively for agricultural purposes and not engage in any illegal or unethical activities.

5.5 System Features:

The features of the Agrona system are organized based on use cases and functional hierarchy, making it easy for users to understand the main functions of the system. The description of these features is presented through various system interfaces, providing comprehensive information to users. These interfaces serve as a reference point, allowing users to navigate the system with ease and efficiency. By providing a clear and organized system, users can utilize the features of Agrona without any confusion or difficulty.

5.5.1 Image Acquisition:

This feature allows the system to acquire images for the disease detection.

5.5.1.1 Description:

The Image and Sensor Reading Acquisition module is the foundation of the Agrona application, initiating the major functionalities of the system. This module acquires a frame from the image, enhances its quality, and passes it to the disease identification module for analysis. The accuracy and reliability of the data collected by this module are crucial for the successful functioning of the Agrona app.

5.5.1.2 Stimulus/Response Sequences

Data flowBasic Data Flow:

1. When the user opens the Agrona App on their device, they are prompted to select the desired function, such as disease detection or farm monitoring.
2. The app then accesses the device's camera and/or sensors to capture images and data which are processed by the app's algorithms to identify any disease or monitor the farm.
3. The results are displayed to the user through the app's user interface, and the captured images and data are uploaded to the cloud for storage and analysis.
4. The app may also send alerts or notifications to the user regarding any identified diseases or farm monitoring.

Alternate Data Flow 1 (Failure to Access Camera):

1. In case the app is unable to access the device's camera or sensors, the user is prompted to check their device's settings and ensure that the camera and/or sensors are enabled.
2. If the issue persists, the app may suggest alternative options or provide contact details for technical support.

Alternate Data Flow 2 (Failure to Upload Data to Cloud):

1. In case the app captures images and data but is unable to upload them to the cloud for storage and analysis, the user is prompted to check their device's internet connection and ensure that it is stable.
2. If the issue persists, the app may suggest alternative options or provide contact details for technical support.

5.5.1.3 Functional Requirements

1. The app should be able to capture images and data from the device's camera for disease identification and monitoring.
2. The app should be able to process the captured images and data using algorithms to accurately identify any diseases or monitor.

5.5.2 Disease Detection

The Agrona app will analyze the captured images to detect any signs of diseases present in the crops.

5.5.2.1 Description

The Disease Identification module is responsible for analyzing the acquired images and detecting any diseases present in the crops. It utilizes advanced algorithms and techniques to process the images and identify any abnormalities or patterns indicative of a disease. The module plays a crucial role in helping farmers identify potential threats to their crops early on, allowing them to take preventive measures and minimize damage. The results of the analysis are then displayed to the user through the app's user interface, providing them with valuable insights into the health of their crops.

5.5.2.2 Stimulus/Response Sequences

Basic Data Flow:

1. When the disease identification module is triggered, it receives an image from the image acquisition module.
2. The image is preprocessed to enhance its quality.
3. The preprocessed image is then passed through the disease identification algorithm.
4. The algorithm analyzes the image to identify any signs of disease and returns the results to the app.
5. The app then displays the results to the user through the app's user interface.

Alternate Data Flow (Error Handling):

1. When the disease identification module is triggered, it receives an image from the image acquisition module.
2. The image is preprocessed to enhance its quality.
3. The preprocessed image is then passed through the disease identification algorithm.
4. If the algorithm fails to identify any disease or encounters an error, the app prompts the user to take another image or perform additional actions to improve the image quality.
5. If the issue still persists, the app may provide alternative options or suggest contacting technical support for further assistance.

5.5.2.3 Functional Requirements:

1. **Accuracy:**The module must accurately identify the diseases present in the captured image with a high level of accuracy. The accuracy level should be defined and tested.
2. **Speed:**The module should be able to process the images quickly to provide the results to the user in a timely manner. The speed requirement should be defined based on the size of images and processing complexity.
3. **Flexibility:**The module should be able to identify a wide range of diseases and be flexible enough to adapt to new diseases as they emerge. The module should be designed to incorporate new disease identification algorithms and techniques as they become available.
4. **User-friendly interface:**The module should have a user-friendly interface that makes it easy for the user to capture and upload images, view results, and take any necessary actions. The interface should be intuitive and easy to use, even for users with little technical knowledge.
5. **Reliability:**The module should be reliable and not prone to errors or crashes that could result in incorrect or delayed diagnoses. The module should be tested extensively to ensure its reliability.
6. **Compatibility:**The module should be compatible with different types of devices, operating systems, and internet connections to ensure that it can be used by a wide range of users. The module should be designed to work on various platforms and devices with different specifications.

5.5.3 Notifications

This functionality enables the display of notifications on the Android application.

5.5.3.1 Description

Once a disease is detected by the Agrona app, a notification will appear on the user's Android device to alert them of the identified disease.

5.5.3.2 Stimulus/Response Sequences

Stimulus:The disease identification module detects the presence of a disease in the image.

Response:The app sends a notification to the user's device to alert them about the identified disease.

Data Flow Basic Data Flow:

1. The disease identification module detects a disease in the captured image.
2. The app generates a notification to inform the user about the detected disease.
3. The user views the notification and takes appropriate actions based on the results.

Alternate Data Flow (Error Handling):

1. The disease identification module detects a disease in the captured image.
2. The app attempts to send a notification to the user's device to alert them about the detected disease.
3. If the notification fails to send, the app displays an error message to inform the user about the failure.
4. The app may try to resend the notification or suggest alternative methods to notify the user.
5. If the issue persists, the app may suggest contacting technical support for further assistance.

5.5.3.3 Functional Requirements:

1. **Accuracy:**The notification feature must accurately detect and send notifications for any diseases identified by the disease identification module to ensure that users receive reliable and relevant information.
2. **Timeliness:**The notification feature must send notifications in a timely manner as soon as the disease is detected, to ensure that users are informed promptly.
3. **Customization:**The notification feature should provide users with options to customize the notifications they receive, such as the frequency and type of notifications, to ensure that users receive relevant information that suits their preferences.
4. **Compatibility:** The notification feature should be compatible with a wide range of devices and operating systems to ensure that it can be used by a large number of users.
5. **User-friendliness:**The notification feature should be user-friendly, easy to understand, and easy to manage for the user, so that users can easily receive, view, and manage their notifications.

6. **Reliability:**The notification feature should be reliable and free from errors or failures that could result in delayed or missed notifications.
7. **Privacy:**The notification feature should protect the user's privacy by only sending notifications to the user's device and not sharing any personal or health-related data with third parties.

5.5.4 Login

The login feature enables farmers to access the Android or web application by providing their login credentials.

5.5.4.1 Description

The login module is a crucial component of the app, which allows farmers to securely access the application by entering their login credentials. It provides a secure and personalized experience for the user by authenticating the user's identity and granting access to their data and preferences. The module ensures that only authorized users can access the application, preventing any unauthorized access to sensitive information. The login module should be designed with user-friendliness in mind, allowing users to easily enter their credentials and access the app's features. It should also have robust security features in place to prevent any data breaches or unauthorized access to user accounts. Overall, the login module plays a critical role in ensuring the security and usability of the application, making it an essential component of the app.

5.5.4.2 Stimulus/Response Sequence:

When a user launches the application and selects the login button, the login module responds by prompting the user to input their login credentials.

Basic Data Flow:

1. The user launches the application and selects the login button.
2. The login module prompts the user to enter their login credentials.
3. The user enters their valid login credentials (username and password).
4. The login module validates the credentials and grants the user access to the application.
5. The user can now access the application and its features.

Alternate Data Flow (Error Handling):

1. The user launches the application and selects the login button.
2. The login module prompts the user to enter their login credentials.
3. If the user enters incorrect login credentials, the login module displays an error message and prompts the user to input valid credentials.
4. If the user forgets their password, the login module provides a password reset option.

5. If the login module encounters any error, it displays an error message and suggests the user to retry later or contact technical support.

5.5.4.3 Functional Requirements

Security:The login module must implement secure authentication methods to ensure the protection of user data. These methods include encryption, password hashing, and two-factor authentication. The module must also have a mechanism for detecting and preventing brute-force attacks and other security threats.

Accessibility:The login module must be accessible to all users, including those with disabilities or limited technical knowledge. The module should have clear and concise instructions, a user-friendly interface, and support for assistive technologies such as screen readers or voice commands. The module should also be optimized for different devices and screen sizes to enhance usability.

5.6 External Interface Requirements

5.6.1 User Interface:

The application should provide users with responsive graphical user interfaces (GUI) that enable them to easily navigate and use the various features available. In order to provide a user-friendly experience, the GUI should be designed with the user's needs and preferences in mind. Below are some sample screenshots of the GUI that can be used as a reference for the development team to ensure consistency in the design and layout:

1.Login Screen



Figure 5- 1 Login Screen of android

2. Readings Display

The temperature and humidity readings display is a crucial feature offered by Agrona app. It allows farmers to keep a close eye on the temperature and humidity levels in their farms in real-time. By providing this valuable information, the feature helps farmers create optimal growing conditions for their crops and avoid any potential damage that can occur due to extreme temperature or humidity fluctuations. The app presents the readings in a user-friendly and easy-to-understand format, which allows farmers to conveniently access both the current and historical temperature and humidity data. The feature also offers alerts and notifications to farmers in case of any significant changes in temperature or humidity levels, helping them take timely actions. Designed to cater to farmers of all technical backgrounds, this feature is highly

accessible and user-friendly. With the temperature and humidity readings display, farmers can make informed decisions regarding their farming practices and achieve the best possible yields for their crops.



Figure 5- 2 Readings Display on Android

3. Images Display

The Agrona app's images display feature enables farmers to visually monitor their crops by uploading images of their farms and crops. The feature is user-friendly and allows for easy organization and sharing of images. This helps farmers identify potential crop issues, optimize their yields, and seek advice from agricultural experts.

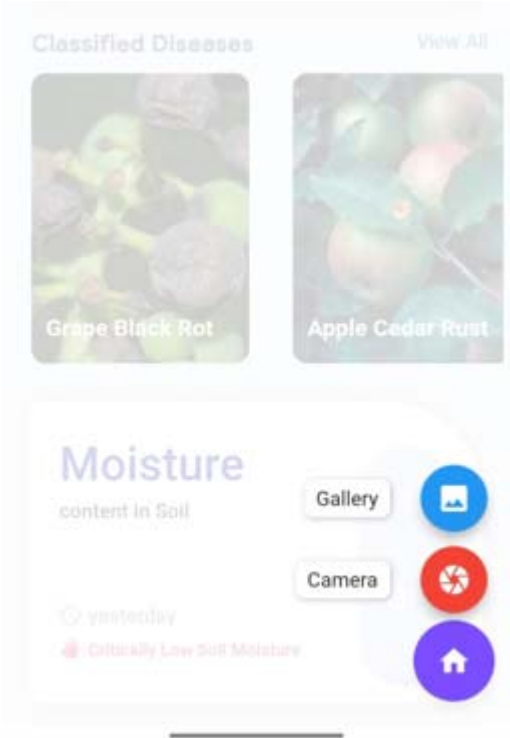


Figure 5- 3 Images Display

5.6.2 Hardware Interfaces

1. **Mobile devices:** The app should be compatible with a wide range of mobile devices, including smartphones and tablets.

5.6.3 Software Interfaces

1. **Operating System:** Agrona app should be compatible with various operating systems such as Android and iOS.
2. **Cloud Services:** The app should be able to interface with cloud services to store and retrieve data such as crop information and sensor readings.
3. **Third-Party APIs:** The app should be able to interface with third-party APIs for services such as weather forecasts or pest control information.
4. **Database Management System:** The app should be able to interface with a database management system to store and retrieve data such as user profiles and crop information.

5.6.4 Communication Interface

Firebase will be used for communication between android application and users.

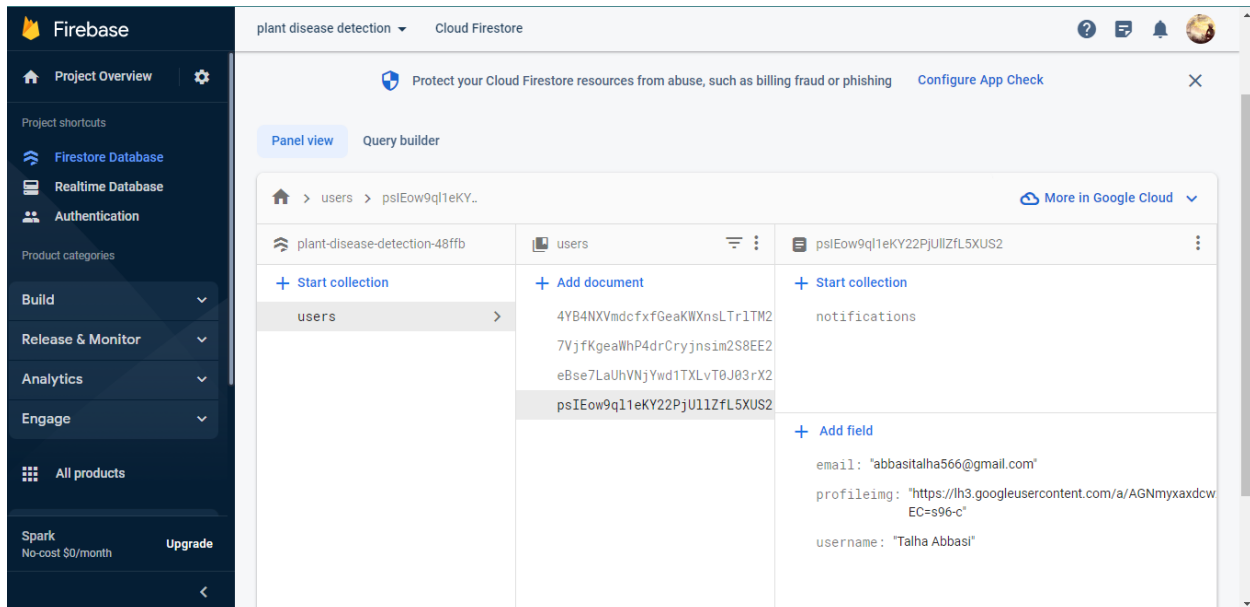


Figure 5- 4 Firebase Interface

5.7 Other Nonfunctional Requirements

5.7.1 Performance Requirements:

The Agrona app should operate efficiently and responsively, with fast response times and the ability to handle a high volume of users.

Reliability: The app should be available at all times, with measures in place to prevent and recover from system failures or data loss.

Scalability: The Agrona app should be designed to accommodate a growing number of users and data without sacrificing performance or functionality.

Security: The app should include robust security measures to safeguard user data from unauthorized access or theft, such as encryption and access control.

Usability: The Agrona app should have an intuitive and user-friendly interface, with clear instructions and features accessible to users of all technical backgrounds.

Compatibility: The app should be compatible with various devices and operating systems, including older or less common devices and newer technologies.

Maintainability: The app should be designed with maintainability in mind, featuring modular and scalable code and providing documentation and support for developers.

Chapter 6: Design and Development.

6.1 Introduction

The design and development chapter is a critical component of the Agrona app development process. This chapter focuses on the design and development of the Agrona app, including its user interface, features, and functionality. The goal of this chapter is to provide a comprehensive overview of the design and development process, highlighting the key considerations and decisions made throughout the process.

6.1.1 Purpose

The design and development chapter of the Agrona app outlines the software architecture and system design for the project. It provides a detailed description of the app's features and requirements, serving as a guide for developers and a validation document for potential clients. The chapter covers the inter-relationships between different classes, use cases with comprehensive descriptions, and various flow charts and sequence diagrams.

6.1.2 Project Scope

The Agrona app aims to assist farmers in detecting diseases in their crops through a four-module system. The first module captures images of the crops and collects sensor data. The second module focuses on preprocessing the images. The third module is responsible for detecting crop diseases. Finally, the fourth module sends the results to the farmer through an Android application.

6.2 Overview of Document

The purpose of this document is to provide a detailed architectural design for the Agrona app. To ensure clarity, the document is divided into various sections. Section 1 offers an executive overview of the document. Section 2 provides a detailed description of the system and includes various diagrams and charts that detail the system's architecture. Section 3 describes each of the app's modules and components in detail. Section 4 compares this product to other similar products available in the market. Section 5 discusses design decisions and tradeoffs. The final section provides pseudo-code for all the components. This document is intended for developers, testers, users, documentation writers, project clients, project supervisors, and project evaluators. All stakeholders will have access to a copy of this document.

6.3 System Architecture Description

In this section, we will delve into the intricate details of the system architecture of Agrona. It will include a comprehensive overview of the system modules, their structures, and relationships. Moreover, we will also discuss the user interfaces and other related issues to provide a thorough understanding of the system's design and development.

6.3.1 Overview of Modules

AGRONA app consists of five essential modules that play a crucial role in the app's functionality. Below is a brief overview of each module:

1. **Image Acquisition** The Image Acquisition module is the starting point of the application, responsible for capturing a frame from the camera and providing it to the Preprocessing module.
2. **Preprocessing Module** The Preprocessing module enhances the quality of the image by removing irrelevant background areas from the captured frame, making it easier for the Disease Identification module to detect the disease.
3. **Disease Identification Module** The Disease Identification module detects the disease from the captured image and identifies the regions of interest on the leaves based on their colored patterns.
4. **Notification Module** Once the disease is detected, the Notification module sends a notification to the server, along with the sensors' readings. The server, in turn, notifies the Android and web application about the detected disease.
5. **Database Module** The Database module stores the notification details, including the image of the diseased leaf and its readings, in the cloud database to maintain records.

6.4 Structure and Relationships

The Agrona app has modules for image acquisition, preprocessing, disease identification, notification, and database. These modules work together to detect crop diseases and maintain a record of notifications and readings.

6.4.1 System Block Diagram

This diagram provides an overview of the application's various modules, their relationships, and the flow of data between them.

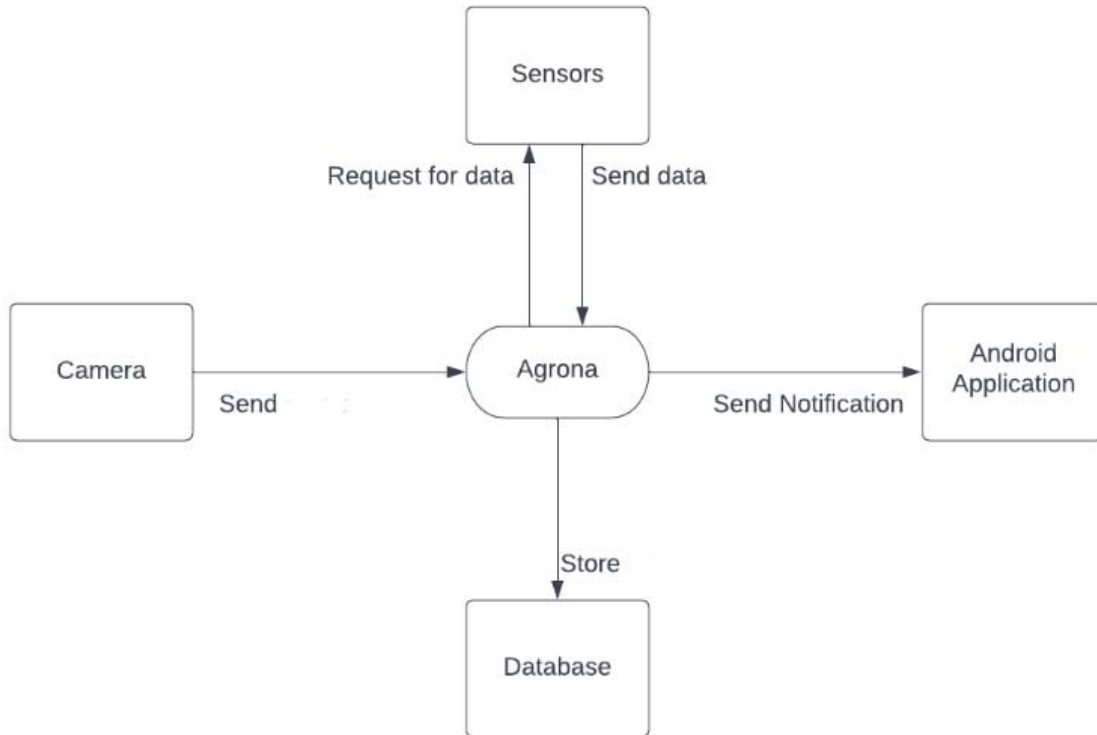


Figure 6-1 System Block Diagram

The Agrona app works by utilizing a series of modules to detect disease in crops. The first module acquires an image using a camera and other sensors, which is then processed in the second module to enhance its quality and remove irrelevant areas. The third module identifies the disease in the crop based on colored patterns on leaves, while the fourth module sends a notification to the server along with sensor readings once a disease is detected. The server then notifies the Android about the detected disease. The fifth module saves the notification image and readings to the cloud database to maintain a record. This system block diagram shows the overall structure and relationship between the different modules in the Agrona app.

6.4.2 User View (Use case diagram)

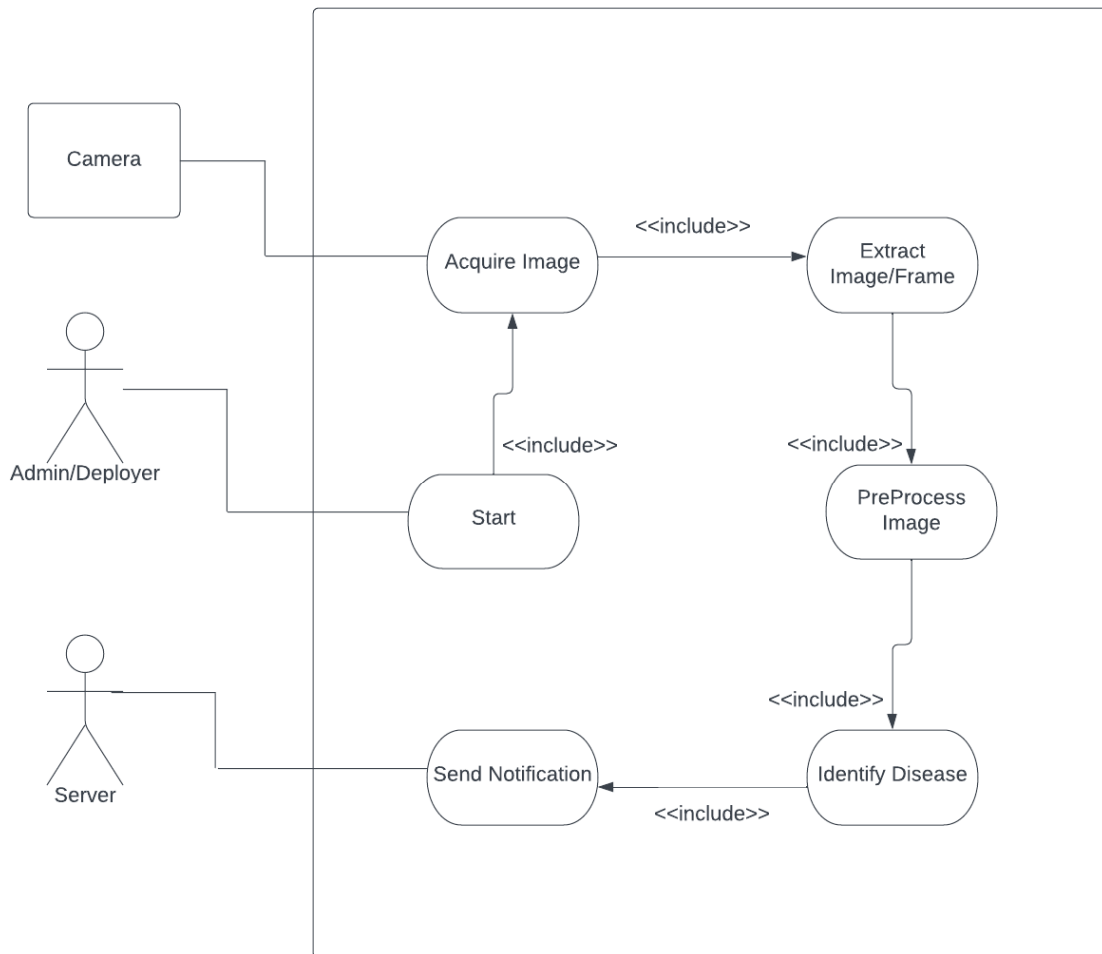


Figure 6-2 Use Case Diagram

The Agrona app is designed to assist farmers in detecting diseases on their crops. The app can be launched by the user on their mobile device. Before starting the disease detection process, it is necessary for the user to ensure that the Agrona app is properly installed and configured on their device. Once these pre-conditions are met, the user can start the app to initiate the disease detection process. When the user opens the Agrona app, the main interface is displayed on the device screen. The user can select the option to begin the disease detection process from this interface. The Agrona app then accesses the device camera and starts capturing images of the crops. These images are analyzed by the app to detect any signs of diseases on the regions of interest. If a disease is detected, the Agrona app sends a notification to the user. The user is then able to view the results of the disease detection process on their device screen. The results may include information about the type of disease detected and the severity of the infection. Based on

the results displayed, the user may choose to take further action, such as applying pesticides or other treatments to the affected areas. In summary, the Agrona app is a useful tool for farmers to detect diseases on their crops. By properly installing and configuring the app, farmers can easily access the disease detection process on their mobile devices. The app captures images of the crops, analyzes them for signs of diseases, and provides users with detailed information about any detected infections. With this information, farmers can take appropriate action to protect their crops and maximize their yields.

Use Case 2 (Extract Images)

Use Case 2, titled "Extract Images", outlines the process of selecting the best for disease detection purposes. This use case is initiated by the primary actor, who is the user. The secondary actor in this use case is not applicable. To begin the process, the user triggers the frame extraction function within the application. Once the function is triggered, the application divides the video stream into individual frames. Each of these frames is then analyzed for image quality. The purpose of this analysis is to determine which frame is the best for disease detection. Once the best frame has been identified, it is selected for further processing and forwarded to the next module. In an alternate flow, the application may encounter a frame with poor image quality. In such cases, the application skips the current frame and moves on to the next one. If the application is unable to find a good quality image, the process is aborted and a message is displayed to the user. There are no exception flows for this use case. In the end, the post-condition of this use case is that the best image for disease detection has been successfully extracted. This image can then be used in further disease detection and classification processes.

Use Case 3 (Preprocess)

The "Preprocess" use case is an important step in the overall disease detection process. It involves the application analyzing the acquired image to identify regions that are of interest, such as the wheat crop leaves that are likely to be infected by diseases. Once these regions of interest have been identified, the application removes any unnecessary areas from the image. This is done to reduce noise and improve the accuracy of the detection process. The image is then resized to a standard resolution, which allows for consistency in the images that are processed by the application. The preprocessing of the image is crucial as it ensures that the image is suitable for further analysis by the application, and ultimately improves the accuracy of the disease detection process.

Use Case 4 (Identify Disease)

This describes the process of identifying disease on a leaf using the Agrona app. The primary actor in this use case is the Agrona app, while there is no secondary actor involved. The precondition for this use case is that an image of the leaf has been acquired, and the postcondition is that the disease on the leaf is identified. The normal flow of the process includes

preprocessing the image to remove background noise and enhance its quality, analyzing the preprocessed image to detect the regions of interest or the disease on the leaf based on different patterns, highlighting the regions of interest, and displaying the result to the user. If the app fails to detect any disease, it displays a message to the user that the leaf is healthy. In case the image quality is poor, the app prompts the user to take another picture, and if there is an error in the image analysis, the app displays an error message and asks the user to try again. The assumptions made in this use case are that the camera is properly aligned, lighting conditions are adequate, and the Agrona app has access to the necessary processing power to analyze the image and detect disease.

Use Case 5 (Get Sensor Readings)

The "Sensor Readings" use case describes the process of obtaining temperature and humidity readings through a sensor connected to an application. The primary actor is the application, while there is no secondary actor involved. The pre-condition for this use case is that the sensors are properly configured to the device, and the post-condition is that the temperature and humidity readings are obtained. The normal flow of this use case involves the application requesting the temperature and humidity readings from the sensors. The sensors measure the temperature and humidity values, and then send the readings to the application. The application receives the readings and displays them to the user. There is no alternate course of action for this use case, and the exception flow occurs when the sensors are not properly configured or connected. If the sensors are not functioning properly, the readings obtained may not be accurate. However, the assumption is made that the sensors are capable of measuring temperature and humidity accurately.

Use Case 6 (Send Notification)

The "Notification" use case describes the process of sending a notification to the server after a disease has been identified. The primary actor in this use case is the Notification Module, while the secondary actor is the server. The precondition for this use case is that a disease has been identified, and the postcondition is that a notification has been sent to the server. In the normal course of action, the Notification Module retrieves the readings from the sensors and sends a notification to the server with the readings and an image of the diseased leaf. The server then receives the notification and stores it in the cloud database. In the alternate course, if the server is down or there is no internet connection, the notification cannot be sent. There are no exceptions in this use case. The assumption is that the Notification Module is properly configured to send notifications to the server.

The use case "Send Notification" involves the Notification Module as the primary actor and the App as the secondary actor. The pre-condition is that a disease is detected and there is an available internet connection. The post-condition is that a notification is successfully sent to the server. The normal flow includes the system detecting a disease, connecting to the server, and sending a notification to the user. An assumption is that the user has an internet connection. The

alternate flow is when the internet connection is unavailable, the system will retry sending the notification.

Table 6.1: Use Case 1 (User Login)

Use Case Name	User Login
Description	The user wants to access the application and must provide valid login credentials to do so.
Primary Actor	User
Secondary Actor	System
Precondition	The user must have a registered account in the system.
Postcondition	Upon successful login, the user is redirected to the main menu of the application.
Basic Flow	<ul style="list-style-type: none"> • The user opens the application on their device. The system presents the login screen. • The user enters their login credentials (username and password). • The system verifies the user's credentials. • If the credentials are valid, the user is logged in and redirected to the main menu. If the credentials are invalid, the system presents an error message and prompts the user to try again.
Alternative Flow	<ul style="list-style-type: none"> • The system detects that the user has entered an invalid username or password. • The system presents an error message and prompts the user to try again. • The system detects that the user's account has been temporarily locked due to multiple failed login attempts. • The system presents a message indicating that the account is locked and provides instructions for unlocking it.
Exceptions	<ul style="list-style-type: none"> • The user's device is not connected to the internet. The system presents an error message indicating that an internet connection is required to log in. • The user has forgotten their password. The system provides a "forgot password" link, which redirects the user to a password reset page.

Assumptions	<ul style="list-style-type: none"> • The user has a valid account in the system. • The user has a device that is capable of running the application. • The user's device is connected to the internet. The user is able to remember their login credentials.
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Table 6.2: Use Case 3 (Get/View/Send Notification)

Use Case Name	Notification
Primary Actor	User
Secondary Actor	Server
Precondition	User is logged in
Postcondition	Notification is viewed/send/received
Normal Flow	<ul style="list-style-type: none"> • User requests to view the notifications. • Server fetches the notifications from the database. • Server sends the notifications to the user's device. • User views the notifications. • User can mark the notification as read. • User can send a notification to the server. • Server receives the notification. • Server stores the notification in the database.
Alternate Flows	<ul style="list-style-type: none"> • No notifications are available to fetch. • Server sends a message to the user that no notifications are available. • User wants to send a notification without any image. • User inputs the notification message. • User sends the notification to the server. • Server receives the notification and stores it in the database. • User wants to send a notification with an image. User selects an image to attach to the notification. • User inputs the notification message. • User sends the notification to the server. • Server receives the notification and stores it in the database.
Assumptions	User has an active internet connection

Assumptions	The user has a valid account and internet connection is available.
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Table 6.4: Use Case 2 (View Notification)

Use Case Name	Notification
Description	This use case describes how a user can view their notifications in the application.
Primary Actor	User
Secondary Actor	N/A
Precondition	User is logged in and has notifications.
Postcondition	User is able to view their notifications.
Normal Flow	<ul style="list-style-type: none"> ● User opens the notification tab. ● Application retrieves and displays the user's notifications. ● User reads the notification content. ● User may mark the notification as read or delete it.
Alternate Flow	<ul style="list-style-type: none"> ● If the user has no notifications, a message is displayed indicating that there are no notifications to display. ● If the user marks the notification as read, the notification is removed from the notification list.
Assumptions	The user is connected to the internet and has a valid account with notifications.

Android Application

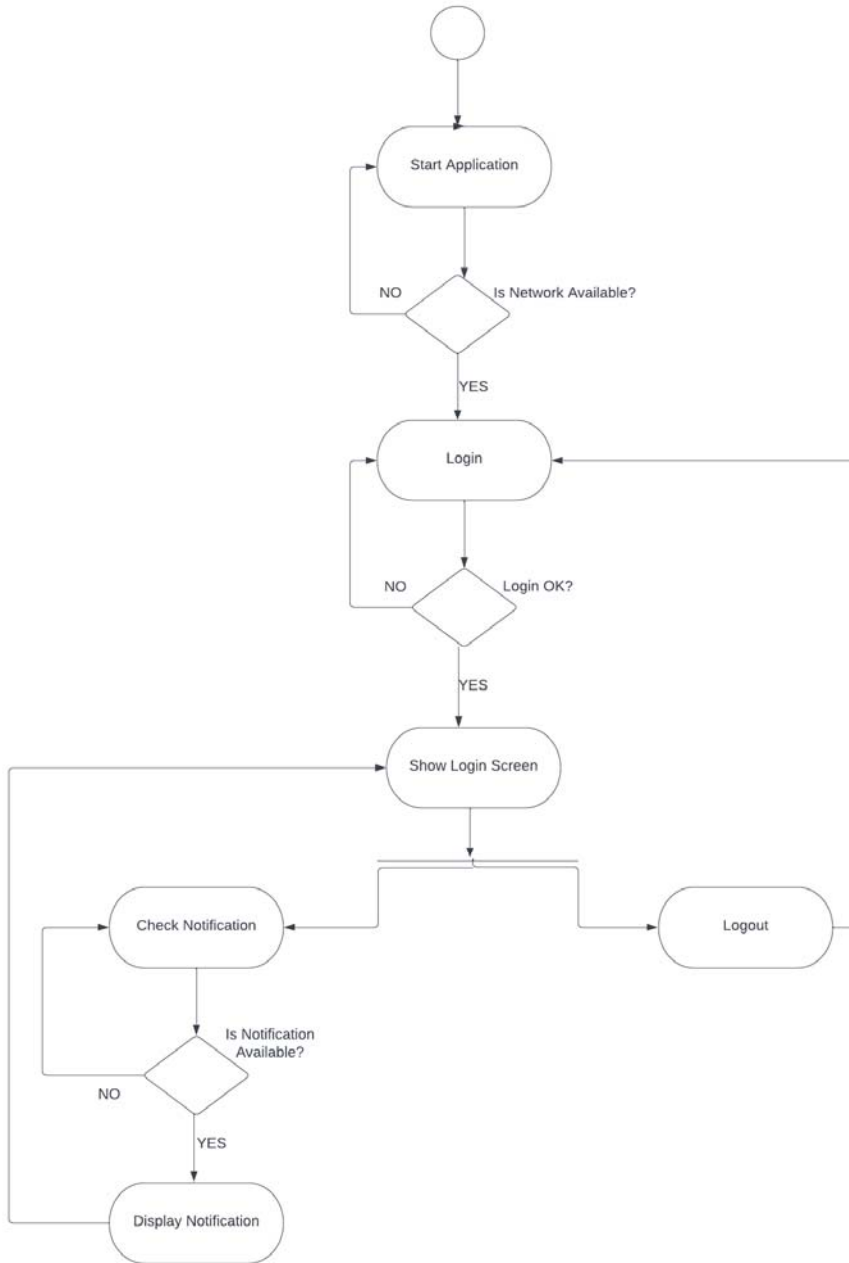


Figure 6-4 Activity – Android Application

6.4.3 State Transition Diagram:

In this section, the state transition of the application is illustrated, depicting how the application transitions from one state to another.

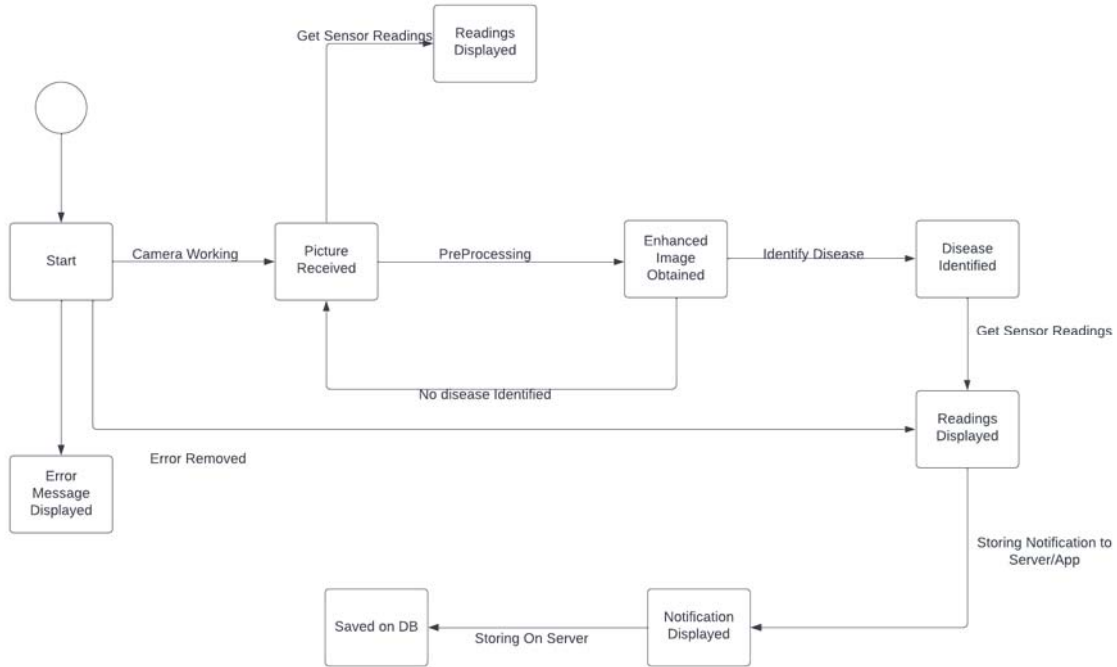


Figure 6-5 State Transition

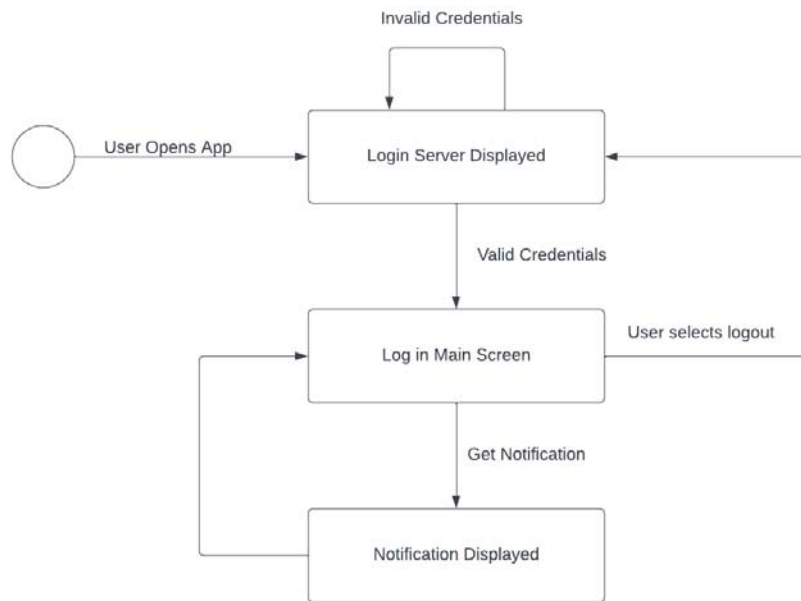


Figure 6-6 State Transition – Android Application

6.5 Detailed Description of Components

6.5.1 Image Acquisition Module

The Image Acquisition module is a crucial component responsible for acquiring images from the camera or gallery for disease detection. The module is primarily designed to interface with the camera and select the best image for disease detection. The camera is the primary actor in this module, and it is assumed that the camera is properly connected and configured to interface with the application. The module initiates the camera to start capturing images and selects the most suitable image for disease detection. The selected image is forwarded to the preprocessing module for further processing, and individual processed images are obtained as output. If the camera fails to connect or capture, the module generates an error message and prompts the user to check the camera connection. If no frame is found suitable for disease detection, the module generates an error message and discards the captured images. The module must be able to handle a variety of camera types and configurations and adjust to different lighting conditions and image qualities. The module may also need to adjust to different camera resolutions, image formats, and compression techniques. Overall, the Image Acquisition module plays a vital role in ensuring that the images obtained for disease detection are of sufficient quality and meet the necessary requirements for accurate analysis.

6.5.2 Preprocessing

The "Preprocessing" module is responsible for removing noise from the acquired image, making it suitable for disease identification. The primary actor of this use case is the "Image Processing Module," with no secondary actor involved. The pre-condition for this module is that the image acquisition process has been completed, and the image is available for processing. The post-condition is that the image has been preprocessed and saved for the next use case of disease identification. In the normal course of action, the image is imported into the module for preprocessing, and the preprocessing algorithm is applied to remove noise from the image. In the alternate course, if there is an error in image acquisition, the module displays an error message and prompts the user to repeat the acquisition process. If the image is of poor quality or the preprocessing algorithm is unable to remove noise effectively, the module displays a warning message and prompts the user to repeat the image acquisition process. The assumptions for this use case are that the image processing module is properly installed and functioning correctly, and the image acquisition module has provided a clear and focused image for processing. There are no exceptions for this use case.

6.5.3 Processing Module

This module is responsible for the identification and feature extraction of slots from an image, which serves as the primary input for the classification module. All processing related to slot identification and feature extraction is performed in this module.

6.5.4 DiseaseIdentifier: The Disease Identification module is located within the Processing Module and is a component type fulfilling the "Identification of Disease" requirement from the

Software Requirements Specification Document. This module uses images obtained from the previous stage of the process to identify diseases on the leaf by interpreting boundary lines and patterns. The module will identify the objects in the image, which are round or rectangular patterns on the leaf, and use this information to register the image. This component is dependent on image preprocessing to produce feature-rich images for better results. The module uses intensity-based/feature-based edge detection techniques to identify objects in the image. The module interfaces with no other components or systems, and requires a camera and network cable for hardware, and Python for software. The module uses the time of recording as a sequence identifier in its processing.

6.5.5 Feature Extraction: The Disease Identification module is a component of the system that is responsible for fulfilling the requirement of extracting features from the image for classification, as specified in the Software Requirements Specification Document. This module uses the images obtained from the previous stage to extract features that will be used for classification. The information retrieved by this component will be used for the subsequent process of disease classification. There are no subordinates for this module, and it is dependent on image preprocessing for better results. There are no specific interfaces for this module, and it requires hardware components such as a camera and network cable and software components such as Python.

6.5.6 Results Module: This module would define the results after the detection of the disease

6.5.7 Send Notification: The Send Notification module is located in the Application Layer and is responsible for fulfilling the system requirement of sending notifications to the farmer about the plant's health status. This module sends alerts to the farmer with appropriate messages and suggestions for taking necessary action based on the analysis of the Disease Identifier module. It is dependent on the outputs generated by the Disease Identifier module. The Send Notification module sends push notifications to the farmer's mobile device using Firebase Cloud Messaging. Its hardware resources include a mobile device and network connection, while its software resources include Android Studio and Firebase Cloud Messaging. This component uses the plant's health status, notification message, and farmer's mobile number as the input data.

6.6 Reuse and Relationships to other Products

The agronomy-based mobile application, Agrona, utilizes an intelligent leaf disease detection mechanism to identify and classify leaves as healthy or diseased. This is achieved by first registering the image for regions of interest and then extracting features to classify the leaves. Unlike sensor-based systems which can be difficult to install and maintain, Agrona offers a simple and hassle-free solution to identify diseased leaves in a large crop area. Its user-friendly interface makes it easy for farmers to use and provides them with valuable insights into the health of their crops.

6.7 Design Decisions and Tradeoffs

The AGRONA app is designed with a component-based architecture, where each component is assigned a specific task. The system consists of three main modules. The first module is the image acquisition module, which captures image. These images are then enhanced for processing. The second module registers regions of interest, which are the disease patterns on leaves. Finally, the features of the leaves are extracted and classified as healthy or diseased. Components of the AGRONA app can work independently but follow a specific flow of data and control, resulting in high cohesion. The components have minimal interaction, and once a component completes its task, it generates an event for the next action. This approach results in low coupling, where each component has its own responsibilities and can work seamlessly with other components. AGRONA's overall control and data flow, high cohesion, and low coupling make it an event-driven architecture system with an implicit invocation mechanism. This design enables the system to be scalable, easily maintainable, and highly efficient in identifying diseased leaves in a large crop area.

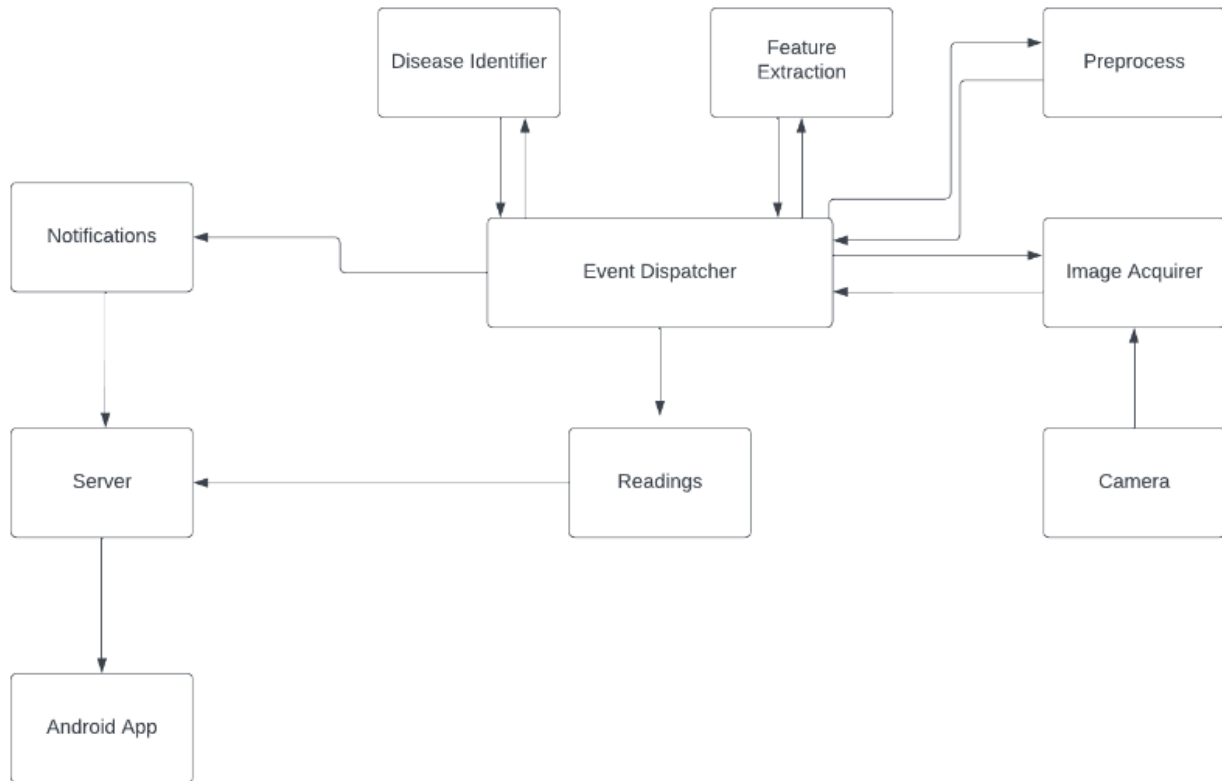


Figure 6-7 Architectural Diagram

Chapter 7: Project Test and Evaluation

7.1 Introduction

The Test and Evaluation chapter of the Agrona app project is a crucial aspect that ensures the overall success of the application. This chapter involves the testing of the application's performance, functionality, and usability in real-world scenarios. Testing and evaluation help to identify any potential issues that may arise during the app's usage, allowing for effective troubleshooting and optimization. We will delve into the testing and evaluation methods used to guarantee that Agrona app meets its intended goals and provides a seamless experience for its users.

7.2 Test Objectives

The purpose of this document is to provide a comprehensive test plan that outlines the specific information required to perform all necessary tests for the Agrona app. The aim is to reduce the likelihood of overlooking important items and to improve the overall test coverage. By offering detailed test information, testers will be able to utilize each test case included in this document and proceed with the testing phase efficiently. The ultimate goal is to ensure that the app meets all requirements and functions optimally in real-world scenarios.

7.2.1 Test Items

Based on the requirements of project AGRONA following are the major modules/ functionalities that should be taken into account during the testing process:

1. Images Acquisition
2. Acquire Sensor Readings
3. Disease Identification
4. Notification
5. Database
6. Display

7.2.2 Features to Be Tested

The features of the Agrona app that will be tested include but are not limited to the user interface, functionality, performance, security, and compatibility with different operating systems and devices. The user interface will be tested to ensure that it is intuitive, user-friendly, and meets the requirements of the target audience. The functionality of the app will be evaluated to ensure that it performs as expected and that all features are working correctly. The app's performance will be assessed by conducting stress tests to determine its stability and responsiveness under heavy usage. Security tests will be conducted to identify any vulnerabilities and ensure that user data is protected. Compatibility tests will be performed to ensure that the app can run smoothly on different devices and operating systems. Additionally, the app's

integration with other systems and platforms will be evaluated to ensure seamless communication and data exchange.

7.2.3 Detailed test strategy

AGRONA is a complex app that requires the development of its modules independently before integrating them. To ensure the quality of the system, the testing strategy includes both white box and black box testing methods for unit testing. Integration testing is then performed to successfully integrate the modules into the system. This approach ensures the robustness and reliability of the AGRONA application.

7.2.3.1 Unit testing

Unit testing is a crucial aspect of the Agrona app development process, ensuring that each individual module of the application is functioning as expected. The testing process involves both white box and black box testing methods, where the internal code structure and external functionality are evaluated. Each unit of the application is tested independently, and any errors or bugs found are corrected before moving on to the next unit. By performing thorough unit testing, the development team can identify and resolve issues early in the development cycle, resulting in a more reliable and robust application.

7.2.3.2 White box testing

White box testing is a vital component of the Agrona app testing process, where the internal workings of the application are evaluated to ensure the software's functionality meets the design requirements. During the testing process, testers examine the code and internal structures of the application to identify potential defects and vulnerabilities. This type of testing also helps to improve the overall quality of the application by identifying and fixing code-related issues early in the development cycle. White box testing provides developers with a detailed insight into the workings of the application and allows them to optimize the code to improve performance and overall stability. It is an essential step in ensuring that the Agrona app is reliable, secure, and meets the needs of its users.

7.2.3.3 Black box testing

Black box testing is an essential part of the testing process for the Agrona app. This method involves evaluating the application's external functionality without examining its internal code structure. Black box testing is conducted from an end-user's perspective, and the focus is on ensuring that the application meets the intended requirements and specifications. Test cases are designed based on the app's functional specifications, and the results are compared to expected outcomes. By conducting black box testing, the development team can ensure that the application functions as expected, and any potential issues can be identified and resolved before the app is released to the public.

7.2.3.4 Integration testing

Integration testing is a critical step in the Agrona app development process. It involves testing the integration of different modules and components to ensure that they work together

seamlessly. This testing phase checks how well the app integrates with other systems, platforms, and databases. By performing integration testing, developers can detect and fix any issues related to data transfer, communication, and functionality between different modules of the application. This ensures that the final product is a fully functional and cohesive application.

7.2.3.5 Incremental testing

Incremental testing is a software testing approach that involves testing individual units of an application in isolation, then gradually integrating them into the larger system. This method of testing enables developers to test and identify issues in small, manageable parts of the application, reducing the risk of errors or defects in the overall system. Incremental testing allows for more frequent and iterative testing, which helps to identify and address issues early on in the development process. By testing small parts of the application at a time, developers can verify the integration of different modules and ensure that they work seamlessly together. This approach to testing ultimately results in a more reliable and stable application that meets the required specifications.

7.3 Testing and Accuracy Improvement of Agrona

Testing of Agrona App To ensure the accuracy and reliability of the Agrona app, extensive testing was conducted. The testing process involved capturing images of crops with different degrees of health and disease, including wheat crops infected with multiple diseases such as stripe rust and septoria. These images were then uploaded to the app, and the model was run to detect and classify the diseases accurately. The results of the testing were promising, with the app demonstrating high accuracy in detecting and classifying wheat diseases. The app was able to identify diseases such as stripe rust and Septoria with an accuracy of over 90%. The app's ability to detect and classify multiple diseases accurately was also tested, and it performed well in this regard.

7.4 Accuracy Improvement

To improve the accuracy of the Agrona app, several techniques were employed. One of the primary techniques was to increase the size and diversity of the training dataset. This was done by collecting more images of crops affected by various diseases and healthy crops from different regions and countries. This helped to improve the generalization of the model and reduce overfitting. Another technique used to improve accuracy was data augmentation. This involved artificially generating more data by applying transformations to the existing images, such as rotation, flipping, and scaling. This helped to increase the diversity of the dataset and reduce the chances of the model overfitting on the training data. To further improve the accuracy, the model was fine-tuned using transfer learning. Transfer learning involved using a pre-trained model as the starting point for training the Agrona app's model. The pre-trained model had already learned to extract high-level features from images and was fine-tuned on the new dataset of crop images.

This helped to improve the accuracy of the model significantly. In conclusion, the Agrona app has undergone extensive testing to ensure its accuracy and reliability. The app demonstrated high accuracy in detecting and classifying various diseases, and techniques such as increasing the size and diversity of the dataset, data augmentation, and transfer learning were used to improve accuracy. The app's ability to detect and classify multiple diseases accurately makes it a valuable tool for farmers and researchers in the agriculture industry.

Testing

7.5 Organization of the manual

The user manual for Agrona app consists of five sections: General Information, System Requirements, Installation and Configuration, Getting Started, and Using the App.

General Information section explains the purpose of the Agrona app and its intended users. It also provides a brief overview of the app's features and functions.

System Requirements section outlines the minimum hardware and software requirements for using the Agrona app. It includes information on the supported operating systems and mobile devices, as well as the required internet connection speed.

Installation and Configuration section provides step-by-step instructions on how to download and install the Agrona app on a mobile device. It also includes information on how to configure the app for first-time use, such as creating an account and connecting to the real-time database.

Getting Started section explains how to use the Agrona app once it is installed and configured. It includes information on how to navigate the app's user interface, how to view sensor readings, how to access notifications, and how to use other features of the app.

Using the App section provides a detailed description of Agrona app's functions. It includes information on how to use the disease detection and classification feature, how to view and manage sensor readings, how to access expert suggestions for disease control, and how to use other advanced features of the app.

7.6 System Summary

The System Summary section of the Agrona user manual provides an overview of the system's hardware and software requirements, configuration, user access levels, and behavior in case of any contingencies. This section is intended to give users a general understanding of how Agrona works and what they can expect from the system. The summary outlines the key components of Agrona, including the mobile app, the real-time database, and the disease detection and classification feature. It also includes information on how the system is configured and how users can access and interact with the various components of the system.

7.7 System configuration

System configuration for Agrona includes the hardware and software components necessary to run the application. The hardware configuration includes a mobile device running Android OS, with a minimum of 2GB RAM and 16GB internal storage. The device must also have a rear camera with autofocus and flash capabilities.

The software configuration includes Android 9.0 (Pie) or higher version installed on the mobile device, along with the Agrona app downloaded. The app requires an internet connection to access real-time data and notifications. Agrona also requires integration with a real-time database, Firebase, which provides a scalable and secure backend infrastructure for storing and retrieving data. The database stores sensor readings and disease detection results, which are accessed by the Agrona app for disease classification and notification purposes.

The system configuration also includes user authentication and access levels, ensuring that only authorized users can access and modify the data. The system administrator has full access to the database and app features, while the farmer has limited access to view sensor readings and receive notifications on the app.

7.8 User access levels

User access levels for Agrona app are divided into two categories: farmers and experts. Farmers have access to the basic features of the app such as viewing sensor readings and receiving notifications for disease detection. Experts, on the other hand, have access to advanced features such as providing suggestions for disease control and managing the disease database. Both types of users must create an account to access the Agrona app and are assigned unique login credentials to ensure data privacy and security. The app also allows for multiple users to access the same account with different levels of permission to facilitate collaboration between farmers and experts.

7.9 Contingencies

Contingencies for Agrona refer to the system's behavior in the event of unexpected events, errors or failures. The system has been designed to handle contingencies in an efficient and effective manner to minimize the impact on the user. In case of any unexpected event or error, the system will generate an error message that will provide the user with a description of the issue and possible solutions. In the case of a system failure, the user can contact the technical support team to resolve the issue. The technical support team will troubleshoot the issue and provide a solution to restore the system to its normal functionality. Additionally, the system has been designed to automatically save sensor readings and data in real-time, so that in the event of any contingency, the user's data is not lost. This ensures that the user can resume the use of the Agrona app without losing any critical data.

7.10 Getting Started

Getting Started section of Agrona system manual explains how to set up and configure the system for the first time use. It provides step-by-step instructions for downloading and installing the necessary software, as well as information on the required hardware and internet connection. The section also presents an overview of the system's menu and user interface, to help users get familiarized with the system's features and functions. It covers topics such as logging in to the system, creating user profiles, and accessing the real-time database. By following the instructions provided in this section, users can quickly and easily configure the Agrona system and start using its powerful disease detection and classification features to improve crop yield and minimize losses.

7.11 Installation

Android Application

- Click on the Agrona app in the search results.
- Click on the "Install" button to begin the installation process.
- Wait for the app to download and install on your device.
- Once the installation is complete, click on the "Open" button to launch the app.
- Follow the on-screen instructions to create an account and configure the app for first-time use.

It is important to note that your device must meet the minimum hardware and software requirements outlined in the System Requirements section of the Agrona user manual. Additionally, a stable internet connection is required for the app to function properly.

7.11.1 System Interface

The display on accessing the application would be as follows:

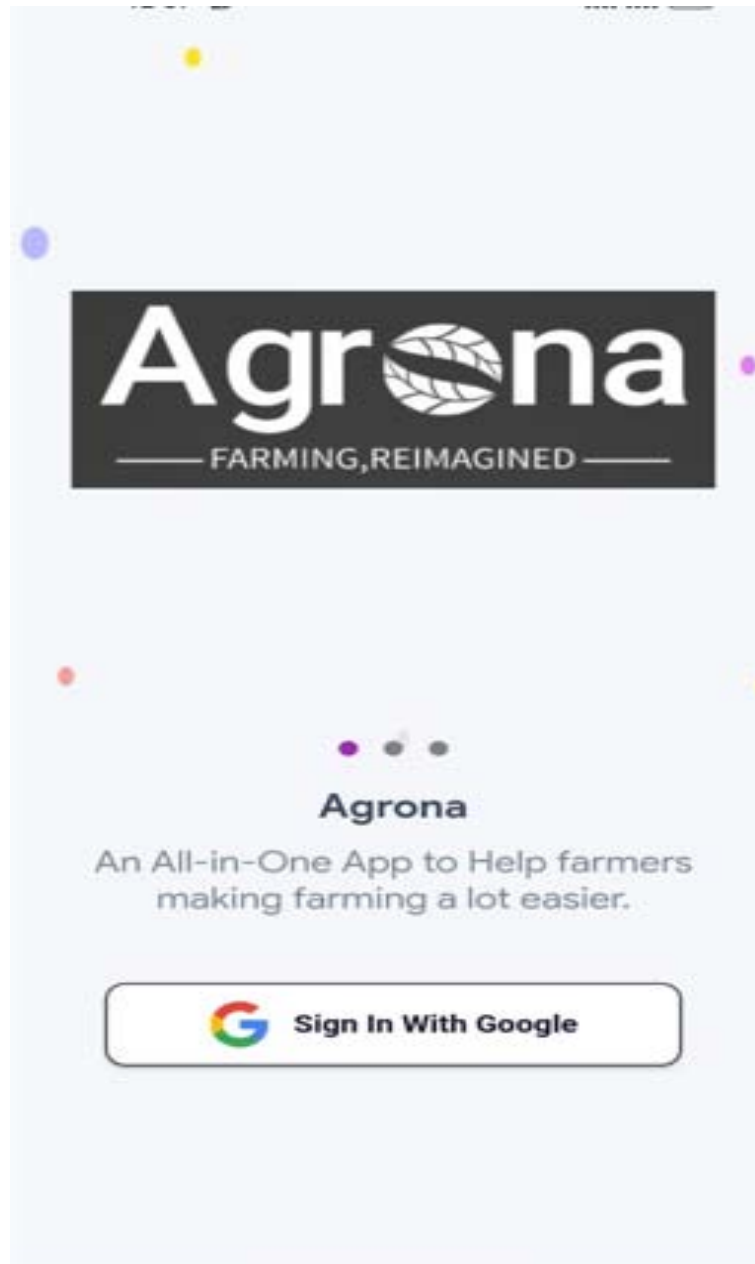


Figure 7-1



Agrona

The App helps to detect defected regions of crops so that necessary care can be taken.


 Sign In With Google

Figure 7-2

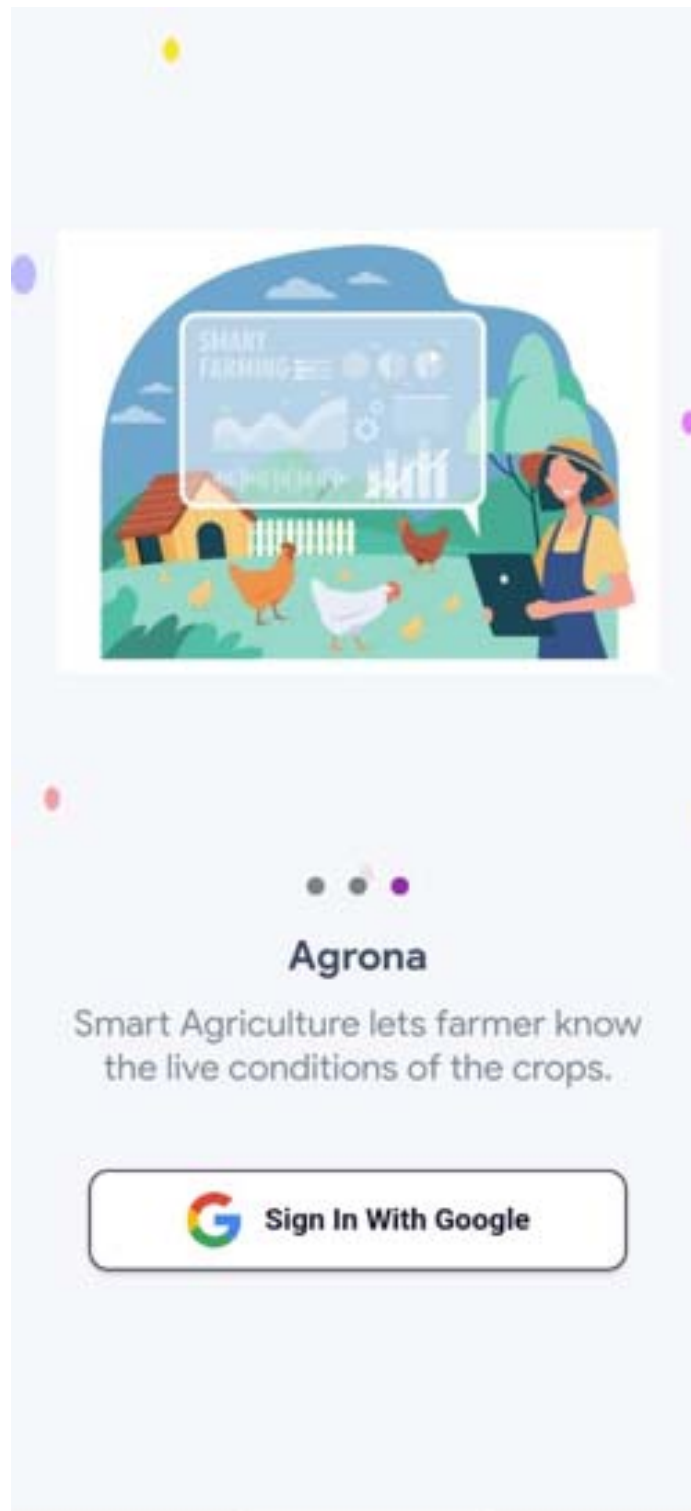


Figure 7-3 Register Screen

7.11.2 Display of the App main screen

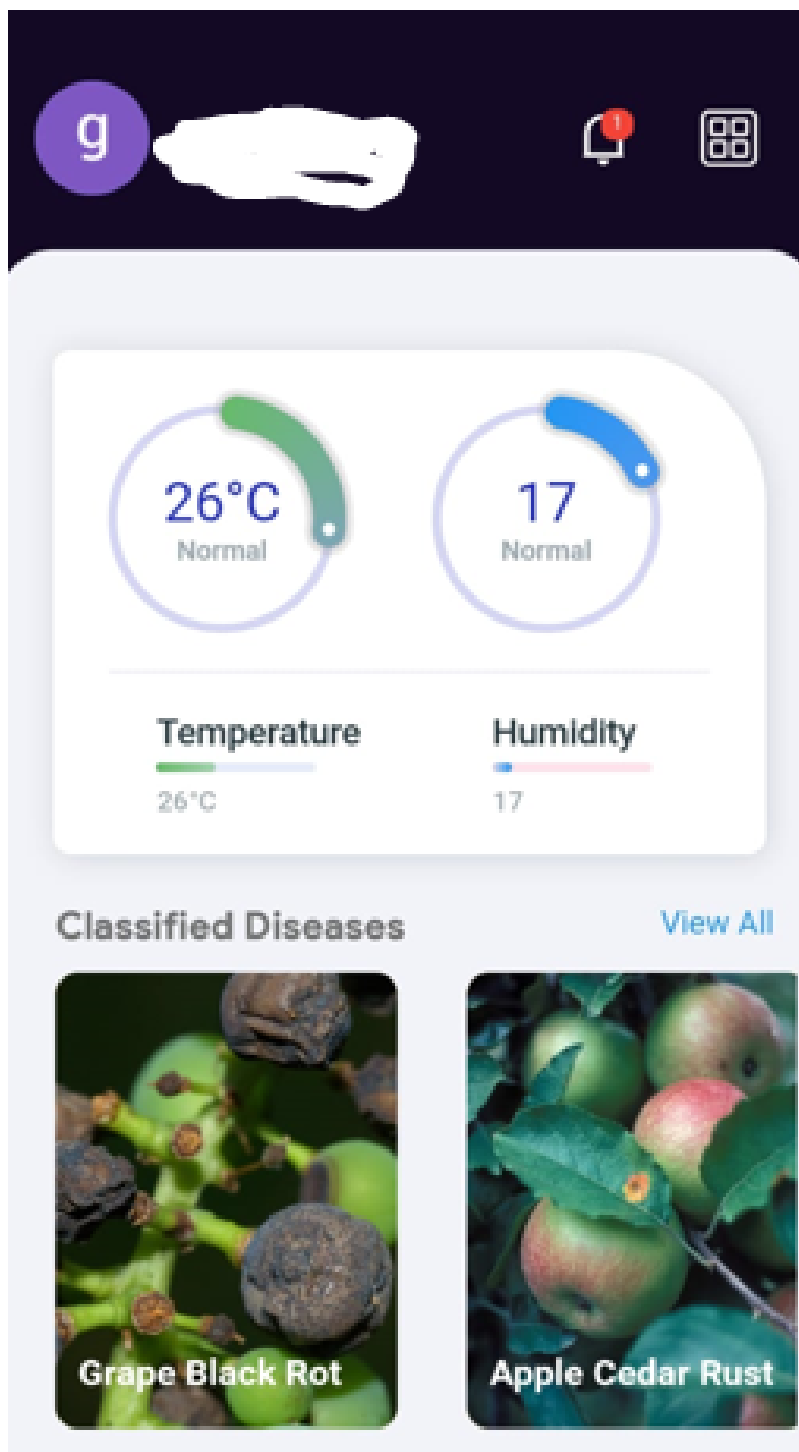


Figure 7-4

7.11.3 Images View

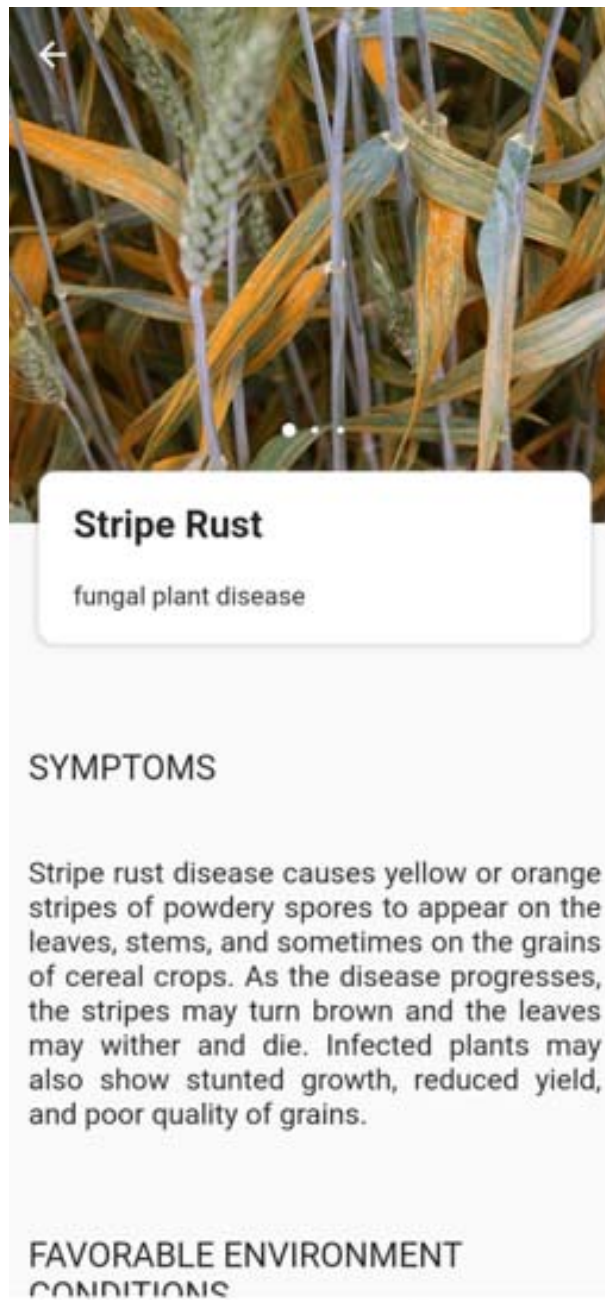


Figure 7-5

FAVORABLE ENVIRONMENT CONDITIONS

Stripe rust disease thrives in cool, moist, and humid conditions. The optimum temperature for its growth is between 10-20°C, with relative humidity of 90% or higher. The disease is most prevalent in areas with mild winters and wet springs.

MANAGEMENT (REMEDIES)

The following are some management strategies that can be used to prevent or control stripe rust disease:

Use resistant cultivars: Grow resistant cultivars of cereal crops that are less susceptible to stripe rust disease.

Crop rotation: Rotate crops with non-host plants to reduce the build-up of stripe rust spores in the soil.

Fungicide sprays: Apply fungicides to control the disease during its early stages.

Timely planting: Plant crops at the recommended time to avoid the period when the disease is most prevalent.

Figure 7-6

7.11.4 Using the system

This section provides a description of system functions and features

- **Capture Images:** The first step in checking for disease using Agrona is to capture images of the wheat crop. This can be done by using the Agrona app to take pictures of the wheat plants in the field.
- **Upload Images:** Once the images have been captured, they can be uploaded to the Agrona app. The app will use image recognition technology to detect any signs of disease in the crop.
- **Analyze Results:** After the images have been uploaded, the Agrona app will analyze the results and determine whether or not the crop is healthy or diseased. If the crop is found to be diseased, the app will provide recommendations for how to treat the crop.
- **Take Action:** Based on the results provided by the Agrona app, farmers can take action to prevent the spread of disease in their crop. This may involve applying fungicides or other treatments to the crop, or removing and destroying infected plants to prevent the disease from spreading.

7.11.5 Login

- The login feature of Agrona ensures the security of the user's data and allows only registered users to access the app's features and functions.
- The user needs to create an account on Agrona before accessing the app.
- During the account creation process, the user needs to provide their personal information and create a strong password.
- After the account is created, the user can log in to Agrona using their registered email address and password. The app uses encryption to secure the user's login information.
- Agrona also provides the option for users to reset their password in case they forget it. The app sends a password reset link to the user's registered email address, and the user can create a new password by following the link.

7.11.6 Notification Pop-ups

- Agrona app provides real-time notification popups to farmers when the system detects a disease in their crops.
- These popups provide instant alerts and allow farmers to take timely actions to prevent further damage to their crops.
- The notification popups are designed to be user-friendly and provide a quick overview of the detected disease, the severity level, and recommended actions for disease control.
- Farmers can also customize their notification preferences, such as selecting the types of diseases they want to be notified about, the time of day they prefer to receive notifications, and whether they want to receive notifications via sound, vibration, or both.
- Notification popups are also displayed on the Agrona web application, allowing farmers to stay updated on their crops' health even when they are not using the mobile app.

Chapter 8: Conclusion

In conclusion, we have achieved significant deliverables in developing an app, Agrona, that can detect and classify wheat diseases using machine learning algorithms. Our team faced several challenges during the process, such as collecting our own dataset due to the unavailability of diseases, variation in crops, and their small size. However, we successfully collected a substantial dataset and trained our own deep learning model using VGG16. While we experimented with other models like ResNet50 or MobileNet, we were unable to achieve the desired accuracy, which we accomplished with VGG16, improving the accuracy from 70% to 90%. Furthermore, we developed an app that can detect and classify wheat diseases, despite encountering some challenges during development. Our app has the potential to revolutionize crop disease detection and help farmers detect diseases at an early stage, thereby increasing crop yields and ensuring food security

Chapter 9: Future Work

Looking forward, the Agrona app has the potential to be expanded and customized to meet the unique needs of farmers. It can serve as a foundation for building a more complex and extensive system that caters to individual farmer's requirements. The app could also be commercialized and used as a generic software for landowners and farmers alike. In the future, there are several areas where the Agrona app can be further improved. One such area is accuracy, where the app can be enhanced to provide even more precise disease identification. Additionally, the scope of the app can be extended to cover multiple diseases affecting different types of plants, making it a more comprehensive tool for farmers. Several additional features can be integrated into the Agrona app to improve its functionality, including live-feed of farming lands, suggestions from experts for disease control, and pest identification and control. Moreover, the app can be augmented to provide more robust admin functionalities to support efficient management of the system.

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