COLLEGE OF COMPUTING AND INFORMATICS TECHNOLOGY

WEED DETECTION AND MONITORING SYSTEM

By

CS22-13

DEPARTMENT OF COMPUTER SCIENCE

SCHOOL OF COMPUTING AND INFORMATICS TECHNOLOGY

A Project Report

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Of Makerere University

Supervisor

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DECLARATION

We Group **CS22-13** do hereby declare that this project report is original and has not been submitted to Makerere University or any other learning institution before.

However, Citations, Quotations and References to other people's work or sources of information where used have been duly made.

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TABLE OF CONTENTS

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LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AI: Artificial intelligence

CWFID: Crop/Weed Field Image Dataset

DCNN: Deep Convolutional Neural Network

FN: False Negative

FP: False Positive

MHU: Makerere University Department of Botany

SGD: Stochastic Gradient Descent

TN: True Negative

TP: True Positive

ABSTRACT

Weeds are a major constraint to the success of crop growth. Crops worldwide are affected by weeds which reduces yields. Even more challenging is how long farmers usually take to determine how they have infested their farms. The traditional method of detecting the weeds by farmers is by use of their human eyes. This has been found to be tedious in a way that is time consuming and labour consuming, especially when dealing with a large piece of land. Also, this method only requires physical presence of the farmers.

The objective of this project therefore was to develop an AI weed detection and monitoring system (mobile application) that acts as a companion to farmers by providing them with day-to-day information about the infestation of weeds on their farms to enable them take immediate, knowledgeable and appropriate decisions. The project involves the system taking pictures of the farm and then processing them (by the trained model), from which the corresponding answers of whether or not, and which type of weed or crop detected is provided. Various methods were used to gather requirements which include interviews and study of the existing systems.

In conclusion, the use of this AI weed detection and monitoring system enables farmers and agriculturalists to take effective and informative decisions about weed control which increases their rate of crop production. In addition, it facilitates remote monitoring of the weed growth on the farm by the farmer effectively.

1.0 INTRODUCTION

1.1 BACKGROUND

Over years, agriculture has been developing and getting modernised. It has a major role in improving the quality of life. An abundance of wholesome food products available at a reasonable cost contributes to a high quality of life. About 70% of the people in Uganda and 28% people in the world depend on farming for food, medicine and employment [2],[3]. As a provider of industrial raw materials, it is an important contributor to economic activity in other sectors of the economy. According to statistics, agriculture forms the backbone of Uganda's economy contributing approximately 37% of the Gross Domestic Product (GDP) [6].

However, several challenges affect the practice of agriculture. By far, the problem of weed detection and monitoring is one of the most pronounced ones. Weeds are a nuisance to agriculture in a way that they limit high production of food, fibre and feed crops on all lands where they occur [1].

They compete with the plants for nutrients and also harbour pests and diseases [4] to the plants hence leading to low yields. The biggest problem with manual(physical) weed detection is that it involves too much effort and monitoring takes a lot of time. When farmers detect weeds in time, they can use several methods of weed control appropriately like chemical (such as using herbicides), biological (involves using nematodes, insects, fungi and bacteria to reduce weed population) and physical methods (such as removing by hands and grazing) [5] to decrease and get rid of the weeds in farms. Figure 1 below shows some of the statistics that elaborate more on how weeds have affected the rate of crop yield production [14].

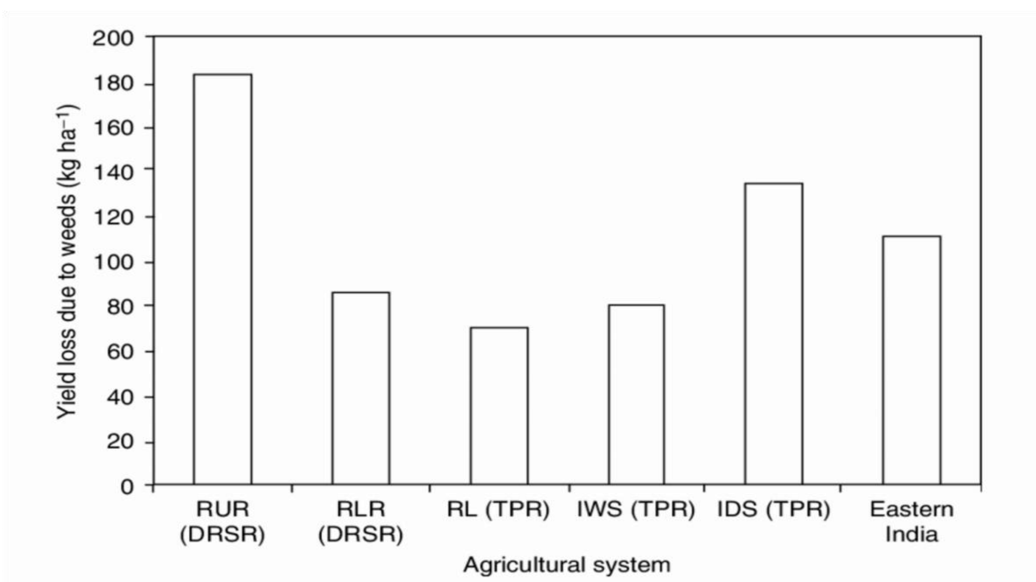


Figure 1 Effects of weeds on the rate of crop yield production.

1.2 PROBLEM STATEMENT

Weed detection is one of the biggest challenges that farmers face in a way that the manual method that is commonly used is time consuming and labour intensive because farmers or labourers have to visit the gardens on a daily basis to monitor the level of weed growth. Therefore, this research proposes a weed detection and monitoring system that aids farmers by providing real time information remotely about weed infestation in a section of the farm under surveillance. The information provided is to be in terms of duration(weeks or days) taken for weeds to grow and be detected at an early stage before they affect crops in order to increase the rate of crop production.. Therefore, with this system, farmers would have saved time, labour expenses and also helped in early planning for the weed control.

1.3 OBJECTIVES

1.3.1 MAIN OBJECTIVE

To develop an automated system that can aid in detecting and monitoring the weeds.

1.3.2 SPECIFIC OBJECTIVES

- To collect data specifically images which will be used to train the model.
- To clean and annotate the collected data
- To build and train a machine learning model to identify and distinguish between crops and the weeds.
- To test the model for accuracy and errors during every stage of training the model.
- To build a mobile application gives feedback information to the farmer.

1.4 SCOPE

The system is able to detect weeds and crops, specifically we have trained it to detect at most two types of weeds (elephant grass, commelina benghalensis also known as wandering Jew) and two types of crops (maize and beans). The system works during day time for clear collection and analysis of information and also sends notification and feedback to the farmer via a mobile application for proper decision making.

1.5 SIGNIFICANCE

The system will provide timely information on the presence of weeds which will enable farmers to make timely decisions for instance on the appropriate time to do the weeding. The system will also improve on the efficiency and rate of crop production which will improve on people's (farmer's) standards of living and create markets for the products. Such a project will further attract and incorporate a large percentage of people into the agricultural sector including investors which will be a good step in improving the economy of Uganda. Furthermore, the project will come up with a new dataset that can aid in future research in the field of agriculture.

2.0 LITERATURE REVIEW

2.1 INTRODUCTION

A weed is any unwanted plant growing along with the useful agriculture products, it can also be described as any plant that interferes with the objectives of farming. Different research has been carried out on weeds for example, a floristic study was carried out on terrestrial weed species of Kampala (Uganda). The aim of the study was to identify weed species, to determine their life forms and their phytogeographical distribution and to compile a checklist. An inventory was made throughout the man-made habitats of Kampala and voucher specimens were collected and deposited at the Herbarium of the Department of Botany of Makerere University (MHU). Three hundred and thirty-one species, belonging to 204 genera and 64 families, were identified. The most important families are Asteraceae (45 spp.), Poaceae (44 spp.) and Papilionaceae (33 spp.). Most of the species are therophytes (38.7%) and of pan tropical distribution (48.9%) [11].

These Weeds compete with crops for sunlight, water, nutrients, and space. In addition, they harbour insects and pathogens, which attack crop plants. Therefore, weeds should be identified, detected and removed early from the farm in order to increase the crop yields.

During the study of our literature, we revised some of the currently available methods used for detecting and monitoring the weeds and also some of the already automated (trained and tested) systems that are currently available for weed detection together with their challenges.

2.2 AVAILABLE SYSTEMS (MODELS) FOR WEED DETECTION

Several Machine Learning Algorithms and Deep learning models have been developed to aid in image classification tasks. Among these are the deep convolutional neural networks (DCNN) which were trained and labelled by experts using different datasets. These include; U-Net Model, SegNet, FCN (FCN-32s, FCN-16s, FCN-8s), DepLabV3+, VGGNet, AlexNet, Google Net [9]. Among the above mentioned deep learning architectures, SegNet, FCN, U-Net, and DeepLabV3+ [8] are the four important deep learning architectures that were trained, evaluated and employed for crop and weed separation using two published benchmark UAS datasets these include Crop/Weed Field Image Dataset (CWFID) (Haug and Ostermann, 2014) [8] and the Sugar Cane Orthomosaic datasets (Monteiro and Von Wangeheim, 2019) [8]. The Sugar Cane Orthomosaic dataset was made using a sample sugarcane orthomosic [8] which was patched into 50 images of 540 × 540 pixels size each for training and testing purposes. According to the study (experiment), the above deep learning models were fine-tuned to classify the UAS datasets into three classes (background, crops, and weeds) [8]. The models were trained using Stochastic Gradient Descent (SGD) with a minibatch size of 2, a learning rate of 0.001, and a maximum epoch of 10. A 10-fold cross-validation procedure was used to assess the performance of these models. The following paragraphs clearly indicate the classification accuracy which was attained by each model in the experiment.

The SegNet model was developed and proposed by Badrinarayanan et al. (2017) [8] for pixel-wise segmentation applications and it has a smaller number of trainable parameters which can be trained end-to-end using stochastic gradient descent. Based on the above experiment, the SegNET model achieved a classification accuracy of 62.6% which is the lowest as compared to the rest of the models.

The FCNs were developed by Long et al. (2015) [8] for semantic segmentation applications by replacing the three fully connected layers of VGG16 with fully convolutional layers to maintain the 2-D structure of images. The classification accuracy of FCN-32s, FCN-16s and FCN-8s were 68.4%, 77.2% and 81.1% respectively.

The U-Net Model was proposed by Ronneberger et al. (2015) [8] for biomedical image segmentation. It is based on FCNs, and its architecture was modified to work with fewer training data to give more precise segmentation results. Its classification accuracy was 77.9%.

The DeepLabV3+ is an encoder-decoder network that was developed by a group of researchers from Google (Chen et al., 2018) [8]. It uses Atrous convolutions to overcome the issue related to the excessive downsizing in FCNs due to consecutive pooling operations. Its classification accuracy for crop and weed separation was 84.3%.

Experimental results showed that DepLabv3+ could precisely extract weeds compared to other classifiers [8 - 9].

2.3 CONCLUSION

From the study of our Literature, the challenge with the above-mentioned Deep learning models is that they were trained on the kind of data with images of isolated crops or in an arranged setting meaning that their performance is restricted to detecting an isolated plant with a specific type of weed species. This therefore means that they cannot detect weed species in mixed gardens (cluttered gardens) depending on the environment and the kind of data on which they were trained. Therefore, this research intends to come up with a machine learning model that is able to detect weeds in clutter (mixed gardens) together with mixed crops which is a real case for existing gardens.

3.0 RESEARCH METHODOLOGY

3.1 INTRODUCTION

This section explains and describes the selected methodology for the research, data collection, and analysis, project design and implementation among others. Thus, the instruments, approaches, processes and techniques, computer hardware and software tools that were used in the research study. We researched the implementation methods/technologies before starting on the actual development.

3.2 RESEARCH STRATEGY

The project utilised qualitative research methods in determining all the needs or requirements of the system and to conduct an on-site observational study for evaluating the usability of the system. During the study, willing participants living around Kampala and Makerere University were sampled.

3.3 RESEARCH DESIGN

Experimental research design was used to come up with all the necessary data for our proposed hypothesis through use of surveys.

3.4 DATA TECHNIQUES AND PROCEDURES

Data collection is the process of gathering and measuring information on targeted variables. Data was collected from reviewing literature, questionnaires, taking pictures on mixed farms and conducting interviews. The study collected both primary and secondary data from which qualitative data was generated. Data was analysed and insights that support decision making were extracted.

3.4.1 DATA COLLECTION TECHNIQUES

3.4.1.1 Interviews

An interview is a method of collecting data which involves presentation of oral-verbal stimuli and reply in terms of oral-verbal responses, while conducting an interview the interviewer lists topics or questions (interview guide) that will be discussed at each interview. We conducted semi-structured interviews which required asking the same questions for each interview we made, but keeping their responses flexible hence meaning that follow up questions were included if a subject answers in an unexpected way.

Therefore, different farmers were interviewed to identify the most common types of weeds that greatly affect certain or specific crops and how they affect them.

3.4.1.2 Questionnaires

A questionnaire is the document that contains several questions about a specific research area that is supplied to individuals to get their opinions inform of responses. Questionnaires were supplied to different individuals to find out other challenges faced by farmers when carrying out the weed monitoring activity.

3.4.1.3 Observation

Observations enable you to see and get first-hand information about a topic or study of interest. We physically visited different gardens and farms to get specific information about how the aforementioned weeds manifest and to get their different types and appearances to enable the process of training the model on accurate data.

3.4.2 DATA COLLECTION TOOLS

Tools that were used to collect and store the data included cameras, laptops, mobile phones and recorders.

Summary of the data collection techniques and tools

Data collection technique	Data collection tool used
Interviews	Recorders, cameras
Questionnaire	online questionnaires
Observation	Physical human eyes

Table 1: Summary of the data collection techniques and tools.

Summary of the objectives and the methodology used to attain them

Objectives	Methodology used
To collect data specifically images which will be used to train the model	Used data collection tools such as cameras
To clean and annotate the collected data.	This was achieved with help of packages such as labelImg package.
To build and train a machine learning model, to identify and distinguish between crops and weeds.	Used environment such as google colab and Technologies like keras and tensorflow deep learning frameworks.
To test the model for accuracy and errors during every stage of training the model.	We tested our system with sample/test data and perform user acceptance test and on testing it passed. This was achieved by sharing the app with students to test it and feedback was used to validate the system.
To build a mobile application that gives feedback to the farmer.	This was achieved by using various technologies and tools such as; Flutter, VSCode Editor, Android studio real android devices to test the applications.

Table 2: Objective with its respective methodology technique.

3.4.3 DATA ANALYSIS

Data analysis is a process of inspecting, cleaning, transforming and modelling data with the goal of discovering useful information, drawing conclusions and coming up with proper decision making. During the analysis phase, data was processed in order to remove inconsistencies and extract useful information that was fed to the system. Also, visual and content analysis of data in the form of images was carried out to determine their quality, reliability and appropriateness. UML (Unified Modelling Language) diagrams like use cases were used for modelling requirements gathered.

3.4.4 DATA CLEANING AND ANNOTATION

Cleaning data inform of images involves shaping them into a required size to be fed into the system. The collected data was cleaned by shaping the images into the required sizes, augmented using keras ImageDatagenerator. The LabelImg package was used to annotate (label) and classify different features / patterns of the image into classes and instances which aided in training of the machine learning model.

3.5 DEVELOPMENT TOOLS

In development of this system, quite a number of tools were involved. These tools include;

(a) Tensorflow and Keras:

These were the deep learning frameworks whose power we leveraged to layout the structure of our feature extractor.

(b) Python libraries:

These included Numpy, Matplotlib, and Sklearn metrics. Numpy was used to convert images to an array of numbers for proper processing of the images. The Matplotlib library was used for visualisation of data in form of charts and graphs in order to get useful insights from it. The Sklearn metrics python library was used to generate the confusion matrix report which was used to determine the level of confusion of the feature extractor.;

(c) Google colab notebook:

This was the hosted cloud notebook where instructions for training our feature extractor were written and we also leveraged the power of the google colab GPU for training the feature extractor.

(d) Flutter:

This was a cross-platform mobile application framework whose power we leveraged to write instructions for our mobile applications.

(e) Google drive for storing the datasets:

This was used for storing important files together with our dataset which we used to train the model.

3.6 MODEL TESTING

This involves testing the accuracy and performance of the model. The performance of our model was tested based on the summary of results categorised into the following groups [15]; True positives (TP), True negatives (TN), false positives (FP) and False negatives (FN). The performance of the classification model was visualised through use of a confusion matrix [13] [15] table which provided information that can be used to calculate measures that help to determine usefulness of the model by calculating precision and recall values. Below is the analysis of how our model was evaluated.

True positives (TP): Predicted positive and are actually positive

False Positives (FP): Predicted positive and are actually negative.

True negatives (TN): Predicted negative and are actually negative.

False negatives (FN): Predicted negative and are actually positive.

4.0 SYSTEM DEVELOPMENT.

This chapter explains all the activities and steps undertaken in the development of the android mobile applications that interact together to achieve the functionality of the system.

4.1 SYSTEM ANALYSIS AND DESIGN

This section includes the process of defining the product design tools and modelling techniques that were used in the system development, interfaces and also data for a system to satisfy specified requirements. System modelling techniques that helped us to organise the information, developing a comprehensive representation of the data in a model.

This weed detection and monitoring system consists of two mobile applications, that is to say;

1. Weed detection application (weed master), which simulates the AI model trained to detect (remotely) and monitor weed growth, that would be mounted on a farm.
2. Feedback application, which receives feedback from weed master after detection and analysis informs of images and texts.

4.1.1 System Analysis

System analysis was carried out to understand the developed system and its activities in a logical way. This also helped in knowing the users' requirements for the developed system.

During the system analysis process, various tools and techniques as described earlier on, were used to gather data and information that was required to understand the requirements and operation of the new system that was developed.

During field data collection, we interfaced with individuals like farmers and local people through one-on-one interviews and discussed frequently asked questions like accessing agricultural resources, agri-business, agricultural challenges.

In our investigation it was noticed that most farmers are facing the same challenges with the traditional methods of weed monitoring and detection. Conclusively, more interviews were carried out to learn the challenges and adaptability of a new AI system to solve such challenges experienced by today's farmers/agricultural people.

4.1.2 The Intended Users

The intended users are farmers, investors, Visitors (local people).

4.1.3 System's requirements

This section discusses the configurations and the requirements that our software applications had to meet in order to run smoothly and effectively.

The requirements of the system are categorised into user, functional, and non-functional requirements and system specification.

4.1.3.1 User Requirements

The users should be able to do the following in the system:

Famers (those using the system) and investors should be able to sign in using their google account credentials to be able to start monitoring their farms and to get information on different subjects such as help, about the system.

4.1.3.2 Functional requirements:

- The detection application (weed master application) must be in position to input an image.
- Process the input to generate results of the output class.
- Send feedback to the feedback system (feedback application).
- The feedback application should receive feedback from the detection application in real time.
- The feedback should be in form of images accompanied with textual description of the images.

4.1.3.3 Non-Functional Requirements

These are not directly concerned with specific functions delivered by the system. They pertain to system properties such as: reliability, accuracy to mention but a few.

The following are the non-functional requirements:

- The system should grant access to only authorised users.
- The system should be easy to learn and used by its end users.
- The system should be portable such that it runs on most operating systems.
- The output data should be accurate since the input training data is validated.
- The system should be easy to maintain.
- The system should be less susceptible to failures
- The system should be scalable to take advantage of new datasets where necessary.

4.1.4 System design

This is concerned with how system functionalities are provided by the different components of the system. System design tools such as use case diagrams were used in the development of the system.

4.1.4.1 A Flow Chart diagram for weed detection application

A use case was used to develop a better understanding of the requirements. This gave us a view of the components and entities of the system under design.

In the use case diagram, the user who is an actor first login in using their Gmail which is stored on the cloud server .in addition the user can also logout of the system.

In order for the user to do the detection they can either start observation or import an already existing image.

When the user clicks on start observation the system streams the farm live and takes pictures at a wider angle, which is then analysed and the type of weed detected is returned.

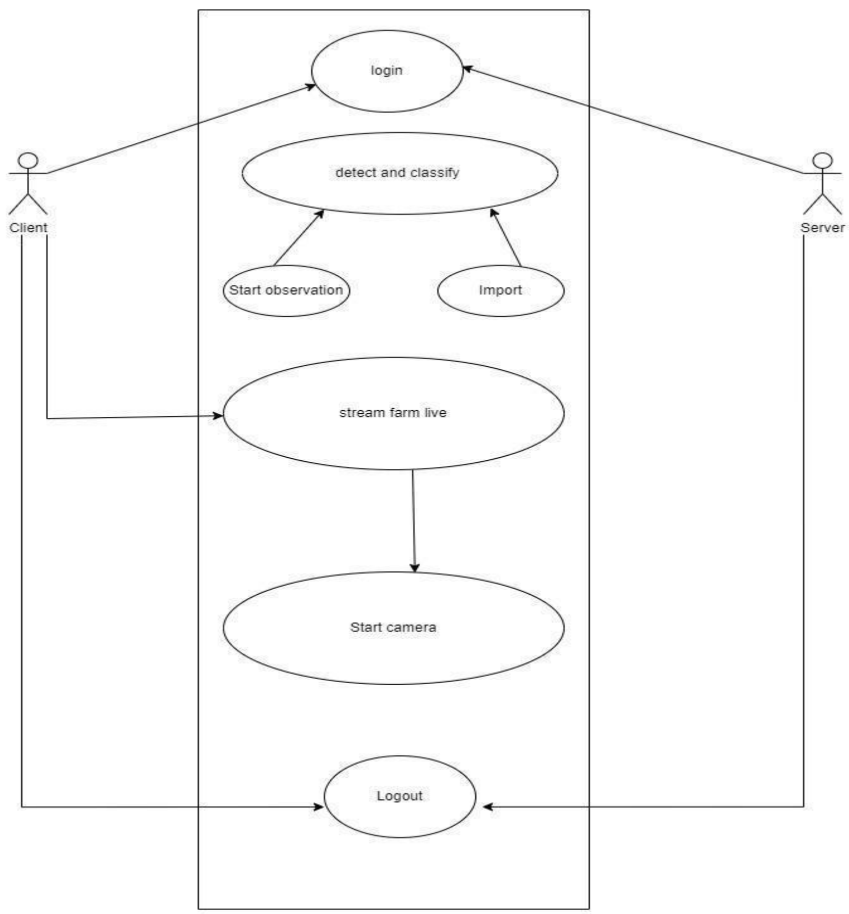


Figure 2: A Flow Chart Diagram showing interaction with the weed master application

4.1.4.2Use case diagram for feedback system(application)

The user logins into the application

A page displaying feedback messages in the form of cards containing both the image taken by the weed detection system(application) and its textual description.

The user can click on which message they want to view

The user can also log out at any time.

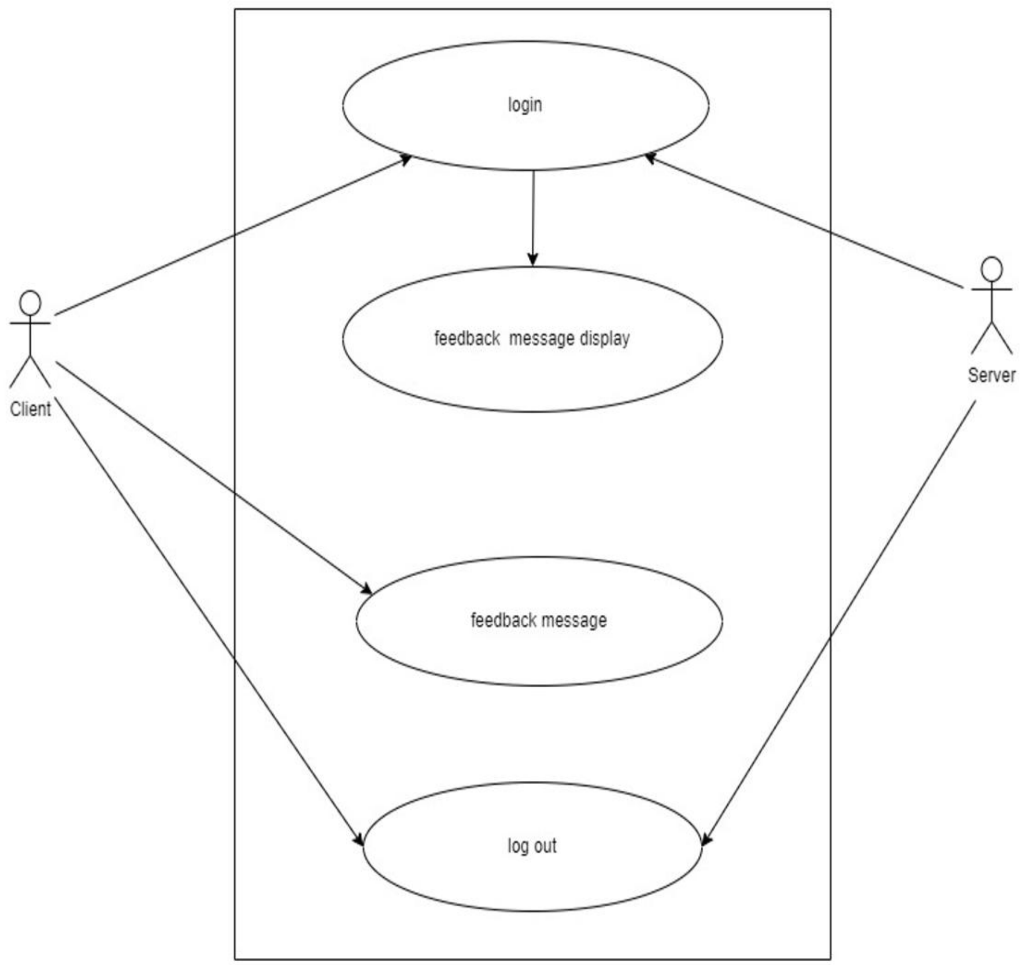


Figure 3: A Flow chart Diagram showing interaction with the weed feedback system.

4.1.5 System building

4.1.5.1 Front End Implementation

For the front end we employed Flutter, a framework made by Google to create beautiful native apps for a range of platforms like web, desktop, Linux, Fuchsia, android and iOS. Flutter is a robust and powerful kit for developing big and scalable software from a single code base and this fits our needs very well.

4.1.5.2 Back End Implementation

For the backend we employed technologies like Node JS and express to build the API that will store the feedback of the weed master application.

4.1.6 How the weed master (weed detection) app works

The mobile app has two main modules under the Menu hood and these include the login page and the home page.

1. LOGIN PAGE

The introductory page of the app, which prompts the user to enter their respective credentials to allow them access their system from wherever they might be most especially remotely.

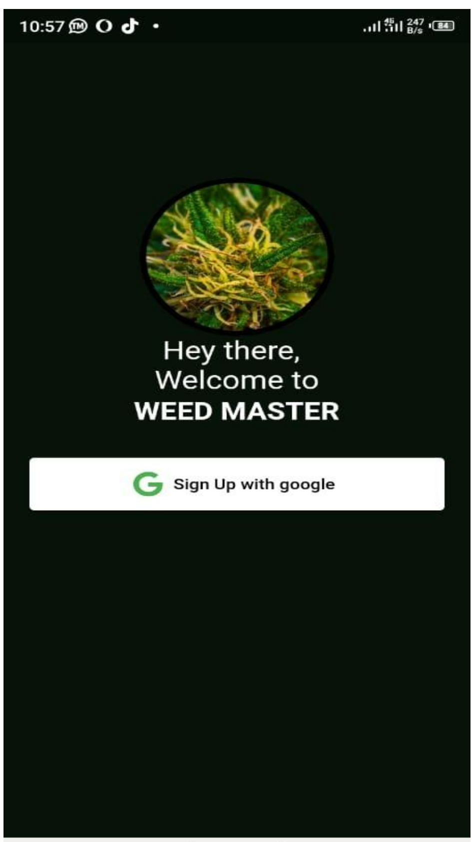


Figure 4: Login page for the weed master application.

2. HOME PAGE.

This is the main face app of the app, it shows the user a welcome message from weed master, app version. It has four sections which include start and import Screens, help, about. A user taps on any of these buttons to inflate the screen with a page

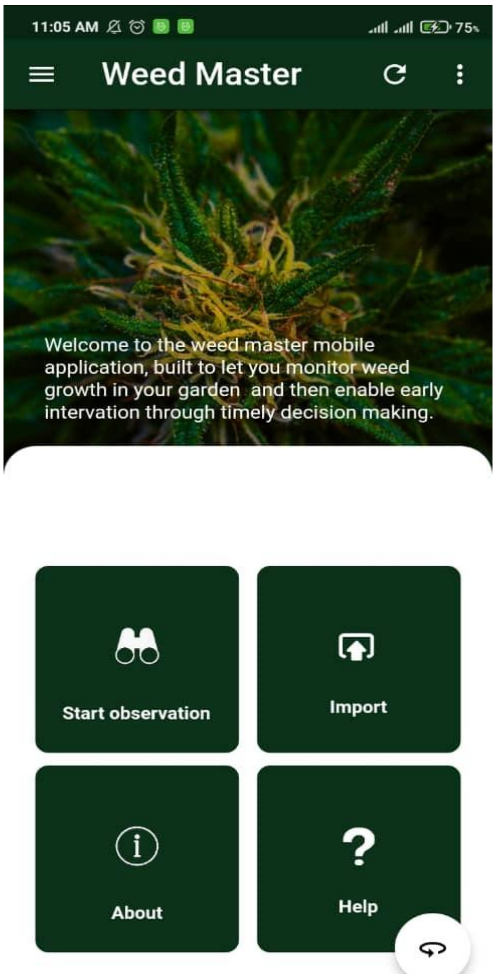


Figure 5: Home page for the weed master application.

i) Start observation

This section allows the user to take a live picture using the phone camera, which is scanned to detect the weed or crop present.

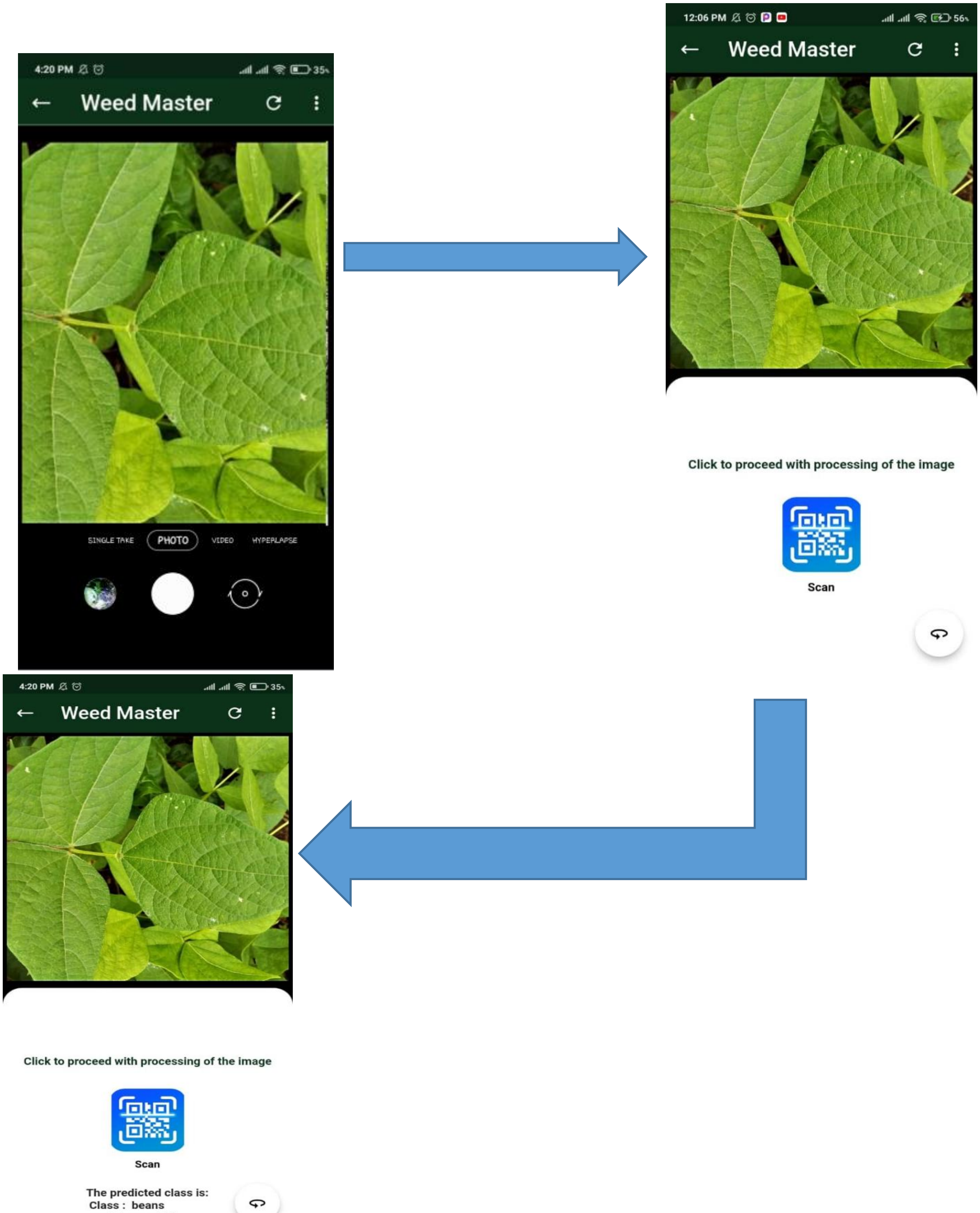


Figure 6: Different Screens for the weed master application navigated to after tapping on the start observation button.

ii) Import

This section allows the user to import pictures that were already taken or already existing on the device and scans (processes) them and then returns the detected weed or crop.

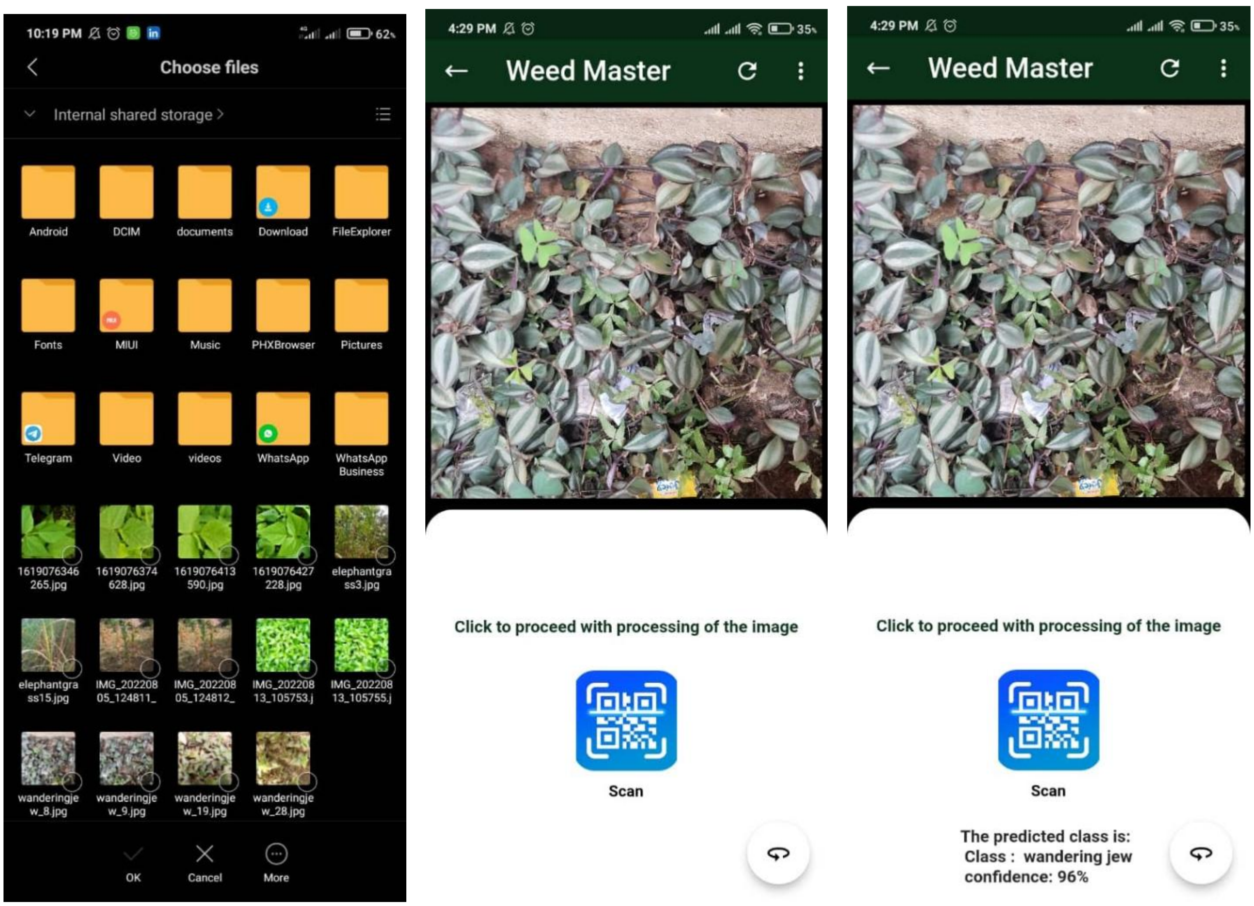


Figure 7: Different Screens for the weed master application navigated to after tapping on the Import button.

iii) Help

This section provides the users with the necessary help on how to effectively use the application in case they encounter any challenge.

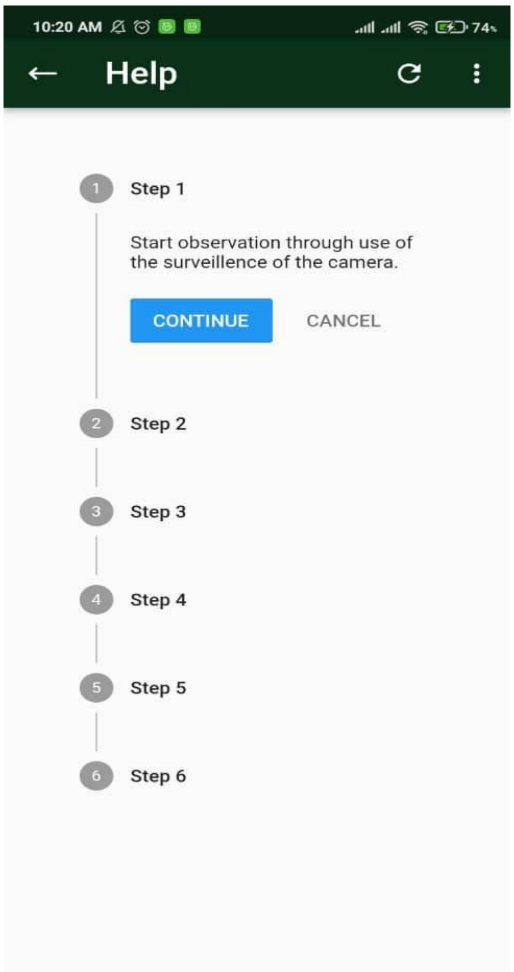


Figure 8: Screen showing how the user can get help on how to use the application.

How the feedback application works

The feedback contains two main pages which include the login page and the home page

1.Login page

This page of the app, prompts the user to enter their respective credentials to allow them access the different messages or feedback sent from the main system, the detection system after detection showing the weeds that have been found in their farms.

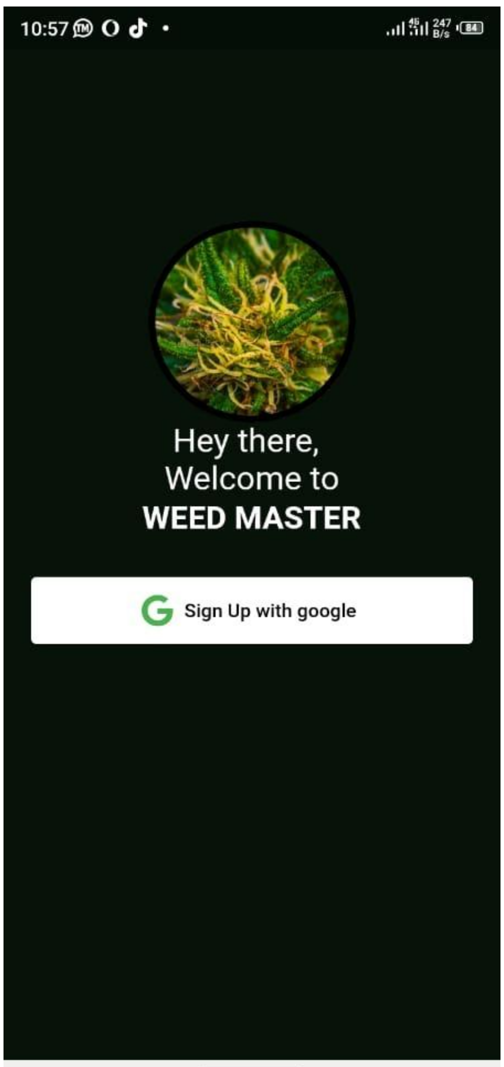


Figure 9: Screen showing the login page for the feedback application.

2.The home page

This section of the application is a display of feedback messages sent from the detection application respective of the time the detection took place, that is to say the latest message which represents the latest detection carried should be the topmost message and historical messages down.

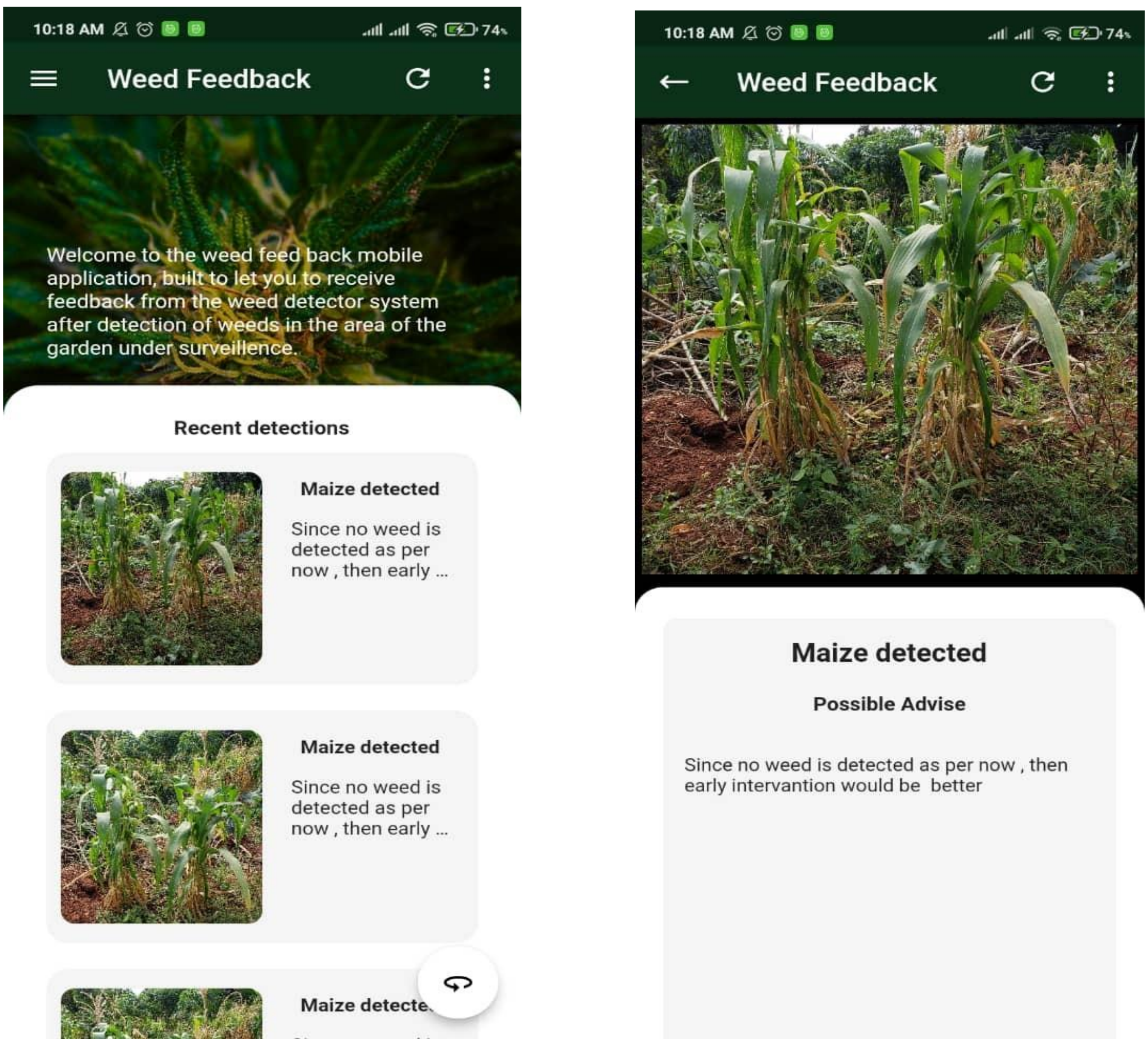


Figure 1: Screens showing different weed or crop detected together with possible advice/recommendations to the farmer.

5.0 RESULTS/FINDINGS

This chapter contains the discussion on how each of our objectives were met and a summary of our results/findings of the system.

5.1 Collecting the data to form a new dataset.

We collected various images of maize, beans, wandering jew and elephant grass from different areas around Makerere University and near Kampala to form the new dataset with four different classes. This was because the available datasets contained images which were not good for the predicted new environment (mixed gardens) on which the model was going to be tested since they contained images of crops with infected leaves which were better for crop disease related problems.

We collected a total of 5769 images to make our new dataset for the classifier which was split into 77% (4432 images) training set and 23% (1337 images) as the validation set. Under the training set, the class of beans contained 1606 images, elephant grass contained 1051 images, maize contained 875 images and wandering jew contained 900 images. The validation set was distributed as follows: beans class contained 600 images, elephant grass contained 332 images, maize contained 200 images and wandering jew contained 205 images.

5.2 Building and training a machine learning model.

When building the model, we uploaded the dataset to the cloud since we had limited resources to train the model on the local machine. The process of training began with launching a google colab notebook and then installing and importing the required libraries such as tensorflow, Numpy and keras. Then the uploaded dataset was linked to the google colab environment.

Then the structure of the different layers of our convolutional neural network model were laid down using the tensorflow and keras high level APIs.

The summary of the model was analysed and it was then complied with a loss function of categorical cross entropy to return its loss during training and an optimizer (ADAM) which makes a new guess for the next iteration basing on the results of the previous iteration together with some evaluation metrics such as accuracy and loss of the model during the training process.

Train data generators and Validation data generators were then made through use of the keras imageDatagenerator which were to help in flowing of the data from the dataset in batches during the training process of the model.

After the model was trained on the dataset by fitting it with the training data generator and then validated on the validation datagenerator for twenty iterations(epochs) with a batch size of 300 and 12 steps per epoch from which the final model was obtained. The training logs were analysed in the form of statistics and then different graphs of training accuracy, training loss, validation accuracy and validation loss were plotted.

The model was then tested on various images while iterating to check on its performance and hyper tuning of parameters which could help in increasing its performance was done accordingly whenever bad results were obtained. The end goal of all this was to come up with an accurate convolutional neural network model.

The model (feature extractor) was then saved as a .h5 file and then converted to lite model using the tensorflow Lite library in order to enable it to run on devices with low Random Access Memory (RAM) such as mobile phones and Raspberry pi.

5.3 Model Evaluation and Testing

After analysing the logs of the training process, the learning curve of the feature extractor (model) was visualised by plotting graphs of training and validation accuracy together with those of training and validation loss.

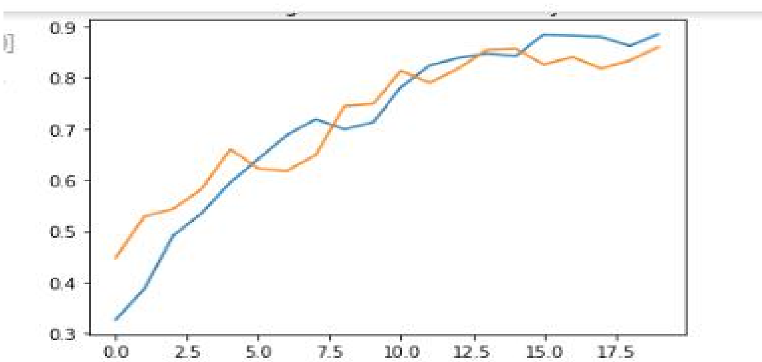


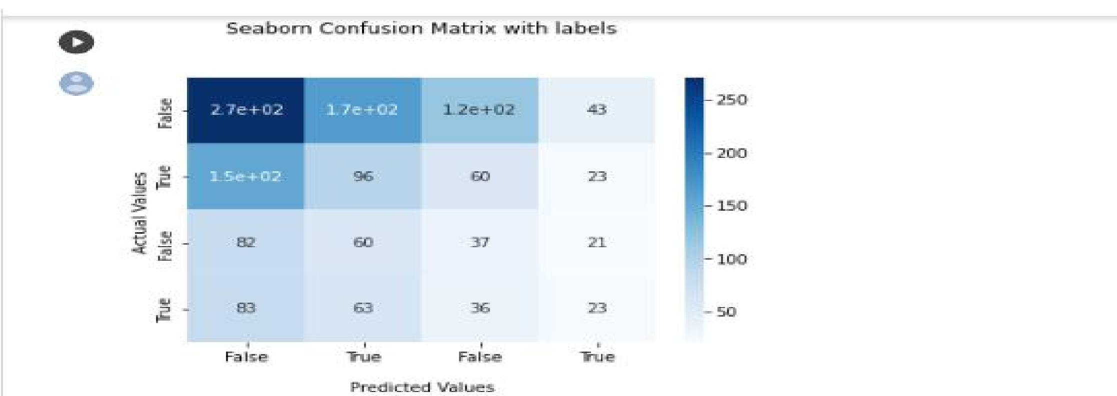
Figure 11: A graph showing training and validation accuracy against number of epochs

The training and validation accuracy graphs clearly depicted that there was a gradual increase in the training and validation accuracy during the training process.

Figure 12: A graph showing training and validation loss against the number of epochs.

The training and validation loss graphs clearly depicted that there was a gradual decrease in the training and validation loss during the training process.

After, the performance of our model was analysed using the F1-score (confusion matrix) table for multi- class metrics from a popular python library called Sklearn metrics which was then visualised using seaborn library by generating different regions of heat maps.



Classification Report

	precision	recall	f1-score	support
beans	0.46	0.45	0.46	600
elephant grass	0.25	0.29	0.27	332
maize	0.15	0.18	0.16	200
wandering jew	0.21	0.11	0.15	205
accuracy			0.32	1337
macro avg	0.27	0.26	0.26	1337
weighted avg	0.32	0.32	0.32	1337

Figure 13: Confusion matrix table showing evaluation of the performance of the feature extractor .

The F1-Score can be obtained using the following formula;

F1-Score = 2*(Precision * Recall) / (Precision + Recall)

Where;

Precision = TP/(TP+FP)

Recall = TP/(TP+FN)

5.4 Discussion of Results

Initially the model's accuracy was low on different test images which we tried to solve by modifying the hyper parameters, for example increasing the Dropout rate for neurons with similar weights to help reduce the level of overfitting and also changed the activation function to Rectified Linear Unit (RELU) in order to drop negative weights during the training process. This helped in improving the performance of the feature extractor.

During testing of different images, a lot of confusion arises between maize and elephant grass images and also between beans and wandering jew to some extent. This could be caused due to the nature of leaves of both plantations but we tried to solve this problem by retaking images of all classes in different angles to reduce the level of confusion.

When the model is tested on images with content outside the scope (maize, elephant grass, wandering jew and beans), it eventually returns one of the above classes basing on the features in the image with an amazing metric of reduced confidence to clearly indicate that the input is indeed a True negative (TN). This is because the model was trained to classify four classes therefore this means that it categorises any input to one of those four classes but with different levels of confidence.

The generated classification report by the confusion matrix table showed that the beans class achieved the highest f1-score because it had the highest support in the dataset.

5.5 TESTING

Testing involved internally checking the implemented system to identify errors and weaknesses and to correct them accordingly.

5.6 Hardware Requirements

Hardware	Minimum System Requirements
Memory	1GB of RAM or higher
Capacity space	8GB

Table 3: Hardware Requirements

5.7 Software Requirements

software	Minimum System Requirements
Android version	5.0 and above
iOS version	12.5

Table 4: Software Requirements

5.8 DISCUSSION

This section is a means of ascertaining whether the system is in fulfilment of the set objectives.

i. The investigation of the inaccessibility of facts and information to target groups was achieved through the use of data collection methods mainly Online Survey questionnaires. Another data collection method was the study of the existing systems. More importantly, it was during the data collection process that user requirements for the system were established.

In order to design a weed master detection and monitoring System, use case and Flow Chart diagrams were used. Use cases helped us examine the type of interaction and the actors involved. The use-case enabled us to identify the individual interactions with the system.

In terms of implementation of the above-mentioned system, many technologies were employed to bring the system requirements and design to life. These included various software and tools; Flutter, VS Code Editor, GitHub, Python TensorFlow, keras, Node JS and express.

Testing and validation of the system involved inputting various images from which results were analysed and hyper tuning of the parameters was done accordingly.

5.8.1 CHALLENGES FACED DURING THE PROCESS OF DEVELOPING THE SYSTEM

Several challenges were faced during the process of gathering the necessary information and these include;

i) High transport costs incurred when collecting information, especially from distant places where good images could be collected.

ii) Inadequacy and insufficient amounts of data because all species of weed we required were not that common to find around.

iii) Limited resources such as good cameras to take photos and computers with limited resources to train model.

iv) Limited time (sessions) to train the AI model effectively on google colab free version, since we did not have that good computing power.

6.0 CONCLUSION

Weed master is a totally free, easy to install, safe, user friendly, efficient, multi featured, reliable and simple mobile application that helps and enables users to monitor and manage their farms easily and efficiently by decreasing on effort and time costs and yet again improving on the rate of yield production.

The aim is to make agriculture the best revenue generating sector in Uganda.

7.0 RECOMMENDATIONS

All public, private institutions and investors in Uganda operating and dealing in products in the agricultural sector, not forgetting local farmers themselves should consider the implementation of weed master application in order to improve on their production and generate more revenue.

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9.0 APPENDIX

This section comprises a time frame and instruments that were used (e.g., Questionnaire, interview schedule etc.).

9.1 PROJECT PLAN

Duration	Activity	Deliverable
3 weeks	Research and validation of solutions	A well-researched proposal after the guidance from agricultural experts.
6 weeks	Collecting data of different crops and various weed species, also carrying out annotation of the data.	Proper identification of features and patterns in the data needed for training the system.
7 weeks	Training, Testing and Validation of the model.	A prototype of the working and polished model.
1 week	Laying out designs of the mobile application.	Low and Hi-fidelity design of the UI of the mobile application.
3 weeks	Mobile application building	A working mobile application.
2 weeks	Inter- connect ability	Notifications from the system to the mobile application.

Table 5: Projects plans

9.2 Questionnaire and interview Guide

While conducting our research, collecting and gathering the necessary information or data we needed to implement our project, as aforementioned we used techniques such as interviews and questionnaires.

Below is a list of guiding interview questions that helped us to successfully conduct the interview

1. What’s your name sir/Madam?

2. What’s your current profession sir/madam?

3. Have you ever involved yourself in any agricultural activity?

4. What’s your personal view about the impact of agriculture on the economy of Uganda?

5. What are the challenges you think the agricultural sector is facing in Uganda?

6. Weed is highly said to be one of the biggest drawbacks of agriculture, specifically crop production, do you agree or disagree?

7. Let’s talk about elephant grass and wandering Jew, ever heard of any of them before?

8. How do you think these two all the other weeds affect farmers and their yields of crops?

9. What are the current common methods used by farmers to get rid of weeds in their farms?

10. Do you think these methods used by the farmers are really effective for their cause?

9. What would be your advice or remedies to farmers to be able to fight these weeds?