2018

Fall armyworm prediction model on the maize crop in Kenya: an internet of things based approach

Shantal M. Ateya
Faculty of Information Technology (FIT)
Strathmore University

Recommended Citation

Musungu, S. A. (2018). *Fall armyworm prediction model on the maize crop in Kenya: an internet of things based approach* (Thesis). Strathmore University. Retrieved from https://su-plus.strathmore.edu/handle/11071/5995

Fall Armyworm Prediction Model on the Maize crop in Kenya: An Internet of Things based Approach

SHANTAL MUSUNGU ATEYA

Submitted in partial fulfilment of the requirements for the Degree of Master of Science in Information Technology at Strathmore University

Faculty of Information Technology
Strathmore University

April 2018

Declaration

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

Student Name: Shantal Musungu Ateya

Signature:……………………………………………

Date: ……………………………………………

Approval

The thesis of Shantal Musungu Ateya was reviewed and approved by the following:

Dr. Joseph Orero (PhD)

Senior Lecturer, Faculty of Information Technology

Strathmore University

Signature:……………………………………………

Date: ……………………………………………

Professor Ruth Kiraka

Dean, School of Graduate Studies

Strathmore University

Abstract

In March 2017, the agricultural sector in Kenya experienced a FAW pest infestation that resulted in the loss of agricultural yields amounting to millions of shillings. The fall armyworm pest caught farmers and agricultural organizations by surprise when it hit most major maize farming regions in Kenya. Currently, both large-scale and small-scale farmers rely on manual observation of the maize crop for detection of the FAW. This comes weeks after the pest has fully matured and began causing damage to crops. The late detection of the FAW in turn results to delays in administering effective pest control measures which forces farmers to incur high costs in administering appropriate control measures. With the ineffectiveness of late manual observations, there is need for an early technology-based solution that will allow farmers to prepare in advance for possible FAW infestations

This study proposes the development of a prediction model of a FAW invasion using Internet of Things and machine learning techniques. We suggest the development of a model that automatically predicts a possible invasion by the FAW based on several factors. The key parameters used in the study will be soil temperature and humidity collected through sensors placed in the maize fields. These factors favour the development of the pupa stage of the FAW which later matures into moths that fly to different fields. Based on the parameters, the model will be able to detect the presence of FAW pupa in the soil and issue early warnings to farmers thus allowing for preparation and appropriate counter measures. The study will provide performance evaluation of the model based on the accuracy of the classification, the precision and recall ratio of the collected parameters. The developed model achieved an accuracy of 82.06%.

Key Words: fall armyworm, machine learning, internet of things, sensors, prediction

Acknowledgement

My heartfelt gratitude goes to my supervisor Dr. Joseph Orero for his continued support, patience and dedication in the course of my study. His guidance and commitment helped me a great deal in achieving the research objectives. I would also like to show appreciation to the rest of the Faculty of Information Technology (FIT) members for their comments and recommendations. My earnest appreciation goes to DAAD for the opportunity and support towards attaining the necessary resources that enabled successful completion of my research study. I thank my colleagues for their support and enlightenment in the course of my research and the farmers in the affected regions who provided feedback that guided my study. I must express my gratitude to my family for their support and encouragement throughout my study.

Acronyms and Abbreviations

ANN- Artificial Neural Networks

FAW- Fall Armyworm

FPN – Forward propagation Neural Network

IoT- Internet of Things

KALRO- Kenya Agricultural and Livestock Research Organisation

KPHIS- Kenya Plant Health Inspectorate Service

NBC- Naïve Bayes Classification

SVM –Support Vector Machine

WSN- Wireless Sensor Network

Table of Contents

Declaration i

Abstract ii

Acknowledgement iii

Acronyms and Abbreviations iv

List of Figures viii

List of Equations ix

List of Tables x

Chapter 1 : Introduction 1

- 1.1 Background to the Study 1
- 1.2 Problem Statement 2
- 1.3 Objectives 3
- 1.4 Research Questions 4
- 1.5 Justification 4
- 1.6 Scope and Limitations 4

Chapter 2 : Literature Review 5

- 2.1 Introduction 5
- 2.2 Agriculture in Kenya 5
  - 2.2.1 Maize Farming in Kenya 5
- 2.3 Pests Affecting Maize Farming in Kenya 7
  - 2.3.1 Fall Armyworm Invasion in Kenya 7
  - 2.3.2 The Fall Armyworm Pest 8
- 2.4 Current Techniques used in the Identification of Crop Pests 12
  - 2.4.1 Manual Crop Examination 12
  - 2.4.2 Pheromone Traps 13
  - 2.4.3 Automatic Pest Detection 13
  - 2.4.4 Mobile Applications 14
- 2.5 Internet of Things (IoT) in Agriculture 15
- 2.6 Machine Learning in Agriculture 16
  - 2.6.1 Artificial Neural Networks (ANN) 17
  - 2.6.2 Support Vector Machine (SVM) 18
  - 2.6.3 Naïve Bayes Algorithm 20
- 2.7 Related Work 21
  - 2.7.1 A Cognitive Vision Approach to Early Pest Detection in Greenhouse Crops 21

2.7.2 Real-Time Monitoring Model for Early Detection of Crop Diseases 23
2.7.3 Pest detection and control techniques using wireless sensor network: A review 23
2.7.4 Vision-Based Model for maize leaf disease identification: a case study in Nyeri County .. 24
2.8 Conceptual Framework 25
Chapter 3 : Research Methodology 26
3.1 Introduction 26
3.2 Research Design 26
3.3 Data Collection 26
3.3.1 Secondary Data 26
3.3.2 Primary Data 27
3.4 Instruments of Data Collection 27
3.4.1 Questionnaires 27
3.4.2 Structured Interviews 27
3.5 Target Population and Sampling 28
3.6 Model Training 28
3.6.2 Modelling Accuracy 28
3.6.2 Model Testing and Validation 29
3.7 System Development Methodology 30
3.8 Ethical Considerations 31
Chapter 4 : System Design and Architecture 32
4.1 Introduction 32
4.2 Requirements Analysis 32
4.2.1 Functional Requirements 32
4.2.2 Non-Functional Requirements 33
4.3 System Architecture 34
4.4 System Behavioural Modelling 35
4.4.1 Use Case Narration 35
4.4.2 Use Case Diagram 40
4.4.3 Sequence Diagram 41
4.5 Process Modelling 42
4.5.1 Context Diagram 42
4.5.2 Level 1 Data Flow Diagram 43
4.6 Partial Domain Model 44
Chapter 5 : System Implementation and Testing 46

5.1 Introduction 46
5.2 Components of the Prediction Model 46
5.2.1 IoT System Components 46
5.2.2 ANN Model 47
5.2.3 Server Side Application 48
5.3 Implementation of the FAW Prediction Model 48
5.3.1 Capturing of Data by Sensors 48
5.3.2 Storing Sensor Parameters 53
5.3.3 Storing Observable Characteristics 54
5.3.4 Storing User Details 55
5.3.5 ANN Implementation and Modelling 55
5.3.6 SMS Notification and Recommendation 56
5.4 Model Training 57
5.5 Model Testing 58
Chapter 6 : Discussions 59
6.1 Introduction 59
6.2 Results of the Study 60
6.3 Prediction Confidence 60
6.4 Validation of the Model 61
6.4.1 Confusion Matrix 61
6.5 Validity of the Proposed Solution 62
6.7 Research shortfalls 63
Chapter 7 : Conclusion and Recommendations 64
7.1 Conclusions 64
7.2 Recommendations 65
7.3 Future Work 66
References 67
Appendix 73
Appendix 1: Originality Report 73
Appendix 2: Interview Guides 74
Appendix 3: Interview Feedback 75
Appendix 4: Artificial Neural Network Code 77
Appendix 5: Support Vector Machine Code 78
Appendix 6: Sample Training & Testing Data 79

List of Figures

Figure 2-1: Fall Armyworm Lifecycle 9
Figure 2-2: FAW Damaged Leaf 11
Figure 2-3: IoT Agricultural Expert System........ 16
Figure 2-4: ANN Structure 18
Figure 2-5: Support Vectore Machine........ 19
Figure 2-6: Wireless Sensor Network Model 24
Figure 2-7: Conceptual Diagram........ 25
Figure 3-1: RAD Development Methodology 30
Figure 4-1: System Architecture 35
Figure 4-2: Use Case Diagram........ 40
Figure 4-3: Sequence Diagram 42
Figure 4-4: Context Diagram 43
Figure 4-5: Level 1 DFD Diagram........ 44
Figure 4-6: Partial Domain Model 45
Figure 5-1: DHT11 Module........ 47
Figure 5-2: ESP32 Module 47
Figure 5-3: ESP32 & DHT11 Set-up 49
Figure 5-4: DHT11 Deployment in Soil........ 49
Figure 5-5: DHT11 Sample Temperature & Humidity Readings 50
Figure 5-6: Soil Parameters in Local-Host........ 53
Figure 5-7: Real-Time Temperature & Humidity Readings 54
Figure 5-8: SMS Notification & Recommendation 57
Figure 6-1: ANN Confusion Matrix........ 61
Figure 6-2: SVM Confusion Matrix........ 62

List of Equations

Equation 2:1: Naives Bayes Algorithm........20
Equation 3:1: Accuracy Formula........29
Equation 3:2: Precision Formula........29
Equation 3:3: Recall Formula........29

List of Tables

Table 5-1: Observable Characteristics in the Environment..55
Table 5-2: Model Test Cases 58

Chapter 1 : Introduction

1.1 Background to the Study

Agriculture in Kenya is known to be the primary economic activity of farmers who also depend on the same for their livelihood. Maize farming in Kenya faces both biotic and abiotic challenges that greatly affect productivity. In biotic, maize farming is greatly affected by diseases such as leaf blzight and downy mildew and pests such as the arm-worms and stem borers. Productivity of the crop is also held back by minimal resources and management by farmers at all levels (Rutkoski et al., 2012).

Pests and diseases which are considered a common challenge cause a lot of losses to both large-scale and small-scale farmers (Smith, 2015). A majority of small-scale farmers in Africa lack knowledge, information and training on early preparedness, avoiding and control of pests and diseases. Over the years, farmers in Kenya have become well versed with specific kinds of pests and diseases thus developing preventive mechanisms through use of pesticides, use of good quality seeds and intercropping. With every situation, farmers are forced to adapt to the new crop threats.

The most recent case of pest attacks on maize in Kenya is that of the invasion of fall army worms (FAW) in April 2017. The regions most affected by the invasion were Rift Valley and Western Kenya which later spread to other regions such as Nyanza, Central and Coast. This was the first time the armyworm pest had been detected in Kenya thus catching farmers and the entomologists by surprise. Other sub-Saharan countries faced with the armyworm infestation such as Zambia, Malawi and Zimbabwe have lost approximately 90,000 hectares, 17,000 hectares and 130,000 hectares of crop respectively (Jones & Thornton, 2013). During the attack, Kenya lost approximately 15,000 hectares of maize that can be valued at kshs. 1.3 billion (Craig, 2017). The significant losses from the FAW armyworm resulted from unpreparedness by the farmers, entomologists and the ministry of agriculture. Farmers in Kenya are only versed with the common pests and diseases in Kenya which made it difficult to respond to the new FAW pest (Jones & Thornton, 2013).

Farmers in Kenya rely on human visual examination in detecting pests and diseases which gives room for errors and inaccurate information. Regardless of the new technologies and studies conducted on automatic detection, farmers tend to notice attacks by pests and diseases at a later stage after most of the crops have been damaged. Following the recent situation, the Kenya Agricultural institutions together with the farmers are forced to embrace the new threat while devising appropriate control measures and solutions to their current dilemma (Smith, 2015).

This dissertation introduces an early detection and warning model of the FAW pest that will allow pre-preparedness by farmers and agricultural institutions. Automatic detection and early prediction techniques are common in agriculture due to their level of accuracy and speed and are known to have been successful in their implementations. The development of the model will involve the use of soil parameters that are temperature and humidity together wiin determining the presence of FAW pupa in the soil. The model will scout for possible existence of the FAW pest in the course of the crop stages using IoT technologies and machine learning techniques with the aim of providing an early warning to the farmers and concerned institutions.

1.2 Problem Statement

Early 2017 saw Kenyan maize farmers in various parts of the country experience the fall armyworm invasion for the first time. Away from maize, the armyworm can destroy a wide range of crops such as millet, sorghum, cabbages, wheat, onion and bananas resulting in massive losses of yields. It is evident that there is limited knowledge or no preparedness by farmers towards the FAW pest invasion which resulted to destruction of the maize crop in many parts of the country and consequently low yields. Farmers are forced to use already existing pesticides and control measures that do not match the FAW while taking up other expensive control measures. While the experts are yet to get long-term solutions to this menace, the country is currently relying on pesticides and research programs worth millions of shillings which are unaffordable to most and costly to the government. Currently, there are no effective technological advancements for detecting the FAW. Unless such technological approaches are implemented to fight possible invasion, there will be national food insecurity as well as loss of income to farmers.

1.3 Objectives

General Objective

This research aims at developing an early detection and warning model for FAW pest infestation and thereby providing an early warning and recommendation to farmers and agricultural institutions in Kenya.

Specific Objectives

i. To investigate the challenges farmers face in controlling fall armyworm pest infestation,

ii. To investigate the problems associated with the existing methods of maize-crop pest detection,

iii. To review the existing models, applications and machine learning techniques for crop pest detection,

iv. To develop a prediction model to determine a possible FAW invasion,

v. To validate the prediction model,

1.4 Research Questions

i. What challenges do farmers face in controlling FAW pest infestation?
ii. What problems are associated with existing methods of pest detection?
iii. What are the existing models, applications and machine learning techniques for crop pest detection and prediction?
iv. How will the prediction model be designed?
v. How will the prediction model be validated?

1.5 Justification

This study is beneficial to all farmers both large-scale and small-scale and the existing agricultural institutions in Kenya. Statistics show that Africa has been affected by the armyworm invasion resulting to massive loss of crop yields in hectares. Now that the FAW has found its way in Kenya, it is here to stay hence the need for appropriate control measures by farmers. The result of this research will result in the early detection and prediction of FAW occurrences and consequently provide early warnings to farmers and affected institutions. With this information, farmers will improve their preparedness levels and deploy effective control measures for the pest (Kim & Yoo, 2014).

1.6 Scope and Limitations

This study is limited to predicting FAW's possible infestation on the maize crop in Kenya. Other crops that are otherwise affected by the same pest are not considered in this study. The study will adopt IoT technologies in identifying FAW presence in the environment and an artificial neural network (ANN) algorithm in building the prediction model.

Chapter 2 : Literature Review

2.1 Introduction

This chapter reviews the relevant literature in the fall armyworm pest invasion to further comprehend and investigate the research problem. The recent fall armyworm invasion in Kenya and Africa including control measures adapted is reviewed. The chapter also reviews the different machine learning algorithms and their application in detection of pests and diseases in agriculture. There is also a conceptual framework of the proposed model.

2.2 Agriculture in Kenya

The agricultural sector plays an important role in the Kenyan economy. Approximately two-thirds of the Kenyan population relies on crop cultivation and rearing of livestock for their survival and livestock. According to AGRA (2016), agriculture accounts for approximately 20-25% of the country's gross domestic product (GDP). Additionally, agriculture contributes 65% to Kenya's overall exports hence the conclusion that the growth of the country's economy is highly reliant on development in agriculture (AGRA, 2016). While Kenya may rely heavily on agriculture, farmers countrywide both large scale and small scale face a number of challenges that impede the production of the crop. The country experiences a variation in climate change with farmers relying on rain-fed agriculture thus affecting planning activities and productivity. Other challenges include extension services which entail availability of knowledge, technology and resources to farmers with regard to successive farming, and pests and diseases. Poor infrastructure throughout the country also affects the transportation of farm products (Sarfo & Jayne, 2016).

2.2.1 Maize Farming in Kenya

In Kenya, maize is the single most widely grown crop following its adaptability to a range of climatic conditions. Both large-scale and small-scale maize farmers depend on the crop for income generation. The chief growing areas however include Trans Nzoia, Uasin Gishu, Bungoma and Nakuru. Other parts of the country like Western region and Nyanza have maize being grown alongside other crops such as beans and potatoes. The crop is planted at the onset of the rainy season and harvested in the dry season to avoid grain rotting incidents (Rutkoski et al, 2012).

The most common problem affecting maize farming in Kenya is the attack by pests and diseases which tend to affected survival of young plants or general yields for mature plants. While maize is attacked by a wide range of pests and diseases, there exist major or regular pests or diseases. These tend to affect the different parts of the maize plant at different stages of growth. The different stages of the maize crop affected by pests and diseases include emergence stage, vegetative stage, silking or tasselling stage and the grain fill stage. The vegetative stage pests such as locusts, armyworms, and white-grubs are the most destructive. Maize farmers with the help of Kenya Plant Health Inspectorate Service (KPHIS) and (KALRO) have developed control measures that have enabled the survival of the maize crop and continuous yields over the years. Farmers have commonly adapted the use of pesticides and inter-cropping in fighting the pests and diseases epidemic on the maize crop which has been successful over the years (Smith, 2015).

In Kenya, approximately 40 percent of farmers; both large scale and small scale lose their crop yields to pests and diseases resulting in a negative impact on food availability and security. Most farmers discover pest and disease infestations too late like in the recent army worm invasion resulting in massive losses and use of inappropriate control measures. Inadequate knowledge by farmers and the government in dealing with the pest resulted in the use of inappropriate pesticides that incurred huge cost in an effort to contain the pest (Jones & Thornton, 2013).

2.3 Pests Affecting Maize Farming in Kenya

Maize farming in Kenya faces attacks from a variety of insects and pests with few of them being considered a menace to the crop. Pests are known to attack the maize crop during the different stages of growth including the post-harvest stage resulting in different forms of damage. The most common pests known to Kenya's maize farming include cutworms, locusts, African armyworms, weevils and stem borers. The pests known to affect the maize crop have different characteristics and environmental adaptability which make them unique with regards to management practices. Additionally, the pests are known to exist either in the soil or the crop itself while others are known for moving from one location to another. For this reasons, farmers together with agricultural institutions have to develop unique pest management techniques to each insect. Over the years, farmers have however devised solutions that help prevent excessive damage of crops by the pests. Today, farmers are acquiring knowledge on appropriate pest control and management. They also rely on pest control through the use of pesticides that are readily available in the market, inter-cropping of different crops in the fields and planting of pest-resistant crop breeds (Njuguna, Njau & Thuita, 2017).

2.3.1 Fall Armyworm Invasion in Kenya

Also known as ***Spodoptera Frugiperda***, the fall armyworms were detected in Kenya or the first time and no one was prepared for this. Unlike the African armyworm, the fall armyworm has a voracious appetite that enables it to feed on approximately 80 varieties of crops. The pest destroys the leaves of plants leaving it unproductive and stunted hence the massive loss. The pest was first identified in March 2017 in Western Kenya and went on to spread to other parts of the country (Smith, 2015). The regions most affected by the invasion were Rift Valley and Western Kenya which later spread to other regions such as Nyanza, Central and Coast. This is the first time the armyworm pest has been detected in Kenya thus catching farmers and the entomologists by surprise. Other countries faced with the armyworm infestation such as Zambia, Malawi and Zimbabwe have lost approximately 90,000 hectares, 17,000 hectares and 130,000 hectares of crop respectively. From the assessment by researchers, Kenya has lost approximately 15,000 hectares of maize that can be valued at kshs. 1.3 billion (Craig, 2017). The country like its counterparts Uganda and Tanzania ended up allocating approximately $7.85 million for purchasing chemicals that can fight the fall armyworm. The pest is known to be resistant to existing control measures such as chemicals and pesticides hence the need for more permanent long-term solutions.

2.3.2 The Fall Armyworm Pest

This is a pest that causes damage to approximately eighty (80) crop species preferably grassy plants such as maize, sorghum, millet, rice, sugarcane and wheat. It previously originated from Southern and Central America and is known to have recently hit west and sub-Saharan Africa. In the year 2016, the fall armyworm found its way to east Africa beginning in Tanzania and later saw its way to Kenya in March 2017. The pest is notoriously mobile and seems to move in armies hence the name “armyworm”. The fall armyworm is also known to quickly develop resistance to synthetic pesticides thus increasing the vulnerability of affected regions (Charleston, 2013).

2.3.2.1 Life cycle of the fall armyworm

a. Eggs- The fall armyworm lays up to 2000 eggs in a span of four days usually on immature maize plants. Eggs are deposited in layers and attached to foliage. Eggs hatch within 3 to 5 days.

b. Larvae- At this stage, the larvae feed for approximately 2 to 3 weeks. In the first six (6) days after hatching, the young caterpillars superficially feed on undersides of leaves resulting in semi-transparent patches. The next stage of 6-14 days is where the fall armyworm does much damage to the maize plant. After maturity, they drop to the ground to pupate. They feed on leaf margins of the maize crop leaving behind the tough leaf midribs and the stalk.

c. Pupa- this stage of the armyworm takes place in the soil for approximately 9 to 13 days resulting in the emergence of adults. They caterpillars usually burrow 2 to 8 cm into the soil.

d. Adult- this takes 8 to 9 days resulting in an adult moth that moves to a different region to restart their life cycle (Flanders, Ball & Cobb, 2017).

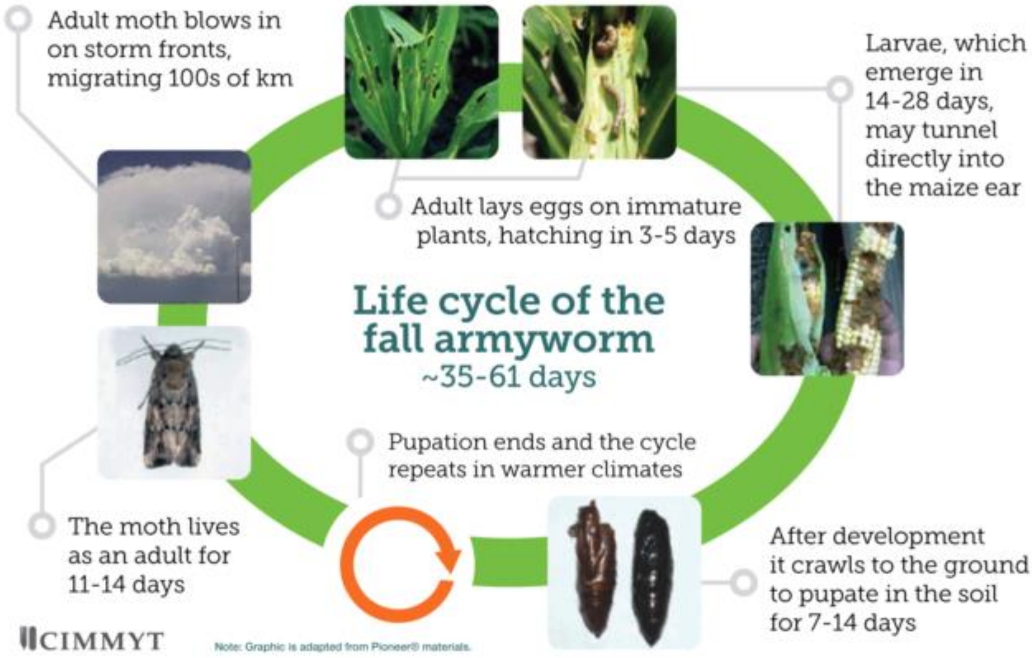


Figure 2-1: Fall Armyworm Lifecycle

(Chinwada, 2016)

Figure 2-1 above is a representation of the FAW’s lifecycle. The detection of the FAW presence in the field can be done at the all stages of the pest depending on the methodology employed.

2.3.2.2 Factors Supporting Breeding of the Fall Armyworm

They occur in large numbers in situations where heavy rainfall follows a persistent dry season or in cold, wet springs. They tend to take shelter in the soil or throats of plants during the day and emerge to feed after sunset thus making it impossible to identify them. Invasion of fall armyworms occur after cool wet seasons. The pest tends to survive in any temperatures above 10^0 C or warm climates. The laying of eggs is associated with very heavy rainfalls hence early detection should begin at this stage towards the end of the rainfall season (Charleston, 2013). The fall armyworm is flies approximately hundred (100) kilometred a day thus allowing it to migrate by prevailing winds over larger distances. In Africa, the drought that came in late 2016 and early 2017 followed by heavy rainfall created a perfect condition for the breeding of the armyworms. Wet or moist seasons allow the larvae or caterpillar to grow into moths which thereafter fly to reproduce in other regions (Flanders, Ball & Cobb, 2017).

2.3.2.3 Visible Characteristics

FAWs have a distinct white inverted ‘Y’ at the front of the head. They are also brown with distinct yellow stripes on their bodies. The FAW also has the ability to reproduce and spread quickly. The adult moths are grey in colour with a white dot at the centre of each front wing and dark margins on the hind wings. The visible characteristics distinguish them from the other moth species thus aiding an ease of identification The most common signs of damage by the armyworm include chewed leaves and faecal pallets at the base of plants as shown in figure 2-2. After development of the larvae, the armyworm at this stage hides in whorls of the plant thus making it difficult to detect or control (Hendrik & Bertone, 2016).

2.3.2.4 Damages

Any damage by fall armyworms leaves behind ragged-edged holes on tassels and plants. The fall armyworms feed on foliage of maize plants. Fall armyworms attack crops that are three to four weeks old resulting in an early destruction. An attack on the maize plant at this early vegetative state results to 100 percent loss unless control measures are taken. The caterpillar or larvae stage is the most destructive since they feed on the reproductive parts of leaves or plants. With this kind of destruction, the young plants fail to survive while slightly mature plants tend to experience reduced yields (Capinera & Smith, 2015).

FAW: signs of infestation at a later stage

Fall armyworm damage to young maize plants. D Visser ARC-VOP Roodeplaat

Fall armyworm infestations often are only noted at a later stage, when large holes, accompanied by larval droppings (excrement), are noticed in the whorls and on surrounding leaves. When dry, the excrement takes on a very characteristic appearance, that of sawdust. The caterpillars usually hide deep in the whorl while the excrement they produce serves as a protective barrier which also helps to camouflage them from predators from above.

Figure 2-2: FAW Damaged Leaf

(Chinwada, 2016)

2.3.2.5 Control Measures

Several measures have been put in place by different regions to control the invasion of armyworms. Such include use of host plant resistance, use of pesticides, inter-cropping with legumes, use of diverse farming systems and genetic engineering whereby stronger hybrids are planted instead of the usual maize seeds. With such control measures, the infestations by armyworms have reduced by approximately 20 to 30 percent, especially for intercropping. Farmers in the United States have resorted to pheromone traps and backlight sampling since they are adaptable to regional changes (Capinera & Smith, 2015). This method signals the presence of moths in the area thus allowing farmers time to get other control measures such as insecticides. While treatment by a variety of pesticides is possible, early warning is the most preferable. Early detection and warnings of a possible fall armyworm invasion will allow farmers to adopt different approaches to farming or engage in early preparations that will not otherwise be affected by such. In early detection and warning, the most appropriate stage for stopping them is when larvae are still small and still underneath the leaves or the period before the eggs hatch (Charleston, 2013).

2.4 Current Techniques used in the Identification of Crop Pests

Various techniques have been applied in the identification of different crop pests. This is wholly dependent on the type of crop being affected, type of farming (large-scale or small-scale) and resources available for detection.

2.4.1 Manual Crop Examination

The most common and traditional method of pest detection and identification is through naked eye examination which entails searching the fields for leaf damages or using traps. While this may be effective in a number of ways, manual examination becomes difficult in large fields. Manual examination also happened at a later stage in the crop lifecycle that is after the damage by crop pests has been done and it is quite visible to the farmer. The late detection of pests by farmers results in delayed adaption of appropriate control measures which negatively affect crop yields. Other manual techniques for pest analysis include sticky traps and black light traps that are set out in the fields by farmers. Manual examination also calls for human experts in crop pests which turn out to be time-consuming and expensive to farmers. With such complications, there is need for automatic systems that use different technologies to examine crops and detect pest infestations (Shi, Wang & Zhang, 2015).

2.4.2 Pheromone Traps

These are used to the presence of pests in the environment. The problem with pheromone traps is they fail to determine the damage levels by pests. The traps are suited for capturing moths such as the FAW worm moths that begin the lifecycle by moving to new regions and laying eggs. In trapping FAWs, pheromone traps should be placed in the fields during the moist or rainy season and in the night since the pests are nocturnal. The trap attracts and traps male pests that are attracted to the sex pheromone. Once trapped, the pests can be collected for observation and analysis thus managing the monitoring and control of pest infestations (Popa, 2011).

2.4.3 Automatic Pest Detection

Over the years, agricultural research institutes together with technology experts have designed computer vision techniques that make use of images of crops in analysing and identifying pests or diseases (Martin & Moisan, 2014). Most common pest detection and identification technologies include real-time data monitoring and image-processing techniques which makes use of image processing techniques that capture pests and classify them based on set out algorithms and features (Rajan, & Radhakrishnan, 2016). Digital image-processing techniques have been applied extensively in agriculture especially in the crop pests and diseases management. This allows images to be captured by cameras and processed using image processing techniques that allow detection of pests. The common technique accompanying image processing is the use of SVM (Support Vector Machine) classifier which is used for the classification of pests based on the features (Prakash, Shreekant & Mayur, 2015),

2.4.4 Mobile Applications

There exist several mobile apps that help farmers identify diseases and pests and provide recommendations on the most suitable solutions. Most of these mobile apps are made available for free by the government or agricultural institutions to aid farmers in the fight against the pest and diseases menace of crops. The mobile apps provide tailor-made and independent information on pest detection as well as triggers, symptoms and preventive measures that guide the decision making of most farmers. ‘Plantix’, a plant damage diagnostic app that was developed by PEAT is a good example. The app assists farmers by recognizing pests, plants diseases and other form of damages by sending photos. The app also provides an immediate diagnosis of the disease of pest and recommends possible solutions. In the United States, ‘the Citrus Pests Key’ app is designed to aid farmers in the identification of various pests based on their visible features and damages. The ‘Plantix’ app also provides early warning signs and predictions of crop yields and failures based on weather forecasts and processed data (Manoja & Rajalakshmi, 2014).

In February 2018, an app “uLima” was launched in Nairobi to help provided information to farmers in different locations across the world. The mobile applications allow farmers to sort out best farming practices that would otherwise solve their farming challenges (Ocharo, Mutai, & Sayagie, 2018). The “m-Farm” app; a familiar technology amongst the Kenyan farmers helps my matching local buyers with local farmers in the country. The app also allows users to view price trends thus matching the beneficiaries. Kenya in particular is moving towards smart farming with the government and stakeholders aiming towards a wide audience of farmers. In the next few years; it is possible to say that even the non tech savvy farmers will have a working knowledge on how to interact and benefit from the apps (Ocharo, Mutai, & Sayagie, 2018).

2.5 Internet of Things (IoT) in Agriculture

IoT has managed to transform the agricultural industry worldwide by enabling farmers deal with the ever-rising challenges in farming. The development of IoT applications have managed to address challenges associated with cost-effectiveness, productivity and decision-making at all levels. The new IoT technologies in farming have been made available to both large-scale and small-scale farmers worldwide. Today, farmers have turned to IoT in promoting farming practices and decision making. With the help of sensors, different parameters such as temperature and humidity can be measured thus enabling accurate and timely communication to key stakeholders. The technology has paved way for productive means of cultivation and animal rearing through the use of cheap and ready-to-install sensors. Recently, IoT has been implemented in the control of pests and diseases while improving crop yields. In pest control, sensors are used to monitor the behaviour and movement of pests while analysing environmental parameters thus providing information that guides the application of appropriate control measures (Kulalvaimozhi, Germanus, & Peter, 2017).

The figure 2-3 below illustrates a sample IoT based expert system implemented to use real-time data from the environment gathered through sensors. Based on the requirements of the system, the served processes the uploaded data and sends out recommendations to the farmers via cell phones (Shekhar, Dagur & Mishra, 2016).

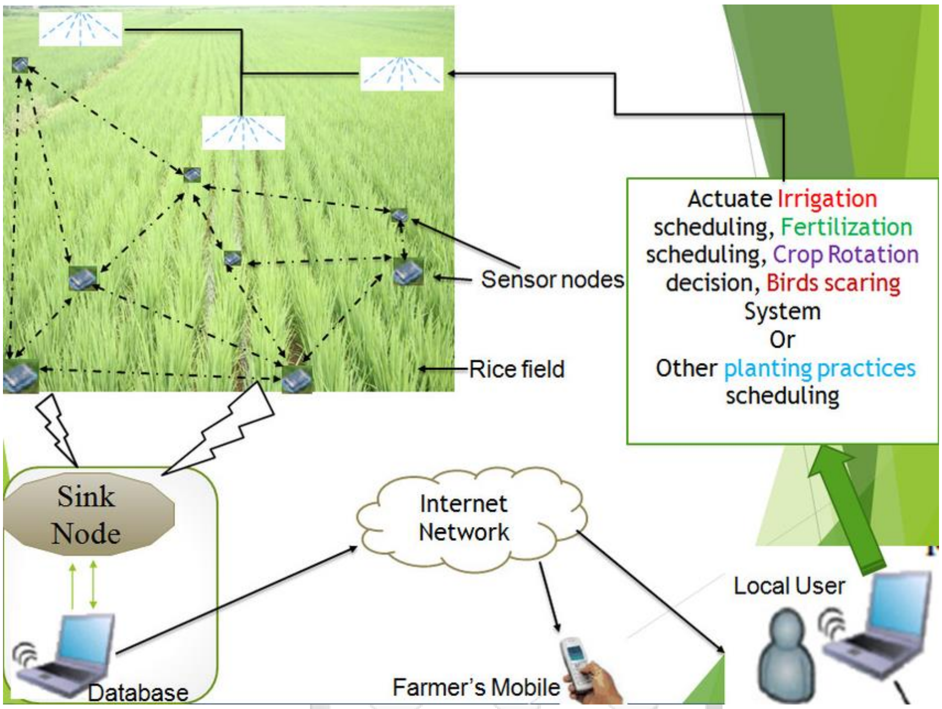


Figure 2-3: IoT Agricultural Expert System

(Shekhar, Dagur & Mishra, 2016).

2.6 Machine Learning in Agriculture

Agricultural activities continue to face major challenges that tend to affect the level of productivity and yields. Despite this, countries continue to work towards meeting the high demand of production which is essential for survival. With the emergence of Artificial Intelligence, the world of agriculture has learnt to embrace this as a solution to many of its challenges and not interruption to the already existing agricultural practices. Applications are being developed for agriculture and this is proving to be effective. Artificial intelligence has enabled the development of expert systems that have support decision making in agriculture based on existing information (Popa, 2011). There has been the use of sensors in collecting and transmitting data on environmental factors such as humidity, temperature and soil properties which are essential in detection of diseases and pests as well as farming techniques to me adopted. Intelligent agents in agriculture have been built to enhance farming activities such as weeding, milking and monitoring the fields. As time goes by, there is proof that Artificial Intelligence continues to be integrated into agriculture and the results are positive (Karandeep, 2016). Countries today are using artificial Intelligence to control attacks by pests and diseases on both plants and animals, determining the appropriate time to weed and apply manure. AI technologies being developed today in agriculture are designed to improve farm produce while reducing costs of farming at all levels. As the trend of adoption and development of artificial intelligence technologies in agriculture continues to rise, there is hope that more agricultural challenges will be solved with time (Gardner, 2010).

2.6.1 Artificial Neural Networks (ANN)

The ANN algorithm is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. ANN has self-learning capabilities that enable it produce better results as more data becomes available. An ANN initially goes through a training phase where it learns to recognize patterns in data whether visually, aurally, or textually. During this supervised phase, the network compares its actual output produced with what it was meant to produce i.e. the desired output. During the training and supervisory stage, the ANN is taught what to look for and what its output should be using the information flowing in the structure (Dey, Bhoumik & Dey, 2016).

ANNs have three interconnected layers with the first layer being the inputs, the second layer and the third layer which is the output. It comprises of nodes that receive a series of entries (X_1,X_2,X_3, ..., X_n) that produce an output (Y). The nodes are interconnected with a weight (W_1,W_2,W_3,...,W_n) which is adjusted until a desired output for the training data set is achieved. Figure 2-4 below illustrates the structure of a NN;

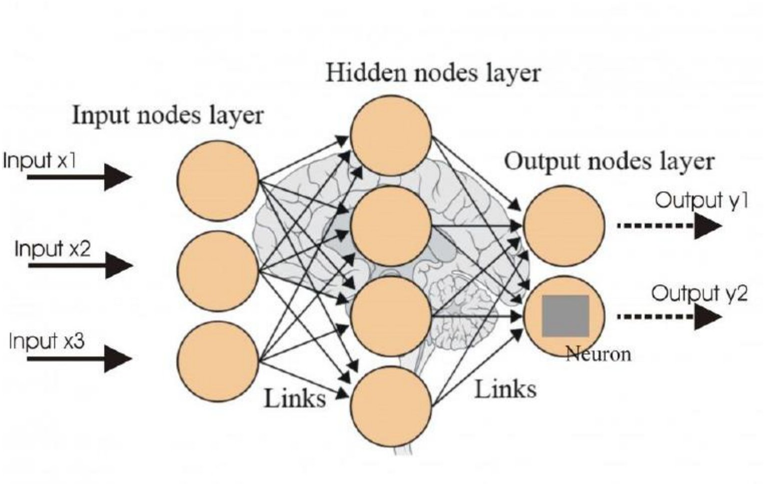


Figure 2-4: ANN Structure

(Brinda & Pushparani, 2016).

Artificial neural network in pest and disease detection has been used in diagnosis processes that are visual and in need of intuitive judgements. ANN is used together with other techniques such as image processing that aid in the collection of data in the field (Miranda, Gerardo & Tanguilig, 2014). Training of the algorithm is done through choosing of features that distinguish the existence or non-existence of pests or diseases on crops (Al-Saqer, 2012). Based on information from the feature extraction stage, the neural network is used to classify pests or diseases. Like the SVM, ANN algorithm in classification also considered accurate with a percentage of 80% (Malathi & Nazar, 2016)

2.6.2 Support Vector Machine (SVM)

This is a type of supervised machine learning method used in regression, classification and outliers detection. Here. The dataset educates the SVM on the classes so that the algorithm can classify any new data. In pest detection, SVM is used for classifying images based on the captured features. SVM algorithm classifies data into different classes by identifying a hyperplane that separates training data sets into classes. SVM maximizes on margin maximization which is the distance between various classes involved in the classification. SVM algorithm is classified into Linear and non-linear SVM. In Linear SVMs, separation of classifiers is by a hyperplane while non-linear SVMs do not use hyperplanes. SVM algorithm is accurate hence offers the best classification performance on training sets while avoiding strong assumptions. SVM algorithm is suitable for stock market predictions and forecasting by financial institutions (Manoja, & Rajalakshmi, 2014).

SVM algorithm is designed to produce a model based on the training data set available on order to perform predictions. It separates a set of training data into two classes: (x_1, y_1), (x_2, y_2),…(x_n, y_n) where x_i is the d-dimensional feature space and y_i is the class label. Based in a Kernel Function (K), SVM algorithm finds an optimal separating hyperplane as indicated in figure 2-5.

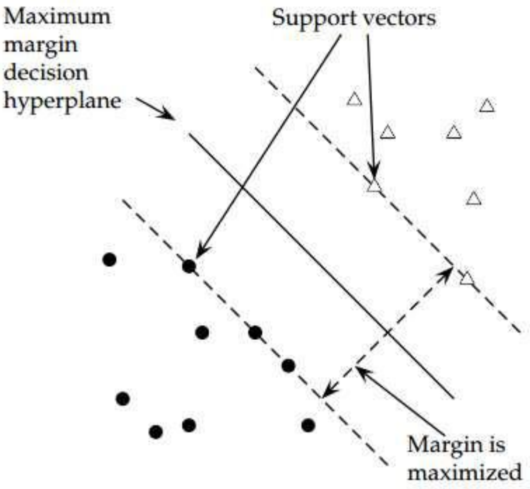


Figure 2-5: Support Vectore Machine

(Mundada & Gohokar, 2013)

Currently, Support Vector Machine algorithm has been used extensively in agriculture especially in the detection of pests and diseases (Rani & Amsini, 2016). In most applications, SVM classifier is used together with other technologies in classifying images of pests or diseases based on their features. The algorithm is used together with other machine learning algorithms such as K-Means Cluster algorithm and regression (Brinda & Pushparani, 2016). Unlike other classification algorithms, SVM is the most preferred since it gives better detection results in pattern recognition and classification. The classifier ensures more precision in the identification of pests or diseases at an early stage (Mundada & Gohokar, 2013).

2.6.3 Naïve Bayes Algorithm

Naïve Bayes is a classification algorithm used on the classification of lengthy data such as documents, emails or text notes. The classifier function in the algorithm allocates an element value of a population from the available categories. The algorithm follows the Bayes Theorem of Probability and it works with the assumption that predictors are conditionally independent of one another within each class. Naïve Bayes algorithm is suited for problems that have large or moderate training data sets and instances with several attributes (Dey, Bhoumik & Dey, 2016).Naïve Bayes applies the equation:

$$\underbrace{P(c \mid x)}_{\text{Posterior Probability}} = \frac{\overbrace{P(x \mid c)}^{\text{Likelihood}}\,\overbrace{P(c)}^{\text{Class Prior Probability}}}{\underbrace{P(x)}_{\text{Predictor Prior Probability}}}$$

$$P(c \mid \mathrm{X}) = P(x_1 \mid c) \times P(x_2 \mid c) \times \cdots \times P(x_n \mid c) \times P(c)$$

Equation 2-1: Naives Bayes Algorithm

(Kulalvaimozhi, Germanus & Peter, 2017)

P(C|X) is posterior probability, P(C) is class prior probability, P(X|C) is likelihood and P(X) is predictor prior probability. From the equation 2:1, the naïve bayes classifier assumes the effect of the predictor value (x) on any given class(c) is independent of values of other predictors hence the class conditional independence assumption.

The most common applications of Naives bayes are sentiment analysis, document categorization and email spam filtering. Sentiment analysis has been used in Facebook to classify status updates of individuals as either positive or negative emotions. Document categorization is used by Google to index documents. In email filtering, the algorithm classifies emails as spam or not spams (Shi et al, 2015). The algorithm is incremental and fast and deals with both discrete and continuous variables.

2.7 Related Work

This section reviews several existing studies and approaches related to the research problem. The research studies describe the current trends adopted in the prediction of pests and diseases in crops using different machine learning technologies. Currently, there exist various studies on the progress of machine learning technology in agriculture both domestic and international in a quest to solve the ever-growing challenges affecting farmers. The most common machine learning technologies adapted include support vector machine (SVM), Artificial Neural Networks (ANN), Vision-Based Models and Bayesian Network techniques.

2.7.1 A Cognitive Vision Approach to Early Pest Detection in Greenhouse Crops

In this study, the authors Boissard, Martin and Moisan explore the challenges of manual detection of pests and diseases on horticultural crops which turn out to be expensive and time –consuming. The authors' goal is early detection of existing biogressors. The strategy adopted follows an automatic interpretation of plant images of leaves scanned from the site. The proposed solution is a cognitive vision system that combines knowledge-based, image-processing and learning techniques. The illustration of the system is an automatic detection and tallying of the white fly (Trialeurode Vaporariorum) pest at a mature stage (Boissard, Martin& Moisan, 2008).

In the study; the author discusses image processing in detail. Image processing is used in the conversion of images into digital forms that can have different operations performed on them in order to extract useful information. In agriculture, IP has been used in the detection of leaf or crop diseases based on several visible features thus allowing appropriate monitoring and control measures. Image processing promotes visualization, image restoration and sharpening, retrieval and recognition (Kulalvaimozhi, Germanus, & Peter, 2017). The steps include:

i. **Image acquisition** - This stage entails obtaining images of samples from the environment through sensors. After acquisition, the image is converted into numerical form for processing.

ii. **Image pre-processing** - The aim of pre-processing is to gain a proper view of the processes image compared to the original image. Image processing entails compression (reducing size of image), enhancement (modification of the contrast and brightness of the image) and measurement.

iii. **Image segmentation** - This involves the extraction of different attributes of the original image. The digital image is partitioned into many segments thus changing representation into much simpler forms that allow gathering of statistics and identification of objects of interest. Image segmentation methods include Otsu’s method, K-Means clustering, watershed segmentation and texture fillers.

iv. **Feature extraction** - This is a technique of reducing the dimensions of an image while representing the important parts thus enhancing the completion of image matching and retrieval tasks. This task is combined with feature detection and matching to solve computer vision problems such as image recognition and detection.

v. **Classification** - This entails the identification and labelling of features identified in the image. Different machine learning algorithm classifiers can be used to achieve different classifications. The common classification algorithms used in image processing include ANN, SVM and K-Means.

2.7.2 Real-Time Monitoring Model for Early Detection of Crop Diseases

In his study (Toroitich & Orero, 2016) suggest the use of Internet of Things (IoT) technology and other machine learning techniques in the prediction of the potato late blight disease. This follows the challenges experienced in the use of manual human vision systems on identifying diseases on crops. Research findings prove that manual systems are ineffective when it comes to early detection of the potato blight disease. The key parameters used in the study were humidity and temperature. In monitoring the conditions of the potato blight disease in the farms, humidity and temperature sensor probes were placed on potatoes. Using historical weather data and variety tolerance on the disease, an artificial neural network for disease prediction was built. In developing the solution, the author used a back propagation neural network model for the prediction of the disease (Toroitich & Orero, 2016).

2.7.3 Pest detection and control techniques using wireless sensor network: A review

This study centres around Pakistan, a country that depends on agricultural practices for economic survival. The authors suggest the use of Wireless Sensor Networks (WSN) which has been highly adopted in the monitoring of different parameters in agriculture. The WSN strategy will require real-time monitoring of agricultural data which is essential in pest detection and controls. The other technique used by the authors is precision agriculture which ensures precise understanding, evaluation and estimation of crop conditions while determining different requirements. The WSN technology uses embedded devices or nodes that process and transmit data collected from sensors in the field (Azfar, Nadeem & Basit, 2015). Figure 2-6 below illustrates conceptual model of WSN in precision agriculture.

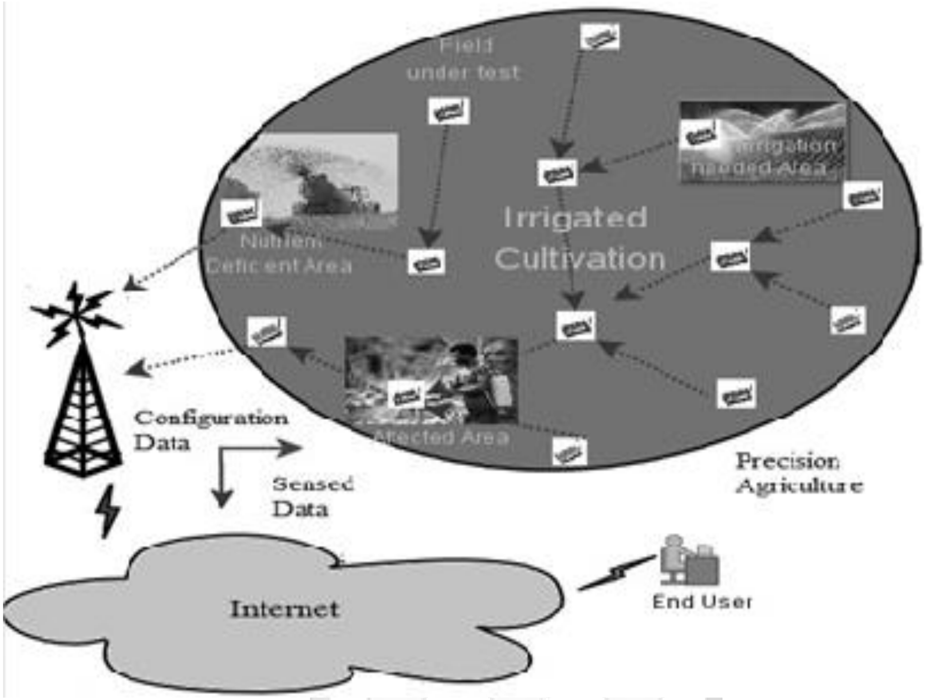


Figure 2-6: Wireless Sensor Network Model

(Azfar, Nadeem & Basit, 2015)

2.7.4 Vision-Based Model for maize leaf disease identification: a case study in Nyeri County

The study proposed an artificial intelligence model that would identify the maize leaf disease. The model required the acquiring and extraction of images on leaf colour features. Artificial neural network was also used to identify the disease through the implementation of a back propagation learning algorithm which is effective in adaptive learning, fast and accurate in output. All data obtained in the study was segmented into test and training data sets for the model. In evaluating the performance of the model, accuracy of the classification, recall ratio, F-Measure and the precision was used resulting in a 78.94% accuracy and 0.778 precision (Maina, 2016).

2.8 Conceptual Framework

Figure 2-7 illustrates how the model of the proposed system. The model uses soil parameters from the maize farm together with historical data on the signs and symptoms of the FAW pest in the soil. Information on the FAW pest i.e. soil parameters will be collected from the environment and analysed to determine if they support the successful existence of the pest in the crop fields. Thereafter, an artificial agent is trained to provide predictions based on the results of the classification. For positive prediction, a warning message is sent to the farmer or the extension officer in form of SMS.

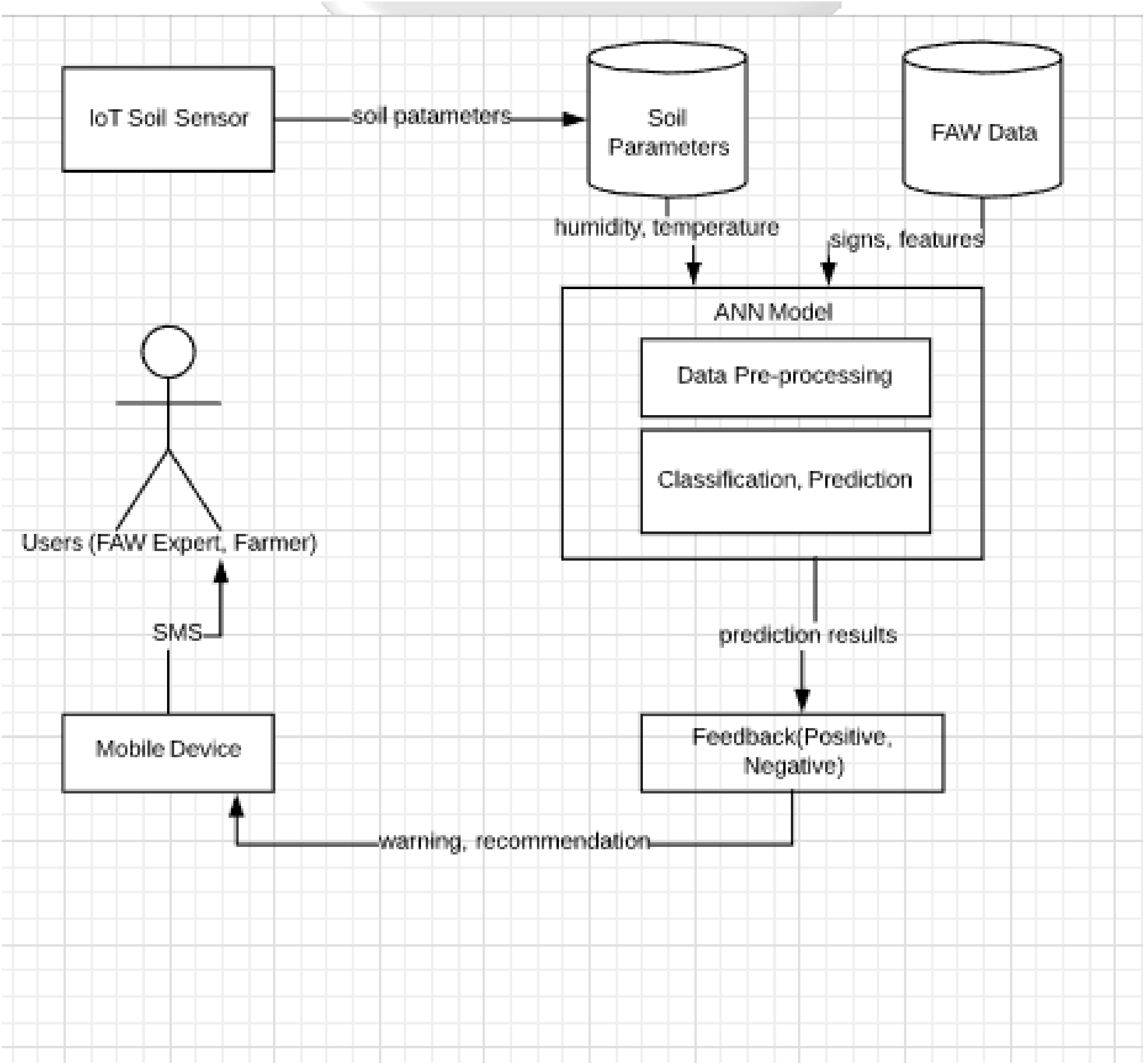


Figure 2-7: Conceptual Diagram

Chapter 3 : Research Methodology

3.1 Introduction

This chapter describes the methods and procedures used in the research study. Research methodology was guided by the research questions and objectives presented in chapter 1. This chapter reviews the research methodology of the study and outlines the research strategy, research methods, and approach and data collection methods. The study area is that of FAW invasion in Kenya. The main objective of the study is to develop a model that will detect and predict a possible presence of the FAW in the soil and thereby sending early warning signs and recommendations to farmers, experts or agricultural research centres for early preparation.

3.2 Research Design

This study follows a qualitative and quantitative research design that is descriptive in nature. Descriptive research design describes the current state in the area of research and the existing issues. In this case, it gives complete descriptions of groups, situations and sometimes individuals. Descriptive research design will use data collection instruments such as questionnaires, interviews and mail surveys.

3.3 Data Collection

3.3.1 Secondary Data

Secondary sources are the already published documents such as journals, newspapers, books, articles, government publications and internal records. Unlike the primary sources, this is quick and easy method of data collection. This is often second-hand information that has already been recorded and collected by other people for a different use other than the current research problem. In this study, secondary data will be used to gain insight in the current trends of pest and diseases on crops and what has been done so far in regards to detection and prediction. Secondary data provided Quantitative information which aims at objectively measuring the study area using statistical and mathematical tools.

3.3.2 Primary Data

Primary source is raw data from the field of study. This will either be quantitative or qualitative following descriptive type of research. Qualitative research in primary data sources is unstructured and exploratory in nature as it aims at gaining insights on the topic at hand.

3.4 Instruments of Data Collection

3.4.1 Questionnaires

This will be the most common method of data collection in the study related to FAW invasions. The key respondents will be a few farmers who experienced the damage of the invasion and experts in the filed working on the same from the ministry of agriculture or KALRO. The aim is to obtain responses from a certain percentage of the selected target response in case others fail to respond. The questionnaire will be set in advance by the interviewer and it will have the introduction and body section. The data collected in the questionnaire address information on biographic data and data related to the research questions.

3.4.2 Structured Interviews

Structured interview follows the format of setting a set of predetermined questions which will be prepared by the interviewer in advance. This type of interview was selected as it is more reliable and valid. It allows all respondents to be asked the same set of questions which brings about consistency and accuracy in data collected. Questions in the structured interview are closed-ended which requires respondents to provide a specific response.

3.5 Target Population and Sampling

Target population for the study will be farmers and agricultural experts who had a first-hand experience with the FAW situation. The farmers and experts will provide responses through interviews on the characteristics of the armyworm invasion, the control measures employed to control the pest and the extent of damages. Data collected for the study will be FAW soil parameters; temperature and humidity and their levels in the crop fields. The properties obtained with be used together with historical data to predict a possible existence of FAW in the soil. The ANN model was adopted and used in the classification of the results as either positive or negative.

3.6 Model Training

In the study, this will involve provision of inputs to the proposed model for processing and training on the input data and expected output. The training data will be fed into the selected machine learning algorithm. The algorithm to be used in this research will be the Artificial Neural Networks which is powerful for predictive modelling. The training data obtained will be fed into the algorithm in order to determine the presence of FAW pest in the soil based on the parameters obtained from the environment. The dataset will then be split into training, validation and testing data. Several iterations will be undertaken in the course of the training process with each process aimed at reducing the error rate and adjusting inputs. Each dataset collected will be partitioned into training set and test set in order to determine the possibility of FAW attacks or positive presence in the soil.

3.6.2 Modelling Accuracy

The accuracy of the model is the total number of correct predictions. In calculating the proportion of the predicted positive cases, the study will use Precision (P) using TP (True Positive Rate) and FP (false positive rate). The accuracy in this case is the proportion of the correct predictions from the obtained predictions.

For accuracy; true positive (TP), true negative (TN), false positive (FP) and false negative (FN) are used in the accuracy equation

Accuracy is given in the equation:

$$\text{Accuracy (A) is therefore} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}$$

Equation 3-1: Accuracy Formula

Precision is the percentage of positive cases (in percentage) that are found to be correct

$$\text{Precision (P)} = \frac{\text{TP}}{\text{TP+TN}}$$

Equation 3-2: Precision Formula

In calculating the proportion of positive cases that were identified correctly which is Recall or sensitivity):

$$\text{Recall (R)} = \frac{\text{TP}}{\text{TP+FP}}$$

Equation 3-3: Recall Formula

F-measure ratio represents the average between the recall and precision ratios:

$$\text{F} - \text{Measure} = \frac{2 * \text{precision} * \text{recall}}{\text{recall} + \text{precision}}$$

Equation 3-4: F-Measure Formula

3.6.2 Model Testing and Validation

This will entail the use of test data from thse existing data set to check the correct training of the proposed model by analysing the actual model output versus the expected output. Through validation, any errors identified in the performance evaluation will be used to adjust the model and make the necessary corrections for a much accurate model. In presentation, both inputs and outputs will be represented as tables while output will follow graphical representations. Tables will aid in the display of precision and accuracy.

3.7 System Development Methodology

The development of the system followed the Rapid Application Development (RAD) methodology which focuses on development of applications over a short period. This hastens the development cycle resulting in the development of quality products in a more efficient and cost-saving manner. The RAD development model have phases such as analysis, design, building and testing distributed into a series of short and iterative development cycles as shown in figure 3-1. The lifecycle of the methodology comprises of three stages that are requirements planning, user design, rapid construction and transition.

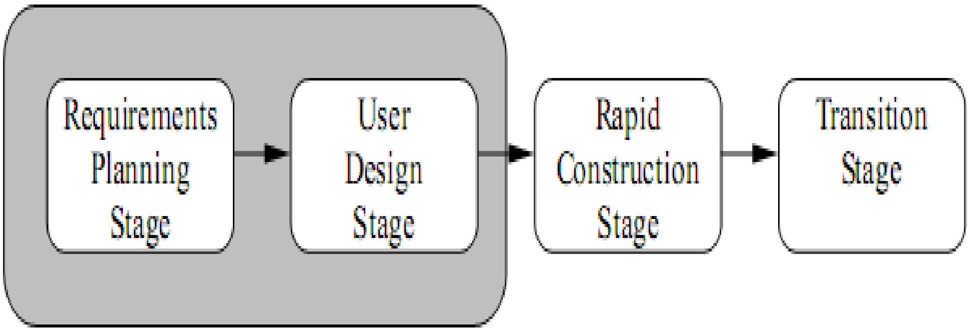


Figure 3-1: RAD Development Methodology

a) Requirements Planning Stage

This stage entailed collection of relevant data on the FAW pest in the environment to enable the development of the prediction model. Statistics on the recent case were obtained from the ministry of agriculture and the Kenya Agricultural & Livestock Research Organization (KALRO). This was to provide a clear understanding of the fall armyworm invasion and provide insights on the solution.

b) User Design Stage

This stage entails the design of the prototype and architecture of the proposed solution. There will be the design of Unified Modelling Language (UML) diagrams to describe flow of information and interaction of the different system components. Applications used in drawing the use cases, class diagrams, sequence diagrams and data flow diagrams will be the StarUML and Visual Paradigm 14.1.

c) Rapid Construction Stage

This stage involves the implementation of the model following the information in the user design stage. The development language used will be Python. This will then be followed by testing and validation of the proposed model through conducting of experiments.

d) Transition Stage

This stage follows the implementation and testing tasks with the prototype model being deployed for prediction of a possible FAW invasion and instant communication of early warning to the farmers or agricultural institutions. It also encompasses development of user training plans and documentation for the prototype users.

3.8 Ethical Considerations

The research study is subject to certain ethical issues and considerations. The researcher provided a written introduction for the purpose of authenticity while respondents provided an acceptance and signed consent on their participation in the research. The researcher's introduction is meant to reassure respondents that the participation is voluntary and therefore free to withdraw or fail to respond if uncomfortable. The participants were also informed on the objectives of the study with a reassurance that the answers provided would be treated as confidential and used for academic purposes only.

Chapter 4 : System Design and Architecture

4.1 Introduction

This chapter explores the design and architecture of the proposed FAW prediction model. It illustrates the interconnection between the system components and interaction. The system design and architecture of the proposed system will be achieved through UML diagrams

4.2 Requirements Analysis

The requirements analysis in this chapter will review user expectations for the proposed system. Any existing project requirements must be thought of thoroughly or balances by all stakeholders of the system. The section below discusses functional and non-functional requirements of the FAW prediction model. From the objectives in chapter one and user requirements, this part of the paper outlines the various requirements that will be achieved in the research.

4.2.1 Functional Requirements

Functional requirements simply specify what the system should do in regard to function, behaviour and input or output which are meant to support user tasks, activities or goals. The functional requirements of the FAW prediction model include:

i. The system should allow the FAW expert to register the farmer
ii. The system should be able to retrieve environmental soil parameters (temperature and humidity) and log the data into an internet server
iii. The system should accurately classify the results as either positive or negative in predicting the presence of FAW in the soil using artificial neural network model
iv. The system should send out a warning message or notification to users (FAW expert and farmer) based on the results of the classification

v. The system should provide a recommendation to farmers based on treating the presence of the FAW pest in the environment

4.2.2 Non-Functional Requirements

In definition, these are qualities or properties the proposed system must have. The most common requirements include speed, accuracy or appearance of the system. These requirements describe the overall attributes of a system. Failure to address non-functional requirements results in undesirable results, unsatisfied users and wasted project resources. For the propose system, non-functional requirements include:

i. **Availability** – this describes the degree to which users (farmers or entomologists) can depend on the proposed system at all times. The system should be available at all times regardless of the environmental or external factors that may affect this.

ii. **Reliability –** this describes the extent through which the system performs its specified functions consistently and without failure at any point in time.

iii. **Accuracy** – the prediction results of the proposed system should meet certain levels of accuracy. With accuracy of results and prediction in the system, there will be objective decision making with regard to preventing fall armyworm.

iv. **Usability** – the system should allow users to easily learn and operate its functions. It should also enable users to prepare specific inputs and interpret expected outputs in the course of their interaction with the system.

v. **Maintainability** – this describes the ease in which faults or errors in the system can be found and fixed to match user requirements.

vi. **Response Time** – the proposed system should have a maximum response time from the time of the prediction by the model to the time a warning message is sent out to the farmers or experts.

4.3 System Architecture

System architecture provides an understanding of the proposed system's design, structure and user requirements that must be supported or achieved by the system. For the proposed system, the system architecture will address how different system components support the achievement of the system's functionality. Figure 4-1 below illustrates the sub-systems and interconnections between them in the FAW prediction model. The components in the proposed system architecture include users, the Internet of Things tools (soil sensor, Arduino, ESP32 and WI-FI module), the expert's station, database or server and the machine learning model.

Once the IoT nodes are placed in maize farm to retrieve soil parameters that are sent to an internet server and database for storage. The data in the server sends status feedback to the FAW expert work station. The FAW workstation feeds historical information on signs and symptoms of the FAW pest that will be used together with the soil parameters for prediction. The Machine learning component comprises of the pre-processor, ANN model and the classifier. Based on the data received from the two servers/ databases, the component processes the data, feeds it to the neural network and provides a classification as (positive or negative). The results of the classification are what is sent to the farmer and FAW expert as the prediction together with recommendations towards a positive FAW prediction.

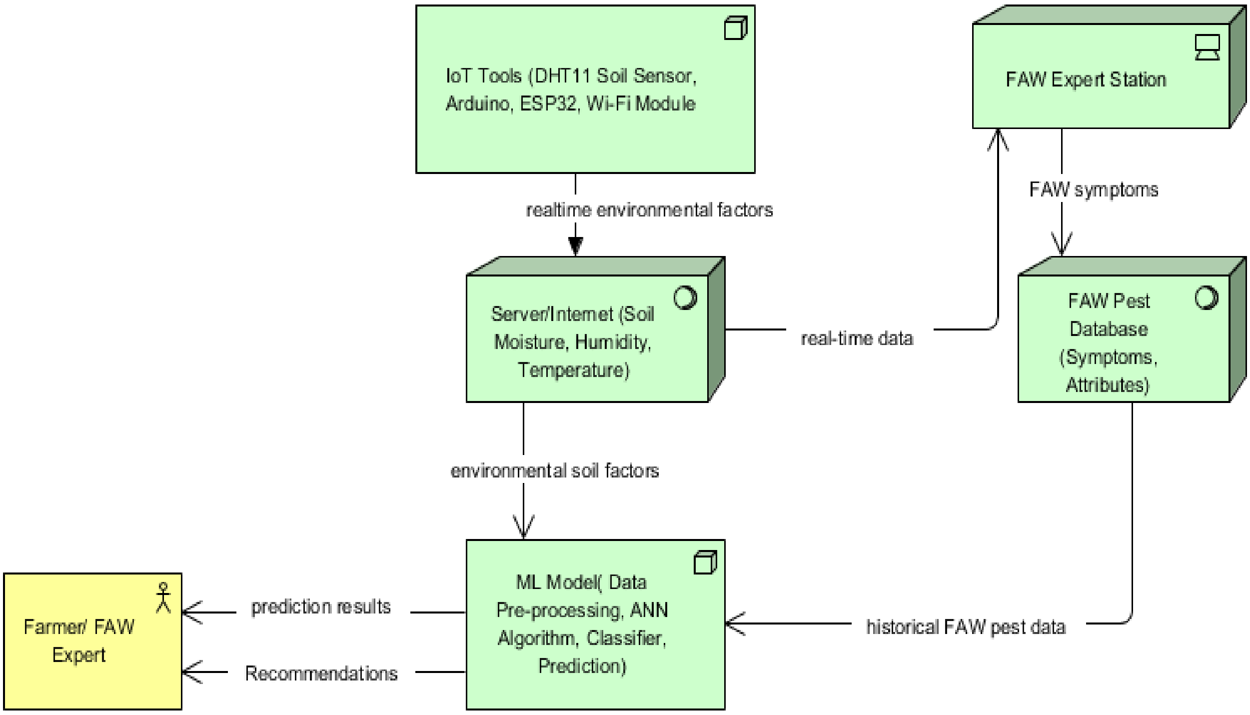


Figure 4-1: System Architecture

4.4 System Behavioural Modelling

This is considered the most effective method for modelling system and user requirements. The use diagram shows sets of actors, use cases and their associated relationships. The actors in this system are the farmer and the FAW expert.

4.4.1 Use Case Narration

This is the textual representation of the proposed system's events encountered in when the actors interact with the system.

Use Case:

Registration of farm- farmer details

Primary Actor:

i. FAW Expert

Precondition:

i. Farmer must have a maize farm in Kenya

ii. Farmer must have a phone (smart phone or feature phone i.e. which can receive SMS notification)

Post Condition:

i. Farmer and farm details must be successfully uploaded to the system database

ii. Uploaded details of farmers (contacts and location) must be confirmed to be accurate

Main Success Scenarios

Actor Intention	**System Responsibility**
1. FAW expert initiates farmer registration – farm, name, contacts, location	2. System stores farm details for future communication
	3. System confirms user registration to FAW expert and system
4. User exits the system	

Extensions or Alternative Flows:

a. At any time the system fails to successfully register farmer details; the user repeats the process

Use Case:

Retrieve soil parameters (humidity and temperature)

Primary Actor:

FAW Expert, Farmer

Precondition:

i. User must have the soil sensors i.e. DHT 11 Module, ESP8266,

ii. Farmer and farm details must be registered

iii. Soil sensors should be correctly placed in some part of the farm

Post Condition:

i. Real-time data on soil parameters are successfully sent to an internet server

Main Success Scenarios

Actor Intention	**System Responsibility**
1. FAW expert initiates classification and prediction by setting up soil sensors in the farm	2. System retrieves soil environmental parameters (humidity and temperature)
	3. System sends parameters to the internet server
4. FAW expert views real-time parameters from the farm	5. System uses soil parameters and historical data to predict presence of FAW in the soil
	6. System classifies the input as either positive or negative
	7. System generates feedback to be sent out to FAW expert and farmer
	8. System sends warning message and recommendation if result is positive
9. Farmer and FAW expert receive warning message and	

recommendation in form of SMS notification

Extensions or Alternative Flows:

a. At any time the system fails to retrieve soil parameters, FAW expert must repeat the setting up process in the soil

Use Case:

Send feedback to farmer/ FAW expert

Primary Actor:

FAW Expert, Farmer

Precondition:

i. Successful prediction of the FAW pest invasion by the proposed system

Post Condition:

i. System to give a recommendation on the best course of action
ii. System to send out notification as SMS to farmer and FAW expert

Main Success Scenario

Actor Intention	**System Responsibility**
1. FAW expert registers farmer information in the system i.e. contacts, farm location	2. System returns the output of the classification and prediction
	3. System sends notification SMS to user

4. User views feedback on prediction
   and recommendation

Extensions or Extensions or Alternative Flows:

a. At any time the send feedback function fails; system should be restarted to send feedback or contact system administrator

Use Case:

Log real-time soil sensor data, Implement ML classification algorithm, Predict positive or negative presence in the soil, generate output and send notification to the users.

Primary Actor:

i. System

Precondition:

i. The soil parameters (temperature and humidity) were successfully logged and stored on the internet server

Post Condition:

i. Successful prediction (negative or positive) of the FAW pest in the soil

Main Success Scenario

1. The soil sensors retrieve soil parameters (temperature and humidity) and the information is transmitted to the internet server
2. Based on the information available i.e. soil parameters, historical information on FAW signs and symptoms; the system uses the classical feed forward neural network to predict negative or positive presence of the FAW in the soil
3. After prediction; the system validates and tests the accuracy of the prediction through test data

4. System generates output i.e. prediction results depending on the information available in the internet server and that collected by the sensors.

4.4.2 Use Case Diagram

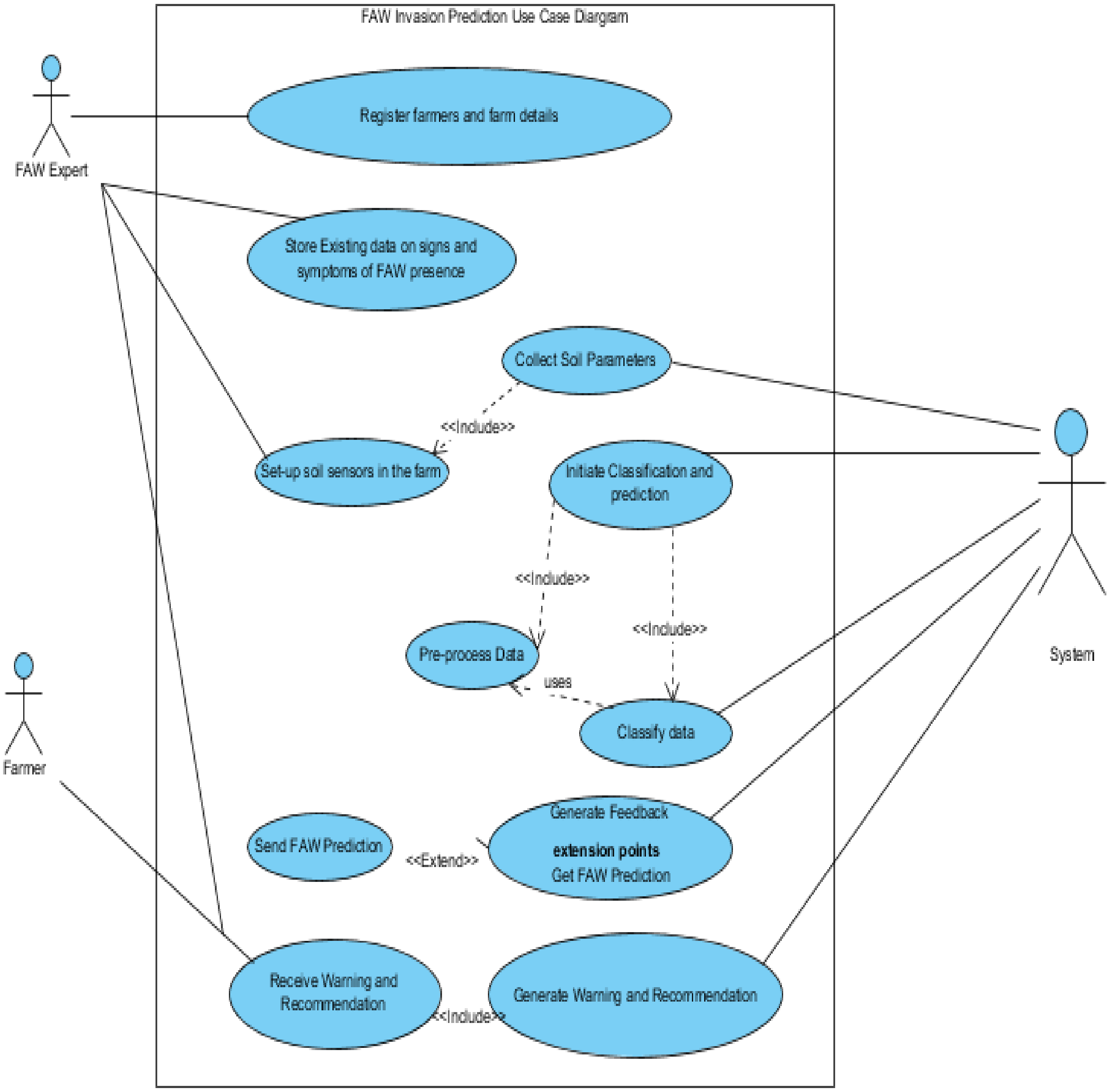


Figure 4-2: Use Case Diagram

Figure 4-2 above illustrates the use case diagram of the proposed system. The actors in the system include the farmer, FAW expert and the system together with the proposed use cases

4.4.3 Sequence Diagram

Sequence diagrams are interaction diagrams showing the time ordering of messages between different objects in the system. The FAW expert sets up soil sensors in identified farms. After this, details of the farmers including contacts are registered into the system. The FAW expert also collects and stores additional information on signs and symptoms of the FAW pest presence in the environment. The soil parameters of the maize farm are collected through sensors and sent to the internet server. The parameters together with historical data in the system are pre-processed and used in the classification and prediction of the FAW presence in the soil. The results of the prediction are generated and a warning sign together with recommendations are sent out in form of SMS notifications to the farmer or FAW expert. In the proposed system, the sequence diagram is illustrates in figure 4-3 below:

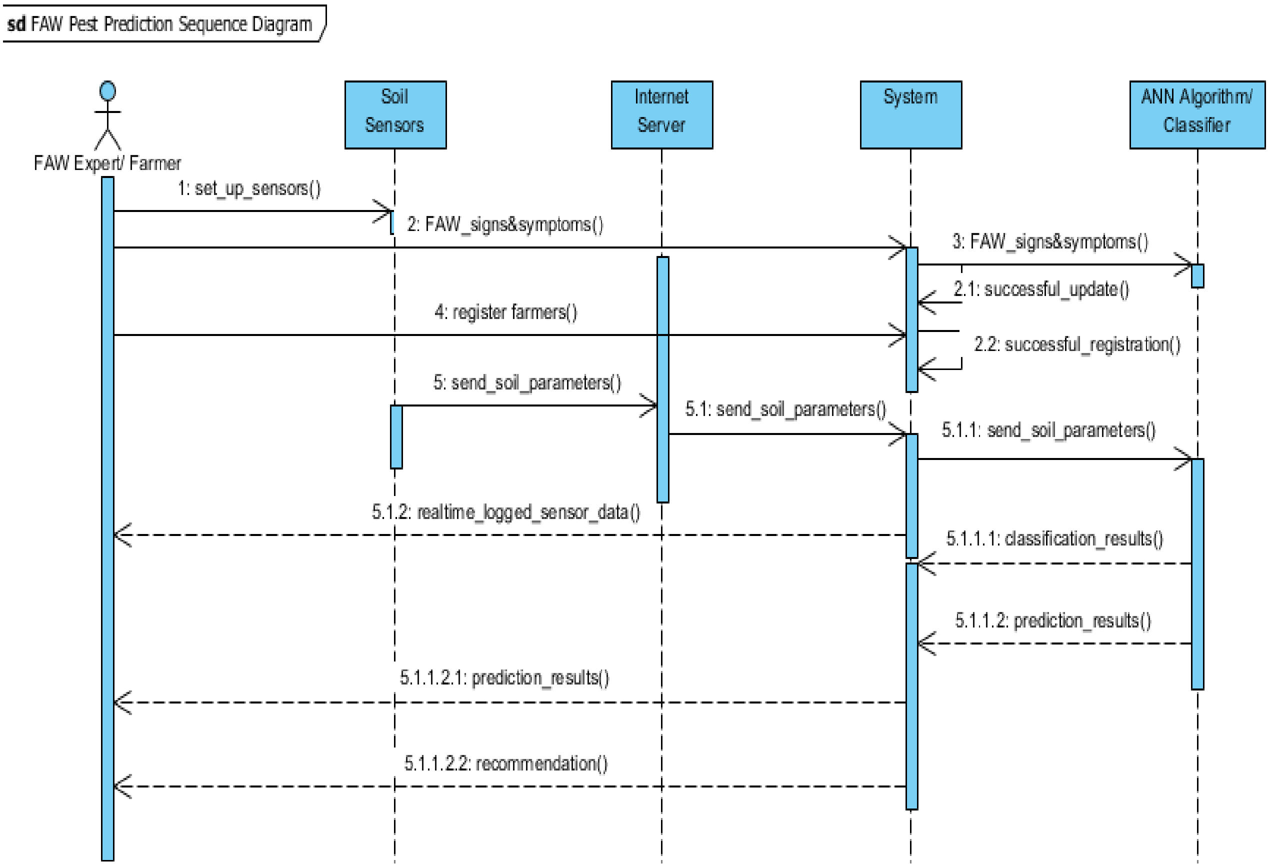


Figure 4-3: Sequence Diagram

4.5 Process Modelling

4.5.1 Context Diagram

This is a model of the proposed system defining its interactions with immediate external entities. The main entities in the proposed prediction system include farmers, FAW expert, sensors and the Prediction model. From the diagram, the illustration is that of first hand interaction between the entities and the system together with any messages exchanged. The context diagram defines the boundaries of the proposed system. Figure 4-4 below illustrates the context diagram of the proposed system;

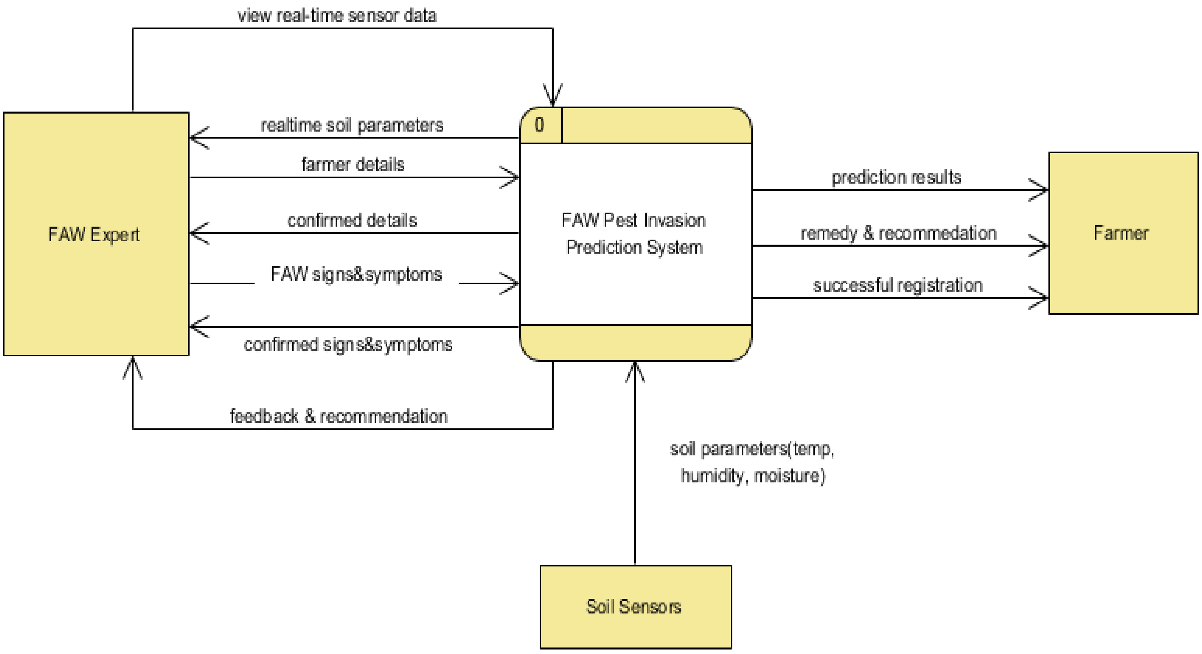


Figure 4-4: Context Diagram

4.5.2 Level 1 Data Flow Diagram

The level 1 DFD diagram depicts the second level processes of the FAW prediction model. For the proposed system, the level 1 DFD diagram provides a detailed breakdown of the context diagram in figure 4.4 above. The additional software components include the data stores and data flows between the system processes. Figure 4-5 below elaborates the main processes of the entities and how they interact with the system. The first process in the FAW prediction model entails the registration of farmer details (contacts and location) which will be used when sending out warning messages and recommendations. The FAW expert in process two then updates historical information on the FAW signs and symptoms. These are to be used together with the soil parameters in the prediction process. Process three entails the logging of soil parameters from the soil into the internet server. The same information can be viewed by the FAW expert in form of graphs. The following processes entail processing of data and feeding the same to a neural network in order to perform predictions. The results of the prediction are sent out as a warning sign to the farmer and FAW based on the classification (positive or negative). The process is accompanied by recommendations on the next possible course of action.

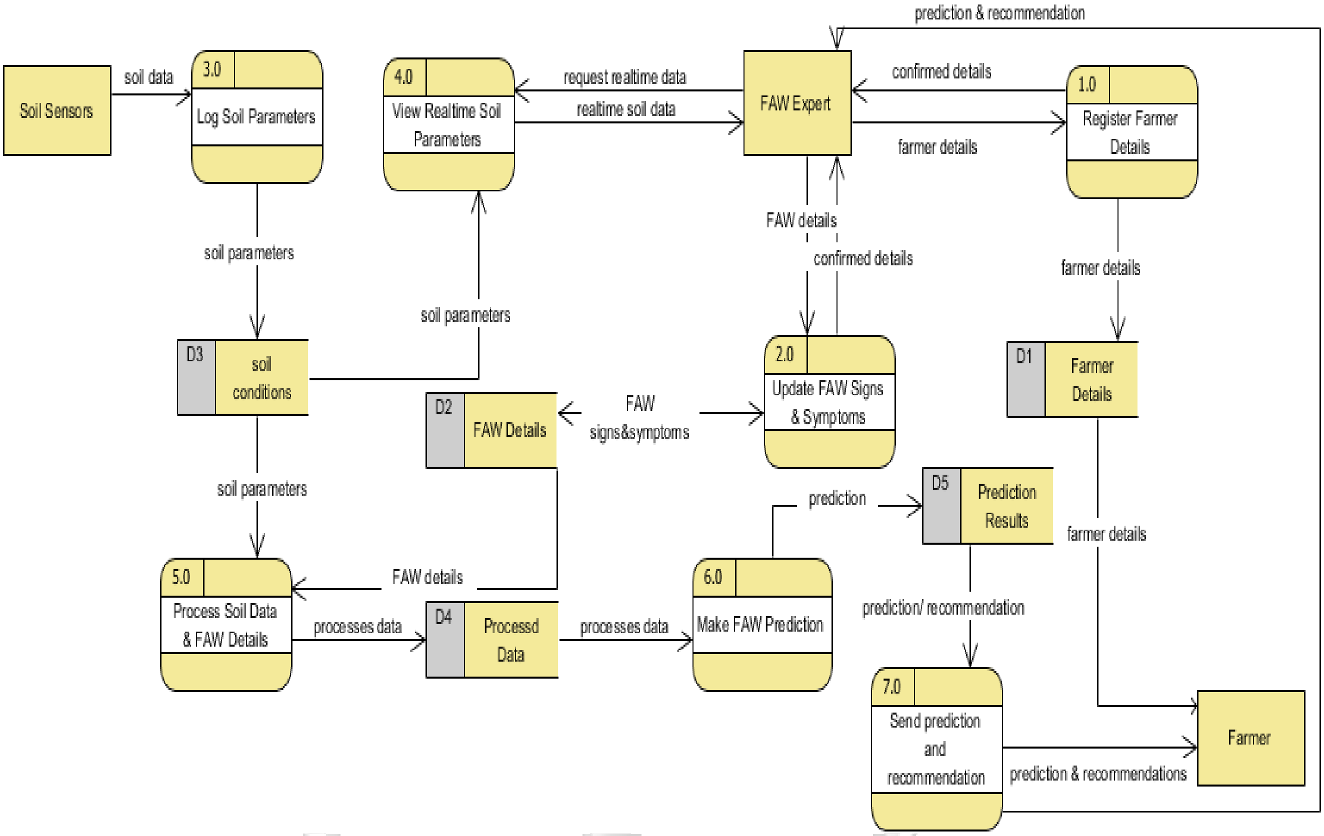


Figure 4-5: Level 1 DFD Diagram

4.6 Partial Domain Model

Figure 4-6 illustrates a domain model that comprises of real-world objects or conceptual classes of the proposed system. The diagram comprises of conceptual classes, associations between the conceptual classes and attributes of the conceptual classes. The domain model of the proposed system comprises of the classes; FAW expert, FAW details, ANN model, farmer, soil parameters, sensors, feedback, SMS module and the sensors. The classes interact at different points from farmer registration, sensors retrieving soil information and processing of the uploaded data by the ANN machine learning model. The result is prediction results and warning SMS sent out to farmers together with recommendations on the next possible course of action

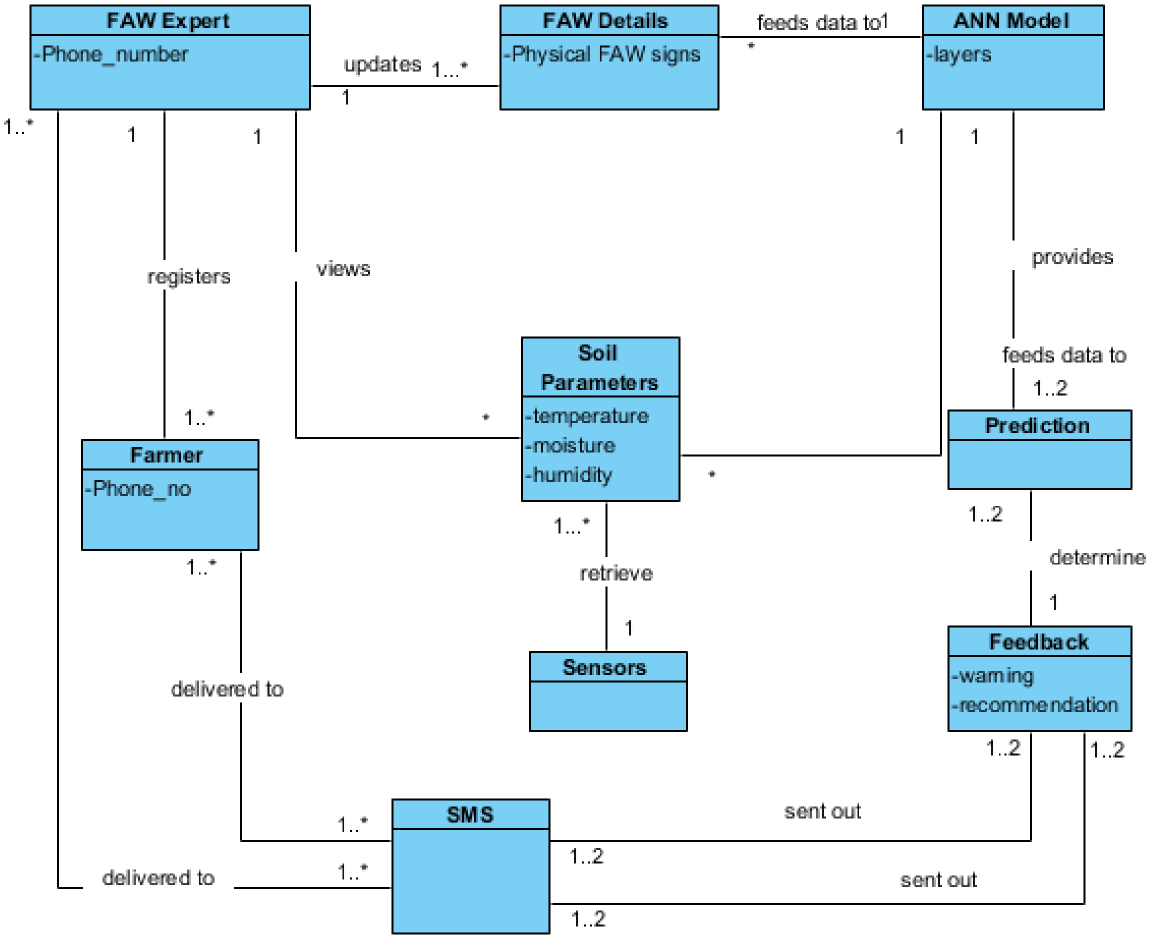


Figure 4-6: Partial Domain Model

Chapter 5 : System Implementation and Testing

5.1 Introduction

This chapter explores the actual implementation of the proposed system. The soil sensors (DHT 11 Module) were deployed in the soil to capture data on temperature and humidity levels. The DHT 11 module was connected to the ESP32 Development board which is used as a micro-controller following its Wi-Fi capabilities. Data readings were successfully uploaded to the server for pre-processing. Forward propagation neural network algorithm was used with the uploaded data to provide predictions on presence of FAW pest in the environments. Based on the results of the prediction, a warning SMS notification is sent out to the farmers and FAW experts together with recommendations. There is also real-time monitoring by the FAW expert on the temperature and humidity readings through graphs.

5.2 Components of the Prediction Model

5.2.1 IoT System Components

The IoT system monitors and retrieves soil parameters using DHT11 soil sensors and ESP32 development board. The data obtained from the sensors is sent to a local host server where it's processed and fed into the Machine learning model for classification and prediction of the FAW pest in the soil. The IoT components used in the system include:

a. DHT11 Module- the DHT11 sensor is illustrated in figure 5-1. This module was chosen because of its stability and digital signal outputs. The sensor retrieves humidity and temperature parameters from the soil.

Figure 5-1: DHT11 Module

b. ESP32 – the ESP32 development board is as illustrated in figure 5-2. This module was used as the master controller. This new ESP module combines both Bluetooth and Wi-Fi wireless capabilities together with its dual core. When connected with the DHT11 module, ESP32 receives data from the sensors and send the same to the local-host server which can be made available on the internet through the Ngrok apache.

Figure 5-2: ESP32 Module

5.2.2 ANN Model

In developing the prediction model of FAW armyworm invasion; a forward propagation (BP) Neural Network algorithm was used. Inputs fed into the ANN model include the soil temperature and humidity collected by the sensors deployed in the soil. Other inputs include observable characteristics logged into the system by the FAW expert based on the feedback from the farmers and KALRO officials. The ANN algorithm three nodes as discussed below are interconnected through weights.

a. **Input Layer –** This first component of ANN and its nodes are passive such that no data modification takes places at this layer. The input layer in the model receives inputs or variables from the external environment that are then sent to the hidden layer. The variables include the temperature, humidity and observable common characteristics.

b. **Hidden Layer –** Unlike the input layer, the nodes here are active such that they modify data from the input layer generate a desired output. At this layer, a number of computations are done on the inputs received and the result transferred to the output layer.

c. **Output Layer -** The output layers receives data from the hidden layer and processes the same using weights to produce an output that is sent out to the external environment.

5.2.3 Server Side Application

Data readings from the soil sensors were uploaded to the localhost server. The Ngrok multiplatform software was used in the implementation of the server side part of the system. The software was used to establish a secure tunnel from the localhost application on the laptop to the internet. This way, the web server on the local machine hosting data on the proposed system was exposed to the intern. Once the localhost is exposed on the internet; users such as the FAW experts interacting with the expert can access the s

5.3 Implementation of the FAW Prediction Model

The section below discusses the actual implementation of the proposed prediction model using the components discussed in section 5.2 above.

5.3.1 Capturing of Data by Sensors

In the study; data on environmental parameters supporting the survival of the FAW pupal stage in the soil was collected through sensors. The DHT11 module sensor was used in this study. The micro-controller (ESP32) uses the DHT11 sensor to get the humidity and the temperature from the field and the heat index computed. Figure 5-3 and 5-4 below illustrates a sample set-up and deployment of the IoT components on the laptop and soil:

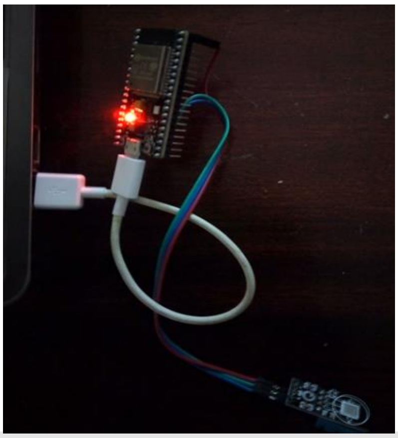


Figure 5-3: ESP32 & DHT11 Set-up

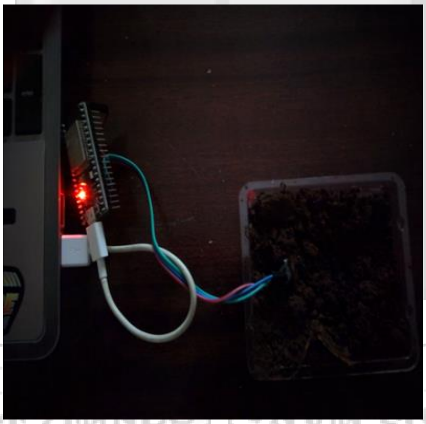
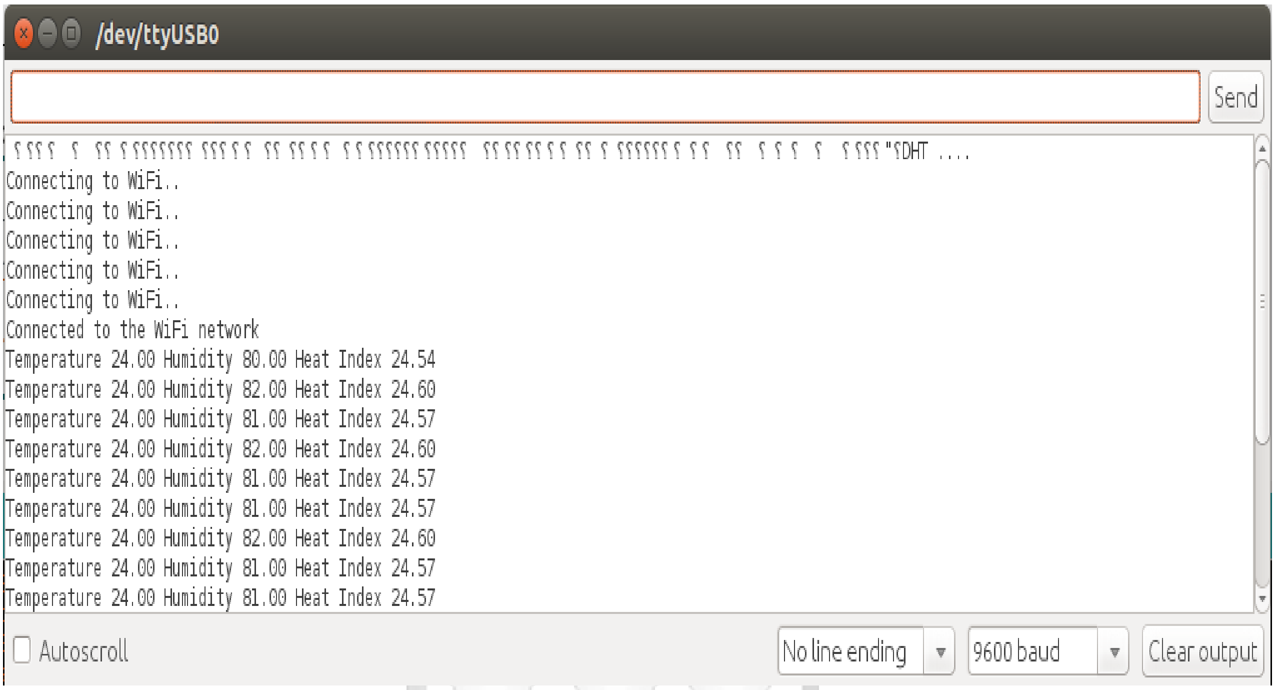


Figure 5-4: DHT11 Deployment in Soil

For the setup the DHT11 module has 3 pins utilized; one for the voltage (5 Volts), ground and the last pin serves as the output/input pin that passes the signals to the micro-controller. The data readings obtained after deployment of the sensors in the soil are shown in figure 5-5 below:



```
ʕʕʕʕ ʕ ʕʕ ʕʕʕʕʕʕʕʕ ʕʕʕʕʕ ʕʕ ʕʕʕʕ ʕʕʕʕʕʕʕʕʕʕʕʕ ʕʕʕʕʕʕʕʕ ʕʕ ʕ ʕʕʕʕʕʕʕ ʕʕ ʕʕ ʕʕʕ ʕ ʕʕʕʕ"ʕDHT ....
Connecting to WiFi..
Connecting to WiFi..
Connecting to WiFi..
Connecting to WiFi..
Connecting to WiFi..
Connected to the WiFi network
Temperature 24.00 Humidity 80.00 Heat Index 24.54
Temperature 24.00 Humidity 82.00 Heat Index 24.60
Temperature 24.00 Humidity 81.00 Heat Index 24.57
Temperature 24.00 Humidity 82.00 Heat Index 24.60
Temperature 24.00 Humidity 81.00 Heat Index 24.57
Temperature 24.00 Humidity 81.00 Heat Index 24.57
Temperature 24.00 Humidity 82.00 Heat Index 24.60
Temperature 24.00 Humidity 81.00 Heat Index 24.57
Temperature 24.00 Humidity 81.00 Heat Index 24.57
```

Figure 5-5: DHT11 Sample Temperature & Humidity Readings

The sample arduino code for retrieving temperature and humidity readings from the soil and sending the same to the server is as below:

```
#include "DHT.h"

#include <WiFi.h>

#include <HTTPClient.h>

#define DHTPIN 13     // what digital pin we're connected to

#define DHTTYPE DHT11   // DHT 11

// Wifi credentials

const char* ssid = "Shantel";

const char* password =  "Shan125";
```

```
HTTPClient http;

DHT dht(DHTPIN, DHTTYPE);



void setup() {

  Serial.begin(9600);

  Serial.println("DHT ....");

  dht.begin();

//  initialize wifi

  WiFi.begin(ssid, password);

  while (WiFi.status() != WL_CONNECTED) { //Check for the connection

    delay(1000);

    Serial.println("Connecting to WiFi..");

  }

  Serial.println("Connected to the WiFi network");

}

// send the details to the server

void send_to_server(float temperature, float humidity,float heat_index){

  // print to serial monitor console
```

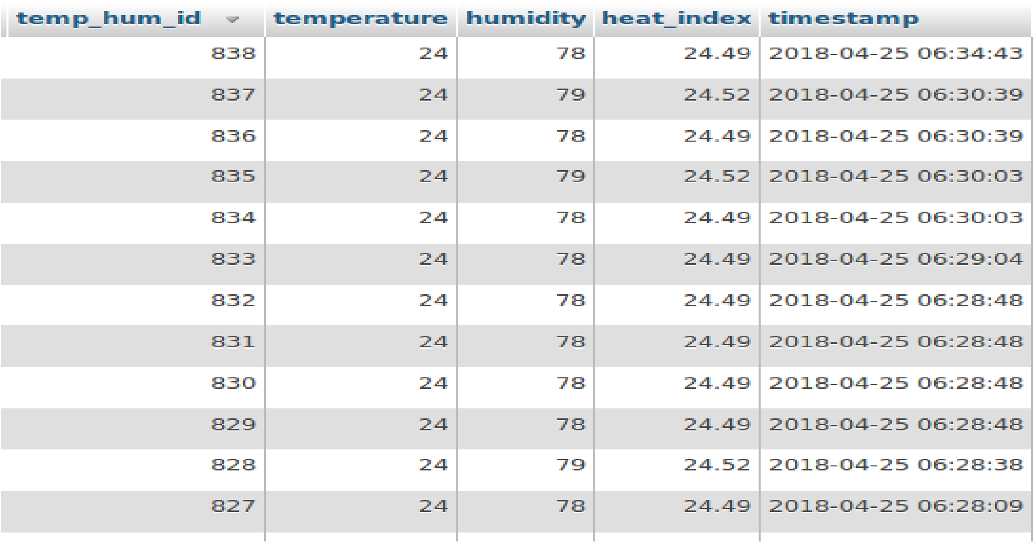
```
  Serial.println("Temperature "+String(temperature)+ " Humidity "+String(humidity)+ " Heat Index "+String(heat_index));


http.begin("http://125937ae.ngrok.io/shantel/backend/arduino/insert_temp_hum/"+String(temperature)+"/"+String(humidity)+"/"+String(heat_index));
  http.addHeader("Content-Type", "text/plain");            //Specify content-type header
  http.POST("POSTING from ESP32");
}
void loop() {
  // Wait a few seconds between measurements.
  delay(2000);
  // Reading temperature or humidity takes about 250 milliseconds!
  // Sensor readings may also be up to 2 seconds 'old' (its a very slow sensor)
  float humidity = dht.readHumidity();
  // Read temperature as Celsius (the default)
  float temperature = dht.readTemperature();
  // Check if any reads failed and exit early (to try again).
  if (isnan(humidity) || isnan(temperature)) {
    Serial.println("Failed to read from DHT sensor!");
```

```
   return;
  }
  // Compute heat index in Fahrenheit (the default)
  // Compute heat index in Celsius (isFahreheit = false)
  float heat_index = dht.computeHeatIndex(temperature, humidity, false);
  // call method to send details to server
  send_to_server(temperature,humidity,heat_index);
}
```

5.3.2 Storing Sensor Parameters

Data readings collected in figure 5-5 are uploaded to local host server as indicated in figure 5-6.



temp_hum_id	temperature	humidity	heat_index	timestamp
838	24	78	24.49	2018-04-25 06:34:43
837	24	79	24.52	2018-04-25 06:30:39
836	24	78	24.49	2018-04-25 06:30:39
835	24	79	24.52	2018-04-25 06:30:03
834	24	78	24.49	2018-04-25 06:30:03
833	24	78	24.49	2018-04-25 06:29:04
832	24	78	24.49	2018-04-25 06:28:48
831	24	78	24.49	2018-04-25 06:28:48
830	24	78	24.49	2018-04-25 06:28:48
829	24	78	24.49	2018-04-25 06:28:48
828	24	79	24.52	2018-04-25 06:28:38
827	24	78	24.49	2018-04-25 06:28:09

Figure 5-6: Soil Parameters in Local-Host

The fall armyworm pupa is known to survive in soil temperatures ranging between 24^{0}C to 28^{0}C and humidity levels ranging between 60% to 71%. In extreme temperatures and humidity levels; the pest fails to survive. The readings are also used for real-time monitoring of the humidity and temperature levels by the expert as illustrated in figure 5-7 below:

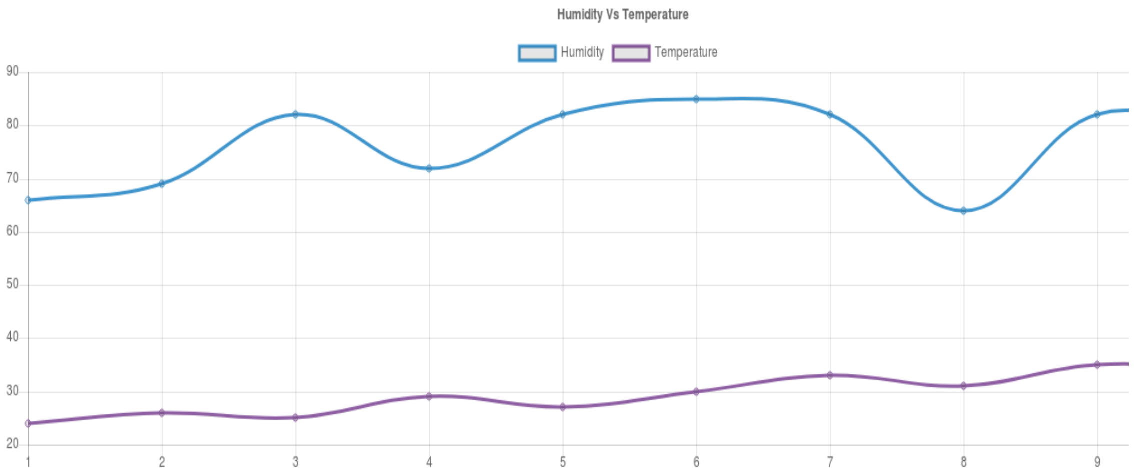


Figure 5-7: Real-Time Temperature & Humidity Readings

5.3.3 Storing Observable Characteristics

The other parameters or inputs updated in the used in the system include observable features identified by the FAW experts or farmers in the maize fields. Such information is gathered overtime through manual observation by both users and from feedback gathered in the questionnaires. Table 5-1 below illustrates the common observable characteristics gathered in the maze fields:

Observable Characteristics In the Maize Fields	Present	Not Present
Presence of Moth in the field	1	-1
Damaged leaves or plants >10 plants	1	-1
Presence of egg Masses on leaves	1	-1

Presence of reddish -brown loose cocoons	1	-1
Larvae with yellow (‘y’) shaped mark at the head	1	-1
Number of Moths captured in Pheromone Traps >15	1	-1
Dry Soil or Moist Soil	1	-1
Presence of maize predators in the environment	1	-1

Table 5-1: Observable Characteristics in the Environment

5.3.4 Storing User Details

The details of the farmers i.e. name, phone number and farm location are updated by the FAW expert in the system. This way; farmers can receive SMS notifications on the prediction results of the model and a recommendation based on the prediction.

5.3.5 ANN Implementation and Modelling

The proposed system employed the used of the forward propagation NN algorithm to generate predictions on a possible FAW invasion. The input layer receives inputs captured by the soil sensors which are temperature and humidity and passes them to the hidden layer for computation and pre-processing. The output layer uses the nodes from the hidden layer to make classifications and predictions. In the ANN algorithm, the initial weights are set to 1 and -1. An epoch is then done to the algorithm such that data inputs to be learned are presented to the learning machine. Learning by the ANN algorithm takes place; three objects are selected. These include the pattern lists (inputs), categories (outputs) and the classifier (FFNet). The outputs are then passed through a sigmoid function that ranges between 0 and 1. The weights transmitted to the hidden layer for classification are fixed. The classification process by the algorithm occurs by selecting categories that are associated with outputs that have the largest output values. The output layer's output were either positive or negative in confirming the presence of FAW pest in the environment.

5.3.6 SMS Notification and Recommendation

Based on the results of the prediction; the system is triggered to send a warning message and thereafter a recommendation based on the prediction. If the prediction is negative; the system sends a notification to farmers and FAW experts informing them there is not FAW in the fields. A sample SMS message content for negative prediction is:

"No FAW present in the soil or farm; farm is safe for now"

If the prediction is positive the system sends a warning notification to the users followed by recommendations based on the stage of the maize crops. A sample SMS message content for a positive prediction is:

"FAW Present in soil. Please prepare to take appropriate measures to avoid further damage"

The proposed remedies send out to the farmers and experts include the appropriate pesticides and bio-pesticides to use and whether they should be applied on the maize plant or the soil. Sample remedies send out to the farmers are described below:

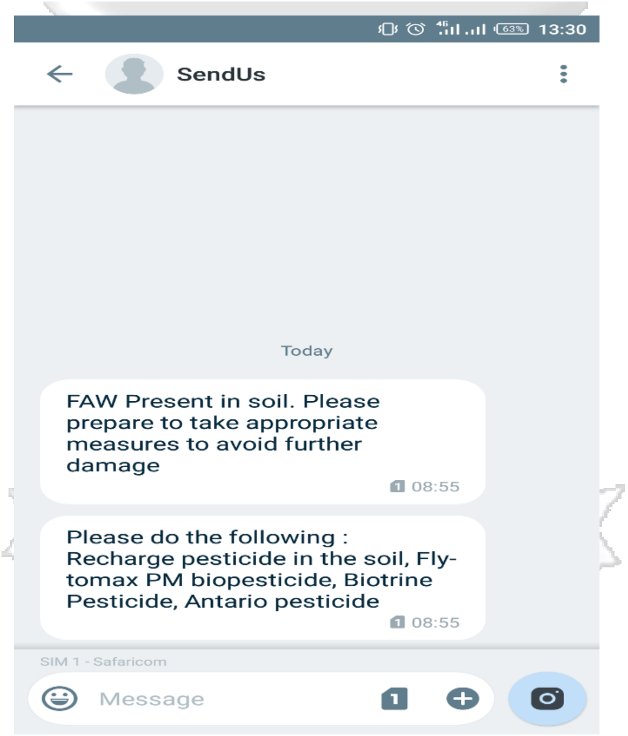
i. **Recharge pesticide in the soil-** this will help kill the FAW pupa in the soil thus preventing maturity to adult moths. Recharge pesticide is suitable for vegetative or young maize crops

ii. **Flytomax PM bio-pesticide** – this is suitable for the killing of larvae, pupae and the adult moths. It will work by suppressing the appetite of FAW larval stage resulting in their decline. Best effective when combined with biotrine

iii. **Biotrine Pesticide** - If there is acute leaf damage, pray the pesticide on the maize crop foliage. This penetrates the leaf surface and reaches the FAW burrowed in the plant. Biotrine be used in conjunction with the Recharge soil treatment powder to tackle soil dwelling pupae.

iv. **Antario pesticide** – used together with recharge and biotrine in the early stages of the infestation to minimize leaf damage,

Figure 5-9 below illustrates SMS warning and recommendation notification sent out to registered farmers and the FAW experts.



FAW Present in soil. Please prepare to take appropriate measures to avoid further damage
08:55

Please do the following : Recharge pesticide in the soil, Fly-tomax PM biopesticide, Biotrine Pesticide, Antario pesticide
08:55

Figure 5-8: SMS Notification & Recommendation

5.4 Model Training

The final model is often used in the training of new data to make predictions. The training data used were the average temperature and humidity levels from the past weather data for the period June -2016 to April-2018. Here, the training samples were passed through the ANN and the prediction results obtained from the model. The training data and validation data were split into a 50:50 ratio. Table 5-2 below illustrates temperature and humidity data used in the model training.

5.5 Model Testing

The section discusses the test cases considered in the development of the FAW invasion prediction model. The samples test cases were used to determine whether the developed system satisfies the proposed requirements.

Test Case	**Importance**	**Test Results**
Does the application allow the FAW expert to register farmer details?	High	Successful registration of farmer details by the FAW expert
Does the application successfully capture temperature and humidity parameters from the soil?	High	Soil parameters captured by soil sensors
Does the application successfully upload sensor data to the server?	High	Sensor data uploaded successfully to the server
Does the application provide real-time data to the FAW expert?	Medium	FAW experts able to access real-time data on temperature and humidity readings in form of graphs
Does the application send out a warning message and recommendation to farmers	High	Notification or SMS successfully sent to the users with warning and recommendation.

Table 5-2: Model Test Cases

Chapter 6 : Discussions

6.1 Introduction

This chapter discusses the results of the developed solution in light with the objectives and research questions outlined in chapter one. The main objective of this study was to develop a prediction model for FAW infestation and issue a warning message as well as recommendations to farmers on the best course of action. The model utilized the ANN algorithm in performing predictions based on the inputs collected from the environment. In achieving correct classifications and predictions, the inputs used in the prediction model include soil temperature, humidity and observable characteristics collected from the maize fields by farmers and FAW experts.

The research study established that the FAW pest is known to survive in environments with temperatures ranging from 24^0 C to 28^0 C and humidity levels ranging from 65% to 75%. The temperature and humidity levels coupled with soil moisture influence the survival of the FAW pupa in the soil thus affecting their maturity time and development into adult moths which are notorious for spreading to unaffected farms. The observable characteristics identified in chapter 5 are common to other pests such as the African armyworm and the cutworm except for a few cases.

6.2 Results of the Study

The experiments of this study were conducted in maize fields and in soil samples obtained from a maize farm with history of pest infestation. The sensors are deployed in the soil to capture soil humidity and temperature levels. Users provide feedback on features observed in the maize fields which are used as inputs in the prediction process. The data is processed and fed to the ANN algorithm which formulates predictions based on several computations. The server then sends predictions and recommendations to the farmer and FAW experts in form of SMS notifications as illustrated in figure 5.9 above.

6.3 Prediction Confidence

This study used two ML algorithms in achieving classification and prediction results. The two ML algorithms used in the study were ANN and SVM. The study used confidence which is the ability of the prediction model to achieve a similar performance when a new data set with similar characteristics with the training data set is used. From the results; model confidence of the SVM algorithm was at 0.9598 while that of the ANN algorithm was at 0.9781. The ANN algorithm in this case is considered the more robust of the two.

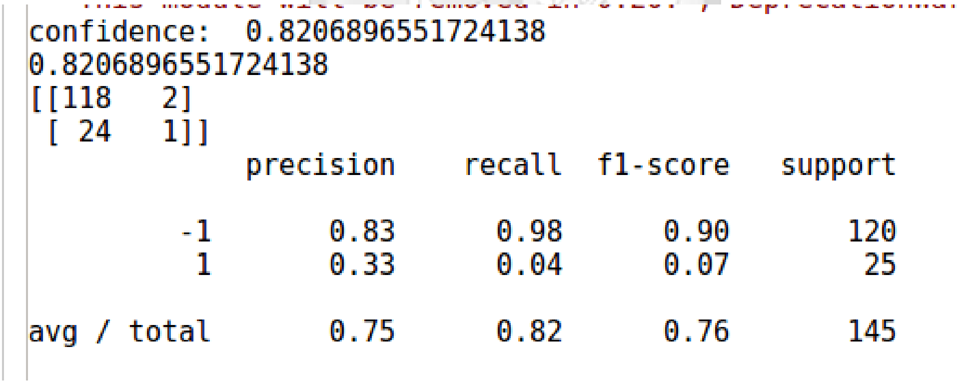
6.4 Validation of the Model

6.4.1 Confusion Matrix

The table illustrates the model's confusion matrix describing the performance of the model given a set of test data. The confusion matrix of the developed solution outlines a summary of the prediction results such that numbers of incorrect and correct predictions are highlighted. The study used a total of 145 instances which were used in the training and testing of the model. The results are illustrates in the figures 6-1 and 6-2. Both SVM and ANN algorithm were used in the model creation and below are the results. The presence of the FAW in the field is represented by (1) while that of absence in the field is represented by (-1).

a. ANN Model Results

The results of the ANN model are as shown in figure 6-1:



```
confidence:  0.8206896551724138
0.8206896551724138
[[118   2]
 [ 24   1]]
             precision    recall  f1-score   support

         -1       0.83      0.98      0.90       120
          1       0.33      0.04      0.07        25

avg / total       0.75      0.82      0.76       145
```

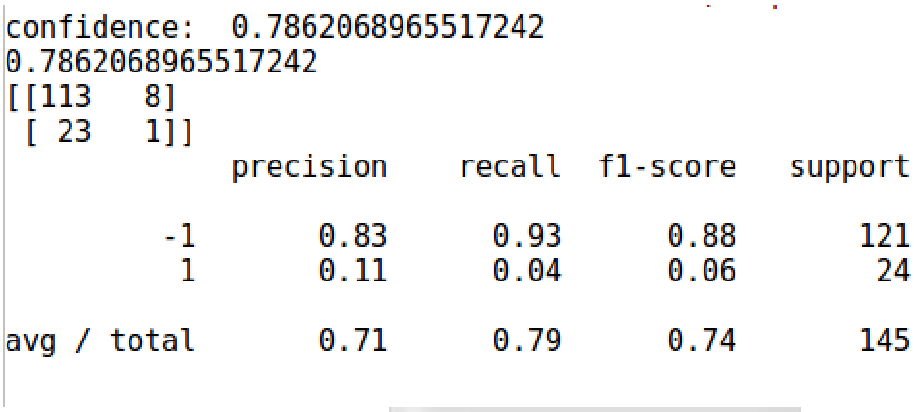
Figure 6-1: ANN Confusion Matrix

a. From the confusion matrix, the accuracy of the model is **82.06%** for given the formula in chapter 3 above
b. The recall ratio of the model is 0.98 for absence of FAW in the field and 0.04 for presence of the FAW in the fields.
c. The precision ratio of the model is 0.83 for negative match and 0.33 for a positive match of FAW in the farm.

d. The F-measure of the model is 0.90 for a negative match and 0.07 for a positive match in the field.

b. SVM Model Results

The results of the confusion matrix for the SVM algorithm are as shown in figure 6-2:



```
confidence:  0.7862068965517242
0.7862068965517242
[[113   8]
 [ 23   1]]
             precision    recall  f1-score   support

         -1       0.83      0.93      0.88       121
          1       0.11      0.04      0.06        24

avg / total       0.71      0.79      0.74       145
```

Figure 6-2: SVM Confusion Matrix

a. The accuracy of the model is 78.62% given the formula

b. The recall ratio of the model is 0.93 for absence of FAW in the field and 0.04 for presence of the FAW in the fields.

c. The precision ratio of the model is 0.83 for negative match and 0.11 for a positive match of FAW in the farm.

d. The F-measure of the model is 0.88 for a negative match and 0.00 for a positive match in the field.

6.5 Validity of the Proposed Solution

Several models and solutions have been developed for the purpose of predicting presence of pests and diseases in the environment. Kenya however is a long way from this as the country grapples with the menace that is the FAW. Currently; farmers are issued with pheromone traps that are placed in maize farms to capture FAW moths thus preventing further spreading. Farmers and KALRO experts also rely on vision-based method of identification for the presence of the armyworm in the fields. The proposed solution employs the use of IoT technology in gathering environmental data and sending the same to a server. Sensors are able to capture data which is used in predicting the positive or negative presence of the FAW in the soil and environment. Farmers lack the knowledge on appropriate control measures to use on the FAW resulting in the pest developing resistance towards common pesticides in Kenya. This system also provides recommendations to farmers on the best pesticides to apply in farms in the case of a positive prediction. With the system; there will be automatic monitoring of farms thus saving time spent on manual observations. Farmers will also be able to receive accurate recommendations appropriate to their farms thus controlling the problem of the FAW pest.

6.7 Research shortfalls

The developed solution had several limitations that may otherwise affect its validity.

i. While the FAW pest is known to attack a variety of plant species; this study focused on the maize crop which happened to be most affected in the country.
ii. The model worked with the assumption that not all farmers are tech-savvy or rather have access to smartphones. For this reason; only the FAW experts interact with the system by updating farmer details and observing real-time data from the sensor readings
iii. The model employed the use of WI-FI technologies in the farms which may not work for all farms as intended by the proposed system.
iv. This study used environmental samples from Dec 2016 to March 2018 since this was the time the FAW pest was first detected. The result was use of 145 instances in the training and testing of the model which greatly influenced the prediction results of the model

Chapter 7 : Conclusion and Recommendations

7.1 Conclusions

Kenya continues to face the FAW pest invasion with the pest attacking most maize-planting regions in Kenya. The pest continues to develop resistance against common pesticides resulting in desperation amongst the affected farmers. The government and agricultural institutions like KALRO continue to invest heavily in research with the aim of finding a more permanent solution. Currently, the country's immediate solution is the use of pheromone traps which have been distributed to farmers countrywide. The pheromone traps will capture the FAW male moths in the fields thus preventing their mating and spread to other regions. Other solutions include manual inspection by farmers and experts to scout for damaged leaves and presence of caterpillars in the farm. So far, KALRO has spent over Kshs. 300 Million in the fight against the pest and more will probably be spent in the next few years until a permanent solution is sort.

This study has presented a prediction model for the FAW pest in the environment given a set of parameters. The technologies adopted include IoT and Artificial Neural Network ML algorithm. The first part of the developed solution consisted of the deployment of soil sensors in maize fields. The sensors were used to collect environmental soil parameters supporting the existence of FAW pupa in the soil. In implementing the system, the sensor data from the farm should be sent to a server. The data is fed to a NN algorithm that processes the same and provides prediction results and recommendations which are sent out to the farmer and experts mobile devices in form of SMS. Validation of the different machine learning algorithms used in model was determined by prediction confidence. SVM algorithm had a confidence level 0.9598 while that of the ANN algorithm was at 0.9781 thus making the ANN algorithm the more suitable of the two.

The use of IoT sensors in this study allows farmers, FAW experts and KALRO to interact thus improving the production of maize crop in Kenya and devising remedies that are made available to all. The ability to communicate appropriate recommendations to farmers and experts makes it easy for farmers to purchase the right pesticides and have early preparedness.

7.2 Recommendations

The conducted study provides the recommendations below:

a) The researcher recommends the use of pupa’s burrowing depth in the soil in the soil to determine the recommendation sent out to farmers. Pesticide application on FAW pupa that burrows deeper into the soil (approximately 8 centimetres) has a different impact compared to the pupa that burrows at approximately 2 centimetres.

b) The developed model could be expanded to analyse all pests affecting the maize crop in Kenya, their characteristics and most effective remedies.

c) The researcher recommends the use of new pesticides that have been effective in other countries to fight the FAW pest. FAW in Kenya has developed resistance towards the common pesticides thus forcing the country to source out new solutions. Some of the new pesticides which have proven to be effective in Tanzania will go a long way. The recommended pesticides to be adopted include Recharge, Flytomax PM, Biotrine and Antario.

d) The researcher recommends use of more inputs from the environment to perform the prediction. This study used environmental samples from Dec 2016 to March 2018 since this was the time the FAW pest was first detected. The result was use of 145 instances in the training and testing of the model which greatly influenced the prediction results of the model. This may also include images from the field and statistics from the pheromone traps.

7.3 Future Work

a) While the study has provided general recommendations for the FAW situation; future studies could focus on providing solutions to the different stages of the FAW invasion. The pesticides used are only effective on certain stages of the crop and the pest.

b) Future studies should consider the use of image processing techniques in identifying the positive matches of the FAW moth. The pheromone traps deployed in the farms capture a variety of nocturnal moths unless specific scents particular to the FAW are applied in the trap. In deploying this; pheromone traps could be fitted with camera and motion sensors that would be triggered to capture images of trapped moths for processing. The result would be a positive or negative match to the FAW images in the system. Presence of pests in the environment can be well diagnosed if cameras are deployed in the fields with traps and sensors used to capture environmental data.

c) The proposed system employed the use of Wi-Fi technologies in transmitting data readings to the server. Future studies may employ the use of GSM instead of Wi-Fi module. This way, automatic location of farms may be picked up.

d) Future studies of FAW prediction could focus on predicting the presence of FAW pest in already harvested maize. Cases have been reported of the FAW pest getting into Africa through imported maize thus causing the current situation.

References

AGRA. (2016). Africa Agriculture Status Report 2016: Progress towards agricultural transformation. Nairobi, Kenya: Alliance for a Green Revolution for Africa (AGRA).

Al-Saqer, S. M. (2012) “A robust recognition system for pecan weevil using artificial neural networks,” American Journal of App. Sci..

Azfar, S., Nadeem, A., & Basit, A. (2015). Pest detection and control techniques using wireless sensor network: A review. Journal of Entomology and Zoology Studies,3(2), 92-99. Retrieved August 10, 2017.

Boissard .P., Martin.V., & Moisan.S. (2008) A Cognitive Vision Approach to Early Pest Detection in Greenhouse Crops. Computers and Electronics in Agriculture, Elsevier, 2008, 62 (2), pp.81-93.

Brinda,P. & Pushparani, M. (2016). Analysis of Early Leave Pest Detection. International Journal on Recent and Innovation Trends in Computing and Communication,4(5), 2321-8169, 11-13. Retrieved August 10, 2017.

Capinera, J., & Smith, J. E. (2015). Fall Armyworm, Spodoptera frugiperda. 1(2), 1-6. Retrieved August 10, 2017.

Charleston, K. (2013). Maize insect pest management(2nd ed., Vol. 1, pp. 1-13, Rep.). State of Queensland: Queensland Department of Agriculture, Fisheries and Forestry.

Chinwada, P. (2016). Training Manual On Fall Armyworm. 1(2), 1-202. Retrieved March 12, 2018.

Corrales, D., Corrales, J., & Figueroa-Casas, A. (2015). Towards Detecting Crop Diseases and Pest by Supervised Learning. 19(1), 207-228.

Craig, J. (2017, May 16). Fall Armyworms Descend on East Africa. Retrieved July 25, 2017, from https://www.voanews.com/a/armyworms-east-africa/3853083.html

Dey, A., Bhoumik, D., & Dey, K. (2016). Automatic Detection of Whitefly Pest using Statistical Feature Extraction and Image Classification Methods. International Research Journal of Engineering and Technology,3(9), 950-959. Retrieved August 10, 2017.

Flanders, K., Ball, D., & Cobb, P. (2017). Management of Fall Armyworm in Pastures and Hayfields(2nd ed., Vol. 1, pp. 1-8, Rep.). Alabama Cooperative Extension System.

Gardner. D. (2010). The Appliance of New Science and Frontier Technologies to Transform UK Agriculture And UK Agri-Food, Farm Management Conference, p.9, 89-92

Hendrik, J., & Bertone, M. (2016). The New Invasive Fall Armyworm (Faw) In South Africa. Arc--Plant Protection Research Institute, 1, 1-2.

Jessica Rutkoski et al.(2012), “Evaluation of Genomic Prediction Methods for Fusarium Head Blight Resistance in Wheat”, The Plant Genome, vol. 5, pp.51–61,

Jones, P. & Thornton, P.(2013), ‘The potential impacts of climate change on maize production in Africa and Latin America in 2055’, Global Environmental Change, 13.

Karandeep K, (2016) “Machine Learning: Applications in Indian Agriculture”, International Journal of Advanced Research in Computer and Communication Engineering, Vol.5, no.4, pp.342-344,

Kim, Y. H., & Yoo, S. J. (2014). Crop Pests Prediction Method using Regression and Machine Learning Technology: Survey. 2013 International Conference on Future Software Engineering and Multimedia Engineering,6, 52-56. Retrieved July 25, 2017.

Kulalvaimozhi, V., Germanus, A., & Peter, J. (2017). IMAGE PROCESSING IN AGRICULTURE. International Journal Of Advancement In Engineering Technology, Management and Applied Science (IJAETMAS),4(3), 142-151. Retrieved August 20, 2017.

Maina, C. N. (2016). Vision-Based Model for maize leaf disease identification: a case study in Nyeri County (Thesis). Strathmore Univeristy. Retrieved from http://su-plus.strathmore.edu/handle/11071/4820

Malathi, M., & Nizar, S. (2016). Pest detection system with artificial intelligent agricultural forecasting techniques. International Conference on Current Research in Engineering Science and Technology,1(1), 2348 - 8549, 120-124. Retrieved August 10, 2017.

Martin, V., & Moisan, S., (2014), Early pest detection in greenhouses

Manoja, M., & Rajalakshmi J. (2014). Early Detection of Pests on Leaves Using Support Vector Machine. International Journal of Electrical and Electronics Research,2(4), 187-194. Retrieved August 10, 2017.

Miranda, J., Gerardo, B., & Tanguilig, B. (2014). Pest Detection and Extraction Using Image Processing Techniques. International Journal of Computer and Communication Engineering,, 3(3), 1-4. Retrieved April 22, 2018.

Mundada, R., & Gohokar, V. (2013). Detection and Classification of Pests in Greenhouse Using Image Processing. IOSR Journal of Electronics and Communication Engineering (IOSR-JECE), 5(6), 57-63. Retrieved August 10, 2017.

Njuguna, J., Njau, J., & Thuita, A. (2017). Africa Agriculture Status Report 2017. The Business of Smallholder Agriculture in Sub-Saharan Africa, 1-180. Retrieved April 1, 2018.

Ocharo, B., Mutai, E., & Sayagie, G., (2018, February 05). Kenya tech firm launches agriculture mobile app. Retrieved November 1, 2017, from https://www.businessdailyafrica.com/corporate/companies/Kenya-tech-firm-launches-agriculture-mobile-app/4003102-4292892-59ggbz/index.html

Popa, C. (2011). Adoption of Artificial Intelligence in Agriculture. Bulletin UASVM Agriculture,68(1), 1843-5246, 1-10. Retrieved August 10, 2017.

Prakash M., Shreekant .G & Mayur .A. 2015), Plant Leaf Disease Detection and Classification Using Image Processing Techniques", International Journal of Innovative and Emerging Researchin Engineering Volume 2, Issue 4, 139-144.

Rajan, L., & Radhakrishnan, B. (2016). A Survey on Different Image Processing Techniques for Pest Identification and Plant Disease Detection. International Journal of Computer Science and Network,5(1), 137-141. Retrieved August 10, 2017.

Rani, R., & Amsini, P. (2016). Pest Identification in Leaf Images using SVM Classifier. International Journal of Computational Intelligence and Informatics,6(1), 30-41. Retrieved August 10, 2017.

Sarfo, D., & Jayne, T. (2016). Africa Agriculture Status Report 2016. Progress towards Agricultural Transformation in Africa, 1(2), 1-300. Retrieved February 22, 2018

Shekhar, Y., Dagur, E., & Mishra, S. (2016). Intelligent IoT Based Automated Irrigation System. International Journal of Applied Engineering Research, 12(18), 1-15. Retrieved April 22, 2018.

Shi, Y., Wang,, Z., Wang, X., & Zhang, S. (2015). Internet of Things Application to Monitoring Plant Disease and Insect Pests. International Conference on Applied Science and Engineering Innovation,1(4), 31-34.

Smith J. (2015). Crops, crop pests and climate change – why Africa needs to be better prepared. CCAFS Working Paper no. 114. Copenhagen, Denmark. CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS). Available online at: www.ccafs.cgiar.org

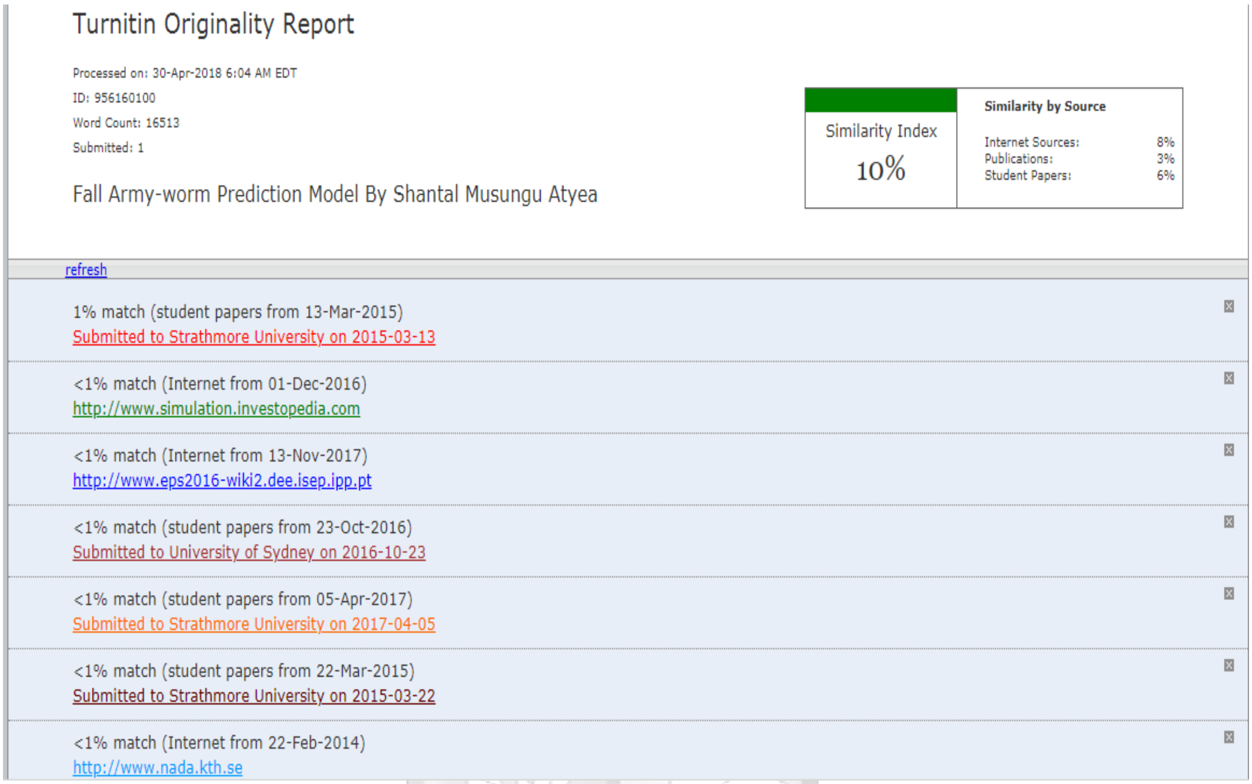
Toroitich, P., & Orero, D. (2017). Real-Time Monitoring Model for Early Detection of Crop Diseases. 1(1), 1-6. Retrieved August 10, 2017.

Vibhute .A & Bodhe,S.K (2016); “Applications of Image Processing in Agriculture: A survey; International Journal of Computer Applications”.


VT OMNES
VNVM SINT

Appendix

Appendix 1: Originality Report



Turnitin Originality Report

Processed on: 30-Apr-2018 6:04 AM EDT
ID: 956160100
Word Count: 16513
Submitted: 1

Fall Army-worm Prediction Model By Shantal Musungu Atyea

Similarity Index
10%

Similarity by Source	
Internet Sources:	8%
Publications:	3%
Student Papers:	6%

1% match (student papers from 13-Mar-2015)
Submitted to Strathmore University on 2015-03-13

<1% match (Internet from 01-Dec-2016)
http://www.simulation.investopedia.com

<1% match (Internet from 13-Nov-2017)
http://www.eps2016-wiki2.dee.isep.ipp.pt

<1% match (student papers from 23-Oct-2016)
Submitted to University of Sydney on 2016-10-23

<1% match (student papers from 05-Apr-2017)
Submitted to Strathmore University on 2017-04-05

<1% match (student papers from 22-Mar-2015)
Submitted to Strathmore University on 2015-03-22

<1% match (Internet from 22-Feb-2014)
http://www.nada.kth.se

Appendix 2: Interview Guides

Farmer Interview

i. Was your farm affected by FAW?

ii. How did you know that the pest damaging your crop was the FAW?

iii. Was the entire region around your farm affected too?

iv. What was the damage level in your farm?

v. What have you learnt about the FAW so far?

vi. What have you adopted so far to contain the FAW?

KALRO Representative

i. How many counties in Kenya have been affected by the FAW pest so far?

ii. What crop species have been affected most?

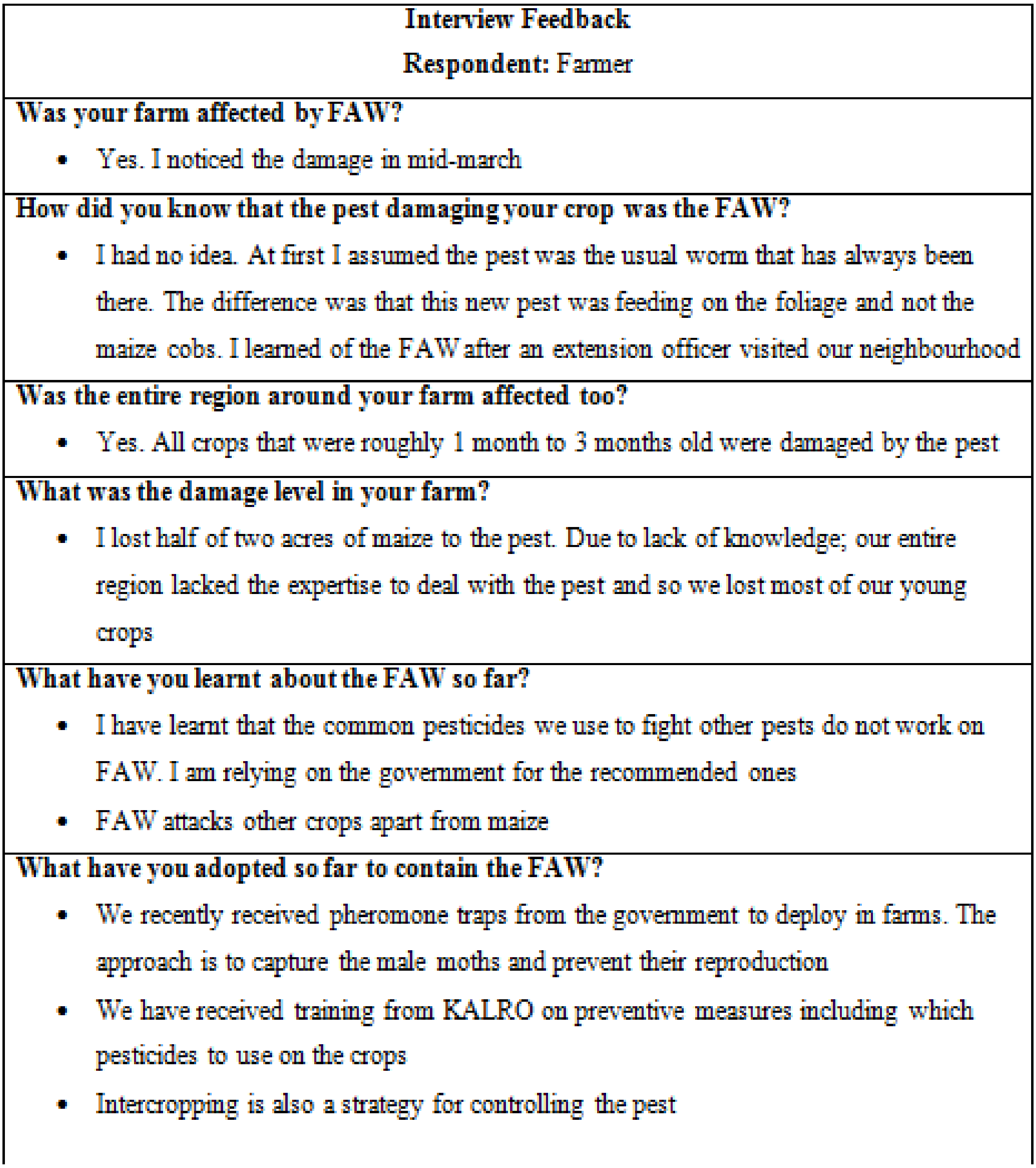
iii. What has KALRO done to control the spread of FAW in Kenya?

iv. What are the common observable characteristics reported by farmers?

v. Which pesticides are you advising farmers to use in the control of FAW?

vi. How soon can Kenya find a permanent solution to FAW menace?

Appendix 3: Interview Feedback



Interview Feedback

Respondent: Farmer

Was your farm affected by FAW?

- Yes. I noticed the damage in mid-march

How did you know that the pest damaging your crop was the FAW?

- I had no idea. At first I assumed the pest was the usual worm that has always been there. The difference was that this new pest was feeding on the foliage and not the maize cobs. I learned of the FAW after an extension officer visited our neighbourhood

Was the entire region around your farm affected too?

- Yes. All crops that were roughly 1 month to 3 months old were damaged by the pest

What was the damage level in your farm?

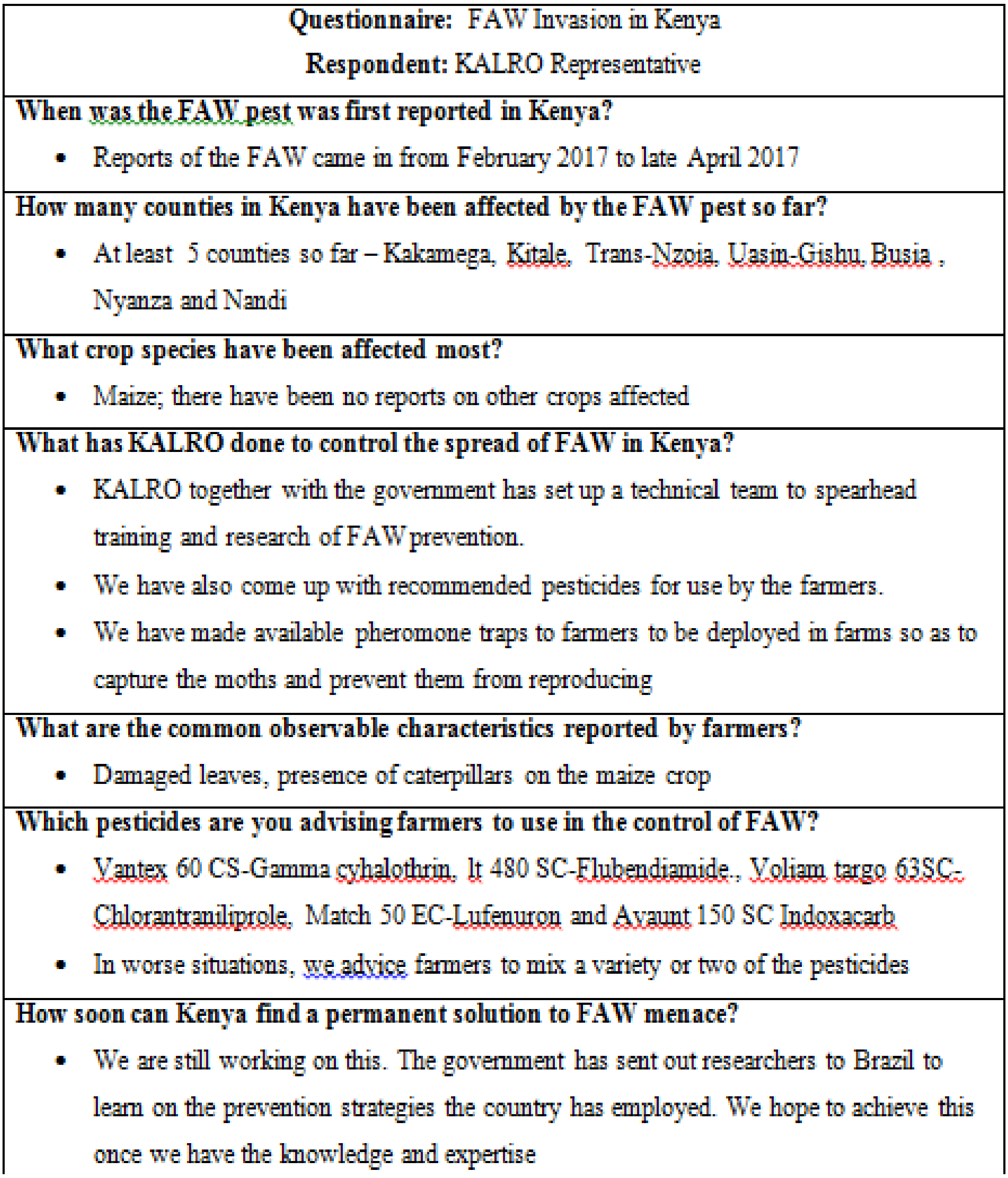
- I lost half of two acres of maize to the pest. Due to lack of knowledge; our entire region lacked the expertise to deal with the pest and so we lost most of our young crops

What have you learnt about the FAW so far?

- I have learnt that the common pesticides we use to fight other pests do not work on FAW. I am relying on the government for the recommended ones
- FAW attacks other crops apart from maize

What have you adopted so far to contain the FAW?

- We recently received pheromone traps from the government to deploy in farms. The approach is to capture the male moths and prevent their reproduction
- We have received training from KALRO on preventive measures including which pesticides to use on the crops
- Intercropping is also a strategy for controlling the pest



Questionnaire: FAW Invasion in Kenya

Respondent: KALRO Representative

When was the FAW pest was first reported in Kenya?

- Reports of the FAW came in from February 2017 to late April 2017

How many counties in Kenya have been affected by the FAW pest so far?

- At least 5 counties so far – Kakamega, Kitale, Trans-Nzoia, Uasin-Gishu, Busia , Nyanza and Nandi

What crop species have been affected most?

- Maize; there have been no reports on other crops affected

What has KALRO done to control the spread of FAW in Kenya?

- KALRO together with the government has set up a technical team to spearhead training and research of FAW prevention.
- We have also come up with recommended pesticides for use by the farmers.
- We have made available pheromone traps to farmers to be deployed in farms so as to capture the moths and prevent them from reproducing

What are the common observable characteristics reported by farmers?

- Damaged leaves, presence of caterpillars on the maize crop

Which pesticides are you advising farmers to use in the control of FAW?

- Vantex 60 CS-Gamma cyhalothrin, It 480 SC-Flubendiamide., Voliam targo 63SC-Chlorantraniliprole, Match 50 EC-Lufenuron and Avaunt 150 SC Indoxacarb
- In worse situations, we advice farmers to mix a variety or two of the pesticides

How soon can Kenya find a permanent solution to FAW menace?

- We are still working on this. The government has sent out researchers to Brazil to learn on the prevention strategies the country has employed. We hope to achieve this once we have the knowledge and expertise

Appendix 4: Artificial Neural Network Code

```
from sklearn.neural_network import MLPClassifier


import pandas as pd

import numpy as np

from sklearn import preprocessing, cross_validation, svm

from sklearn.svm import SVR

from sklearn import metrics


# df = pd.read_csv('shantel.csv')

df = pd.read_csv('labeled_shantel.csv')

array = df.values

X = array[:,0:6]

Y = array[:,6]


X_train, X_test, y_train, y_test = cross_validation.train_test_split(X, Y, test_size = 0.3)

# Training

clf = MLPClassifier()

clf.fit(X_train,y_train)

# Testing

confidence = clf.score(X_test, y_test)

print("confidence: ", confidence)

ypred=clf.predict(X_test)

print(metrics.accuracy_score(y_test,ypred))
```

```
print(metrics.confusion_matrix(y_test,ypred))

print(metrics.classification_report(y_test,ypred))
```

Appendix 5: Support Vector Machine Code

```
import pandas as pd

import numpy as np

from sklearn import preprocessing, cross_validation, svm

from sklearn.svm import SVC

from sklearn import metrics

# df = pd.read_csv('shantel.csv')

df = pd.read_csv('labeled_shantel.csv')

array = df.values

X = array[:,0:6]

Y = array[:,6]

X_train, X_test, y_train, y_test = cross_validation.train_test_split(X, Y, test_size = 0.3)

# Training

clf = SVC(probability=True)

clf.fit(X_train,y_train)

# Testing

confidence = clf.score(X_test, y_test)

print("confidence: ", confidence)

ypred=clf.predict(X_test)

print(print(metrics.accuracy_score(y_test,ypred)))

print(metrics.confusion_matrix(y_test,ypred))

print(metrics.classification_report(y_test,ypred))
```

Appendix 6: Sample Training & Testing Data

Year	Month	Date	Low Temperature	High Temperature	Average Temperature	Low Humidity (%)	High Humidity (%)	Average Humidity (%)
16	**Dec**	1	18	31	24	27	78	57
		2	18	30	24	43	88	65
		3	18	31	24	40	94	74
		4	17	28	22	45	100	73
		5	19	31	24	24	73	51
		6	18	32	25	11	68	34
		7	16	31	23	23	78	51
		21	18	34	26	6	69	34
		22	20	33	27	15	100	43
		23	16	33	24	13	68	36
		24	16	32	24	20	73	39
		25	18	33	26	21	64	37
		26	18	34	26	14	73	37
		27	19	32	26	21	65	46
		28	19	32	26	17	74	44
		29	21	30	26	22	73	55
		30	21	31	26	26	83	57
		31	18	31	24	27	94	62
17	**Jan**	1	21	29	25	33	78	57
		2	19	29	24	41	88	71
		3	16	31	23	22	94	65
		4	16	32	24	15	83	49
		5	18	33	26	14	73	33
		6	16	35	26	16	68	39
		7	17	32	24	21	65	44
		8	19	33	26	22	69	46
		9	17	32	24	21	78	51
		10	21	33	27	13	78	52
		11	16	34	25	13	72	39
		12	17	32	24	10	59	35