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Developing an automatic identification and early warning and monitoring web based system of fall army worm based on machine learning in developing countries

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***Abstract*— To combat the fall Army worm (FAW-Spodoptera frugiperda) pest which has a negative impact on world food security, there is need to come up with methods that can be used alongside conventional methods of spraying. Therefore this paper proposes a machine learning based system for automatic identification and monitoring of Fall Army worm Moths. The system will aim to address challenges that are associated with trap based FAW monitoring such as manual data collection as the system will automate the data collection process. The study will aim to automate the data collection process by developing a machine learning algorithm for FAW moth identification. The study will develop web and mobile applications integrated with Geographic information system (GIS) technology in addition to trap automation. The tools developed in this study will aim to improve the accuracy and efficiency of FAW monitoring by reducing the aspect of human intervention. At the time of writing this paper, only the web based tool prototype has been developed, therefore this paper mostly focuses on the design of the web based tool. The paper also provides a brief quantification of the chosen machine learning technique to be used in the study.**

***Index Terms*— Artificial Neural Networks, Fall Army Worm, Identification, Machine learning, Single Board Computer, Pheromone.**

I. Introduction

AMONG insects classified as a threat to food security by the Food Agriculture organization of the United Nations (FAO) is the Fall Army Worm (FAW-Spodoptera frugiperda) which has been a nuisance to the food crops in Africa since its reported presence on the continent [1]. Its presence has been reported in over 30 sub-Saharan African countries where it has caused extensive damage to crops especially maize fields. The Fall Army worm possess characteristics that make unique and more devastating than other crop attacking insects [3]. The Fall Army worm can feed on more than 80 different crops, it is capable of spreading very quickly across large geographical areas, it can persist throughout the year meaning that it does not only affect crops planted during the rainy season but also the irrigated plants as well and Its able to lay over 1500 eggs which becomes FAW moths within a space of 28 days [3]. The impact of the Fall Army worm has been felt at national, continent and household level mostly in maize producing countries such as Zambia [4]. According to [4], the potential impact of FAW on the continents maize yield lies between 8.3 and 20.6 million tons per annum of total expected production of 39m tones per annum and with losses lying between $2,481m and $6,187 per annum of total expected value of $11,590.5m per annum. [4] Further states that FAW directly affects capital costs, through increased labour and increasing cost of production due to costs of control.

The Fall Army worm presents a challenge on how to find control measures that can be used together with the traditional methods of spraying. In order for the spraying of pesticides to be done there is need for the pest to be detected in an area to be sprayed. The challenge that currently exist is coming up with efficient methods that can act as FAW monitoring and early warning systems. [3] Stated that there has been limited proven approaches to prevent and avoid FAW and efforts to suppress the pest is largely focused on the use of synthetic pesticides which has a high potential to damage human, animal and environmental health. Currently one of the methods being used in Africa is the use of pheromone traps to lure the male FAW moth. Pheromone traps are traps that are set in the field evenly spaced containing some female hormone that attracts male moths. The set traps are monitored after a number of days and the trapped moths are counted and recorded on the data collection sheets. The Pheromone trap FAW monitoring is an inefficient warning system as it is not only a tedious, time consuming, expensive and labour intensive process but it is prone to error as the recorded moths may be overstated or understated providing false data to interested stakeholders. And owing to the short life cycle of the FAW, taking days to monitor the FAW is not an efficient method [5]. Therefore the need to improve on the methods used in the monitoring of the pest can never be overemphasized. Over the years several methods have been proposed that can be used in the field of insect monitoring and identification [6]. With the major technological advancements that the world has seen in recent years, we can try to improve on the methods that have already been done or come up with completely new methods. This research aimed at coming up with a Fall Army Worm monitoring and early warning System. The system will be machine learning based. The research will aim to automate the counting of moth thereby reducing the field visits and shorten data collection intervals to within minutes. In addition the system will provide effortless monitoring of farm areas using fewer resources. The system will employ machine learning preferably artificial neural network (ANN) techniques for identifying the FAW Zambian species. Further the system will provide a portal integrated with GIS providing a near real time occurrence of the pest in the country.

II. Similar Work

This section of the paper gives a review of literature that focuses on similar related research work as well as how similar challenges have been addressed elsewhere. The literature review mainly focuses on the identification and classification of insects even though it is not the main focus of this paper as it's the core for the success of the research and since the machine learning work is yet to be done. We also review the current insect identification method being used.

A. Image based insect identification and classification

To maintain the diversity of species within the ecosystem, various scientists in the world including computer scientists have gained an interest in the field of biodiversity and out of 1.3 million known species on this earth, insects account for more than two thirds of these known species. For many years now, there have been different kinds of interactions between humans and insects and these interactions requires that insects are observed in close contact either by taking them to the lab or capturing their images. Several attempts have been made to create a method to perform insect identification accurately mainly because accurate insect identification requires great knowledge and experience on entomology [6]. A shortage of entomologists and the labour intensive process of collecting insect samples has led scientists trying to come up with methods that will do automatic insect identification and classifications.

[7] applied data mining techniques to effectively identify images of 774 live moth each belonging to different UK moth species. They extracted feature vectors from each of the moth images and used the machine learning toolkit WEKA to classify the moths by species using the feature vectors. The ML Toolkit was able to achieve a greater level of accuracy (85%) using support vector machines without manual specification of a region of interest at all [7]. They stated that the most important factor in the success of any machine learning-based image classification system is the features that are extracted. They captured the features on the moth's wings by calculating the moth's centroid by centering a square over the centroid and taking samples from 200 patches inside the main square [7]. The method was effective in capturing the wing patterns but disadvantaged smaller species that occupied less space in the image. They suggested that while the challenge of smaller species in the image affected their work, future work should be able to address the challenge when using the same techniques that they used in their work. In their work on image identification and analysis, they showed that data mining can be usefully applied to automatic identification of species.

[9] Presented an artificial neural networks method for classification and identification of anopheles mosquitos based on the internal transcribed spacer2 (ITS2) data of ribosomal DNA string. They implemented the method using two different multi-layered feed-forward neural network model forms, namely, multi input single-output neural network (MISONN) and multi-input multi-output neural network (MIMONN) [9]. They employed a number of data sequences in varying sizes of different Anopheles malarial vectors and their corresponding species coding in the development of the neural network models. Their results demonstrates the efficiency of neural networks models in the extraction of information.

[12] Described a computer-vision-based system to recognize and classify insects as being harmful and non-harmful to the growth of cotton. They based the recognition and classification of the cotton insect upon a neural network approach. In their work, they showed that neural networks can be applied effectively to the classification of insects and suggested that to demonstrate the viability of using trained neural networks directly in the field, further work is required [12]. The concluded their work by speculating that in the future, field deployable systems would allow farmers to identify the type of insects that inhabit a specific ecosystem and choose which biological or pesticide to use as a control [12].

[13] Designed an automatic identification system for insect images at the order level. They designed several relative features according to the methods of digital image progressing, pattern recognition and the theory of taxonomy and used artificial neural networks and a support vector machine (SVM) as pattern recognition methods [13]. From the results of the tests they conducted, they found that the tests conducted using ANN performed very well as compared to the tests conducted using SVM. They also concluded that to improve their insect order identification system, they need to focus on feature extraction and design of newer and more effective features from the insect order [13].

There has been a number of systems designed and suggested that can be used to come up with an effective method for insect image identification and classification and most of the methods used suggests the automation of the whole process by using machine learning techniques such as artificial neural networks (ANN) and Support Vector Machine (SVM). ANN are information processing systems constructed and implemented to model the human brain and have the ability to learn using their experience [14]. Provided with a good number of samples, ANN are capable of generalizing to other samples they are yet to encounter [14]. The use of ANN in most of the image identification systems reviewed has shown that they can effectively be trained to efficiently identify and classify images of insects. The reviewed systems showed that there are a number of factors that affect the performance of the identification system such as environmental factors i.e. temperature, humidity etc., image quality and resolution, the diversity of species, features of species such as different sizes of captured species, system placement areas and so on. Therefore to design an effective and efficient FAW identification and classification system, most of the above factors will have to be considered.

B. Trap based insect identification and classification

Insects can have both positive and negative impact on the livelihood of human beings hence the reason why they receive a lot of scientific attention. For instance bees play an important role in the pollination of plants hence one of the reasons why we have food from plants. Some insects are a nuisance to humans like the FAW which has had a negative impact on the supply of food where ever they are reported. The negative impact of insects has led to scientists developing methods that can be used to monitor their presence. One of the methods that has been used from time in memorial is the traditional method of traps. According to [15], traps that are developed for capturing insects are varied according to the purpose for trapping, the targeted insect and the habitat in which they are used. Traps are used for the general survey of insect diversity or for the detection of new invasions of insects in an area and may be used as direct control measures e.g. mass trapping, perimeter trapping or can be used for suppressing population buildup of insects [15]. There are many trap types which include interception traps commonly used for faunal surveys in ecological studies which are suspended nets with an invagination along the top leading to a collecting funnel, sticky commonly used for faunal surveys in agricultural studies which are either panels, cylinders or spheres covered with sticky materials that retain insects that fly onto the panel [15].

One of the commonly used traps in the monitoring and controlling of the FAW insect are pheromone traps which can be classified as a sticky trap owing to the sticky material that is sometimes used to trap the FAW once in the trap. Pheromone traps use pheromones to attract male insects. A pheromone is a chemical secreted by (usually) a female insect to attract males for mating which can travel by air very long distances and hence are very useful for monitoring insect presence [3]. The pheromone traps are useful for detection of early pest infestations, definition of areas of pest infestations, tracking the buildup of pest population and assisting in the decision making process for pest management [3,4]. Pheromone traps are of different designs manufactured by different manufacturers as shown by Fig. 1 and Fig. 2. Fig. 1 uses a sticky surface coated with a special non-drying glue which retains the insect once it flies onto it. The sticky trap has been used in Malaysia and found to be more effective in capturing small moths [16]. The Funnel pheromone trap shown in Fig. 2 has a funnel section and a bucket. It has a pheromone dispenser holder is located on top of the funnel under an umbrella type cover. Insects attracted to the trap fly around the pheromone dispenser until exhausted and then fall into the trap as shown. Insects find it impossible to fly out of the bucket and are eventually killed by the pesticide inside the bucket. The effectiveness of the bucket trap was tested in the capturing of male moths in corn fields [17].

The trap method of insect identification and classification is the traditional method and has been used from time in memorial and has been found to be effective in the monitoring, mass trapping and control of insects. However good this method is, it has disadvantages such as it requires regular monitoring of and counting of insects. The traps if full needs to be emptied which requires going to the fields. The method if used as a monitoring and early warning system is prone to early and takes time, day's most of the time for the warning to be past to the relevant stakeholders hence delaying the decision making process. An automation of the counting process by the use of the latest technology we can go a long way in speeding up the early warning process thereby speeding up the decision making process. .

Fig. 1. Sticky surface trap [21].

Fig. 1. Bucket pheromone trap [22].

C. Preferred Machine Learning Technique-Artificial Neural Networks

Work on Artificial neural networks from its inception has been motivated by the Human brain. The brain is a highly complex, nonlinear, and parallel computer. It has the capability to organize its structural constituents, known as neurons, so as to perform certain computations (e.g., pattern recognition, perception, and motor control) many times faster than the fastest digital computer in existence today [14]. A neural network is a processing device, either an algorithm or a hardware whose design was inspired by the human brain. The neural networks have the ability to learn by example which makes them very flexible and powerful. For neural networks, there is no need to devise an algorithm to perform a specific task, meaning there is no need to understand the internal mechanism of that task [14]. The computing and the entire world has a lot to gain from neural networks. They can successfully be applied to solve many complex problems in the world which is the reason why scientists have taken advantage of them to try and solve many problems. The use of Artificial Neural Networks in this study is owed to its ability to perform well in object detection. The ability of ANN using layers where each layer is responsible for feature extraction makes ANN the best choice for this study. We intend to automate the image capture process hence the more features that we can extract the high the accuracy of identifying the image. The training dataset will be collected with the help of entomologists who have a better understanding of the insect. Training dataset collection will be taken by doing field visits and capturing images of live and dead FAW moth at different points. The most important images will be those taken at the trap as the automated cameras will be part of the trap. The more images we will get the more chances of increasing the accuracy of identification after the ANN is trained. We intended to develop an algorithm using MATLAB simulations then implementing that algorithm in the research system. Artificial neural networks have successfully been applied in so many areas in the world to solve complex problems as can be seen from the work done by the reviewed work. Their ability to generalize and learn makes them a capable tool in solving many complex problems. In addition they are capable of handling large amounts of data. Hence this makes ANN as the preferred strategy to be used in this study.

III. METHODOLOGY

This section describes the techniques used in the development of the web based Integrated Pest Management System. Detailed requirements and various conceptual models pertaining to the system are given.

A. System Development Methodology

An Agile incremental Development approach has been chosen for this research. Incremental development involves the creation of multiple usable versions of the product called vertical increments and each increment builds upon the previous version by adding user-visible functionality by analyzing any errors or omissions in the requirements to be revealed long before the system is handed over. Prototyping also brings up new requirements which is useful when time is in short supply or the development team lacks familiarity with the system's problem domain [23]. Hence in this paper we present the first version of the web based.

B. System Architecture

Fig. 3 shows a simple proposed model of how the data will flow. First the data will be collected at the trap site by the modified and automated pheromone traps. Depending on the cellular network connectivity at that particular time, the collected data will be sent to the cloud server for processing. Once received, the image identification system will identify and classify the image as FAW moth and load the data in the database. Once the data is loaded onto the database, the relevant stakeholders can access it via the web based or mobile app.

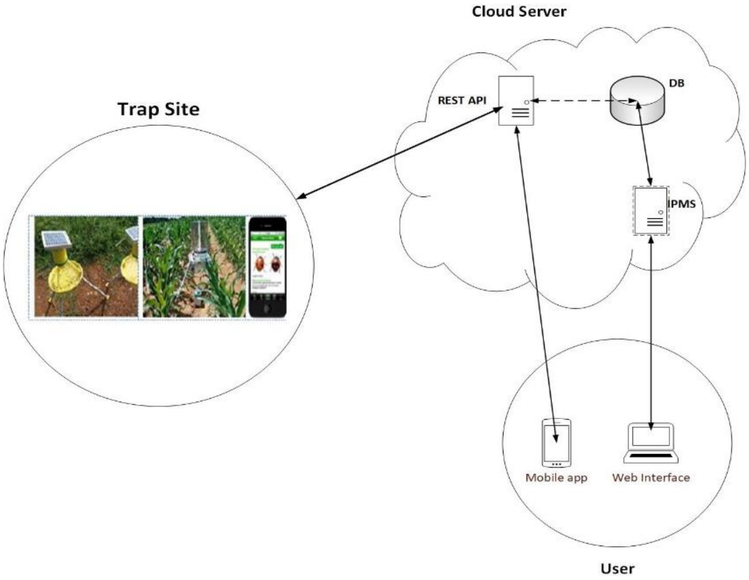

Fig. 3. Proposed model

C. Requirements

This subsection describes some of the system requirements that were identified for the web based system. The requirements have been split into functional and non-functional requirements.

1) Functional Requirements

- User must be able to manage farms
- User must be able to manage farmers
- User must be able to manage traps
- User must be able to manage crops
- User must be able to manage Lures
- Use must be able to manage their profile
- User must be able to manage Insects
- User must be able to manage surveys
- User must be able to manage locations
- User must be able to set insect thresholds per ward
- User must be able to manage data collection methods-Automated trap or field visits
- User must be able to View statistical reports(graphical or tabulated)
- User must be able to view spatial data (Map of Zambia showing location of traps in each farm) per province and be able to zoom in upto farm zoom level.
- User must be able to print reports, maps and so on.

2) Non Functional Requirements

- System must be easy to use
- System must be Intuitive
- System must be able to accommodate a large number of users
- System must be scalable
- System must be able to handle hardware related issues and continue providing the required services.
- System must meet the defined requirements
- System should provide role based access.

D. System Development Tools

PHP- Hypertext Processor

It is a server-side scripting language which is often used to develop static websites or dynamic websites or web application. Data from the database can be retrieved using PHP and rendered using HTML in a web browser [24].

Yii Framework

Yii is an open source, object-oriented, component-based MVC PHP web application framework [25]

HTML/CSS- Hypertext Markup Language and Cascading Style Sheets

HTML is a mark-up language used for the purpose of defining elements on a web page.CSS defines how the elements defined in HTML are to be rendered on the web page [26].

JavaScript

This is an object oriented programming language that is used to do web page content manipulation. It enables the provision of interactive effects on the browser.

MySQL

It is an open source relational Database management system. It is used mainly to provide an interface where data can be stored, deleted and manipulated [27].

E. Entity-Relation Model

Below model shows the designed database entity relationships

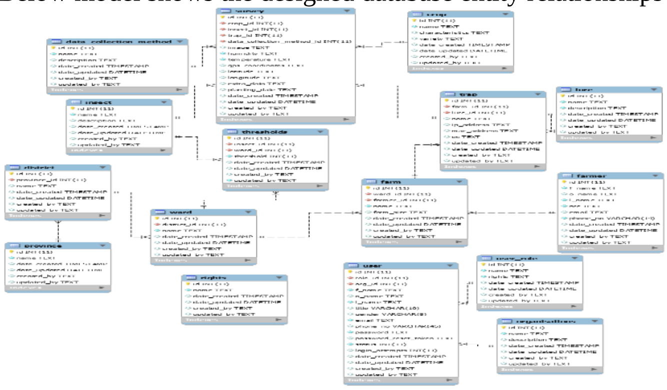

Fig. 4. Entity Relation Model

F. Use Case Models

Figure 5 shows the system functionalities that are available to the system administrator in the system. The use case sums up functionalities available to other users aswell.

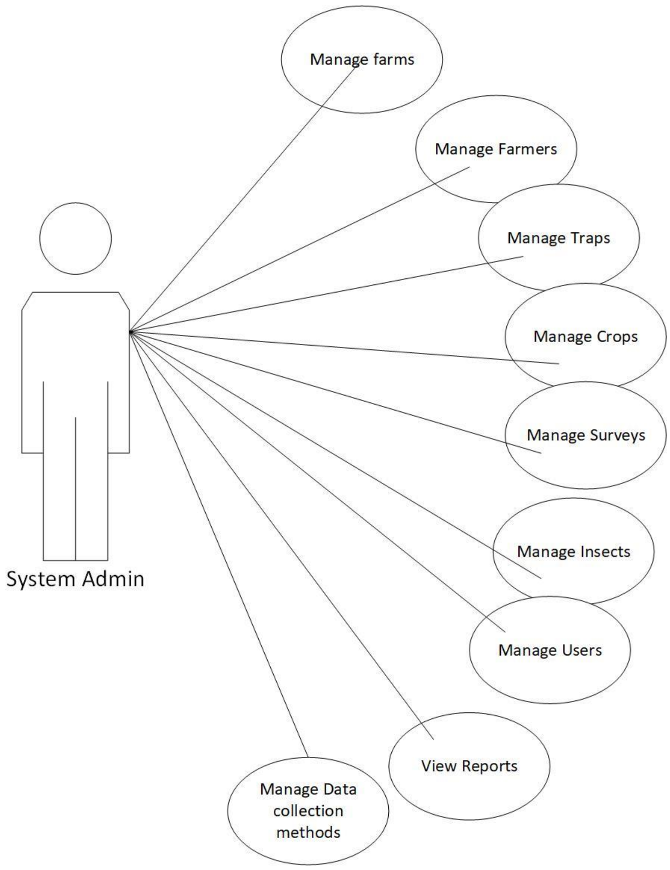

Fig. 5. System Admin use case diagram

G. Selected System Sample Pages

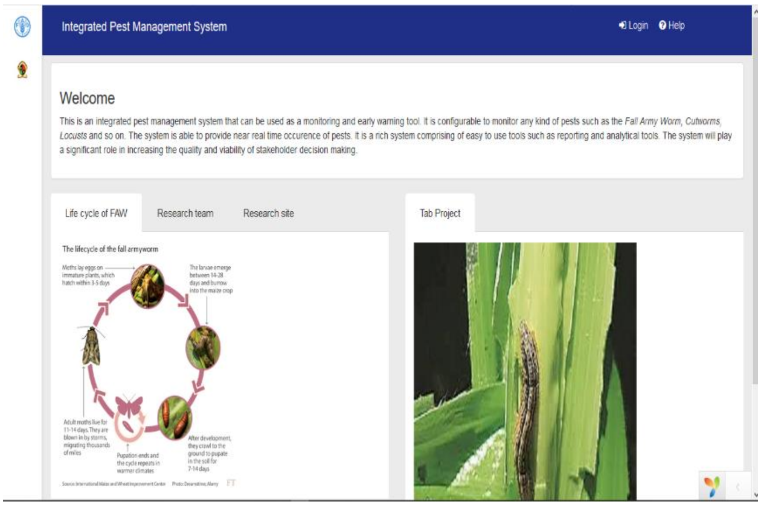

Fig. 6. System landing page

Figure 6 shows the landing page of the system. It describes what the system is all about.

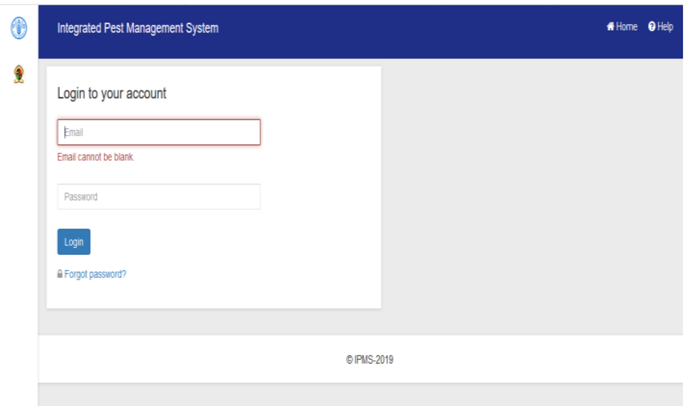

Fig. 7. System Login page

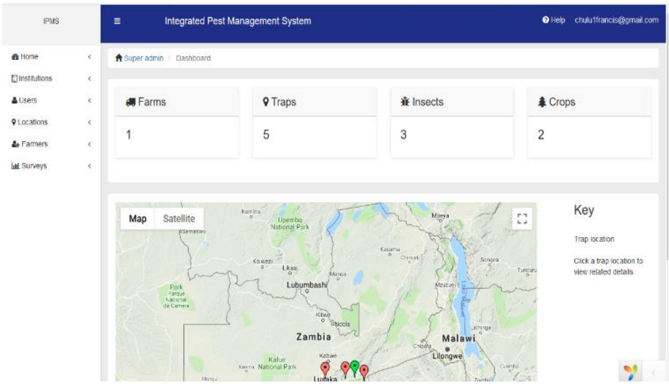

Fig. 8. System Login page

Figure 8 shows the User Home page upon Login. The home page show the number of registered farms, traps, insects and crops. It also shows a map of the location of each registered trap.

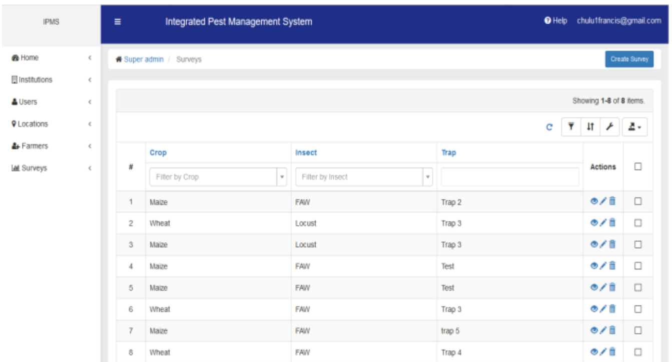

Fig. 9. View Survey

Figure 9 shows the view surveys landing page. One can view, edit and delete a survey depending on the system access level. The page also has several other buttons that can used to generate several reports in PDF or excel format.

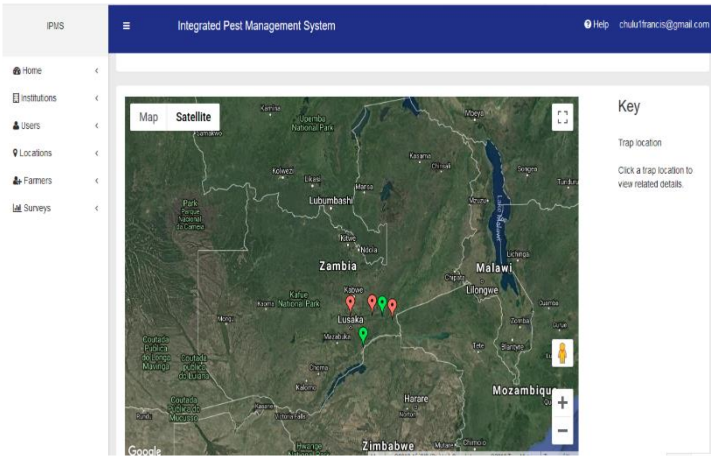

Fig. 10. Trap location map view

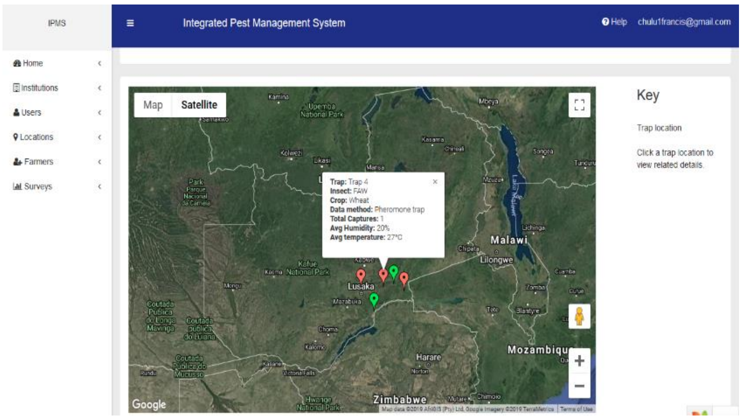

Fig. 11. Trap details view

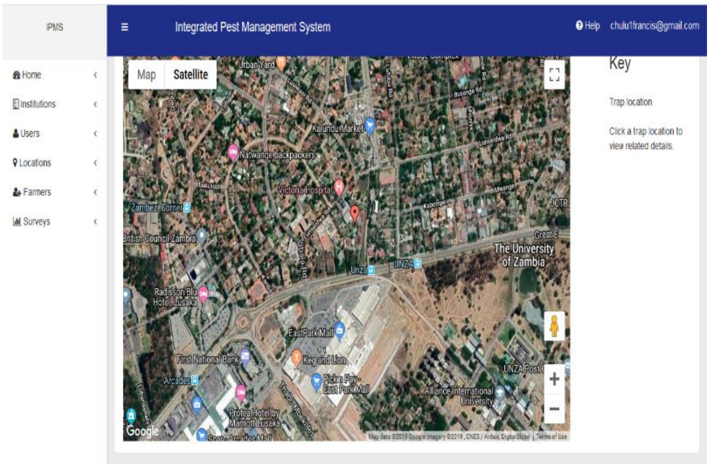

Fig. 12. Zoomed in trap location

Cardinal to this system is the location of the traps on the Zambian Map. Figures 10, 11 and 12 shows trap spatial data. The Map will show the markers in different colors based on threshold settings per word. Red marker will show that the FAW army worm in that area where the trap is located in almost destroying all the crops action needs to be taken and green shows that the FAW numbers in that area are below the threshold. In this version of the prototype the markers serve as warning points of the system as it currently did not have notifications to farmers or any registered stakeholder. Figure 10 Shows the Trap details such as name, number of captures per trap, average Humidity, average temperature when one clicks the marker. Figure 11 the zoomed in view of the map for each trap.

IV. Conclusion

As earlier stated this papers main focus was on the web based system but we provided machine learning related work as machine learning is very cardinal to this research and the presented system is dependent on the machine learning based automation of the data collection traps. This version of the system is usable but provides a manual data entry by a user. We have presented the initial version of the web based prototype and shows that there is still a lot of components that needs to be implemented. The next version of the prototype will have some of the following components

- Zooming in into the trap on the map should show the land parcel of the farm where the trap is located.
- The trap details on the map should show all the details pertaining to that trap such as farm owner details.
- The system should be able to send notifications to the relevant stakeholders via Email or SMS when a threshold on a trap has been reached.
- The system should be able to show a heat map of Zambia per province showing the most affected province to the least affected province
- The system should be able to identify the FAW using machine learning technique Artificial Neural networks

References

[1] "Four threats to global food security and what we can do about them," The conversation, Available online: https://theconversation.com/four-threats-to-global-food-security-and-what-we-can-do-about-them.

[2] Day, Roger & Abrahams, Phil & Bateman, Melanie & Beale, Tim & Clottey, Victor & Cock, M.J.W. & Colmenarez, Yelitza & Corniani, Natália & Early, Regan & Godwin, Julien & Gomez, Jose & González-Moreno, Pablo & Murphy, Sean & O. Mensah, Birgitta & Phiri, Noah & Pratt, Corin & Silvestri, Silvia & Witt, Arne, "Fall Armyworm: Impacts and Implications for Africa," Outlooks on Pest Management, Vol. 28, pp. 196-201, October 2017.

[3] J.E. Huesing, B.M. Prasanna, D.McGrath, P.Chinwada, P.Jepson, J.L. Capinera, "Fall Armyworm in Africa: A Guide for Integrated Pest Management," 1st ed. 2018.

[4] P. Abrahams; M. Bateman; T. Beale; V. Clottey; M. Cock; Y. Colmenarez; N. Corniani; R. Day, R. Early, J. Godwin, J. Gomez, P. G. Moreno; S.T. Murphy; B.O. Mensah, N. Phiri, C. Pratt; G. Richards, S. Silvestri, A. Witt, "Fall Armyworm: Impacts and Implications for Africa, Evidence Note (2)," September 2018.

[5] L. Feng, B. Bhanu, J. Heraty, "A software system for automated identification and retrieval of moth," Pattern Recognition, Vol. 51, pp. 225-241, September 2016.

[6] S. N. Asiah Hassan, N. N. S. Abdul Rahman, Z. Zaw Htike, S. Lei Win, "Vision Based Entomology: A Survey," International Journal of Computer Science & Engineering Survey, Vol. 5, pp. 19-32, January 2014.

[7] M. Mayo, A. T. Watson, "Automatic species identification of live moths," Knowledge Based Systems, Vol. 20, pp. 195–202, February 2007.

[8] P. Boniecki, K. Koszela, H. P. Boniecka, J. Weres, M. Zaborowicz, S. Kujawa, A. Majewski, B. Raba, "Neural identification of selected apple pests," Computers and Electronics in Agriculture Systems, Vol. 110, pp. 9-16, September 2015.

[9] A. K. Banerjee, K. Kiran, U. Murty, C. Venkateswarlu, "Classification and Identification of mosquito species using artificial neural networks," Computational Biology and Chemistry, Vol. 32, pp. 442–447, June 2008.

[10] J. Wang, L. Ji, A. Liang, D. Yuan, "The identification of buttery families using content-based image retrieval," Biosystems Engineering, Vol. 111, pp. 24-32, 2012.

[11] M. Do, J. Harp, K. Norris, ", A test of a pattern recognition system for identification of spiders," Bulletin of Entomological Research, Vol. 89, pp. 217-224, 1999.

[12] H. Gassoumi, N.R, N.R. Prasad, J.J. Ellington, "Neural Network-Based Approach for Insect Classification in Cotton Ecosystems, January 2000.

[13] J. Wang, C. Lin, L. Ji, A. Liang, "A new automatic identification system of insect images at the order level," Knowledge-Based Systems, Vol. 33, pp. 102-110, March 2012.

[14] M. Negnevistky, "Artificial Neural Networks" in Artificial Intelligence, a guide to intelligent systems, 2nd ed. Harlow, England: Pearson Education limited, 2005, Ch. 6, pp. 165–216.

[15] D. Epsky, Nancy, Morrill, Wendell, Mankin, Richard, "Traps for Capturing Insects" in Encyclopedia of Entomology, 2008, Ch. 10, pp. 3887-3901. Available online: https://www.researchgate.net/publication/303661972_Traps_for_Capturing_Insects

[16] Ahmad, S. Nurulhidayah, Kamarudin, Norman. (2011), "Pheromone Trapping in Controlling Key Insect Pests: Progress and Prospects," Oil Palm Bulletin.

[17] S. Guerrero, J. Brambila, R.L. Meagher, "Efficacies of Four Pheromone-Baited Traps in Capturing Male Helicoverpa (Lepidoptera: Noctuidae) Moths in Northern Florida," Florida Entomologist, Vol. 97(4), pp. 1671-1678, December 2014.

[18] J. Phiri, Z. Tie-Jun, Z.C. Hui, M. Jameson, "Using Artificial Intelligence Techniques to Implement a Multifactor Authentication System," International Journal of Computational Intelligence Systems, Vol. 4, pp. 420-430, June 2011.

[19] J. Phiri, J.I Agbinya, "Fusion of multi-modal credentials for authentication in digital identity management systems," International Conference on Wireless Broadband and Ultra-Wideband Communications, Vol. 34, pp. 20, August 2007.

[20] Z. Zhou, Y. Jiang, Y. Yang and S. Chen, "Lung cancer cell identification based on artificial neural network ensembles," Artificial Intelligence in Medicine, Vol. 24, pp. 25-36, April 2001.

[21] Source:http://web.entomology.cornell.edu/shelton/swede-midge/images/DETECTION/trap2large.jpg

[22] Source:https://4.imimg.com/data4/BY/BP/MY-5420398/pheromone-trap-250x250.jpg
[23] I. Sommerville, Software engineering. Boston: Pearson, 9th ed., 2011. OCLC: ocn462909026.
[24] K. Tatroe, R. Lerdorf and P. Maclntyre, Programming PHP. Sebastopol, CA: O'Reilly Media, 3rd ed., 2013. OCLC.
[25] B. Keck, Yii 2 for Beginners. British Columbia: Leanpub, 2014.
[26] J. Duckett, HTML & CSS: design and build websites. Indianapolis, Indiana: John Wiley & Sons Inc, 2014. OCLC: ocn871305670.
[27] http://www.eweek.com/c/a/Database/Oracle-Discusses-MySQL-Database-Plans-854185/
[28] J.Phiri and Tiejun Zhao, "Identity Attributes Quantitative Analysis and the Development of a Metrics Model using Text Mining Techniques and Information Theory", Proceedings of IEEE International Conference on Information Theory and Information Security, pp. 390-393, 2010
[29] Jackson Phiri, Tiejun Zhao and Jameson Mbale, "Identity Attributes Mining, Metrics Composition and Information Fusion Implementation using Fuzzy Inference System", Journal of Software, Vol. 6, No. 6, pp. 1025-1033, 2011.