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Automated Fall Armyworm (*Spodoptera frugiperda*, J.E. Smith) Pheromone Trap Based on Machine Learning

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Abstract: Maize is the main food crop that meets the nutritional needs of both humans and livestock in the sub-Saharan African region. Maize crop has in the recent past been threatened by the fall armyworm (*Spodoptera frugiperda,* J.E Smith) which has caused considerable maize yield losses in the region. Controlling this pest requires knowledge on the time, location and extent of infestation. In addition, the insect pest's abundance and environmental conditions should be predicted as early as possible for integrated pest management to be effective. Consequently, a fall armyworm pheromone trap was deployed as a monitoring tool in the present study. The trap inspection is currently carried out manually every week. The purpose of this paper is to bring automation to the trap. We modify the trap and integrate Internet of Things technologies which include a Raspberry Pi 3 Model B+ micro-computer, Atmel 8-bit AVR microcontroller, 3G cellular modem and various sensors powered with an off-grid solar photovoltaic system to capture real-time fall armyworm moth images, environmental conditions and provide real-time indications of the pest occurrences. The environmental conditions include Geographical Positioning System coordinates, temperature, humidity, wind speed and direction. The captured images together with environmental conditions are uploaded to the cloud server where the image is classified instantly using Google's pre-trained InceptionV3 Machine Learning model. Intended users view captured data including prediction accuracy via a web application. Once this smart technology is adopted, the labour-intensive task of monitoring will reduce while stakeholders shall be provided with a near real-time insight into the FAW situation in the field therefore enabling pro-activeness in their management of such a devastating pest.

Keywords: Internet of Things, Integrated Pest Management, Fall Armyworm, Raspberry Pi, Machine Learning

Introduction

The agriculture sector is a major contributor to job creation, health, family cohesion, wealth and political stability in most African economies (MoNDP, 2018). In the sub-Saharan Africa, maize is among the cash-crops and most grown crops in addition to being the staple food crop that meets the nutritional needs of both humans and livestock. It is grown in almost all parts of the country especially the rural areas (Smale *et al.*, 2011). Therefore, the economical importance of maize and its role in securing Zambia's food and nutrition security including political stability cannot be over looked. Kwasek (2012) stated that food security is achieved when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life. Threats to food security include but not limited to climate change, droughts, emerging diseases, salty soils, fertilizer dependence and pests (Thompson, 2016). According to MoA (2019a), the greatest threats to national food and nutrition security in Zambia include illegal export of maize, also known as smuggling and fall armyworm infestation, among others. In this paper, we focus on the trapping of adult fall armyworm moths.

The main objective of this paper is to bring automation to the FAW trap and reduce on the labour-intensive tasks which include field visits, manual counting and recording of the moths by field inspectors. We modify the trap and integrate Internet of Things (IoT). The IoT technologies include a Raspberry Pi 3 Model B+ micro-computer, Atmel 8-bit AVR microcontroller, 3G cellular modem and various sensors which include the pi camera, DHT11 temperature/humidity, Davis anemometer, powered with an off-grid solar photovoltaic system for capturing FAW images and environmental conditions in the field. This work is a build-up on the preliminary works that were published by Chiwamba *et al*. (2019; 2018) and Chulu *et al*. (2019a; 2019b).

The system captures an image of the funnel path every second alongside environmental conditions and saves the image on local folder. The captured images together with environmental conditions are uploaded to the cloud server where the image is classified instantly using Google's pre-trained InceptionV3 machine learning model. The object is uploaded using the 3G cellular modem. Once the sending is successful, the image is deleted from the local drive on the Raspberry Pi as a way of managing the storage space dynamically and avoid over filling the SD card.

Literature Review

Fall Armyworm

The Fall Armyworm (FAW) (*Spodoptera frugiperda*) is a lepidopteran pest and it is native to the Americas (Day *et al*., 2017). The FAW is named after the Autumn (Fall) due to its presence during the said season in North America where it lays eggs and the larvae develops (Nagoshi *et al*., 2009; Plessis *et al*., 2018). According to Plessis *et al*. (2018), the FAW gained prominence when it was found to be attacking crops during the mid-19th Century in the Southern United States. Prasanna *et al*. (2018) further reports that the FAW has been found to be a more devastating pest than many others pest in Africa due to its ability to feed on over 80 different crop species; spread quickly across large geographic areas; and being persistent throughout the year. The FAW feeds on leaves and stems of a variety of plants including economically important maize, forage grass, rice, sorghum, sugarcane, cotton and vegetable crops, among others (Banson *et al*., 2019).

According to IAPRI (2019), the FAW mating occurs at high temperature and low humidity hence the high prevalence of the infestation in long periods of drought. The tropical habitat is ideal for the FAW to quickly reproduce and spread without pause. The FAW life cycle is a four staged one as shown in Fig. 1 and it takes about 30 days during the warm summer months and may extend to 60-90 days in cooler temperatures (IAPRI, 2019; 2018; Capinera, 2007).

It is believed that the FAW was introduced to Africa through transportation and subsequent widespread dispersal by the wind (Cock *et al*., 2017). In 2017/2018 season, the Zambia FAW infestation affected approximately 130,000 hectares of crops which resulted in over USD $3 million for control costs during the early stages of its introduction (Otim *et al*., 2018). Day *et al*. (2017) reported that the impact of FAW ranges between 22% and 67% of yield in Ghana and Zambia, respectively. Similarly, Kenya and Ethiopia reported estimated yield losses of 32% and 47%, respectively (Kumela *et al*., 2018). The above-mentioned losses will continue with the establishment of the FAW in Zambia.

Addressing the food security threat posed by FAW requires surveillance, monitoring and scouting of the spread of FAW to ensure adequate crop protection. Knowing the time, location and extent of infestation is vital to pest control. The current African response to FAW has faced several challenges arising from weak monitoring, surveillance and scouting systems. Other challenges include delayed recognition of the pest's widespread presence across the continent and lack of information about the dynamics of FAW migration that would allow effective prediction of where infestation might occur next. The spread of FAW has resulted in indiscriminate spraying of pesticides, often without knowing whether chemical control is necessary or effective within the local context (Prasanna *et al*., 2018).

Meagher (2001) stated that the monitoring of FAW male moths should be done with a multicomponent sex pheromone as a lure in traps. This is a type of insect trap that uses pheromones to lure insects to the trap. The trap can be used to detect early pest infestations such as the first occurrence of migratory pests; define areas of pest infestations; track the build-up of a pest population and help in decision making for pest management (Ahmad and Kamarudin, 2011; Baker *et al*., 2011; Anderson *et al*., 2012; Guerrero *et al*., 2014). Furthermore, Cluz *et al*. (2012) reported that the use of pheromone traps data in insecticide application was found to be more effective with a larval mortality rate above 90% in maize fields. Some notable pheromone traps are the sticky and Funnel (green lid/yellow funnel/transparent bucket) as shown in Fig. 2 and 3 respectively. Figure 4 shows the Funnel (green lid/yellow funnel/transparent bucket) components.

Historically, the sticky trap has been found to be more effective in capturing FAW male moths when positioned approximately one meter above the ground in and around the preferred hosts such a maize (Mitchell, 1979). The Funnel (green lid/yellow funnel/transparent bucket) pheromone trap has been found to outperform other pheromone traps including the sticky trap when trapping FAW moth in maize fields. Given its efficacy, it is no surprise that the Government of the Republic Zambia with the help of the FAO has secured over 2200 pheromone traps to be used in the monitoring and surveillance of the FAW moths (MoA, 2019b).

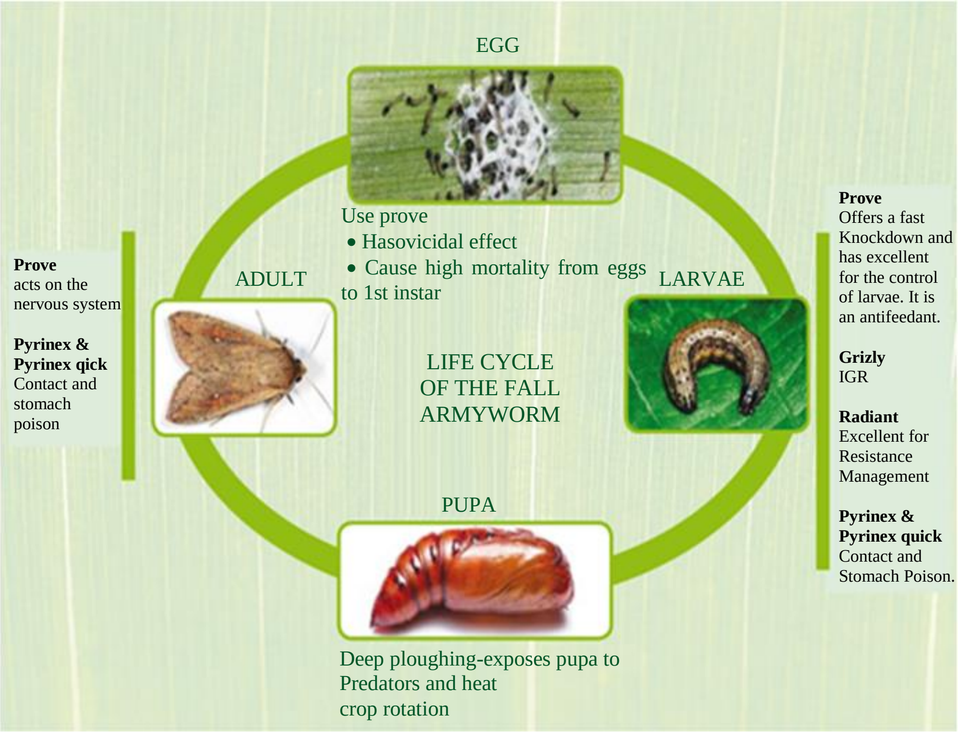

Fig. 1: FAW life cycle (Cereals, 2019)

Fig. 2: Pheromone trap that employs a sticky surface (Indiamart, 2019)

Fig. 3: Funnel/bucket pheromone trap (LSU, 2019)

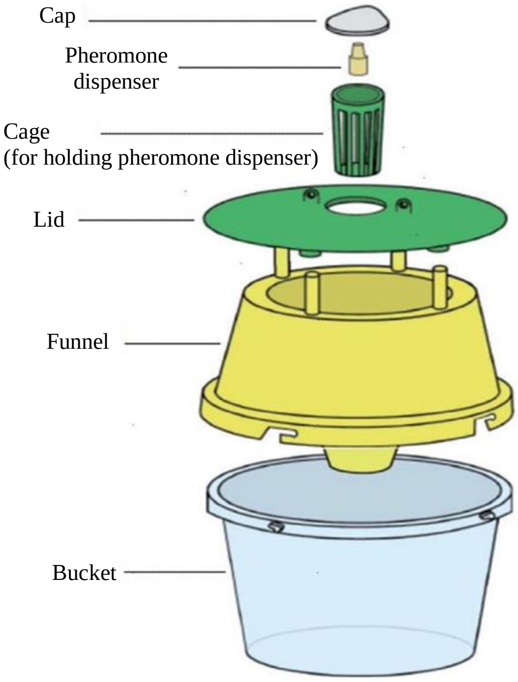

Fig. 4: Funnel/bucket pheromone trap components (FAO, 2018)

Internet of Things

In the recent years, the use of Information and Communication Technologies (ICT) and transducers to ensure optimum application of resources to achieve high crop yields and reduce operational costs in the agriculture sector has been observed. This concept of adding sensors and intelligence to basic objects is referred to as the Internet of Things (IoT). IoT refers to the billions of physical devices around the world that are now connected to the internet, collecting and sharing data using different types of protocols. IoT can be looked at as a network of objects which are embedded with technologies

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that helps to communicate and engage inside themselves and exterior environment (Chihana *et al*., 2018). The IoT concept was first developed in 1999 by a Radio Frequency Identification (RFID) development community (Shi *et al*., 2019; Bilal, 2017) and it has recently become more relevant to the practical world largely because of the growth of mobile devices, embedded and ubiquitous communication, cloud computing and data analytics.

Application of IoT

IoT has many applications including smart home, smart city, smart grids, smart retail, smart supply chain, industrial internet, connected car, connected health (digital health/telehealth/telemedicine) among others (Gour, 2018; Chihana *et al*., 2018). According to Muangprathub *et al*. (2019), the applications of IoT in the agriculture sector can be used to improve crop yields or quality and reduce costs. The seamless integration of transducers and the IoT in agriculture can raise the sector to levels which were previously unimaginable. IoT has the potential of streamlining procedures, reduce wastage and enhance productivity in the agriculture sector. According to Ayaz *et al*. (2019), IoT can help to improve the solutions of many traditional farming issues, like drought response, yield optimization, land suitability, irrigation and pest control by following the practices of smart agriculture. Further benefits can come from the quantity of fertilizer that has been utilized to the number of journeys the farm vehicles have made or the spray of pesticides (Ayaz *et al*., 2019). The major applications, services and transducers being used for smart agriculture applications are shown in Fig. 5.

IoT Architecture

IoT architecture consists of different layers of technologies supporting the scalability, modularity and configuration of IoT deployments in different scenarios. The IoT architecture has been presented using different layer numbers and names by many researchers (Yelizavet and Florentino, 2019; Chihana *et al*., 2018; Bilal, 2017; Sethi and Sarangi, 2017; Vermesan *et al*., 2013). In this paper, we discuss the ITU Y.2060 IoT architecture (Yelizavet and Florentino, 2019; Vermesan *et al*., 2013) shown in Fig. 6.

IoT Application Layer

The IoT application layer is the top most layer which covers “smart” environments/spaces in domains such as agriculture, homes, smart cities, grids, building, transport, retail, supply chain, healthcare environment and energy. It interacts directly with the end user by providing services and determining a set of protocols for message passing at the application level (Yassein *et al*., 2016). According to Haikun *et al*. (2018), connection to IoT management system platform by users is achieved using browser or client software through Ethernet/3G network.

IoT Service and Application Support Layer

In literature, some scholars refer to this layer as the Management Service Layer (Gour, 2018; Chihana *et al*., 2018). It is the layer that is responsible for processing the information through analytics, information extraction, security controls, process modeling and management of devices and gadgets. Business and process rule engines are among the most important features of the layer. IoT brings connection and interaction of objects and systems together providing information in the form of events or contextual data such as temperature of goods, current location and traffic data. Some of these events require filtering or routing to post-processing systems such as capturing of periodic sensory data, while others require response to the immediate situations such as reacting to emergencies on patient’s health conditions. The rule engines support the formulation of decision logics and trigger interactive and automated processes to enable a more responsive IOT system (Yelizavet and Florentino, 2019).

IoT network Layer

As the devices and gadgets produce enormous volumes of data, a robust and high performance wired or wireless network infrastructure is required to transmit this data. Due to the diversity of the IoT, it is often tied with heterogeneous protocols to support Machine-to-Machine (M2M) networks and their applications. These networks can be in the form of a private, public or hybrid models and are built to support the communication requirements for latency, bandwidth or security (Haikun *et al*., 2018). According to Chihana *et al*. (2018), the network layer is responsible for ensuring that the transmission of transducer data to the next layer is achieved in a scalable and flexible manner.

IoT Device Layer

This is the layer that is made up of smart objects integrated with transducers that enable the interconnection of the physical and digital worlds allowing real-time information to be collected and processed (Bilal, 2017). According to Chihana *et al*. (2018), the layer consists of sensor networks, embedded systems, RFID tags and readers or other smooth sensors. The sensors have identification and capacity to take measurements such as temperature, air quality, wind speed, wind direction, humidity and pressure among others. The sensor may also have a degree of memory, enabling them to record a certain number of measurements. Most of these sensors require connectivity to the sensor gateways which can be through a Local Area Network (LAN) such as Ethernet and Wi-Fi connections or Personal Area Network (PAN) such as ZigBee, Bluetooth and Ultra Wideband (UWB)

(Bilal, 2017). Some sensors do not require connectivity to sensor aggregators therefore their connectivity to backend servers/applications can be provided using Wide Area Network (WAN) such as GSM, GPRS and LTE. For those sensors that use low power and low data rate connectivity, they typically form networks commonly known as Wireless Sensor Networks (WSNs) (Shi *et al*., 2019).

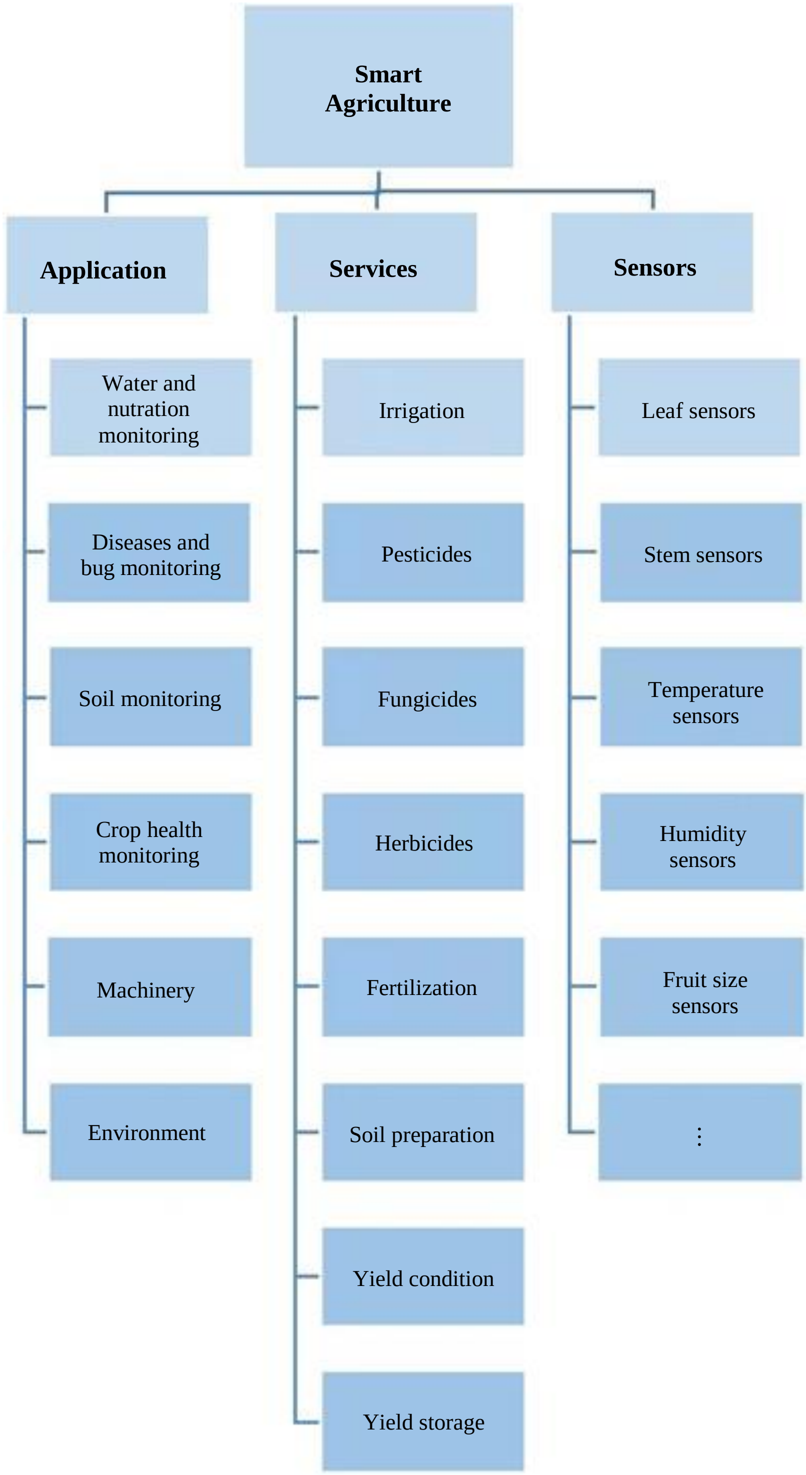

Fig. 5: Major applications, services and transducers for smart agriculture (Ayaz *et al*., 2019)

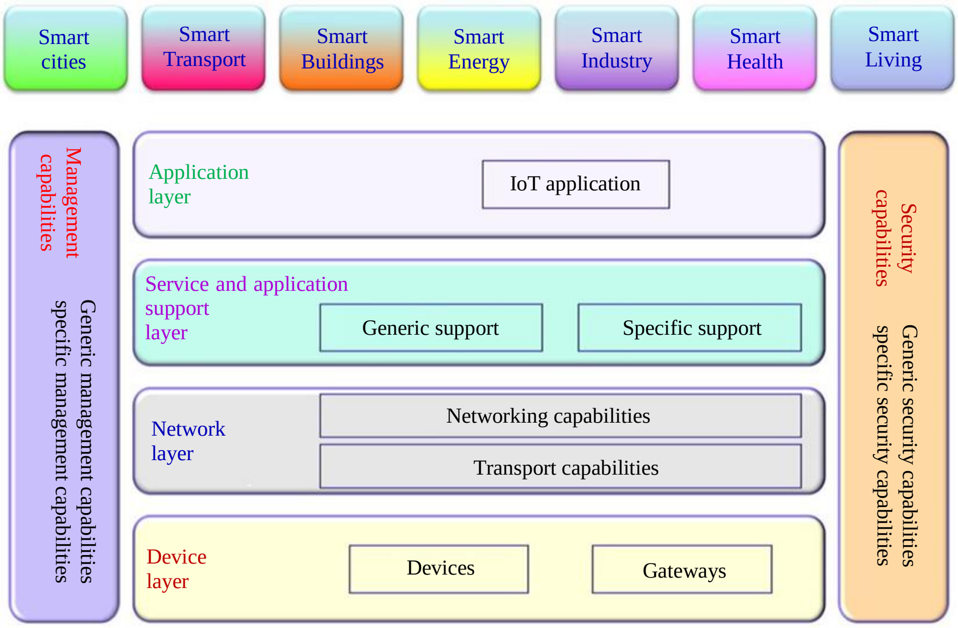

Fig. 6: IoT Architecture. (Vermesan *et al*., 2013)

Machine Learning

Machine Learning (ML) is a subfield of soft computing within computer science that studies the design of algorithms that can learn. Similarly, Patel (2019) define ML as the science of getting computers to learn and act like humans do and improve their learning over time in autonomous fashion by feeding them data and information in the form of observations and real-world interactions. ML includes adaptive mechanisms that empower computers to learn by example, learn by analogy and learn from experience (Negnevitsky, 2005).

ML algorithms include Convolutional Neural Network (CNN), Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTMs), Stacked Auto-Encoders, Deep Boltzmann Machine (DBM) and Deep Belief Networks (DBN). According to Ding and Taylor (2016), the use of CNN for identifying and counting pest in field traps has the potential to effectively remove the human from the loop and achieve a complete automated, real-time pest monitoring system. Similarly, Martineau *et al*. (2017) reported that many researchers had acknowledged that CNN had outstanding performance in terms of image classification accuracy.

ML model can be built using transfer learning. Transfer learning allows building of accurate machine learning models in a timesaving way by starting from patterns that have been learned when solving a different problem (Marcelino, 2018). Instead of starting from scratch, it leverages on previous learning's and this is usually expressed through the use of pre-trained models. A pre-trained model is a model that was trained on a large benchmark dataset to solve a problem similar to the one that is being solved. In the work of Marcelino (2018), it was reported that transfer learning had become the core of several state-of-the-art image classification solution. The pre-trained models include but not limited to Mask R-CNN, YOLOv2, MobileNet, VGG-Face Model, 3D Face Reconstruction from a Single Image, Google Inception, ImageNet, VGG-16, Xception, VGG19, ResNet50, InceptionV3 and InceptionResNetV2.

Related Works

In literature, some works use electronic devices to feed data into some control station. For example, the work of Marković *et al*. (2017) used a Raspberry Pi 3 micro-computer with four Cortex-A53 processing cores, 1.2 GHz and two level of cache memory to monitor the Western Corn Rootworm (WCR) trapped by the sticky WCR pheromone trap. The pi camera was attached to the Raspberry Pi 3 and used to capture images of the sticky surface of pheromone trap. The counting of insects was done using the python module installed on the Raspberry Pi 3 by defining the number of pixels with dark or near dark colour and removing the impurities. While the system had a 0.3% accuracy, the system behaviour was not tested on unclear images and other objects that could be caught in the trap.

Eliopoulos *et al*. (2018) introduced a device for automatic detecting and reporting of crawling insects in urban environments which complied with the context of smart homes and smart cities. The device architecture embraced the IoT concepts by modifying the sticky pheromone trap and integrating it with a microcontroller, image sensor, infrared light sensor to detect targeted insect and capture they picture which were delivered to an authorized person/stakeholder using Wi-Fi. The results showed that the e-trap had potential application in tourism, hospitality, health, military and residential places. Furthermore, the trap achieved a detection accuracy ranging from 96 to 99%.

In the work of Potamitis *et al*. (2014), an Arduino Mega2560 microcontroller platform (Atmel ATmega2560 microcontroller, 16 MHz clock speed, 256 KB Flash, 8 KB SRAM, 4 KB EEPROM) powered by a 4.8 Volt battery NiMH power supply was used to perform the counting of insects entering the trap and recognize the species. In order to sense the insects, an optoelectronic (TCRT5000) sensor and phototransistors were placed at the entrance of the McPhail trap to detect light interruption due to the partial occlusion from insect's wings as they flew into the trap. The output of the optoelectronic sensor was analog and, it was sent to the Arduino Mega2560 microcontroller to perform the counting of insects passing the beam and recognize the class the insects belonged to. The events was stored in the device's memory and transmitted once per day as text message via the GSM expansion board SM5100B to a predefined recipient. With the real time count and classification of insects present per trap, stakeholder's efficiency was enhanced by knowing the time and location of insect infestations as early as possible.

Similarly, Facello and Cavallo, 2013), used an Arduino Uno microcontroller platform (Atmel ATmega328P microcontroller, 16 MHz clock speed, 2KB Flash, 2 KB SRAM, 1 KB EEPROM) powered by a 43W solar panel, 18Ah Pb battery to monitor pests in vineyards and orchards. The trap was equipped with a 2592×1944 pixels (5Mpixels) wide-angle lens 6mm focal length IP camera, temperature/humidity sensor and LED illuminator. The sensor, led and camera were connected to the Arduino Uno board running a custom firmware developed for the application. The led and IP camera were powered separately using a 12V and up to 0.3A power supply because the 5V and 0.04A from Arduino was not sufficient. The Arduino Uno communicated and was controlled through a standard USB connection on the embedded mini-ITX pc-board (Intel DN2700MT). The main software running on the mini-ITX pc-board governed all the necessary operations needed to acquire, store and transmit the images and environmental information. The images were stored on the a local disk and they were automatically uploaded and synchronized with a free file hosting service on the web using a standard Wi-Fi connection. Remote users were given access to the images by simply connecting to the webpage.

Zhong *et al*. (2018) designed and implemented a vision-based counting and classification system for flying insects using a YOLO pre-trained model and Support Vector Machines learning algorithm. The system was based on a sticky pheromone trap that was installed in the field to trap flying insects and camera attached to a raspberry pi to capture real-time images. When compared with the conventional methods, the test results showed an average counting accuracy of 92.50% and average classifying accuracy of 90.18%. These results were breakthrough towards smart and intelligent agriculture applications which could forecast the occurrence probability of pests to enable agricultural workers provide suitable prevention and control measures.

We see more work in Muminov *et al*. (2017) when a solar powered audible intelligent bird repeller system is developed based on Arduino UNO microcontroller to deter domestic birds which are a major threat in the field of agriculture causing damage to economic field crops, storage houses and also dirtying human life area. The other system components included a solar panel (7W, 12V), an intelligent PWM solar charge controller, 12V battery, MP3 Player, amplifier (Stereo 20W Class D Audio Amplifier - MAX9744), two 20W speakers, three sonar sensor and PIR sensor. The SD Card was loaded with domestic bird's predators' calls and special sounds (such as gunshot sounds) stored using the MP3 file format. The signal level of predators' calls and special sounds were played out via the speakers and increased using the amplifier while the solar panel was used to charge the battery and power the amplifier, speaker and Arduino Uno. The other components were powered by the Arduino Uno. The system algorithm was designed in such a way that it was able to play special sounds which had not played for a long time. This technique was applied due to an acknowledgment that birds can learn sounds overtime and that would render the repeller ineffective.

Other works proposed a solar powered rice black bug light trap that would help reduce rice black bug infestation based on an Arduino Uno microcontroller platform and C++ programming language (Calderon, 2017). The notable components included a 12V 20W standard polycrystalline solar cells panel, 30×40×15 (width × length × thickness) clear acrylic square box,150 LED size 7×7 mm, 5A battery charger, 12V 14Ah Sealed Lead Acid battery, light sensor switch circuit, DS1307 Real-Time Clock (RTC) and high voltage circuit of mosquito trap all enclosed in steel box to prevent any damages. The proposed design was assessed in terms of efficiency, functionality, maintainability, reliability, usability and cost-effectiveness of the materials using questionnaires and a 3.7 overall weighted mean was observed where experts' response was highly acceptable.

A custom-made microprocessor hardware embedded with a SIM card and the Global System for Mobile Communications (GSM) antenna to transmit accumulated detection results of all insects entering the trap using Short Message Service (SMS) to the base station is seen in the work of Potamitis *et al*. (2015). The insects were lured and as they flew into the trap, an optoelectronic sensor composed of an array of photoreceptors that acted as a receiver and an array of infrared LEDs on the opposite side of the circular entrance guarded the entrance by forming a light gate. The insect wings interrupted the flow of infrared light from emitter to receiver. The optoelectronic sensors captured an analog signal of the wingbeat recording which was sent to the microprocessor embedded in the trap. The job of the microprocessor was to analyze the frequency content of the acquired recording and calculate the distance metric from the spectrum of the unknown incoming recording to the spectrum of pre-stored prototype spectra of the pest results in order to identify the insect. Other efforts are seen the in the work of Holguin *et al.* (2010), when two electronic trap prototypes based on a microcontroller from Microchip Technology Inc. Model PIC18F8722A to automate the labour-intensive operations of monitoring insect populations and reduced the cost of integrated pest management programmes are compared. The trap in question was the bucket pheromone. The first trap used Light Dependent Resistor (LDR) sensors and the second one used Infrared (IR) sensors. The LDR-based traps were tested in a laboratory environment while the IR-based traps were tested in apple fields.

Materials and Methods

The modification of the FAW pheromone trap to bring about automation started with the PV systems design followed by trap fabrication and ended with integration. The high-level systems design of the automated FAW pheromone trap is shown in Fig. 7 and the Modified FAW Trap Block Diagram is shown in Fig. 8.

Step I- Solar PV Systems Design

The researchers growing energy needs can be satisfied by the enormous energy from the sun which provides over 150,000 terawatts of power to the Earth (Crabtree and Lewis, 2007; Camacho *et al*., 2010). Crabtree and Lewis (2007) reported that the Earth surface only receives about half of that energy while the other half is reflected to the outer space. The main components of a solar PV system include solar panel, charge controller and battery. Figure 9 and this section highlights the procedures used to determine the ratings and quantities for each of these components.

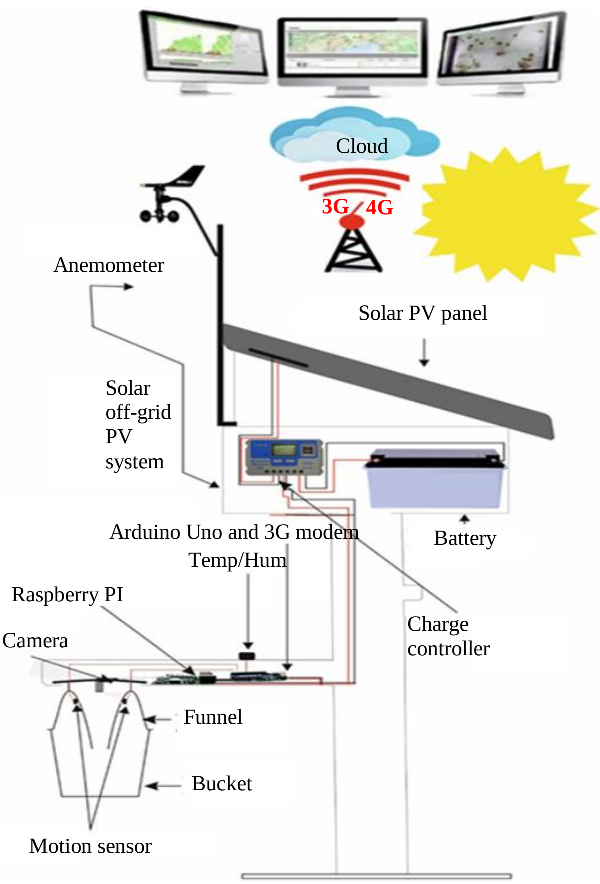

Fig. 7: High level design of the automated FAW pheromone trap

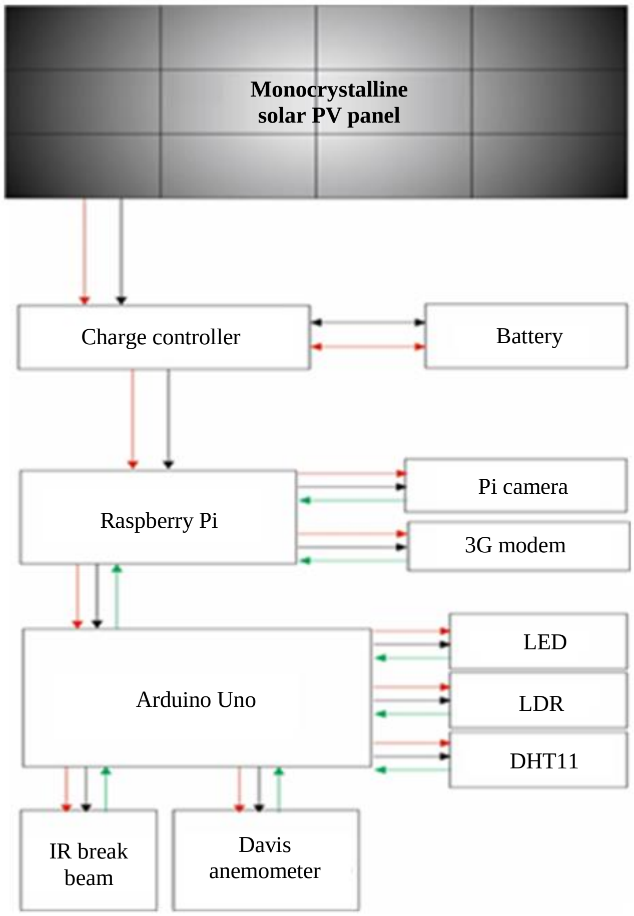

Fig. 8: Modified FAW trap block diagram

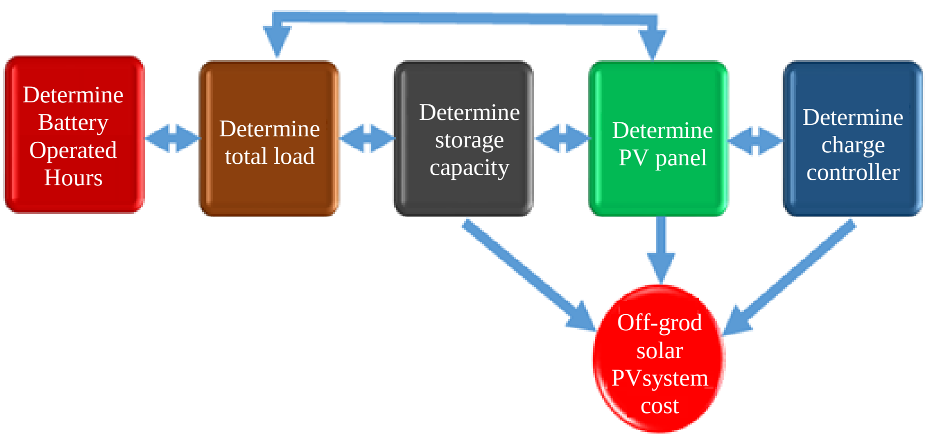

Fig. 9: Solar PV Design Model

Determine Battery Operated Hours

Climatemps (2019) reported that Lusaka, the capital city of Zambia at latitude 15°25'S and longitude 28°27'E receives a minimum of 5 h, an average of 7:35 h and a maximum of 09:42 h sunshine per day. This is in agreement with the results obtained by (Mwanza *et al*., 2017). We determined the battery operated hours using Equation 1:

$$Tb = Td - Ts \tag{1}$$

Where:
Tb = The battery operated hours (hrs)

Td = The total hours in day (hrs)
Ts = The minimum sunshine hours per day (hrs)

Determine Total Load

Many researchers modify the already existing traps by integrating single-board computers, microcontrollers and various sensors (Holguin *et al*., 2010; Facello and Cavallo, 2013). At this stage, we identified all the electronic components to be used to realize an automated energy independent pheromone trap and used Equation 2 to estimate the load for the Off-grid solar PV system:

$$p = \sum_{k=1} i_k \times v_k \times t_k \quad (2)$$

Where:
P = The total load (Wh)
i_k = The current for a single component (A)
v_k = The voltage for a single component (V)
t_k = the running hours for single component (hrs)

The subsections that follow gives detailed descriptions and specifications of the components used.

Single-Board Computer and Microcontroller

A Single-Board Computer (SBC) is a complete computer built on a single circuit board, with microprocessor(s), memory, Input/Output (I/O) and other features required of a functional computer. Some notable SBC's available on the market include Raspberry Pi, The Beagles PandaBoard, MK802, MK808, Cubieboard, MarsBoard, Hackberry Udoo and MinnowBoard among others (Maksimović *et al*., 2016). In the work of Maksimović *et al*. (2016), the Udoo is found to be the best in performance but expensive while Raspberry Pi remained an inexpensive computer and very successful in diverse range of research applications in Internet of Things (IoT). In addition, the Raspberry Pi offers support for a large number of input/output peripherals, network communication and can interface with many different devices and used in a wide range of applications. Table 1 gives the Raspberry Pi 3 Model B+ specifications.

A microcontroller is a small computer on a single integrated circuit and Arduino Uno is among the mostly used (Maksimović *et al*., 2016; Ferdoush and Li, 2014). Arduino is an open-source single-board microcontroller development platform with flexible, easy-to-use hardware, software components and supports two working modes: stand-alone or slave connected to a computer via USB cable (Cvijikj and Michahelles, 2011). Table 2 gives the Arduino Uno Rev 3 specifications.

DHT11 Temperature/Humidity Sensor

The DHT11 is digital environment sensor used to measure the moisture and temperature of the surrounding air. It is low cost temperature and humidity sensor. Characteristics of this sensor are given in Table 3. The sampling rate for the DHT11 is 1Hz or one reading every second, the operating voltage for sensor ranges from 3 to 5 volts, while the max current used when measuring is 2.5 mA. In the work of Ferdoush and Li (2014), the DHT11 is used to measure the humidity and temperature in grape fields. Table 3 gives the DHT11 sensor specifications.

IR Break Beam

The use of light sensors in detecting and counting of insects has been seen in the of works Potamitis *et al*. (2015; 2014) and Holguin *et al*. (2010). One of the notable light sensor is the Infrared (IR) break-beam. According to Adfruit (2019), the Infrared (IR) break-beam is a motion detector with an emitter side that sends out a beam of human invisible IR light and a receiver across the way which is sensitive to that same light. Adfruit (2019) goes on to state that the break beams are faster and allow better control of where you want to detect the motion as compared to Passive IR sensing. The IR break beam is offered as 3 mm or 5 mm. The 3 mm sensing distance is about 25 cm while the 5 mm is about 40 cm. Both can be powered from 3.3 V or 5 V. The 5 V power gives a better range and it is the recommend one. Table 4 gives the 3 mm sensor specifications.

Pi Camera Module

The raspberry pi camera module v2 is a high definition vision sensor that comes with a Sony IMX219 sensor (Raspberry, 2019). The IMX219 is a diagonal 4.60 mm (Type 1/4.0) Complementary Metal-Oxide-Semiconductor (CMOS) active pixel type image sensor with a square pixel array and 8.08M effective pixels. It operates with three power supplies, analogue 2.8 V, digital 1.2 V and IF 1.8 V and has low power consumption drawing between 200-250 mA. It achieves high sensitivity, low dark current and no smear through the adoption of R, G and B primary colour pigment mosaic filters. This chip features an electronic shutter with variable charge-storage time. The camera module can be used to take high-definition video at 1080p30, 720p60 and VGA90 video modes, as well as stills photographs. According to Raspberry (2019), it is attached to Raspberry Pi through the Camera Serial Interface (CSI) port and it works with Raspberry Pi 1, 2, 3 and 4 models. It can be accessed through the Multimedia Abstraction Layer (MMAL) and Video4Linux (V4L) Application Program Interfaces (APIs) in addition to numerous third-party libraries built for it such as Picamera Python. In the works of Marković *et al*. (2017), the pi camera is attached to the Raspberry Pi 3 and used to capture images of the sticky surface of WCR pheromone. Table 5 gives the pi camera module V2 specifications.

Table 1: Raspberry Pi 3 Model B+ specifications

Chip	Broadcom BCM2837B0, Cortex-A53
	(ARMv8) 64-bit SoC @ 1.4GH
RAM	1GB LPDDR2 SDRAM
Network	2.4GHz and 5GHz IEEE 802.11 b/g/n/
Interface	ac wireless LAN, Bluetooth 4.2, BLE
Card	Gigabit Ethernet over USB 2.0
	(maximum throughput 300 Mbps)
Ports	UART Extended 40-pin GPIO header
	Full-size HDMI4 USB 2.0 ports, 4-pole
	stereo output and composite video, CSI camera
	Micro SD port
Power	Micro USB 5V/2.5A DC power input

Table 2: Arduino Uno Rev 3 specification

Microcontroller	ATMega328P
Operating Voltage	5V
Input Voltage (recommended)	7-12V
Input Voltage (limit)	6-20V
Digital I/O Pins	14 (of which provide PWM output)
PWM Digital I/O Pins	6
Analog Input Pins	6
DC Current per I/O Pin	20 mA
DC Current for 3.3V Pin	50 mA
Flash Memory	32 KB (ATmega328P) of which 0.5 KB used by bootloader
SRAM	2 KB (ATmega328P)
EEPROM	1 KB (ATmega328P)
Clock Speed	16 MHz
LED_BUILTIN	13
Length	68.6 mm
Width	53.4 mm
Weight	25 g

Table 3: DHT11 sensor specifications

	DHT11
Temperature Range/Accuracy	0 to 50/±2C
Humidity Range/Accuracy	20-80%/±5%
Sampling Rate	1Hz (one reading every second)
Size	15.5×12×5.5 mm
Operating Voltage	3 to 5V
Max Current During Measuring	2.5 mA

Table 4: IR Break beam 3mm sensor specifications

Sensing Distance	Approx. 25cm/10"
Power Voltage	3.3 to 5.5VDC
Emitter Current Draw	10 mA@3.3V, 30 mA@5V
Output Current	100 mA sink
Capability of receiver: Transmitter/Receiver LED Angle: 10°	10°
Cable Length	234 mm/9.2
Dimensions:	20×1×8 mm/0.8"×0.4×0.3"
Weight (of each half)	3g
Response Time:	<2 ms

Table 5: Pi camera Module V2 specifications

Size	25×23×9 mm
Weight	3g
Power Voltage	3.3 to 5.5VDC
Still Resolution	8 Megapixels
Video mode	1080p30, 720p60 and 640×480p60/90
Sensor	Sony IMX219
Sensor resolution	3280×2464 pixels
Sensor image area	3.68×2.76 mm (4.6 mm diagonal)
Pixel size	1.12×1.12 µm
Optical size	1/4"

Table 6: Quectel EC25 Mini PCle 4G/LTE module specifications

Shield	Raspberry Pi 3G-4G/LTE Base Shield V2
LTE FDD	B1/B3/B5/B7/B8./B20
LTE TDD	B38/B40/B41
WCDMA	B38/B40/B41
GSM	B3/B8
Data Speeds	LTE FDD: Max 150Mbps (DL)/Max 50 Mbps (UL); LTE TDD: Max 130 Mbps (DL)/Max 35 Mbps (UL); DC-HSDPA: Max 42 Mbps (DL); HSUPA: Max 5.76 Mbps (UL); WCDMA: Max 384Kbps (DL)/Max 384Kbps (UL); EDGE: Max 296 Kbps (DL)/Max 236.8 Kbps (UL); GPRS: Max 107 Kbps (DL)/Max 856 Kbps (UL)
Interface	USB 2.0 with High Speed up to 480 Mbps; 1.8V/3.0V (U)SIM Card; UART×1
Protocol	TCP/UDP/PPP/FTP/HTTP/NTP/PING QMI/CMUX/HTTPS/SMTP/MMS/ FTPS/SMTPS/SSL/FILE
Supported OS	Windows XP - 10, Windows CE 5.0-7.0* ; Linux 2.6-4.1; Android 4.x-7.x
Current Consum-ption	3.6 mA @Sleep, Typically35mA @Idle; 750 mA @WCDMA data transfer, Typ. (GNSS OFF); 950 mA @LTE data transfer, Typ. (GNSS OFF); 75Ma@Searching, GNSS, Typ. 55 mA @Tracking, GNSS, Typ
Output Power	Class 3 (23 dBm ± 2 dB) for LTE; Class 3 E2 (24 dBm +1/-3 dB) for UMTS; Class (27 dBm ±3dB) for EDGE; 850/900 MHz; Class E2 (26 dBm ±3 dB) for EDGE 1800/1900 MHz; Class 4 (33 dBm ±2 dB) for GSM 850/900 MHz Class 1 (30 dBm ±2 dB) for GSM;1800/1900 MHz

Quectel EC25 Mini PCIe 4G/LTE Module

This is an interface between the raspberry pi and internet. According to Sixfab (2019a), the Quectel EC25 Mini PCIe is a series of LTE category 4 module adopting standard PCI Express® MiniCard form factor (Mini PCIe). Sixfab (2019a) goes on to state that it is optimized specially for Machine-to-Machine (M2M) and IoT applications and delivers 150Mbps downlink and 50Mbps uplink data rates. The EC25 is integrated with Global Navigation Satellite System (GNSS) to provide quicker, accurate and dependable positioning. It is inserted in the Raspberry Pi 3G-4G/LTE base shield V2 which has both the UART and USB communication for the raspberry (Sixfab, 2019b). For detailed specifications Table 6.

Table 7: Davis Anemometer specifications

Range: Wind Speed	1 to 200 mph, 1 to 173 knots, 0.5 to 89 m/s, 1 to 322 km/h
Range: Wind Direction	0° to 360° or 16 compass points
Range: Wind Run	0 to 1999.9 miles (1999.9 km)
Accuracy: Wind Speed	±2 mph (2 kts, 3 km/h, 1 m/s) or ±5%, whichever is greater
Accuracy: Wind Direction	±7°
Accuracy: Wind Run	±5%
Resolution: Wind Speed	1 mph (1 knot, 0.1 m/s, 1 km/hr)
Resolution: Wind Direction	1° (0° to 355°), 22.5° between compass points
Resolution: Wind Run	0.1 m (0.1 km)
Measurement Timing: Wind Speed Sample Period	2.25 2nds

Davis Anemometer

The anemometer and wind vane are the other devices used for sensing environmental conditions. The anemometer measures the wind speed while the wind vane measures wind direction. Davis (2019) has combined the two functions and called the devices Davis anemometer. Cactus (2014) has shown that the Davis anemometer can be interfaced with Arduino Uno to create a weather station, this is in agreement with the results obtained by Kong (2017). Table 7 lists some of the Davis anemometer specifications.

Determine Storage (battery) Capacity

As PV cells generate electricity during sunshine, a rechargeable battery system is required to store it for use in the absence of sunshine. Currently, the battery types include Lithium-ion, Nickel, Sodium sulfur, Flow redox and Lead acid among other. According to Daniel *et al*. (2014) lead acid batteries have been found to be reliable and cost-effective while Maya *et al*. (2018) reports that the lithium-ion is a high energy efficiency battery rated at 90% despite the high cost and safety concerns compared to the lead acid at 85%. To determine the battery size, we used Equation 3:

$$Ah = \frac{E}{Vdc} \times F_{Safe} \tag{3}$$

Where:
Ah = The battery Amp hour (Ah)
E = The total load (Wh)
Vdc = The system Voltage preferred (V)
F_{safe} = The Safe Factor

Determine the Solar PV Panel

Conversion of the solar energy to electricity can either be direct or indirect. According to Taşçıoğlu *et al*. (2016), the indirect method is through collecting and Concentrating the Solar Power (CSP) to produce steam which is then used to drive a turbine to provide the electricity while Bayrak and Cebec (2011) states that the direct method uses the Photovoltaic (PV) cells. The most used PV cells are the polycrystalline and monocrystalline. Abdelkader *et al*. (2010) reported that the monocrystalline PV cells were more efficient compared to the polycrystalline and this is in agreement with results obtained by several authors (Taşçıoğlu *et al*., 2016; Husain *et al*., 2018) a. We used Equation 4 to determine the solar PV panel wattage size (AlShemmary *et al*., 2019):

$$PVW = \frac{F}{T} \times F_{Safe} \tag{4}$$

Where:
PVW = The PV power required (W)
E = The total load (Wh)
T = The minimum sunshine hours per day (hrs)
F_{safe} = The Safe Factor

Determine the Charge Controller Capacity

Storing power from solar PV cells into a battery requires a charge controller. According to Maya *et al*. (2018), charge controller controls the rate of flow of the charge carriers and protect the battery from overcharging in addition to preventing battery over discharge and electrical overload. We determined the charge controller capacity by applying Equation 5:

$$CCAO = \frac{PVW}{Vdc} \times F_{Safe} \tag{5}$$

Where:
$CCAO$ = The charge controller amp out (A)
PVW = Solar PV panel power (W)
Vdc = The system voltage in direct current(V)
F_{safe} = The Safe Factor

Costing the PV System

We prepared the System Requirements Specification (SRS) based on the battery (Voltage/Amp hour), solar PV panel (Voltage/Wattage) and charge controller (Voltage/Amperage) determined in Equation 3 to 5 We then used the SRS to obtained quotations from various solar system suppliers.

Step II- Trap Housing Fabrication

We used 40×50 mm and 40×50 mm square tubes to fabricate the solar housing, 3mm metal sheet to house the battery, 1.2×22 mm outside diameter GI pipe to hold the Anemometer, 2 mm sheet metal to house the Charge Controller, Raspberry PI 3 Model B+, Arduino Uno Rev 3 and support the FAW Funnel (green lid/yellow funnel/transparent bucket) pheromone trap. We then attached everything to the 3×90 mm inside diameter black pole.

Step III- Integration

The 12V 100Watt solar monocrystalline PV panel is used to generate the electricity and it is connected to a 12V 15A charge controller. In order to avoid overcharging, over discharge and electrical overload of the 55 Ah battery, we connect it on the battery side of the charge controller. We then power the raspberry pi using one of the USB port on the charge controller. The pi camera is connected to the CSI camera connector and mounted on the top cover (lip) next to the lure holder of the FAW pheromone trap. The Raspberry Pi 4G/LTE shield with Quectel EC25 Mini PCle 4G/LTE module is connected to one of the USB ports on raspberry pi using the 90-degree right angle micro USB cable in order to achieve maximum data rates as opposed to the UART which is limited to a data rate of about 900 Kbit/s downlink and uplink. The Arduino Uno is connected to the raspberry pi USB port in a slave mode. The Davis anemometer is connected to pin A4 for wind direction, digital pin 2 for wind speed, 5V power and ground on the Arduino Uno while the IR break beam motion sensor is connected to pin 6 on Arduino Uno. The DHT11 Temperature/Humidity sensor is connected to the Arduino Uno 5v pin, GND pin and pin 4. The 3W led is connected to 13 and 5 Vpin while the photocell is connected to 5v pin, GND pin and A0.

The raspberry pi is loaded with Raspbian GNU/Linux 9.9 stretch, python 2.7.13, SQLite database and Arduino IDE 2:1.0.5 dfsg2-4.1. We use python to develop two custom-made programs. The first program captures an image of the funnel path every second alongside environmental conditions and saves the image on the local folder of 16 Gb SD card while the temperature, humidity, GPS coordinates, image identifier, wind speed and direction are saved in the SQLite database. The second program sends a picture together with environment conditions to the cloud server together as a JSON object by establish an internet connection using Raspberry Pi 4G/LTE shield with Quectel EC25 Mini PCle 4G/LTE module and Application Programming Interface (API).

Results

Step I- PV Systems Design

The automated FAW Pheromone Trap was designed to run for 24 h per day taking into account the five minimum sunshine hours for Lusaka. When we applied Equation 1, we got a total of 19 battery operated hours. The main components of the automated FAW pheromone trap that required to be powered by Off-grid solar PV system are listed in Table 8. When Equation 2 was applied, we got a total of 412.72 Wh as the system load. Table 8 shows the total system load (power) for each individual system component.

We then applied Equation 3 to determine the battery size in terms of Amp hours. We used a 1.25 safe factor and 12 Vdc due to the max power requirement for Arduino Uno to obtained a 42.99 Ah battery size which was then rounded off to 55 Ah industry offering. We then chose to use a 12V 55 Ah system voltage lead acid battery because it was readily available on the Zambian market as opposed to a Lithium ion battery of the same size. The detailed specifications for the battery are shown in Table 9. We obtained the solar PV panel wattage by applying Equation 4. We applied a safe factor of 1.25 and the result was 103.18 W. We then rounded off the wattage and settled for an 100watt monocrystalline panel due to its efficiency and availability on the Zambian market. The detailed specifications of the solar panel are shown in Table 10. Thereafter, we used the solar panel wattage (100W) as the PVW, battery voltage (12V) as the Vdc and a safe factor of 1.25 to determine the charge controller and the result was an 8.33A which we rounded off to 15A charge controller due availability. The detailed specifications for the charge controller are shown in Table 11. The total cost of the Off-grid solar PV system came to USS$ 190.00 as shown in Table 12.

Step II- Trap Housing Fabrication

Our fabricated trap housing is shown in Fig. 10 and 11 shows the inside of the case housing the Charge Controller, Raspberry PI 3 Model B+ and Arduino Uno Rev 3. The housing case is also used as the holder for the FAW Funnel (green lid/yellow funnel/transparent bucket) pheromone trap.

Table 8: Main component of the automated FAW pheromone trap

Item description	Power Per item (W)	Hours per day	Power per day
Raspberry PI	12.500000	19	237.50
Arduino Uno	3.000000	19	57.00
IR Break Beam	0.150000	19	2.85
DHT11	0.125000	19	2.38
3G Modem	3.750000	19	71.25
PI Camera	0.150000	19	2.85
LED	3.000000	12	36.00
LDR	0.002500	19	0.05
Anemometer	0.150000	19	2.85
Total Load			412.72

Table 9: Solar Rechargeable Battery specifications

Type	AGM sealed lead acid maintenance free
Voltage	DC 12V
Amp Hour	55

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Table 10: Solar PV panel specification

Type	Monocrystalline
Voltage	12
Wattage	100
Size Rated Max Voltage	18.5V
Rated Max Current	5.40A
Open circuit voltage Voc	21.5V
Short circuit current Isc	6.20A
Dimension	1/4"

Table 11: PWM 15A 12/24V Digital Charge Controller specifications

Charging Mode	PWM (Pulse Width Modulation)
Voltage	12/24V
Current	15A
Display Type	Digital
Low Voltage Disconnect	10.8/21.6V
Low Voltage Reconnect	12.6/25.2V
Built-In Protections	Over charging, over discharging, overload and Reverse connection
Other features	Automatic identification of system voltage level

Table 12: Off-grid solar PV system

Item description	Quantity	Total price US$
100 W Solar PV panel	1	60
15A charger controller	1	15
55Ah battery	1	100
Accessories	1	15
Total		190

Fig. 10: Fabricated trap housing

Fig. 11: Housing case for the Charge Controller, Raspberry PI 3 Model B+ and Arduino Uno Rev 3

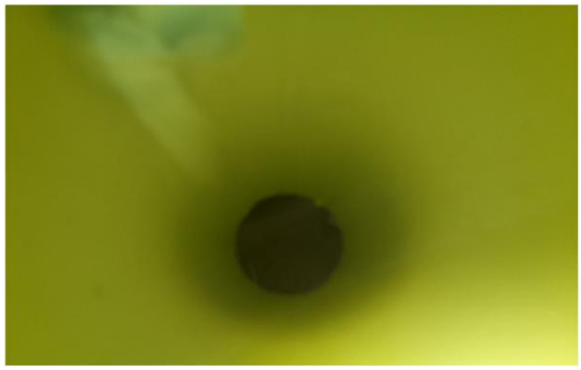


Fig. 12: Moth in flight in the funnel path

Step III- Integration

Figure12 shows an image of a moth in flight in the funnel path while Fig.13 shows the local folder with captured images on the Raspberry Pi. Figure 14 shows records corresponding to the captured images alongside temperature, humidity, GPS coordinates, wind speed and direction saved in SQLite database table on the Raspberry Pi. The image identifiers is the primary key and corresponds to the filenames shown in Fig. 13. The image and environmental conditions are combined in a JSON object and uploaded to the cloud server using an API. Figure 15 shows the daily trap capture summaries on the Web Application Dashboard while Fig. 15 shows the details of a single record on a webpage uploaded to the cloud server. The ML attribute (prediction accuracy) is based on the Googles pre-trained InceptionV3 Machine Learning model adopted by Chiwamba *et al*. (2019) and Chulu *et al*. (2019b). The model achieved a 90% plus prediction accuracy for all images that contained a FAW moth as shown in Fig. 16 while a percentage less than 60% was observed for images that did not contain a FAW moth as shown in Fig. 17.

DOI: 10.3844/jcssp.2019.1759.1779

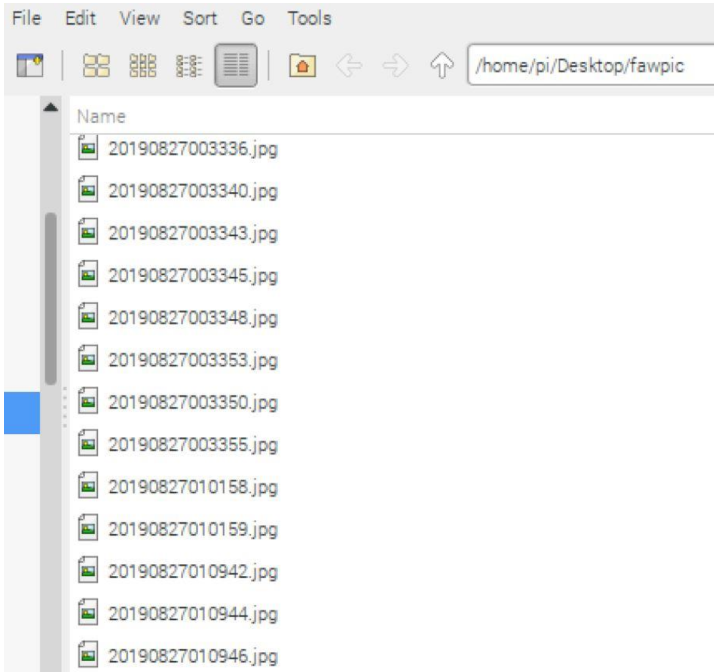


Fig. 13: Local folder with captured images on the Raspberry Pi

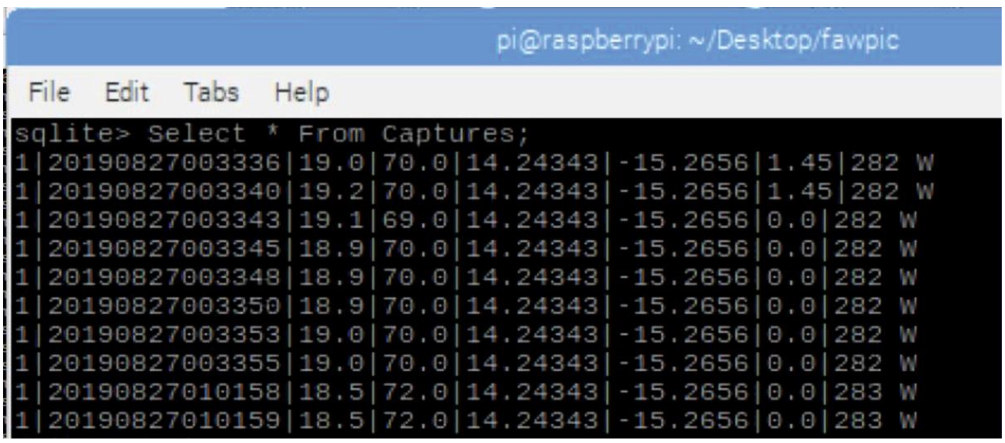
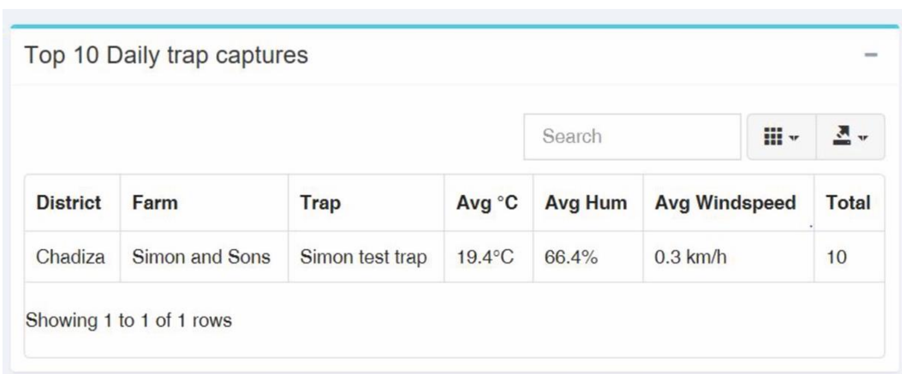


Fig. 14: Capture records in SQLite database table on the Raspberry Pi


Top 10 Daily trap captures

Search

District	Farm	Trap	Avg °C	Avg Hum	Avg Windspeed	Total
Chadiza	Simon and Sons	Simon test trap	19.4°C	66.4%	0.3 km/h	10

Showing 1 to 1 of 1 rows

Fig. 15: Daily trap Capture summaries on the Web Application Dashboard

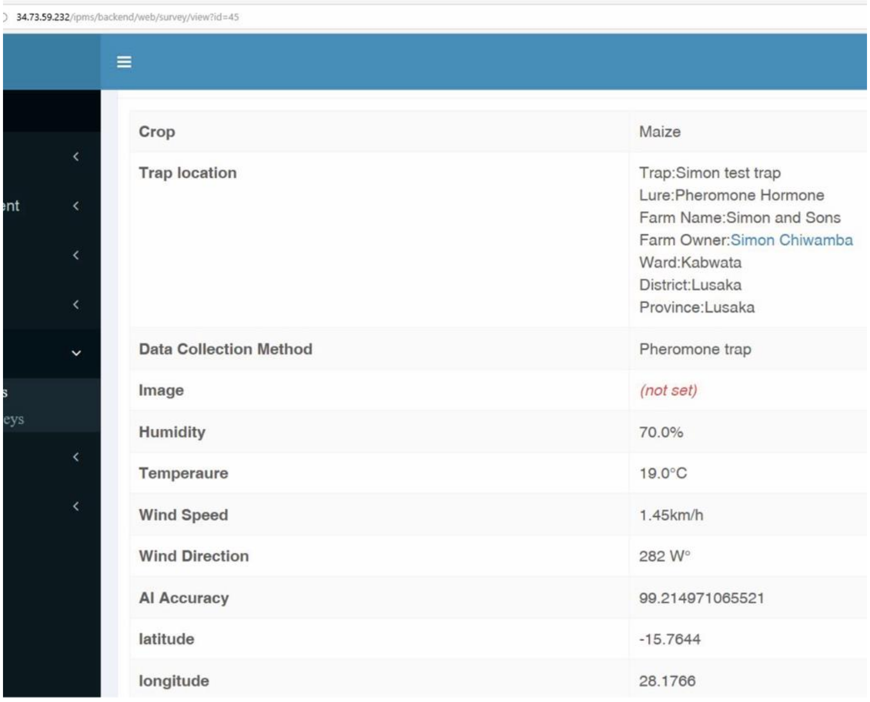


Fig. 16: Detailed single trap capture on the web application

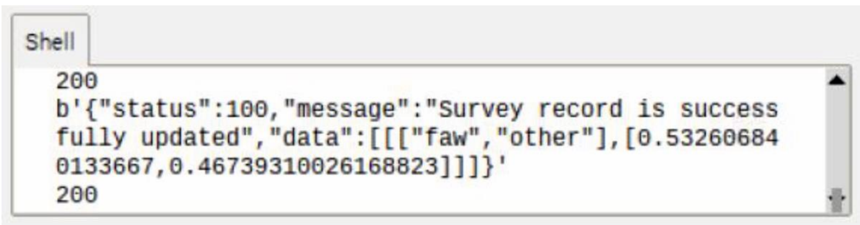


Fig. 17: Prediction Accuracy an image without FAW moth

Discussion

We modified the FAW trap and integrated it with various sensors which included the camera, temperature, humidity, motion, photocell powered by an off-grid solar PV system for capturing FAW images and environmental conditions in the field. The greatest challenges included but not limited to, off-grid solar PV system configuration, FAW motion sensing and Raspberry PI camera capture timing. We had to upsize or down size the off-grid solar PV system components in order to align them to what was readily available on the Zambian market. On the FAW motion sensing, the IR Break Beam could not detect the FAW moth motion accurately leaving as with the Raspberry PI camera as the only way to remotely monitor the presence of the FAW moth on the trap. After setting the PI camera to capture FAW moth images every second, we observed that the PI camera captures ranged between 1s to 5s when we cross-checked the image id (record) in the database and image names in the folder. We then adjusted the timing to 5s and we instantly observed a 5s consistency in the capture interval. Furthermore, we observed that API took more than 5s to return prediction accuracy hence adjusting the image data upload to 10s.

Our modified trap can be improved in a number of areas including but not limited to reduced solar panel and battery size; reduced trap size and weight; integration of optoelectronic sensors similar to the ones used in the work of Potamitis *et al*. (2015); reduce on the data transfer rate and avoid stressing the cloud server by performing primary image classification on the Raspberry Pi.

Conclusion

Our automated FAW trap embraces the IoT concepts by integrating a Raspberry Pi 3 Model B+ micro-computer, Atmel 8-bit AVR microcontroller, 3G cellular modem and various sensors powered with an off-grid solar photovoltaic system to capture real time FAW moth images and environmental conditions including GPS coordinates, temperature, humidity, wind speed and direction in the field. The captured images together with environmental conditions are uploaded to the cloud server where the images are classified instantly using machine learning to determine whether the image contains a FAW moth or any other insect. The users are provided with an easy to use web application platform that shows near real-time indication of the FAW pest occurrence. Furthermore, users can view the population dynamics of the FAW together with environmental conditions and use the information to design suitable pest control strategies. The designed system has the potential to increase accuracy of monitoring, shorten data collection intervals, reduce field visits and minimize human intervention for a more efficient and effortless early warning and monitoring system that provides a near real-time insight into the FAW situation in the field.

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Author’s Contributions

Simon H. Chiwamba: Conception and design, acquisition of data and analysis and interpretation of data. Drafting the article and reviewing the article.

Jackson Phiri: Drafting the article and reviewing the article critically for significant intellectual content. Approval of the revised version for to be submitted.

Philip O.Y. Nkunika: Reviewing the article critically for significant intellectual content and giving final approval of the version.

Claytone Sikasote: Conception and design.

Monde M. Kabemba: Reviewing the article critically for significant intellectual content.

Miyanda N. Moonga: Acquisition of data and reviewing the article critically for significant intellectual content.

Ethics

We, the authors agree with the publication of this manuscript and confirm that it does not contain ethical issues. All cited references are stated in the references section.

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