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Farmer centered large scale e-surveillance and control of crop pests in Kenya

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A B S T R A C T

With advancement of mobile technology and the property of mobile phones of being ubiquitous and pervasive, innovative applications in agriculture that are context specific and individualized to farmers' needs can now be developed. This is because mobile phone based agricultural innovations are readily leveraged to provide farmers with information ranging from farm preparation and pre-harvest to post harvest and farm produce marketing. In this regard, this paper proposes a farmer centric pest e-surveillance solution framework, a digital platform that uses mobile devices, image processing and crowdsourcing to assist smallholder farmers in low income countries to effectively identify and control crop pest invasion, and to connect them with local agro-vet stores and extension service providers for assistance. This way, we can assist small holder farmers in rural Africa to learn about crop pests, to detect and respond to pest invasion, and to control the effects of such pest invasion by providing timely, accurate, relevant and readily consumable information in the local languages of the farmers. This also makes it easy to perform large-scale pest surveillance in the rural farming community

1. Introduction

The world population is expected to increase by at least 30% yearly until 2050 (FAO 2018) which calls for strategies to ensure food production even amidst current and foreseeable challenges that come with increases in population such as degradation in land productivity, unreliable rain, climate change, fluctuations in prices of agricultural produce among others. This has led to exploration of potentials of different technologies such as biotechnology, digital technologies – i.e., remote sensing, cloud computing, Internet of Things etc. – artificial intelligence and machine learning among others on their role towards improving agricultural productivity given these challenges (Tata & McNamara 2018). Thus, digital revolution in agriculture to support data-informed decision making towards improving farm productivity and across to agricultural value-chain. Moreover, digitization in agriculture has made it possible to gauge and predict farm production, weather, market and climate variability, and just on-time solutions such as in precision farming (Bronson 2015). This includes the big data phenomenon that uses the inherent connection and relations within a large dataset to discover knowledge that can improve the farming practices. Such data easily gathered using drones, satellites, smart phone applications, crowd sourcing – so called citizen science – and the unconventional sources such as social media platforms allow the farmers and the community to report on prices of agricultural produce and inputs (Bronson 2015). Harnessing the benefits that come with digitizing agriculture has to focus on its ability to empower the farmers to share their experiences to learn from each other. This has the advantage of breaking the barriers to adoption of the digital solution, as the early adopters would lead the other farmers to embrace the solution (Eitzinger et al. 2019). In addition, this interaction and farmer engagement results in a farmer centric solution that assists local ownership of the innovation by the farmers and, thus, guarantees its adoption.

In the recent years, there has been a significant increase in mobile phone penetration in Sub-Saharan Africa. Report by GSMA[3] shows that as of 2017, the mobile phone adoption in Sub-Saharan

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Africa was at 44% and is projected to reach at least 52% in 2025[4]. This can be attributed to the affordable mobile phone calling rates and the flexible browsing bundle packages that have been experienced in the recent past in the region. Notably, this access to mobile-phone connectivity has empowered the consumers and is significantly driving economic growth as users can now access most essential services including financial services and credit facilities, health and education services, and utilities through their mobile phones (Awuor et al. 2016; Tadesse & Bahiigwa 2015). There are massive opportunities to deliver personalized and context-aware mobile-based services to these mobile users. Thus, to ensure food security and to improve agricultural productivity in Sub-Saharan Africa, mobile-based phone technology has been exploited and leveraged to provide farmers with relevant, accurate, timely and consumable agricultural information ranging from farm preparation to pre-harvest and post-harvest crop and farm produce management. This includes information on pest and disease control, precision farming and irrigation, market availability and produce pricing, access to credit facilities and extension services among other services including livestock management (Awuor et al. 2013; Mohanraj et al. 2016).

Given the changing climatic conditions, and unreliable and erratic raining patterns that require adoption of new types of crops and farming skills, farmers are mostly in desperate need of information on modern farming methods and practices that can increase the yields of their farms. This illustrates the extent to which access to agricultural information, which is very costly to access in Sub-Saharan Africa (Tadesse & Bahiigwa 2015), is crucial to the farmers in decision-making. By using market prices that are easily accessible and readily available through mobile phones, (FAO 2018; Tadesse & Bahiigwa 2015) illustrates that such information could assist smallholder farmers to decide on better pricing for their produce. In addition, this saves farmers from having to make frequent market travels and to avoid repeated loading and unloading at the market to show-case their produce to buyers and brokers. Example of such a service is SokoniSMS64 (FAO 2018; Tata & McNamara 2018) which enables farmers in Kenya to access market prices of agricultural products from around the country. Some of the mobile-based agricultural services in Kenya include Kilimo-Salama, iCow and CocoaLink. Kilimo-Salama is a micro-insurance mobile based “pay as you plant” type of insurance plan in Kenya that safeguards the farmers against poor weather conditions (Awuor & Rambim 2014; Kassie et al. 2018). It also provides instant weather information to assist farmers to manage their cropping, similar to Tigo-Kilimo in Tanzania. On the other hand, iCow[5] is a mobile phone based solution that assists the farmers to keep track of their cows’ gestation including track of their feed types and schedules, local veterinary contact information, and precise market prices of their cattle. The CocoaLink is a free voice and text message based mobile solution in Ghana that provides farmers with best farming practices, crop disease prevention, and crop marketing in both English and local language (Awuor & Rambim 2014).

As most farmers are now aware of availability of massive agricultural resources that can be accessed via their mobile phones and are increasingly searching for information using these devices, it is notable that farmers are mostly not able to find relevant and accurate just-in-time information (Awuor et al. 2013; Tadesse & Bahiigwa 2015). Mostly, the information provided to the farmers is not timely and in a format that is readily consumable. This is in part due to language barrier as most of the contents are provided in English while most of these farmers have low literacy levels in addition to not being able to speak or comprehend English as a language. The other reason is that most of these rural farmers in Africa have basic feature-phones that do not support multimedia in which most of the contents are delivered in. In addition, farmers tend to get a lot of content from online sources and through their mobile devices, some of which are difficult to validate and authenticate, which potentially leads to the well-known problem of information overload. Thus, there is a need for farmer-centered agricultural information systems (AIS) that seek to deliver agricultural information to the farmers in a format that they can access and consume. This is the core problem explored in this paper with a desire to design a farmer-centered AIS for pest control.

[3] https://www.gsma.com/mobileeconomy/sub-saharan-africa/
[4] https://whiteafrican.com/top-20-african-states-by-mobile-penetration/
[5] http://www.icow.co.ke

While AIS can be either web-based or mobile application, the design of an AIS system always needs to focus on providing the farmers with a unique and satisfying experience as it provides the farmers with information that they need, in addition to being easy to use. This essentially implies that AIS has to provide farmers with timely, relevant and accurate information in formats that are readily consumable. In this regard, most AISs are currently being presented in the local languages of the farmers and employ call center agents that farmers can call anytime and attend to the farmers' queries in their local languages. AIS also uses voice-assistant that enables the farmers who are not able to write or read and to interact with AIS to get personalized assistance delivered to them in their mother-tongues. AIS has also used SMS and USSD to support farmers with basic-feature phones. An exhaustive discussion on design of AIS including participatory and collaborative design, and both pull and push based designs can be found in (Awuor et al. 2016).

With advancement of mobile technology and the property of mobile phones of being ubiquitous and pervasive, numerous AIS applications that are context specific and individualized to the farmers' needs can now be developed. By leveraging numerous sensors in smart phones and technologies such as machine learning and artificial intelligence, data mining and analytics, cloud computing and Internet of Things, participatory sensing and crowdsourcing, remote sensing, online content and social media among others, AIS is now able to provide farmers with comprehensive and integrated digital solutions to their needs. This approach can be used to develop solutions to some of the stubborn problems currently faced by the farmers thus assisting farmers to be proactive to animal and crop pests and disease inversion, for instance in low-income countries such as Kenya, or to carry out large scale pest and disease surveillance in such countries. In this regard, this paper proposes a novel mobile phone-based AIS framework for large scale pest surveillance in low income countries that leverages "passive" big data sources from remote sensing and crowd-sourcing coupled with machine learning to assist farmers detect and report pest invasion, and to connect them with local extension services for help.

The rest of this paper is organized as follows: Section 2 presents the problem statement and the contribution of this paper, Section 3 provides related literature review, Section 4 presents the proposed system and framework design, while Section 5 presents the results and discussion. The conclusion and the way forward is presented in Section 6. Preliminary results and early version of this paper was presented at the IST-Africa 2019 (Awuor et al. 2019).

2. Problem Statement

The rural Africa community is typically characterized by poor infrastructure ranging from inaccessible roads to limited electricity connection and poor Internet coverage. This coupled with low literacy levels and the fact that most people involved in farming in the rural community are aged population makes crop pest surveillance and control an uphill task but a necessity (Sine et al. 2010). Besides, other issues such as language barriers and lack of accessibility to timely and relevant information on pest identification, control and prevention makes farming in the rural community an unrewarding venture (Togola et al. 2018). However, with ever increasing penetration of mobile phones in these communities, we argue that we can leverage these phone owners (who are mostly farmers) to assist in pest surveillance through a mobile phone based crowd-sourced platform. Thus, we propose a platform built on farmers' participatory sensing, SMS, USSD, pattern recognition and incentive design where the farming community can report cases of pest using an SMS or USSD. Notably, some of the farmers in these rural communities are professionals (such as local teachers or health practitioners etc.) who in most cases possess smart phones. So in addition to SMS and USSD, we incorporate a mobile phone based image recognition app that can automatically recognize pests in the farms "on-the-fly" and send the information to the surveillance center. This way, a farmer with basic-feature phones (so called "mulika mwizi" locally) can either report instances of crop pests through an SMS or USSD. They can also send requests (through SMS or USSD) to the system so that a nearby field agent (so called smart farmer) can be requested to assist with the pest identification. In return, the platform provides farmers with free information on how to mitigate and control the identified pest. Besides, the farmers are also referred to nearby local agro-vet store that stocks the relevant pesticides. It also connects the farmers to the local agricultural extension service providers for assistance. To motivate field agents, who are essentially local farmers with smart mobile phones, to assist the local community in pest identification, the field agents are rewarded with points (when they respond to a local farmer's request). These points can be accumulated and be used to buy calling airtime or data bundles for internet (on a partnership with a local mobile service provider such as Safaricom or Airtel – in the case of Kenya). Thus, we can be able to visualize the invasion and spread of any pest and control its effects in the region.

To this end, objective of this paper is twofold. Firstly, we propose a framework for large scale AIS pest surveillance and then we design a mobile phone based farmer centered pest e-surveillance system for large scale crop pest surveillance in low-income countries such as Kenya. Secondly, we develop a proof-of-concept for the proposed pest surveillance system and report on some of its experimental results. This paper reports the initial stage of this AIS pest e-surveillance project that focusses on identification of fall army-warm (FAW) pest in Maize, Millet and Sorghum in Western Kenya which is currently a big challenge to the farmers in Sub-Saharan Africa. We look forward to leveraging the proposed framework to build an e-surveillance platform for crop pests in Wheat, Millet, Sorghum, Maize, Rice, and Cassava in the next phase of this project.

3. Related Work

Mobile phones can now be leveraged for offline and remote crop pest and disease diagnosis through such tools such as machine learning, crowdsourcing and participatory sensing, computer vision among others (Hughes & Salathé 2015). For example, PlantVillage platform developed in (Hughes & Salathé 2015) is an open access repository of curated images on healthy and infected crops leaves that is being used to identify and predict crop diseases. We explore this approach to build a machine learning and crowd-sourced based mobile device crop pest detection and identification.

The study by (Camargo & Smith 2009a, 2009b) focuses on crop disease identification – in the case of cotton – that involves segmenting and extracting features from the affected regions on cotton plant which are used as inputs in the classification algorithm that is built on Support Vector Machine. The features that are considered to add little on no information to the classifier are discarded so as to improve the accuracy of the classifier. The goal was to leverage analysis of digital images collected remotely to help the farmers to identify early symptoms of plant disease and to respond accordingly. The plant disease identification proposed in (Smith) uses image texture due to its ability to guarantee that patterns can always remain identical even when the preliminary conditions are changed e.g., when due to different light intensity when a picture is taken.

The survey work done by (Singh et al. 2016) demonstrates that given the massive data currently available on crop pests and disease – mostly from high-throughput imaging technologies including satellite images sensor data of plants – can now provide a large corpus to build and train classifiers to assist in plant disease and pest identification, classification, quantification and evaluation, and prediction. Some of these algorithms can be found in (Singh et al. 2016). In achieving this, the plant dataset is divided into two, i.e., the training dataset and the testing dataset, typically in the ratio of 0.8: 0.2 such that both the sets represent the entire population. The training set is used to calibrate or derive the classifier so called the model while the testing dataset is used evaluate the performance of the classifier. The next step is to validate the performance of the classifier on new set of data in regards to accuracy, precision, recall etc. So long as the performance is deemed sufficient, the classifier can be used on routine basis to identify, classify, quantify and even to predict given aspects of interest. Given that the classifier would continuously be exposed to new set of patterns form new data, the classifier updates itself and learns new insights that might have not been learnt in the initial training. Generating of the classifier, also referred to us the learning process, can be done as supervised or unsupervised depending on the problem to be solved and objective of the learning. The first case is where the model is provided with label instances and thus uses these known cases to perform the classification or identification while on the second case, the model is required to learn by itself i.e., without any guide or labelled instance. (While extensive discussion on how to build a classifier is generally out of scope of this paper, interested readers can consult machine learning references such as (Chi et al. 2016), (Hashem et al. 2015), (Potena et al. 2016), (Saxena & Armstrong 2014) and citations there-in in addition to deep learning whose application in agriculture has exhaustively discussed in (Kamilaris & Prenafeta-Boldú 2018) and (Mohanty et al. 2016).

The work in (Bauer et al. 2009) focuses on early and reliable detection of leaf diseases towards improving productivity in precision agriculture using conditional random fields. They use non-destructive approach to investigate the evolution of sugar beet leaf disease over time. This proposed algorithm demonstrates that with proper selection of features and enough dataset, leaf diseases can achieve at least an accuracy level of 0.95. However, the algorithm does not focus on pixel-level detection that could significantly improved the performance index of the algorithm. Similarly, (Wang, et al. 2008) has proposed an artificial neural network based method that spectrally predict late blight infections on tomatoes towards increasing efficiency of managing and controlling the disease infestation to increase crop production.

Of all the literature reviewed, none focus on large scale surveillance of pests in remote regions which is typically characterised with ill-developed infrastructure, high level of illiteracy, digital divide and disproportionate gander-based access to technology in addition to strict cultural and religious norms that great influence how people interact, access, use and adopt digital solutions. This scenario is mostly witnessed in developing nations, such as Kenya, where any invasion of a crop pest and/or disease causes massive losses before the government can even detect that there is a crop pest and/or diseases invasion leave alone responding to provide a remedy to farmers. While providing a treatment plan or extension services to the farmers is essential during an invasion and even to learn how to mitigate such an invasion in the future, the first step has to do with knowing when the invasion occured (including predicting the likelihood of its occurrence). Thus, this paper focuses on leveraging the advancement in technology to empower the small-holder farmers in the remote locations in developing nations to detect and report invasion. This way, these farmers can be provided with "just-in-time" mechanisms to curb the pest invasion.

4. System Design

Farmers and consumers need healthy plants and quality plant products for consumption. Efforts to improve plant health have been evolving with increased understanding of plant ecology and pest management. In spite of success in controlling the crop pests, pesticides adversely affect public health and environment (Luvisi et al.2016). Residues of pesticides in food crops have often been reported to exceed their acceptable limits. Moreover, some crop pests have since built resistance to these pesticides while for others such as Fall-Army Warm (FAW), there are no known effective pesticides. However, by continuously scouting and monitoring the farm for crop pests, these pests can be controlled and their effects mitigated. This process is defined as crop pest surveillance (Sharma et al. 2014). For the sake of clarity, crop pest surveillance in this paper (similar to (Sharma et al. 2014)) is defined as constant watch and scout on the population dynamics of pests, its incidence and damage on crops to forewarn the farmers to take up timely and necessary crop protection measures. (For the sake of illustration, the performance of the proposed framework is evaluated on control of FAW.)

FAW is an invasive crop pest that is rapidly spreading and threatening food security across Sub-Saharan Africa and stands to exacerbate global poverty and hunger (Prasanna et al. 2018) (Day et al. 2017). FAW is known to attack at least 80 different plant species[6] including rice, maize and sorghum and can fly for nearly 1,000 miles under 30 hours speed (Bateman et al. 2018; Day et al. 2017; Prasanna et al. 2018). This implies that FAW can easily migrate within neighbourhood farms in a short time and can cause massive losses in the process. Thus mitigating FAW and controlling its effects has to be a deliberate quick response in terms of noticing its invasion and being pro-active to contain and control its spread. This must include communicating any noticed sign of its invasion among the neighbouring famers so as to reduce its risk. Increasingly available digital technologies including sensors, geospatial imagery and data analytics can be leveraged to allow smallholder farmers to gain useful advice and make informed decisions (Bateman et al. 2018; Day et al. 2017; Prasanna et al. 2018). Thus, this paper proposes pest e-surveillance solution aimed to enable smallholder farmers and those who support them to accurately identify incidences of FAW in their crop field, and to provide

[6] http://www.enstartup.com/2018/07/05/three-ugandan-app-developers-shortlisted-usaids-fall-armyworm-tech-prize/

timely, context appropriate, and empowering insights for smallholder farmers to treat the incidences of FAW.

To this end, we propose a Digicult, pest e-surveillance digital platform that uses a mobile device, image processing and crowdsourcing to help farmers effectively fight FAW invasion. Digicult provides a digital training resource to train farmers through their mobile devices on detection and prevention of FAW. The digital training resource supports crowdsourcing to ensure that farmers without smart mobile phones can have access to the trainings through local smart-farmers, so called field agents, who may have smart phones. Digicult also provides a monitoring mechanism to assist the farmers in detection, monitoring and assessment of FAW outbreaks and threat levels in their farms and in their neighbourhoods. This module collects regular inspection reports from farmers and performs data analysis and image processing to detect outbreaks and threat levels. In addition, Digicult provides treatment options when FAW is detected and preventive mechanisms to stop or control invasion of FAW. This way, farmers in the neighbourhood where FAW has been detected can be alerted to be cautious and to look out for possible FAW invasion in their respective farms and recommend preventive mechanisms to these farmers. Moreover, Digicult collects, analyses and shares data on FAW obtained from the interactions between the system and the farmers so as to establish the behaviour of FAW in the different areas where it has been reported towards informing development of strategies to mitigate it.

Though the Digicult platform is farmer centered and focuses on empowering farmers to curb FAW and its effects, it is also a digital tool for extension workers, agro-vets store, local and regional governments and other stakeholders working with farmers to combat FAW. In this regards, Digicult has three components: a central server (web based database, so called web app), a mobile application and SMS-USSD service. The Web based database, so called central server, hosts all the information related to the platforms. For instance, it is used to monitor and visualize the outbreak and spread of FAW. It is also used to connect local farmers with crowd-sourced local field agents to assist them with local training and FAW detection. The database also registers and stores agro-vet details and recommends to farmers the local agro-vets who may be stocking the pesticides to manage FAW.

Using the Digicult mobile app[7], smart farmers are able to learn about FAW (detection, control and prevention) and to educate their fellow farmers who may be illiterate or not having smart phones on critical information about FAW. The application contains a light-end image processing module which automatically detects FAW on the crop. The farmer only needs to position the phone's camera on the suspected crop pest and the application assists her to identify if it is FAW or not and also reports the level of infection or damage. The mobile app also provides a geographical mapping (i.e., information visualization) of FAW infection and spread reported in the platform and recommends and connects the affected farmers with the nearest local agro-vets stores and extension service providers for assistance. The app has a follow up mechanism to ensure that the farmers who report FAW cases are assisted and that all farmers perform a regular FAW checks on their farms. The SMS-USSD[8] module is available for users who do not have smart phone and thus cannot access the mobile app. Through a simple *384*422# code, the famers are able to create accounts, report FAW and to request for assistance in their local languages thus allowing them to interact with Digicult platform.

[7] Digicult android prototype is operational and can be download from https://bit.ly/2OEl9OR

[8] User manual on how the Digicult SMS-USSD service operates can be accessed from https://bit.ly/2OEl9OR

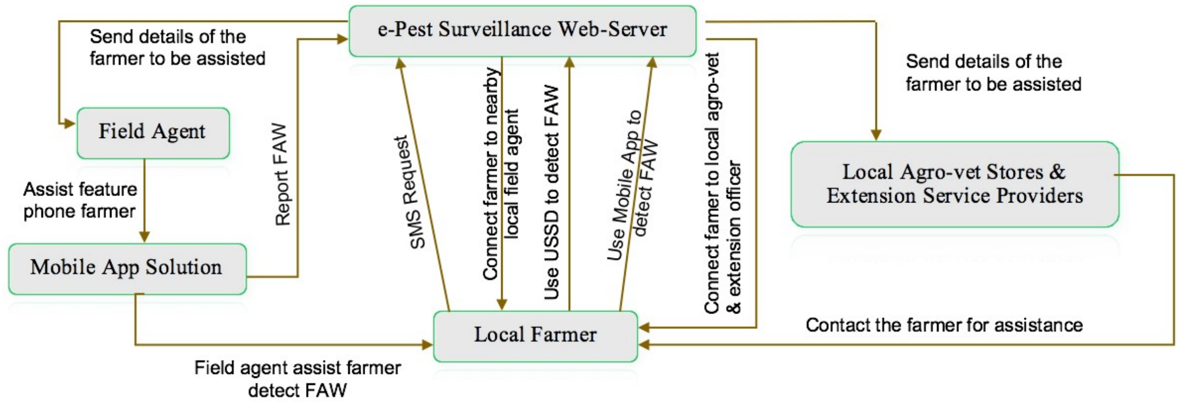

Figure 1. Mobile Phone based Pest Surveillance for Fall Army-warm

In the following section, we describe how the proposed solution works. The farmers, and local agro-vets stores and extension officers are registered (capturing their names and locations) in the pest e-surveillance platform. Farmers with smart phones who may want to double as field agents are also registered. Now, when a farmer suspects an insect on a plant to be a pest, he has three possible options to identify it and to get connected to the local agro-vet store or extension officer for assistance as illustrated in Figure 1.

i. Smart farmers (i.e., field agents) may install the pest e-surveillance solution, so called Digicult app, in their phones and can identify pests while offline and automatically send SMS to the system with information on the pest identified, the location where it is identified and the mobile number of the field agent who has submitted the SMS.

ii. The farmers can send an SMS with the word pest to a prescribed code that delivers the request to the system. The system identifies the farmer and his location and sends a message to the nearest field agent to go assist the farmer to identify the pest. Using the Digicult app in their phones, the agent can identify the pest and send SMS to the system. The SMS contains the pest identified, and the mobile number of the field agent and that of the farmer who had sent the SMS request asking for assistance.

iii. Lastly, the farmer can use an USSD, a short code that basically collects the insect's observable features which are then sent to the system and used to infer if the observed insect is a pest and in that case which pest. In case of positive identifications of insects as a pest, the farmer is referred to a local agro-vet that stocks the pesticide for the identified pest or gets connected with a local extension officer for assistance. This would be somewhat an incentive for the farmers to want to use the system. As mentioned a prior, the agents are rewarded with points for every farmer that they assist on referral by the system (the points are intended to be convertible to calling airtime or data bundles). Both the mobile app and the system backend leverages machine learning and image recognition to identify insects as pests "on-the-fly" and to deduce that an insect is a pest from the submitted USSD features respectively.

Farmers can use Digicult in four ways: to learn about FAW through the digital training content; to perform a plant infection detection with the image processing assistant and to obtain a solution recommended. Farmers also get connected to the nearby extension worker and to find nearby and reliable agro-vets stores where they can purchase pesticides; and to monitor the spread of FAW in nearby locations and in the region using the infection report map.

The digital training content is designed in close partnership with FAW expert and updated regularly to make sure that the farmers are provided with the latest relevant information on FAW. The content range from the recognition and detection of FAW invasion to the presentation of best agricultural practices to prevent FAW invasions. The content is tailored to the location of the farmers to ensure that the recommended practices are suitable and adoptable by the farmers, and in a language that the farmers understand. The multimedia based FAW inversion detection tool assists the farmers to automatically identify FAW invasion “on-the-fly” from the pictures taken by the farmer during the scouting. This tool also recognizes the stage of FAW invasion on the crop in order to recommend effective treatment plan. The treatment recommendation uses artificial intelligence to learn from previous experiences and FAW experts on suitable techniques given the location of the farmer, then recommends a set of appropriate actions that can be taken by the farmer to combat the invasion. The solution also provides a notification to farmers to inspect the farm for FAW if and when FAW has been reported in the farmers’ neighbourhood. This way, farmers are able to detect FAW early when FAW still has little damage on the farms. Farmers also have access to local and nearby vetted agro-vet stores which are recommended to them to purchase pesticides. The agro-vet stores are preliminarily vetted by Digicult during their registration and a system of customer review is used to ensure that the quality of service offered by these agro-vet stores is acceptable.

5. Results and Discussion

Due to space limitation, only the results on detection and visualization of FAW invasion are presented in this paper[9]. To detect FAW, the farmer opens the Digicult app and positions the camera on the pest suspected to be FAW. If the pest is detected as FAW, Digicult provides the threat level and automatically connects the farmer to a local agro-vet store and extension service providers to assist the farmer. This is illustrated in the Figure 2 below. The local, regional and national governments, and all the other stakeholders can view a report on the spread of FAW in the country using the visualization map extracted from the database as shown in Figure 3 below.

In order to control the spread of FAW and reduce the risk of future humanitarian crisis, smallholder farmers need improved access to immediate, accurate and actionable information on how to mitigate, identify and combat the fall army-worm. Digital technologies can be utilized in expanding the frontiers of information access in Sub-Saharan Africa.

The first problem encountered by farmers when fighting FAW is lack of reliable knowledge about FAW and best farming practices against FAW. By providing digital trainings, Digicult ensures that farmers receive reliable information on prevention, detection and treatment of FAW.

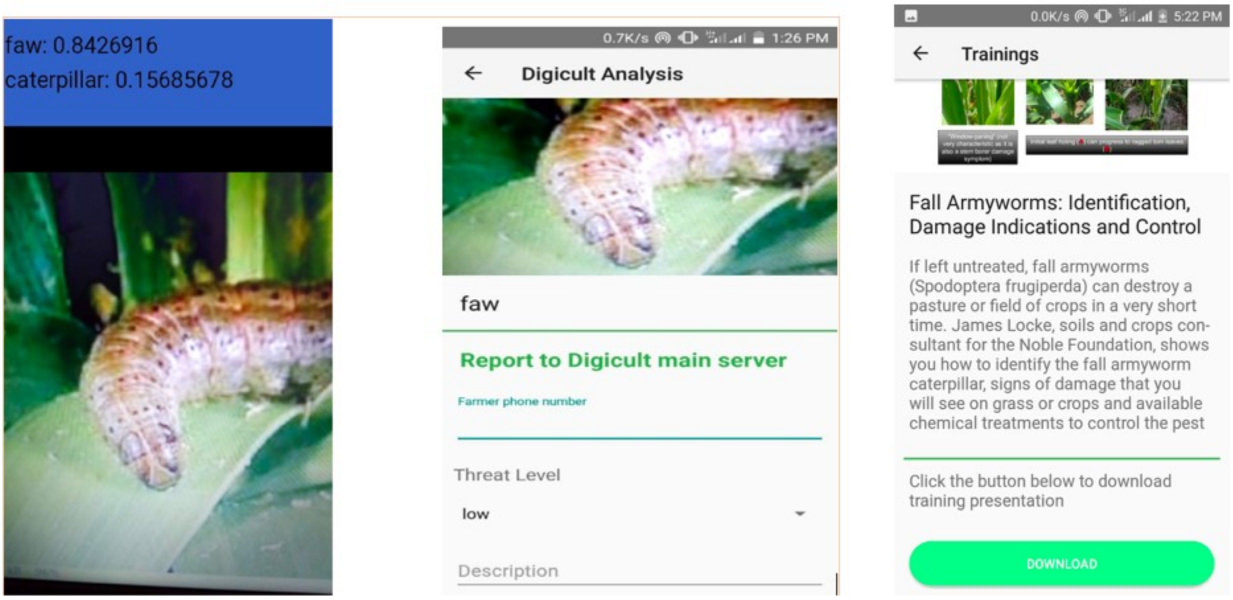

Figure 2. Detect of FAW and Farmer Training

[9] The results on user registration, seeking help, FAW training i.e., web app and USSD, SMS and mobile app, can be accessed from the user manual files stored in https://bit.ly/2OEl9OR that also contains the .apk source file of the proposed solution

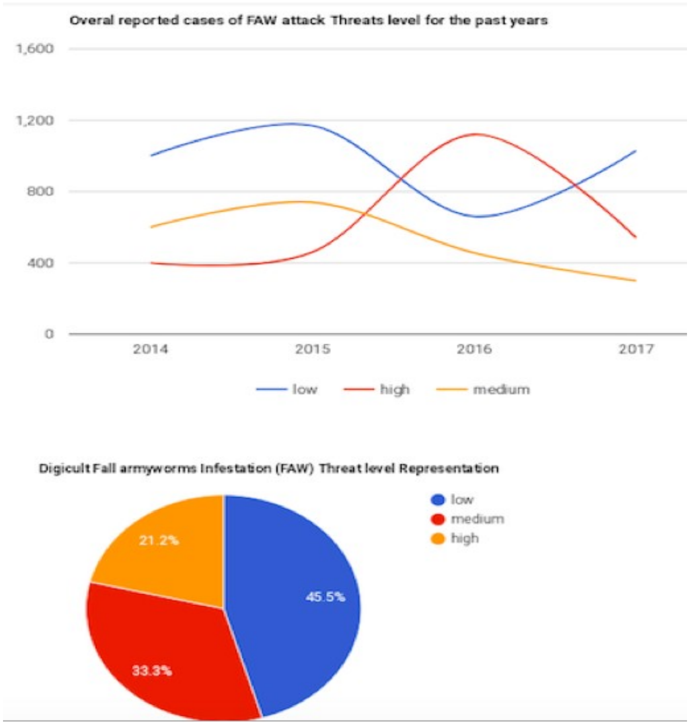

Figure 3. FAW inversion spread and visualization

The second problem encountered by farmers is lack of suitable communication equipment to stay up to date on FAW. By providing digital trainings to farmers with smart phones, these famers can share these insights with their colleagues who may not have smartphones through local social groups such as farmers or religious forums. The third problem is the detection of FAW. By providing an image processing assistant, Digicult can ensure that farmers are able to accurately identify FAW infection in a short time. Moreover, Digicult connects the farmers with the extension workers that can provide additional information and measures to contain the pest. Through the pest invasion info-graph, farmers can also know when to scout their farm for possible pest invasion. From the preliminary testing results (in Kakamega county, Lurambi sub-county in Kenya), the proposed pest e- surveillance platform on FAW is noted to have the following impact: enables the farmers to effectively prevent FAW attacks by following prevention practices; provides timely diagnosis of FAW and treatment options; and makes it possible to visualize the spread of FAW towards immediate and rapid response to its mitigation.

Digicult provides a monitoring module to assist farmers in the detection, monitoring and assessment of FAW outbreaks and threat level. This module collects regular inspection report from farmers and performs data analysis and image processing to detect outbreaks and threat levels with the assistance of experts if needed. Then it provides actionable treatment to the farmers, connects them to local experts (and agro-vet stores). It also provides visualization map for government and other entities to assess and to map the spread of FAW in the region. We hope that through an e-surveillance pest control platform such as Digicult, we will be able to change how farmers seek and access information from traditional e.g., word of mouth to more reliable approaches like mobile based access. In addition, we can change how the farmers and the government respond to FAW, that is, from crisis management approach to preventive approach; and also be able to incentivize more researchers to focus on fall armyworm given the availability of massive data collected by the system.

In summary, the local small-holder farmers and field extension officer thought that Digicult is a good product with great potential of providing much need support to them. Farmers reported a genuine appreciation for the the Digicult's heat map feature due to its integration of access to local extension officers. Female farmers reported that sometime they would wish that they are attended to by female field agents crowd-sourced within their communities and not just some random person (worse male) whom they do not even know. This was noted to be against culture and norms in some communities.

While Digicult would simply connect the farmer who has reported an incidence of FAW with any available agent to assist him/her with the identification of the pest, future design will ensure that societal cultural norm such as same gender service support is provided.

Towards self-sustainability of Digicult, we envisioned that the farmers would pay some subscription fee or usage fee whenever they use the service. However, field test with the farmers indicated that they would not be willing to pay every time they used the solution as they considered it highly prohibitive. This could prevent penetration and adoption of Digicult among the farmers. In this regards, we may need to re-think and re-design a realistic business model that is cognizant of the users' characteristics. We notice that the typical business models adopted in most of digital solutions may not necessarily apply in the context of small-holder farmers in developing nations who are not only struggling with low penetration of mobile phones but other issues such as gender, culture, and digital divides, in addition to low literacy levels and poor infrastructure. This is a potential area of research as this would inform the adoption of digital solutions in these communities.

6. Conclusion

Data analytic tools and machine learning tools are providing a new and powerful mechanism to offer farmers support and access to services that would otherwise be expensive to get such as remote onsite diagnose of crop disease, identification of crop pests, and extensive service on control and mitigation of these pests and diseases. This paper proposes a framework and design of digital solution for large scale crop pest e-surveillance in low-income countries. Specifically, we propose a farmer centric mobile phone-based digital solution for pest crop management, pest e-surveillance system for fall army-worm. The solution leverages advancement in mobile technology such as big data and machine learning, crowd-sourcing and participatory sensing, pattern recognition, SMS and USSD, and incentive design. This way, we can assist small holder farmers in rural Africa to learn about crop pests, to detect and respond to pest invasion, and to control the effects of such pest invasion by providing timely, accurate, relevant and readily consumable information in the local languages of the farmers. This also makes it easy to perform large-scale pest surveillance in the rural farming community.

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