Smart Agricultural Technology 5 (2023) 100260

Contents lists available at ScienceDirect

Smart Agricultural Technology

journal homepage: www.journals.elsevier.com/smart-agricultural-technology

Design and implementation of IoT sensors for nonvisual symptoms detection on maize inoculated with *Exserohilum turcicum*

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ARTICLE INFO

Edited By: Dr Spyros Fountas

Keywords:
IoT
Nonvisual
Maize disease detection
Timeseries
VOC
Ultrasound

ABSTRACT

Diseases on maize crops are highly caused by chronic and emerging pathogens that results in stagnant growth in the plant system. Several initiatives have been adopted to manage disease on crops which include new cultivation practices, genetic engineering, plant breeding and chemical control which have only proven to perform better on laboratory-based approaches. Meanwhile, small holder farmers can hardly afford such intervention mechanisms because they are costly and require highly skilled labor. With the advancement of technologies in Internet of Things (IoT) and different artificial intelligence models, non-visual signs of disease are being explored and experimented in this work for nonvisual early disease detection purposes. Volatile Organic Compounds (VOCs), Ultrasound, Nitrogen, Phosphorous, Potassium (NPK) fertilizer are profiled on control maize and inoculated maize with *Exserohilum turcicum* fungus to generate time series data. Dataset generated are preprocessed, analyzed, and visualized using pandas and matplotlib python tools. Machine Learning algorithms have been inferenced on the dataset; Statsmodel for trends and seasonality detection and Pruned Exact Linear Time (PELT) for change point detection. Analysis of data on the implemented Internet of Things technology in this experiment has achieved nonvisual detection of Northern Leaf Blight (NLB) disease on maize within four days post inoculation from monitored Volatile Organic Compounds and ultrasound emission.

1. Introduction

Diseases on maize crops are highly caused by chronic and emerging pathogens that results in stagnant growth in the plant system [1]. Meanwhile [2] has reported a great maize loss due to plant disease by 40% of yield production in East Africa and [3] realized that food security as a part of zero hunger sustainable development goal number two (SDG-2) is becoming almost unattainable given the increase in global human population. Currently, several initiatives have been adopted to manage disease on crops which include new cultivation practices, genetic engineering, plant breeding and chemical control [4] that have proven to perform better on laboratory-based approaches. On top of these initiatives, small holder farmers are still huge practitioners for using traditional application of excessive use of agrochemicals with or without the presence of diseases on plants, and this approach has caused many undesired side effects on human consumptions such as cancer, acute poisoning, and pesticide residue in food just to mention a few [5]. Therefore, a reduction on the use of agrochemicals in plants is highly needed by applying the needed chemical at the right time with the right amount as recommended by [5].

In the other traditional and technology-based context, farmers rely on visual observations to detect maize diseases [6] with or without the help of smart devices. This same approach is also applicable by most vision based Deep Neural Networks (DNN) [7–9] to detect and identify a disease [10,11], and [12]. However, visual symptoms are the impact of late disease detection, at this stage a plant disease cycle has already gone through different phases like inoculation, penetration, infection, incubation, reproduction, and survival. Hence, it requires high intervention measures to stop the disease from infecting the plant even more [13].

Nonvisual disease detections methods that are currently available include Polymerase Chain Reaction (PCR) and Enzyme-Linked Immunosorbent Assay (ELISA) [14] more technologies have been identified on Table 1. These techniques are performed by following chemical based procedures in a scientific laboratory. The approach requires a plant to be

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https://doi.org/10.1016/j.atech.2023.100260
Received 30 March 2023; Received in revised form 27 May 2023; Accepted 27 May 2023
Available online 29 May 2023

Table 1
Different technologies used for various crop disease detection and identification before and after visual symptoms.

Crop Name	Disease Name	Detection Phase	Technology Used	Parameters Measured	Limitations	Strength	Refs.
Potato	Potato Tuber (Virus Disease)	Early Asymptomatic -Penetration	Extraction and Real Time - Polymerase Chain Reaction and - enzyme linked immunosorbent assays	Leaf Samples	Expensive to be affordable for small holder farmers,	Effective method since there are lab works involved	[20]
Maize	Chlorotic Mottle (Virus Disease)		Quartz Crystal Microbalance Biosensor	Leaf Samples			[21]
Milkweed	Caterpiller & Aphids	Early Asymptomatic - Inoculation and Penetration	Volatile Organic Compound (Portable Gas Chromatography)	Chromatogram	Require no contamination of air, it can hardly separate the emitted gas with other gas emitted in the environment	Very effective method for early disease detection	[22]
Citrus Fruit (Valencia Orange)	Penicillium Digitatum (Bacterial Disease)		Gas chromatography–mass spectrometry (GC–MS)	Bioluminescence Signal - VOC	Postharvest Method, Heavy, Expensive		[23]
European privet (Ligustrum vulgare L., 1753	General Condition		Wireless Sensor Network for & Neural Network Regression	Illuminance, Temperature, Relative Humidity & Total VOC	Unstable performance in the presence of high Relative Humidity but stabilizes with time		[24]
Maize	Northern Leaf Blight (Fungi Disease)	Late Symptomatic - Reproduction	Artificial Intelligence (Deep Learning) & KNN Ensemble	Leaf Images	Prediction can only happen after symptoms have started to occur	Better for approach for identifying disease classification	[10, 11, 25]
Pomegranate	General Crop Condition	Late Symptomatic - Inoculation to Reproduction	IoT Sensors and Machine Learning (Hidden Markov Model)	Temperature & Humidity	Prediction from environmental data is not able to classify a particular disease and it is not able to confirm the presence of a particular disease pathogen	Better approach for monitoring environmental factors so they do not favor survival of a pathogen on a particular plant	[26]
General			IoT Sensors	Temperature, humidity, soil moisture (water content in the soil), pH (Acidity and Alkalinity), Moving Objects (Infrared Sensor)			[27]
Strawberry			IoT Sensors	Temperature, humidity, CO2 concentration, and Illumination Intensity			[7]

subjected to a destructive procedure, with highly skilled personnel and techniques are expensive for a smallholder farmer to afford such service [15]. An alternate method to overcome such limitations for nonvisual disease detection Volatile Organic Compounds emitted by plants have been explored for a while now by several research works. [4,16,17] observed that plants emit VOCs in a unique pattern when infected by a disease and this can be profiled as a plant's mode of communication. There are also different modes of plant's communication, as presented in [18] that when a plant is stressed/unhealthy it emits sounds. The same has been observed on fertilizer consumption where the rate varies when a crop becomes unhealthy as per [19], hence a special interest on these parameters.

With the advancement of technologies in Internet of Things (IoT) and different artificial intelligence models, this research work pioneers in exploring nonvisual signs of plant diseases. Implementation of this innovation contributes to early disease detection and timely intervention as well offering a promising direction towards effective plant disease management. Nonvisual signs incorporated in this study include volatile organic compounds (VOC), Ultrasound and Nitrogen, Phosphorous Potassium (NPK) on maize crops with and without *Exserohilum turcicum* fungus. The identified parameters have the potential of generating timeseries data that can be modeled via several approaches like how these recent works [28,29] have employed Nonlinear Autoregressive (NAR) and Nonlinear Autoregressive models with Exogenous Inputs (NARX) with hidden neural layers on univariate time series data with the aim of forecasting price trends on cash markets in the field of agriculture, drawing inspiration from these sophisticated approaches the study takes advantage of the available advanced analytical methods detect the presence of Northern Leaf Blight on maize crops.

Beside using IoT for nonvisual early detection phase, another source of delay to start interrupting a detected disease cycle is that, most smallholder farmers still require assistance from the fewer plant pathologists or extension officers in order to validate and understand a disease and also define intervention measures [26,8]. Additionally, it is important to note that social and cultural barriers discourage the effective delivery of extension services to farmers, some of the cultural beliefs for instance prohibits male extension officers to interact with the female farmers hence delays disease detection process [30,31]. Interestingly, the use of technology like chatbots has demonstrated to be a great tool to assist end users via natural language conversation, especially in the case where end users have regular repetitive queries and also have low digital literacy to interact with complex technologies, which is the case for most smallholder farmers. Chatbots have been recently used to support farmers in their agriculture activities [32,33]. With respect to the above state of the art, our research contribution is to converge IoT and AI chatbots in the near future to develop an automated early disease detection service that is user friendly making it easy to interact with small holder farmers while reducing physical reliance to extension officers. With this study, a tailored nonvisual disease detection approach will support small holder farmers to conduct early intervention on maize crops and hence improve yield crops by utilizing affordable IoT technology.

This paper is organized as follows: section II provides an implementation approach of the experiment performed on maize crops together with the use of IoT sensor technology, section III gives a highlight of the preprocessed data and together and the data observation from the performed experiment lastly, section IV is the conclusion and a reflection on future work.

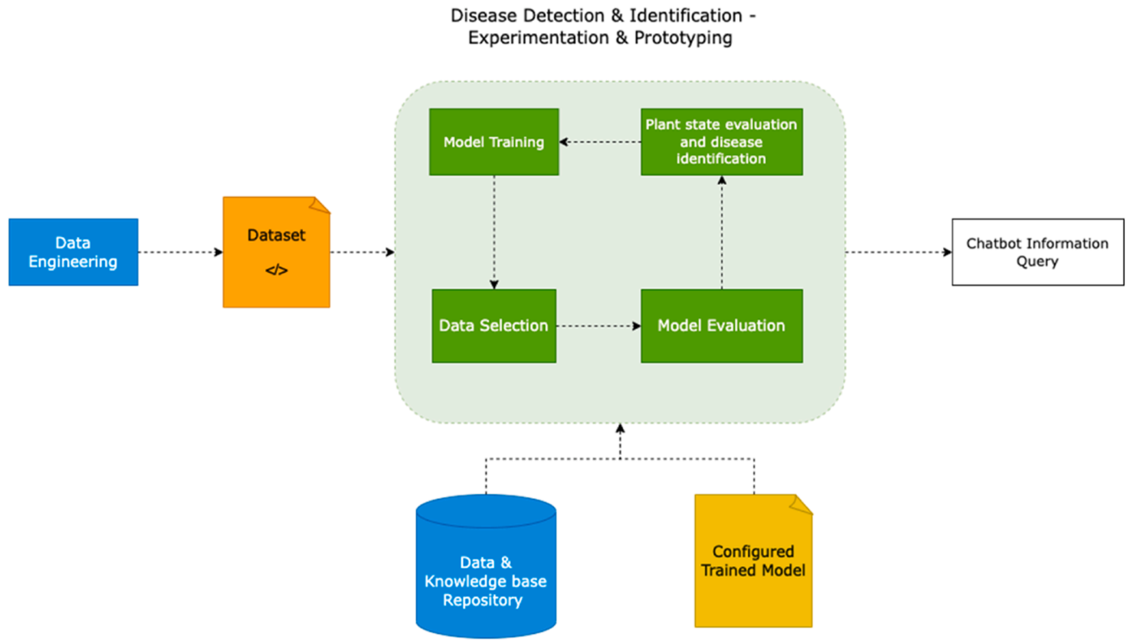

Fig. 1. Dataflow on the convergence framework for non-visual disease detection.

2. Materials and methods

2.1. Convergence framework architecture

A farmer-centric framework to perform maize nonvisual early disease detection with the use of IoT sensor data and present data to a low digital literacy farmer using chatbot may provide a reliable, rapid, and cost-effective alternative to the challenge and it is the implementation approach for this work. Data is generated and collected in two modes; first mode is from IoT sensor data with considered parameters that are volatile organic compounds, ultrasound and soil fertilizer parameters. Second mode is knowledge base data to develop a recommender chatbot system for guiding farmers managing maize crop diseases. Converging multiple technologies is an innovative part of this work whereby we bring together different types of technological solutions for uniform problem solving [34]. In this study, the collected data from several states or modality will be used as input to train a machine learning model for crop disease detection and prediction. Referring to Fig. 1 data in different forms undergo a pre-processing and cleaning process that can be used to train the model. The obtained predictive output together with the collected data from agricultural experts via questionnaire and interview will then be fed on the chatbot, finally the system will be able to provide the appropriate measure to farmers as far as the detected maize disease detection are concerned.

2.2. Non visual symptoms disease detection requirements

Crop diseases occur under a given favorable conditions with a simultaneous interaction of pathogens, environment, and host (plant); this is also termed as disease triangle. With a prolonged favoring climatic environment condition, a pathogen can grow, reproduce, and affect a particular host. Implementation of any intervention measure to stop a plant disease from spreading further requires a disruption in any of the earlier identified components on a disease triangle. Apart from that, a disease cycle is another important dimension towards identifying nonvisual plant disease parameters that include the following stages: inoculation, penetration, infection, and survival.

From the disease triangle, once a disease occurs the pathogen is invisible at this earlier stage of a disease cycle that is inoculation. Advantageously, some parameters such as Volatile Organic Compounds, Ultrasound and Fertilizer consumption can be monitored by learning the emission pattern to identify the presence of such pathogens on a plant. Fig. 2 shows a clear concept of the need for performing an early disease detection on plants since early intervention can be achieved and reduce

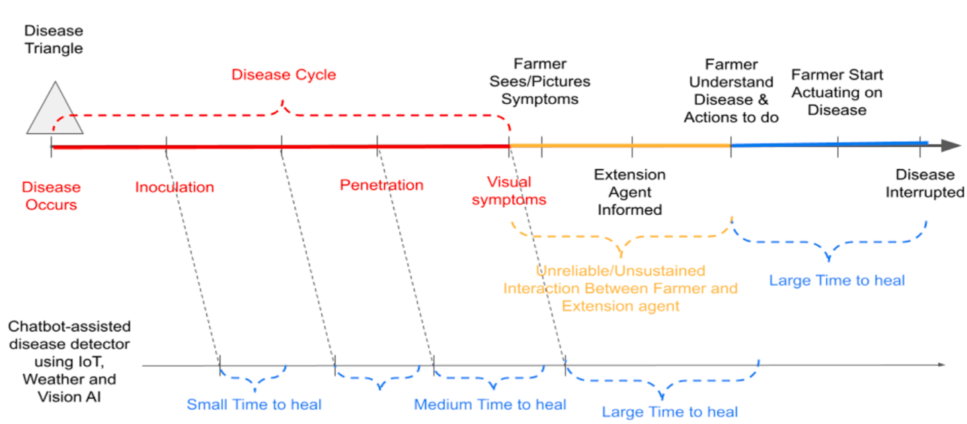

Fig. 2. Plant disease development cycle.

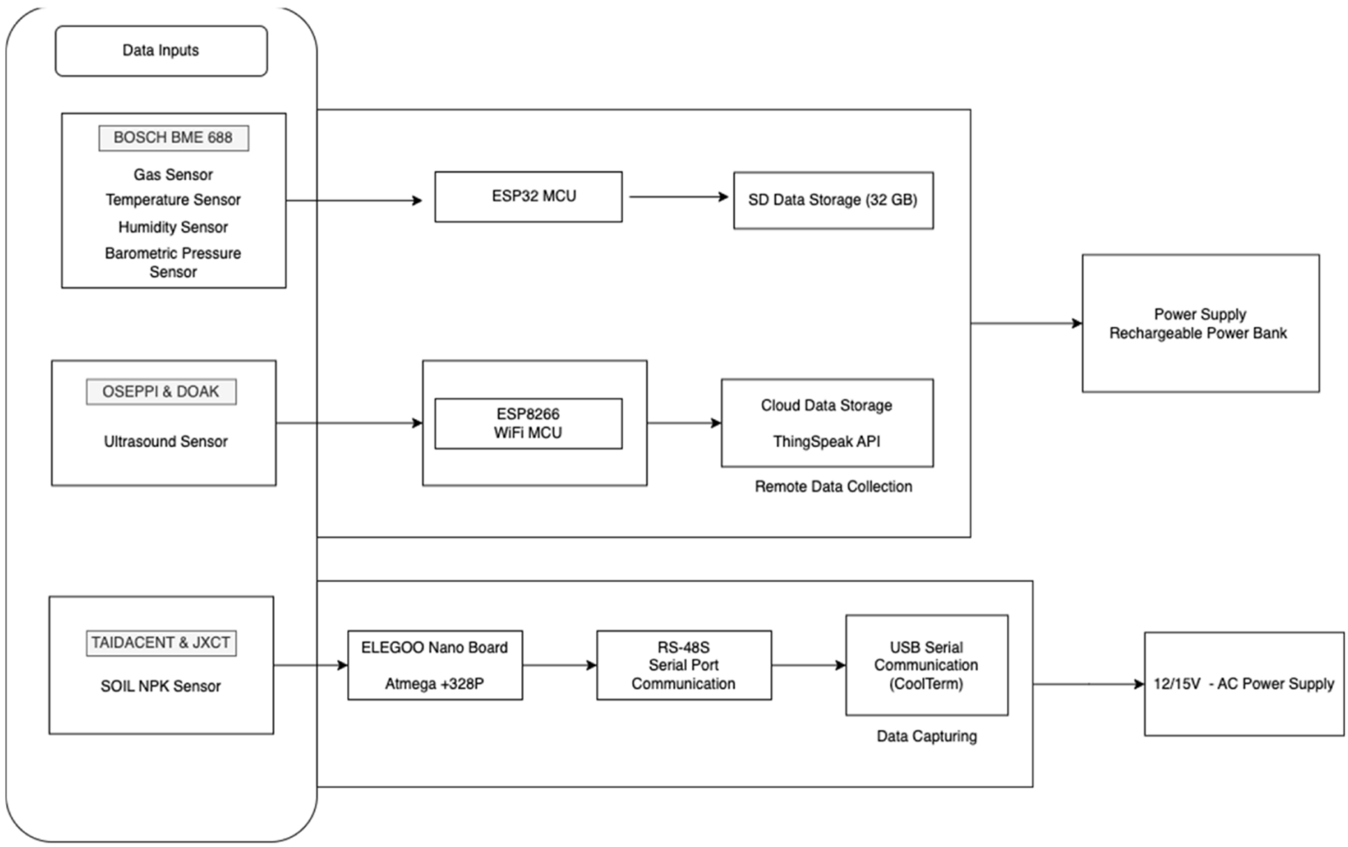

Fig. 3. Block diagram for the designed IoT system.

the cost for managing crop disease for smallholder farmers.

2.3. Experimentation approach for dataset generation

In this study, with a survey done to small holder farmers and agricultural stakeholders Northern Leaf Blight (NLB) is identified as one of the most neglected and chronic disease for maize plants in East Africa. NLB is caused by *Exserohilum turcicum* fungus, symptoms are relatively large gray elliptical or cigar-shaped lesions that develop on leaves ranging from 1 to 6 inches long [35]. In 2007, NLB alone caused 15% of the total grain yield loss in Tanzania and Kenya [36,37].

A controlled experiment was done to generate inoculum spores of *Exserohilum turcicum* fungus at Sokoine Univerity of Agriculture in Tanzania. Four maize varieties were selected based on the farmers and seed suppliers' suggestions. Maize varieties selected are DK8033, DK9089, SeedCo 719 (Tembo) and SeedCo 419 (Tumbili). Each maize variety was sown in a single pot considering a standard distance of 7 cm from each other. Two Treatments (control and inoculated) were placed with eight pots each and pots were randomly placed to subject plants to an equal chance of receiving humidity, temperature, and light. Irrigation took place twice per week and NPK fertilizer of 10 was applied in two weeks' time post sowing.

Exserohilum turcicum was isolated from NLB diseased plants from a maize field. Sterilized pieces of tissue were transferred into sterile potato dextrose agar (PDA) medium and incubated at 24 °C for 14 days at 12 h light/dark cycles (HK & JN) to induce sporulation. Following that, pure

Fig. 4. VOC, Ultrasound and NPK sensors on planted maize crops.

cultures were sorted and mixed with distilled water. The spore mixture was then pipetted and quantified to 10^6 spores/ml by adding more sterile water. The resulting suspension were filled into prepared bottles ready for inoculation onto six leaved maize seedlings (8 weeks old). Set of plants were inoculated by pouring distilled water on control plants (T1) and a prepared suspension of inoculum spores on inoculated plants (T2). The inoculation process took place in the evening to allow spores survival because it requires an adequate humidity condition.

2.4. IoT based data colletion

IoT sensor technology was implemented to perform a noninvasive and nonvisual disease detection. IoT sensors were placed next to maize varieties post inoculation for measuring the following parameters: (1) total volatile organic compounds (VOCs), (2) soil's nitrogen, phosphorus, potassium (NPK), (3) ultrasound. Fig. 3 shows a block diagram for the designed IoT system to collect data on maize crops and Fig. 4 shows positioned IoT sensors.

2.4.1. Total Volatile Organic Compound

Bosch BME688 Development Kit was used for collection of VOCs data, this tool is widely used for gas sensing in different use cases such as detecting leakage of harmful or noxious gasses. The identified tool contains gas sensors that can measure the unique electronic fingerprints that enable identification of gas emission patterns of a particular object. The development kit operated on a power supply of 5000 mAh. uses ESP32 microcontroller, with CR1220 coin cell battery for real time tracking and a 32GB microSD for data storage.

2.4.2. Ultrasound

Values of sound data were collected by two sensors used interchangeably. DAOKI and OSEPP Sound Microphone Sensor were programmed and operating on ESP8266 microcontroller. Using a WiFi module, data was transferred over the cloud on a real time basis and later exported for analysis.

2.4.3. Nitrogen, Phosphorus & Potassium (NPK)

Taidacent Soil NPK and JXCT soil NPK sensor were used to measure the fertilizer consumption over time. Sensors were programmed and operated on ELEGOO Nano Board CH 340/ATmega+328P and serial communication between board and sensor itself was facilitated by RS-485 module. Power supply was generated from direct current (DC) powerline. Data was captured from the USB port with the help of CoolTerm software for accessing the USB serial port and then store data in excel format.

3. Results and discussion

3.1. Dataset and data preprocessing

Data collection between healthy and inoculated maize crops are generated in time-series that are organized in rows and columns format. Maize VOCs data for healthy were 34,812 and for inoculated were 38,621 rows. Features of the collected data includes Date and Total VOCs (Ohms) metadata for the placed gas sensor. Timestamp for both control and inoculated crop was from 26th August 2022 to 11th October 2022 since the targeted parameter patterns were collected to be able to identify the correlation of data before visual symptoms and hence the time stamp identified above.

Data from the sound sensor was captured via Decibel measurement with a total of 16,949 rows for control (T1) and 172,595 rows for inoculated (T2). For this case the metadata is Date and Sound Level, also representing the time series data collected overtime.

NPK fertilizer consumption data collected summed up to 37,440 rows for control (T1) maize variety and 23,955 rows for inoculated (T2) maize variety. Three individual parameters for NPK, that is Nitrogen, Phosphorus and Potassium in (mg/kg) metrics. The data are univariate which refers to VOCs, Ultrasound Levels and NPK are independent from one another that categorizes our variable to be exogenous.

Table 2
Dickey fuller test on VOCs data.

Total VOC Dickey Fuller Test (Control Maize):	
Test Statistics	−10.260305904747089
p-value	4.2538635031500405e-18
#Lags Used	52
Number of observations used	34,759
Critical Values (1%)	−3.4305381464654054
Critical Values (5%)	−2.8616231560701784
Critical Values (10%)	−2.566814261365793
Total VOC Dickey Fuller Test (Inoculated Maize):	
Test Statistics	−8.156155234278934
p-value	9.40807059183648e-13
#Lags Used	54
Number of observations used	38,566
Critical Values (1%)	−3.4305195725589184
Critical Values (5%)	−2.8616149470988113
Critical Values (10%)	−2.5668098919472118

Table 3
Dickey fuller test on ultrasound data.

Ultrasound Dickey Fuller Test (Control Maize):	
Test Statistics	−6.894682160759222
p-value	1.3281864632799207e-09
#Lags Used	44
Number of observations used	16,904
Critical Values (1%)	−3.430736908027531
Critical Values (5%)	−2.8617109980249285
Critical Values (10%)	−2.5668610178758686
Ultrasound Dickey Fuller Test (Inoculated Maize):	
Test Statistics	−13.253266519843939
p-value	8.689417848955201e-25
#Lags Used	42
Number of observations used	17,252
Critical Values (1%)	−3.43072910232179
Critical Values (5%)	−2.861707548432376
Critical Values (10%)	−2.5668591817077266

3.2. Checking for data stationarity

Dickey fuller Test (ADF) was used to test for data stationarity, this is an approved statistical method to prove the null hypothesis on the data [38]. ADF test is applied to check if the generated dataset agrees or rejects the null hypothesis by comparing the obtained p-value with the threshold value which is 0.05. Results for the stationarity check for both of our dataset on VOC are shown on Table 2 and ultrasound level are shown on Table 3.

Results obtained after testing VOCs and sound level data, shows an observation that p-value is greater than the threshold value, for this case the data is nonstationary and test statistics for both parameter values are not near and within the critical values region, in this case it further proves that data is nonstationary. In this case [39] argues that, when data is not stationary it can only mean that, there's and observed strong trend and seasonality in terms of volatile organic compounds emission on both plants and ultrasound: therefore, confirming that it is possible to acquire predictable pattern results.

3.3. Identification of VOCs patterns

For this experiment, an observation was done on the emission of total Volatile Organic Compounds (VOCs) using an electronic gas sensor. Collected data shows that there is a variation between the VOCs

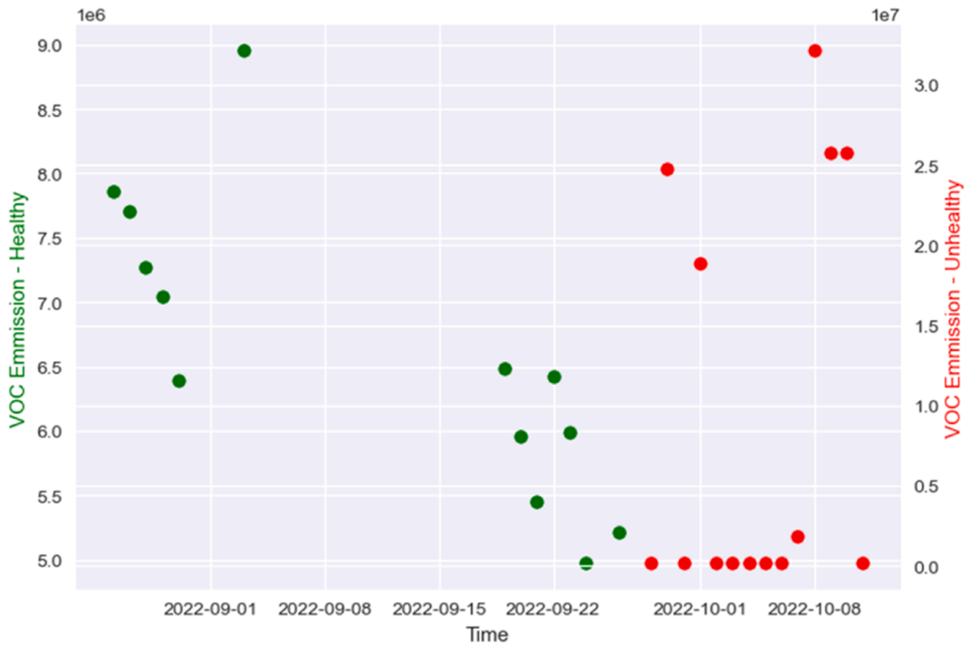

Fig. 5. General VOCs emission for both healthy and inoculated maize.

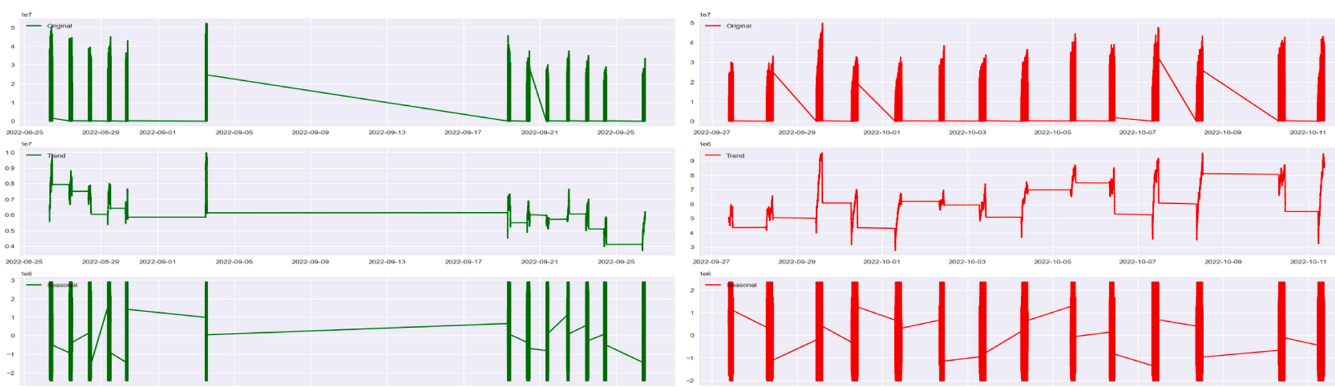

Fig. 6. Trend of the VOCs emission for healthy maize (green) and inoculated maize (red).

emission for the control maize plant versus the NLB inoculated maize plant. The implemented technology is currently not able to identify specific VOCs gasses such as Hexanol and the like, but it is able to give information on variation of the total emitted gasses. The IoT based sensor response pattern for both controlled and infected maize plants are shown on Fig. 5. Additionally, VOCs profiles were sampled overtime since the inoculation to be able to study the nonvisual symptoms pattern for disease prediction. The profiled emission for the control maize plant seemed to decrease overtime while for the NLB inoculated maize plant showed a steady increase overtime.

Thorough observation was also applied on the dataset using statsmodel library for decomposition of time series data into trend and seasonality as shown in Fig. 6. For this case, in the trending aspect of our decomposed data we are looking at a pattern of VOC emission that spans across daily periods for both control and inoculated maize variety and this algorithm is a powerful tool to be applied on the time series data, based nature of our problem [40]. The general formula for the statsmodel additive formula is presented as shown on equation one.

$$Y(T) = S(t) + T(t) + e(t) \tag{1}$$

On recent advancement of time series research works, this work finds compatibility with the use of Nonlinear Autoregressive (NAR) model for forecasting in cash markets [29]. The study shows the effectiveness on the use of classical models for nonlinear time series prediction as the study is accurately focusing on accurately forecasting cash markets. This work has similarly relied on statsmodel as a machine learning approach on monitoring the trend of VOC emission overtime.

Currently, there are not so much research works that have invested on nonvisual detection of disease symptoms for plants, and even for the available works done on studying VOCs demands major chemical procedures. In our study we have observed that there's a correlation between gasses emission with time for the healthy and controlled maize varieties. A study done on tobacco by [41] shows that, upon infection with tobacco mosaic virus (TMV) VOC emission increased, another study on tomato plants by [42] observed a significant emission of VOC emission upon infection of TMV. Generally, [5] argues that plants use VOC as a signal of communication towards physiological processes and moreover the research indicates the possibility of capturing these volatile organic compounds in the greenhouse environment as implemented in our experiment with a low powered and noninvasive IoT device. Additionally, the emission of VOC from plant leaves is considered as a defense mechanism from the abiotic or biotic stresses [43,44], hence capturing the emission pattern overtime is the right approach to be able to detect plant diseases without involving invasive procedures or

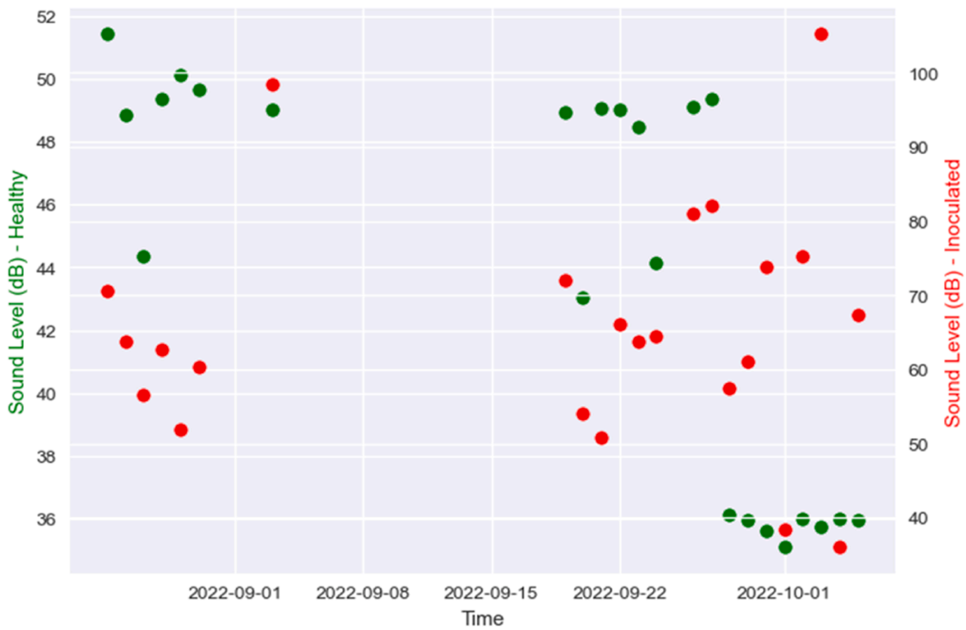

Fig. 7. General ultrasound emission for both healthy and inoculated maize.

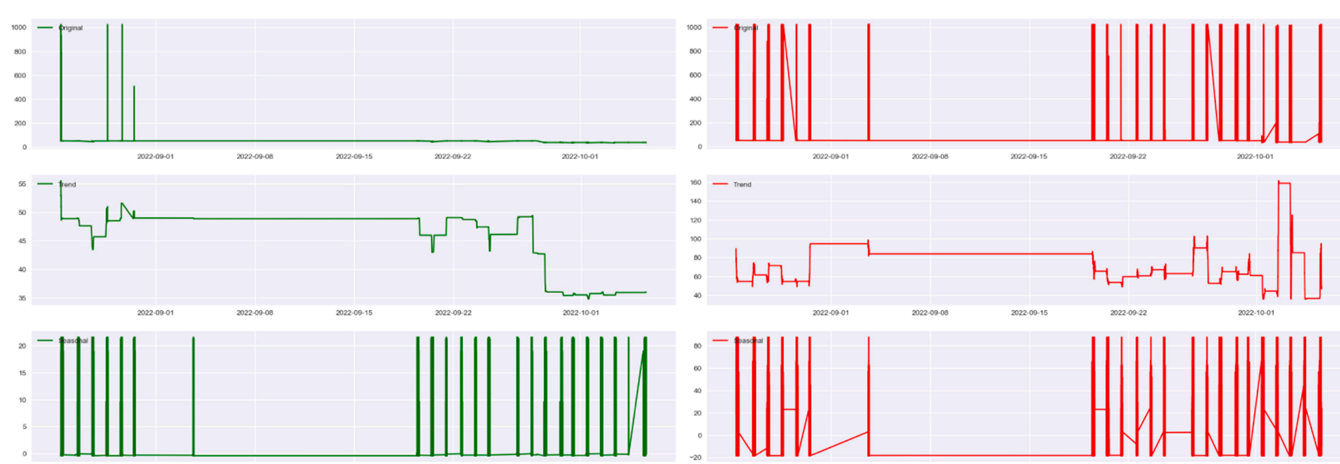

Fig. 8. Trend of the Ultrasound emission for healthy maize (green) and inoculated maize (red).

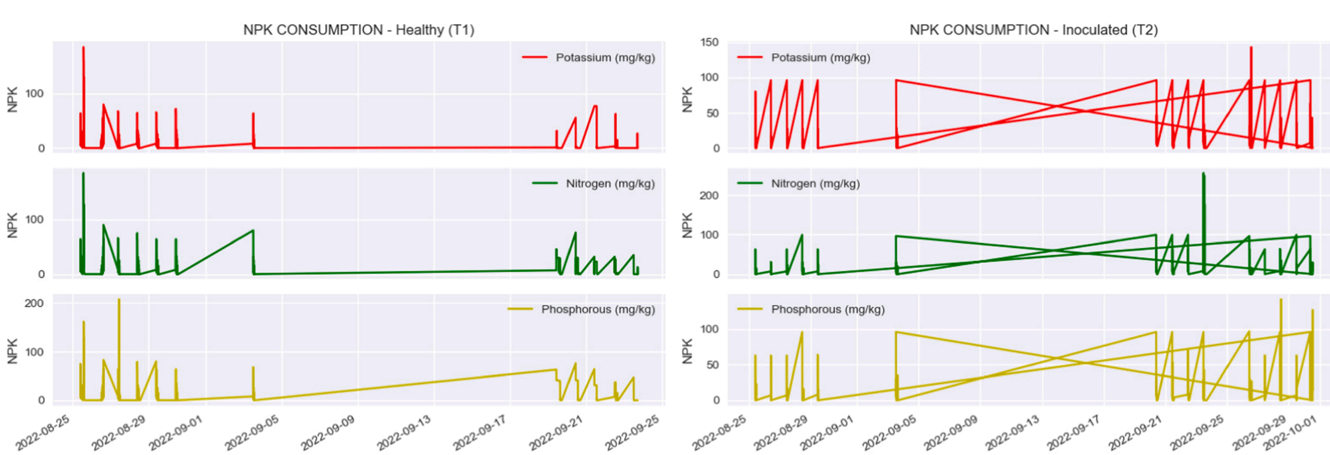

Fig. 9. General NPK emission for both healthy and inoculated maize.

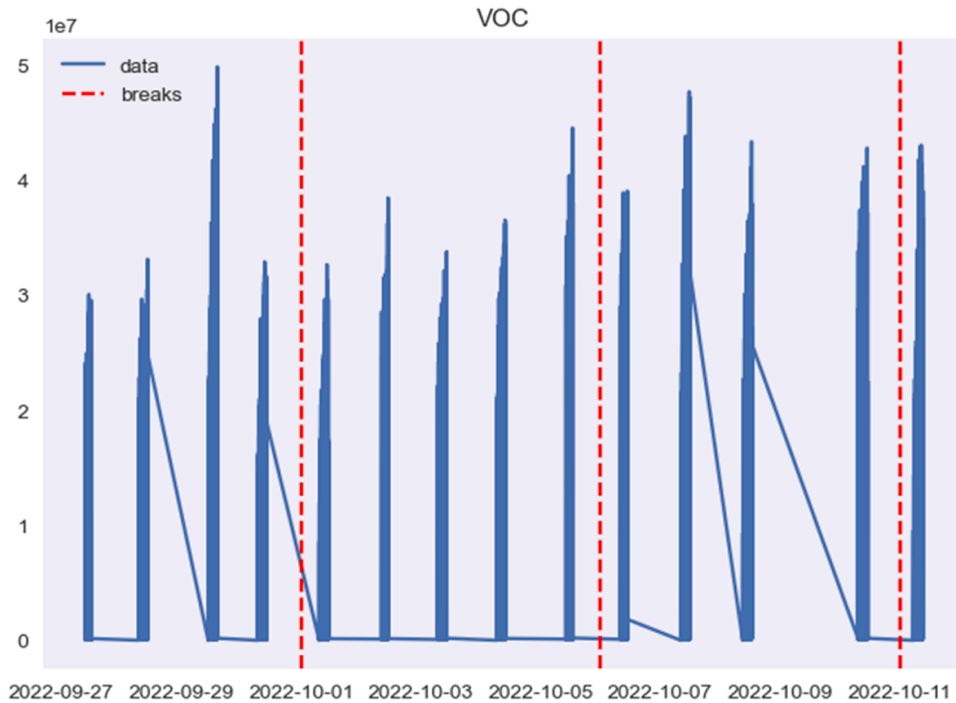

Fig. 10. Change point detection on VOCs Data for Treatment Two/ NLB inoculated maize.

waiting for visual symptoms from plants leaves.

3.4. Ultrasound emission patterns

Microphone placed next to each maize plant stem demonstrated the ability to capture the ambient sound level for the greenhouse environment on both maize varieties on decibel metric. Fig. 7 shows values of ultrasound level for healthy maize of about 50 dB which is equal to ambient sound level and different from the inoculated sound level values that had greater values. More observation has also been attained on the data by applying the statsmodel to study the trend and daily seasonality of ultrasound emission from the plant. Fig. 8 shows the trend and daily seasonality values for both healthy and maize plants.

Trend values for healthy maize ranges from 55 dB decreasing to 35 dB max, given the residual values as compared to the inoculated maize with values ranging from 40 dB to 160 dB max. Daily captured values for healthy maize averaged 20 dB in contrary with the inoculated sound values that averaged on 80 dB, and it can only mean that sound emission is a proof that a plant is under a distress condition.

Meanwhile, there are limited number of studies done as far as the

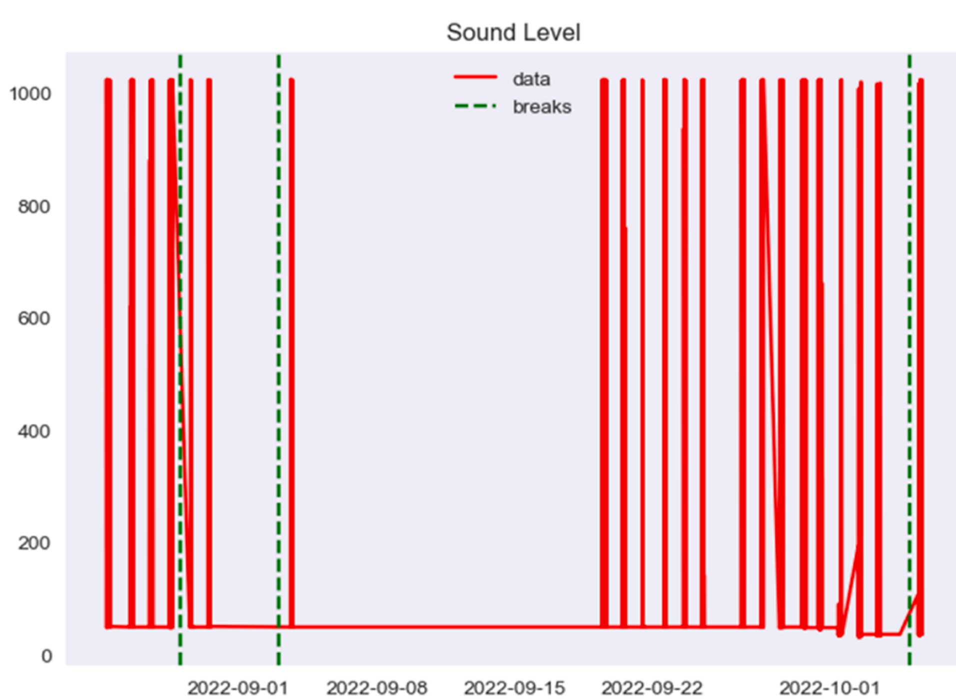

Fig. 11. Change point detection on ultrasound data for treatment two/NLB inoculated maize.

Fig. 12. Visual symptoms on NLB inoculated maize on experimentation site.

concept of detecting and managing plant diseases is concerned but implemented technologies such as PlantWave [45], as a device that places wearable sensors to detect slights electrical variations from plant leaves and convert them into musical sound proves that it is possible to leverage such concept into detecting the plant disease [46,47] brings forth the idea of bioacoustics as one of the fields that needs more recognition with its potential to be used for recognizing plants' psychological processes. Additionally with the observation done on this study, inoculated maize plants had higher levels of ultrasound emission given different timestamps.

3.5. NPK consumption pattern

Data collected from NPK sensors dipped into that soil to show the consumption rate by displaying the value of NPK in mg/kg against the original values of NPK introduced to the soil. Value collected from the soil with healthy maize and inoculated maize varieties could not give a conclusive analysis result and hence there was no specific relationship in NPK fertilizer consumption on healthy versus NLB inoculated maize variety. However, on Fig. 9 data shows a steady rate value for healthy maize as compared to the NLB inoculated maize.

3.6. Change point detection

On the collected dataset for VOC and Ultrasound, a machine learning algorithm was applied to detect the abrupt shift in time series trend that could easily be identified on the graphs. Change point detection was applied to help in identifying the exact date when earlier identified parameters were changing as a method for sending signals due to the result of maize plant change of metabiological processes. We used an offline change point detection method to analyze the whole data sequence for more accurate results using the rupture python package. The implemented search method for both inoculated VOC and ultrasound data was Pruned Exact Linear Time (PELT). The method was selected in our study because it provides quick and optimal results that leads to an approximate solution [48]. With the PELT algorithm every sample data is sequential, no data is discarded and with linearity produces a considerably less computational power as compared to other rupture methods or algorithms [49]. This is approach is already inline with the already established approached as implemented by Xu and Zhang [29,50] on the application of machine learning models for short term prediction and PELT was selected due to it's efficiency to provide optimal results without discarding data as echoed by Xu [50] on the value of model recalibration.

From the analysis, Fig. 10 shows a change in VOC emission started from 01 to 10–2022 and 06–10–2022 as seen on the break points. With these results it proves that disease can be detected within three to seven days after inoculation given that Treatment two (T2) was inoculated on 29–09–2022 and as well detection of disease can be achieved seven days before visual symptoms. According to the plant disease cycle, it takes fourteen days for a plant disease to be visually seen after inoculation has successfully taken place.

Fig. 11 similarly with ultrasound data shows pattern change on 29–08–2022 just four days post inoculation that in our experiment took place on 25–08–2022 for treatment two (T2) of maize varieties. This proves that a disease can be detected in less than seven days after inoculation and as well before visual symptoms. Meanwhile, from our experiment it took about 14 days for visual symptoms to be seen in maize leaves after the inoculation as shown on Fig. 12.

4. Conclusion

Most research works around agriculture including this one keeps on proving that it is possible to use technology for implementing several agriculturally based solutions. This work has been able to show the direction towards nonvisual disease detection approach on plants especially maize crops. The use of Internet of Things, algorithms such as statsmodel and PELT to identify the change in VOCs and ultrasound emission and as well inclusion of laboratory-based experiment as disease inoculation approach has brought shown that; low powered and low-cost resourced technology can be utilized to help smallholder farmer in Sub-Saharan countries to adopt such technologies and perform earlier intervention on disease crop managed. While the study has presented an innovative approach toward nonvisual disease detection through the application of IoT technology and specific algorithms. This study was constrained by the number of embedded devices mounted on maize crops, extent of dataset generated that focused on a single maize crop and a specific fungus, *Exserohilum turcicum.* Additionally, controlled environment in this study shows promising results further field tests are required to validation under actual farming environments.

In future, the approach will be broadened to cover more pathogens and more time to generate more comprehensive time series dataset for training deep learning models for inferencing purposes. Field validation trials are expected to be set for validation to confirm the efficiency and practicality of the presented solution. Generally, the research work presented here underscores the contribution of IoT technology toward plant disease management by timely intervening the process through monitoring nonvisual signs through interactive and accessible tools for global food security.

CRediT authorship contribution statement

Theofrida J. Maginga: Conceptualization, Methodology, Formal analysis, Writing – original draft, Visualization. **Pierre Bakunzibake:** Supervision. **Emmanuel Masabo:** Supervision. **Deogracious P. Massawe:** Validation, Investigation, Resources. **Promise R. Agbedanu:** Conceptualization, Visualization. **Jimmy Nsenga:** Conceptualization, Supervision, Writing – review & editing, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgment

This work is a part of PhD work supported by The PASET – Regional

Scholarship and Innovation Fund hosted at the African centre of Excellence in Internet of Things, Rwanda. Experimental works have been hosted by Sokoine University of Agriculture, Tanzania.

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