SMART EARLY WARNING OF BORER (DIATRAEA SACCHARALIS) ATTACK ON SUGARCANE CROP

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By

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Certificate of Approval

This is to certify that the research work presented in this thesis, entitled **"SMART EARLY WARNING OF BORER (DIATRAEA SACCHARALIS) ATTACK ON SUGARCANE CROP"** was conducted by Rana Muhammad Nadeem under the supervision of Dr. Arfan Jaffar.

No Part of this thesis has been submitted anywhere else for any other degree. This thesis is submitted to the Faculty of Computer Science and Information Technology, The Superior College, Lahore in partial fulfillment of the requirements for the degree of Doctor of Philosophy in field of Computer Science and Information Technology at The Superior College, Lahore.

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Rana Muhammad Nadeem

Dedication

TO THE NAME OF MY MOTHER, AMINA BIBI (LATE)

FOR

HER SUPPORT AND ENCOURAGEMENT AT EVERY PHASE OF LIFE

Published Work

In 2021, one paper was submitted in the Intelligent Automation & Soft Computing journal with an impact factor of **1.64** as per 2020 SCIE. In this research paper (Nadeem et al., 2021), the researcher improved his methodology on the environmental datasets and proved that his methodology could work with high accuracy.

1. Nadeem, R. M., Jaffar A., Saleem,R. M.,(, 2021). “IoT and Machine Learning based Stem Borer Pest Prediction” Intelligent Automation & Soft Computing, 2021. (Published)

Abstract

Pests are the major reason for decline in agriculture productivity. Early prediction of pest attack and warning system are extremely helpful for valuable control of pest attack. Before time caution of pest attack is also helpful for implementation of Integrate Pest Management (IPM) approach. Sugarcane is the most important cash crop that is strictly artificial with borer attack. Internet of Things (IoT) and machine learning assisted early forecast of borer attack on Sugarcane crop is proposed. The life cycle of the pest is dependent on prevailing environmental conditions. The IoT provides real time crop field environment circumstances for prediction of the pest attack based on weather conditions. The real time temperature, humidity, windspeed and rainfall are monitored from the crop field by the proposed IoT architecture. The real time environmental condition is processed by the machine learning model to forecast the occurrence of the borer attack by predicting the population of the borer on sugarcane crop. The major aim of the study is to improve the productivity in agriculture by effective control. The study also aims to apply the judicious use of the pesticides to hold up sustainable improvement in agriculture by implementation of precision agriculture practices. The Naïve bays machine learning algorithm is applied for the calculation of the borer attack. The crop field real time environmental conditions and crop field surveillance is used to instruct and test the machine learning model. The environmental conditions from year 2015 to year 2020 are used in order to evaluate the machine learning model. Field assessment is also executed each year to assess the validity of the model by observing the crop for presence of borer attack.

Keywords: Internet of Things, Borer, Sugarcane crop, machine learning, precision agriculture

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Acronyms

AODV	Ad-hoc On-demand Distance Vector routing
CDNF	Centroid Distance Neighborhood Features
CLCV	Cotton Leaf Curl Virus
CNN	Convolution Neural Network
CSA	Climate Smart Agriculture
DSR	Dynamic Source Routing
DSS	Decision Support System
EC	Electric Conductivity
EMI	Electromagnetic Induction
ETL	Economic Threshold Level
ETL	Economic Threshold Level
FAAS	Farm as A Service
FAO	Food and Agriculture Organization
FN	False Negative
FP	False Positive
FPR	False Positive Rate
GA	Genetic Algorithm
GDP	Gross Domestic Product
GPS	Global Positioning System
ICT	Information and Communication Technologies
IoT	Internet of Things
IPM	Integrate Pest Management
IT	Information Technology
ML	Machine Learning
PA	Precision Agriculture
ROC	Receiver Operating Characteristics
SVM	Support Vector Machine
TN	True Negative
TP	True Positive
TPR	True positive Rate
UAV	Unmanned Aerial Vehicles
WSAN	Wireless Sensor and Actuator Network
WSN	Wireless Sensor Network

CHAPTER 1 INTRODUCTION

Agriculture is suffering from poor productivity due to the impacts of typical weather transformation. One of the suggestion of weather change is the enhanced pest attack on the crop. Pest attack on the crops is the major issue agriculture has been facing in the last few decades. On the other end, agriculture productivity needs to produce for a huge population across the world. Pest attacks are one of the reasons that havea significant impact on productivity in agriculture. There is an immense need to improve productivity in agriculture by dealing with all the issues that are the reason for lowering productivity.

Global climate change has stern impact on agricultural production. The insect life cycle depends on agriculture(Raghavendra et al., 2014). Weather and environmental condition can be used for the prediction of the pest population.

Sugarcane is the most important cash crop and is also harshly affected by diverse types of pests. This study suggests stem borer attack prediction on sugarcane crop by directly sagacity environment conditions from the crop field using the Internet of Things (IoT). Data-driven machine learning judgment is made to forecast the pest population from directly sensed crop field temperature, humidity, windspeed, and rainfall circumstances. In a directly procession sensed atmosphere circumstances and the data-driven decision by the Naïve Bays agreement loom help to specifically forecasting the quantity of the pest attack much or less the Economic Threshold point (ETL). The arrangement of the projected solution is mediator in sense of the presentation of the machine learning model and the accuracy of the planned way out in the forecasting of the stem borer attack on the sugarcane crop. The most important intend of the planned result is to seize up sustainable development in agriculture by the use of the Internet of Things (IoT) to imprison the crop field perspective and machine learning to construct a data-driven verdict.

The production of sugarcane crops is decreasing due to the severe attack of borer (Diatraeasaccharalis). Precision agriculture approaches would be proposed to predict the borer (Diatraeasaccharalis) outbreak on Environmental parameters to take prevention measures. Internet of Things (IoT) and Machine Learning (ML) based borer (Diatraeasaccharalis) insect attack prediction for any Sugarcane crop would be made using in-situ monitoring field environment parameter temperature, humidity, rainfall, and wind speed. ETL would be utilized to train and test on the different machine learning models, to predict borer (Diatraeasaccharalis) attacks in the future while using environmental parameters temperature, humidity, rainfall, and windspeed, etc.

Due to the significance of sugarcane crop in all over the world the Developing countries has cash crop that boost industries.

Pest attack is the foremost dilemma of all over the crop. Sugarcane productivity is also persistently exaggerated by the various types of borers and shoot borer is one more most important pest attacks on the sugarcane crop. The borer can source of loss to the Sugarcane crop from 35 to 70% of the crop(Scri, 2018). There is a enormous necessitate for the get into play of current technology to deal with the problem. Untimely forecasting of the pest populations and their assault can be extraordinarily practical for the effectual systematize of the pest attack and to hold up other approach of pest assault to be effective(Nibouche et al., 2019).

Stem borer (*Diatraeasaccharalis*,)of the Sugarcane crop is a serious problem that can causea 30-70% decrease in crop production(Zuurbier & Vooren, 2008). The Sugarcane borer attacks young wound particularly from April to August while the temperature is far above the ground, coupled with squat humidity in the chosen area(B. Péné & Coulibaly-Ouattara, 2019). The larvae of Sugarcane borer, after originate, feed on young shoots with drooping and drying of shoots. The larvae make the 'dead-heart' configuration that impedes the growth at the point of invasion. The impacts of the Sugarcane borer on sugarcane crop are revealed in Figure 1-1.

. The economic entrance point of the assault is that 15% of the total crop is affected by the dead heart. The larva is dirty white with brown stripes on the body shown in Figure 1-2.

Figure 1-1: Impacts of Sugarcane borer attack (Scri, 2018)

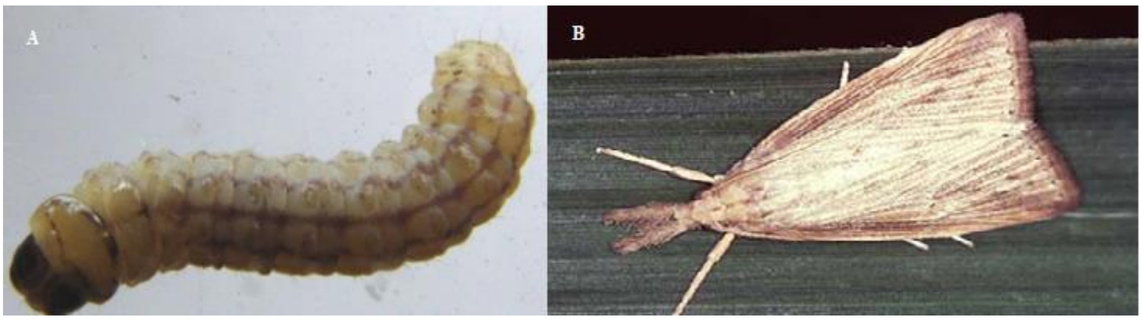

Figure 1-2: Larvae and adult of Sugarcane borer (Scri, 2018)

KavinAsthon is the person who first coined the term Internet of Things (IoT) and believes that the Internet of Things (IoT) would be as fascinating as the

Internet(Asthon, 2009). Internet of Things has exposed many flourishing function including the different tradition of elegant areas, elegant traffic organization, smart homes, and elegant patient care. Including initiation of the Internet of Things (IoT),the world is influential into new structure with stimulating applications.

Internet of Things (IoT) also has shown many successful applications in agriculture to expand accuracy agriculture and smart function(Rodríguez et al., 2017). The most profound applications in these regards are crop field environment monitoring and control, precision irrigation management, site-specific treatment, and yield predictions. Internet of Things (IoT) has revolved into the base technology for exactness agriculture put into practice. Exactness agriculture is the procedure to transaction with crop field disparity to use contribution according to the existing situation. Internet of Things (IoT) has shown many successful applications to support precision agriculture practices(Aiello et al., 2018). The most profound applications are environmental monitoring, crop plant health monitoring, environment control, yield monitoring as shown inFigure 1-3.

The IoT had become an extremely important and vital part of life. Forest fire awareness, air impurity detection, crop field monitoring, are the core applications of IoT in agriculture. Smart cities using the IoT for overpopulated cities is the great prospect of the IoT. This will help us to spend our lives happily without having any medical issues. Internet of Things(IoT) applications help us to understand how we are using the resources and how we can save them for our future in every sphere of life.

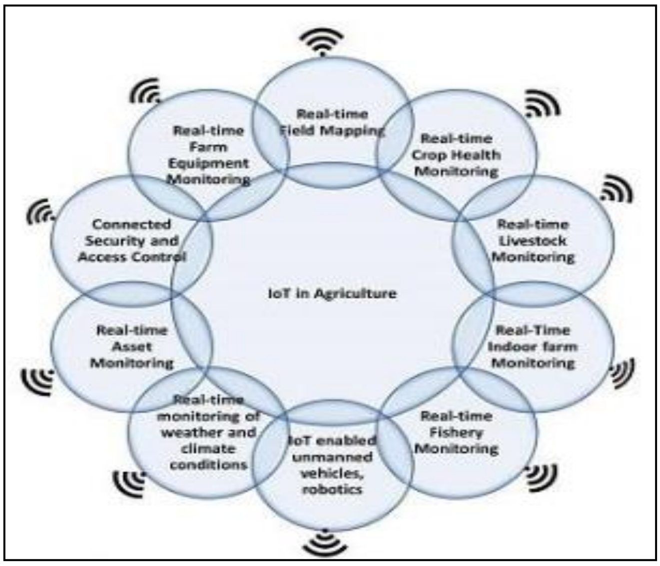

Figure 1-3: Internet of Things (IoT) applications in Agriculture(IoT, 2017)

1.1 Problem Description

The early prediction of the pest attack is very important to control their damage to the crop and to improve crop production. Early warning and assessment of the pest attackare important for the Integrated pest management approach to be successful. The pest population is strongly related to the environmental conditions. Pest population assessment based on the environmental conditions needs to base on factual data directly from the crop field. There is an immense need for a solution that can assess the crop field ecological surroundings and envisage the residents of the pest based on real-time data.

1.2 Problem Statement

The borer (Diatraeasaccharalis) attack on sugarcane crops causes serious harm to sugarcane crop growth, resulting in a serious reduction of production. The early warning and assessment of pest attack are important to effectively control the pest attack.

1.3 Research Motivation

Climate change is a global challenge that leads to many severe effects on sugarcane crop production. The attack of sugarcane crop insect without any prediction and control measures results in the loss to the farmers due to the severe impact of the borer (Diatraeasaccharalis) attack on sugarcane crop production. Moreover, borer (Diatraeasaccharalis) attack prediction cannot be achieved without environment parameters that may lead to the failure in achievements in the required objectives.

As the population of the world is growing rapidly day by day, the demand for foods is increasing all over the world. Smart farms have shown tremendous success in the agriculture sector. The production of farms turned into profit after the inclusion of smart farming. Smart farming practices are empowered with artificial intelligence, robotics, and other computer data to sustain and maintain the agriculture sector profitable. As compared to the 3rd generation farming the smart farming, enhanced the corps production five to seven times more profitable. After the emergence of smart farming, the agriculture sector has become more profitable increasing the production of corps. For maintaining sustainable production of corps, smart farms can contribute a lot.. (Wolfert, 2017)

Research Questions

The followings are the major questions that the proposed study aims to address by implementing the IoT-assisted in-situ monitoring of the sugarcane crop disease and application of machine learning to produce optimized recommendations.

1. How the borer attack can be predicted based on prevailing environmental conditions?
2. How IoT can be used to capture the borer (Diatraea saccharalis) attack prediction by using environment parameters in the field?

3. How machine learning capabilities can be used to predict the borer (Diatraea saccharalis) according to the environmental parameters?
4. What is the accuracy of the borer prediction model in the prediction of borer attack on sugarcane crop?

1.4 The hypothesis of the Study

Following is the hypothesis of the study.

The IoT and machine learning model can accurately predict the borer attack on the sugarcane crop.

1.5 Research Objectives

The study aims.

1. To propose a model of borer attack forecasting base on environmental conditions.
2. To implement the proposed model using machine learning and IoT capabilities.
3. To test the precision of the proposed model in the prediction of borer attack.

1.6 Organization of the Study

The study is organized into seven chapters each one with different objectives. The highlights of these chaptersare given here to have a quick view of the organization of the study.

1.6.1 Introduction

This chapter sets the foundation of the study with a brief introduction to the problem, objectives of the study, and research motivation.

1.6.2 Background of the study

This chapter provides the background of the study by elaborating the important information, The Internet of Things (IoT) and its role in agriculture, sugarcane crop, and borer attack-related information is provided in this chapter.

1.6.3 Literature review

This chapter presents the recent related work while using Information and Communication technologies especially the IoT and machine learning with the purpose to identify the research gap for the study.

1.6.4 Material and Method

This chapter presents the model of the borer attack, the machine learning model, and IoT architecture. The implementation of the proposed model is also described.

1.6.5 Environmental data analysis

In this chapter, the environmental conditions for the selected period are given and discussed based on which the model is presented.

1.6.6 Evaluation and discussion

In this chapter, the proposed model is evaluated for its accuracy in the prediction of the borer attack. The accuracy of machine learning is also evaluated in terms of different measures.

1.6.7 Conclusion and Future work

This chapter concludes the study and gives the future work for the proposed solution to effectively deal with the issue.

CHAPTER 2 BACKGROUND OF THE STUDY

This chapter presents an introduction to the Internet of Things (IoT) and machine learning concepts and their role in agriculture. The use of the Internet of Things (IoT) in agriculture for precision agriculture and smart farms management is also described. The use of machine learning in agriculture and its potential applications are also elaborated. This chapter also presents the importance of sugarcane, and the impact of pests especially the borer on the Sugarcane crop.

2.1 Internet of Things (IoT)

Internet of Things (IoT) is a network of physical objects sensors that can seamlessly connect with other objects using the Internet as a communication pathway. IoT has the potential to offer services according to the context and adjust services with context(Gubbi et al., 2013). The context-aware services using the IoT make the IoT an enabling and game-changing technology for many different areas of life. Smart city, smart traffic management, and smart house are the core applications of the IoT. The IoT industry has shown remarkable progress in recent years in terms of hardware, infrastructure, and application development(Ranger, 2018).

Internet of Things (IoT) is a new paradigm that has roots in the Mark Weiser Ubiquitous computing. IoT term was first used by Kevin Ashton. The advent of the Internet has opened the way to many exciting applications in different fields. Ubiquitous computing, Wireless Sensor Network (WSN) also reshaped into IoT with the advent of the Internet. Internet facilitates communication between objects without the establishment of an extra network. Global object communication is the main reason for the success of the IoT in the world using cost-effective communication(Bertino et al., 2016).

IoT has revolutionized the world with exciting applications. The emergence of smart homes, smart vehicles, smart cities, and smart health are the miracles of the Internet. Internet of Things (IoT) has changed the world to a large extent and has the potential to change it more dramatically in near future. IoT is enabling technology that has the potential to change the world dramatically. IoT is a framework of technologies to pull information from sensors, objects, and networks for streamlined services(Zeinab & Ahmed, 2017).

IoT is the enabling technology and the success of the IoT can be estimated from the fact that up to 2030, industrial IoT would expand to fourteen trillion dollars. With the emergence of Artificial Intelligence, blockchain, cloud computing, and data analytics, the IoT role is more expanded. IoT can also deal with the issues of environmental sustainability by reducing pollution and carbon footprints. With enhanced security features the IoT has the potential to create sustainable and efficient developments by dealing with issues(Ng & Wakenshaw, 2017).

2.2 Role of the Internet of Things (IoT) in Agriculture

IoT has shown remarkable progress in different fields of life. Amazing applications have emerged in different aspects of life. From homes to traffic management and from patient care to pet monitoring, many fields of life are revolutionized by the IoT. Agriculture is also strong candidate for IoT applications(Uddin et al., 2017). Due to the ability of the IoT to capture the context of services, IoT is a strong candidate to deal with the issues related to agriculture. IoT applications in terms of environmental monitoring, precision irrigation water management, crop yield monitoring are very common nowadays(Brewster et al., 2017).

IoT has shown remarkable progress in different fields of life. Amazing applications have emerged in different aspects of life. From homes to traffic management and from patient care to pet monitoring, many fields of life are revolutionized by the IoT. Due to the ability of the IoT to capture the context of services, IoT is a strong candidate to deal with the issues related to agriculture. IoT applications in terms of environmental monitoring, precision irrigation water management, crop yield monitoring are very common nowadays

IoT applications are not only about monitoring environmental conditions, breeding animals, and producing crops but have huge scope to deal with issues in agriculture from different perspectives. According to markets, the smart agricultural market is going to meet 11.23 billion dollars. Due to enhanced connectivity to the farms, there are lesser chances of cattle loss, less water consumption, and more crop productivity. Farmers would be much aware of the facts due to the availability of real-time data from the crop field using IoT(Ahmed et al., 2018).

The IoT technology can effectively deal with the problems and issues in agriculture and help to improve productivity by conservation of natural resources. Scarce natural resources like irrigation water, land resources extensively demand the judicious use of the natural resources. IoT assisted real-time monitoring of the crop field helps to conserve natural resources and improve agriculture productivity(Ayaz et al., 2019).

The popularity of IoT can be estimated from the use of IoT devices in the agriculture sector. Up to 2020, twenty-five billion IoT devices have been deployed in the agriculture sector, with a twenty percent (20%) annual increase. According to the UN Food and Agriculture Organization (FAO), there would be seventy percent (70%) more food required to meet the huge surge in the human population. Agriculture on the other hand is suffering from poor productivity to meet the challenge. IoT has the potential to meet the challenge to deal with lower productivity in a better way using the enhanced information pool and context-aware applications(Ng & Wakenshaw, 2017).

Figure 2-1: IoT assisted application for agriculture(Guest, 2018)

Reduction in natural resources and climatic changes have aggravated the issues to produce more for the increased population. In many parts of the world, agriculture is striving to deal with the impacts of climatic changes like poor productivity, yield, and pest issues. There is a need to deal with the issues in agriculture by using modern means of technology. IoT has the potential to deal with the issues. IoT has come up with many solutions to deal with the issues related to reduced natural resources and poor productivity. IoT has the potential to develop many solutions in precision and climate-smart agriculture(Uddin et al., 2017).

IoT has a potential role in the development of protected agriculture solutions. The success of protective agriculture depends upon the effective monitoring and control of environmental conditions. IoT has the potential to achieve success in agriculture. The concept of protected agriculture is briefly connected with (IoT). Its uses can help for stable temperature and environment for growth the animal and plants. The environment of protected agriculture is completely and largely artificially controlled(Elijah et al., 2018).

2.2.1 Internet of Things and Precision Agriculture

Precision agriculture is the use of information technology to extract crop field information to in order to inter and intra crop field variations. Precision agriculture is the division of the crop field into different management zones based on the different criteria and treats these individually to conserve the resources and improve productivity. Every management zone is treated individually according to the information as shown in Figure 2-2. To divide the soil into different management zones different maps are drawn and most important are the yield maps, fertility maps, salinity maps, and soil moisture maps. IoT brings efficiency to agriculture and makes food products available to consumers(Popović et al., 2017).

IoT connects the agriculture and farming situated in rural areas. Connected farms can manage resources and operations efficiently with the help of IoT. Agricultural applications in smart precision farming will enable the industry to increase operational efficiency with the help of IoT. In the agricultural field, the robots and analytical tools for monitoring crops are used with the help of IoT for autonomous operations. Technologies hold increasing production and connect with rural areas(Ahmed et al., 2018) A Complex System Productivity is affected by variability in the following six groups: Agriculture practices need to adjust with different types of variabilities in the field. Some of the major variabilities are yield monitoring, crop variability, soil variability, and fertility variability.

Precision Agriculture (PA) is to manage this variability by conservations of the resources. Smart farming based on IoT technologies enables them to grow productivity and reduce waste. Crop prediction helps the farmer to decide a plan regarding the production. The objective of PA is to guarantee the benefit, supportability, and security of the climate(Pham & Stack, 2018).

Figure 2-2: Soil mapping for the management zone

Precision agriculture is a management strategy that gathers information and qualities of land and environment at some specific place and then justifies which crop will give a maximum product with minimum resources, time, and more specifically less effort. In other words, Precision Agriculture (PA) is the use of technology and other resources to get maximum output from certain fields.

History remembers the name of John Deere as the inventor or the man who brought efficiency to precision agriculture. He did experiment on a wide-scale and showed the worth of precision agriculture to the world. Now the only question that arises is that is it appliable at every stage or not. The answer is no because it can be implemented for large farms only because it is more costly than traditional agriculture. Precision farming aims to maximize the productivity of the crop and improve environmental quality. Precision farming is the use of available modern technologies to find spatial lands to improve net growth.

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Crop field monitoring is the most important part of PA. These sensors are fixed in the field or mounted on drones. These sensors mounted on the machinery and agriculture equipment are also very common. The use of remote sensing and satellite imagery is also used in PA to effectively make management zones. The most important sensors used in this respect are the soil moisture sensor, Electric Conductivity (EC) sensor, Nitrogen level sensor, soil temperature, and soil pH sensor. The use of the sensorsis very common for the purpose to identify the variations and treating them accordingly. Sensing technologies are being developed to facilitate the applications for the purpose.

Sensors mounted on the agriculture machinery and equipment are also used to derive different types of information from the field for different types of PA applications. The information extracted from these mounted sensors is used to draw different maps as shown in Figure 2-3. These maps are very useful for variable rate applications of inputs. Variable-rate input applications according to the management zone is a very important application for the developments in PA. Variable-rate use of fertilizers according to the fertility mapping is a very important application. Like this many other variable rate applications are also important and emerging to support sustainable developments in agriculture.

Figure 2-3: Machinery mounted sensors for crop field mapping (Sela, 2020)

Drones, satellite imagery, and remote sensing are very promising technologies for PA applications. Automated control of machinery and field maps for a variable rate of input applications is very useful for different applications. InFigure 2-3, the data from the drones are used to draw maps in the form of heat maps. This information about the field for moisture, fertility, and salinity level would be very promising to deal with different issues. It is a good way of managing the farms which are mainly dependent on Information Technology to make sure that both crops and soil receive what they need for best health and productivity. The major objectives in this regard should be.

1. Profitability
2. Sustainability
3. Environment protection

Environment monitoring should include accessing real-time data of the soil, the condition of crops, and some other relevant information. Software like predictive analytics uses the obtained data to provide detailed guidance about crop rotation, best planting and harvesting times, and how the soil can be managed properly. Sensors are also good for such type of data acquisition. These sensors can monitor and measure the moisture and temperature of the soil. Understanding the climate and comparing seasonal variations in rainfall amounts and temperature levels were the small steps that enabled farmers to adjust irrigation and fertilizer levels for heal their crops. The emergence of the Internet-of-Things and new sensor technologies such as the helical solar shield for temperature sensors reach new levels of measurement accuracy and repeatability that allow detailed and accurate analysis of meteorological data and allow farmers to regulate irrigation and fertilizers, several times a season for a balanced yield and healthy harvests.

Integrated with the use of drones as sensor carriers, farmers can get a bird'seye view of crop health and variability without stepping on every square meter of their fields. Using drone cameras, they know theearth well enough to interpret the results in the context of their farm. Global Positioning System (GPS) technology and tractor automation enable the precise application of fertilizers, water, andpesticides for their conservation usage.

Figure 2-4: Data from drones to map soil information (Sela, 2020)

2.2.2 Internet of Things (IoT) and Smart farms

Many fields have contributed to improve productivity in agriculture. Biological and chemical sciences have contributed to the development of green revolutions. The fourth revolution in agriculture is related to the use of Information Technology (IT) to support sustainable development. Smart farms are emerging to leverage farm resources for their efficiencies and developments in agriculture(Wolfert et al., 2017). The use of robotics, image processing autonomous vehicles and auto control of equipment are the core technologies for smart farm developments. Smart farms are concepts for the use of Information and Communication Technologies (ICT) in agriculture to improve productivity(Araby et al., 2019).

Smart farms are the farms made for reducing human labor and wastage of chemicals and waters(Bu & Wang, 2019). Smart farms use the technology named smart farming in which modern Information and Communication Technologies (ICT) is used for getting efficient results of crops with less(Mekala, Mahammad Shareef, 2017) labor and other expenditures. Benefits of smart farms:

- Less waste of water and chemical:
- Reduction in the required labor force

- Efficiency in processes

Smart farm practices include information of,

- Weather conditions
- Soil conditions
- Sub soils conditions along with water
- And finally, sun rays’ conditions on area

Data is collected by different remote sensors, satellite connections, and using different artificial intelligence in smart farms. After the collection of this data, a precious artificial environment is created named smart farms, where different types of sensors are placed e.g., moisture, temperature, light, etc.

The developments in the smart farms can be ascertained that up to 2018 around industrial IoT market was USD 1.8 billion globally. Industrial IoT in agriculture is likely to expand by 9.6 billion by 2050. Industrial IoT has a compound 20% growth rate. IoT focuses on applications for agriculture to deal with issues emerging due to extreme climate changes, environmental impacts, and global warming impacts. The use of IoT for smart farm development traces back to the use of sensors in the crop field. IoT has revolutionized agriculture activities by improving the processes and activities in the crop field(Talavera et al., 2017).

The developments in the smart farms can be ascertained that up to 2018 around industrial IoT market was USD 1.8 billion globally. Industrial IoT in agriculture is likely to expand by 9.6 billion by 2050. Industrial IoT has a compound 20% growth rate. IoT focuses on applications for agriculture to deal with issues emerging due to extreme climate changes, environmental impacts, and global warming impacts. The use of IoT for smart farm development traces back to the use of sensors in the crop field.

IoT has potential applications in agriculture for crop field monitoring, precision irrigation water management, by real-time observations of temperature, humidity, and wind speed. In recent years, IoT has shown promising applications for environmental monitoring, growth observations, disease prediction, soil salinity mapping, erosion monitoring, and water stress monitoring. The emergence of new types of sensors, cloud services, and data analytics abilities has signified the use of IoT for agriculture purposes(Mohanraj et al., 2016).

The agriculture of smart farming will be introduced to reduce the time and increase the quality and quantity of the raw material. The future of the world is depending on the new revolution and new farming system with the help of robots and rain-gauged trackers and notebooks(Kamilaris, Kartakoullis, et al., 2017).

Figure 2-5: State of IoT and Agriculture(Guest, 2016)

The data from the sensors captured from the field is relocating to the cloud services. From the cloud, the data is processed and is available for different types of analytics. After processing and analytics, the data is transferred to the user in terms of different information. This is the generic architecture of most of the applications of

IoT in agriculture. Smart farm developments are increasing day by day to increase productivity in agriculture(M. S. Liao et al., 2017).

As compared to the 3rd generation farming the smart farming enhanced the corps production and made it five to seven times more profitable. After introducing smart farming agriculture,the sector has become more profitable increasing the production of corps fields or decreasing the work of the farmers and saving the financial investment of the farmers. For maintaining sustainable production of corps, smart farms are a very good choice to improve yield, productivity and improve environment-friendly practices(Salam, Abdul, Shah, 2019).

Smart farms are also a very good choice for large as well as small farms. Farms spreading over large areas are easy to maintain using the smart farms' management capabilities. In farms with small areas the issue related to productivity are resolved due to better use of the resources. The smart farm is the better choice to improve productivity and improve processes to conserve the use of the resources especially natural resources(Kamilaris, Gao, et al., 2017).

World’s population is increasing that requires advancement in agriculture for increase in the food supply to meet the need of the population. Internet of Things (IoT) can revolutionize the world and now it relies on analytical strategy rather than probabilistic strategy (Ayaz et al., 2019).

Site-specific treatments by analyzing the soil and environment heterogeneity using the IoT is very beneficial from the agriculture point of view. Soil fertility mapping, yield monitoring, site-specific treatments are very promising applications of IoT in agriculture. This type of application proves to be very effective in reducing the issues related to the agriculture sector. The IoT is letting the productive farming of agriculture be data-driven, leading to cost-effective and timely management and production of farms and simultaneously reducingenvironmental impacts. Smart farms also tend to overcome the water shortage issue. IoT will be useful for smart irrigation systems according to crop needs. Many IoT assisted smart irrigation water solutions emerged and developed over time to deal with water scarcity issues and to conserve the use of irrigation water. Data-driven management and recommendation of irrigation water for the efficient use of the irrigation water has shown significant improvements over the years.

2.3 Machine Learning and agriculture

Machine Learning is a smaller unit of artificial intelligence. Although this is the branch of computer science that is used to learn about the data and fits that data to learn the facts of the people under that given data. This is used to learn about the machines and to train them to work according to people's instructions within the given limit of time. Machine learning collects data on statistical approaches to configure according to the facts and then puts them to the machines learning senses.

Machine learning is a concept of using information from previous experiments. In agriculture, machine learning is used for farm planning, field mapping, soil sampling, crop inspection. The GPS-based application is used to consent to farmers to exertion during stumpy visibility field circumstances such as rain, dust, fog, and darkness in past, it was complicated for the farmers to recount the expansion and land inconsistency and resources. But machine learning made it easy as now we can generate hybrid seeds for special kind of lands and environment for maximum growth.

PAMany companies are now programming and designing robots to perform important tasks related to agriculture. It works faster than cutting and thenhuman labor. This is a good example of machinelearning in agriculture.

Companies are now using technologies and intensive learning algorithms. Data is collected using drones andsoftware that monitors crops and soil.By using new methods in agriculture, farmers can find effective ways to protect their crops and protect them from weeds.In agriculture, machine and deep learning have the potential to help forecast yields and fertility status. For these tasks, it is necessary to use as many available sources of data as possible. The potential source of data for machine learning applications is from remote sensing and sensors deployed in the field.

2.4 Agriculture in Pakistan

Agriculture and farming play a dominant role in the economy of a country. As Pakistan is mainly an agricultural country, more than 60% of the Pakistani population depends on agriculture for sustaining their life and agriculture is the most important occupation for most families in India. But in the present scenario, it has been observed that the involvement of Agriculture to GDP is dilapidated nowadays and we are in the insist on to increase the crop yield with effectiveness and with fine competence. In agriculture, irrigation is the major determinant as the monsoon rainfalls are very impulsive and unsure hence water scarcity is a big challenge in the agriculture sector.

Due to this reason, there exists a demand for technical knowledge to make the irrigation system more efficient. The conventional irrigation system has been practiced in the past. To improve these conventional methods, there has been developed system using advanced technologies in Wireless Sensor Network (WSN) which helps in reducing crop wastes, prevents excess watering to crops, and helps in increasing crop yields.

Pakistan is an agricultural country where around seventy percent of the people are directly or indirectly related to agriculture. The economy of Pakistan is heavily dependent on the agriculture sector. Agriculture has around twenty-four percent of the contribution in Gross Domestic Product (GDP) of the country. Half of the labor of Pakistan is involved with agriculture and eighty-five percent (85%) of the foreign earning comes from agriculture product export. Agriculture also supports local industries by providing the raw material for the local industries in Pakistan (Saeed Azfar et al., 2015).

The agriculture sector in Pakistan is badly affected by the pest attack. Cotton is the main crop of Pakistan that is heavily affectedby whitefly and Cotton Leaf Curl Virus (CLCV). It causes a loss of 2.3 million bales every year that is the main reason for very low yield and cotton production in Pakistan Textile industry of Pakistan is heavily affected due to the low production of cotton since 1993.Sugarcane is also a cash cropthat is the major source of income for the farmers and is brutally exaggerated by dissimilar types of pestsincluding the borer. The sugar industry in Pakistan is also dependent on Sugarcane production whose production is badly affected due to pest attacks.

2.5 Sugarcane crop

Sugarcane is the cash crop that is used to produce sugar from the juice extract from the stem of the Sugarcane. The crop has a historic origin in South and Southeast Asian countries. Around five hundred years ago crystallized sugar was made in India. In the 7th century, China exported sugar from India and in the 8th century, it was brought to Mesopotamia (Egypt) by the Arabs. From Egypt, it transferred to central and South Africa and from there to Central and South America. Christophe Columbus moved it to the Caribbean region.

Up to the 7th century, Cuba was the main supplier of the world sugar. In 1950, Cuba is at the top in Sugarcane production. Due to the downfall of the Soviet

Union,the sugar industry in Cuba collapsed and Brazil came at the top with India at the second position in global Sugarcane production. Pakistan is at fifth position in Sugarcane production. The worldwide ranking of Sugarcane production is shown inTable 2-1 and sugar production in Table 2-2. Sugarcane is also a source of many other by-products except sugar. Ethanol is the by-product that can reduce imports.

Table 2-1: Sugercane producing countries ranking

	2007	1999-01	1989-91	1979-81	1969-71	1959-61	1949-51
Brazil[1]	1	1	1	1	2	3	3
India[3]	2	2	2	2	1	1	1
China[1]	3	3	4	5	8	6	8
Thailand[1]	4	4	6	12	20	27	43
Pakistan[1]	5	5	7	7	6	9	12
Mexico[3]	6	6	5	4	4	4	6
Colombia[3]	7	9	9	8	11	7	5
Australia[1]	8	7	12	10	9	12	11
United States[2]	9	10	10	9	7	5	4
Philippines[3]	10	11	11	6	5	8	10
Indonesia[1]	11	12	8	11	12	11	18
South Africa[3]	12	13	13	13	10	15	13
Argentina[2]	13	14	14	14	13	10	9
Cuba[2]	17	8	3	3	3	2	2
Puerto Rico[2]	>100	88	56	40	21	13	7

Table 2-2: Suger production ranking

	2007	1999-01	1989-91	1979-81	1969-71	1959-61	1949-51
Brazil	514.1	335.8	258.6	147.8	78.5	56.6	32.2
India	322.9	297.0	223.2	144.9	128.7	87.3	52.0
China	105.7	75.1	63.9	33.8	19.6	15.0	8.0
Thailand	64.4	51.3	37.0	17.7	5.4	1.9	0.3
Pakistan	54.8	48.4	36.2	29.1	23.8	11.6	6.4
Mexico	50.7	46.1	40.8	34.4	33.3	18.8	9.8
Colombia	40.0	33.1	27.4	24.7	13.2	12.5	11.1
Australia	36.0	35.3	24.2	23.4	17.6	9.4	6.5
United States	27.8	32.1	26.6	24.5	21.4	16.0	13.5
Philippines	25.3	25.6	25.2	31.5	25.3	12.0	7.1
Indonesia	25.2	24.2	27.6	19.5	10.3	9.6	3.1
South Africa	20.5	22.1	18.9	17.3	14.6	8.2	4.7
Argentina	19.2	17.9	15.9	15.6	10.2	10.4	7.6
Cuba	11.1	34.2	80.8	69.3	60.5	58.3	44.5
Puerto Rico	0.0	0.1	0.9	2.0	5.0	9.4	9.7
Sum of above	1,317.5	1,078.2	907.1	635.5	467.1	337.0	216.5
World	1,524.4	1,259.4	1,053.5	768.1	576.3	413.0	260.8

Source: FAOSTAT, online database at http://www.fao.org, accessed July 2008; FAO, 1987.

Sugar beet is also the source of sugar, but efficient agronomic activities promote Sugarcane production across the globe. Sugarcane crop is 8-10-month long in duration and susceptible to a wide variety of insects. Sugarcane production is 10-65, affected by the pest attacks. Sugarcane crop is affected by 288 types of different insects. Around one dozen of these insects cause serious damage to the quality and quantity of sugarcane(Srivastava et al., 2013). Borer and aphids are the major pests of the sugarcane crop.

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Sugarcane is the major cash crop of Pakistan. It is used to make sugar that serves the needs of the country and is the source of revenue by export. Sugar is used in many industries in the country.

2.6 Importance of Pest Management

Pest attacks are the major implication of global environmental change. Pest attacks have irreversible impacts on crop and animal health and cause significant loss to production. The pests can cause substantial losses to the agriculture sector. According to one estimate, the pests can cause a loss to the farmers from 20 to 80% of the total production. The annual loss to the wheat is 50%, cotton up to 45%, and Sugarcane up to 30% due to pest attacks around the world. This is significant over the world production of food for the ever-growing human population.

Pests can cause several damages direct and indirect damage to the crop. The losses due to pests are high in developed and developing countries like Pakistan. There are around ten thousand species of insects. Only ten percent of the species of insects'species are known as major pests of the crops and plants. According to an estimate one-third of the crop production is lost due to pest attack. in terms of economic values around forty-billion-dollar loss occurs annually due to pest attack. Another impact of pest attack is due to intensive use of pesticides for the control of pest attack. Around three million metric tons of pesticides are used annually for the control of pest attack. This huge pesticide usage has severe implications on the environment and ecology of other habitats.

There are many methods to control the pest attack. Chemical, biological, and physical methods are very common. Apart from losses by direct attack of the pests the cost to control their attack and to prevent from the damage to the attack are also very significant. The environmental impacts of these control strategies are also very damaging. Extensive use of the pesticides in last few decades has caused environmental pollution and loss to other species.

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Integrated Pest Management (IPM) is the approach to control pests with different techniques to reduce impacts on the environment. The use of every technique to control and prevent pest requires early information regarding pest attack. Early pest attack warning system makes the pest prediction control more effective and successful. The success of every strategy is heavily dependent upon the early prediction of the pest population. Moreover, early prediction of pest population and early warning systems are very useful in effective control of the pest attack.

Judicious use of chemicals for pest population control is also very important. The efficient use of the chemical for pest attack control is important from an economic perspective and environment protection aspect. The use of pesticides for the pest attack not only affects the economic outcomes of the farmers but also hasa severe impact on the environment and other socio-economic impacts. Judicious use of chemicals for a pesticide for pest attack is important to support sustainable developments. Early prediction of pest attacks would be very helpful in dealing with the issues more efficiently and effectively.

Keeping in view the issue and its implications there is an immense need for a solution that can help to deal with the issue effectively. There is need of a solution that minimizes the use of chemical and help for their judicious use. Early warning and pest population prediction could be much constructive for an efficient effective strategy against the pest attack. The integrated Pest Management (IPM) approach demands the emergence of novel tools and techniques for early identification of the pests attack.

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Pest attacks cause serious economic damage to the crop by the direct and indirect methods. Pest attack protection enhances the cost of the crop by using different measures to protect the crop like pesticide usage.. Judicious use of pesticides requires early knowledge of the pest population. For the timely and targeted level of pesticide usage of early pest attack prediction is essential. Visual inspection is the common method of pest identification or detection of pest attack. This is a labor-intensive, time-consuming and costly method. Most of the pests are not identifiable by the naked eye at the early stages. There are essential needs for alternative methods to predict the possibilities of pest populations and hence pest attacks.

The history of pest control dates back to 2500BC in Sumerians where they used Sulphur to control the pest. Chinese around 1200BC used chemicals to control pests in the Shange dynasty. Chinses developeda more sophisticated approach to pesticide usage for the control of pest attacks. Around 750BC, the use of ash to control the pests is found in history. In 500BC Chinese used the mercury to control the lice. Around 440BC Egyptian people used the nest around their beds to prevent mosquito attacks. Around 300BC use of the predatory insects was common to control the pest. In 13BC the rat-proof grain storage bin was made. In 70AD use of the oil from plant extracts usage as pest repellents were reported.In 1000AD the predatory insect was transferred from one area to another in Arab to save date palm from ants.

In the very early history of mankind, efforts were made to keep insects and pests from human life and crops. In the 20th century usage of chemicals for control of pestswas very popular. In 1921 first time airplane was used to spray the crop field with pesticides. In 1962 ultraviolet lamps were started to be used for the control of the pest. From the last century, the impacts of insects on human life are realized and efforts were made to control to improve productivity in agriculture.

2.7 Borer of Sugarcane

Sugarcane borers are the major pest of Sugarcane crop that can cause serious damage to the sugarcane crop. Gurdaspur borer, stem borer, root borer, and top borer are the major borers of the Sugarcane crop. Along with borers, bugs, mites, thrips, and worms are also pests of sugarcane that have devastating effects on sugarcane crop. A large quantity of pesticides is used to control the attack of these pests. Judicious use of pesticides and effective control of these pests required the implementation of the Integrated Pest Management (IPM) approach. For efficient and effective implementation of the IPM approach, early prediction of the pest attack is very crucial.

Table 2-3: Sugarcane pest and loss

Serial No	Pest Name	%age of yield loss	% reduction in sugar level
1	Termite	34	5.4
2	Whiter grub (L)	100	Complete drying-100
3	White grub (H)	80	6-7
4	White Fly	87	3
5	Pyrilla	32	4
6	Black Bug	36	3
7	Scale Insect	33	3
8	Root Borer	36	4
9	Stalk borer	34	3
10	Internode borer	35	3
11	Early shoot borer	34	2

Gurdaspur borer was first identified in 1980 in Pakistan. Its major attack is found in the months of July to September that is the major growth period of the sugarcane crop. Female lay 100-300 eggs on the leaves along the midrib. The hatching period of the Gurdaspur Borer is 5-10 days. The larvae of the Gurdaspur borer enter the hole at the top of the cane. The larva feeds on the cane and makes spirals galleries. The life of the larvae is 35-40 days, and it similarly infects one adjacent cane. The impact of the larvae feeding is a dry cane of the sugarcane crop. The tunnel and dry top of the borer by Gurdaspur borer is shown in Figure 2-6.

Figure 2-6: Effects of Gurdaspur borer

The top borer of the sugarcane is also a major pest of the sugarcane crop. The scientific name of the top borer is *Diatraeasaccharalis* (*Fabricius*). The native place of the top borer is the western hemisphere and is also found in Pakistan, India, and China. Its life spans over the entire life of the sugarcane crop from March to November. The eggs are laid at the leaves and cane stalk. Larva enters the cane stalk through the nodes by making holes. Pupa emerges by making a hole in the cane. April to July is the period with maximum damage. It completes four to five generation life cycle on one crop period and all the life cycle, damage the crop.The early generation makes the red streaks on the crop with s special bunchy top. Top borers not only reduce the quantity but also have devastating impacts on the quality of the juice.

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Figure 2-7: Sugarcane top borer and its impacts

Stem borer of sugarcane crop is also the major borer type pest of sugarcane crop. It can reduce yield from 35% to 70%. Its caterpillarsstart the attack on shoots from April to June and its larvae start the attack from the base of the plants. Wilting and whirling occurs in the plant that results in whirling and drying of the plant. The drying of the plants reduces the quality and quantity of the plants. New shoots emerge at the point of infestation result in the formation of dead hearts. The moth, larvae, and dead heart in sugarcane are shown in Figure 2-8.

Figure 2-8: Stem borer of sugarcane with the larva

Root borer is the major pest of sugarcane crop in Pakistan, Bangladesh, and India. It was first identified in India in 1885. The root borer can affectcane production from 65% to 75%. Root borer affects the complete life cycle of the crop and has adverse impacts at all the stages of the crop. The major attack is found from May to November. Temperature from 31 to 35 ^{o}C and high humidity are the favorable environmental conditions for the successful life cycle of the root borer. High temperatures with low humidity, low temperatures with low humidity are not suitable environmental conditions for the proliferation of the root borer on sugarcane. The moth and impacts of root borer are shown in Figure 2-9.

Figure 2-9: Root borer of Sugarcane with impacts on sugarcane crop

2.8 Environmental conditions and Sugarcane borer

With the advent of the concept of heat units many methods of determination of thermal physiological time heat used for the phenology of organisms in agriculture and animal sciences. Many models emerged based onthe "law of effective temperature", which describes the response of a particular organism to the temperature. The response of an organism to the temperature is described by many linear and nonlinear models.

Environmental conditions have profound impacts on the insect's growth. Entomologists have a great interest in the development of mathematical models to determine the impacts of environmental conditions on the growth of insects. Temperature is the main attribute of a climate and environmental condition.Therefore, most of the model of insect developments are temperature driven. In this regard initially, temperature relation to plant growth is determined.Similarly, efforts were made to describe models for the insect to relate their growth with temperature. Bonnet in 1779 tried to relate the reproduction rate of Aphis F. Many efforts were made to describe the models of insect developments withthe temperature. Many insect growth predictive models developed in the last century. With the advent of computers, many computer-based models also emerged to predict the insect population in response to temperature.

Insects are adaptable to certain environmental conditions and temperature is the important environmental factor. Every insect species has an optimal temperature range for its growth. Below the optimum temperature the rate of growth of insects decreases and at one stage it ceases. On the other side, the growth of the population also decreases with the rise of temperature from the optimal temperature range. It is based on the fact that the temperature has a subtle impact on the enzymatic activities of the poikilothermic organism like insects and their growth depends on the enzymatic activities.

The Law of effective temperature is the basis of all models that describe the temperature-dependent development rate of the poikilothermic organism. The law of effective temperature defines a species-specific thermal unit that is related to a time unit that must be accumulated to complete a development life cycle. The development of a specific species is related to a thermal unit that must be accomplished for certain days, for the accomplishment of the development life cycle of that species. The number of generations of a particular insect can be estimated by the law of effect using Equation 2-1.

$$K = D(T - To)$$

Equation 2-1: species-specific thermal constant

Where k=species specific thermal constant, T=temperature and T_0 is the Development zero temperature. The species-specific thermal constant is the time required for completion of the developmental process and is measured indegree days (DD).

$$\frac{1}{D} = -\frac{To}{K} + \frac{1}{k}T$$

Equation 2-2: species-specific thermal constant

The species-specific thermal constant can be obtained by a linear transformation of the above function by using Equation 2-2 for per day development rate.

Rainfall and borer population shows an inverse relationship.with each other. Flooding of cane with rainwater washout the plants from the larva.Immersion of cane with rainwater may also lead to the death of the larvae. Rainfall with cold temperature also reported in death of larvae.Equation 2-2 define a linear degree-day model, that can be obtained by fitting the growth rate to a simple linear equationgiven by Equation 2-3.

$$y = a + bT$$

Equation 2-3: Linear equation

The base temperatureor lower threshold temperature level is obtained by Equation 2-4. Where 1/slope is the thermal constant or average duration in degree days. From Equation 2-3, it is clear that the thermal constant is the product of the degree of temperature above the threshold level and time.

$$Tb = -a/b$$

Equation 2-4: Lower threshold temperature level (Damos & Savopoulou-Soultani, 2012)

Figure 2-10, shows the relationship between the temperature and development rate of larvae of G. molesta.Figure 2-10 shows the relationship between the temperature and development rate by Equation 2-3. The linear model for the relationship between the linear rate and temperature is defined by Equation 2-5, when Tm=10^0C.

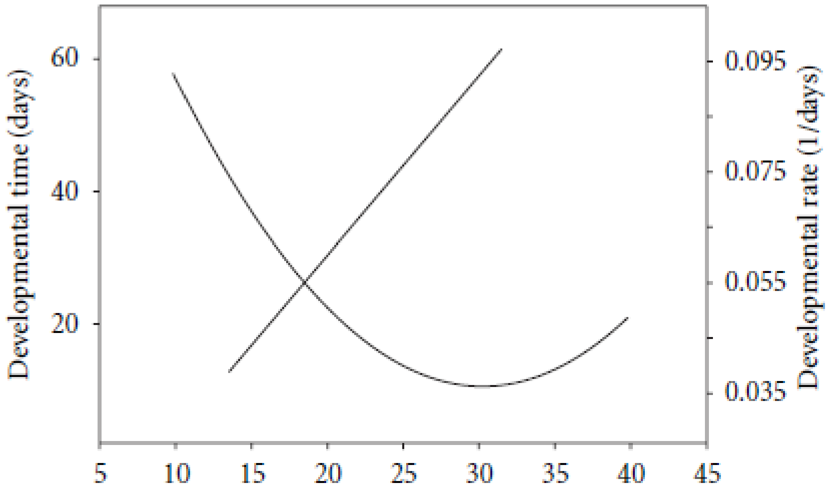

Figure 2-10:Relationship between development rate and temperature of G. molesta(Damos & Savopoulou-Soultani, 2012)

$$,y = 0.041x - 0.0412$$

Equation 2-5: Relationship between the development rate and temperature

Apart from linear models,non-linear models are also used for extreme temperature relationship between the development rate and time.

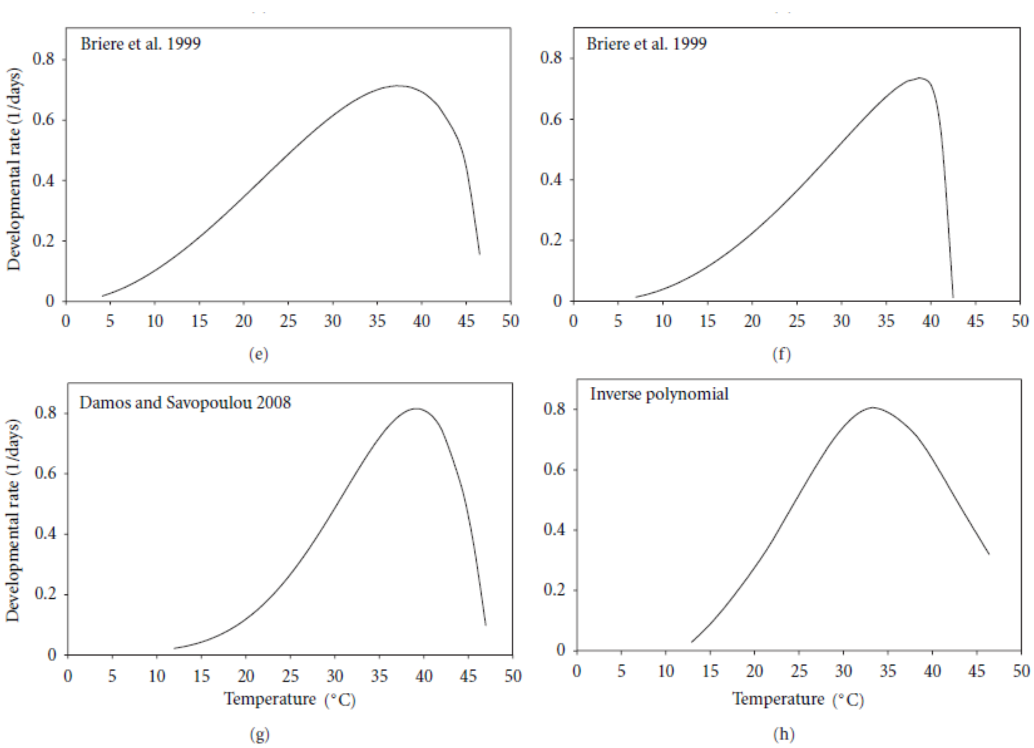

Figure 2-11: Non-linear relationship model betweeninsect development rate and temperature(Damos & Savopoulou-Soultani, 2012)

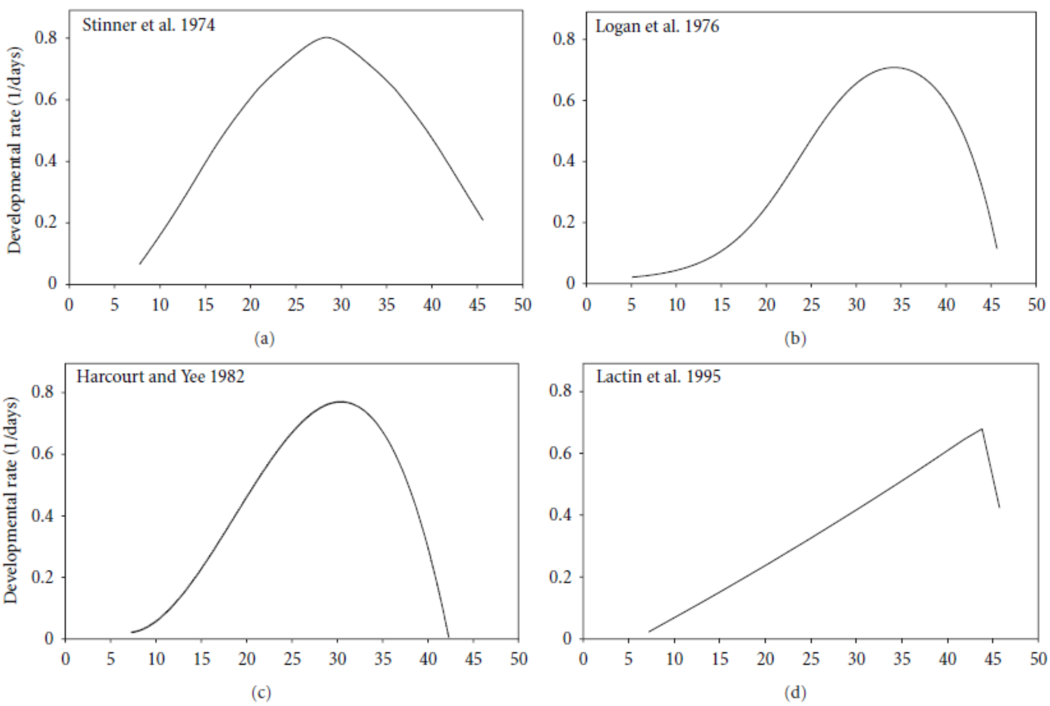

Figure 2-12: Non-linear relationship model between development rate and temperature(Damos & Savopoulou-Soultani, 2012)

According to o all models the there is no growth below the lower threshold level. At optimal temperature, the maximum development rate occurs. The development rate also starts o decrease above the threshold level and reaches a lethal temperature where the development rate again reaches zero.Apart from the linear and nonlinear models different biophysical and statistical models are also present to relate the development rate of insects with the temperature.

Another aspect of pest prediction on basis of temperature is the time duration of favorable temperature for maximum development rate. A single instance of a temperature is no guarantee of a maximum development rate. The accumulation temperature concept is used to describe the time of the temperature it requires o achieves the maximum development rate that is called effective accumulation temperature or thermal time. According to the law of effective temperature, the accumulation of the development stage completion requires a definite amount of heat energy. Accumulated effective temperature can be estimated from the definite heat energy required to complete a development life cycle, several methods are present to determine the degree days in accumulated methods like average methods, modified average methods, and modified sine wave method are very common.

In the average method, the number of degree days is obtained by subtracting the base temperature from the daily average temperature given by Equation 2-6

$$DD = \left[\frac{minT + maxT}{2}\right] - Tmin$$

Equation 2-6: Number of degree days

This approach ignores the daily minimum temperature that falls below the minimum threshold level, hat usually occurs in spring and autumn season.To overcome this issue, the minimum temperature (mint) is replaced with a lower threshold temperature (Tmin) by Equation 2-7. This method is also called the modified average method.

$$DD = \left[\frac{Tmin + maxT}{2}\right] - Tmin$$

Equation 2-7: Modified average method

2.9 Management

Sampling for pest scouting in sugarcane is done five cane stalks from five different plants three meters apart from each other can give an accurate representation of the borer pest density.

Sampling for pest scouting in sugarcane is done five cane stalks from five different plants three meters apart from each other can give an accurate representation of the borer pest density.

CHAPTER 3 LITERATURE REVIEW

IoT has shown successful applications in monitoring and control of environmental conditions. The real-time monitoring of farmland and crop field conditions has a predominant role in improving productivity in agriculture. Farms are connected and farmers can have real-time remote access to the field conditions. The real-time monitoring using the WSN and IoT also shows many other applications like irrigation water management, yield predictions, and pest identification. For the identification of the research gap for the study, the various application of IoT and WSN are explored.

In this section, the most important findings of the literature reviews are specified below.

DušanMarkovi´ et al. have used temperature and humidity to environmental monitoring for crop pest appearance prediction. The author implemented many machine learning algorithm with maximum accuracy 86%. (Marković et al., 2021).

Jun Liu et al. proposed pest detection using image processing based deep learning . it checks the quality of plant and implement deep learning algorithm for detection of pest plant.(Liu and Wang, 2021)

Internet of Things (IoT) assisted environment monitoring applications emerged to assess plant growth. Greenhouse monitoring is one of the core areas of Internet of Things applications for environmental monitoring.Y. Yun Han et al., proposed IoT based crop fields assisted crop characteristics observations(Han et al., 2017). Atefeh Mir et al. proposed Internet of Things (IoT) based water quality monitoring (Mir et al., 2017) Tanmay Baranwal et al. proposed grain storage monitoring to detect intruders attack (Baranwal et al., 2016). Wladimir E. Soto-Silva et al. proposed IoT-assisted supply chain management for perishable protection (Soto-Silva et al., 2017).

Real-time assessment of soil moisture content is important for geological and agricultural applications. Kong, Q. et al, proposedreal-time soil moisture contents in sand soil using the Shear Mode Piezoceramic Transducers and Active Sensing(Kong et al., 2017).Amina Antonacci et al. proposed the development framework for biosensors to promote smart farming while reducing environmental pollution. The emergence of IoT and other related technologies has streamlined the forefront of the emergence of biosensors (Antonacci et al., 2018).Arun Khatri-Chhetri et al. said that climate change is emerging as a threat to agriculture and it affects most people in all the world. The study is conducted to assess farmers' preferences and willingness to pay for selected Climate-Smart Agriculture (CSA) technologies in diverse rainfall zones. CSA implementations have the potential to the reduction of the impact of climate change on agriculture. Socio-economic data and information on the climate of the study area were used to assess the preference of farmers for CSA(Khatri-Chhetri et al., 2017).

Otoniel López et al. proposed a pest trapping monitoring system using the low-powered image with the purpose to determine the efficiency of the proposed system. The proposed system is linked with a central station to storeand process the information related to the efficiency of the trapping system(López et al., 2012).

The proposed system will be used for the management and detection of fungal diseases. The study proposed an Internet of Things system design consisting of a device. It can send real-time environment data to a machine learning algorithm and to cloud storage to predict the upcoming environmental conditions for fungal prevention and detection. Air temperature, rainfall, wind speed, and relative air humidity is processed and accessed by a remote computer for management and analysis purposes. SVM (Support Vector Machine) was used to develop a machine-learning algorithm. It was used to process the raw data and predict short-term wind speed, relative air humidity, and air temperature to forecast the occurrence and extent of dangerous fungal diseases over the local crop field. Together, the prediction and environmental data made only available by the Internet of Things system will eventually support crop field managers by enabling good prevention and management of fungal disease spread(Truong et al., 2017).

Mare Srbinovska*et al.* proposed and developed a vegetable greenhouse monitoring system (Srbinovska et al., 2015). Nurzaman Ahmed *et al*. proposed a smart farm application for environment monitoring (Ahmed et al., 2018). Julio Caesar et al. recommended the Internet of Things (IoT) solution for environmental monitoring in a protected environment (Ramos-Fernández et al., 2016). Xiaojie Shi et al. explored the Internet of Things (IoT) applications in agriculture (Shi et al., 2019). Tomo Popovic et al. proposed an Internet of Things (IoT) based ecological monitoring system to promote sustainable developments in agriculture(Popović et al., 2017). S. Mohamed et al. also recommended Internet of Things (IoT) based greenhouse environment monitoring and control (Mohamed, 2015) . P. Ferentinoset al. proposed protected environment monitoring using Internet of Things (IoT) (Ferentinos et al., 2017).

V. Ramachandran *et al.* recommended IoT assisted irrigation water recommendation system (Ramachandran et al., 2018) Peyman Afrasiabikia et al., proposed an efficient irrigation water distribution system (Afrasiabikia et al., 2017). Navarro-Hellín, H. et al. proposed smart irrigation using the Internet of Things (IoT) applications (Navarro-Hellin et al., 2016) K. Sakthiveluet al. recommended irrigation water management using Internet of Things (IoT) applications (Sakthivelu et al., 2016). Qingzhao Kong et al. proposed an Internet of Things (IoT) based irrigation water recommendation system (Kong et al., 2017). Mohanraj et al., proposed the Internet of Things (IoT) assisted irrigation water for the conservation of irrigation water(Mohanraj et al., 2016). Bertha Mazon-Olivo proposed automated irrigation water management to conserve the irrigation water (Mazon-Olivo et al., 2018). Along with these many smart irrigation recommendations and management schemes are emerged (Rojo et al., 2016)(Navarro-Hellin et al., 2016)(Mulenga et al., 2018)(Gocić et al., 2015).

Many different types of Internet of Things (IoT) applications emerged in recent years. Christopher Brewster *et al.* explored the potential prospects of IoT and challenges of IoT in agriculture (Brewster et al., 2017)Tamoghna Ojha *et al.* explored the potential applications of the Internet of Things (IoT) in agriculture. (Ojha et al., 2017). Olakunle Elijah *et al*. explored prospects and challenges for the Internet of Things (IoT) in agriculture applications (Elijah et al., 2018).

Stefanos A Nikolidakis proposed energy-efficient Internet of Things (IoT) based environment monitoring and irrigation water recommendation system. Different types of Internet of Things (IoT) automation control solutions for use of other types of technologies like cloud and big data handling are proposed. Jesus Martin Talavera *et al*. planned mechanical organize of tools with the Internet of Things (IoT) and cloud work out incorporation (Martín et al., 2017).

K.V.Raghavendraet al .make out the association among the pest and weather situation on cotton crops. The proposed model uses regression analysis to determine the relationship between pest growth and environmental conditions (Raghavendra et al., 2014). The machine learning-based approach is very effective in the prediction of the pest population and the determination of the pest population(Shang & Zhu, 2019).

K.V.Raghavendraet al .make out the association among the pest and weather situation on cotton crops. The proposed model uses regression analysis to determine the relationship between pest growth and environmental conditions (Raghavendra et al., 2014).

Ramesh.S, and Vydeki.D recommended IoT based plant sickness exposure system. The proposed solution assesses the plants' health on image processing based and detects the occurrence of the disease.(Ramesh.S, 2018),. M. Ayaz et al. discover the probable of the Internet of Things (IoT) based key to covenant with climate altration. Adaption of Climate-Smart Agriculture (CSA) is explored and its potential advantages are discussed in detail.(Ayaz et al., 2019)

ShanmugaPriya.S and Abinaya.M proposed weather-based pest predictions using data cluster technique (S & Abinaya.M, 2018)

The study proposes an information system with the purpose to improve productivity in agriculture. The proposed information system identifies different factors that cause a loss in agriculture productivity. Pest and disease are an important issue in agriculture that causes loss in agriculture productivity and the study uses the statistical data of weather conditions to find the relationship between the disease and weather conditions on corn crops(Syarif et al., 2018). Shital B. et al., plant disease prediction using the automated method for early warning to prevent damage to crop plants(Bankar et al., 2014).

Every year the demand for food and other agricultural products is increasing, and human beings are putting their total efforts to fulfill the needs of food and other agricultural items. Every passing year it is hard to meet the required food supply target. Science and Information technology is working to develop such tools and machinery to enhance food production. Information technology can help us use sensors and networks to enhance soil fertility and control the production of food. Various terminologies are used today such as PA smart agriculture and precision farming etc.

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Foughali Karim et al. stressed the importance and potential advantages of IoT in agriculture. The proposed web of things-based crop field environment monitoring is proposed to improve crop production. The software dashboard will show all the facts and requirements about their crops.This automated web of things will alert about the access of water and will talk about the end of water or other pesticides requirements to grow the crops with higher precision(Karim et al., 2017b).

This combined with declining natural resources, restricted access to arable land, and unpredictable climate change make food security a major concern in many lands. Olakunle Elijah et al. proposed the use of the Web of Things (IoT) to improve efficiency and profitability in the agricultural sector.

There is a shift in perspective from the use of remote control (WSN) as an important driver of savvy horticulture in the use of IoT and DA. IoT includes a few new features available, for example, WSN, radio proof duplication, computer distribution, middleware frameworks, and end-user applications. The study proposed several advantages and disadvantages of IoT have been identified.

Luca Bencini et al. developed a system using sensors to observe crop-field and automate irrigation system is calculated and overviewed. This scheme gives a plan about the wireless transmission of sensor data from fields to the controller, storing it in a database, and controlling requisite field restraint from a mobile application(Bencini et al., 2009).

Maurya and Vinod Kumar Jain proposed Wireless Sensor Network (WSN) based approach to control irrigation water for efficient use of the irrigation water. Soil moisture, soil temperature, and air humidity are sensed from the crop field to assess the irrigation water requirements. The direct sensed environmental conditions are transferred to the base station wherethe threshold level for irrigation water requirements is identified. The routing protocol is proposedfor the entire fieldcoverage, a region-based static clustering approach is used for the transfer of data from the sensor to the base station.(Maurya & Jain, 2016).

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Christos Goumopoulospropose the speakingplant approach as a PA application. The study proposed an adaptable decision support system using the speakingplant approach. The proposed solution uses the Wireless sensor and Ecuador network (WSAN) to propose autonomous closed-loop zone-specific irrigation water. Machine learning capabilities are used to learn new rules o cope with new changes and extraction of knowledge (Goumopoulos et al., 2014).

Ke-tao Chen et al. proposed multilayer soil temperature and moisture monitoring using the Wireless Sensor Network (WSN) approach. The proposed system is based on three parts of sensing layer, gateway node, and processing node. Ral time soil temperature and moisture are observed a 10cm, 20cm, 30cm, and 40cm for various applications. Real-time soil moisture andtemperature monitoring are very effective in the assessment of plant growth and irrigation water requirements determination. (K. T. Chen et al., 2014)

Colin Gilmore et al. proposed a grain bin monitoring system using the Electromagnetic induction (EMI) system. The proposed solution is capable of identification of spoiled grain in industrial storage. The proposed system is based on image processing to identify the spoiled grain. The spoilage system increases the temperature and humidity level and uses the 3D image of the grain to identify the spoiled grain(Gilmore et al., 2017)

Saeed Azfar proposed a pest-control mechanism based ona wireless sensor network (WSN) The performance of the proposed solution s evaluated in term of accuracy. The study also analyzes different types of strategies for pest control including technological and non-technological. They also analyze the pest monitoring techniques in agriculture. The proposed solution s very effective in the identification of pest using WSn and show high accuracy in identification of pest (Saeed Azfar et al., 2015)

Cohen, Y. proposed MedCila named Decision Support System (DSS) for the control of medfly in citrus orchids. The proposed solution is based on data acquisition, modeling of criteria ,integration of the MedCila, and evaluation of the MedCila. The performance of the proposed solution named MedCila reduces the number of sprays to control medfly. The proposed solution decides based on Stanford uncertainty for the rule-based decision tree(Cohen et al., 2008)

Georgina Stegmayer proposed automatic identification of quarantine disease on fruits to identify the affected fruits to replace an expert person for the task.The proposed solution is based on a classifier and training of the model on illness symptoms The model for identification of the disease is tested against the apple scab, black spot, and citrus canker. The evaluationshows high accuracy of 84% even on a small subset of data(Stegmayer et al., 2013).

S.Azfare al., explored the techniques of pest identification using the Wireless Sensor Network (WSN). The major techniques and application of environmental monitoring using the WSN for pest identification are reviewed and advanced sensing technologies for the environment monitorng to identify the pes are reviewed. (S. Azfar et al., 2018).

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Navin Srivastava et al. proposed Sugarcane pest identification using acoustics-based technology. The proposed solution uses the acoustics sensor to detect the noise base pest identification using the threshold level of the noise. The proposed solution used the Zigbee communication technology that connects the sensor to the control station where processing takes place. The low energy deployment of the sensor is ensured with large geographical area coverage (Srivastava et al., 2013).

Dames et al. reviewed different temperature-driven linear and nonlinear models of insect growth with temperature. The study also made a statical evaluation criterion of a model to describe physiological time and response to temperature growth of insects consequences of insectspatiotemporal arrangments(Damos & Savopoulou-Soultani, 2012).

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Alan Mainwaring et al. proposed a complete solution of habitat monitoring environment, from sensor networks to architectureof the proposed solution. The study presents the complete architecture for a sensor network in habitat monitoring. The habitat monitoring is evaluated in terms of the sensor network, the software and hardware platform, network services, power management, communication, node management, from design to implementation (Mainwaring et al., 2002).

According to the study the image processing playsa key role in the detection of plant disease to improve the quality of PA practices The author believes that automatic detection of the plant is very helpful in implementation of the control mechanism due to early detection of the onset of disease against the manual disease detection (Chaudhary et al., 2019).

A multilayer classification is used to detect the leaf diseases in tomatoes. The objective of the proposed solution is to present a simple model o tomato disease detection with minimal computing resources usage. The proposed algorithm is effective in terms of accuracy and efficiency for the detection of tomato diseases (Pragya et al., 2019).

Jiten Khurana*et al.* proposed an image-based leaf detection model. The study proposed an integrated deep learning framework with a model named VGG-19. The model is based on feature extraction for the identification of leaf diseases to reduce losses in the agriculture sector. The proposed model is very accurate against other models and with high accuracy of 98%(Khurana et al., 2019).

Anbarasi M. et al. proposed image processing and Convolution Neural Network (CNN) based identification of disease-affected plants. Android app is proposed for automated monitoring of the plants and identification of the disease plants from the healthy plants(Anbarasi et al., 2019).

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Swapna C. and Shahji present plant leaf disease detection using the leaf disease CentroidDistance Neighborhood Features (CDNF) with Genetic Algorithm (GA) optimization. Initially, the disease affected area is segmented from the leaf. This method initially segments the disease affected regions from the leaf. The feature extraction and detection of the disease plants is accurately performed by the proposed model(Swapna & Shaji, 2019)

Sarika Datir and Wagh proposed WSN assisted powdery mildew disease prediction for the grape's crops. Etiological-based disease prediction has theadvantage to predict the disease earlier than the incidence of the disease. The weather-based disease prediction helps to take corrective control strategies to prevent the disease(Datir & Wagh, 2014).

Jinpeng Wang et al., proposed multimedia WSN oriented image processing-based plant disease prediction for plant disease detection. The proposed approach usesshape, size, texture, and color to identify the healthy plant s from the affected plants.The emergence of IoT enables the long erm sensing and data quality for the detection of disease from the different feature sets of the plants. The study also presents an emulation-based architecturefor to accurate prediction of disease (Wang et al., 2014).

Abd EL-Kader and Muhammad El-Basioni present a review of the WSN for the development of PA solutions. The use of the WSN for potato crop growth monitoring is made(Abd El-Kader & Mohammad El-Basioni, 2013).

R. W. Mankin(Mankin et al., 2011) proposed an acoustic-based pest and pest infestation identification solution. The proposed solution used the ultrasonic sensor and acoustic technology o identify pest and pest infestation by the sound the pest made in the crop while attack.

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R. W. Mankin proposed image-based remote crop field environmental condition monitoring to automate the farm operation and process. The use of the IoT reduces the cost of remote monitoring of the farm conditions and improves agriculture productivity(Mankin et al., 2016).

Balaji Banu(Bhanu et al., 2014) proposed environment conditions monitoring like temperature, humidity, and soil moisture. The proposed solution is based on Zig bee protocol, ATMEGA8535, and IC-S8817 with a wireless sensor node.The sensed data from the sensor node is stored in a database and communicated to the end-user through a web application.

Fujian Li et al. proposed a greenhouse climate monitoring and control solution using the IoT. The proposed solution uses the fuzzy neural network for effective control of the greenhouse climate conditions. The proposed solution is based on a master node to control the climate conditions (F. Li et al., 2016).

Alan Mainwaring et al. proposed a complete solution of habitat monitoring environment, from sensor networks to architectureof the proposed solution. The study presents the complete architecture for a sensor network in habitat monitoring. The habitat monitoring is evaluated in terms of the sensor network, the software and hardware platform, network services, power management, communication, node management, from design to implementation (Mainwaring et al., 2002).

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WeiminQiu, et al., (Qiu et al., 2015), proposed greenhouse environment monitoring and control using the IoT. Joseph Haule, (Haule & Michael, 2014) proposed IoT assisted greenhouse environment monitoring control. The proposed system is a complete solution for data acquisition, processing, and end-user display functions.The objective of the proposed systems is to develop an effective environment monitoring system to reduce the cost of the system. The proposed IoT environment monitoring system is based on a gateway for Linux operating system with wireless technologies. The proposed solutionsreduce labor costsby using wireless communication.

Joseph Haule and Michael (Haule & Michael, 2014)describe the WSN uses in agriculture for improving the production in agriculture. Water is a scarce resource and optimization of water usage is crucial for agriculture practices in agriculture. The proposed solution determines the time, amount, and frequency of irrigation water requirements by the proposed system. The proposed system is described in terms of low power requirements, improved throughput, communication time, communication errors, and latency in the network to effectively monitor the environment for the irrigation water recommendation system.

R. W. Mankin(Mankin et al., 2011) proposed an acoustic-based pest and pest infestation identification solution. The proposed solution used the ultrasonic sensor and acoustic technology o identify pest and pest infestation by the sound the pest made in the crop while attack.

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,Dragoş Mihai Ofrim,(Ofrim et al., 2010)proposed WSN based environment monitoring system with improved performance in terms of flexibility and network performance. The development guidelines are describing from design to implementation of the environment monitoring system.

Vijay Kumar and Rosario proposed environment and soil monitoring for efficient use of the irrigation water and fertilizer application. The proposed system is very helpful in the conservation of agriculture resources(Vijayakumar & Rosario, 2011).

Lin Zhang et al., (Zhang et al., 2010)proposed a low energy WSN network for agriculture crop field environment monitoring system to decide on the use of the inputs. The proposed system is easy to configure and withstand environmental conditions for a longer period in a crop field.

G. Nisha and Megala(Nisha & Megala, 2015) proposed an automated irrigation system by directly sensing the environment monitoring system using the WSN system. The proposed solution is based on Zigbee network to effectively control the sensor node to monitor the soil moisture, temperature, and humidity from the crop field.

. Alan Mainwaring et al.(Mainwaring et al., 2002) proposed WSN assisted habitat monitoring system. The proposed solution is described from different design aspects likehardware design, network design, node design. The proposed architecture for habitat monitoring proved tobe very effective in its objective to monitor the

Lei Xiaoand Guo (Xiao & Guo, 2010)proposed WSN based environment monitoring system for PA implementation purpose to realize the true outcomes of the PA practices.

Wei and Lin proposed a fuzzy RBP Neural Network non-linear model of pest prediction because pest prediction is complex and non-linear. The proposed non-linear model of pest prediction is very accurate and simple in nature(Wei & Lin, 2009).

Fu (Fu, 2012)proposed an intelligent agriculture system for fruits in China using the IoT. The major attributes of the proposed model are the use of RFID, sensors, and many new technologies for the implementation of the intelligent agriculture system.

Ling-ling Li et al.(L. L. Li et al., 2011)proposed the theoretical and practical aspects of WSN based greenhouse environment control. The proposed solution is described in terms of hardware and software control for the design and implementation of the greenhouse environment monitoring system.

R. Balamuraliand K. Kathiravan(Balamurali & Kathiravan, 2015)proposed real-time environmental monitoring and automated actuator for the control of the implementation of PA practices. WSN is very effective and promising in providing the solution for PA practices. The study analyzes the various routing protocols for PA practices. The AODV (Ad-hoc On-demand Distance Vector Routing), Multipath Distance Vector Routing), DSR (Dynamic Source Routing), and Integrated MAC and Routing protocol (IMR) are analyzed for PA applications.

Dragoş Mihai Ofrim(Ofrim et al., 2010) proposed an environment monitoring system for efficiency, flexibility, and performance improvements in agriculture.

Rachel Cardell-Oliver(Cardell-Oliver et al., 2004)proposeda soil and environment monitoring system and also evaluate the proposed system for observation of soil moisture. The proposed system is very reactive to the change in soil moisture conditionsupon irrigation and rainfall. The dynamic response of the proposed solution makes it an ideal solution to deal with different problems in agriculture.

Duan Yan-e(Yan-E, 2011)believes that Information technology has a crucial role in improving productivity in agriculture. The Agriculture Information System can enhance the productivity in agriculture by focusing on the efficient management of the resources.

Wei and Lin proposed a fuzzy RBP Neural Network non-linear model of pest prediction because pest prediction is complex and non-linear. The proposed non-linear model of pest prediction is very accurate and simple in nature(Wei & Lin, 2009).

Fiona Edwards Murphy(Edwards-Murphy et al., 2016) proposed WSN based honey bee colony monitoring system for the effective growth of honeybee colony. The major characteristics of the low energy system to support long term monitoring and observations. The proposed system used cloud integration for live monitoring purposes.

Sonal Verma(Verma et al., 2010)proposed crop field environment condition monitoring using the IoT to streamline the process and practices with objectives to improve productivity .Sreekanth and Kavya proposed a crop field environment using image base remote monitoring with IoT capabilities (Sreekantha & Kavya, 2017).K.Sathish Kannan and G.Thilagavathi(Sathish Kannan & Thilagavathi, 2013) proposed an air quality monitoring system for the determination of air quality index system for the user, the environment experts, and the public. The data is stored that is accessible to view historical environmental conditions for the comparison purpose.

Xiao Yang et al., (Yang et al., 2016) proposed image-based detection of the quality of lettuce by observing the anthocyanin, which is a very important characteristic of red lettuce. The color quadratic model is very accurate to determine the contents of anthocyanin in red lettuce. The machine vision model is very promising in the identification of the quality of produce.

Jinhu Liao et al., (J. Liao et al., 2015) proposed a Zigbee farmland monitoring system with GPS to transfer data to the server. The proposed solution aims to improve productivity with a cost-effective solution.

Chen et al. proposed an energy harnessing solution for WSN agriculture. Plant electrolytic power is used for the energy supplies to the sensor node for long time monitoring in agriculture (X. Chen et al., 2012).

WeiminQiu et al.,(Qiu et al., 2015) planned automated intellectual conservatory environment monitoring and organize for the development in agriculture efficiency.

Nelson Sales(Sales et al., 2015)proposed an irrigation automation process with WSN real-time monitoring of crop field environment conditions. The major objective of the proposed solution is to apply irrigation water conservation methods.

Gao, Demin (Gao et al., 2020) proposed IoT and Unmanned Aerial Vehicles (UAVs) basedcrop field monitoring for disease detection using the spectrum analysis technology. The proposed solution is implemented on the wheat crop for the identification of the disease attack on wheat.

TokihiroFukaet al.(Fukatsu et al., 2012) propose a pest counting technique by real-time monitoring of pest traps and using the high-resolution image from the traps. The image processing technique is practical to settle on the incidence of the pest attack.

Ferro, E et al., (Ferro et al., 2014) proposed a snail detection system using the WSN to promote the judicious use of the pesticide.

Tripathy, A. K. et al.,(Tripathy et al., 2011) proposed WSN environment monitoring for finding out the relationship between the crop field weather and pest disease occurrence. The study finds the co-relation of weather with the occurrence of pests and disease. The study implements the proposed model on thrips pest and bud necrosis disease.

Tripathy, A. K. et al., (Tripathy et al., 2014) proposed a model to find the association among the disease and weather situation to determine the incidence of disease. The study finds the relationship between the leaf spot disease of groundnut.Patil, Jyothi (Patil & D. Mytri, 2013) propose an analytical model of thrips pest prediction in cotton crops using a multilayer perception neural network. The evaluation of the model shows that model is very effective in the prediction of thrips in cotton.

ShanmugaPriya.S(S & Abinaya.M, 2018) proposed a correlation-based pest prediction in cotton. The proposed solution is implemented for thrips pests in the cotton crop that is very accurate in predicting the occurrence of thrips.Lee, Haemin(Lee et al., 2017) proposed IoT-assisted crop field monitoring of environmental conditions and finding the association among the pest population and weather circumstances. The co-relation helps to identify the pest and diseases in orchids based onthe environmental condition.

Raghavendra, K. V.(Raghavendra et al., 2014) propose the statistical analysis of weather conditions to find the correlation between the weather conditions and pest populations. Multiple regression model is developed to predict the occurrence of pest on cotton and a Co-efficient of determination for each pest is utilize to evaluate the incidence of pest disease.

M.A. Ebrahimi(Ebrahimi et al., 2017) proposed thrips pests on strawberries using the computer vision and image processing approach. The proposed solution used the Support Vector Machine (SVM) model of pest detection.

Li, Ting (T. Li et al., 2008) proposed association rule and semi-supervised machine learning approach for the detection of flee beetle on the vegetable. The proposed solution aims for the early warning of the pest attack on vegetables.Chen, Xianyi(X. Chen et al., 2012) proposed energy-efficient WSN monitoring of crop field environment conditions by using the electrolyte characteristics of the plants.

BratislavPredic(Predic et al., 2018) proposed weather-based prediction of the fruits disease using the data mining approach. Araby, Alaa Adel (Araby et al., 2019) proposed IoT-assisted crop field monitoring for the detection of unhealthy plants using the WSN and intelligent model of disease detection. The proposed solution is implemented on tomato and potato crops.Damos, Petros, and Sultani(Damos & Savopoulou-Soultani, 2012) presented the different methodical models of pest life cycle development based on temperature and other important weather conditions. The study also elaboratesthe law of effective temperature.

Table 3-1: Summary of related work

Author and Reference	**Contribution**	**Type of Sensor**	**Technology**	**Pest**	**Crop**
Demin Gao(Gao et al., 2020)	UAV and Image processing based	Vision and Weather	Image Processing	Disease	Wheat

	disease detection				
M.A. Ebrahimi(Ebrahimi et al., 2017)	Image processing based pest detection	Vision	Support Vector Machine	Thrips	Strawberry
Shashank Chaudhary(Chaudhary et al., 2019)	Image processing disease detection review	vision	Image processing	Disease	Plants
Navin Srivastava et al (Srivastava et al., 2013)	WSN based pest identification	Acoustics			Sugarcane
Alan Mainwaring (Mainwaring et al., 2002)	WSN based habitat monitoring	WSN	Architecture of WSN	Environment	Habitat
Pankhuri Pragya(Pragya et al., 2019)	Vision	Image Processing	Convolution Neural Network	Tomato	Disease
Jiten Khurana	vision	Image	Deep	Tomato	Disease

(Khurana et al., 2019)		Processing	Learning		
Pankhuri Pragya (Pragya et al., 2019)					
Anbarasi M (Anbarasi et al., 2019)	Andriod App	Image Processing	Deep learning	vegetables	Disease
Swapna C (Swapna & Shaji, 2019)	Vision	Image Processing	Centroid Distance Neighbourhood Features (CDNF) and Genetic Algorithm (GA)	General Plants Leaves	Disease
Sarika Datir(Datir & Wagh, 2014)	WSN assisted weather base disease prediction	Weather base Disease prediction	The architecture of the prediction	Grapes	Powdery Mildew disease
Jinpeng W (Wang et al., 2014)	WSN assisted	Image processing	Model of pest	General	Plant Diseases

	Vision-based Disease detection		prediction		
R. W. Mankin(Mankin et al., 2016)	Acoustics	Noise	Signal Processing	Pest	Palm tree
R. W. Mankin(Mankin et al., 2011)	Acoustics	Noise	Signal Processing	Pest	General
TokihiroFuka (Fukatsu et al., 2012)	pheromone trap monitoring for pest counting	Image Processing	Image Processing	Bug	Rice
Ferro, E (Ferro et al., 2014)	WSN based snail pest detection to reduce the	Photoelectric Sensor	Motion detection	Snail	General

	pesticide usage				
Wei, Yan Ling(Wei & Lin, 2009)	The non-linear pest detection model	Image processing	Fuzzy RBP Neural Network		General
Tripathy, A. K. et al., (Tripathy et al., 2011)	Finds relationship between weather and pest/disease	WSN weather and Surveillance	Weather	Thrips and Bud necrosis	Cotton
Materne, Ntihemuka(Materne & Inoue, 2018)	IoT assisted farmland monitoring	Regression, correlation	Logistic regression	Diseases	Plant
Collier, R. H. (Collier, 2016)	Proposed Model of pest prediction	Models	Pest and disease predictions	Disease and pest	General
Syarif, Iwan(Syarif et al., 2018)	Information system to identify	Statistical methods	Statistical approach	Disease and pest	Corn

	the causes of productio n loss in agricultur e				
Liu, Gang (G. Liu et al., 2005)	Disease prediction using the neural network	Backpropag ation neural network	Machine Learning	Ringspot disease	Fruit disease
Patil, Jyothi (Patil & D. Mytri, 2013)	Pest prediction of the cotton crop	Analytical	Multilayer Perception neural network	Thrips	Cotton
ShanmugaPriya.S(S & Abinaya.M, 2018)	Pest prediction in cotton using clustering technique	Statistical technique on weather conditions	Co-relation	Thrips	Cotton
Arnaud S. R. M. Ahouandjinou(Ahou andjinou et al., 2017)	Pest identificat ion and	Acoustics	Ultrasonic sensor to detect	Maroca	Maroca Culture

	anticipate their attack		sound		
Shang, Yu and Zhu, Yating(Shang & Zhu, 2019)	Proposed an intelligent model of pest prediction	Artificial Neural Network	Machine Learning	Disease and Pest	General
Lee, Haemin(Lee et al., 2017)	Weather-based pest prediction on the bases of co-relation	Weather and pest population correlation	Co-relation	Disease and Pest	Orchids
Paul Boissard(Boissard et al., 2008)	Automated disease detection in horticulture plants	Vision	Image Processing	Roses Disease	Horticulture crops
Raghavendra, K. V.(Raghavendra et al., 2014)	Weather-based pest prediction	Statistical Analysis	Multiple Linear Regression	Thrips, Aphids, Jassid,	Cotton

	in cotton using Statistics analysis		Model	White Flies	
Otoniel López (López et al., 2012)	Pest trap monitoring system to detect the occurrence of pest and performance of the trap	Vision	Image processing	Pest	General
Tripathy, A. K. et al.,(Tripathy et al., 2014)	Correlation between weather and pest/ diseases	WSN	Statistical	Leaf spot	Ground Nuts
Liu, Jun, and Wang(J. Liu & Wang, 2020)	Deep learning-based tomato disease	Vision	Deep Neural Network	Tomato Disease	Tomato

	detection				
Chen, Xianyi(X. Chen et al., 2012)	Energy-efficient WSN crop field monitoring by using the electrolyte characteristics of the plant	WSN monitoring	Energy-efficient Crop field monitoring	WSN	General
Li, Ting (T. Li et al., 2008)	Vegetable pest detection	Vision	Semi-Supervised Machine Learning	Flea Beetle	Vegetable Crops
BratislavPredic(Predic et al., 2018)	Weather-based disease prediction in fruits	Weather-based prediction	Data Minning	Disease	Fruits
Araby, Alaa Adel (Araby et al., 2019)	Detection of unhealthy	Monitoring using the IoT	Machine learning	Pest and disease	Tomato and Potato

	plants using the WSN and intelligent model				
Damos, Petros (Damos & Savopoulou-Soultani, 2012)	Mathematical model of insect and pest development	Statistical and Mathematical	Mathematical model	Pest	General

After a comprehensive literature review, it is observed that many pest detection and prediction proposed in recent years. Most of these approaches use vision-based and acousticstechnology. The use of the different approaches is elaborated in **Error! Reference source not found.**. *These studies are also categorized based on disease and pest identification. The ratio of the disease and pest identification is given in Figure 3-1: The ratio of use of different approaches for pest detection and prediction*

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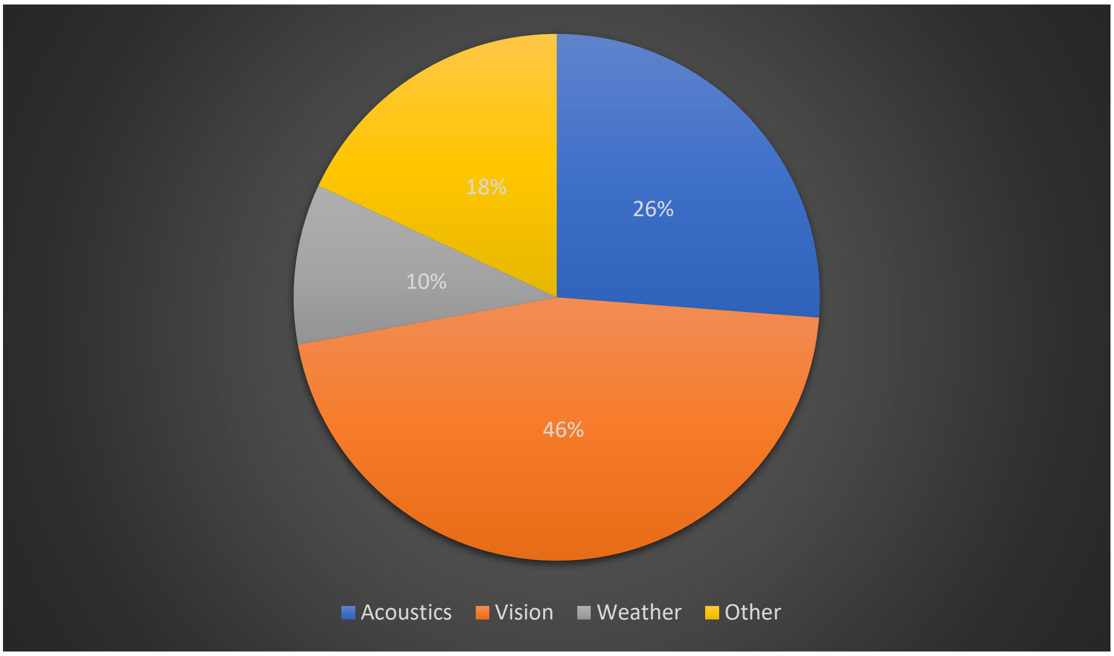

Figure 3-1: The ratio of use of different approaches for pest detection and prediction

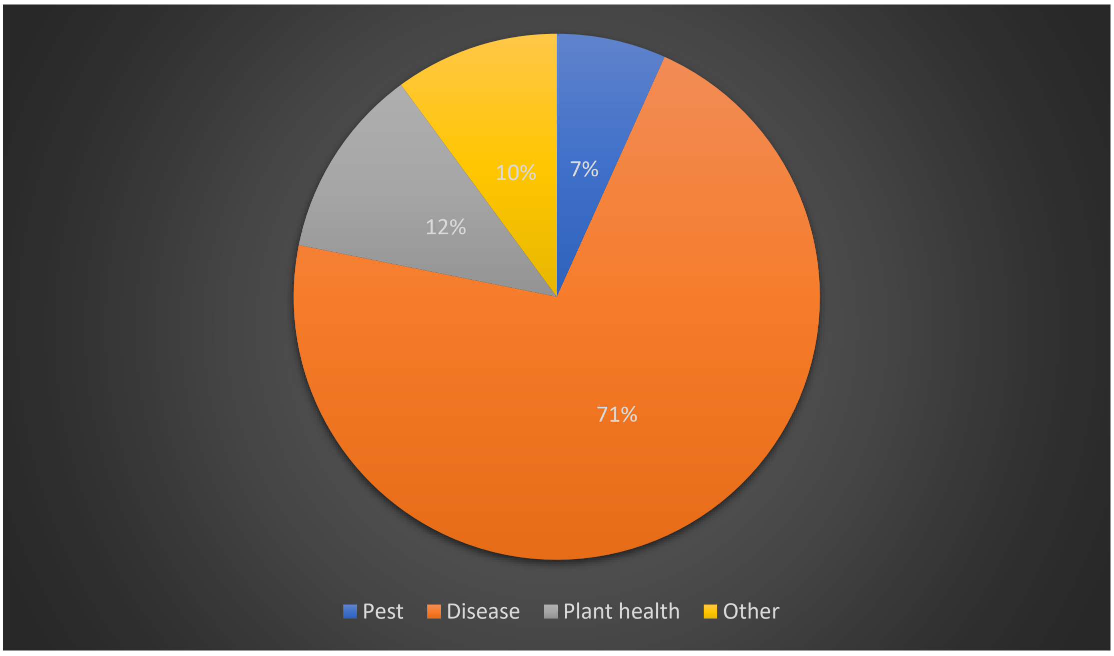

Figure 3-2: Categories of the percentage of disease and pest identification methodology

The study utilizes the straight sensed crop field atmosphere conditions for the pest attack forecasting in Sugarcane crops is never earlier suggested.

The vision-based disease and pest detection only identify the problem upon the occurrence of infestation of the disease and pest. The solution of the occurrence of invasion is mandatory before the well-organized control occurrence of pest and disease.

CHAPTER 4 MATERIAL AND METHOD

This chapter intends to present the proposed model of borer attack prediction by directly sensed environmental conditions and machine learning. The flow chart of the proposed solution is also given. The machine learning model, the IoT architecture, and implementation of the proposed solution is also discussed in this chapter.

4.1 Model of the sugarcane borer attack prediction

Almost all crops are susceptible to some pathogens that can have substantial impacts on their productivity. On the other hand, insects are very complex species with a complex life cycle. The growth of the pest population is at each life cycle stage is heavily affected by environmental conditions. Pest population forecasting, predictions, and early warning define pest growth to the environmental conditions. The pest population prediction based on environmental conditions is very important for Integrated Pest Management activities. The output of the model can be used to guide farmers regarding crop management, effective pest control strategies implementations, and the development of national policy against the pest attack. The proposed model also helpful for the farmers to reduce costs, judicious use of the resources, and support sustainable developments in agriculture. The additional advantage of the proposed model is the judicious use of pesticides that would help reduce the environmental impacts.

The model of pest prediction is proposed to be used with IoT and machine learning potentials. This model is designed to facilitate pest prediction by the machine learning approach. The pest prediction model using machine learning can be applied to any pest for any crop. The model is based on eight steps from pest and crop selection to field validations using the field observations. The eight sections of the proposed model are depicted in Figure 4-1.

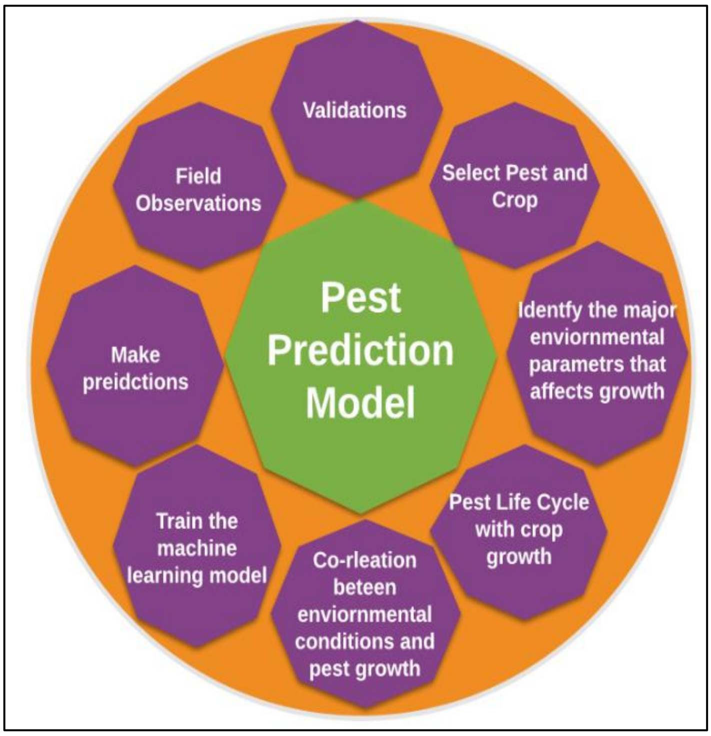

Figure 4-1: Model of Pest Prediction

The model initiates with the selection of pest and crop. Each pest has a different life cycle and etiological conditions. Pest and crop relationship is also different with each crop. The pest attack on different crops is of different nature that needs to consider. After the selections of crop and pest and the impacts of the pest on the crop have been identified, the etiology of the pest needs to understand. The next step is to identify the environmental conditions that have impacts on the life cycle and population of the pest. Some insects are affected by temperature and some by humidity. Some insect pest population is affected by both temperature and humidity. Temperature, humidity, rainfall, windspeed, wind direction, the light intensity is the major influencing factor for certain pest populations.

Once the influencing factors for pest have been identified, the pest life cycle and impacts on crop need to be identified. Some pests affect at larva stage and some at the latter stage. What is the extent of damage pest can make and how pest can affect plant growth, are the important considerations for the model? The economic threshold level of the pest also needs to be identified at this stage. For example, the temperature from 33-38 ^{o}C is favorable for most of the pests and above or below this temperature, the pest cannot grow well. The correlation between pest population and environmental conditions is essential to identify.

The data identified in the previous steps is used to train machine learning. The relationship between pest growth and pest populations hard to define and needs to draw data-driven decisions. The data-driven decision is made using the machine learning model. The initial steps of the proposed model are used to train the machine learning model. The previous steps in the model aim to develop the precise machine learning model for the pest prediction. The model is used to predict the pest population using the environmental conditions. The field observations are made to compare the predictions made by the machine learning model. The field observations and predictions are used to validate the proposed pest prediction model.

4.2 Flow Chart of the sugarcane borer attack prediction

The pest prediction starts with daily observation of environmental conditions from the crop field. Then the daily related observations are arranged into mean weekly environmental conditions to make weekly predictions. The weekly environmental conditions are fed into a machine learning model to make predictions about a particular pest. These predictions are displayed to the user through appropriate applications. The predictions are also validated using the field observation. The field observations are compared against the predictions. The result of the field observations is fed into the machine learning model to strengthen the model in both in case of true and false prediction is made.

The step-by-step working of the pest prediction by the proposed model is shown in the flow chart depicted in Figure 4-2. The pest prediction flow chart shows the start of the prediction with the daily environmental conditions. The step-by-step prediction and validation of the model are shown in the flow chart. The flow chart also shows how the machine learning model is trained with time by field observation. The predictions are also made available to the user using the appropriate platform or for use in the application.

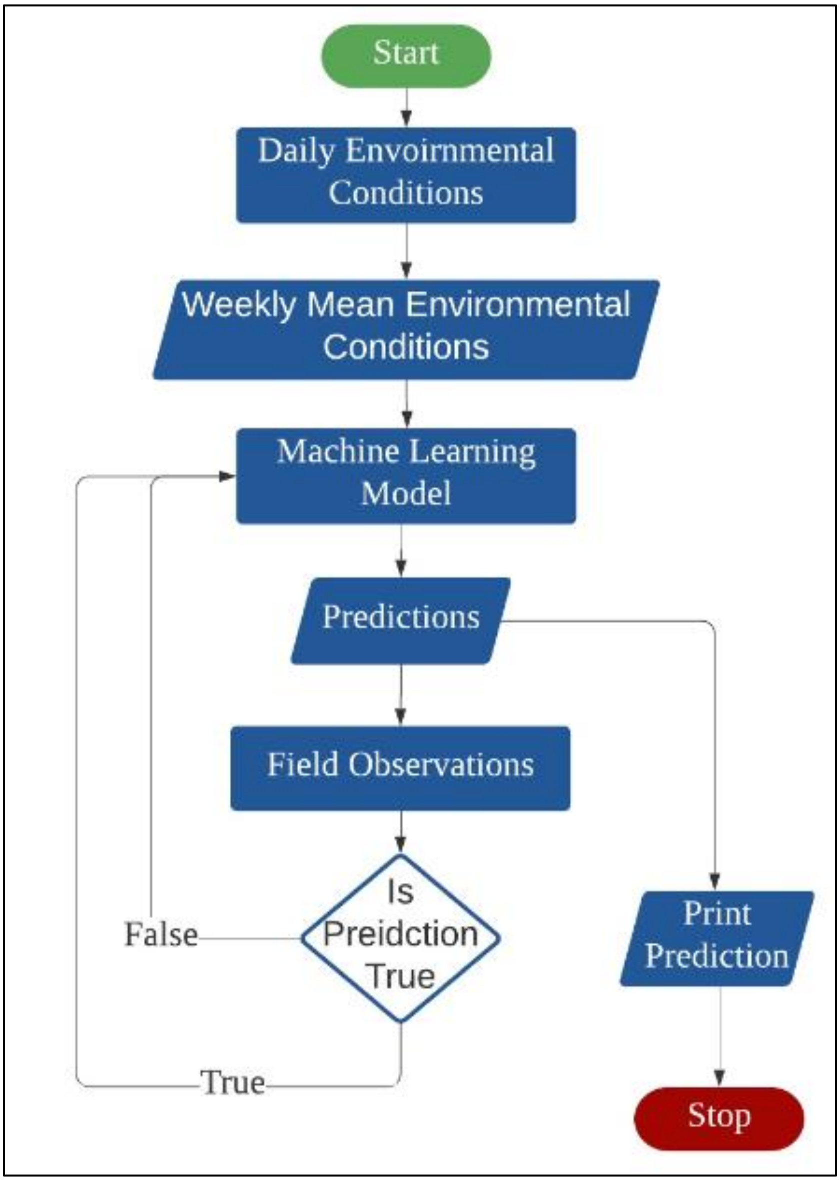

Figure 4-2: Pest prediction flow chart

4.3 Classes for Machine learning model

The predictive feature classes are humidity, temperature, rainfall, and windspeed shown in Table 4-1, Table 4-2, Table 4-3, and Table 4-4. Each parameter class arranges into low, intermediate, and high values. The values of these parameters are given according to the appropriate units for that parameter.

Table 4-1: Humidity classes

Humidity (% age)	
Low	<40
Intermediate	40-60
High	>60

Table 4-2: Temperature classes

Temperature (°C)	
Low	<30
Intermediate	30-35
High	>35

Table 4-3: Rainfall classes

Rainfall (Millimeter)	
Low	<2.5
Intermediate	2.5-7.6
High	>7.6

Table 4-4: Windspeed classes

Windspeed (Miles per second)	
Low	<20
Intermediate	20-40
High	>40

Table 4-5: Pest Prediction Classes

Pest attack prediction (% of the crop)

Low	<15
Intermediate	16-30
High	>30

The python sciket learn library is utilized for the expansion of a machine learning model. The input figures are dividing wall into guidance and test datasets in the ratio of 80:20. The yellow brick collection of python is utilized for the assessment of the machine learning model.

The relationship among the pest inhabitants and environmental situation are mottled in environment and unbreakable to explain. This would craft the complexity hard and data-driven machine learning facilitate verdict are designed. Naïve Bays is functional as a machine learning algorithm for a machine learning model of pest forecasting. The naïve Bays model is based on the Bays theorem of the provisional probability that the prospect of a juncture is based on the before now transpire incident given by Equation 4-1.

$$P(t|S) = \frac{P(S|t)P(t)}{P(S)}$$

Equation 4-1: Conditional Probability Bays theorem

Where t and S are the events and P(t) is the probability of event t, P(S) is the probability of event S, P(S|t) is the evidence and P(t|S) is the posterior probability given that evidence has occurred. The naïve Bay model is selected for implementation purposes due to the following reason.

1. It can give an idea about much precision with fewer data for the training set.
2. Temperature, humidity, and rainfall have an independent impact on pest populations, and Naïve Bays work best when data independence survive in forecaster variables.

The evidence is partitioned into independent classes by Equation 4-2, Equation 4-3, and Equation 4-4.

$$P(t|s_1, s_2, \ldots \ldots .. s_n) = \frac{P(s_1|t)P(s_2|t) \ldots P(S_n|t)P(t)}{P(S)}$$

Equation 4-2: The conditional probability with partitioned evidence

$$P(t|s_1, s_2, \ldots \ldots .. s_n) = \frac{P(t) \prod_{i=1}^{n} Ps_i}{P(S)}$$

Equation 4-3: The conditional probability with partitioned evidence

$$y = argument_y P(t) \prod_{i=1}^{n} Ps_i$$

Equation 4-4: The highest probability for y

The highest probability for “y” is taken byEquation 4-4.

4.3.1.1 MachineLearning Model

The planned resolution is for the reason that the pest borer population grows healthy in far above the ground temperatures and small humidity. The borer attack on sugar make bigger with the lift up of temperature and with the decrease of humidity. Rain also decreases the pest inhabitants due to the tragedy of the larva. Temperature, humidity, and rainfall are considerable parameters for the growth of pest populations. Therefore, this parameter is straight acumen from the crop field by the projected architecture revealed in Figure 4-3.

The temperature and humidity are place into average weekly conditions to build weekly forecasting. If the average weekly utmost temperature over 35 C and low humidity with a smaller amount than 40%, relatively the calculation be inclined to be positive otherwise negative(Scri, 2018). Average weekly temperature, average weekly humidity, average weekly windspeed, and maximum weekly rainfall are specified byEquation 4-5, Equation 4-6, Equation 4-7, and Equation 4-8.

$$AverageWeeklyMaximum\ Temperature(Tavg) = \frac{T_{max}}{7}$$

Equation 4-5: Average Weekly maximum Temperature

Where "*Tavg*" is the average weekly maximum temperature, "*Tmax*" is the daily maximum temperature.

$$AverageWeeklyMaximum \text{ Humidity } (Havg) = \frac{H_{max}}{7}$$

Equation 4-6: Average Weekly maximum Humidity

The windspeed of the location is observed in terms of daily maximum windspeed and average daily maximum windspeed over a week by Equation 4-7.

$$AverageWeeklyMaximum \text{ Windspeed } (Wavg) = \frac{W_{max}}{7}$$

Equation 4-7: Average Weekly maximum Windspeed

Where "*Wavg*" is the average maximum weekly rainfall, and "*Wmax*" is the daily maximum windspeed.

The rainfall of the location is observed in terms of daily maximum rainfall and maximum rainfall over a week by Equation 4-8.

$$WeeklyMaximymRainfall(Rmax) = Max_{Rxi}$$

Equation 4-8: Weekly maximum rainfall

Where "*Rmax*" is the weekly maximum rainfall, "*Rxi*" is the daily maximum rainfall.

4.3.1.2 Comparison of other machine learning algorithms

4.4 Proposed Architecture of the solution

The prediction of borer attack is made on directly sensed environmental conditions from the crop field. The IoT architecture for environmental condition monitoring is described in the form of layer architecture. The proposed is based on five layers. These five layers are from sensing, transmission, storage, processing, and the end user. The sensed ecological environment is transmitting to the cloud using the entrance. The data from the make unclear is fed into the machine learning model to make forecasting. The forecasting are put across to the end-users. The flow of information is shown in Figure 4-3.

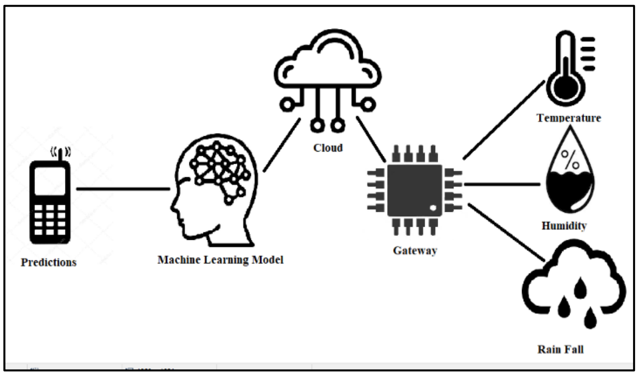

Figure 4-3: Flow of information of Proposed Solution

4.4.1 Sensor Layer

The sensing layer is responsible for the sensing of environmental conditions from the crop field. The sensing layer is based on the different types of sensors for capturing the environmental conditions that are important for the pest population. The most important are the temperature, humidity, rainfall, and windspeed. These sensors at the sensor layer work to collects the environmental conditions from the field.

4.4.2 Data transfer layer

The data from each sensor layer is transferred to the server for storage and processing purpose using the transfer layer. The gateway layer from each sensor node collects data and transfer it to the server. This layer also discriminates the data from each sensing node and transfer it to the server.

4.4.3 Data Storage Layer

The data received from the sensor layer is transferred to the server is stored at the server by using the data storage layer. The data from the sensor is stored for processing purposes. The environmental data and field observations are stored in the database to train and validate machine learning.

4.4.4 Processing Layer

The data received from the sensor is stored and processed to predict the attack of a borer on Sugarcane using the machine learning purpose. The machine learning model is also trained using the data and after observing the field.

4.4.5 End-User Layer

The end-user layer is based on the end-user applications to convey information to the user about the borer attack and the predicted population of the borer on weekly basis. The end-user application is based on the mobile application.

4.5 Implementation

The implementation of the proposed solution is also made to collect data and to make predictions. The sensor used in implementation and prototype development is discussed in this section.

4.5.1 Sensors and Hardware

NodeMCU is utilized as a device hub. The information from the sensor is moved to the Firebase cloud utilizing the NodeMCU device. These sensors and modules are displayed in Figure 4 4..

Figure 4-4: NodeMcu development board

4.5.1.1 Temperature and Humidity Sensor

For execution principle, it is set aside in mind that the cost of the way out should be least amount. DHT22 can find the exact heat/temperature and Moisture/humidity sensor. It is a dependable instrument with a precision of 0.05 in heat/temperature analysis. The DHT22 sensor is shown in Figure 4-5 and its characteristics in Table 4-6.

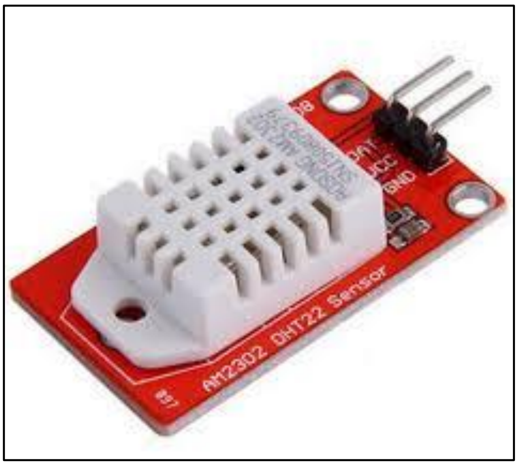

Figure 4-5: DHT22 Temperature and humidity sensor

Table 4-6: Temperature and humidity sensor characteristics

Characteristics	Value
Output	Serial
Range	Temperature -40 ~ 80 ^{0}C Humidity 0 ~ 98
Accuracy	Temperature 0.5 ^{0}C Humidity 10°C ~20°C
Voltage	3.3~5.5

4.5.2 Rain Sensor

This is a lightweight and cheap sensor that is used with an Arduino development board to observe the rain in millimeters. The rain sensor is shown in Figure 4-6 with characteristics in Table 4-7.

Figure 4-6: Rain Sensor

Table 4-7: Rain Sensor Specifications

Characteristics	Value
Output	Serial
Range	Temperature -40 ~ 80 ^{0}C Humidity 0 ~ 98
Accuracy	Temperature 0.5 ^{0}C Humidity 10°C ~20°C
Voltage	3.3~5.5

4.5.3 Wind speed sensor

The wind is also an important factor in the distribution of pests from one location to another. To record the wind, an anemometer is used to collect windspeed from a particular location. The three cups windspeed is used and the voltage is mapped to windspeed by using code signals. The anemometer used for the implementation purpose is shown in Figure 4-7 with the specification in Table 4-8.

Figure 4-7: Anemometer

Table 4-8: Windspeed Sensor Specifications

Characteristics	Value
Output	Serial
Range	0-1023 Voltage Level
Accuracy	0.5
Voltage	5~30 V

4.5.4 Prototype and Deployment

The hardware trial product is in a straight line organized in the crop area to sense the selected environmental circumstances. The developed model is displayed in Figure 4-8. The developed prototypes are deployed in the field to collect real-time data from the field. The field sensor is covered in a protective box to withstand harsh environmental conditions for a longer period. This hardware prototype senses the environmental parameters and transfers the data to the server using the transfer layer. The data at the server is stored and processed by the machine learning model. The machine learning model uses the directly sensed data from the field for the training, testing and prediction purpose.

Figure 4-8: Hardware prototype in the field

The data at the server is processed and stored. Different data analytics capabilities are also added at the server applications to have a quick analysis of the environmental conditions as shown in Figure 4-9. The environmental data at the server can be analyzed by different means using the data analysis module. Environmental parameters data analysis is also shown in Figure 4-10.

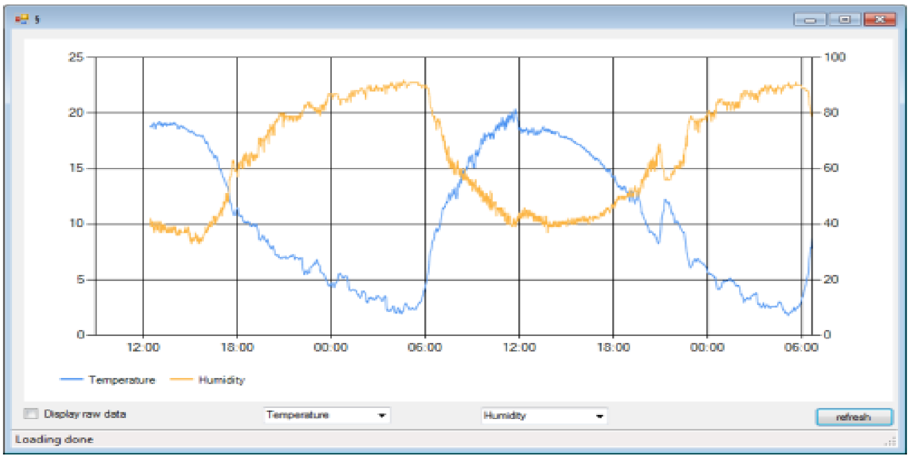

Figure 4-9: Temperature and Humidity data analysis at the server application

Figure 4-10: Environment monitoring dashboard

The server application also allows making configurations and adjustments with the hardware prototypes to streamline the data acquisition from the sensor to the server applications. Figure 4-11 shows the connectivity parameters of the server applications with different sensor modules of the hardware prototype. Figure 4-12, shows the fine-tuning of the environmental parameters from the hardware module.

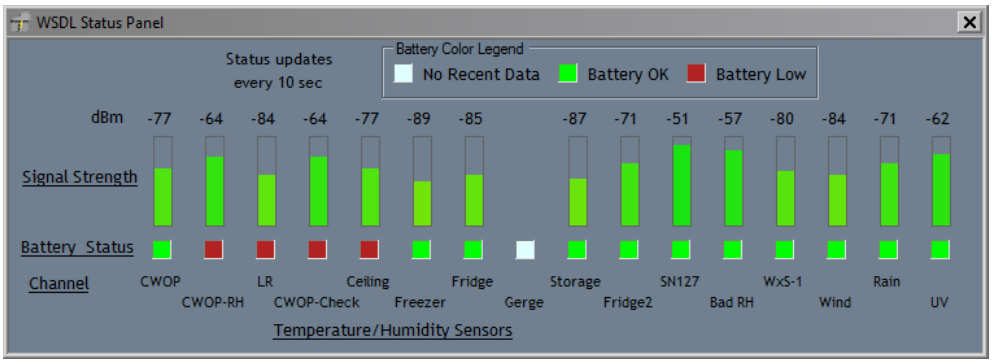

Figure 4-11: Sensor connectivity configuration module

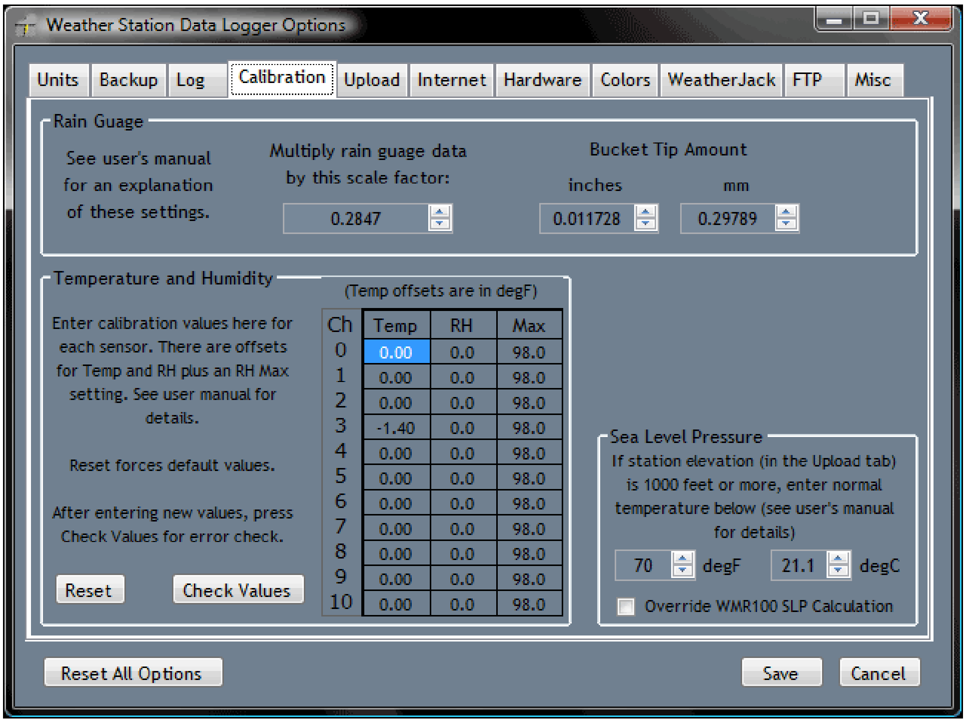

Figure 4-12: Server application configuration

The end users can access the information through the mobile application and can also observe the crop field environmental conditions as shown in Figure 4-13.

Figure 4-13: Mobile application for end-user environmental monitoring

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CHAPTER 5 ENVIRONMENTAL DATA ANALYSIS

The Sugarcane borer is exaggerated by far above the ground temperature and attached with elevated humidity. The boosting of the Sugarcane borer is increased with far above the ground temperature/heat and high moisture/humidity. The rainfall decreases the pest inhabitants therefore it is also used in the forecasting representation and given in this section. The predictions are made on weekly basis, therefore, the average weekly temperature, humidity windspeed, and rainfall are also displayed. The rainfall maximum value for the week is used to predict therefore the weekly maximum rainfall is used in making predictions .Figure 5-1 shows the installation of the prototype in the field for real-time environmental condition monitoring.

Figure 5-1: Installation of the crop field environment monitoring prototype

5.1 Temperature Data Analysis

The pests development is depend on high temperature. The high temperature from 33 to 40 favors the pest population. In Figure 5-2 the temperature in degree centigrade is shown, where it is observed that the summer period from May to

September is favorable for the development of borer attack in Sugarcane. The blue line shows the daily maximum temperature and the orange line shows the average weekly maximum temperature. The average weekly temperature is obtained by Equation 5-1.

$$AverageWeeklyMaximum\ \mathrm{Temperature}(Tavg) = \frac{T_{max}}{7}$$

Equation 5-1: Average Weekly maximum Temperature

Where "*Tavg*" represent the weekly average maximum temperature, "*Tmax*" represent the the daily maximum temperature.

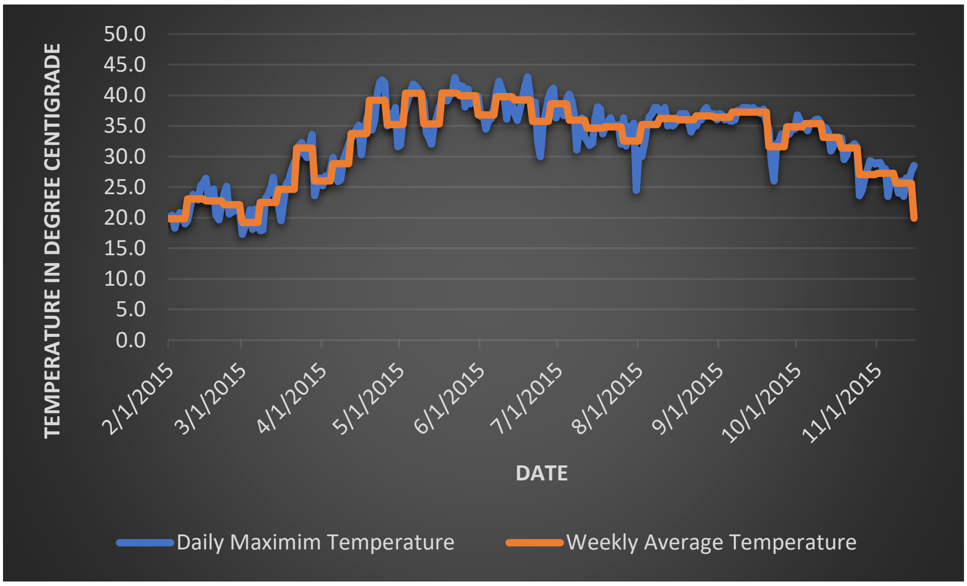

Figure 5-2: Crop field temperature for the year 2015

The temperature for the year 2016 for the selected months of Sugarcane crop is shown in Figure 5-3. The period from April to June is hot and is favorable for the development of the sugarcane borer population above the Economic Threshold Level (ETL). This is the period where the sugarcane borer attack is favorable in the context of temperature. The temperature from April to September can range between 32 to 48 degrees centigrade. The blue line shows the daily maximum temperature and the orange line shows the average weekly maximum temperature.

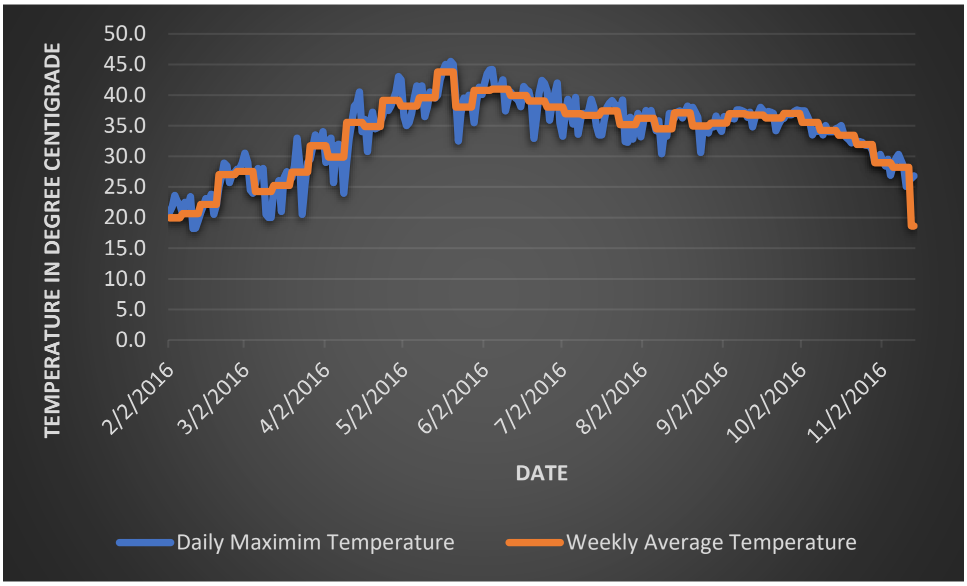

Figure 5-3: Crop field temperature for the year 2016

In Figure 5-4, the temperature in degree centigrade is shown or the year 207, where it is observed that the summer period from April to September is favorable for the development of borer attack in Sugarcane. The blue line shows the daily maximum temperature and the orange line shows the average weekly maximum temperature.

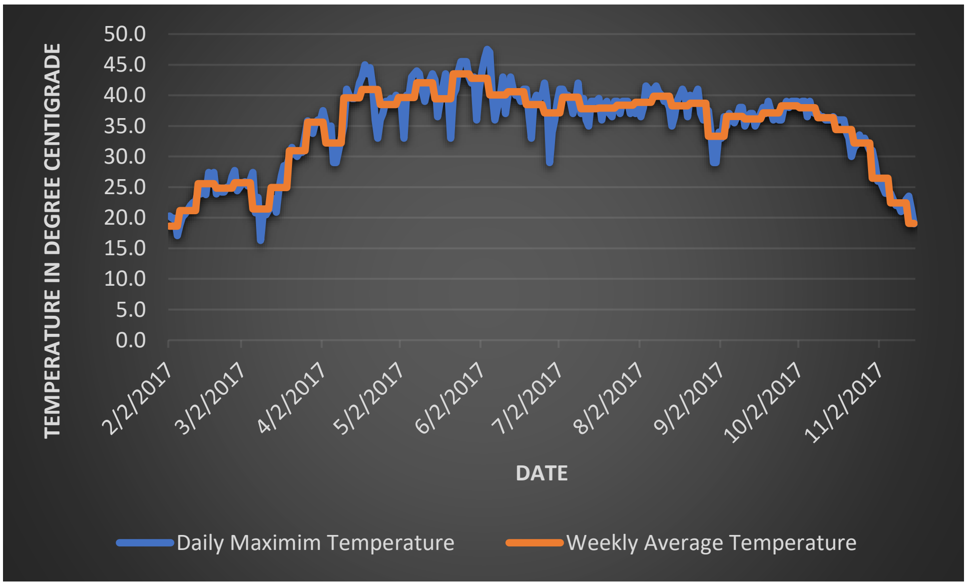

Figure 5-4: Crop field temperature for the year 2017

The temperature for the year 2018 for the selected months of Sugarcane crop is shown in Figure 5-5. The period from April to June is hot and is favorable for the development of the Sugarcane borer population above the Economic Threshold Level (ETL). This is the period where the Sugarcane borer attack is favorable in the context of temperature. The temperature from April to September can range between 32 to 48 degrees centigrade. The blue line shows the daily maximum temperature and the orange line shows the average weekly maximum temperature.

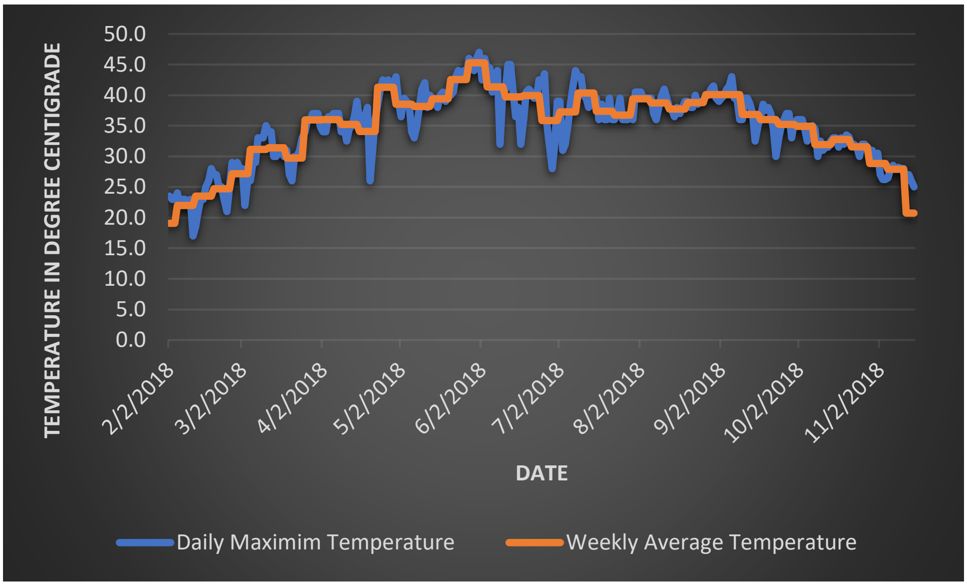

Figure 5-5: Crop field temperature for the year 2018

In Figure 5-4, the temperature in degree centigrade is shown or the year 207, where it is observed that the summer period from April to September is favorable for the development of borer attack in Sugarcane. The blue line shows the daily maximum temperature, and the orange line shows the average weekly maximum temperature.

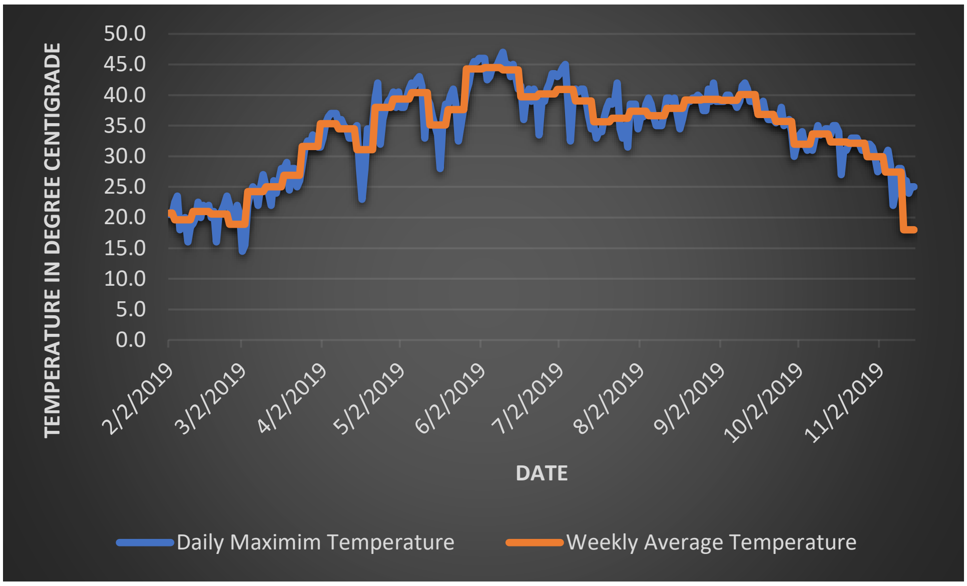

Figure 5-6: Crop field temperature for the year 2019

5.2 Crop field Humidity data analysis

The humidity for the year 2015 for the selected months of Sugarcane crop is shown in Figure 5-7. The period from July to September is humid and is favorable for the development of the sugarcane borer population above the Economic Threshold Level (ETL). This is the period where sugarcane borer attack is favorable in the context of temperature and humidity. 40 to 70 percent is the range of humidity in the month of July to September. The blue line shows the daily maximum humidity, and the orange line shows the weekly maximum humidity level.

$$AverageWeeklyMaximum\ \text{Humidity}\ (Havg) = \frac{H_{max}}{7}$$

Equation 5-2: Average Weekly maximum Humidity

Where "*Havg*" represent the average maximum weekly humidity, "*Hmax*" represents the daily maximum humidity. In the data analysis section, the blue line shows the daily maximum humidity level, and the orange line show the average weekly humidity level.

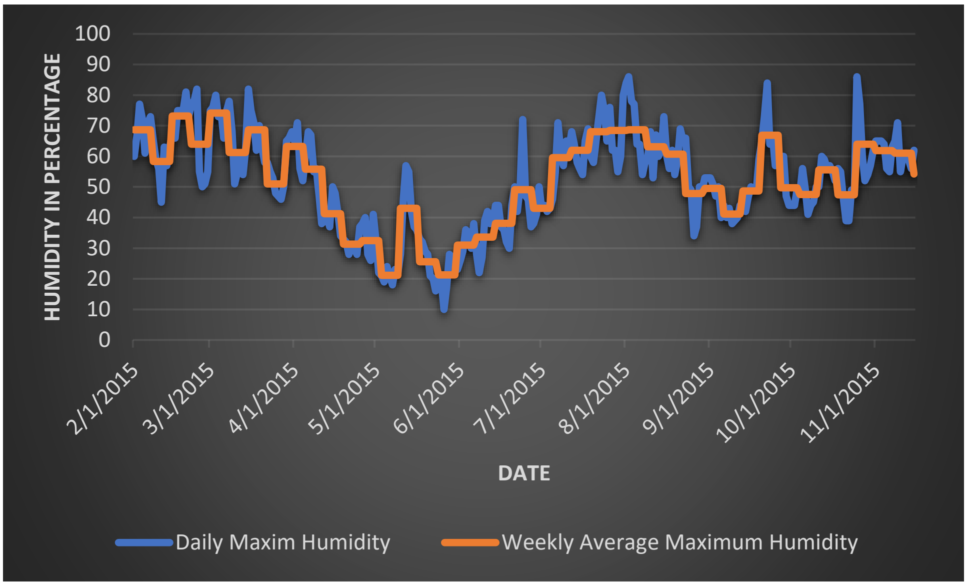

Figure 5-7: Crop field humidity for 2015

The humidity for the year 2016 for the selected months of Sugarcane crop is shown in Figure 5-8. The blue line shows the daily maximum humidity level and the orange line show the average weekly humidity level.

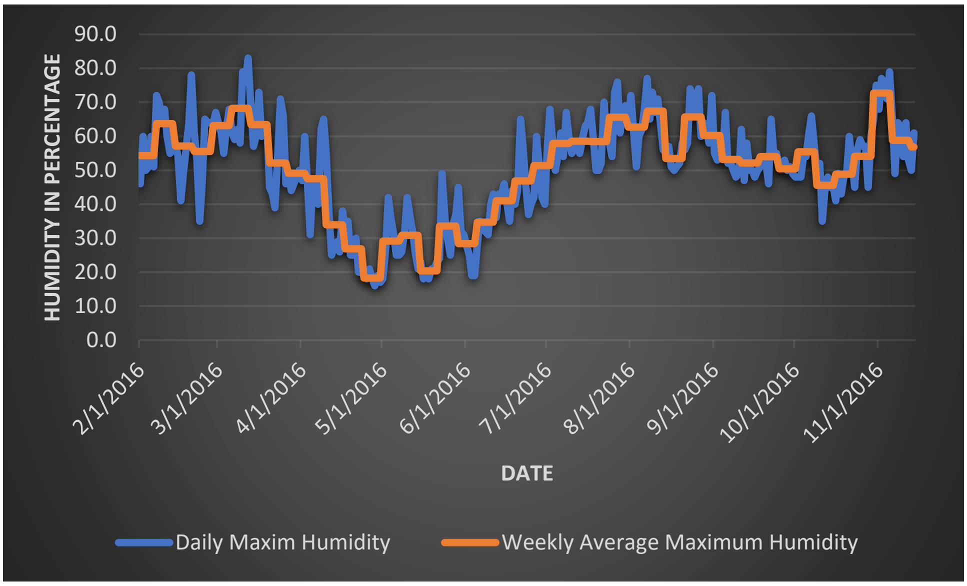

Figure 5-8: Crop field humidity for 2016

The humidity for the year 2017 for the selected months of Sugarcane crop is shown in Figure 5-9. The blue line shows the daily maximum humidity level and the orange line shows the average weekly humidity level.

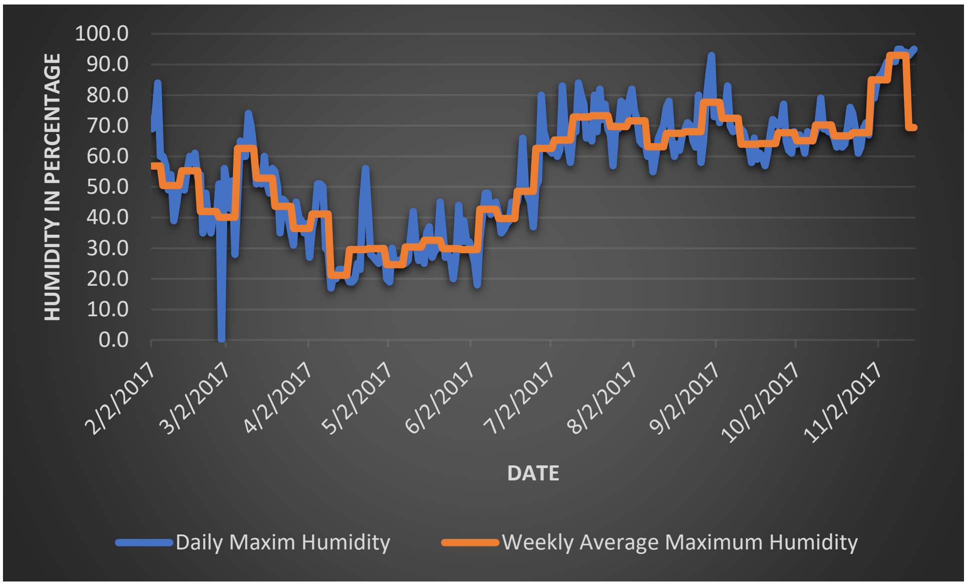

Figure 5-9: Crop field humidity for 2017

The humidity for the year 2018 for the selected months of Sugarcane crop is shown in Figure 5-10. The blue line shows the daily maximum humidity level and the orange line shows the average weekly humidity level.

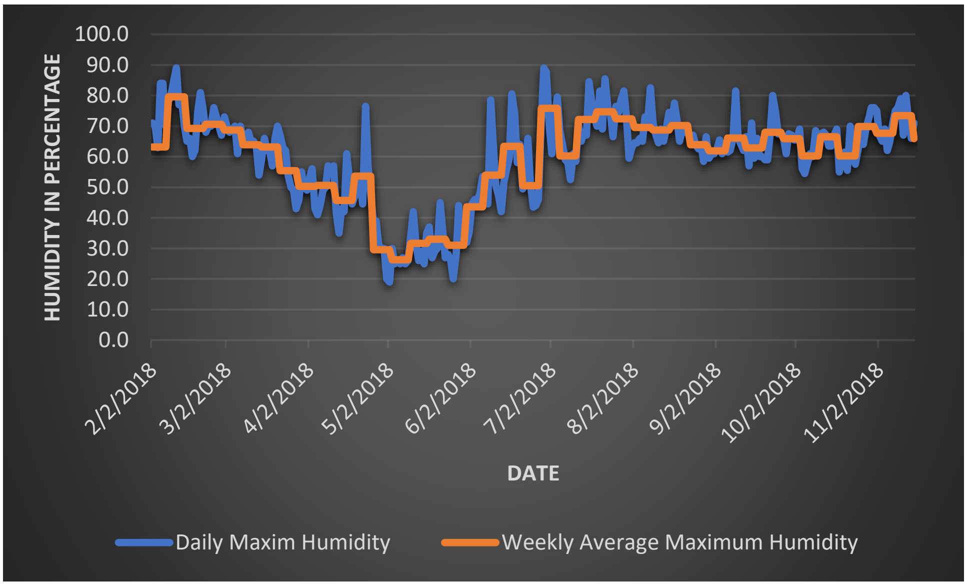

Figure 5-10: Crop field humidity for 2018

The humidity for the year 2015 for the selected months of Sugarcane crop is shown in Figure 5-11. The blue line shows the daily maximum humidity level and the orange line to show the average weekly humidity level.

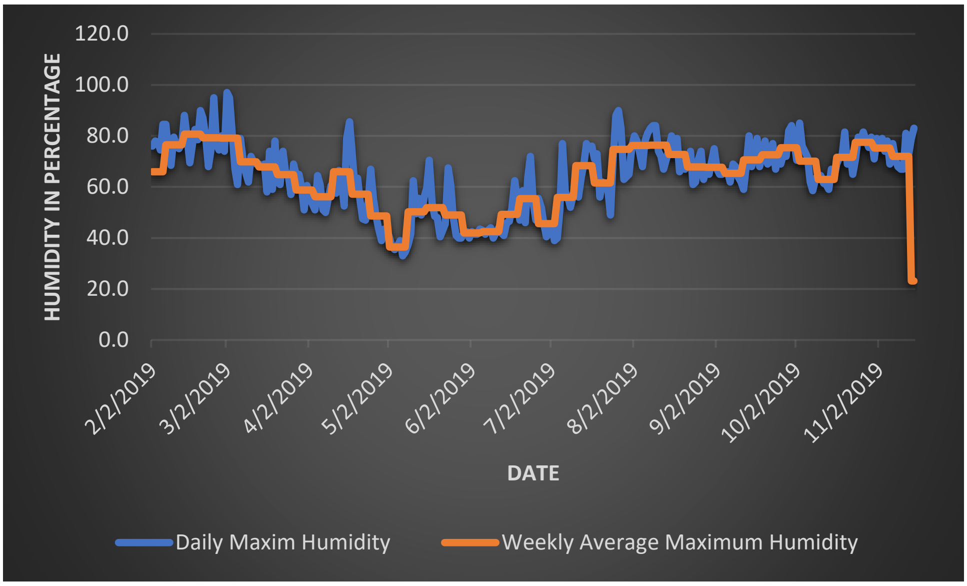

Figure 5-11: Crop field humidity for 2019

5.3 Crop field rainfall data analysis

The daily rainfall and weekly maximum rainfall for the year 2015 are shown in Figure 5-12. The weekly maximum rainfall is given by Equation 5-3. The blue line shows the daily maximum rainfall, and the orange line shows the maximum level of rainfall in the whole week.

$$WeeklyMaximymRainfall(Rmax) = Max_{Rxi}$$

Equation 5-3: Weekly maximum rainfall

Where "*Rmax*" is the weekly maximum rainfall, "*Rxi*" is the daily maximum rainfall.

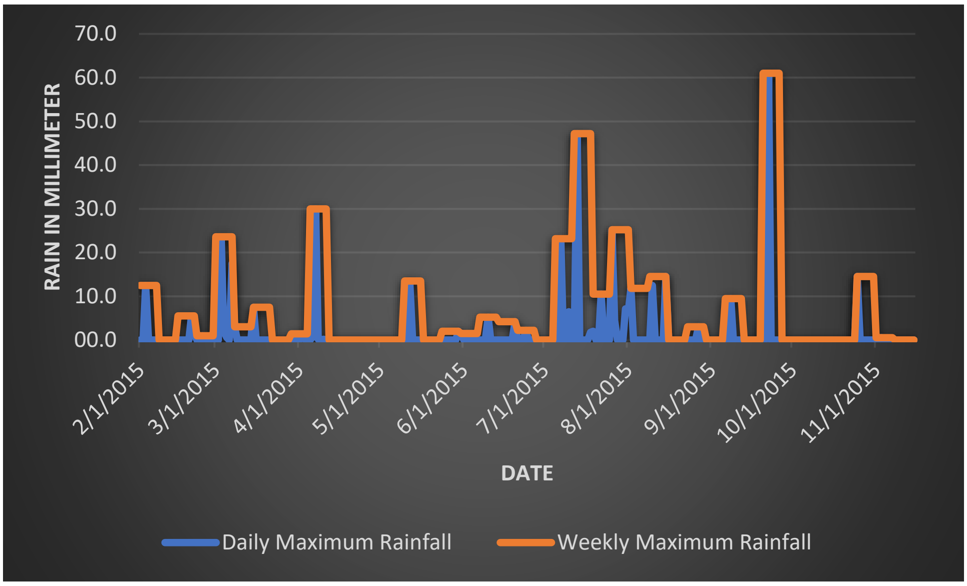

Figure 5-12: Crop field rainfall in 2015

The daily rainfall and weekly maximum rainfall for the year 2016 is shown in Figure 5-13. The blue line shows the daily maximum rainfall and the orange line shows the maximum level of rainfall in the whole week. From the chart, it is observed that July to August is the months with maximum rainfall.

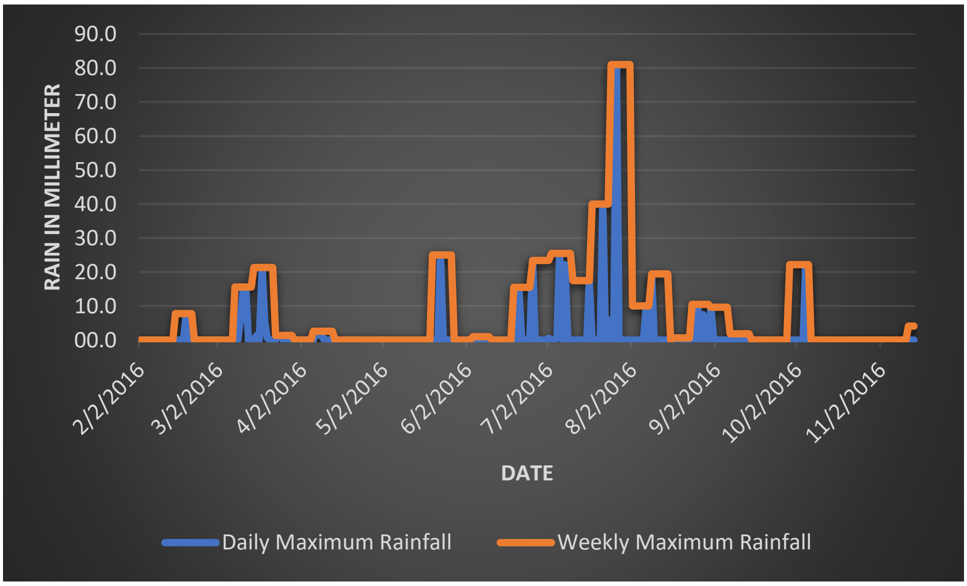

Figure 5-13: Crop field rainfall in 2016

The daily rainfall and weekly maximum rainfall for the year 2017 are shown in Figure 5-14. The blue line shows the daily maximum rainfall and the orange line shows the maximum level of rainfall in the whole week. From the chart, it is observed that July to August is the months with maximum rainfall.

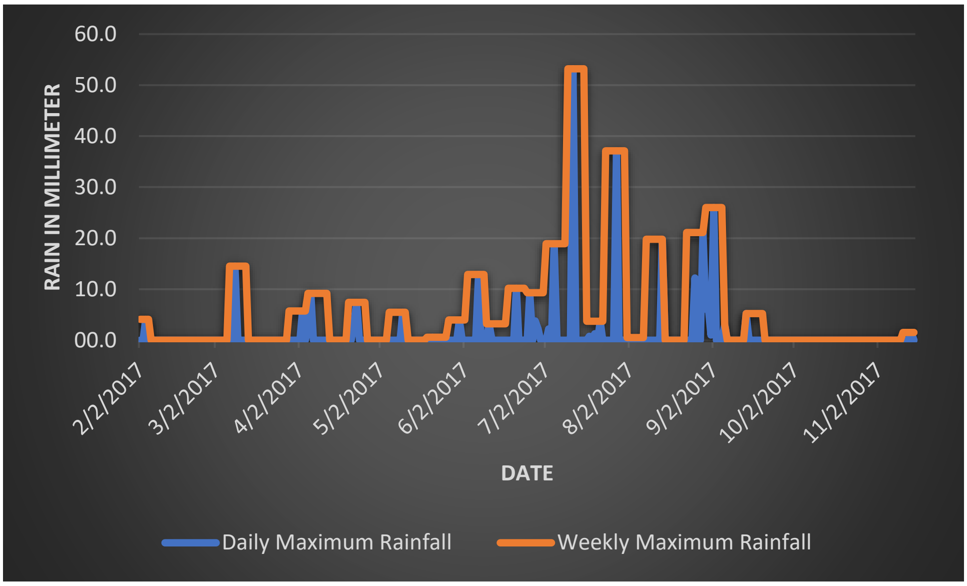

Figure 5-14: Crop field rainfall in 2017

The daily rainfall and weekly maximum rainfall for the year 2018 is shown in Figure 5-15. The blue line shows the daily maximum rainfall and the orange line shows the maximum level of rainfall in the whole week. From the chart, it is observed that July to August is the months with maximum rainfall.

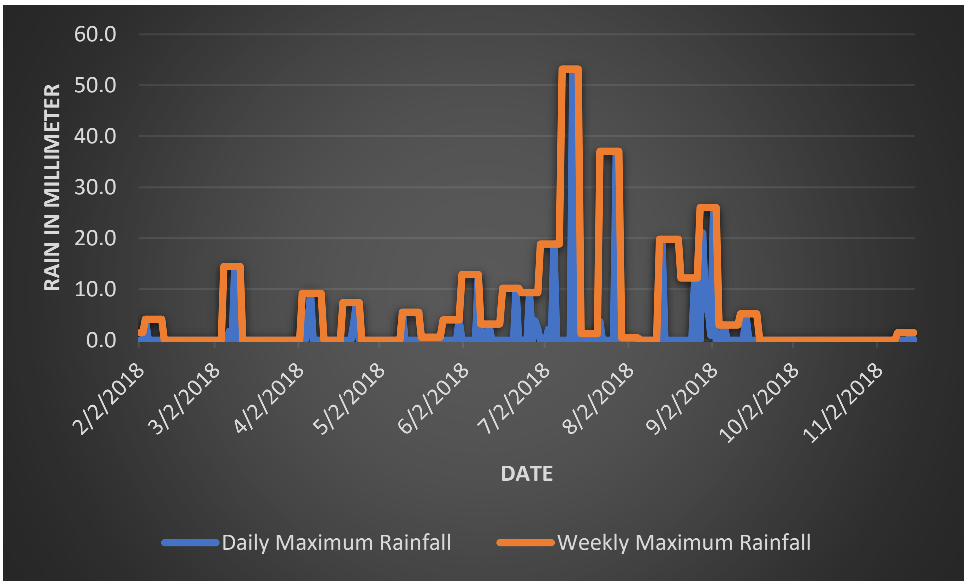

Figure 5-15: Crop field rainfall in 2018

The daily rainfall and weekly maximum rainfall for the year 2019 is shown in Figure 5-16. The blue line shows the daily maximum rainfall and the orange line shows the maximum level of rainfall in the whole week. From the chart, it is observed that July to August is the months with maximum rainfall.

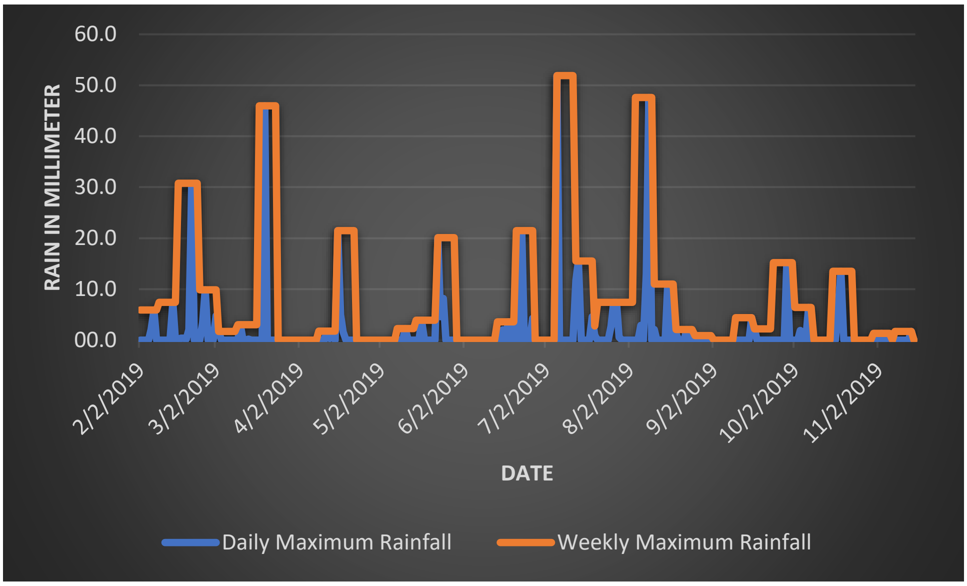

Figure 5-16: Crop field rainfall in 2019

5.4 Crop field Windspeed data analysis

The wind is also an important parameter that affects the growth of pests. Wind play important role in the distribution of the pest moths from one place to another. Wind role in the distribution of the borer attack is very crucial therefore it is considered important for the distribution of the attack from surrounding areas. Daily windspeed along with weekly average windspeed is used to make predictions for the borer attack. The weekly average windspeed is determined by Equation 5-4 where Wxi is the daily maximum windspeed and Wavg is the average weekly windspeed.

$$AverageWeeklyMaximum\ \mathrm{Windspeed}(Wavg) = \frac{Wxi}{7}$$

Equation 5-4: Average Weekly maximum Windspeed

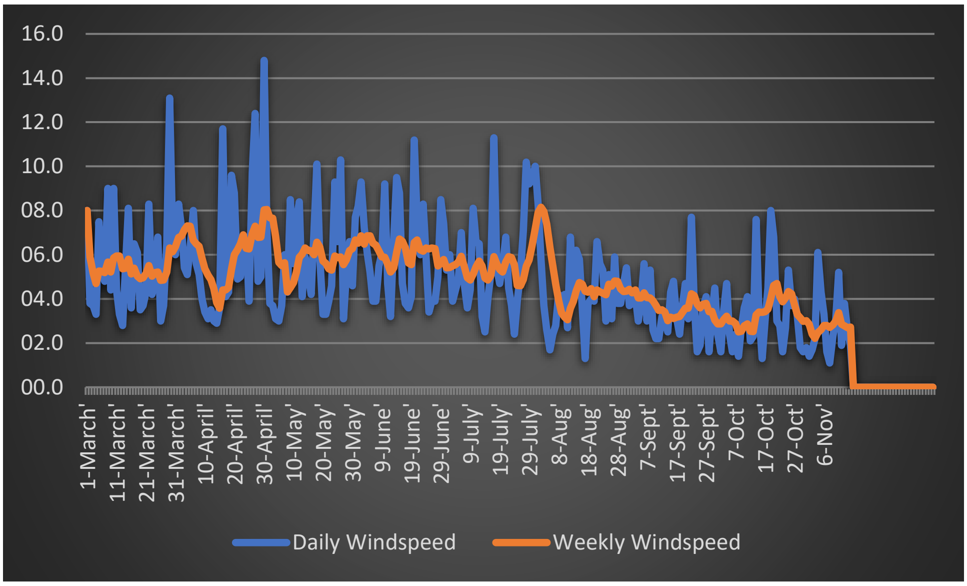

Figure 5-17: Wind Speed data for the year 2015

Figure 5-17 and Figure 5-18 shows the daily windspeed and average weekly windspeed for the year 2015 and 2016. It is observed thatin 2015 the June is with maximum windspeed and in 2016, windspeed is maximum in June. On the general windspeed is high in hot months. Windspeed is maximum before the humidity would be high. This would lead to the distribution of the disease from one area to another before the season is set for hot and humid conditions. In experiment areas the moon soon season start from July where windspeed is lower in the rainy season.

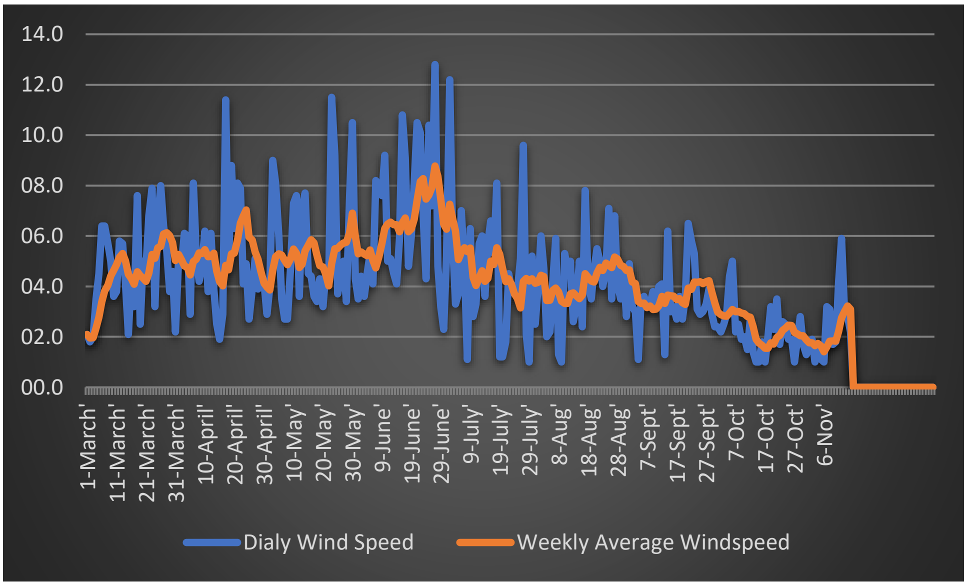

Figure 5-18: Wind Speed data for the year 2016

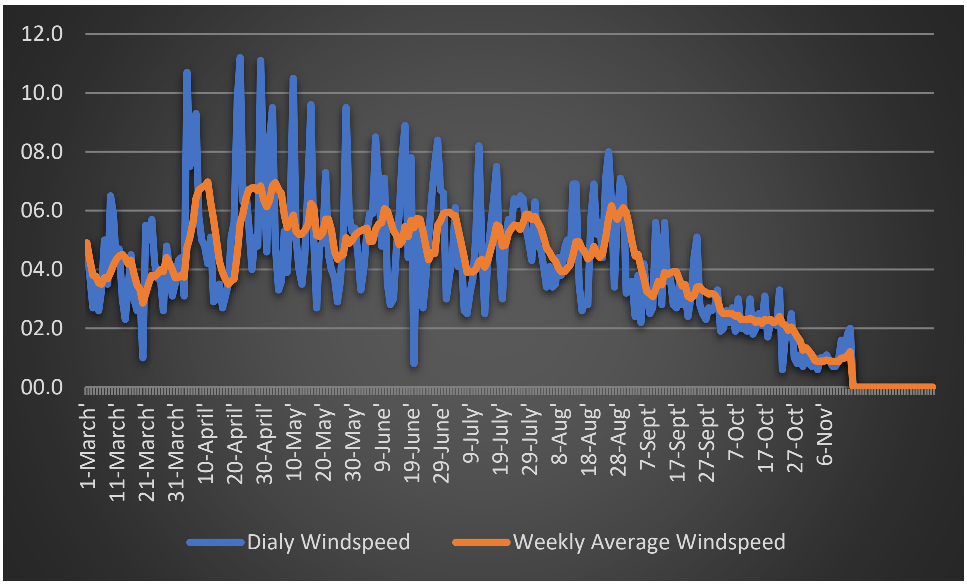

Figure 5-19: Wind Speed data for the year 2017

Figure 5-19 and Figure 5-20 shows the windspeed data for the year 2017 and 2018,respectively. The daily maximum windspeed and average weekly data are shown for both years. In both years the moon season is also with high windspeed that can cause the distribution of pests from the affected field to other areas. The windspeed before the favorable season cause transfer of the pest from the affected areas to the other areas. The windspeed in June tends to rise that can cause the distribution of the disease from one area to another.

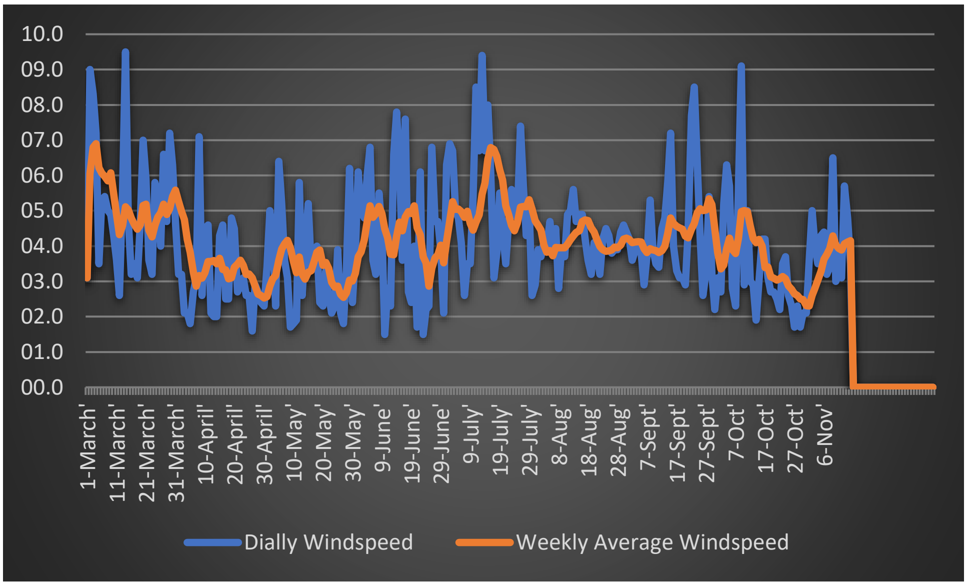

Figure 5-20: Wind Speed data for the year 2018

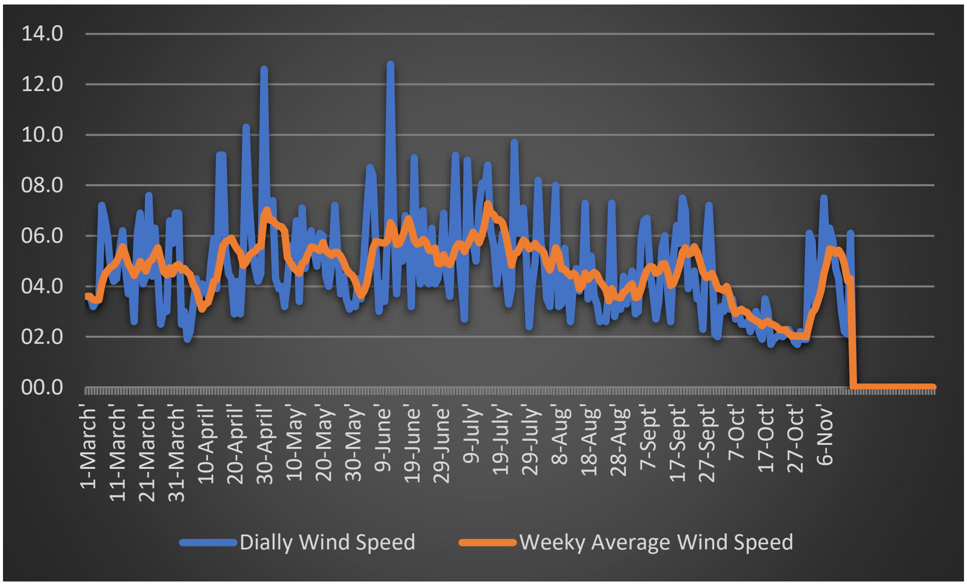

Figure 5-21: Wind Speed data for the year 2019

Figure 5-21 and Figure 5-22 shows the windspeed data for the year 2019 and 2020 respectively. The high windspeed in summer also favors the distribution of the pest from one area to another. Due to the high temperature in April to July the wind is light and hot to move easily from one place to another. The high windspeed just before the rainy season when high temperature and humidity are favorable for the growth of borer is ideal for the spread of the attack over a large area.

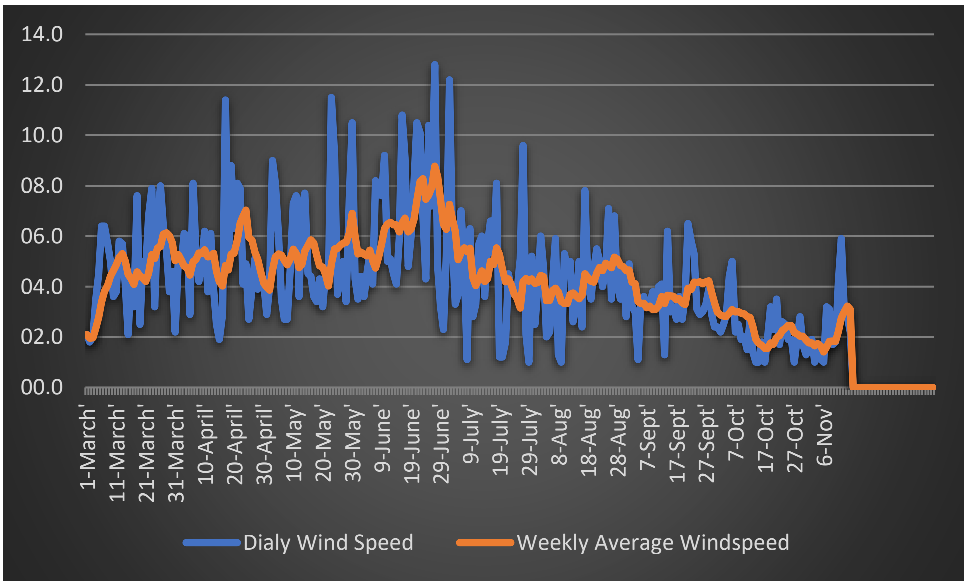

Figure 5-22: Wind Speed data for the year 2020

This machine learning model takes 4 years data in order to preparation. Temperature, humidity, windspeed,and rainfall are the ecological circumstances used to forecasting the borer population development. Every day utmost temperature and weekly average temperature from the year 2015 to 2019 are plotted inFigure 5-23. Daily highest humidity and weekly highest humidity is plotted inFigure 5-24. Daily highest rainfalls and weekly highest rainfall is plotted inFigure 5-25. These ecological circumstances are used to reconcile on the pest population.

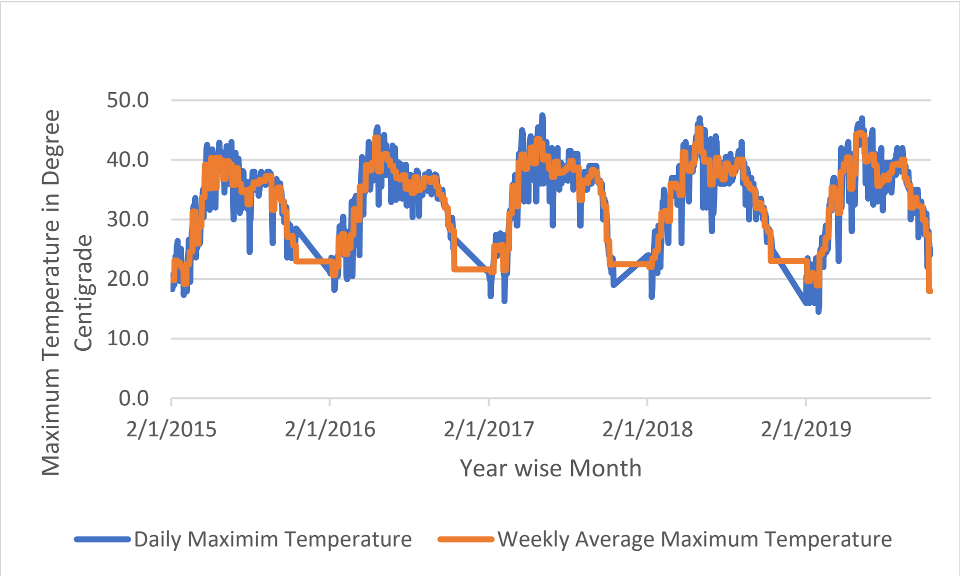

Figure 5-23: Temperature data analysis from 2015 to 2019

FromFigure 5-23, it is experiment that April, May, June, July, and August are the burning months of every year. The temperature tends to reduce from September and reduce slowly in consequent months.

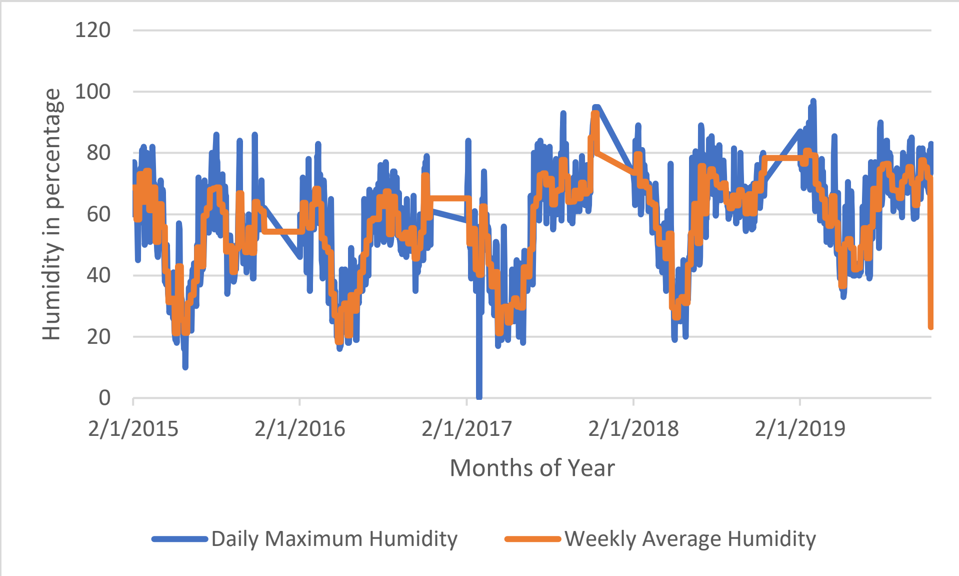

Figure 5-24: Humidity data analysis from 2015 to 2019

From Figure 5-24, it is noticed that humidity is inferior in the months when the temperature is far above the ground in the chosen area. The humidity observation shows a comparable pattern for all years.

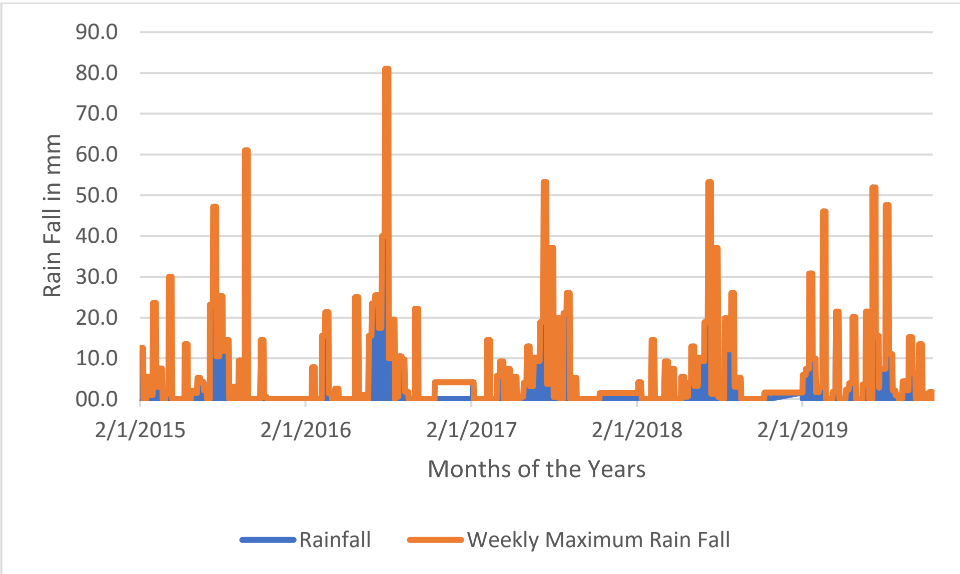

Figure 5-25: Rainfall data analysis from the year 2015 to 2019

FromFigure 5-25, it is noticed that rainfall is lower in the months when the temperature is far above the ground in the chosen area. From the situation, data is experient that April to June are the months when ecological conditions are constructive for the expansion of the borer population. The stem borer cultivate very well in maximum temperatures with low humidity and least rainfall. These months have ecological circumstances that are very constructive for the development of the pest population.

CHAPTER 6 EVALUATION AND DISCUSSION

The chapter intends to evaluate the proposed solution of the borer attack prediction on sugarcane crop. The proposed solution is evaluated on different aspects.

6.1 Comparison of Machine Learning Model

The different machine algorithms have been implemented and the comparison of all implemented machine learning model is given below in table Table 6-1:

Table 6-1Comparison of Implemented Machine Learning Model

ML Algo	**Environmental parameter**	**Accuracy Result**
SVM	Temp, humidity , Rainfall and wind speed	85.6%
Decision tree	Temp, humidity , Rainfall and wind speed	88.9%
KNN	Temp, humidity , Rainfall and wind speed	87.5%
RF	Temp, humidity , Rainfall and wind speed	83%
Linear Regression	Temp, humidity , Rainfall and wind speed	84%
AdaBoosting	Temp, humidity , Rainfall and wind speed	83.4%
Naïve bayes	Temp, humidity , Rainfall and wind speed	91%
RBFN by [Saleem et al 2021]	Temp, humidity , Rainfall and wind speed	82.88%

Naïve bayes by[DušanMarkovi´c et all 2021]	Temp, humidity	75%

The accuracy of the Naïve bayes classifier is high then other classifier as mentioned above table 6.1.

6.2 Evaluation of the machine learning model(Naïve Bayes)

The machine learning model is practiced for its precision, exactitude; bring to mind, and f-measure for its prognostic features. The machine learning model is practiced from the test data locate which is 20 % of the whole data. Precision is the figure of positive forecasting from a positive class and bring to mind is the number of positive forecasting from the whole data set. Compute bala nce the precision and recall measures.. The precision-recall and f-measure for the unrelated projecting features are revealed in the matrix in Figure 6-1.

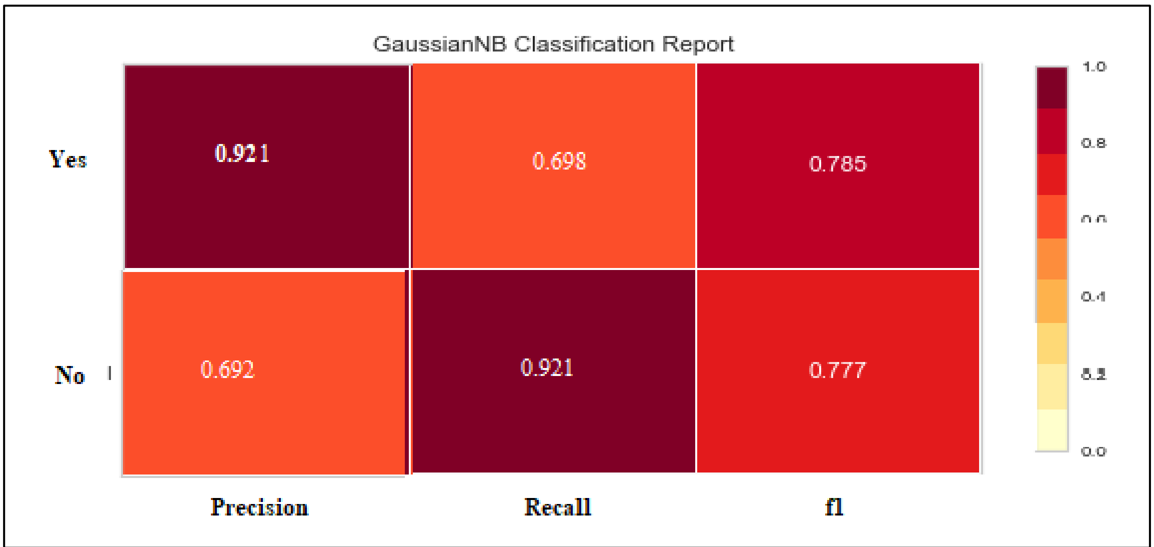

Figure 6-1: Performance matrix of the machine learning model

6.2.1 Accuracy

Accuracy refers to the ratio of correct prediction to the total number of predictions made. The accuracy of the machine learning model is determined from twenty percent of test data and given by Equation 6-1.Machine learning shows 96%

percent accuracy against the test data, 94 % accuracy against the training data set, and 91% accuracy against all the data.

$$Accuracy = \frac{correct\ predictions}{Total\ predictions} \times 100$$

Equation 6-1:Accuracy

6.2.2 Precision

Precision is the measure of the ratio between the true positive (Tp) to the sum of a false positive and true positive. It is also known as specificity.It is said that precision is the ratio of the predictions of the occurrence of borer attack when it is also present in the field (Tp) to the predictions of borer attack when the attack is present (Tp) and not present (Fp) in the field. Precision is given in Equation 6-2 and explained by Figure 6-2. Precision is 0.0921 in case of yes and about 0.692 in case of “No” prediction about borer attack as shown in Figure 6-2.Figure 6-2shows the true positive, false positive, true negative, false-negative for the borer attack prediction as;

Tp: Prediction is true when the borer attack is also present in the field

Tn: Prediction is false when the borer attack is not present in the field

Fp: Prediction is false when the borer attack is present in the field

Fn: Prediction is true when the borer attack is not present in the field

$$Precision = \frac{Tp}{Fp + Tp}$$

Equation 6-2: Precision

6.2.3 Recall

The recall is the ratio of the true positive to the sum of predictions of a true positive and false negative. Both precision and recall are in the range from zero (0) to one (1). The recall is also called sensitivity is given by Equation 6-3. Recall of true predictions is 0.698 and of false predictions is 0.921.

$$Recall = \frac{Tp}{Tp + Fn}$$

Equation 6-3: Recall

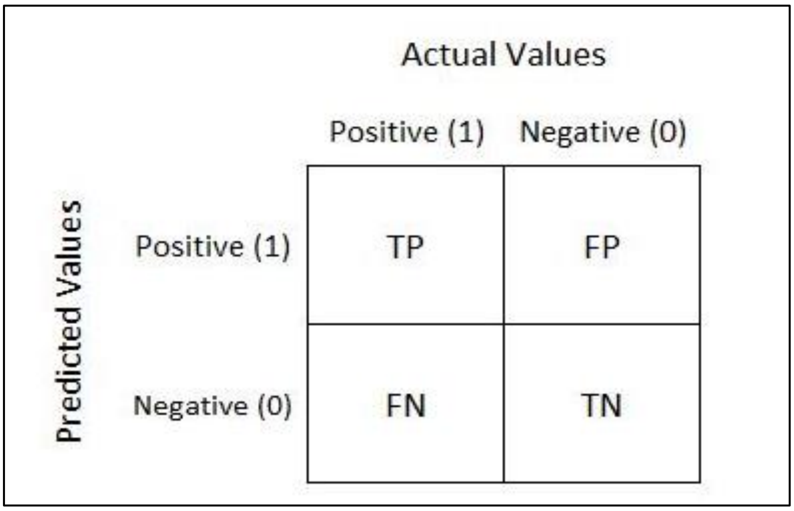

Figure 6-2: Precision and Recall measures

6.2.4 F_1 -Measure

F-measures are used to balance precision and recall. The harmonic mean of precision and recallexpressed by Equation 6-4 is called the F1 measure. The F1-measure of true predictions is 0.785 and of false predictions is 0.777.

$$F_1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Equation 6-4: F1-Measure

6.2.5 Receiver Operating Characteristics (ROC) Curve

ROC is used to model the probability distribution of predictive classes. It plots the False Positive Rate (FPR) against the True Positive Rate (TPR). The area under the curve shows the accuracy of the machine learning model, for the perfect distribution of the predictive class variables. The borer prediction for 'yes' and 'No' classesare plotted in the ROC curve shown in Figure 6-3. The AUC value is 0.96 that shows the perfect distribution of the predictive classes.

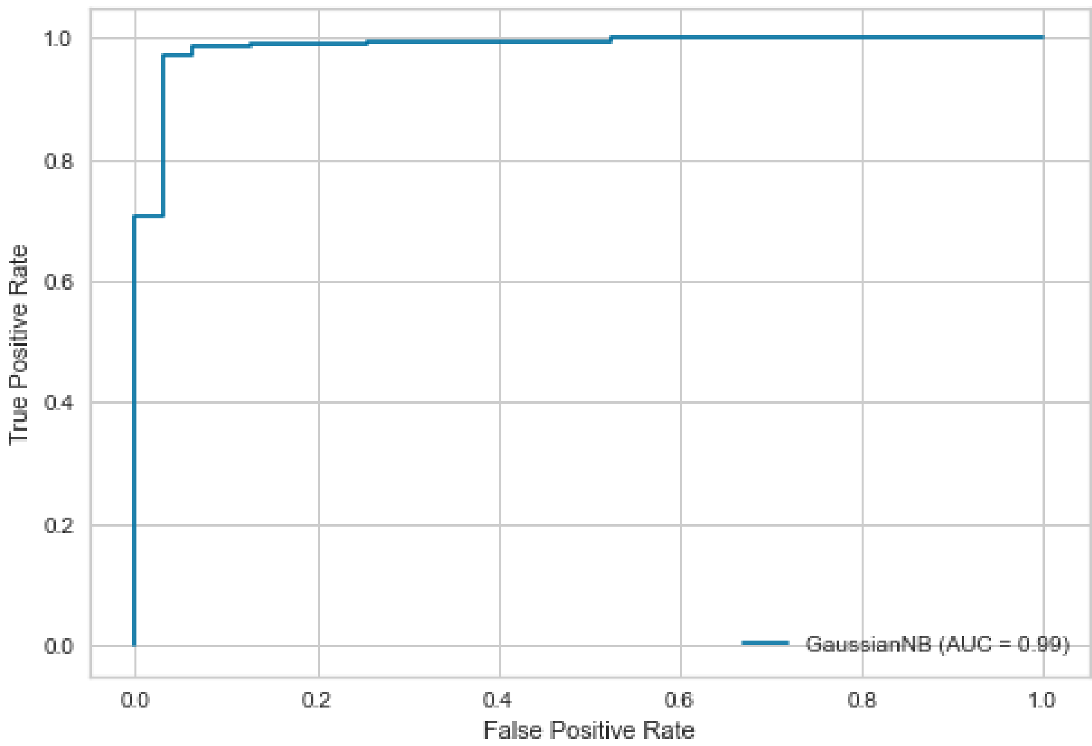

Figure 6-3: ROC Curve for the data

6.3 Evaluation of the proposed borer attack prediction model

The pest finding using the planned method is authenticating alongside the field observations. To scrutinize the field eight acres are chosen. In each acre, one hundred plants are experiential for the assault of borer. If more than fifteen plants out of the experiment plants are exaggerated due to the borer attack the crop is unspecified to be exaggerated, because the Economic Threshold Level (ETL) of the borer is 15% of the plants in one acre of sugarcane. The presence of borer on fifteen percent of the inspected plants is considered above the ETL. The field inspection is done on weekly basis. The field validation is made from 2015 to 2020. In each month four predictions are made. The months are selected from March to November. The accuracy of the prediction is checked against the field observations.

In **Error! Reference source not found.**the pest scouting is performed in the s ugarcane crop. Pest scouting is done every week after predictions are made to validate the prediction model. If the fifteen percent of observed plants are found affected the attack of borer is considered positive. The presence of the larva, moth,or any form of borer life cycle stage is also considered as the presence of borer attack. In the case of a pest is found in the crop, its presence is recorded as the presence of a borer attack.

Figure 6-4: Pest Scouting in sugarcane for borer attack

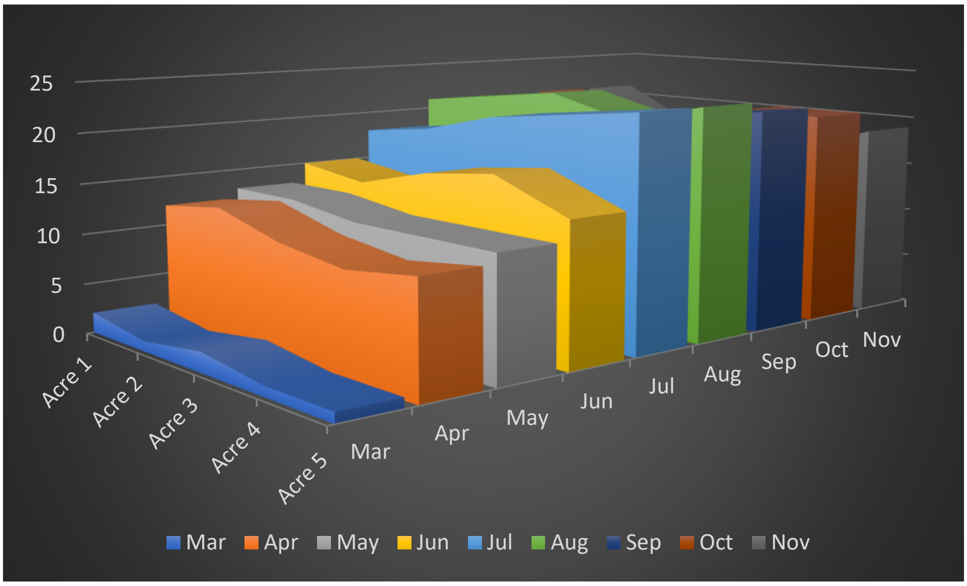

Figure 6-5: Percentage of borer attack in 2015

The borer attack in the crop in the year 2015 and 2016 is shown in respectively. It is observed that attack is more in the months of July, August, and

September when the temperature is united with far above the ground humidity. In March, the attack of borer is not significant as compared to the months when temperature and humidity are higher. The pest population tends to increase from April when the temperature tends to rise and gradually increasesin subsequent months. The borer attack and population are observed maximum from July to September due to high temperature and humidity.

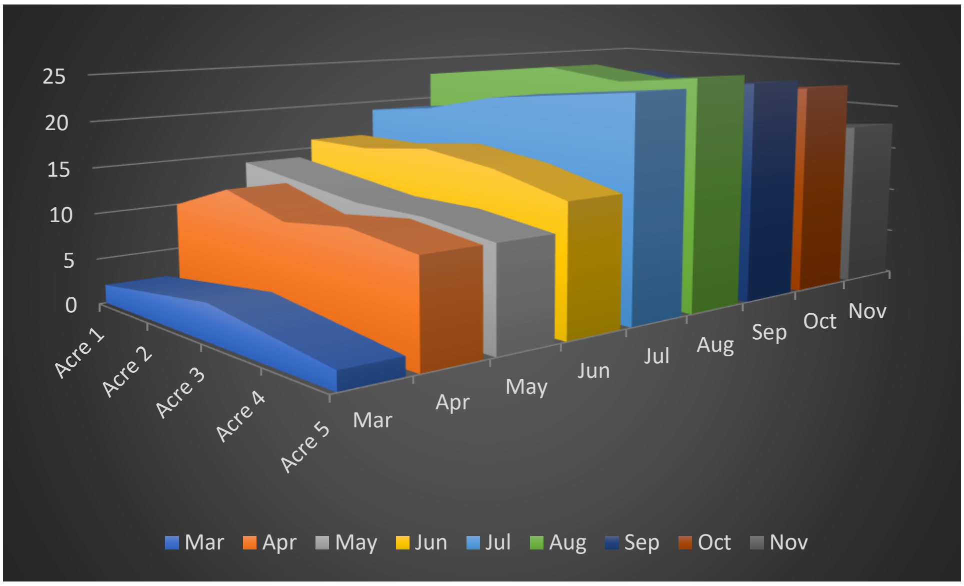

Figure 6-6: Percentage of borer attack in 2016

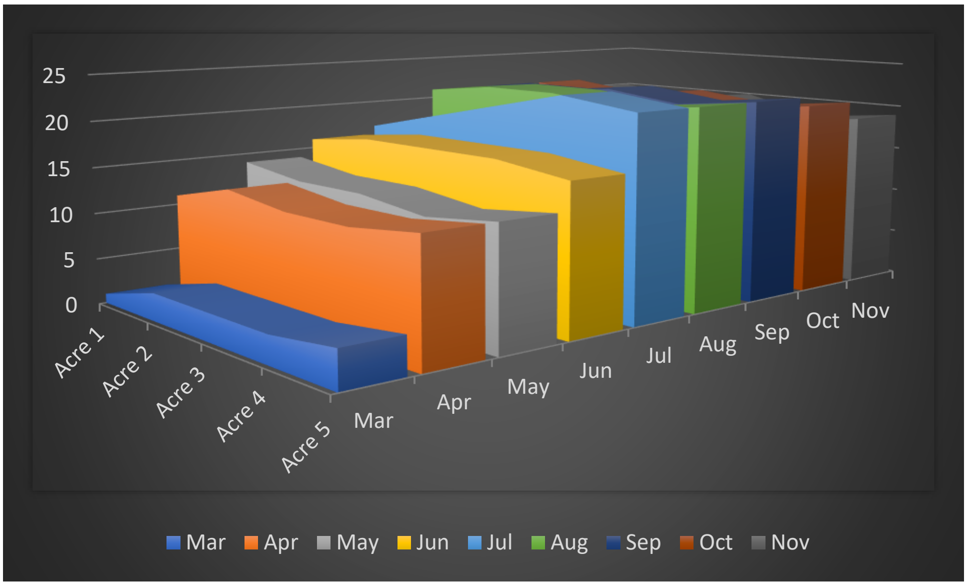

Figure 6-7: Percentage of borer attack in 2017

The sugarcane borer attack observations in 2017 and 2018 are shown in Figure 6-7 and Figure 6-8 respectively. Sugarcane borer attack is minimum in March and tends to increase from April to subsequent months due to an increase in temperature. The borer attack is maximum in July and August due to the existence of high temperature and humidity. July to September are the months with temperature and humidity favorable for the growth of the Sugarcane borer. These years shows observations from March to November, as the Sugarcane crop exists in these months.

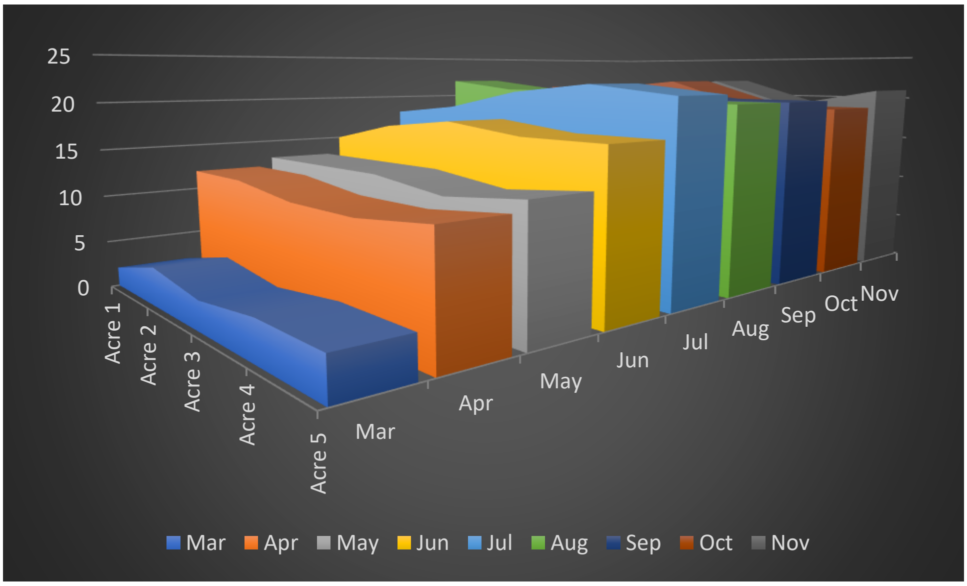

Figure 6-8: Percentage of borer attack in 2018

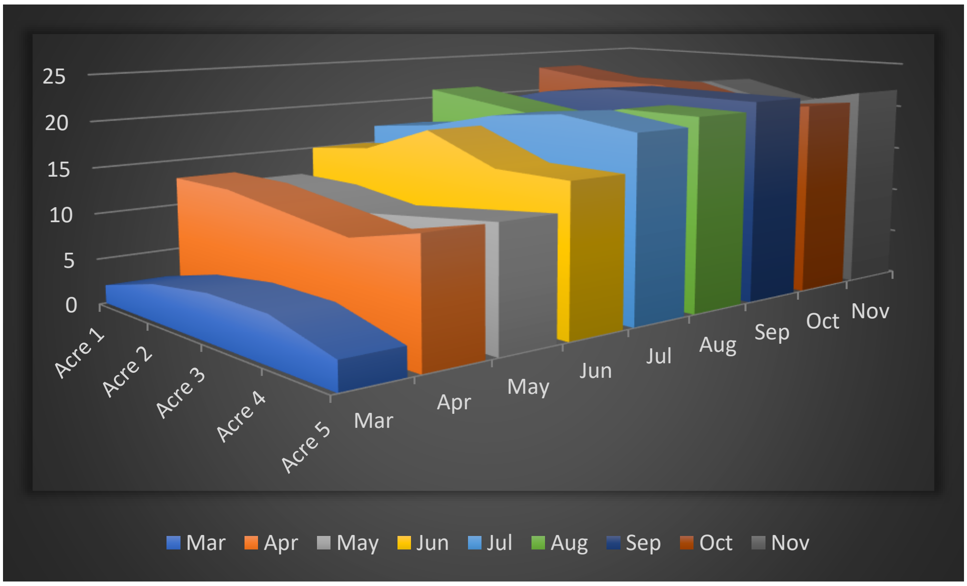

Figure 6-9: Percentage of borer attack in 2019

The borer attack in the crop in the years 2019 and 2020 is shown in Figure 6-9 and Figure 6-10respectively. It is observed that the attack is morevibrant inthe months of July, August, and September when high temperature is coupled with high humidity. In March, the attack of borer is not significant as compared to the months when temperature and humidity are higher. The pest population tends to increase from April to subsequent months.

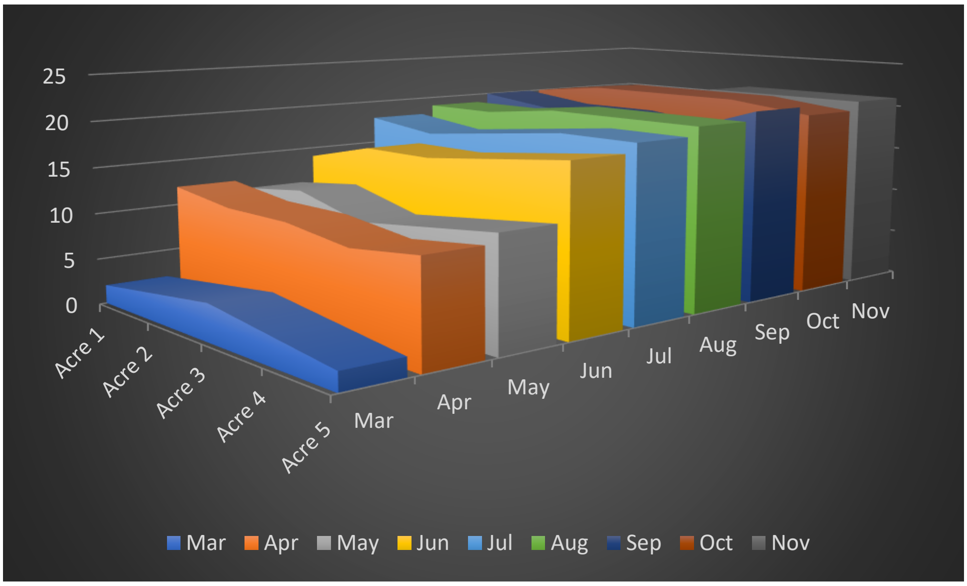

Figure 6-10: Percentage of borer attack in 2020

Table 6-2: Comparision of prediction and field observations in 2015

Month	**W-1**		**W-2**		**W-3**		**W-4**		**Correct**
	Predicted	Field	Predicted	Field	Predicted	Field	Predicted	Field	
Mar	N	N	N	N	Y	N	Y	N	2
Apr	N	N	N	N	Y	N	Y	N	2
May	N	N	N	N	Y	N	Y	N	3
Jun	Y	N	Y	Y	N	Y	Y	Y	3
Jul	N	Y	Y	Y	Y	Y	Y	Y	3
Aug	Y	Y	Y	Y	Y	Y	N	Y	3
Sep	Y	Y	N	Y	N	N	N	N	3
Oct	N	Y	N	Y	N	N	N	N	2
Nov	Y	N	Y	N	N	N	N	N	2

In each month 4 forecasting are made one for every month. The amount of accurate calculation in the dissimilar months for the year 2015 is shown in Table 6-2 and plotted in Figure 6-11. The number of correct predictions in each month is shown out of four predictions each month. The maximum correct predictions are three in May, June, July, August, and September.

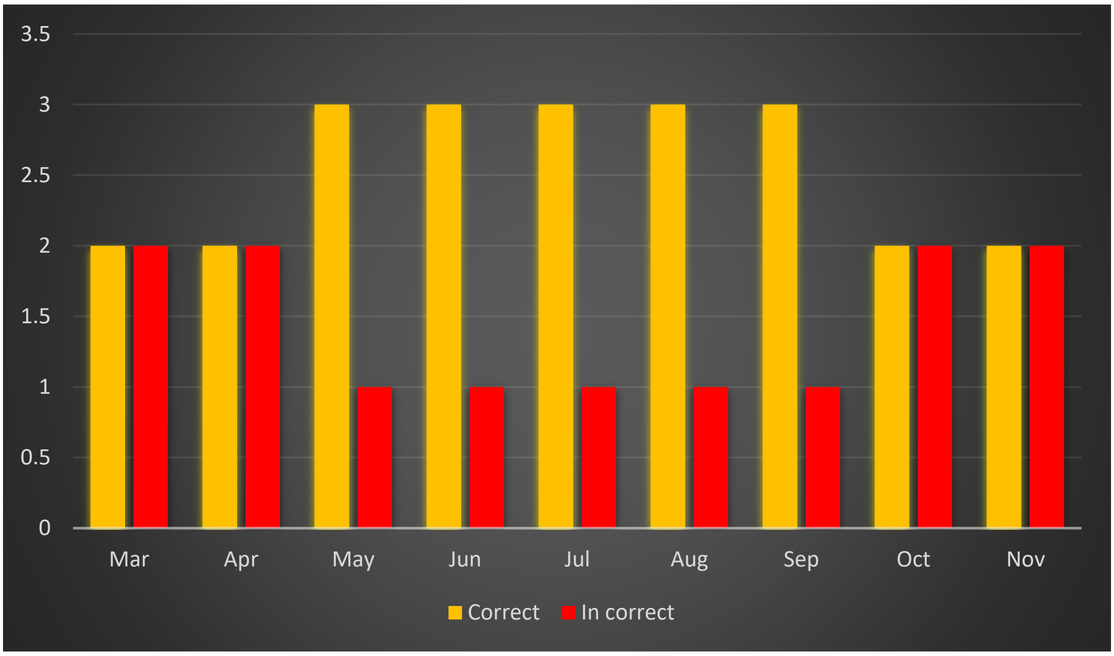

Figure 6-11: Number of correct predictions in each selected month of 2015

Table 6-3: Comparision of prediction and field observations in 2016

Month	W-1		W-2		W-3		W-4		Correct
	Predicted	Field	Predicted	Field	Predicted	Field	Predicted	Field	
Mar	F	F	F	F	Y	F	T	F	2
Apr	F	F	F	F	F	F	T	F	3
May	F	F	F	F	F	F	F	F	4
Jun	T	F	T	T	T	T	T	T	3
Jul	N	T	T	T	T	T	T	T	3
Aug	T	T	T	T	T	T	F	T	3
Sep	T	T	F	T	F	F	F	F	3
Oct	F	F	F	T	F	F	F	F	3
Nov	T	F	T	F	F	F	F	F	2

In each month four forecasting are ended one for every month. The amount of accurate forecasting in the dissimilar months for the year 2016 is shown in Table 6-3and plotted in Figure 6-12. The number of correct predictions in each month is shown out of four predictions each month. The maximum correct predictions are three in May, June, July, August, and September .Figure 6-12 shows the accuracy of the correct and incorrect prediction in 2016, for selected months.

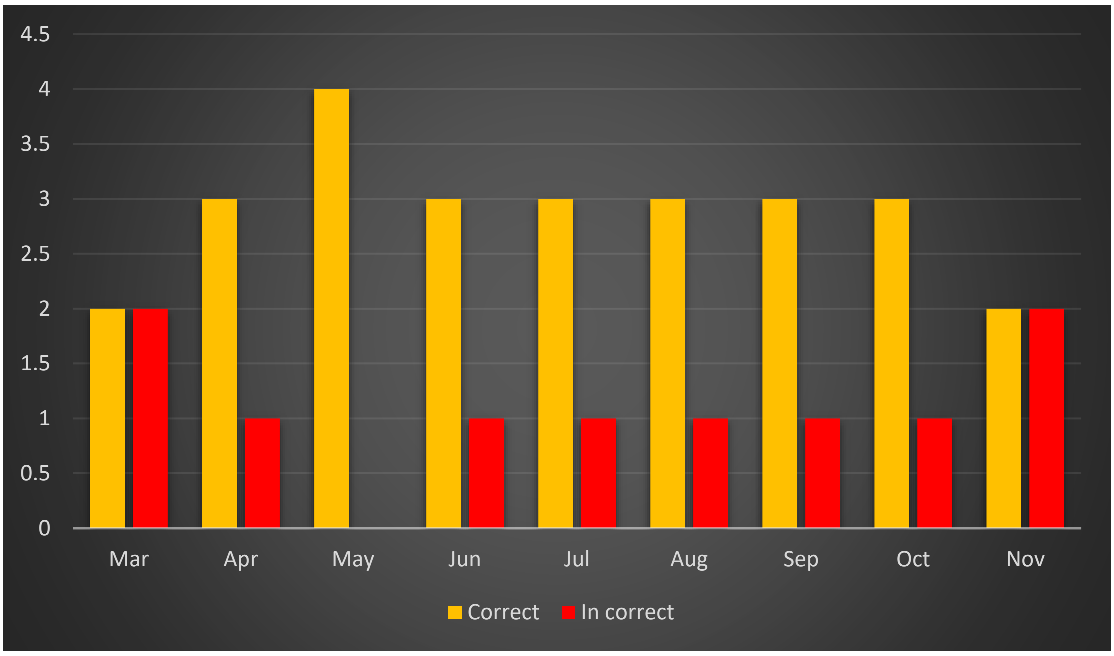

Figure 6-12: Number of correct predictions in each selected month of 2016

Table 6-4: Comparision of prediction and field observations in 2017

Month	**W-1**		**W-2**		**W-3**		**W-4**		**Correct**
	Predicted	Field	Predicted	Field	Predicted	Field	Predicted	Field	
Mar	F	F	T	F	T	F	F	F	2
Apr	F	F	F	F	F	F	T	N	3
May	F	F	F	F	T	F	F	F	3
Jun	F	F	T	Y	T	T	T	T	4
Jul	F	T	T	Y	T	T	T	T	3
Aug	T	T	T	Y	T	T	F	T	3
Sep	F	T	T	Y	F	F	F	F	3
Oct	T	T	T	Y	F	F	F	F	4
Nov	T	F	T	Y	F	F	F	F	3

The amount of accurate forecasting in the dissimilar months for the year 2017 is shown in Table 6-4and plotted inFigure 6-13. In June four predictions are true while in March only two predictions are true. In the remaining months, three out of four predictions are true. The accuracy of the proposed solution in terms of accuracy of the prediction improved in 2016 as compared to 2015 and 2016. Figure 6-13 shows the correct and incorrect predictions for each selected month in the year 2017.

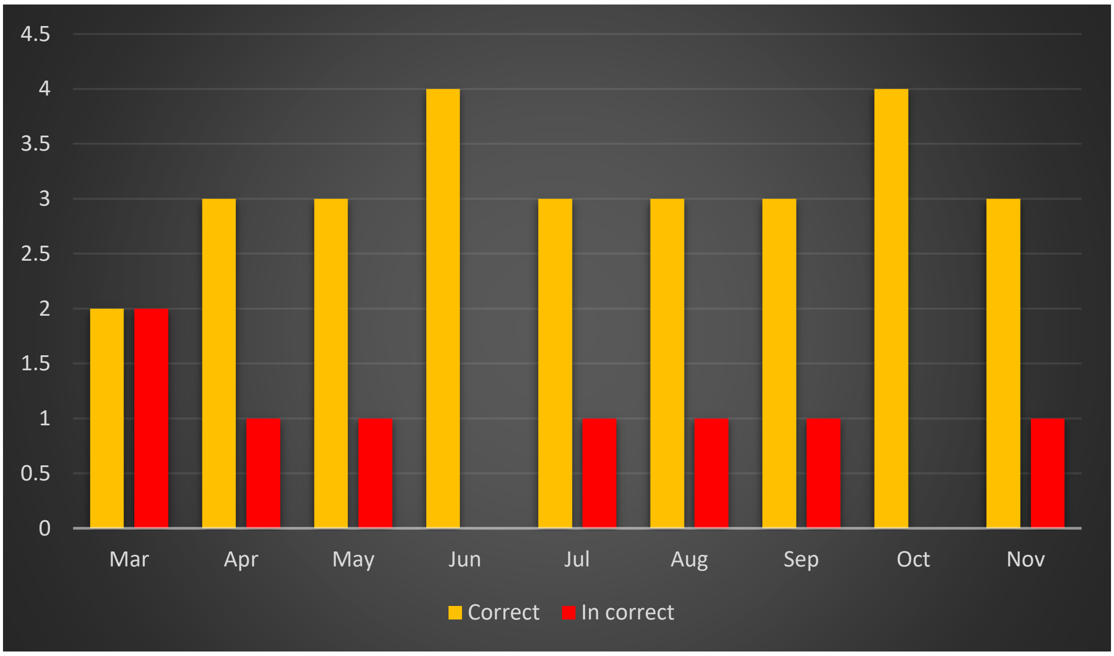

Figure 6-13: Number of correct predictions in each selected month of 2017

Table 6-5: Comparision of prediction and field observations in 2018

Month	**W-1**		**W-2**		**W-3**		**W-4**		**Correct**
	Predicted	Field	Predicted	Field	Predicted	Field	Predicted	Field	
Mar	N	N	N	N	N	N	Y	N	3
Apr	N	N	N	N	N	N	Y	N	3
May	N	N	N	N	N	N	N	N	4
Jun	Y	N	Y	Y	N	N	Y	Y	3
Jul	N	Y	Y	Y	Y	Y	Y	Y	4
Aug	Y	Y	Y	Y	Y	Y	N	Y	3
Sep	Y	Y	N	Y	N	N	N	N	4
Oct	N	Y	N	Y	N	N	N	N	4
Nov	Y	N	Y	N	N	N	N	N	3

The amount of accurate forecasting in the dissimilar months for the year 2018 is shown inTable 6-5 and plotted in Figure 6-14.In 2018 four months have all predictions correct whereasthe remaining months have only one incorrect prediction. Again, the accuracy of the prediction increases from the previous years.Figure 6-14 plot the correct and incorrect predictions for the year 2018 in selected months. May, July, September, and October have no incorrect prediction for selected months.

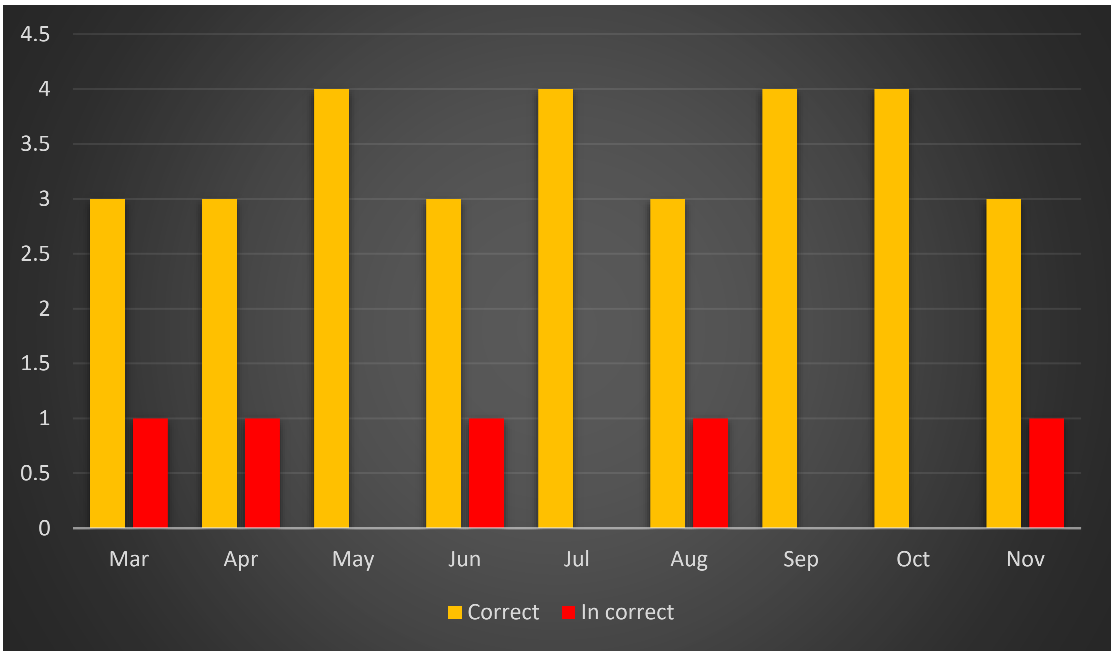

Figure 6-14: Number of correct predictions in each selected month of 2018

Table 6-6: Comparision of prediction and field observations in 2019

Month	**W-1**		**W-2**		**W-3**		**W-4**		**Correct**
	Predicted	Field	Predicted	Field	Predicted	Field	Predicted	Field	
Mar	F	F	F	F	F	F	T	F	3
Apr	F	F	T	F	T	T	T	T	3
May	F	F	F	F	F	F	F	F	4
Jun	F	F	T	T	T	T	T	T	4
Jul	F	T	T	T	T	T	T	T	3
Aug	T	T	T	T	T	T	F	T	3
Sep	T	T	T	T	T	F	F	F	3
Oct	F	F	F	F	F	F	F	F	4
Nov	F	F	T	F	F	F	F	F	3

The amount of accurate forecasting in the dissimilar months for the year 2019 is shown in Table 6-6and plotted in Figure 6-15. In three months, all four predictions are true, and the minimum correct predictions for any month are three. This indicates that the prediction accuracy has improved significantly over the previous years.Figure 6-15, shows the accuracy of the predictions by proposed solution in 2019 for selected months.

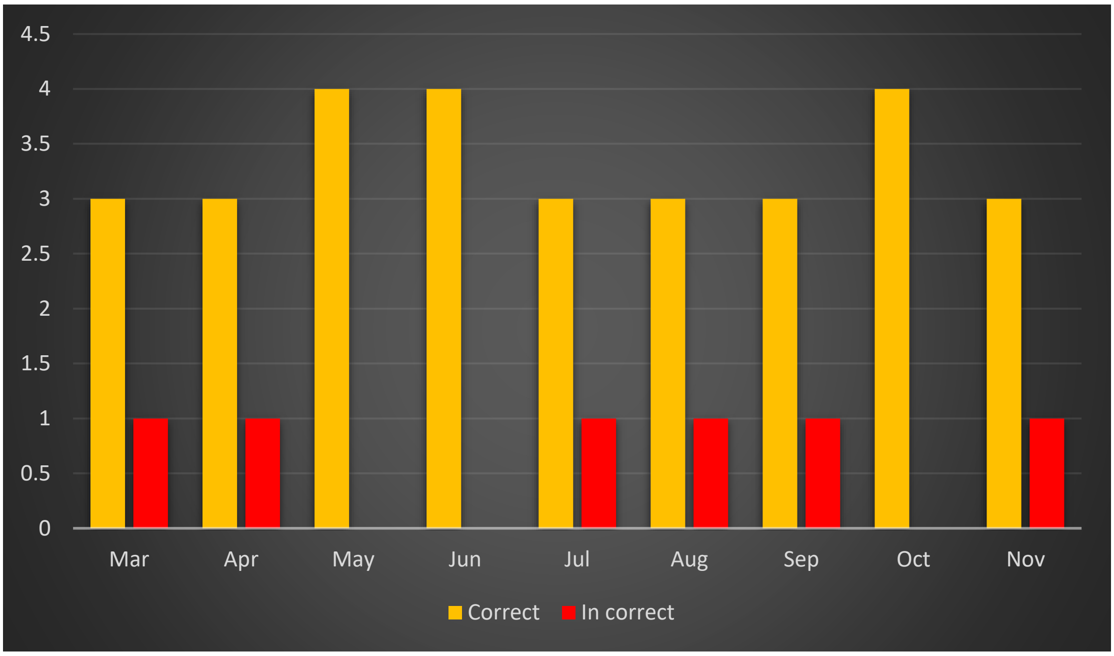

Figure 6-15: Number of correct predictions in each selected month of 2019

Table 6-7: Comparision of prediction and field observations in 2020

Month	**W-1**		**W-2**		**W-3**		**W-4**		**Correct**
	Predicted	Field	Predicted	Field	Predicted	Field	Predicted	Field	
Mar	F	F	F	F	F	F	T	F	3
Apr	F	F	F	F	F	F	F	F	4
May	F	F	F	F	T	F	F	F	3
Jun	F	F	T	T	T	T	T	T	4
Jul	F	T	T	T	T	T	T	T	3
Aug	T	T	T	T	T	T	T	T	4
Sep	T	T	T	T	T	T	F	F	4
Oct	F	T	F	F	F	F	F	F	3
Nov	F	F	T	F	F	F	F	F	3

The amount of accurate forecasting in the dissimilar months for the year 201 is shown in Table 6-7and plotted in Figure 6-16.In 2020 the four months are with all accurate predictions. The accuracy of the predictions has increased this year. Figure 6-16, shows the accurate and incorrect predictions for selected months of the year 2020. In four months three predictions are correct and in four months all of the four predictions are true.

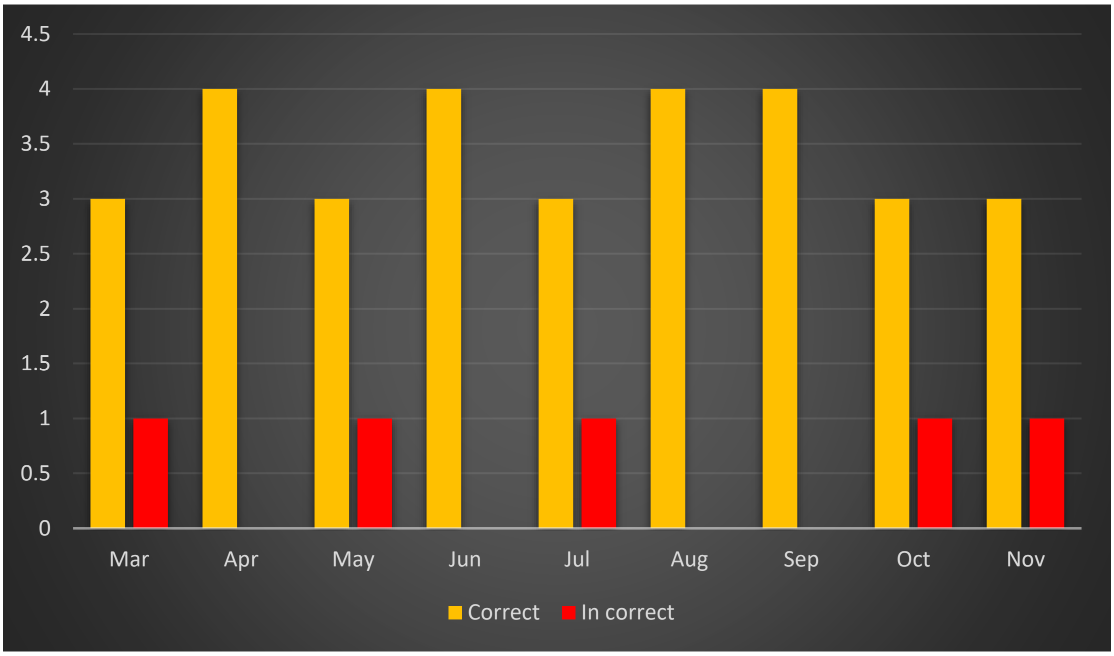

Figure 6-16: Number of correct predictions in each selected month of 2020

Table 6-8: Year wise accuracy of prediction by proposed solution

Months	2015	2016	2017	2018	2019	2020
Mar	2	2	2	3	3	3
April	2	3	3	3	3	4
May	3	4	3	4	4	3
June	3	3	4	3	4	4
July	3	3	3	4	3	3
August	3	3	3	3	3	4
September	3	3	3	4	3	4
October	2	3	4	4	4	3
November	2	2	3	3	3	3

Figure 6-17 and Table 6-8summarize the predictions of the year on monthly basis. In each month of every year, the precision of the forecasting get better with years. With observations and training of machine learning with new data is added to the model that improves the model over the years. This is also reflected in Figure 6-17, from where is obvious that the presentation of the planned solution enhance over time.

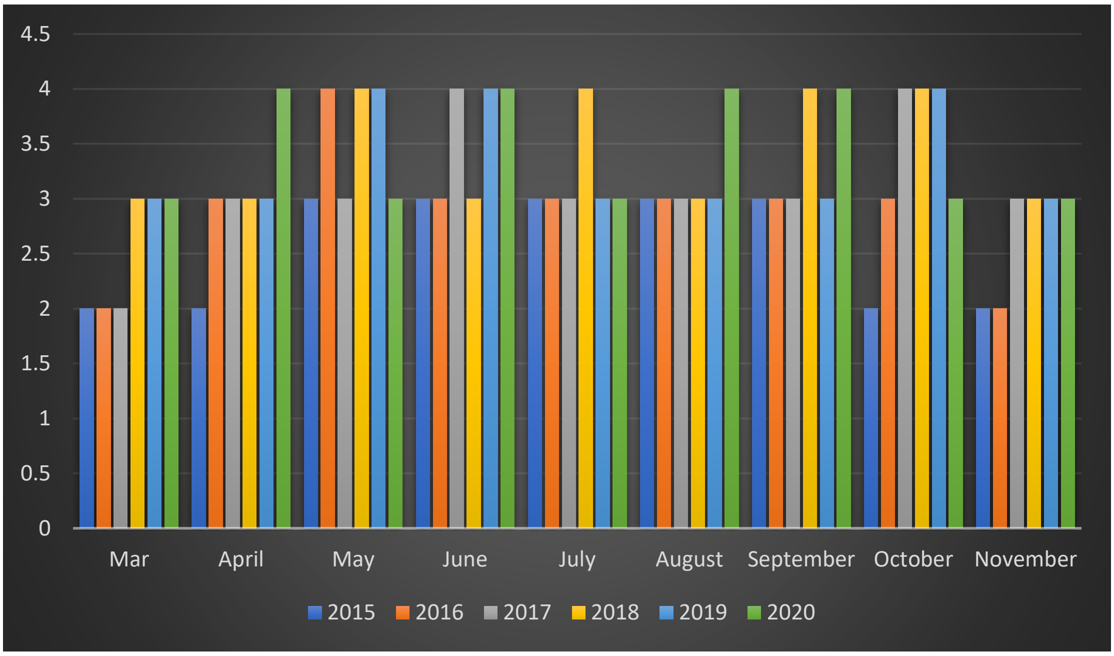

Figure 6-17: Monthly performance of the predictions over the years

Table 6-9: Year-wise prediction accuracy

Year	Correct Prediction	Incorrect Prediction	Percentage of correct Prediction
2015	23	13	64
2016	26	10	72
2017	28	8	78
2018	31	5	86
2019	30	6	83
2020	31	5	84

Table 6-9, and Figure 6-18 shows the year wise accuracy of the prediction. This also reveal that precision get better from 2015 to 2020 slowly. In 2015 64% forecasting are accurate, in 2016 72%, in 2017 78%, in 2018 86 % and in 2020 84% percent predictions are correct. Figure 6-18, shows the correctness of the calculation over the year. It is observed that the number of correct predictions increases with time and the number of incorrect predictions gradually decreases.

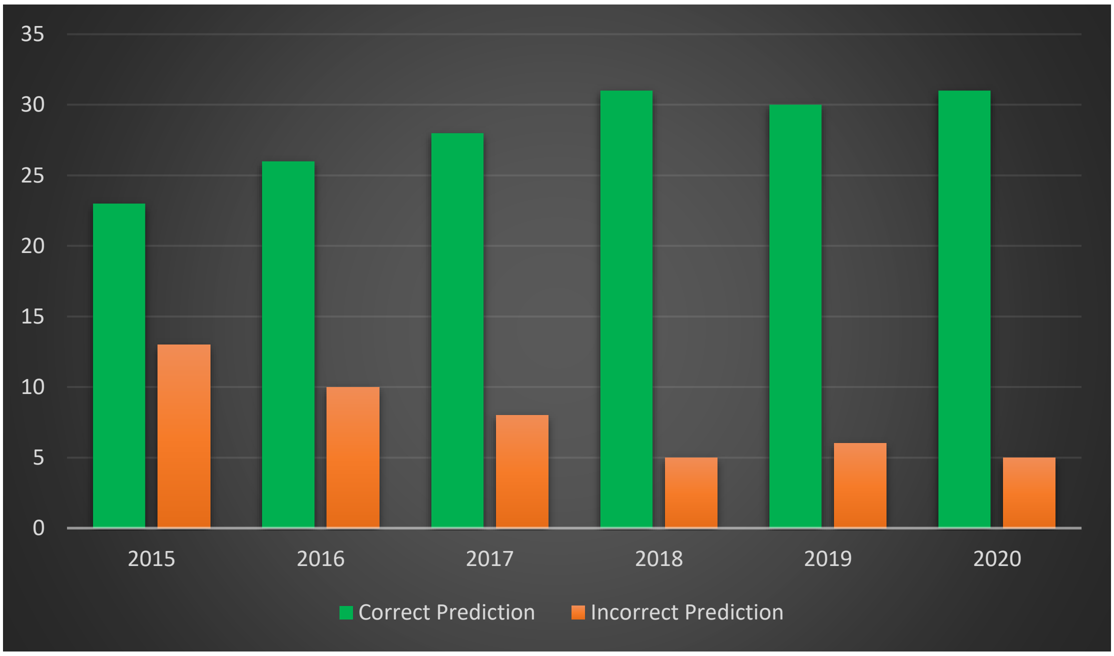

Figure 6-18: Year-wise accuracy of the predictions

6.3.1 Discussion

The evaluation of the machine earning model shows high accuracy when tested against the test data set, training data set and complete data set with 96%, 94%, and 91% respectively. The precision, recall, and f-measure of difference predictive features are also good to justify the performance of the machine learning model to be adequate for the implementation of the proposed solution. The performance of the machine learning is good to be implemented for the proposed solution. The ROC curve shows the good distribution of the predictive classes.

The field validations of the proposed solution are also made and it shows gradual improvements in performance from the year 2015 to 2020.The accuracy of the prediction improves from 2015 to 2020 gradually. In 2015, 64% predictions are correct, in 2016 72%, of predictions, in 2017 78%, of predictions, in 2018, 86% of predictions, in 2019,84% of predictions are correct and in 2020, 84% percent of predictions are correct. It is observed that the number of correct predictions increases with time and the number of incorrect predictions gradually decreases with time due to improvements in the machine learning model.

The overall performance of the proposed solution is good to be used for the early warning of borer attack prediction based on environmental conditions. The machine learning model and its prediction performance by validations through field observations also reveal the accuracy of the proposed solution to be effectively used for the prediction of borer attack in Sugarcane crop. From the machine learning evaluation and field evaluation, it is noted that the performance of the machine learning is very good in predictions of the borer attack on the sugarcane crop. The field evaluation also shows the accuracy of the models for the prediction of the borer attack. The field evaluation shows the accuracy of 84% prediction in 2019 and 2020 when predictions are compared against the field observations.

The accuracy of the model in the prediction of the borer attack on sugarcane crops can be very useful for implementation of the PA practices supporting sustainable development goals. The proposed solution would also be useful for the early prediction of the borer pest to effectively deal with the issue with judicious use of the resources. The proposed solution also effective in the implementation of effective IPM strategies for the borer attack on sugarcane. The early prediction of the model also makes reduce the use of pesticides used as a predictive strategy. The judicious use of the pesticide also contributes towards the reduction in environmental pollution and sustainable growth.

CHAPTER 7CONCLUSION AND FUTURE WORK

This chapter concludes the work and also presents the future work for the study.

7.1 Conclusion

IoT and machine learning-based borer attack prediction is proposed in the study. The model of the borer attack prediction is with the implementation of the model using the IoT and machine learning model. Naïve Bays classification algorithm is used for the implementation purpose. The machine learning model is very accurate with 96% accuracy in prediction when tested against the test data set. The field evaluation of the proposed solution is also made using the directly sensed environment conditions from the crop field. The crop field temperature, humidity, windspeed, and rainfall are used to predict the population of the borer pest for the sugarcane crop. The directly sensed environment conditions are captured using the implementation of the prototype. The prototype is designed according to the proposed architecture to ensure crop field data is easily accessible at the server for processing. The sensor node senses the data from the environment conditions and transfers it to the server for processing and predictions. The application uses cloud integration for sensor data transfer to the server. The server processes the data and predicts the population of the pest attack according to the prevailing environmental conditions. The forecasting are made according to the law of effectual environment conditions via the means and standard of the circumstances for the -law of effectual environment situation to forecasting the development of insects. The predictions made mature by planned elucidation are also mediator by straight examination from the field statistics from the year 2015 to the year 2016. Each year the inspection is also built-in into the model as a training data place to get superior the performance of the planned model. It is experiment that the forecasting accuracy get better year by year from 2015 to 2020. The accuracy of the proposed solution shows that it would be a good tool for effective PA practices.

7.2 Limitation

The proposed model predicts the population of the pest attack based onenvironmental conditions. Other factors also affect the population that is not considered in the model like the presence of predators and the use of pesticides may reduce the occurrence of the pest attack.

7.3 Future Work

The model can be extended to any other pest to predict the population of the pests and generate early warning systems.

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Appendix A

Environment Data

Table 7-1: Enviornmentment Data of 2015

From	To	Weekly Average Maximum Temperature	Weekly Average Maximum Humidity	Weekly Average Maximum Rainfall	Weekly Average Wind Speed
2/1/2015	2/7/2015	19.8	69	12.5	7.1
2/8/2015	2/14/2015	23.1	58	0	3.8
2/15/2015	2/21/2015	22.8	73	5.5	7.5
2/22/2015	2/28/2015	22.1	64	1	3.5
3/1/2015	3/7/2015	19.2	74	23.6	6.4
3/8/2015	3/14/2015	22.5	61	3	8
3/15/2015	3/21/2015	24.6	69	7.5	8.5
3/22/2015	3/28/2015	31.4	51	0	8.6
3/29/2015	4/3/2015	26	63	1.4	8.2
4/5/2015	4/11/2015	28.8	56	30	10.7
4/12/2015	4/18/2015	33.7	41	0	9.7
4/19/2015	4/25/2015	39.2	31	0	4.9
4/26/2015	5/2/2015	35.2	32	0	6.6
5/3/2015	5/9/2015	40.3	21	0	9.7
5/10/2015	5/16/2015	35.3	43	13.5	6.7
5/17/2015	5/23/2015	40.4	26	0	4.7
5/24/2015	5/30/2015	39.9	21	2	6.4
5/31/2015	6/6/2015	36.8	31	1.5	7.7
6/7/2015	6/13/2015	39.8	34	5.2	5.8
6/14/2015	6/20/2015	39.2	38	4.2	6.7
6/21/2015	6/27/2015	35.8	49	2.2	8.6
6/28/2015	7/4/2015	38.6	43	0	6.3
7/5/2015	7/11/2015	36	60	23.2	5
7/12/2015	7/18/2015	34.6	62	47.2	5.7
7/19/2015	7/25/2015	34.9	68	10.5	5.6
7/26/2015	8/1/2015	32.5	68	25.2	5
8/2/2015	8/8/2015	35.2	69	11.8	5.5
8/9/2015	8/15/2015	36.2	63	14.5	4.8
8/16/2015	8/22/2015	36	61	0	3.7
8/23/2015	8/29/2015	36.6	48	3	4.5
8/30/2015	9/6/2015	36.4	50	0	5
9/6/2015	9/12/2015	37.3	41	9.5	5.2

9/13/2015	9/19/2015	37.3	49	0	4.4
9/20/2015	9/26/2015	31.6	67	61	3.9
9/27/2015	10/3/2015	34.8	50	0	4.4
10/4/2015	10/10/2015	35.4	48	0	4.4
10/11/2015	10/17/2015	33.1	56	0	4.4
10/18/2015	10/24/2015	31.4	47	0	4.3
10/25/2015	10/31/2015	27.1	64	14.5	4.9
11/1/2015	11/7/2015	27.3	62	0.5	3.4
11/8/2015	11/15/2015	25.6	61	0	1.3

Table 7-2: Enviornmentment Data of 2016

From	To	Weekly Average Maximum Temperature	Weekly Average Maximum Humidity	Weekly Average Maximum Rainfall	Weekly Average Wind Speed
2/1/2016	2/6/2016	23	54	0	5.7
2/7/2016	2/13/2016	20.6	64	0	3.4
2/14/2016	2/20/2016	22.1	57	0	4.1
2/21/2016	2/27/2016	27	56	7.8	4.5
2/28/2016	3/5/2016	27.6	63	0	5.2
3/6/2016	3/12/2016	24.2	68	0	2.1
3/13/2016	3/19/2016	25.2	63	15.6	3.9
3/20/2016	3/26/2016	27.4	52	21.3	3.9
3/27/2016	4/2/2016	31.7	49	1.4	4.5
4/3/2016	4/9/2016	29.9	48	0	5.3
4/10/2016	4/16/2016	35.6	34	2.6	3.4
4/17/2016	4/23/2016	34.9	27	0	4.5
4/24/2016	4/30/2016	39.1	18	0	7.5
5/1/2016	5/7/2016	38.2	29	0	6.4
5/8/2016	5/14/2016	39.6	31	0	6.5
5/15/2016	5/21/2016	43.8	20	0	8.2
5/16/2016	5/27/2016	43.8	20	0	5.5
5/28/2016	6/3/2016	38.1	34	0	4.3
6/4/2016	6/10/2016	40.8	28	1	6.3
6/11/2016	6/17/2016	41	35	0	6.2
6/18/2016	6/24/2016	39.9	41	0	7.3
6/25/2016	7/1/2016	39	47	15.5	7.7
7/2/2016	7/8/2016	38	51	23.4	4.3
7/9/2016	7/15/2016	36.9	58	25.5	4.7
7/16/2016	7/22/2016	36.7	59	17.5	3.5
7/23/2016	7/29/2016	37.4	58	40	3.2

7/30/2016	8/5/2016	35.2	66	81	5.6
8/6/2016	8/12/2016	36.2	63	10	3.5
8/13/2016	8/19/2016	34.5	67	19.5	1.7
8/20/2016	8/26/2016	37.1	53	0.6	3.2
8/27/2016	9/2/2016	34.9	66	10.5	4.3
9/3/2016	9/9/2016	35.4	60	9.7	4.1
9/10/2016	9/16/2016	36.9	53	1.8	2.5
9/17/2016	9/23/2016	36.8	52	0	2.5
9/24/2016	9/30/2016	36.3	54	0	3.5
10/1/2016	10/7/2016	37	50	22.2	3.1
10/8/2016	10/14/2016	35.6	55	0	2.2
10/15/2016	10/21/2016	34.2	46	0	1.8
10/21/2016	10/27/2016	33.4	49	0	2
10/28/2016	11/3/2016	31.9	54	0	1.8
10/29/2016	11/4/2016	31.9	54	0	2.4

Table 7-3: Enviornmentment Data of 2017

From	To	Weekly Average Maximum Temperature	Weekly Average Maximum Humidity	Weekly Average Maximum Rainfall	Weekly Average Wind Speed
2/1/2017	2/5/2017	21.6	65	4.1	5.1
2/6/2017	2/12/2017	21.2	50	0	3.2
2/13/2017	2/19/2017	25.6	55	0	2.4
2/20/2017	2/26/2017	24.8	42	0	4.9
2/26/2017	3/4/2017	24.8	42	0	4.2
2/27/2017	3/5/2017	25.7	40	0	3.5
3/6/2017	3/12/2017	21.4	63	0	4.2
3/14/2017	3/20/2017	24.9	53	0	4.6
3/21/2017	3/27/2017	31	44	0	5.8
3/28/2017	4/3/2017	35.6	36	0	6.3
4/3/2017	4/9/2017	32.2	41	5.7	5.1
4/10/2017	4/16/2017	39.6	21	9.2	4.6
4/17/2017	4/23/2017	40.9	30	0	6.8
4/24/2017	4/30/2017	38.5	30	7.4	10
5/1/2017	5/7/2017	39.6	25	0	7.8
5/8/2017	5/14/2017	42.1	30	5.5	5.4
5/16/2017	5/22/2017	39.4	33	0	7

5/24/2017	5/30/2017	43.5	30	0.6	6.6
5/31/2017	6/6/2017	42.8	30	4	5.1
6/7/2017	6/13/2017	40.1	43	12.9	7
6/14/2017	6/20/2017	40.6	40	3.2	6.3
6/22/2017	6/28/2017	38.5	49	10.2	6.2
6/30/2017	7/6/2017	37.1	63	9.3	6.4
7/7/2017	7/13/2017	39.7	65	18.9	5.6
7/14/2017	7/20/2017	37.8	73	53.2	5.6
7/21/2017	7/27/2017	37.9	73	3.7	4.3
7/28/2017	8/3/2017	38.4	70	37.1	3.2
8/4/2017	8/10/2017	38.9	72	0.5	3.5
8/11/2017	8/17/2017	39.9	63	19.8	5.6
8/18/2017	8/24/2017	38.3	68	0	5.5
8/26/2017	9/1/2017	38.7	68	21.1	4.9
9/2/2017	9/8/2017	33.3	78	26	4.4
9/9/2017	9/15/2017	36.6	72	0	2.8
9/16/2017	9/22/2017	36.1	64	5.2	2.5
9/23/2017	9/29/2017	37.1	64	0	2.3
9/30/2017	10/6/2017	38.3	68	0	1.8
10/7/2017	10/13/2017	38	65	0	1.7
10/14/2017	10/20/2017	36.4	70	0	1.3
10/21/2017	10/27/2017	34.4	67	0	0.9
10/28/2017	11/3/2017	32.2	68	0	1.2
11/4/2017	11/10/2017	26.4	85	0	3.1

Table 7-4: Enviornmentment Data of 2018

From	**To**	**Weekly Average Maximum Temperature**	**Weekly Average Maximum Humidity**	**Weekly Average Maximum Rainfall**	**Weekly Average WindSpeed**
2/1/2018	2/7/2018	22.5	74	1.5	2.5
2/8/2018	2/14/2018	22	80	4.1	3.4
2/15/2018	2/21/2018	23.5	69	0	3.6
2/22/2018	2/28/2018	24.7	71	0	4.1
3/1/2018	3/7/2018	27.1	69	0	3.1
3/8/2018	3/14/2018	31.1	64	14.5	4.1
3/15/2018	3/21/2018	31.4	63	0	4.9
3/22/2018	3/28/2018	29.7	55	0	4.2

3/29/2018	4/4/2018	36	50	0	5.4
4/5/2018	4/11/2018	36	51	9.2	4.5
4/12/2018	4/18/2018	35.2	46	0	2
4/19/2018	4/25/2018	34.1	54	7.4	3.5
4/26/2018	5/2/2018	41.3	30	0	3.2
5/3/2018	5/9/2018	38.5	26	0	3
5/10/2018	5/16/2018	38.1	32	5.5	3.1
5/17/2018	5/23/2018	39.4	33	0.6	2.8
5/24/2018	5/30/2018	42.6	31	0.6	3.8
5/31/2018	6/6/2018	45.3	44	4	3.5
6/7/2018	6/13/2018	41.4	54	12.9	5.5
6/14/2018	6/20/2018	39.7	63	3.2	4.8
6/21/2018	6/27/2018	39.9	51	10.2	3.2
6/28/2018	7/4/2018	35.9	76	9.3	4.8
7/5/2018	7/11/2018	37.3	60	18.9	5.8
7/12/2018	7/18/2018	40.4	72	53.2	6.1
7/19/2018	7/25/2018	37.4	75	1.3	6.5
7/26/2018	8/1/2018	36.7	72	37.1	5.6
8/2/2018	8/8/2018	39.4	70	0.5	3.8
8/9/2018	8/15/2018	38.7	69	0	4.4
8/16/2018	8/22/2018	37.7	70	19.8	4.6
8/23/2018	8/29/2018	38.8	64	12.2	4.4
8/30/2018	9/5/2018	40.1	62	26	3.8
9/6/2018	9/12/2018	40.1	66	3	3.9
9/12/2018	9/18/2018	36.9	66	5.2	3.9
9/19/2018	9/25/2018	36	63	0	3.1
9/26/2018	10/2/2018	35.2	68	0	4.8
10/3/2018	10/9/2018	34.9	66	0	5.7
10/10/2018	10/16/2018	31.9	60	0	4.1
10/17/2018	10/23/2018	32.7	67	0	2.9
10/25/2018	10/31/2018	31.6	70	0	3.1
11/1/2018	11/7/2018	28.8	68	0	3.5
11/8/2018	11/14/2018	27.9	73	0	2.7

Table 7-5: Enviornmentment Data of 2019

From	To	Weekly Average Maximum Temperature	Weekly Average Maximum Humidity	Weekly Average Maximum Rainfall	Weekly Average Windspeed

2/1/2019	2/6/2019	23	78	1.6	4.3
2/7/2019	2/13/2019	19.6	77	5.9	3.3
2/14/2019	2/20/2019	21	81	7.4	3.5
2/21/2019	2/27/2019	20.6	79	30.8	4.7
2/22/2019	2/28/2019	20.6	79	0	3.6
2/28/2019	3/6/2019	18.9	79	9.9	4.8
3/7/2019	3/13/2019	24.2	70	1.7	4.8
3/14/2019	3/20/2019	25	68	3	5.7
3/20/2019	3/26/2019	26.9	68	4.6	7.1
3/27/2019	4/2/2019	31.6	65	0	4.4
4/3/2019	4/9/2019	35.4	59	0	3.6
4/10/2019	4/16/2019	34.5	56	1.8	4.6
4/17/2019	4/23/2019	31.1	66	21.5	4.9
4/24/2019	4/30/2019	38	57	0	6.5
5/1/2019	5/7/2019	39.4	49	0	6.3
5/8/2019	5/14/2019	40.4	37	2.3	5.3
5/15/2019	5/21/2019	35.1	50	3.9	3.2
5/22/2019	5/28/2019	37.6	52	3.9	4.4
5/28/2019	6/3/2019	44.3	49	20.1	4.7
6/5/2019	6/11/2019	44.5	42	0	4.5
6/6/2019	6/12/2019	44.5	43	0	4.8
6/13/2019	6/19/2019	44.1	49	0	5
6/20/2019	6/26/2019	39.7	55	3.6	6.4
6/27/2019	7/3/2019	40.2	46	21.5	6.2
7/4/2019	7/10/2019	40.9	56	0	5.6
7/11/2019	7/17/2019	39.1	68	51.9	5.9
7/18/2019	7/24/2019	35.6	62	15.5	4.5
7/25/2019	7/31/2019	36.2	75	7.4	3.8
8/1/2019	8/7/2019	37.4	76	7.4	3.5
8/8/2019	8/14/2019	36.6	76	47.6	3.6
8/15/2019	8/21/2019	37.9	73	11	5.5
8/16/2019	8/22/2019	37.9	73	11	6.3
8/17/2019	8/23/2019	37.9	73	11	6.5
8/18/2019	8/24/2019	37.9	73	11	6.4
8/25/2019	8/31/2019	39.2	68	2.1	4.8
9/1/2019	9/7/2019	39.3	68	0.9	3.2
9/9/2019	9/15/2019	40.1	65	0	2.8
9/16/2019	9/22/2019	36.9	71	4.4	2.7
9/23/2019	9/29/2019	35.7	73	2.2	4.2
9/24/2019	9/30/2019	35.7	73	15.2	6.2
10/1/2019	10/7/2019	32	75	15.2	5.1

Table 14: Enviornmentment Data of 2020

From	To	Weekly Average Maximum Temperature	Weekly Average Maximum Humidity	Weekly Average Maximum Rainfall	Weekly Average WindSpeed
2/1/2020	2/7/2020	22.5	74	01.5	02.5
2/8/2020	2/14/2020	22.0	80	04.1	03.4
2/15/2020	2/21/2020	23.5	69	00.0	03.6
2/22/2020	2/28/2020	24.7	71	00.0	04.1
3/1/2020	3/7/2020	27.1	69	00.0	3.1
3/8/2020	3/14/2020	31.1	64	14.5	4.1
3/15/2020	3/21/2020	31.4	63	00.0	4.9
3/22/2020	3/28/2020	29.7	55	00.0	4.2
3/29/2020	4/4/2020	36.0	50	00.0	5.4
4/5/2020	4/11/2020	36.0	51	09.2	4.5
4/12/2020	4/18/2020	35.2	46	00.0	2
4/19/2020	4/25/2020	34.1	54	07.4	3.5
4/26/2020	5/2/2020	41.3	30	00.0	3.2
5/3/2020	5/9/2020	38.5	26	00.0	3
5/10/2020	5/16/2020	38.1	32	05.5	3.1
5/17/2020	5/23/2020	39.4	33	00.6	2.8
5/24/2020	5/30/2020	42.6	31	00.6	3.8
5/31/2020	6/6/2020	45.3	44	04.0	3.5
6/7/2020	6/13/2020	41.4	54	12.9	5.5
6/14/2020	6/20/2020	39.7	63	03.2	4.8
6/21/2020	6/27/2020	39.9	51	10.2	3.2
6/28/2020	7/4/2020	35.9	76	09.3	4.8
7/5/2020	7/11/2020	37.3	60	18.9	5.8
7/12/2020	7/18/2020	40.4	72	53.2	6.1
7/19/2020	7/25/2020	37.4	75	01.3	6.5
7/26/2020	8/1/2020	36.7	72	37.1	5.6
8/2/2020	8/8/2020	39.4	70	00.5	3.8
8/9/2020	8/15/2020	38.7	69	00.0	4.4
8/16/2020	8/22/2020	37.7	70	19.8	4.6
8/23/2020	8/29/2020	38.8	64	12.2	4.4
8/30/2020	9/5/2020	40.1	62	26.0	3.8
9/6/2020	9/12/2020	40.1	66	03.0	3.9
9/12/2020	9/18/2020	36.9	66	05.2	3.9

9/19/2020	9/25/2020	36.0	63	00.0	3.1
9/26/2020	10/2/2020	35.2	68	00.0	4.8
10/3/2020	10/9/2020	34.9	66	00.0	5.7
10/10/2020	10/16/2020	31.9	60	00.0	4.1
10/17/2020	10/23/2020	32.7	67	00.0	2.9
10/25/2020	10/31/2020	31.6	70	00.0	3.1
11/1/2020	11/7/2020	28.8	68	00.0	3.5
11/8/2020	11/14/2020	27.9	73	00.0	02.7