UNIVERSITY OF RWANDA
COLLEGE OF SCIENCE AND TECHNOLOGY
AFRICAN CENTER OF EXCELLENCE IN INTERNET OF THINGS

Designing a TinyML-Enabled Early Detection System of Post-Harvest Maize Weevil Infestations

A dissertation submitted in partial fulfillment of the requirements for the award of Master's of Science degree in Internet of Things: Embedded Computing Systems

Submitted By:

Name: Ipyana Issah Mwaisekwa (Ref. No:222023019)

December, 2024

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Declaration

I, IPYANA ISSAH MWAISEKWA, Masters' student from African Center of Excellence in Internet of Things, at University of Rwanda, I declare that this research thesis is my own original work, and it has never been presented before anywhere in the world.

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Bonafide Certificate

This is to certify that this submitted research thesis work report is a record of the original work done by IPYANA ISSAH MWAISEKWA (Ref. No: 222023019), MSc. IoT-ECS Student at the University of Rwanda / College of Science and Technology / African Center of Excellence in Internet of Things, the Academic year 2022/2024.

This work has been submitted under the supervision of Prof. DAMIEN HANYURWIMFURA and Dr. LOUIS SIBOMANA.

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Acknowledgment

I extend my deepest gratitude to Prof. Damien Hanyurwimfura, my main supervisor, whose unwavering dedication, guidance, and expertise have been invaluable throughout the entire journey of my thesis. Prof. Damien's commitment supervision has been instrumental in shaping the quality and direction of this work. His insights and mentorship have been a constant source of inspiration.

I am also profoundly thankful to Dr. Louis Sibomana, my co-supervisor, for his valuable input, support, and encouragement during this research. His perspective and suggestions have significantly enriched the depth and scope of this thesis.

I would like to acknowledge the management of the African Centre of Excellence in Internet of Things at the University of Rwanda for their support, resources, and conducive research environment. Their commitment to fostering academic excellence has provided an invaluable platform for my academic pursuits.

I would like to extend my acknowledgement to the Tanzania Higher Education for Economic Transformation (HEET) from Mbeya University of Science and Technology, for the financial support during the whole Master's studies and all the facilities and resources provided were instrumental in conducting the research and enabling the successful completion of my studies.

To my family, whose unwavering support, understanding, and encouragement have been the cornerstone of my academic journey, I am deeply grateful. Their love and belief in me have been a constant motivation to strive for excellence.

I also extend my appreciation to my colleagues Henry Eric Kapalamula, Destiny Kwabla Amenyedzi, Rehema Mwawado, Micheline Kazeneza, Egas Armando, and Fabiola Ingabire, for their encouragement which has been a constant source of strength throughout this endeavor.

Lastly, to all those who have in various ways contributed to this thesis, whether through their time, knowledge, or support, I offer my heartfelt thanks.

Abstract

Post-harvest losses due to maize weevil *(Sitophilus zeamais)* infestations pose a significant threat to food security and economic stability, particularly in developing countries. This study presents an innovative Tiny Machine Learning (TinyML)-enabled solution for the early detection and real-time monitoring of maize weevil infestations in stored grains. The research integrates acoustic sensing with environmental monitoring to create a comprehensive, non-invasive pest detection system. Over a 101-day period, more than 250,000 audio samples of weevil activity were collected and analyzed, capturing data from both larval and adult stages. Using this extensive dataset, a TinyML model capable of recognizing acoustic signatures indicative of weevil presence was developed and evaluated. The model achieved 98.9% accuracy on the training set and 97.76% on the test set. Through int8 quantization, the model was optimized for deployment on resource-constrained devices, reducing latency from 157ms to 134ms while maintaining 97.70% accuracy. The system was successfully deployed on Arduino Nano 33 BLE Sense and XIAO ESP32S3 Sense platforms, demonstrating its versatility for various agricultural settings. A web-based dashboard was developed, integrating real-time acoustic detection with environmental monitoring of temperature, humidity, and CO2 levels. This solution offers several advantages over existing methods, including early-stage detection, non-invasive monitoring, and accessibility for small to medium-scale farmers. The system's ability to provide continuous, real-time data enables timely interventions, potentially reducing crop losses and economic impact. This study contributes to the field of smart agriculture by demonstrating the effective application of TinyML and Internet of Things (IoT) technologies in pest management. The developed system not only addresses the immediate need for improved pest detection but also lays the groundwork for future innovations in agricultural technology, promising significant improvements in food security and economic stability for farming communities.

Keywords: TinyML, Acoustic sensing, Maize weevil detection, Post-harvest monitoring, IoT in agriculture, Smart pest management

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Abbreviations and Acronyms

API	Application Programming Interface
AUC-ROC	Area Under the Receiver Operating Characteristic Curve
BLE	Bluetooth Low Power
CNN	Convolution Neural Network
CO_2	Carbon Dioxide
CSV	Comma-Separated Values
DCT	Discrete Cosine Transform
DL	Deep Learning
ERP	Enterprise Resource Planning
FFT	Fast Fourier Transform
GPRS	General Packet Radio Service
GSM	Global System for Mobile Communications
HEET	Higher Education and Economic Transformation
HIS	Hyperspectral Imaging
IDE	Integrated Development Environment
IoT	Internet of Things
JSON	JavaScript Object Notation
MCU	Micro Controller Unit
MEMS	Micro-Electromechanical Systems
MFCC	Mel Frequency Cepstral Coefficient
ML	Machine Learning
NIRS	Near-Infrared Spectroscopy
PCB	Printed Circuit Board
PDM	Pulse Density Modulation
R-CNN	Region-Convolutional Neural Network
RGB	Red Green Blue
RTC	Real Time Clock
SPL	Sound Pressure Level
TCP/IP	Transmission Control Protocol/Internet Protocol

TFT LCD	Thin-Film-Transistor Liquid-Crystal Display
TinyML	Tiny Machine Learning
XML	eXtensible Markup Language

Chapter 1 Introduction

1.1 Background

Agriculture is the primary source of livelihood for a significant portion of the population in developing countries, with approximately 70% of people relying on it as their main means of sustenance [1]. In Tanzania, domestic food production is generally sufficient to meet national food requirements. However, many regions consistently face food scarcity due to inherent vulnerabilities, particularly in post-harvest systems [2], [3]. These vulnerabilities lead to elevated food costs due to reduced market availability. Post-harvest losses are estimated to range from 30% to 40% for grains and even higher for perishable commodities [4], [5]. Among the various pests responsible for these losses, the maize weevil (*Sitophilus zeamais*) poses a formidable threat, causing substantial damage to stored maize [6], [7], a staple crop for millions. Traditional pest detection methods often fall short, necessitating innovative solutions to address the economic and food security implications of weevil infestations [8], [9].

Monitoring of these pests is typically conducted through olfactory assessment of grains, monitoring grain temperature, observing airborne insects, using insect traps, or detecting alterations in grain pigmentation [10]. Commonly, the determination of whether storage bags are infested is made by emptying multiple bags of grains and checking for the presence of moving insects [11], [12]. This monitoring method requires substantial manual labor, is time-consuming, and carries the risk of cross-contamination [6][5]. Additionally, it incurs significant expenses in acquiring additional storage materials, such as bags and mats, as the process involves frequent handling and inspections, often leading to the shredding of these materials [8]. In some instances, contamination of un-infested bags can occur, such as when grains are strewn on bare floors, when grains are mixed together, and when there are no protocols in place to separate infected and uninfected bags [6]. These disadvantages, including reduced grain shelf life and market rejection of infected grains, contribute to decreased profitability. To address this issue, it is imperative to develop cost-effective [8], efficient, non-invasive detection methods that can be effectively utilized in rural regions like of Tanzania.

The complex correlation between environmental variables and pest activity has been well-recognized for a considerable period [5]. The development, reproduction, and activities of stored grain pests are influenced by temperature, humidity, and other environmental conditions. Understanding this, incorporating environmental monitoring becomes crucial in improving the precision of pest detection techniques. Additionally, the incorporation of acoustic signatures [6], an emerging practice in precision agriculture, introduces a distinct aspect to the sensing approach, potentially transforming our understanding and management of pest infestations.

As conventional pest management approaches prove insufficient, the integration of advanced technologies becomes imperative to empower farmers with effective and accessible solutions. Existing research on pest management has primarily focused on chemical-based therapies, fumigation, and traditional monitoring approaches [5]. However, the drawbacks of these methods, such as their negative environmental impacts, high costs, and limited availability, have emphasized the need for alternative techniques. Tiny Machine Learning (TinyML), a specialized form of machine learning designed for edge devices or resource-constrained devices [9][10], offers a promising opportunity for creating affordable and real-time solutions for pest identification. This study extends the existing research on TinyML applications in agriculture by focusing on the specific challenges posed by maize weevil infestations.

Current pest management strategies often lack real-time monitoring capabilities, leading to delayed detection and response [5][8]. Around 50% of the overall loss incurred during grain storage can be attributed to technical inefficiencies [1]. Traditional methods rely heavily on periodic inspections and chemical treatments, presenting logistical challenges and environmental concerns. The identified gap lies in the absence of an integrated, affordable, and real-time solution that combines environmental monitoring and acoustic signatures for early detection and continuous monitoring of maize weevils. This study proposes the integration of TinyML [11], specifically tailored for resource-constrained devices [9], to develop a rapid, non-destructive solution that leverages acoustic signatures and environmental monitoring for early detection of post-harvest maize weevil infestations.

This methodology promises to provide farmers with a comprehensive understanding of their storage environments, facilitating early detection and monitoring of post-harvest infestations and improved pest management strategies, while ensuring accessibility and affordability for farmers and storage facility managers [10].

1.2 Problem Statement

Despite the crucial role of stored maize in global food security, post-harvest losses attributed to maize weevil (*Sitophilus zeamais*) infestations remain a significant challenge [4] as shown in Figure 1.1. Traditional pest management approaches, heavily reliant on periodic manual inspections and chemical treatments which lack real-time detection and monitoring capabilities. Approximately 50% of the overall loss incurred during grain storage can be attributed to technical inefficiencies [1]. The drawbacks of these conventional methods, including environmental concerns and high costs, highlight the need for an innovative and sustainable solution tailored to the context of post-harvest maize storage [1][11][16].

Current methodologies fail to integrate advanced technologies capable of combining environmental monitoring and acoustic signatures for the early detection and continuous monitoring of maize weevil infestations. The absence of a comprehensive, accessible, and low-cost solution exacerbates economic losses for farmers and storage facility managers, hinders timely intervention, and poses a threat to global food security [5[13].

Therefore, this study aims to address this critical gap by developing a pioneering TinyML-enabled solution, providing an effective, affordable, and real-time approach to mitigate the economic impact of maize weevil infestations in stored grains. By leveraging acoustic signatures and environmental monitoring, this solution seeks to empower farmers and storage facilities with early detection and continuous monitoring capabilities, ultimately contributing to improved food security and economic sustainability.

Figure 1.1 Maize Weevils on the grains

1.3 Objectives

1.3.1 Main Objective

The primary objective of this research is to develop a TinyML-enabled solution for the early detection and real-time monitoring of post-harvest maize weevil (*Sitophilus zeamais*) infestations by leveraging acoustic signatures and environmental monitoring.

1.3.2 Specific Objectives

i. To characterize the acoustic signatures and environmental factors influencing maize weevil *(Sitophilus zeamais)* activity in stored grains.
ii. To develop a TinyML model capable of recognizing patterns indicative of weevil activity based on these acoustic signatures.
iii. To integrate the TinyML acoustic model with real-time environmental monitoring capabilities for continuous monitoring of maize weevil infestations in post-harvest storage facilities.
iv. To evaluate and optimize the developed TinyML acoustic model for effectiveness, performance, and resource efficiency in real-world grain storage conditions.

1.4 Hypothesis/Research Questions

The primary hypothesis supporting this research is that the integration of acoustic signatures and environmental monitoring data through a TinyML -enabled solution can facilitate early detection and real-time monitoring of post-harvest maize weevil *(Sitophilus zeamais)* infestations in storage facilities.

To investigate this hypothesis, the following research questions will be addressed:

i. What are the acoustic characteristics of maize weevils *(Sitophilus zeamais)* while moving and feeding within stored maize grains, and how can these acoustic signatures be leveraged to develop an accurate TinyML model for detecting weevil activity?
ii. How do environmental parameters, such as temperature, humidity, and carbon dioxide levels, influence the behavior and activity levels of maize weevils, and what are the optimal ranges associated with varying risks of infestation?
iii. Can the integration of a TinyML acoustic model and real-time environmental monitoring capabilities provide an effective and affordable solution for early detection and continuous monitoring of maize weevil infestations in post-harvest storage facilities?
iv. How can the developed solution be optimized for deployment on resource-constrained devices, ensuring accessibility and scalability for small and medium-scale farmers and storage facility managers?

1.5 Study area and Scope of the Research

The research focused on Maize storage facilities in the Iringa, Mbeya, Ruvuma, and Rukwa regions of Tanzania as shown in Figure 1.2. A model was created and evaluated using the storage facility's environmental conditions and acoustic characteristics. The data obtained from the facilities was utilized for experimentation in order to evaluate the efficacy of the suggested solution. To validate the solution based on the smallholder farmer's surroundings, information regarding their practices and traditions related to maize and other grain storage was collected and utilized.

The Southern Highlands region of Tanzania, encompassing Iringa, Mbeya, Rukwa, and Ruvuma, is renowned for its significant contribution to maize cultivation, as substantiated by multiple research studies. Crucial factors that influence the amount of maize produced in this area include climatic conditions, specifically the altitude and precipitation patterns. Furthermore, research conducted on soil fertility in the area has examined the complex correlation between climatic factors and soil quality, which is crucial for maximizing agricultural methods, particularly those pertaining to maize farming. The agricultural significance of the Southern Highlands is underscored by its excellent environment, characterized by moderate temperatures, distinct wet and dry seasons, and diverse topography.

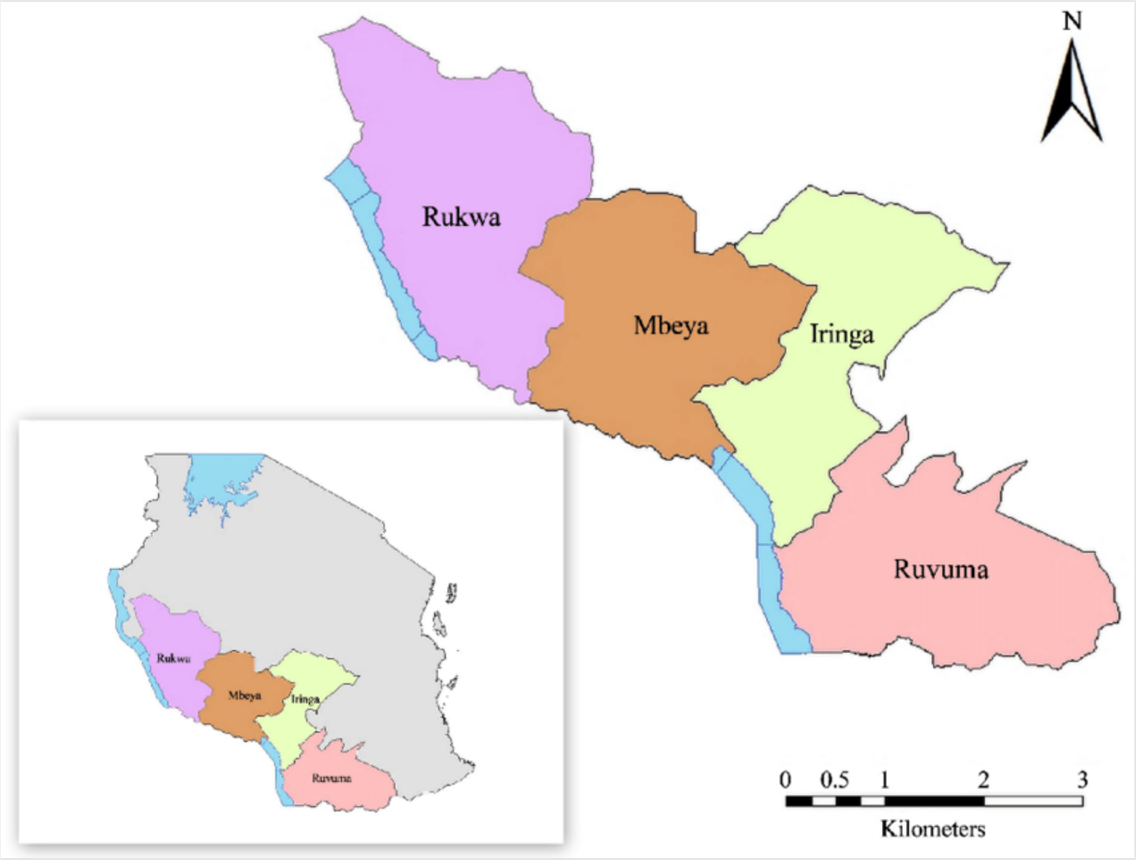


Figure 1.2 Proposed Study Areas

1.6 Significance of the Study

The significance of this research stems from the critical need to address the persistent challenges posed by maize weevil infestations in post-harvest storage, which continue to impact food security and economic stability. Traditional pest management strategies have proven inadequate in providing real-time detection and monitoring capabilities, leaving a void that demands innovative solutions [5][11][17]. By developing a TinyML-enabled system that leverages acoustic signatures and environmental monitoring, this study offers a revolutionary approach to early detection and continuous monitoring of maize weevil infestations.

The proposed solution aligns with the growing demand for sustainable and accessible technologies in agriculture while contributing to the advancement of TinyML applications in resource-limited settings [9][10][16]. The development of a real-time monitoring system further enhances the practicality of the solution, empowering farmers with timely insights for proactive pest management. This research, therefore, serves as a timely and essential endeavor to bridge existing gaps in post-harvest pest management practices, foster resilience in agricultural communities, and contribute to global food security.

By leveraging the power of TinyML and integrating acoustic signatures with environmental monitoring, this study presents a cost-effective and accessible solution tailored to the needs of small and medium-scale farmers. The integration of these technologies holds the potential to revolutionize pest management practices, offering a sustainable and environmentally-friendly alternative to traditional chemical-based approaches.

Chapter 2 Literature Review

2.1 Background

The majority of stored grain insects undergo rapid development at room temperature, exhibiting a high reproductive capacity, with certain female insects capable of laying 100-400 eggs [7]. The duration of adult insects' lifespan varies from a few weeks to several years [10], [14]. Temperature and moisture level are the two main environmental elements that affect the growth of insects. Insects typically thrive and reproduce within a temperature range of approximately 15-20°C [15]. However, when the temperature rises to roughly 25°C, their population begins to pose a threat to crops by causing damage [16]. When the temperature exceeds 35°C, insect pests are unable to survive and cease laying eggs, resulting in their eventual disappearance [6]. Artificial pesticides are efficacious in pest management [11], [17], but their non-biodegradability, high cost, and detrimental effects on human and soil health prevent their ongoing usage among all types of farmers [18], [19]. Therefore, the majority of agricultural practitioners are actively searching for cost-effective and environmentally acceptable natural methods of pest control [10], [20].

2.2 Current Challenges in Pest Detection and Management

Many studies focus on controlled environments, which may not reflect real-world storage conditions, there's often a lack of real-time, continuous monitoring of environmental factors and the interplay between multiple environmental factors is not always fully explored [12], [21]. We propose to address these limitations by implementing a system that continuously monitors multiple environmental factors (Temperature, Humidity, CO_2) in real-world storage conditions [21]. Our TinyML approach will allow for real-time analysis of the complex interplay between these factors and pest activity.

Several postharvest pests have been observed to acquire resistance to early identification of the infestations [4][18]. Agricultural practitioners have been endeavoring to ascertain economically efficient post-harvest solutions that might mitigate the detrimental effects of insect infestation on stored grain [18]. Presently, farmers mitigate the harm by depending on a combination of traditional and artificial grain preservatives [19]. Furthermore, they employ a diverse range of storage structures for the purpose of storing grains, including sacks, baskets, cribs, mud brick silos, underground storage pits, and earthenware pots and gourds. Additional storage methods/structures encompass the hanging of crops on a tree or over the fireplace, roof storage, steel or concrete silos, and air tight plastic bags [10].

Gas tightness is often incomplete in numerous installations, necessitating the use of supplementary instruments to enhance fumigation [18]. Regular surveillance and prompt examination of grains allows for the elimination of pests prior to their potential for causing financial harm. Conventional monitoring techniques involve doing visual inspections both inside and outside storage facilities, analyzing grain samples, measuring fluctuations in temperature within grain storage, and deploying and examining insect traps in many locations [18]. Frequently, this surveillance is insufficiently efficient due to concealed infestations of larvae [19]. Acoustic detection, as demonstrated is a highly promising method that can identify concealed larvae infestations and provide store managers with guidance on when and how to preserve grain effectively [14].

The conventional storage methods are insufficient to ensure the safeguarding of a fundamental food crop such as maize [4], [22]. Furthermore, it is anticipated that the rise in global temperatures will expedite the proliferation of pests in tropical and subtropical regions. Temperature, being the primary and most crucial determinant for insects, will play a significant role in this phenomenon [15]. These variables are expected to persist and present difficulties for farmers in managing pest infestations, as well as compel them to sell excess grains at the lowest rates immediately after harvest. They will do this to reduce the losses caused by post-harvest dangers and partly to fulfill other financial requirements [10], [15].

We have seen that, Traditional methods often rely on visual inspection [4], which can be time-consuming and may miss early-stage infestations. Acoustic detection methods, while promising, often require sophisticated equipment not suitable for widespread deployment in resource-constrained areas [10]. Many current methods lack the ability to provide early warnings before significant damage occurs. Our proposed system combines acoustic sensing with environmental monitoring. This multi-modal approach aims to detect infestations earlier than visual inspections, while being more cost-effective and easier to deploy than current acoustic methods.

2.3 Technological Advancements in Pest Detection

2.3.1 IoT and Sensor-based Solutions

The utilization of IoT-enabled technologies offers intelligent and advanced agricultural services that can enhance sustainability [23], automate processes, and effectively manage climate change occurrences [24]. IoT serves as the interconnection of different devices and sensors closely to the environment where the need of TinyML evolves for enhancing computational capacity on these devices at the edge. TinyML is an advanced technology that can decrease the size of ML and Deep Learning algorithms [25], enabling the use of machine learning on hardware with limited resources [24], [26], [27]. The use of TinyML offers various benefits, such as cost-effectiveness, efficient device performance, data privacy, and the ability to execute complex models without relying on third-party organizations for processing [28]. The hardware requirements for a TinyML system encompass microcontrollers (MCU’s). Mcus have exceptional levels of power efficiency and energy conservation. To facilitate the model inferences, it is necessary to optimize and compress the models. Quantization and pruning are the primary techniques employed for compressing machine learning models. Frameworks utilized for model training, optimization, and MCU implementation are a popular and frequently selected approach among academics and developers [27].

IoT solutions in agriculture require significant infrastructure and connectivity, limiting their applicability in remote areas [29], [30]. Current TinyML applications in agriculture often focus on a single type of data or sensor, potentially missing complex pest behaviors [24]. There's a lack of integrated systems that combine multiple data sources with edge computing capabilities [31], [32]. Our system leverages TinyML to process multiple data streams (acoustic and environmental) directly on low-power devices, reducing reliance on connectivity and infrastructure. This integrated approach aims to provide a more comprehensive and accessible solution for pest detection.

2.3.2 Imaging Techniques

Small-scale farmers often store a limited quantity of grains in their own residences, whereas greater amounts of grains like maize, rice, wheat, turmeric, and millets are stored in warehouses for future use [11]. Despite the use of synthetic pesticides and insecticides to safeguard them, a substantial level of loss remains unavoidable [1]. A system has been developed by [33] to identify and classify six distinct types of insects commonly seen in stored grain. The RGB photos were used to capture the live insects, and an enhanced inception network based on Faster R-CNN was employed to extract feature maps [34]. Researchers at [25] have highlighted that many studies have utilized image processing techniques to autonomously analyze X-ray images for the detection of insect infestations [25]. Although these approaches have shown exceptional performance, the main obstacles associated with these systems are their high cost and the need for intricate operational mechanisms, which can be extremely difficult for farmers with limited technical expertise and financial resources to obtain [35], [36].

Recent advancements in technology have led to the integration of Internet of Things (IoT), Near-Infrared Spectroscopy (NIRS), and Hyperspectral Imaging (HSI) in agricultural pest management, particularly in grain storage and handling operations [37][38]. IoT facilitates real-time monitoring and data collection through interconnected sensors and devices, enabling efficient tracking of environmental conditions and pest activity in storage facilities [11][22]. NIRS, a non-destructive analytical technique, utilizes the near-infrared region of the electromagnetic spectrum to detect chemical and physical properties of materials, making it particularly useful for identifying pest infestations and assessing grain quality [21][22]. HSI, on the other hand, combines spectral and spatial information to create detailed images across a wide range of the electromagnetic spectrum, allowing for the detection and mapping of pest damage and contamination in stored grains [27]

The synergistic application of these technologies offers significant potential for enhancing pest monitoring and detection in grain storage and handling operations [6], [39]. IoT systems can continuously collect and transmit data from NIRS and HSI sensors, providing real-time insights into pest infestations and grain quality [21][28]. NIRS enables rapid, non-invasive detection of pest presence and damage through spectral analysis, while HSI allows for spatial mapping of infestations and contamination across large grain volumes [22]. The integration of these technologies not only improves the accuracy and efficiency of pest detection but also enables predictive modeling and early warning systems for pest outbreaks, potentially revolutionizing pest management strategies in the grain industry [21].

NIRS and HSI equipment is often expensive and requires specialized knowledge to operate and interpret results. These techniques may require samples to be removed from storage for analysis, disrupting the storage environment. The high data volume from these methods can be challenging to process in real-time, especially in resource-constrained settings [40], [41]. Our TinyML-based system aims to provide continuous, in-site monitoring without the need for expensive spectroscopy or imaging equipment. By processing data at the edge, we avoid the challenges of handling large data volumes, making the system more suitable for resource-constrained environments.

Researchers worldwide have explored diverse approaches to monitor grain storage units, particularly focusing on the utilization of acoustic signatures for pest detection [34]. In a distinct study, efforts were directed at refining the performance of detecting larvae feeding internally in wheat grains [4]. This was achieved by establishing guidelines and procedures for shielding an acoustic system within a wheat grain elevator [42]. Recognizing the challenge of a low sound pressure level (SPL) generated by pests like the rice weevil *(Sitophilus oryzae)* larvae, which is only 23 db, researchers recommended shielding the tested grain and attenuating background sound by 70-85 db [4], [14]. Additionally, an innovative study focused on quantifying insects in a 1kg wheat grain sample using an acoustic system. The detector analyzed input from an array of sensors embedded in the container walls, revealing a proportional relationship between the level of sound produced by insects and their weight [14][43]

These advanced imaging techniques often require expensive equipment and controlled lighting conditions [34]. These methods typically can't detect early-stage infestations where visual signs aren't apparent. Image-based systems may struggle with detecting pests inside grains or in dense storage conditions. Instead of relying on visual data, our system uses acoustic and environmental sensors that can detect pest activity even when visual signs are not present [44]. This approach aims to provide earlier detection at a lower cost than advanced imaging systems.

2.4 TinyML and Edge Computing in Agriculture

Many acoustic detection systems require high-sensitivity microphones and extensive sound isolation, limiting their practical application in typical storage facilities [36][45]. Current systems often struggle with distinguishing pest sounds from background noise in real-world conditions [46], [47]. There is a lack of integration between acoustic data and other environmental factors for a more comprehensive pest detection approach [16], [44], [48]. Our system combines acoustic sensing with environmental monitoring, using TinyML to process and integrate these data streams. This approach aims to improve the accuracy of pest detection in real-world conditions while being more robust to background noise than purely acoustic systems [42], [49].

In the pursuit of advanced pest detection in grain storage units, our proposed solution integrates acoustic signatures and environmental monitoring data through a TinyML-enabled approach [50]. By capturing the intricate acoustic patterns generated by maize weevils *(Sitophilus zeamais)* while moving and feeding within stored grains, the system gains the ability to discern patterns indicative of pest activity [50], [51], [52]. Concurrently, monitoring critical environmental parameters, such as temperature, humidity, and carbon dioxide levels, provides insights into conditions conducive to weevil infestations [16].

2.5 Economic and Practical Considerations

The incorporation of TinyML technology addresses the need for energy-efficient and cost-effective real-time analysis, enabling on-device processing and making the solution accessible to small and medium-sized farmers [24], [26], [27]. This integrated approach leverages the acoustic signatures and environmental data to accurately detect anomalous patterns associated with weevil activities, generating timely alerts and empowering farmers to take proactive measures [53].

By combining acoustic analysis, environmental monitoring, and TinyML, our solution represents a significant advancement in pest detection methodologies for stored grains. It contributes to the preservation of grain quality, food security, and economic stability in agriculture by providing farmers with an affordable and accessible tool for early detection and continuous monitoring of post-harvest maize weevil infestations [54], [55].

2.6 Gaps in Current Research and Potential for Innovation

Our TinyML-enabled acoustic detection system offers several distinct advantages over existing pest detection methods in stored grains [43], [56]. Traditional visual inspection methods[43], [57], while common, are labor-intensive, time-consuming, and often miss early-stage infestations. In contrast, our system provides continuous, real-time monitoring without the need for manual intervention [48], [51], [58]. Chemical detection methods [48], such as pheromone traps, can be effective but require frequent replacement and may not detect infestations until they've become significant. Our acoustic approach can detect pest activity at much earlier stages, potentially before visible damage occurs. Imaging-based detection systems, including X-ray and near-infrared spectroscopy [38][59], offer high accuracy but are typically expensive and not feasible for widespread deployment in resource-constrained settings [37]. Our TinyML solution, leveraging low-cost microcontrollers and sensors, provides a more accessible and scalable alternative without compromising on detection accuracy [22], [60], [61]. Furthermore, unlike destructive sampling methods that can damage grain and potentially spread infestations, our acoustic detection is entirely non-invasive. When compared to other IoT-based monitoring systems [41], [51], our solution's edge computing capabilities reduce reliance on continuous internet connectivity and minimize data transmission costs, making it more suitable for rural and remote agricultural settings. By integrating environmental monitoring with acoustic detection [15], [56], our system also provides a more comprehensive view of storage conditions than most existing single-parameter monitoring solutions. This approach detects pest activity and also helps in understanding and mitigating the conditions that promote infestations.

Chapter 3 Methodology

This chapter outlines the comprehensive approach taken to develop a TinyML-enabled early detection system for post-harvest maize weevil infestations. The research process is structured into four primary phases; Data Acquisition and Analysis, TinyML Model Development, System Prototyping, and System Evaluation and Validation.

3.1 Research Design Overview

The research process began with an extensive data collection phase, capturing over 250,053 audio samples of weevil activity over a 101-day period. This was followed by the design and prototyping of custom hardware to house the sensors and processing units. Concurrently, a web-based dashboard for data visualization and system management was developed. The core of the proposed solution, a TinyML model capable of recognizing acoustic signatures indicative of weevil presence, was then developed and optimized for deployment on resource-constrained devices.

3.2 Research Conceptual Framework

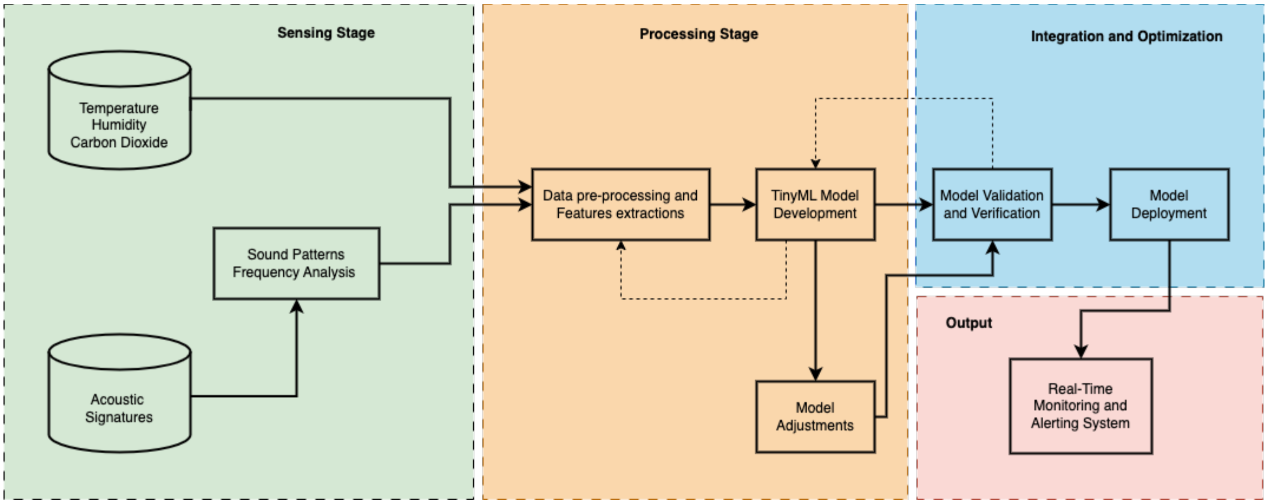


Figure 3.1 Research Conceptual Framework

The research is grounded in a conceptual framework in Figure 3.1, and outlines a systematic approach to developing a TinyML-enabled solution for early detection and real-time monitoring of post-harvest maize weevil *(Sitophilus zeamais)* infestations. The framework comprises three main stages: Input, Processing, and Output.

3.2.1 Input Stage

In this stage, the framework incorporates two primary data sources;

i. *Acoustic Data*

   Complex acoustic patterns generated by maize weevils while moving and feeding within stored grains will be captured using a MEMS acoustic sensor.

ii. *Environmental Data*

   Critical environmental parameters, including temperature, humidity, and carbon dioxide levels, known to influence weevil behavior, will be monitored using appropriate sensors.

3.2.2 Processing Stage

The processing stage involves two parallel processes:

i. TinyML Model Development

   The acoustic data collected in the input stage will be preprocessed and utilized for training and validating a TinyML model. This model will be designed to recognize patterns indicative of weevil activity based on acoustic signatures.

ii. Environmental Data Analysis

   The environmental data acquired from temperature, humidity, and carbon dioxide sensors will be analyzed to establish the optimal ranges associated with varying risks of weevil infestation.

iii. The developed TinyML acoustic model and the environmental data analysis will be integrated to create a comprehensive solution for early detection and continuous monitoring of maize weevil infestations. Additionally, the solution will be optimized for deployment on resource-constrained microcontrollers, ensuring accessibility and scalability for small and medium-scale farmers and storage facility managers.

3.2.3 Output Stage

The final stage of the conceptual framework involves the deployment of the integrated solution on a microcontroller platform. This stage includes the development of a user-friendly interface and the integration of a real-time alerting system. The alerting system will enable farmers and storage facility managers to receive timely notifications and access continuous monitoring capabilities, facilitating proactive pest management strategies.

The conceptual framework incorporates a feedback loop, ensuring that the input data and the solution's performance are continuously monitored and refined, fostering a process of ongoing improvement and adaptation to changing conditions.

3.3 Data Acquisition and Analysis

3.3.1 Collection of acoustic signatures from maize weevil activity

A. Data collection Prototype

The omnidirectional digital microphone (MP34DT05) with Pulse-Density Modulation (PDM) capabilities acoustic sensors integrated on an Arduino Nano BLE 33 Sense shown in the Figure 3.2 with its block diagram on Figure 3.3, were employed to record these complex acoustic patterns over an extended period of three months, encompassing different times of the day (Morning, Noon, and Night). Both sounds from Larvae and adults were collected and followed by preprocessing and feature engineering to extract relevant patterns and characteristics [5], [7], [35]. This step involved techniques such as noise reduction, signal enhancement, and the extraction of relevant acoustic features.

B. Data collection Process

To collect these acoustic data from weevils activities, two soundproof controlled boxes on Figure 3.4 were made, one with 65cm x 65cm x 65cm dimensions and another small box with 30cm x 30cm x 30cm dimensions. The small box was used to keep maize grains inside the large box covered with form materials of 5cm, 10 cm respectively to form three layers in order to control external sounds while collecting data. A plastic kit in figure 5 and maize bad were interchangeably to collect data. The kit was tightened to avoid weevils form getting out. The weevil samples were introduced in kit with in a soundproof controlled box containing 10kg of clean and well dried maize for 10 days. Thereafter maize were taken out to get dried up and remove adult weevils from the grains. Maize were taken back into the soundproof controlled box.

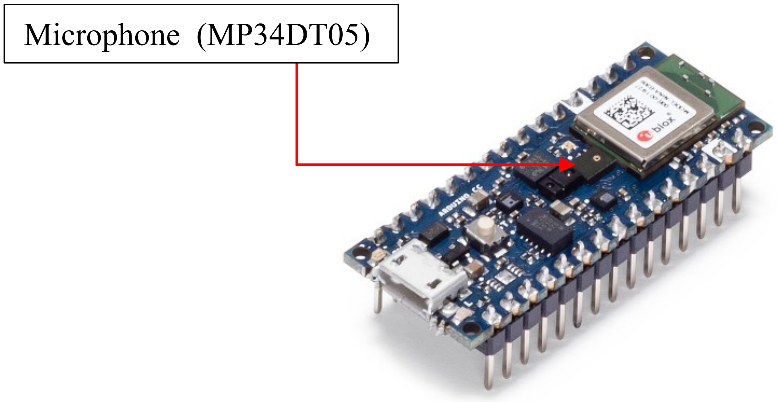


Figure 3.2 Arduino Nano BLE Sense

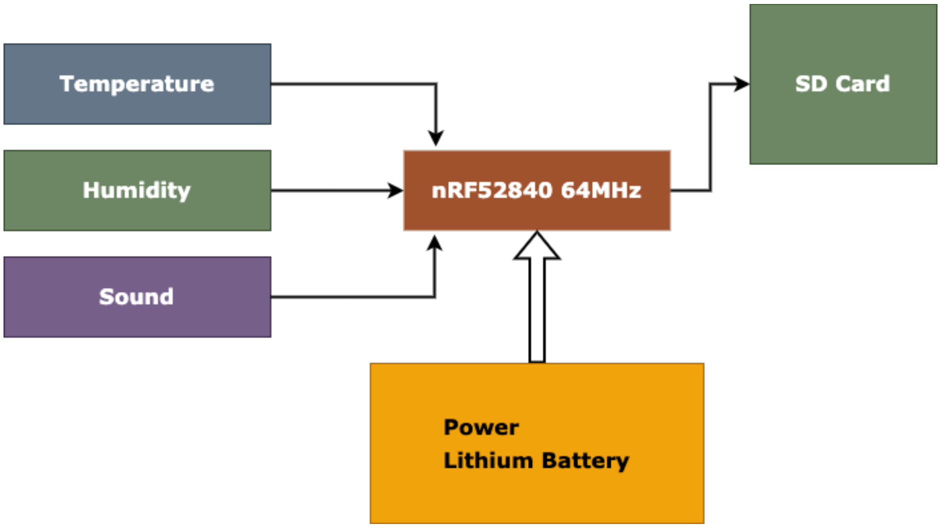


Figure 3.3 Block Diagram of the Data collection hardware setup

The methodology was designed to account for the complex life cycle of the maize weevil *(Sitophilus zeamais),* [16], [48], [62]focusing particularly on two critical stages: the larval stage and the adult stage. We used this approach to ensure that the acoustic signatures captured were representative of the full spectrum of weevil activity throughout their development [53], [63].

Figure 3.4 Sound proof box for data collection

The larval stage was identified as the most critical phase for acoustic monitoring due to its significant impact on grain damage [1], [4]. During this stage in the figure 3.5A, larvae actively feed inside the maize kernels, creating distinct acoustic emissions. Our observations confirmed that this was the most acoustically active and destructive phase of the weevil's life cycle [1], [14]. The feeding activity of larvae produces subtle but detectable sounds as they consume the internal contents of the grain [64], [65].

While less destructive than the larval stage, the adult in figure 3.5B stage of the maize weevil presents its own set of unique acoustic characteristics [14]. Data collection during this phase focused on capturing the movement and feeding patterns of mature weevils. Adult weevils produce distinct sounds as they move across and between grain kernels [7], bore into grains for feeding or egg-laying, and engage in mating behaviors [66]. These activities generate a different set of acoustic signatures compared to the larval stage, characterized by more sporadic and surface-level sounds.

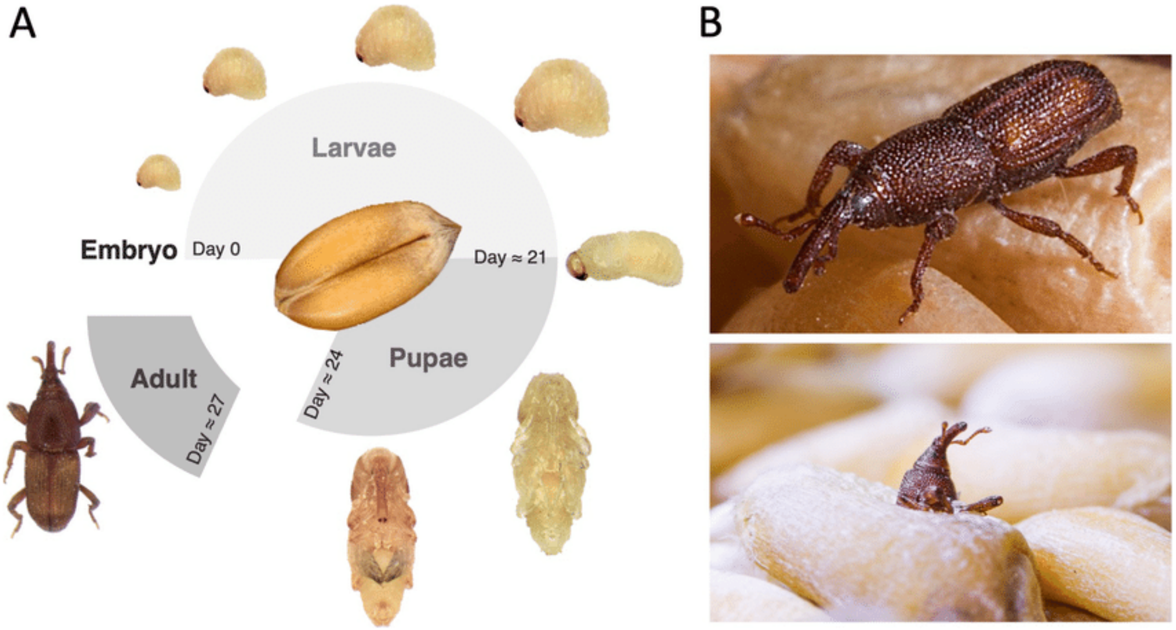
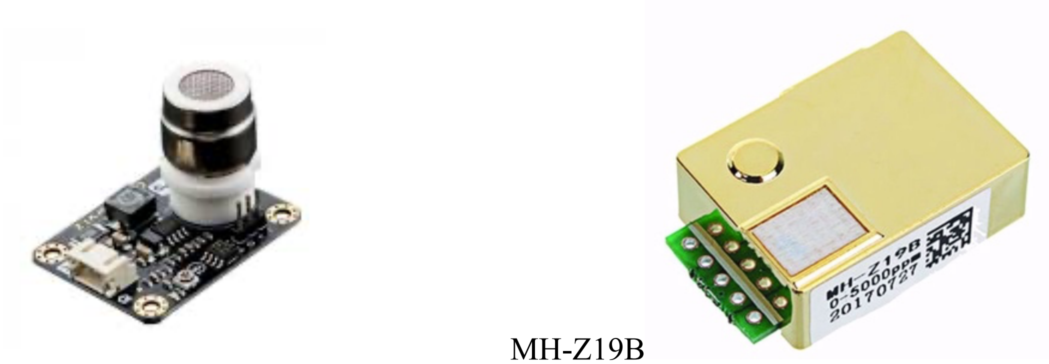


Figure 3.5 Weevils Life Cycle

3.3.2 Monitoring of environmental parameters

In parallel with acoustic data collection, critical environmental parameters, including temperature, humidity, and carbon dioxide levels, was continuously monitored within the storage facilities [39]. MG811 and MH-Z19B carbon dioxide (CO_2) gas sensors in figure 8 were deployed to record these parameters at regular intervals, ensuring a comprehensive understanding of the environmental conditions influencing weevil behavior and activity levels [29][21].



MG811 MH-Z19B

Figure 3.6 Carbon dioxide gas sensors

The collected environmental data was analyzed to identify patterns and correlations between the parameter values and observed weevil activity levels [21] to establish optimal ranges for each environmental parameter, which will be associated with varying degrees of risk for weevil infestations [8], [67]. These optimal ranges will serve as crucial thresholds, enabling the early detection and monitoring system to recognize conditions conducive to weevil activity and provide timely alerts to farmers and storage facility managers [62].

Chapter 4

System Design and Implementation

4.1 System Prototyping

The system prototyping phase served as a translator of our theoretical model into a practical, deployable solution for early detection of maize weevil infestations. This phase involved the integration of hardware components, software development, and the implementation of our TinyML model into a cohesive, functional system. Our prototyping process consisted of three main components, hardware design and implementation, software development for data management and visualization, and integration of TinyML model with hardware components.

A custom printed circuit board (PCB) integrating the XIAO ESP32S3 Sense microcontroller with environmental sensors for temperature, humidity, and CO2 monitoring was developed. This phase included schematic design, PCB layout, and multiple iterations of testing and refinement. A web-based dashboard was created to provide real-time monitoring and data visualization capabilities. This involved frontend development using React.js, backend implementation with PHP and mysql, and the design of a user-friendly interface for both administrators and regular users. The optimized acoustic detection model was integrated into the hardware system, enabling on-device inference.

4.1.1 Hardware design and implementation

In this prototype on Figure 4.1 the XIAO ESP32S3 Sence was used as the microcontroller which has the abilities in running Machine Learning Models, where we interfaced with the SCD41 Sensor which takes Carbondioxide gas, Temperature and Humidity paramerters, mini-GSM SIM800L GPRS TCP IP module for communication, Real Time Clock module (DS3231 RTC) for timer, Round TFT LCD for displaying parameters in real time, Polymer Battery (CT601452) for powering the device, Power Regulator for smooth distribution of among devices.

Figure 4.1 System's prototype

The design of the system started by designing a schematic diagram as shown in figure 4.2, then to have a tangible PCB. The Fritzig was initially used and tested the schamtic connections before we shifted to easyeda platform for the final PCB design for printing.

The prototype was designed and made up with components such as Processing unit, Controllers, Display, Communication module, Time management module, Indicators and Power management.

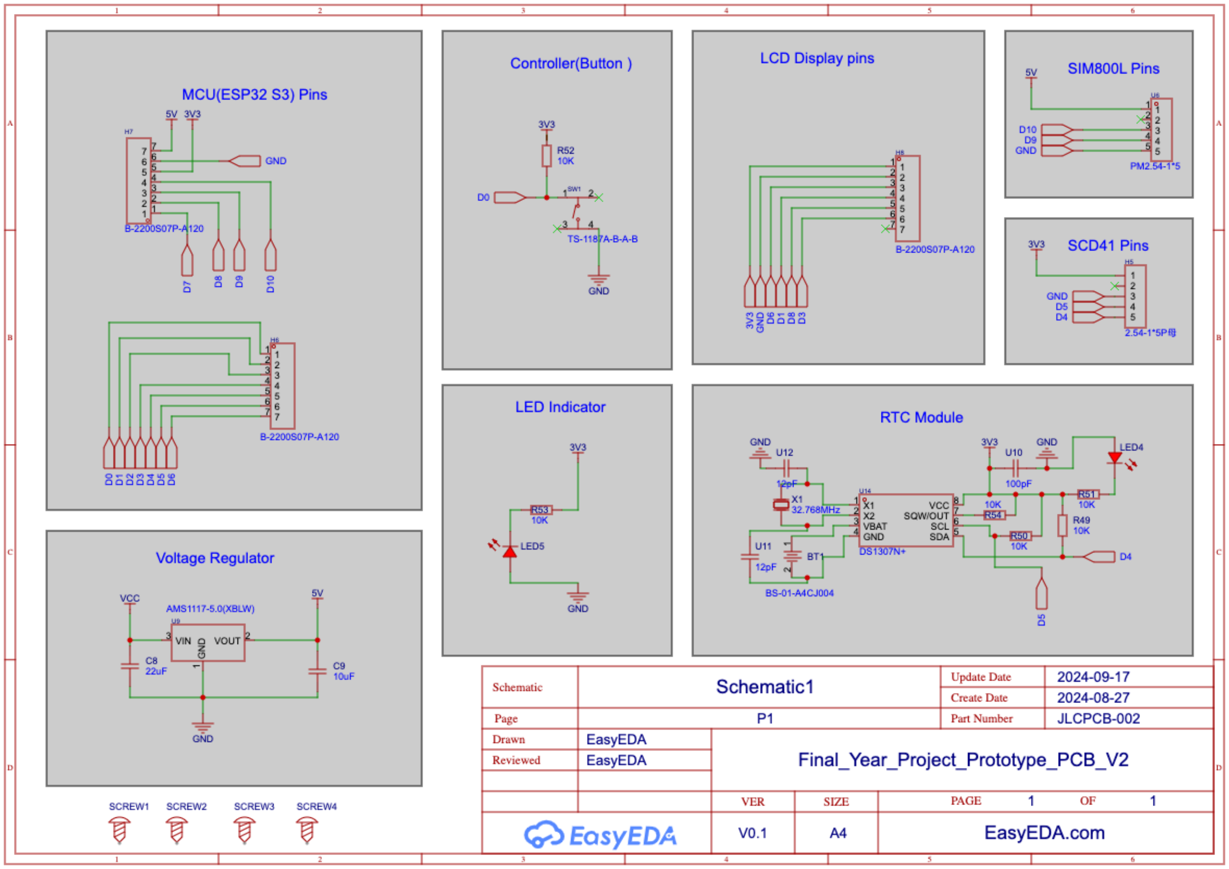


Figure 4.2 Schematic design of the prototype

A. Processing Unit

On the processing unit we used a TinyML XIAO ESP32S3 Sense microcontroller which has omnidirectional digital microphone (MP34DT05) with Pulse-Density Modulation (PDM) campabilities, wifi, Bluetooth Low Energy, SD Card integrated on the board.

B. Controllers' unit

A push button was used to control content displayed on the OLED LCD display and managing power on and off the device. The button was then interfaced with the 10K pull-up resistor to maintain the button state when goes HIGH or LOW.

C. Indicators

i. LED 1

The LED indicator was used to indicate the statue of the device when it is working on not, but also to indicate the level of the battery at the current state so user may decide to take the device and charge.

ii. LED 2

This LED was used to show the power of the thermos battery we attached on the Real-Time Clock (RTC) module to ensure the device is keeping is time information all the time.

D. Display

The 1.28″ Round TFT Display 240×240 was used in this study to display the device’s status information, sensor data and alerts incase the system is malfunctioning.

E. Communication module

Our proposed prototype used two communication modules the embedded ESP32 chip for wifi Connection and a tiny GSM SIM800L for GPRS and SMS communication. The wifi module was used to send data to cloud and GSM for normal messages to the user of the system.

F. Power Management

We build a custom power regulator by using the AMS1117 5V chip to be able to back-boost power from a power source above 5V to 5V since the XIAO ESP32S3 Sense is 3.3V based microcontroller after we found that it will difficult to power device which take 3.7V and above.

4.1.2 PCB Design and Production

After breadboard testing, we printed a Circuit board using CNC Machine for testing the connection, power distribution all the system functionalities as you can see it on the Figure 4.3 and 4.4 as part of validating out proposed system design before the final prototyping step. The system was updated to reduce number of modules to avoid board on board devices power consumption considerations.

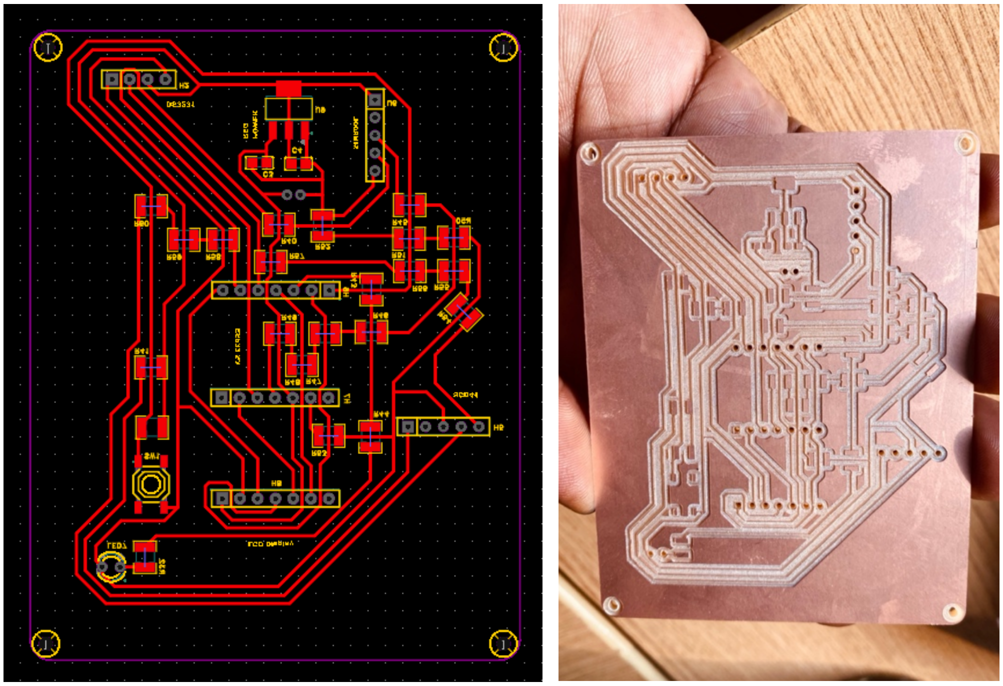


Figure 4.3 Schematic and PCB from the CNC Machine

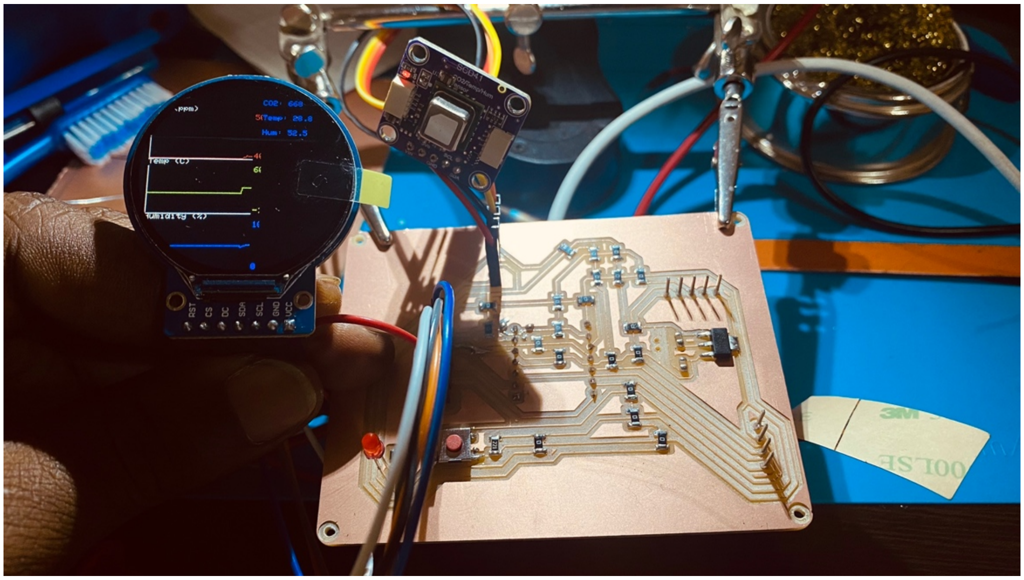


Figure 4.4 Testing the PCB from the CNC Machine

After the testing and verification of the final design of the PCB was done and accommodate changes like power management modules, designing of a custom Real-Time Clock we design two layers Printed Circuit Board and it was order and printed as shown in the figures 4.5 and 4.6 respectively. There after the components were soldered to get ready for the prototype testing.

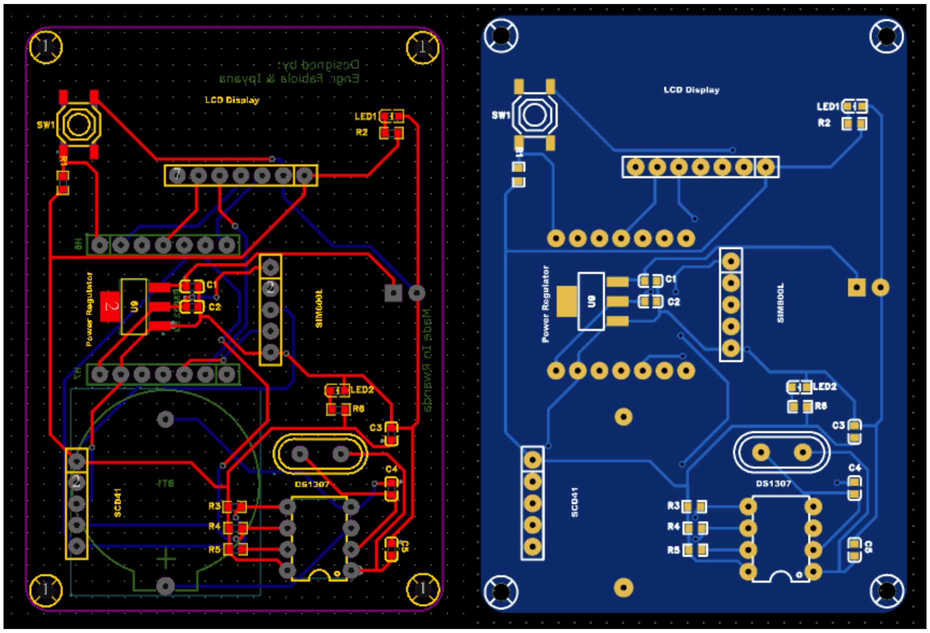


Figure 4.5 Final Prototype schematic and 2D view presentation

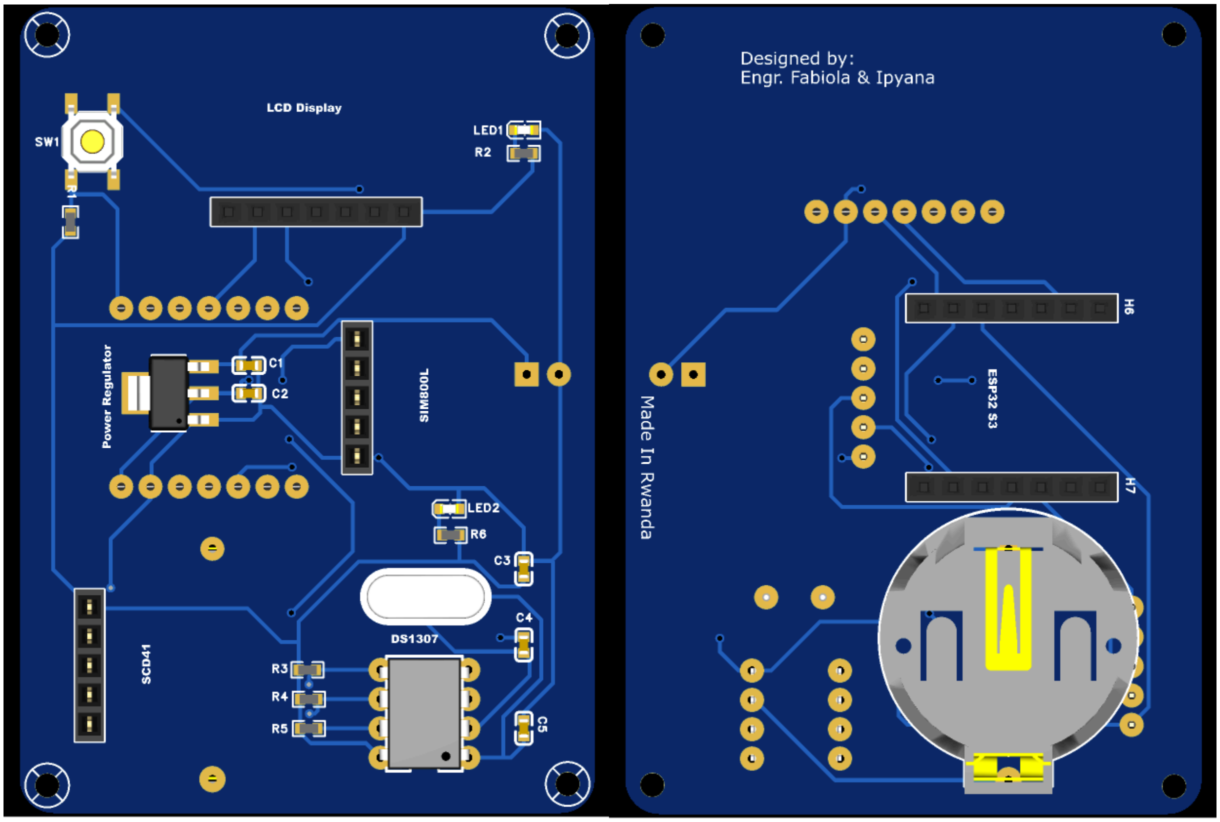


Figure 4.6 Front and back layers 3D View of the prototype

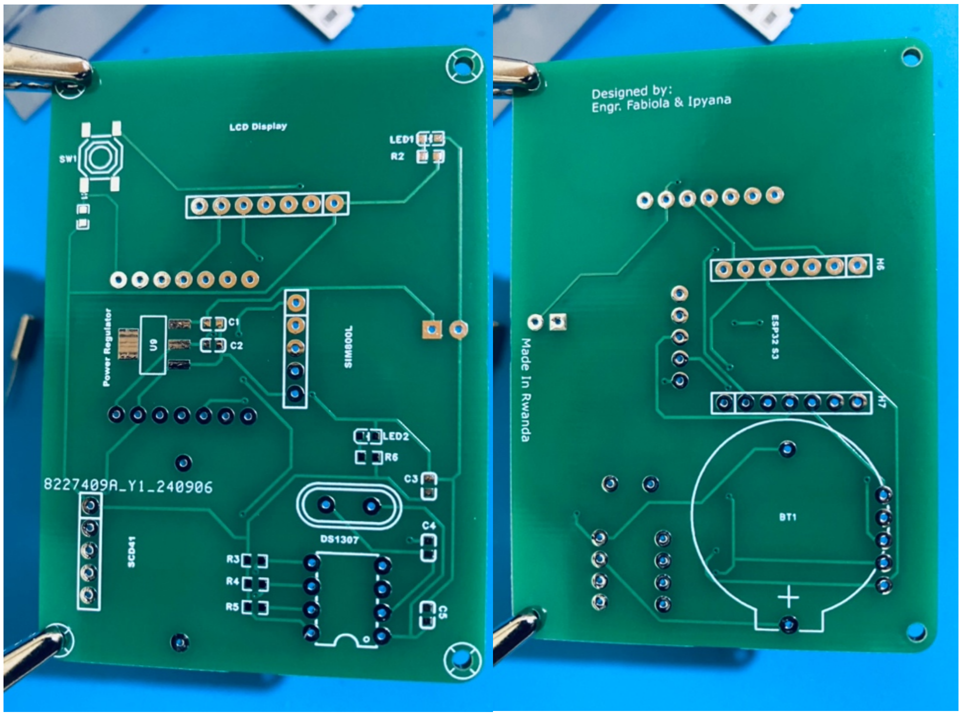


Figure 4.7 Final two layers Printed Circuit Board

The final printed PCB was then tested regarding circuit continuity and short circuit before we mount sensor modules and other components and power the device to check it performance. Components were soldered on the board as shown in Figure 4.8 and test sensors and communication modules if are working as we desired.

4.2 Software development for data management and visualization

The primary aim of developing the prototype's web-based dashboard was to create an intuitive, efficient, and feature-rich interface for users to monitor and manage their grain storage environments. This dashboard serves as the central hub for both administrators and normal users to interact with the device system, visualize sensor data, manage devices, and generate reports.

Key objectives included:

- Providing real-time and historical data visualization of sensor readings
- Enabling efficient device management for users and administrators
- Implementing a robust reporting system for data analysis

- Ensuring a responsive and user-friendly interface across devices
- Maintaining secure access control with role-based permissions

4.2.1 System Architecture

The dashboard is built on a client-server architecture, utilizing modern web technologies to ensure performance, scalability, and maintainability.

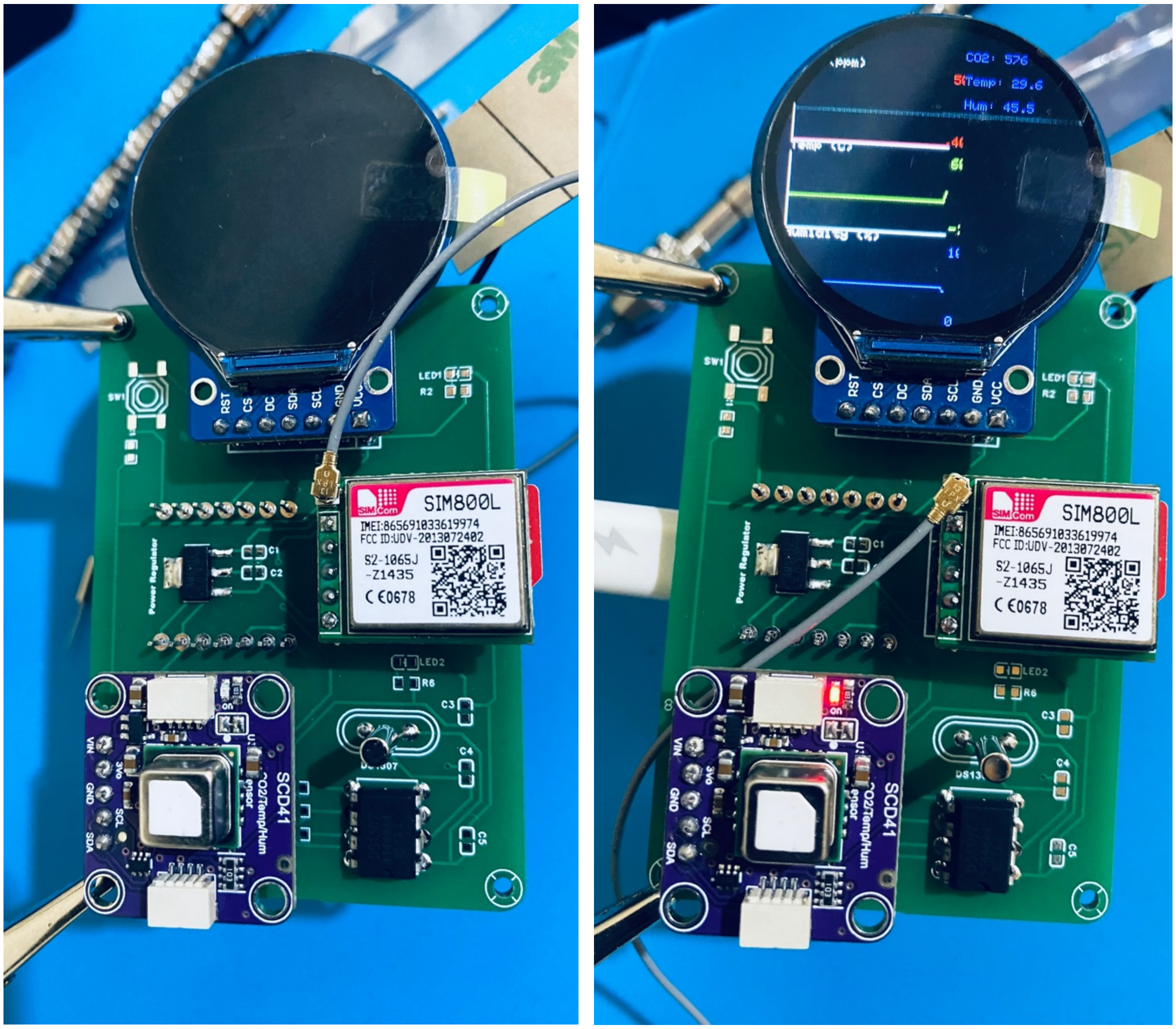


Figure 4.8 Mounting components on the PCB and testing

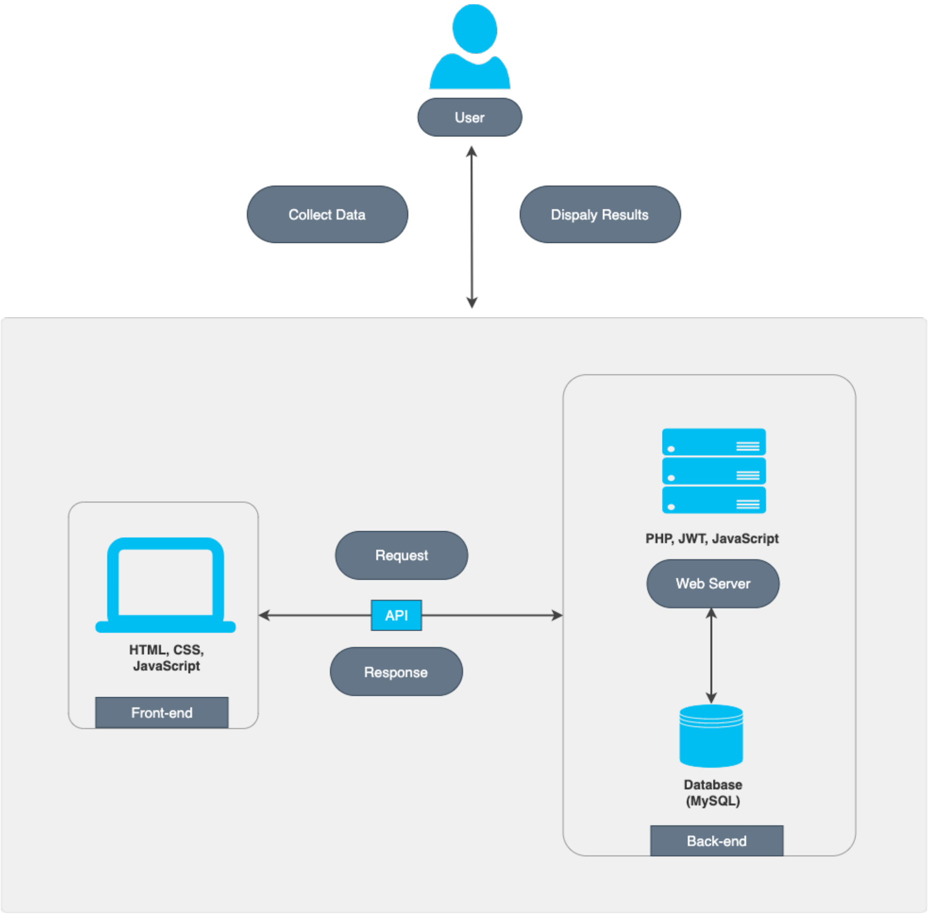


Figure 4.9 System Architecture Diagram

4.2.1.1 ***Front-end Technologies***

A. React.js

This is a Javascript library which enables the creation of a dynamic and responsive front-end user interface through its component-based structure. React's virtual DOM and efficient rendering mechanisms ensure smooth performance, even when handling real-time data updates from multiple sensors. Its modular nature facilitates code reusability and maintainability, allowing for rapid development and easy scaling of the dashboard's features.

B. Tailwind CSS

Tailwind CSS is employed as the primary styling framework for the System's dashboard. This CSS framework accelerates the UI development process by providing a comprehensive set of pre-built classes and allows for highly customizable designs without the need for writing custom CSS, resulting in a consistent and polished user interface

C. Recharts

Recharts is utilized for data visualization within the system. This React-based charting library offers a wide array of customizable chart types, making it ideal for displaying complex sensor data in an intuitive and visually appealing manner and allowing for seamless integration of interactive charts that update in real-time as new data is received.

D. Axios

Axios is implemented as the HTTP client for the System’s dashboard, handling all API requests to the back-end server. This library simplifies asynchronous data fetching, providing a clean and consistent interface for making HTTP requests. Axios' interceptor feature is leveraged to handle common tasks such as adding authentication tokens to requests and managing global error handling and automatically transform JSON data streamlines the process of integrating API responses into the React components, enhancing overall development efficiency.

4.2.1.2 Back-end Technologies

A. PHP

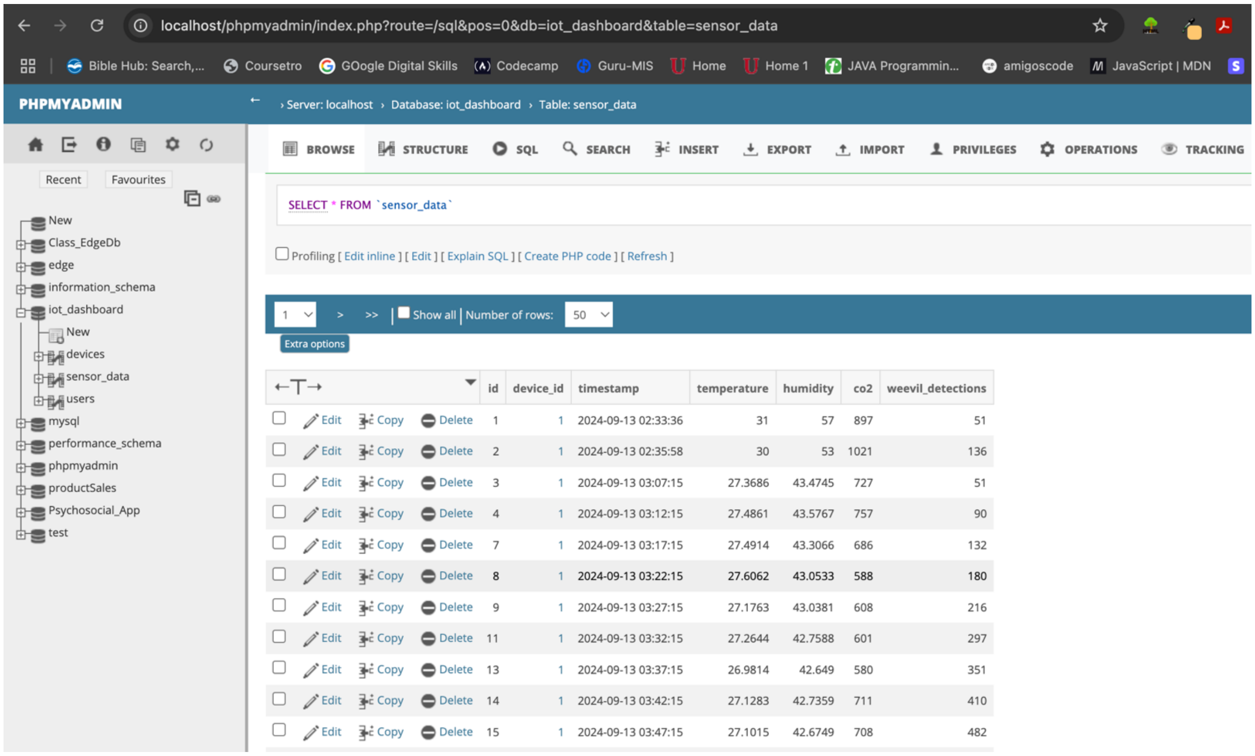
PHP serves as the primary server-side scripting language for the system. Its capabilities are leveraged to handle API requests, process data, and manage server-side logic. PHP's extensive libraries and frameworks facilitate efficient development of restful API’s, enabling seamless communication between the front-end and the database. Its ability to interact with various databases, particularly mysql, makes it an ideal choice for managing complex data operations.

B. Mysql

Mysql is employed as the Relational Database Management System (RDBMS) for the project as Figure 4.10 depicted it. This powerful and reliable database system efficiently stores and manages all sensor data, user information, and system configurations. Mysql's querying capabilities allow for quick retrieval and manipulation of large datasets, essential for generating real-time analytics and historical reports. Mysql's compatibility with PHP further streamlines the data management process, allowing for efficient data storage and retrieval operations.

C. Apache

Apache serves as the web server software for the system, providing a stable and secure environment for hosting the back-end components. Its modular architecture allows for easy customization and optimization to meet the specific needs of the project. Apache's features, including SSL/TLS support, enable secure communication between clients and the server. Its ability to handle concurrent connections efficiently ensures that the system can manage multiple user requests simultaneously, maintaining responsiveness even under high load.



```
SELECT * FROM `sensor_data`
```

id	device_id	timestamp	temperature	humidity	co2	weevil_detections
1	1	2024-09-13 02:33:36	31	57	897	51
2	1	2024-09-13 02:35:58	30	53	1021	136
3	1	2024-09-13 03:07:15	27.3686	43.4745	727	51
4	1	2024-09-13 03:12:15	27.4861	43.5767	757	90
7	1	2024-09-13 03:17:15	27.4914	43.3066	686	132
8	1	2024-09-13 03:22:15	27.6062	43.0533	588	180
9	1	2024-09-13 03:27:15	27.1763	43.0381	608	216
11	1	2024-09-13 03:32:15	27.2644	42.7588	601	297
13	1	2024-09-13 03:37:15	26.9814	42.649	580	351
14	1	2024-09-13 03:42:15	27.1283	42.7359	711	410
15	1	2024-09-13 03:47:15	27.1015	42.6749	708	482

Figure 4.10 Database structure

4.2.1.3 Communication

The system utilizes a RESTful API architecture for communication between front-end and back-end components, offering key advantages. This approach enhances scalability and maintainability by allowing independent scaling and updates of components. It also enables parallel development and testing, with front-end and back-end teams working separately using agreed-upon API contracts. This separation accelerates development, allows for specialized focus, and facilitates effective testing strategies. The back-end team can develop and test API endpoints using tools like Postman or Swagger, while the front-end team can use mock data for UI development and testing, ensuring both data integrity and a smooth user experience.

4.2.2 User Roles and Functionalities

The dashboard implements a role-based access control system, distinguishing between administrator and normal user roles.

4.2.2.1 Administrator Functionalities

The dashboard in Figure 4.11 provides administrators with a comprehensive set of tools to manage the entire system efficiently. These comprehensive functionalities empower administrators to maintain system integrity, ensure optimal performance, and make data-driven decisions for improving grain storage practices across the organization.

Admin Dashboard

System Overview

Total Devices: 3
Total Users: 7

Select Device for Monitoring
D0001 - Nyabugogo

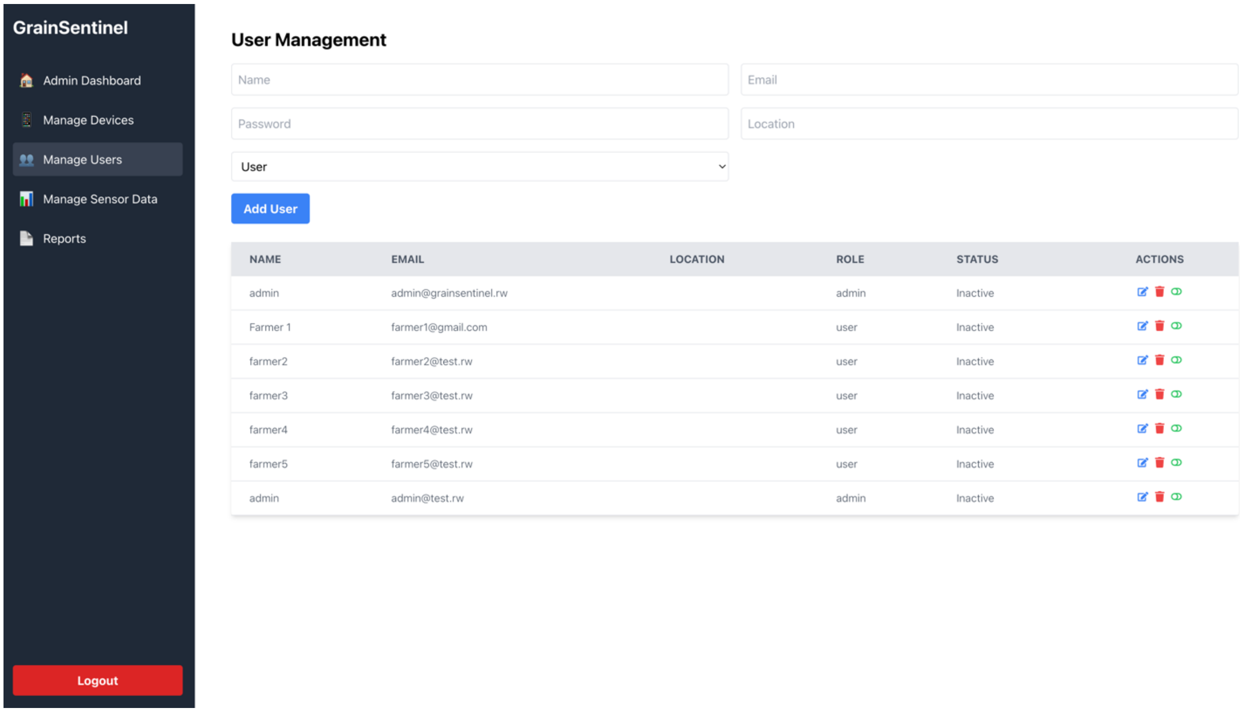
Start Date
09/10/2024

End Date
09/17/2024

2024-09-15 08:43:27
CO2 (ppm) : 560

Figure 4.11 Admin-User main dashboard interface

The system's administrative functions encompass four key areas: user management, device management, data access, and reporting. Administrators can create, edit, and delete user accounts for access control and security. They manage grain monitoring devices by adding, editing, and removing them from the system. Unrestricted access to all sensor data across the network allows administrators to monitor overall grain storage facility health and identify systemic issues. Lastly, they can generate comprehensive system-wide reports to gain insights into trends, anomalies, and performance metrics across all monitored locations.

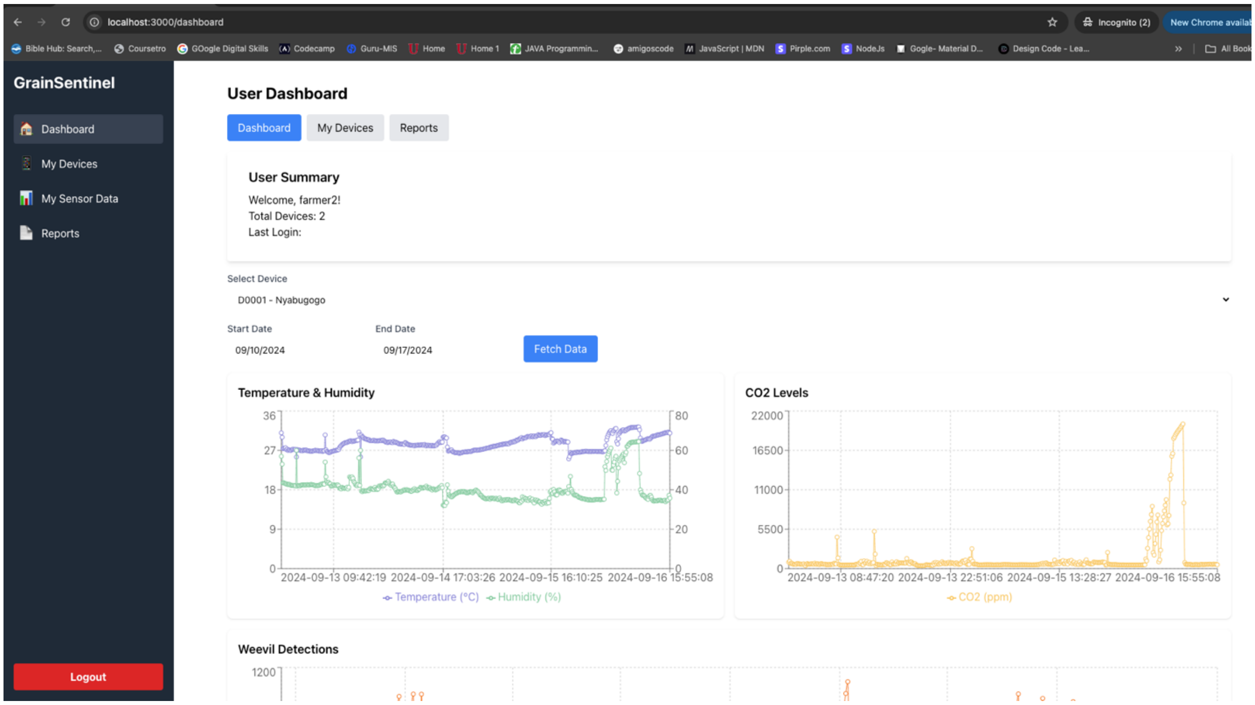


NAME	EMAIL	LOCATION	ROLE	STATUS	ACTIONS
admin	admin@grainsentinel.rw		admin	Inactive	
Farmer 1	farmer1@gmail.com		user	Inactive	
farmer2	farmer2@test.rw		user	Inactive	
farmer3	farmer3@test.rw		user	Inactive	
farmer4	farmer4@test.rw		user	Inactive	
farmer5	farmer5@test.rw		user	Inactive	
admin	admin@test.rw		admin	Inactive	

Figure 4.12 User Management Interface for Administrators

4.2.2.2 Normal User Functionalities

Normal users of the Grain Sentinel dashboard have access to a specific set of functionalities tailored to their responsibilities as shown in Figure 4.13. They can view and manage assigned devices, typically corresponding to the grain storage facilities they oversee. This includes monitoring real-time sensor data on critical parameters like temperature, humidity, and CO2 levels, allowing users to identify patterns affecting grain quality. Additionally, normal users can generate customized reports for their specific devices, set up scheduled reports, and export data for further analysis or presentation.



User Dashboard

User Summary
Welcome, farmer2!
Total Devices: 2
Last Login:

Select Device
D0001 - Nyabugogo

Start Date
09/10/2024

End Date
09/17/2024

Figure 4.13 Normal user main dashboard interface

4.2.3 Dashboard Components

A. User Authentication

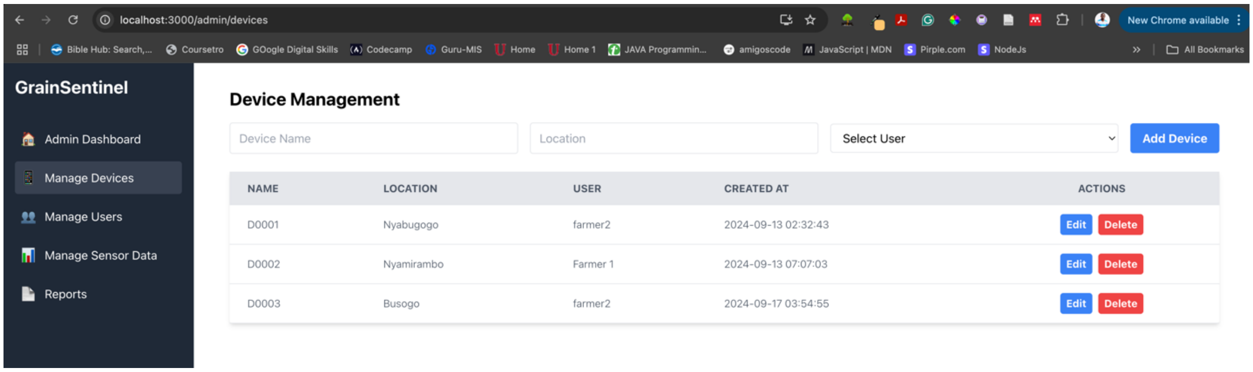
The Grain Sentinel dashboard implements a robust user authentication system to ensure secure access to the platform. It utilizes JSON Web Tokens (JWT) for efficient and secure session management, allowing for stateless authentication and reducing server load. Additionally, the system employs password hashing techniques to protect user credentials, ensuring that even in the unlikely event of a data breach, user passwords remain secure.

B. Navigation and Layout

The dashboard features a responsive design that seamlessly adapts to various screen sizes, ensuring a consistent and user-friendly experience across desktop computers, tablets, and smartphones. At the core of the interface is an intuitive navigation menu, strategically designed to provide easy access to all key sections of the dashboard. It maintains a consistent presence across different views, allowing users to quickly switch between functionalities such as device monitoring, data analysis, and user management.

C. Device Management

The device management component of the dashboard in Figure 4.14, offers a comprehensive interface for overseeing all connected grain monitoring devices. It presents a list view of all devices, displaying key information such as device ID, location, status, and last update time at a glance. Users with appropriate permissions can easily add new devices to the system through a streamlined interface, inputting necessary details and configurations. The component also allows for editing existing device information to keep records up-to-date.

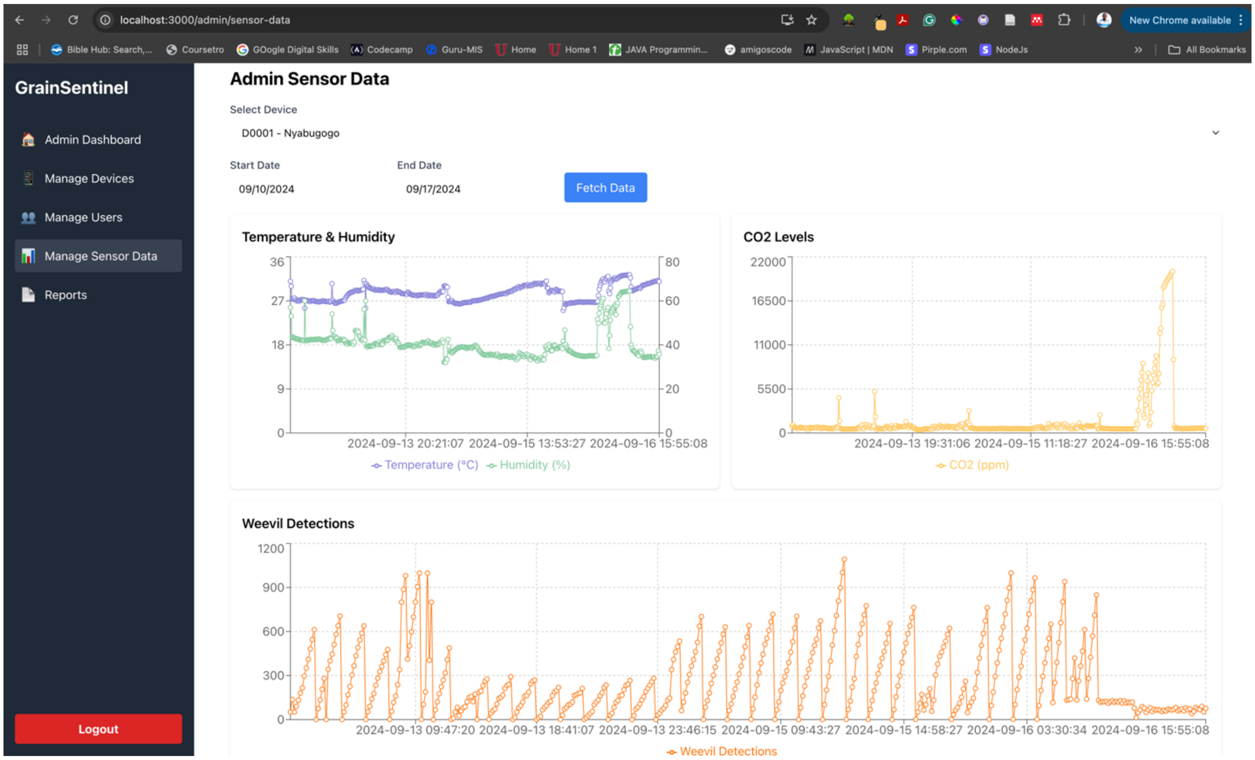


NAME	LOCATION	USER	CREATED AT	ACTIONS
D0001	Nyabugogo	farmer2	2024-09-13 02:32:43	Edit Delete
D0002	Nyamirambo	Farmer 1	2024-09-13 07:07:03	Edit Delete
D0003	Busogo	farmer2	2024-09-17 03:54:55	Edit Delete

Figure 4.14 Device Management Interface

4.2.4 Data Visualization

The dashboard's in Figure 4.15 core features powerful data visualization tools for comprehensive grain storage insights. It includes interactive line charts displaying critical parameters like temperature, humidity, CO2 levels, and weevil detections. A flexible date range selector enables historical data analysis for long-term storage optimization. Real-time data updates ensure current information for immediate monitoring and rapid response. Color-coded indicators highlight abnormal readings, allowing quick problem identification and prioritization. These visualization tools empower users to make data-driven decisions, maintain optimal storage conditions, and prevent potential losses.



Admin Sensor Data

Select Device: D0001 - Nyabugogo

Start Date: 09/10/2024

End Date: 09/17/2024

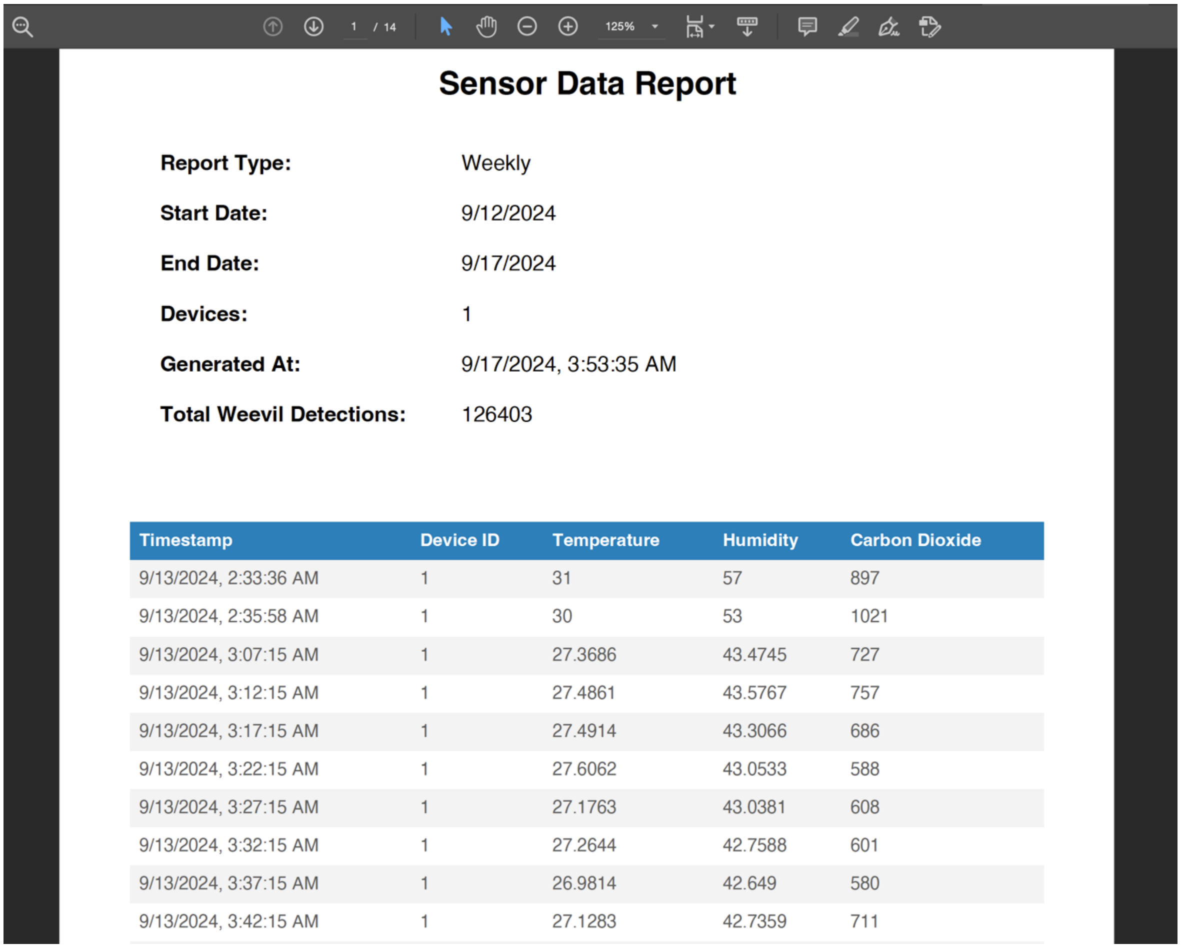
Figure 4.15 Sensor data visualization charts interface

4.2.5 Reporting System

The dashboard's reporting system in Figure 4.16 allows users to generate comprehensive grain storage analyses. It features multi-device selection for direct comparisons, custom date range specification for historical trend analysis, and granular control over report content, including specific sensor type selection. The system supports multiple output formats like PDF for sharing and CSV for further analysis. This flexible reporting capability enables users to derive actionable insights and support informed decision-making processes in grain storage management.

4.2.6 Data Flow and Processing

The system's data pipeline efficiently manages sensor data from collection to visualization. IoT devices in grain storage facilities continuously gather and transmit environmental data to the server. This data is validated and stored in a MySQL database, supporting both real-time monitoring and historical analysis. When users interact with the dashboard, the front-end requests relevant data subsets from the back-end API. The retrieved data is then processed and formatted for visualization using the Recharts library, creating interactive charts. To ensure real-time updates, the system employs polling techniques, periodically fetching and displaying the latest data. This seamless process ensures users always have access to current and accurate grain storage information.



Sensor Data Report

Report Type: Weekly

Start Date: 9/12/2024

End Date: 9/17/2024

Devices: 1

Generated At: 9/17/2024, 3:53:35 AM

Total Weevil Detections: 126403

Timestamp	Device ID	Temperature	Humidity	Carbon Dioxide
9/13/2024, 2:33:36 AM	1	31	57	897
9/13/2024, 2:35:58 AM	1	30	53	1021
9/13/2024, 3:07:15 AM	1	27.3686	43.4745	727
9/13/2024, 3:12:15 AM	1	27.4861	43.5767	757
9/13/2024, 3:17:15 AM	1	27.4914	43.3066	686
9/13/2024, 3:22:15 AM	1	27.6062	43.0533	588
9/13/2024, 3:27:15 AM	1	27.1763	43.0381	608
9/13/2024, 3:32:15 AM	1	27.2644	42.7588	601
9/13/2024, 3:37:15 AM	1	26.9814	42.649	580
9/13/2024, 3:42:15 AM	1	27.1283	42.7359	711

Figure 4.16 System’s Generated Report

4.2.7 Security Measures

The system employs a multi-layered cybersecurity approach to ensure data security and system integrity. It uses HTTPS encryption for all client-server communications, protecting sensitive information during transit. Rigorous input validation and sanitization techniques are implemented to mitigate SQL injection and Cross-Site Scripting (XSS) risks. Rate limiting mechanisms defend against brute-force attacks by restricting login attempts. The Grain Sentinel team conducts regular security audits and promptly applies updates to maintain high security standards and resilience against emerging threats. These comprehensive measures provide users with a secure and reliable platform for managing grain storage data.

4.3 TinyML Model Development

The TinyML model was developed in Edge Impulse Studio platform which provides an environment for developing Machine Learning models for the resource-constrained devices. This platform supports large varieties of these small microcontroller with different capabilities to ensure the models are running well in the devices. The platform automates different processes where the workflow starts with data acquisition, impulse design, EON Tuner, Retrain Model, Live classification, Model Testing, Performance calibration, versioning and deployment. The platform mainly has four main blocks namely, Build, Train, Optimize and Deploy shown in a Figure 4.17.

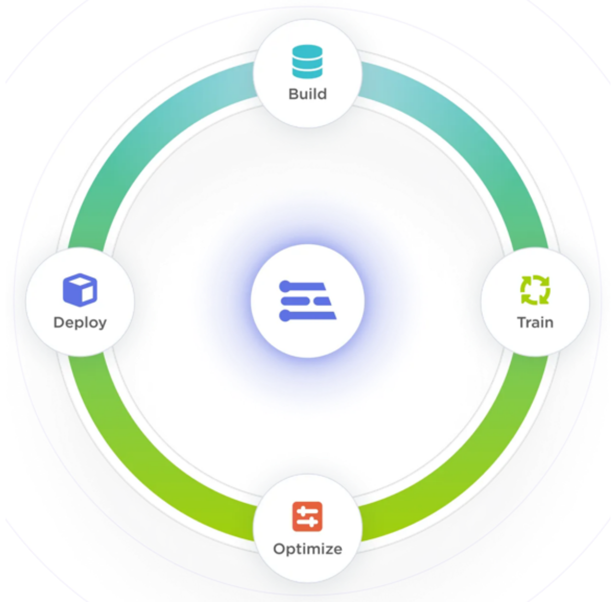


Figure 4.17 Edge Impulse building blocks

4.3.1 Preprocessing of Acoustic Data

The preprocessing and feature extraction of acoustic data were crucial steps in developing the TinyML model for maize weevil detection, utilizing the Edge Impulse Studio platform's automated capabilities. Mel-Frequency Cepstral Coefficients (MFCCs) were employed as the primary feature extraction technique, designed to capture perceptually relevant characteristics of audio signals, similar to human auditory processing.

The MFCC process involved several steps: dividing the audio signal into short frames, applying a Hamming window, performing Fast Fourier Transform (FFT), mapping spectrum powers onto the mel scale, taking logs of powers at each mel frequency, and applying a Discrete Cosine Transform (DCT). This process transforms raw acoustic data into a compact, machine-learning-ready representation.

MFCCs provide a representation of an acoustic signal's short-term power spectrum, derived through a linear cosine transform of the logarithmic power spectrum mapped onto the nonlinear Mel scale. The conversion between linear frequency (*f*) and Mel-frequency (f_{Mel}) is governed by a specific relationship (Equation 1), with MFCCs computed using a discrete cosine transform (Equation 2).

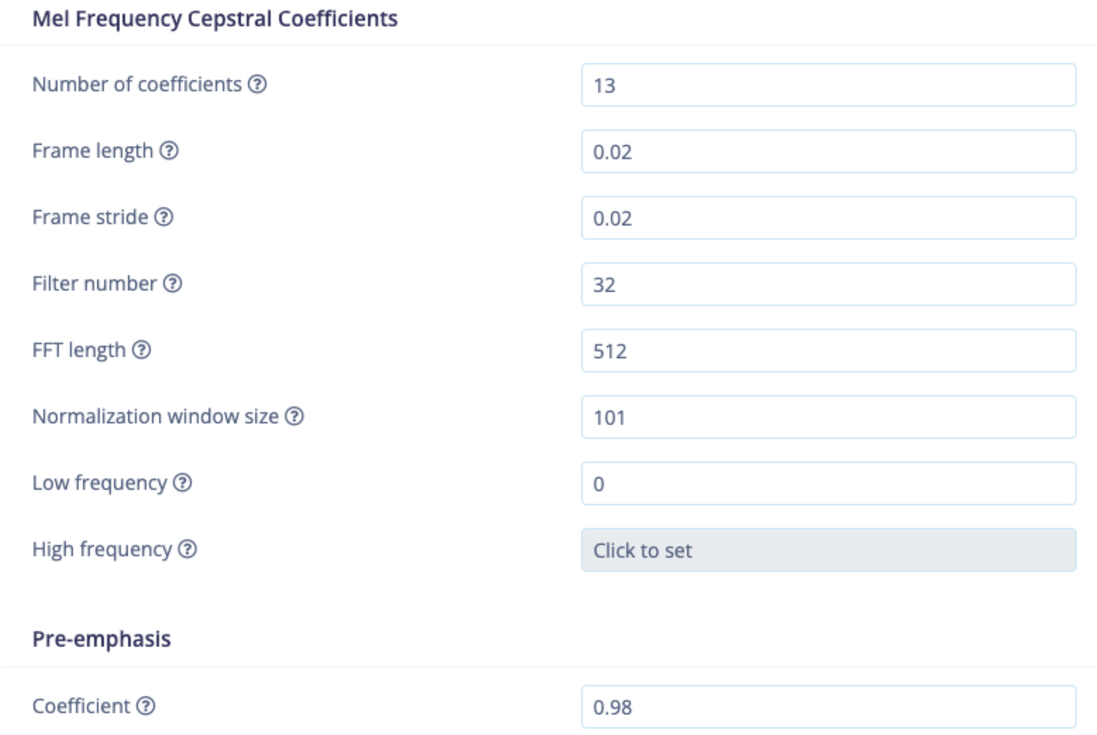
This approach captures the spectral characteristics of the signal, approximating human auditory perception and providing a robust feature set for the maize weevil detection model. Figure 4.18 illustrates the MFCC feature extraction process.

$$f_{Mel} = 2595\backslash log_{10}(1 + \backslash fracf700) \text{ ………….. (1)}$$

$$MFCC\_i = \surd\{\backslash frac\{2\}\{N\}\}\textstyle\sum\_\{j = 1\}\hat{}m\backslash cos(\backslash frac\{\pi\}\{N\}(j - 0.5)) \text{ …….. (2)}$$

Where *N* is the number of bandpass filters and *mj* is the logarithmic bandpass filter output amplitude.

In Edge Impulse Studio, this process involves; Dividing the audio signal into short frames, applying a windowing function (*often Hamming window*), Performing Fast Fourier Transform (FFT), Mapping the powers of the spectrum onto the mel scale, Taking the logs of the powers at each mel frequency, Applying Discrete Cosine Transform (DCT). The resulting coefficients represent the audio signal in a compact form that's suitable for machine learning as shown on the Figures 4.19, 4.20 and 4.21 respectively



Mel Frequency Cepstral Coefficients

Number of coefficients ⓘ	13
Frame length ⓘ	0.02
Frame stride ⓘ	0.02
Filter number ⓘ	32
FFT length ⓘ	512
Normalization window size ⓘ	101
Low frequency ⓘ	0
High frequency ⓘ	Click to set

Pre-emphasis

Coefficient ⓘ	0.98

Figure 4.18 Mel Frequency Cepstral Coefficients setting

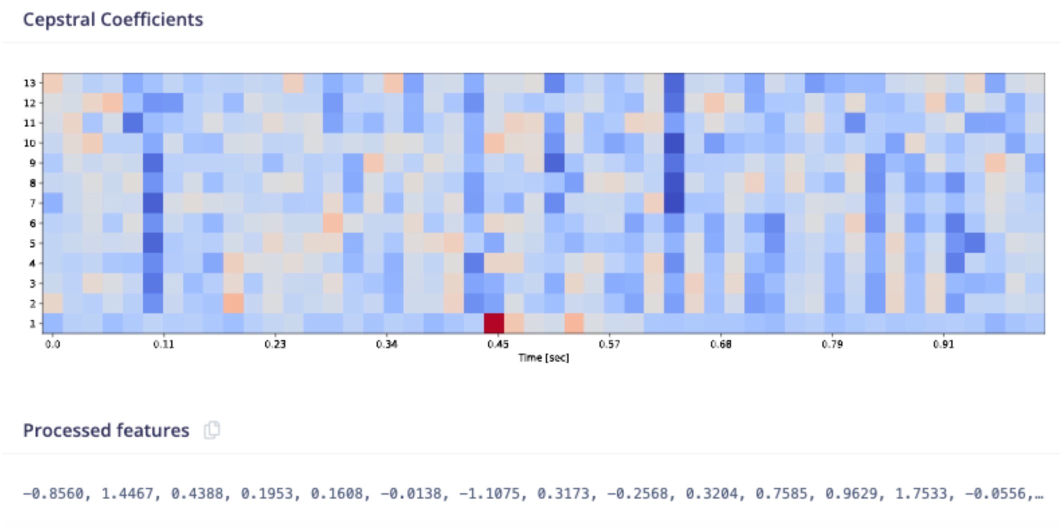
Raw features

`0, -24, 19, 62, 0, 0, 42, 0, 0, 21, -26, -52, -56, -39, 19, 0, -39, -20, -32, -26…`

Label

`Infestation`

Figure 4.19 Raw features



Processed features

```
-0.8560, 1.4467, 0.4388, 0.1953, 0.1608, -0.0138, -1.1075, 0.3173, -0.2568, 0.3204, 0.7585, 0.9629, 1.7533, -0.0556,…
```

Figure 4.20 Generated Processed features

PROCESSING TIME
210 ms.

PEAK RAM USAGE
11 KB

Figure 4.21 Audio extracted features

4.3.2 Design and training of a Convolutional Neural Network (CNN)

To develop an accurate TinyML model leveraging the extracted Mel-Frequency Cepstral Coefficients (MFCC), a 2D convolutional neural network architecture was employed using the Edge Impulse platform. The architecture consisted of an Input Block specifying the input shape based on the MFCC feature extraction technique, a Processing Block generating MFCC features, and a Learning Block comprising several layers.

The Learning Block included a Reshape Layer to convert the input MFCC features into a 2D tensor with 13 columns, followed by three sets of 2D Convolutional/Pooling Layers (32 filters with a kernel size of 3, 16 filters with a kernel size of 3, respectively) with max pooling operations and Dropout Layers (dropout rate of 0.5) to reduce overfitting as shown in figure 29 The output of these layers was then flattened into a 2D vector using a Flatten Layer, which was fed into two Dense Layers, one with 64 Neurons and the last one which is the final output layer with 2 neurons for the final classification task as shown in Figure 4.22.

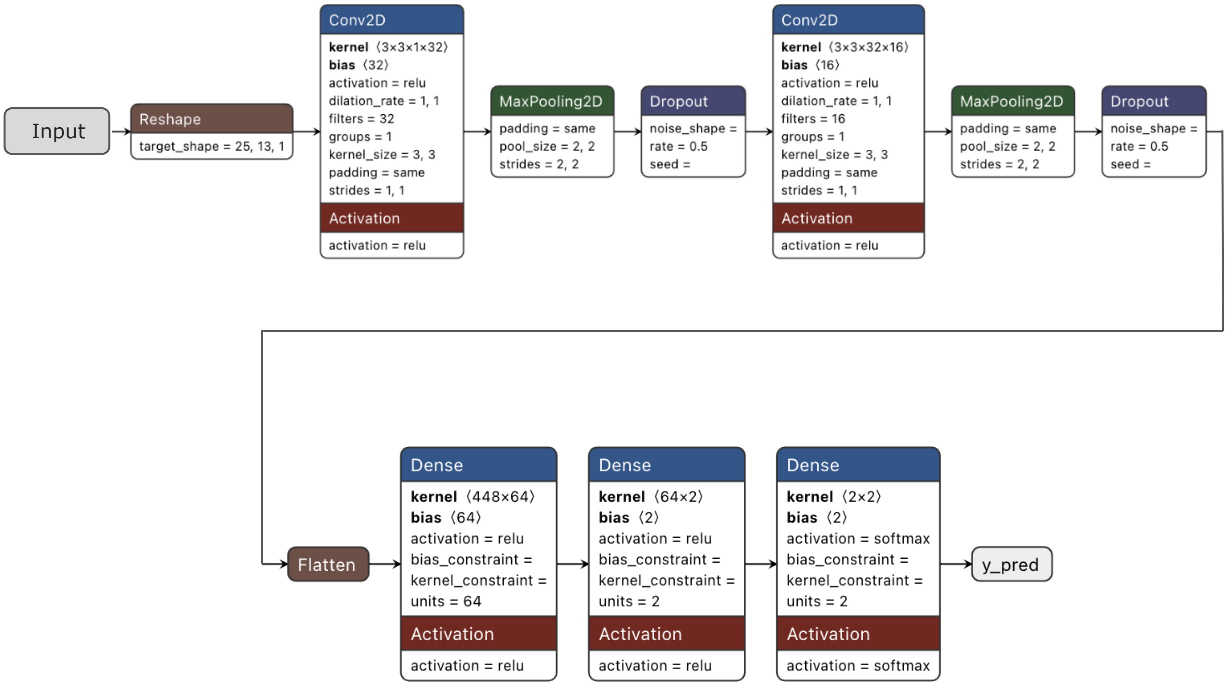


Figure 4.22 Neural Network Architecture

4.3.3 Model optimization for deployment on resource-constrained devices

In this phase, the TinyML acoustic model developed and was seamlessly integrated to create a comprehensive solution for early detection and continuous monitoring of maize weevil infestations. The integration involved deploying the TinyML acoustic model on a microcontroller platform, XIAO ESP32S3 and Arduino Nano 33 BLE Sense as shown in Figure 4.23, which are capable for running the Machine learning models and real-time processing of acoustic data through its built in PDM supported microphone. Concurrently, the environmental monitoring sensors were interfaced with the microcontroller, enabling the continuous acquisition of temperature, humidity, and carbon dioxide data.

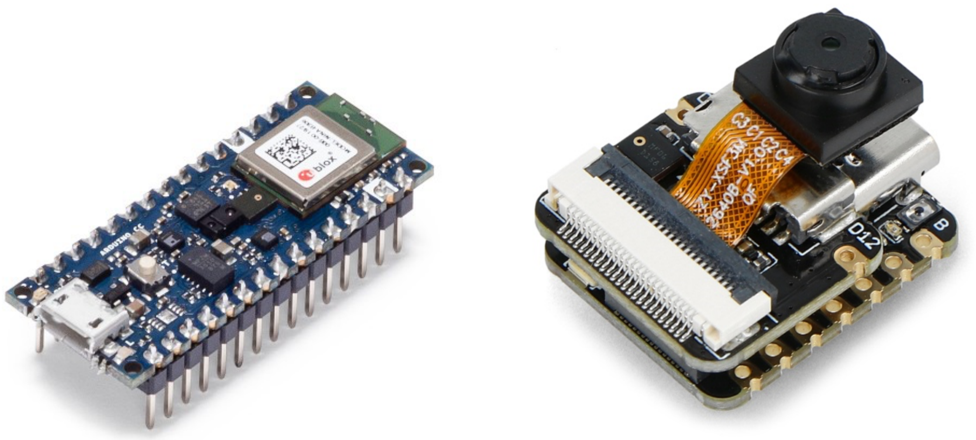


Figure 4.23 XIAO ESP32S3 Sense and Arduino Nano 33 BLE Sense microcontrollers

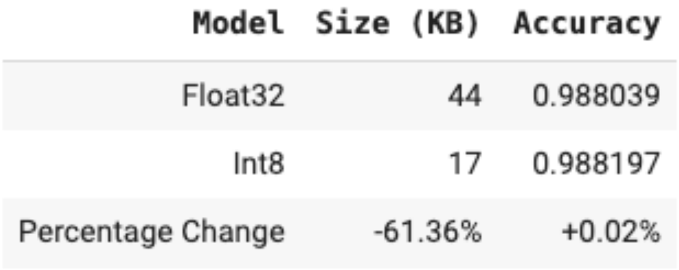
4.3.4 Integration of TinyML model with hardware components

This section provides a comprehensive overview of the process of integrating the TinyML model with the hardware components. It covers key aspects such as model optimization, firmware development, memory management, and power optimization, which are essential for deploying machine learning models on resource-constrained devices, the practical considerations for creating a real-time, efficient system suitable for agricultural settings and the challenges specific to TinyML applications and how they were addressed in our project.

4.3.4.1 Model Optimization

Model optimization for the TinyML solution focused on reducing size and computational requirements while maintaining high accuracy for maize weevil infestation detection. The process involved three key steps:

i. Quantization, converting from 32-bit floating-point to 8-bit integer format, significantly reducing memory footprint while maintaining 97.70% accuracy.
ii. Neural network pruning, removing unnecessary connections to decrease model size.
iii. Advanced compression techniques, including weight sharing, to further reduce the model's footprint. These optimization strategies resulted in a compact, powerful model suitable for real-time inference on resource-constrained devices.



Model	Size (KB)	Accuracy
Float32	44	0.988039
Int8	17	0.988197
Percentage Change	-61.36%	+0.02%

Figure 4.24 Model Optimization Trade-Off

Figure 4.24, illustrates the impact of our optimization process on model size and accuracy. The graph in Figure 4.25, shows the trade-off between model size reduction and accuracy preservation, highlighting the effectiveness of our approach in maintaining high performance while significantly decreasing resource requirements.

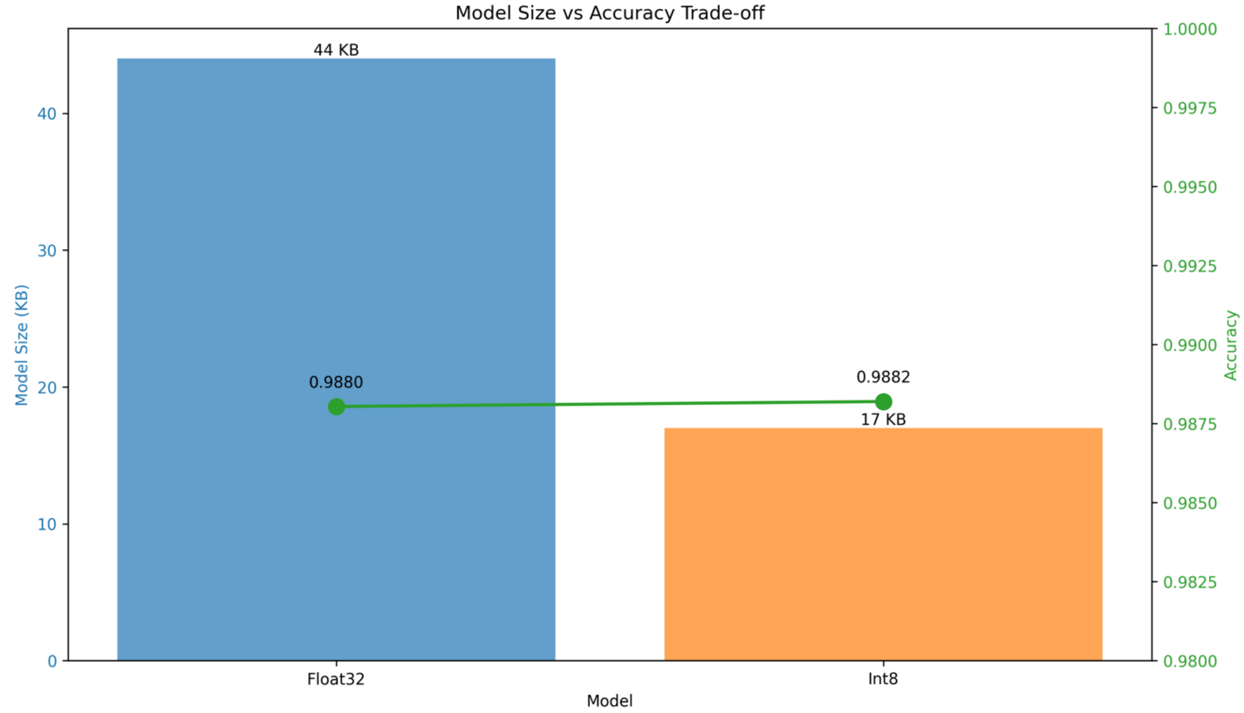
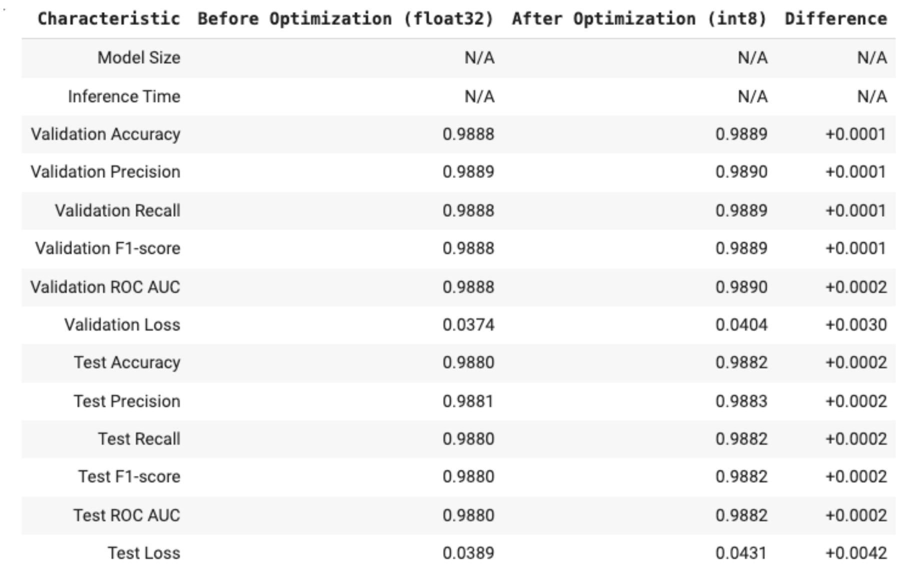


Figure 4.25 Model Size vs. Accuracy Trade-off Graph

Table 4.2, Provides a detailed comparison of the model's characteristics before and after optimization, including parameters such as model size, inference time, and accuracy on both training and test datasets.

Table 4. 1 Model Optimization Comparison



Characteristic	Before Optimization (float32)	After Optimization (int8)	Difference
Model Size	N/A	N/A	N/A
Inference Time	N/A	N/A	N/A
Validation Accuracy	0.9888	0.9889	+0.0001
Validation Precision	0.9889	0.9890	+0.0001
Validation Recall	0.9888	0.9889	+0.0001
Validation F1-score	0.9888	0.9889	+0.0001
Validation ROC AUC	0.9888	0.9890	+0.0002
Validation Loss	0.0374	0.0404	+0.0030
Test Accuracy	0.9880	0.9882	+0.0002
Test Precision	0.9881	0.9883	+0.0002
Test Recall	0.9880	0.9882	+0.0002
Test F1-score	0.9880	0.9882	+0.0002
Test ROC AUC	0.9880	0.9882	+0.0002
Test Loss	0.0389	0.0431	+0.0042

These optimization techniques were instrumental in bridging the gap between the computational demands of our sophisticated acoustic detection model and the resource constraints of edge devices typically available in agricultural settings. The resulting optimized model formed the cornerstone of our TinyML-enabled early detection system, enabling accurate, real-time monitoring of maize weevil infestations directly on low-power microcontrollers.

4.3.4.2 ***Firmware Development***

Custom firmware was developed for the XIAO ESP32S3 Sense and Arduino Nano 33 BLE Sense microcontrollers to enable TinyML-based maize weevil detection. The firmware integrates real-time audio processing, feature extraction, model inference, and power management. It includes an audio sampling routine interfacing with a PDM microphone at 16 kHz, an on-device MFCC feature extraction pipeline, and seamless integration of the optimized neural network for real-time detection. An adaptive power management system utilizing deep sleep capabilities and efficient wake-up triggers ensures long-term operation on battery power. This comprehensive firmware design enables efficient, real-time weevil activity detection in agricultural settings with limited power sources as shown in a flow chat in Figure 4.26.

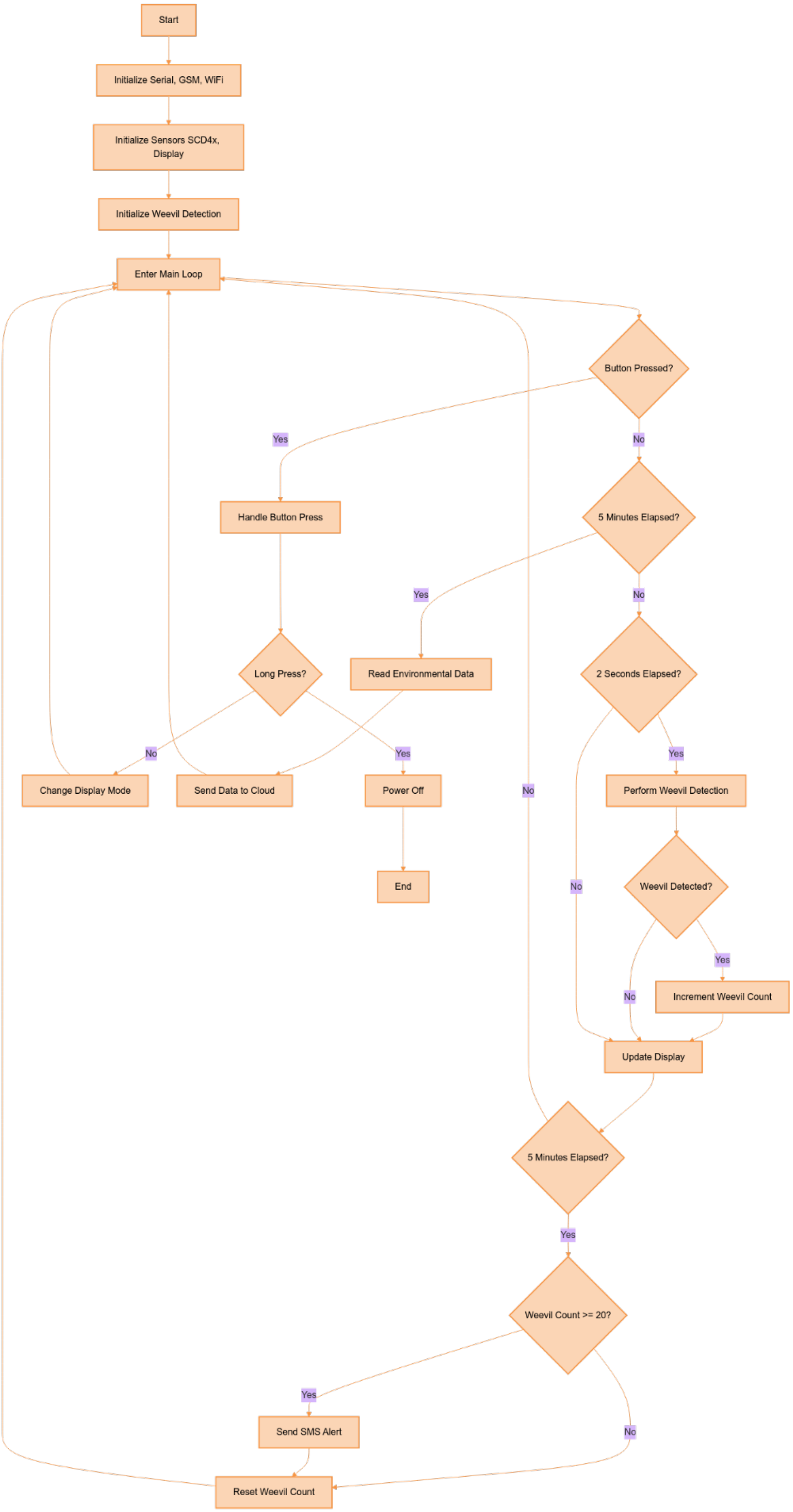
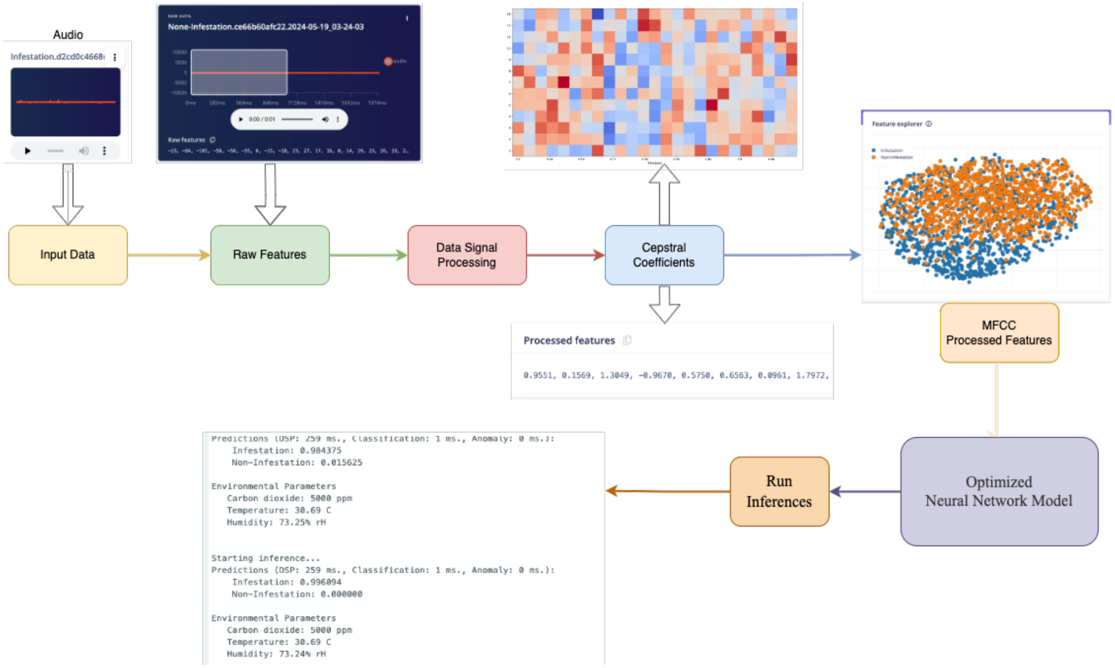


Figure 4.26 Firmware Operational Flowchart

The resulting firmware encapsulates the full functionality of our maize weevil detection system within a compact, efficient package, enabling standalone operation of the XIAO ESP32S3 Sense as an intelligent, energy-efficient sentinel against post-harvest pest infestations. This firmware development process demonstrates the balance required in edge AI applications, where advanced functionality must be achieved within the strict constraints of embedded systems.

4.3.4.3 ***Real-time Processing Pipeline***

The system's real-time maize weevil detection relies on an efficient processing pipeline. It begins with continuous audio sampling at 16 kHz, segmented into overlapping 2-second windows. These segments undergo MFCC feature extraction, transforming raw audio into a compact representation for the TinyML model. The optimized neural network then performs rapid inference on these features to detect weevil activity. A sliding window approach with 50% overlap ensures continuous monitoring without missing acoustic events. Figure 4.27 illustrates this pipeline, showing the data flow from initial audio sampling to final weevil detection output, providing a visual representation of the entire process from input to result.



```
0.9551, 0.1569, 1.3049, -0.9670, 0.5750, 0.6563, 0.0961, 1.7972,
```

```
Predictions (DSP: 259 ms., Classification: 1 ms., Anomaly: 0 ms.):
    Infestation: 0.984375
    Non-Infestation: 0.015625

Environmental Parameters
   Carbon dioxide: 5000 ppm
   Temperature: 30.69 C
   Humidity: 73.25% rH


Starting inference...
Predictions (DSP: 259 ms., Classification: 1 ms., Anomaly: 0 ms.):
    Infestation: 0.996094
    Non-Infestation: 0.000000

Environmental Parameters
   Carbon dioxide: 5000 ppm
   Temperature: 30.69 C
   Humidity: 73.24% rH
```

Figure 4.27 Real-time Audio Processing Pipeline Flowchart

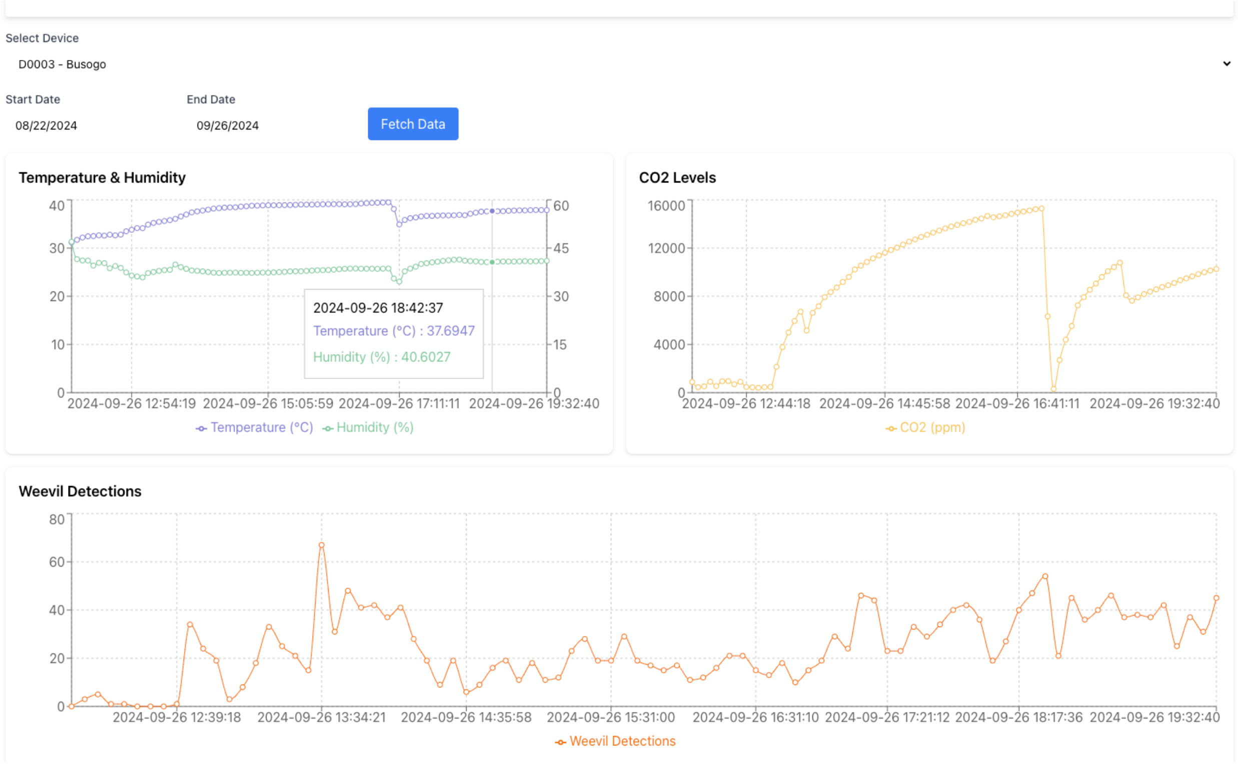
4.3.4.4 Integration with Sensor Data

The integration of our TinyML model's acoustic detection capabilities with environmental sensor data marks a significant advancement in the accuracy and reliability of our pest detection system. We developed a sophisticated synchronization mechanism to align the acoustic detection results with concurrent readings of temperature, humidity, and CO_2 levels from our environmental sensors. We implemented a multi-factor decision-making algorithm that considers both the acoustic signatures and the environmental parameters in its assessment of potential infestations. This algorithm weighs the likelihood of weevil activity based not only on detected sounds but also on whether the current environmental conditions are conducive to weevil behavior. For instance, a sound signature indicative of weevil activity might be given more credence if it occurs within temperature and humidity ranges known to be favorable for weevil propagation.

4.3.5 Field Testing in Simulated Storage Conditions

The system's real-time maize weevil detection relies on an efficient processing pipeline. It begins with continuous audio sampling at 16 kHz, segmented into overlapping 2-second windows. These segments undergo MFCC feature extraction, transforming raw audio into a compact representation for the TinyML model. The optimized neural network then performs rapid inference on these features to detect weevil activity. A sliding window approach with 50% overlap ensures continuous monitoring without missing acoustic events. Figure 4.28 illustrates this pipeline, showing the data flow from initial audio sampling to final weevil detection output, providing a visual representation of the entire process from input to result.

These field tests in simulated storage conditions provided compelling evidence of our system's efficacy and reliability in real-world scenarios, validating its potential as a powerful tool for early pest detection in post-harvest grain storage



Select Device
D0003 - Busogo

Start Date
08/22/2024

End Date
09/26/2024

Figure 4.28 Time Series of Detection Events and Environmental Conditions

Chapter 5 Results and Analysis

The chapter provides an overview of the findings and outcomes obtained from the data collection phase up to the deployment of the Tiny Machine Learning model and its performance metrics during the field testing.

5.1 Analysis of correlations between environmental conditions and weevil behavior

Our study revealed significant correlations between environmental conditions and maize weevil *(Sitophilus zeamais)* behavior [6], [7], providing basic insights for enhancing the accuracy of our detection system. Through continuous monitoring of temperature, humidity, and CO2 levels alongside acoustic data, we observed distinct patterns of weevil activity corresponding to specific environmental parameters [21]. Temperature emerged as a primary influencer, with weevil activity peaking between 25°C and 30°C. A notable increase in acoustic signatures indicative of movement and feeding was detected within this range, while activity sharply declined below 15°C and above 35°C [15], [56]. Humidity also played a vital role, with optimal weevil activity observed between 60% and 70% relative humidity. Interestingly, CO2 levels showed a positive correlation with weevil population density, with elevated levels (above 2000 ppm) often preceding detectable acoustic signatures of infestation by 24 to 48 hours [4]. This early indicator proved valuable for predictive modeling. We also noted diurnal patterns in weevil activity, with peak acoustic signatures typically occurring during night hours as shown in Figures 5.1, 5.2, 5.3, and 5.4 respectively, especially under stable temperature conditions. These correlations enabled us to refine our detection algorithms [68], [69], incorporating environmental thresholds to adjust the sensitivity of acoustic detection. For instance, the system now applies stricter criteria for positive detection when environmental conditions are less favorable for weevil activity, significantly reducing false positives. Conversely, it heightens alertness during optimal conditions, enabling earlier detection of potential infestations. This integrated approach, combining acoustic data with environmental monitoring [8], [9], [70], has markedly improved the overall accuracy and reliability of our maize weevil detection system, providing a more nuanced and context-aware solution for post-harvest pest management.

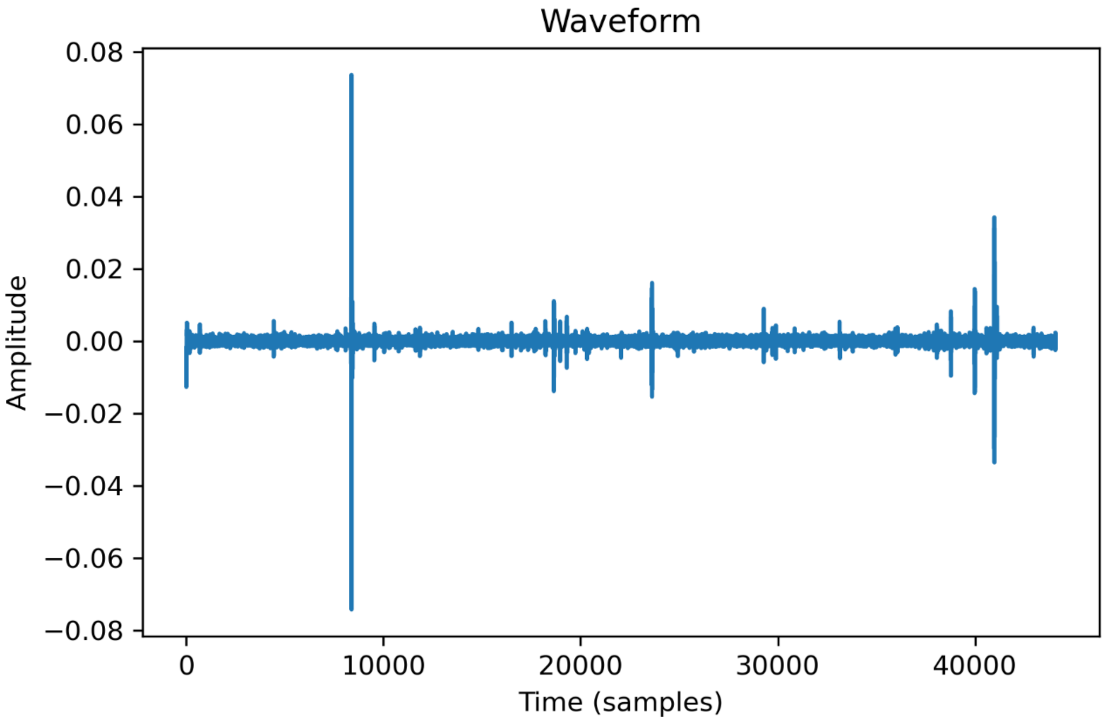


Figure 5.1 Adults acoustic signatures during daytimes

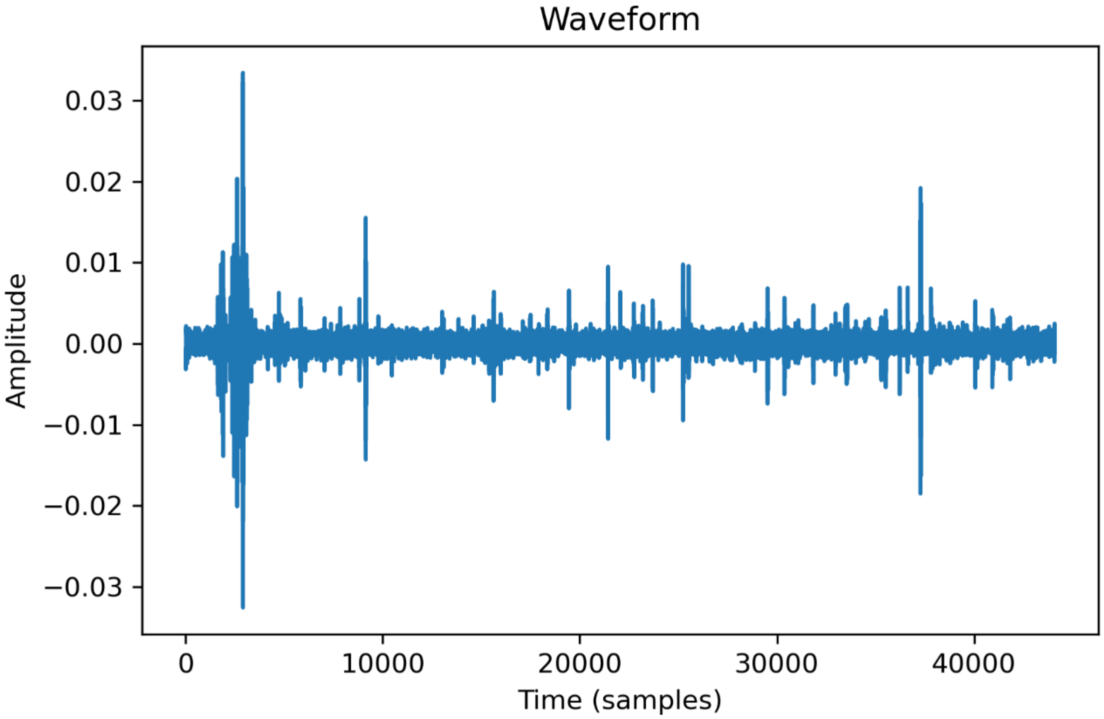


Figure 5.2 Larvae acoustic signatures during daytimes

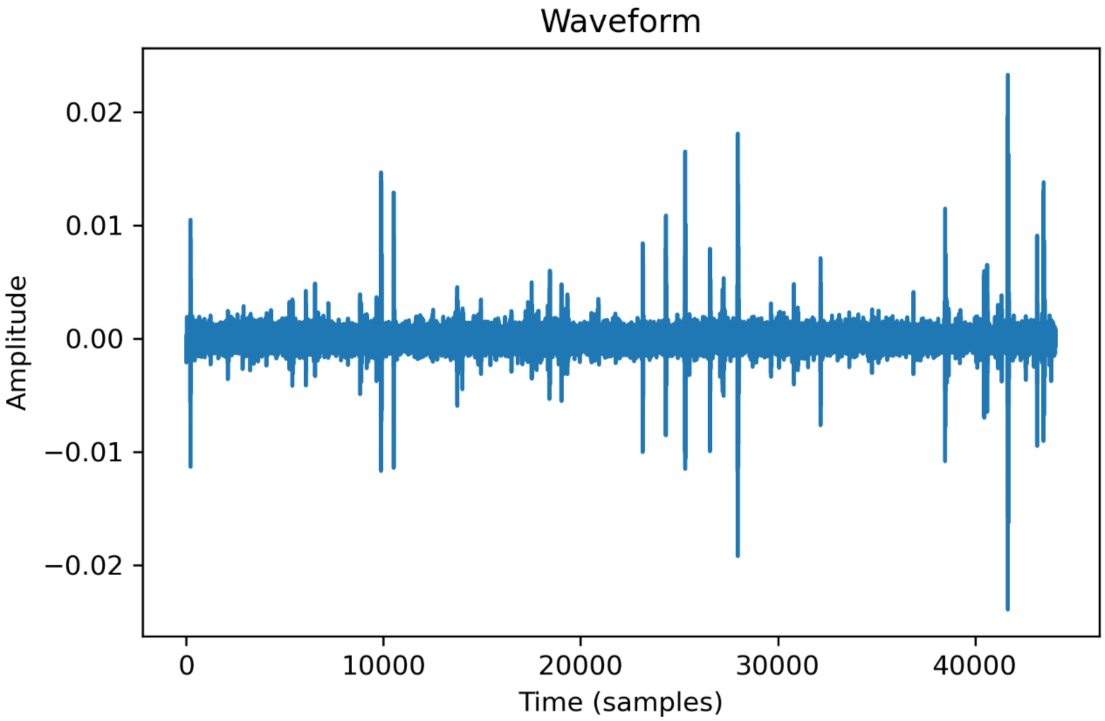


Figure 5.3 Adults sound signatures during night-time

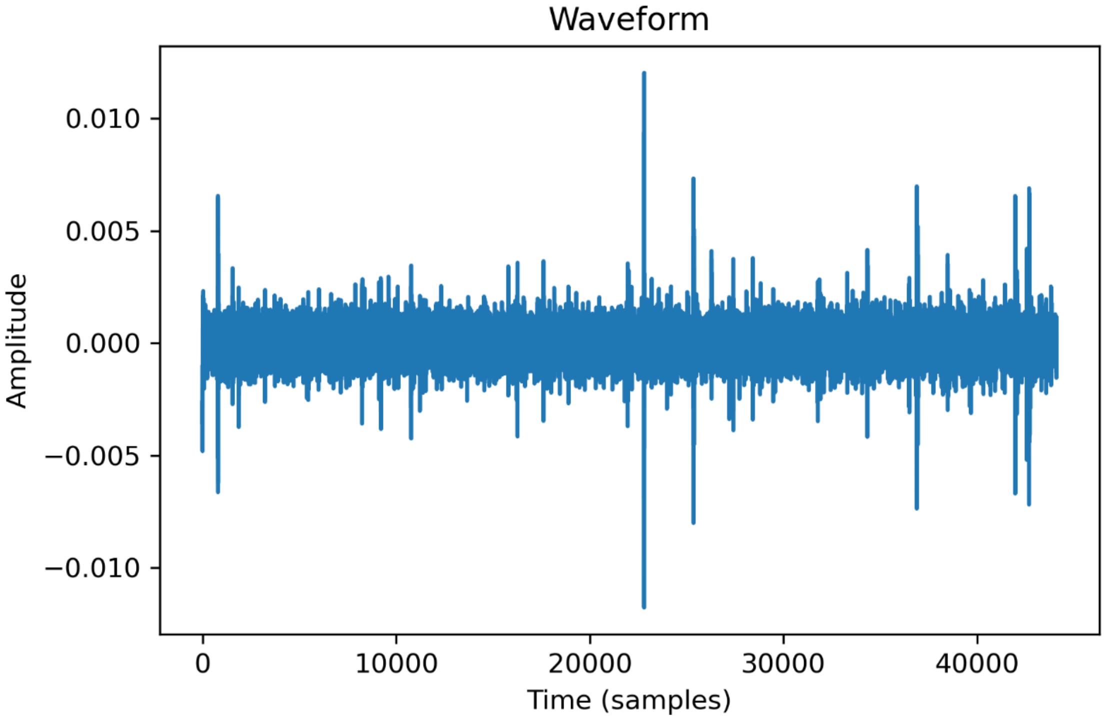


Figure 5.4 Larvae sound signatures during night-time

5.2 Model Training Results

The model training process involved several steps: data splitting (80:20 train-test ratio), feature extraction, impulse creation, and model training. Parameters were adjusted during training, including 25 training cycles, a 0.0005 learning rate, and data augmentation techniques (noise addition, mask time/frequency bands, time axis warping) to prevent overfitting and improve accuracy.

Model profiling reduced the large model to a microcontroller-compatible size, producing quantized (int8) and unoptimized (32-bit) versions. The training resulted in 98.9% accuracy with 0.04 loss, as shown in Figure 5.1. The expected on-device performance included 14 ms inferencing time, 4.9K peak RAM usage, and 41.4K flash usage.

The model performed well on the validation set, achieving 99.0% for Area under ROC Curve, Weighted average Precision, Weighted average Recall, and Weighted average F1 score, as illustrated in Figures 5.5 and 5.6.

Last training performance (validation set)

ACCURACY
98.9%

LOSS
0.04

Confusion matrix (validation set)

	INFESTATION	NON-INFESTATION
INFESTATION	98.3%	1.7%
NON-INFESTATION	0.5%	99.5%
F1 SCORE	0.99	0.99

Metrics (validation set)

METRIC	VALUE
Area under ROC Curve	0.99
Weighted average Precision	0.99
Weighted average Recall	0.99
Weighted average F1 score	0.99

Figure 5.5 Model Training Results

Engine: EON™ Compiler

INFERENCING TIME 14 ms.

PEAK RAM USAGE 4.9K

FLASH USAGE 41.4K

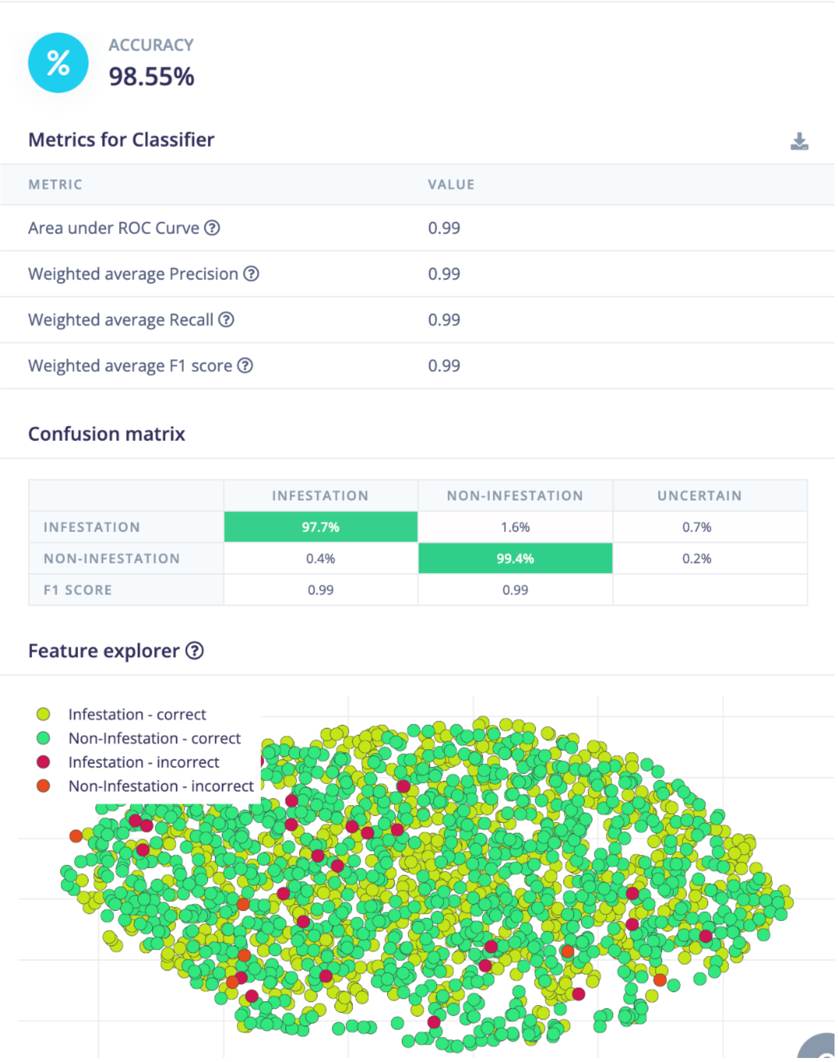
Figure 5.6 Data explorer from the training set

5.3 Model Testing Results

The model was tested using the test dataset to evaluate is accuracy on identifying weevils from the features extracted in the audio data provided. The model showed its ability on classifying weevils and non-weevils by the 98.55% accuracy with Area under ROC Curve on 99.0%, Weighted average Precision 99.0%, Weighted average Recall 99.0%, and the Weighted average F1 score of 99.0%, as shown in figure 5.7.

5.4 Model Performance Metrics

The TinyML model developed for the early detection of maize weevil infestations based on acoustic data demonstrated exceptional performance across both validation and test sets. The model was evaluated using two versions: a float32 precision model and a quantized int8 model, both showing comparable and robust results.



ACCURACY

98.55%

Metrics for Classifier

METRIC	VALUE
Area under ROC Curve	0.99
Weighted average Precision	0.99
Weighted average Recall	0.99
Weighted average F1 score	0.99

Confusion matrix

	INFESTATION	NON-INFESTATION	UNCERTAIN
INFESTATION	97.7%	1.6%	0.7%
NON-INFESTATION	0.4%	99.4%	0.2%
F1 SCORE	0.99	0.99	

Feature explorer

Figure 5.7 Model testing Results

5.4.1 Validation Set Performance

On the validation set, the float32 model achieved an accuracy of 98.88% and an area under the ROC curve (AUC-ROC) of 98.88% in figure 40. The weighted average metrics showed consistent performance with precision, recall, and F1-score all at 98.88%. The quantized int8 model performed slightly better, with an accuracy of 98.89% and an AUC-ROC of 98.90%. Its weighted average metrics were marginally higher, with precision at 98.90%, and recall and F1-score at 98.89%. The marginal improvement in the int8 model's performance is noteworthy. This suggests that the quantization process, which reduces the model's precision to use 8-bit integers instead of 32-bit floating-point numbers, did not negatively impact the model's ability to detect maize weevil infestations. In fact, it slightly enhanced performance, possibly due to a regularization effect that comes with reduced precision.

5.4.2 Test Set Performance

The model's generalization capability was confirmed on the test set, where it maintained its high performance. The float32 model achieved an accuracy of 98.80% and an AUC-ROC of 98.80% on the test set. The weighted average precision, recall, and F1-score were all 98.80%, indicating balanced performance across classes. The quantized int8 model showed a slight improvement, with an accuracy and AUC-ROC of 98.82%, and weighted average metrics of 98.83% for precision and 98.82% for recall and F1-score.

These results indicate strong generalization capability as proven on in the Figure 5.8. The model correctly classified 98.80% of all samples in the test set, which is remarkably close to its validation set performance (98.88%). The AUC-ROC of 98.80% demonstrates the model's excellent ability to discriminate between infested and non-infested samples across various classification thresholds, even on new data.

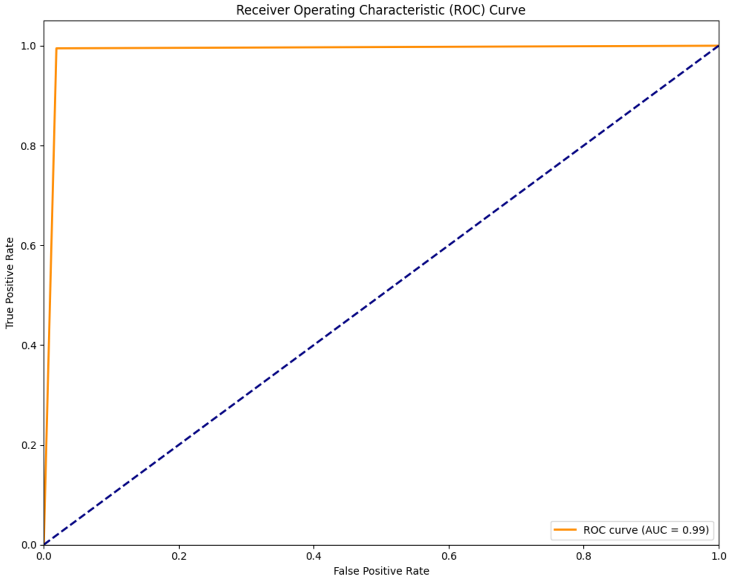


Figure 5.8 Receiver-operating characteristic curve (ROC)

5.4.3 Class-specific Performance

Analyzing the class-specific metrics for the float32 model on the test set reveals the model's effectiveness in distinguishing between infestation and non-infestation cases. For the infestation class in figure 4.5, the model achieved a precision of 99.47%, recall of 98.13%, and an F1-score of 98.79%. The non-infestation class showed similarly high performance with a precision of 98.16%, recall of 99.48%, and an F1-score of 98.81% as shown in Figure 5.10.

5.4.4 Confusion Matrix Analysis

The confusion matrix in Figure 5.9 for the float32 model on the test set shows that out of 15,767 actual infestation cases, the model correctly identified 15,472, with only 295 false negatives. For the 15,835 non-infestation cases, the model correctly classified 15,752, with just 83 false positives. This demonstrates the model's strong ability to minimize both false positives and false negatives, which is crucial for reliable early detection of maize weevil infestations.

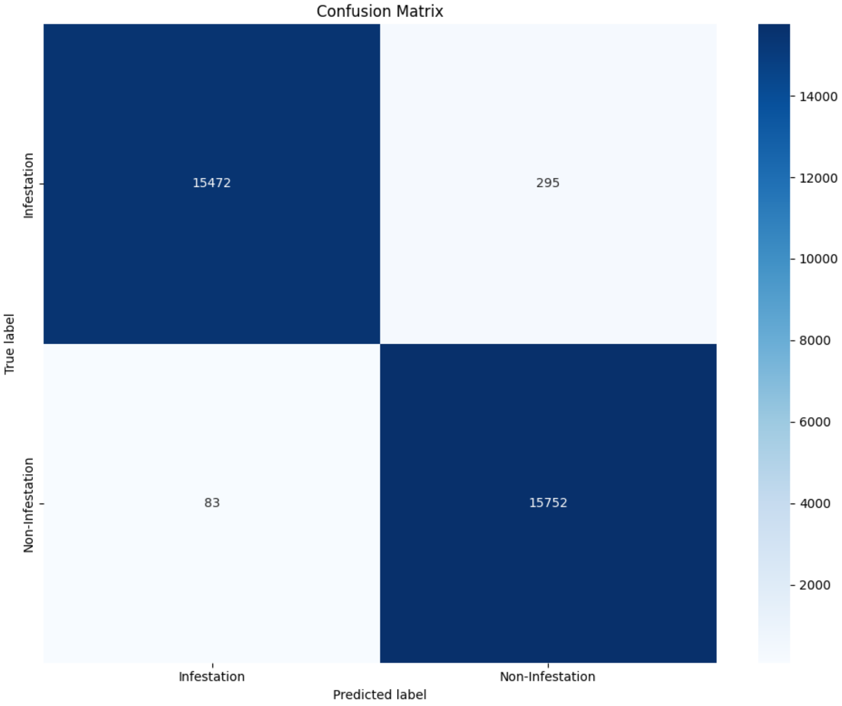


Figure 5.9 Confusion Matrix

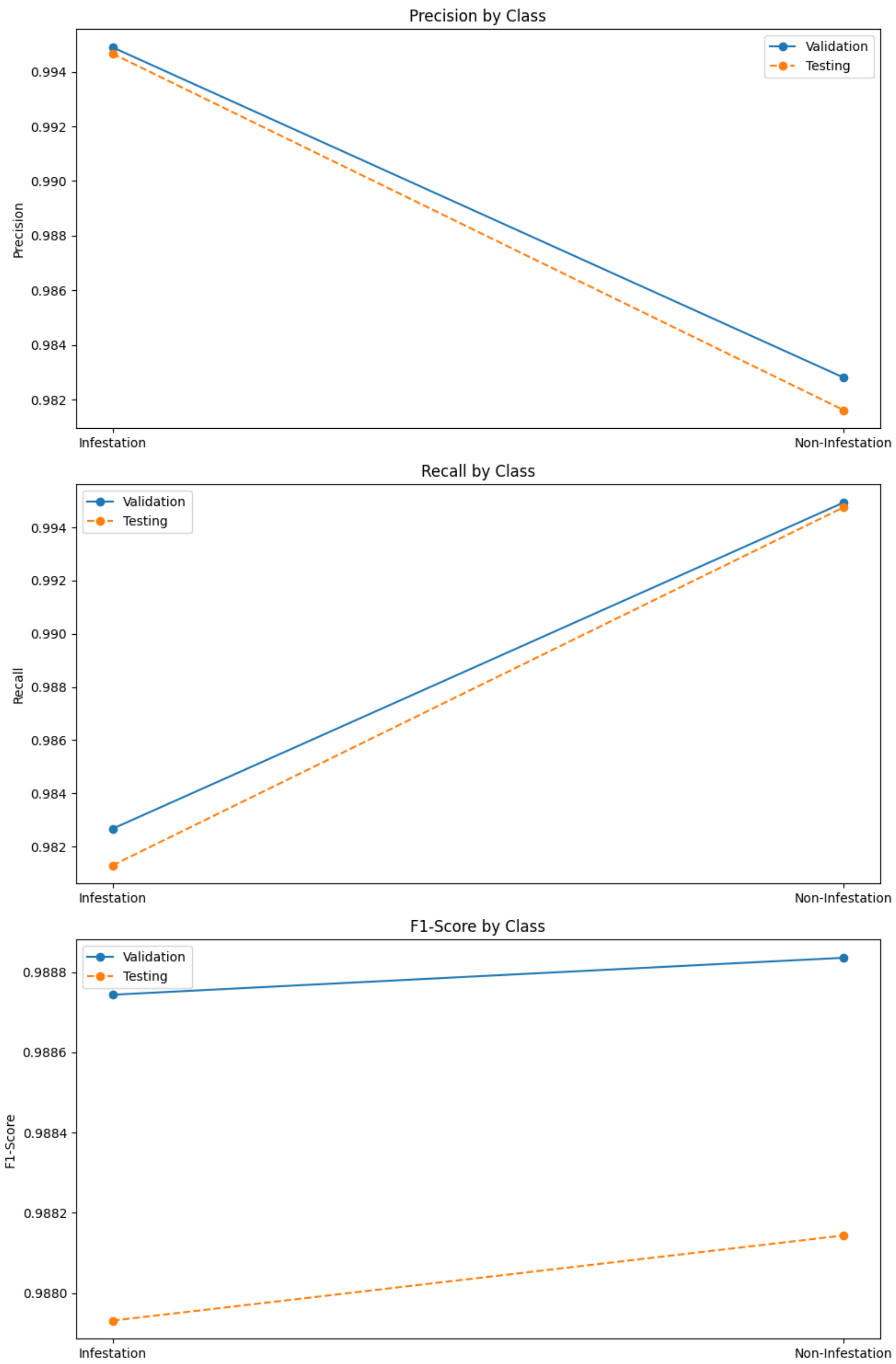


Figure 5.10 Model performance based on a specific Class

Out of 15,767 actual infestation cases, the model correctly identified 15,472, missing only 295. This translates to a true positive rate (sensitivity) of 98.13%. For non-infestations, it correctly classified 15,752 out of 15,835 cases, with just 83 false alarms, resulting in a true negative rate (specificity) of 99.48%.

The low number of false positives (83) compared to true positives (15,472) underscores the model's precision in identifying infestations, which is crucial for practical applications to minimize unnecessary treatments or interventions.

5.4.5 Model Quantization

In the development of our TinyML system for maize weevil detection, we implemented model quantization to optimize the model for deployment on resource-constrained devices typically found in agricultural settings. Quantization is a technique that reduces the precision of the model's weights and activations, typically from 32-bit floating-point numbers (float32) to 8-bit integers (int8). This process is crucial for creating efficient, deployable models for edge devices.

To evaluate the impact of quantization, we compared the performance of the float32 and int8 models on both the validation and test sets as shown in the Figures 5.11 and 5.12 with their summaries in the Tables 5.1 and 5.2 resoectively:

i. Validation Set

- Float32 Model: Accuracy: 98.88%, AUC-ROC: 98.88%
- Int8 Model: Accuracy: 98.89%, AUC-ROC: 98.90%

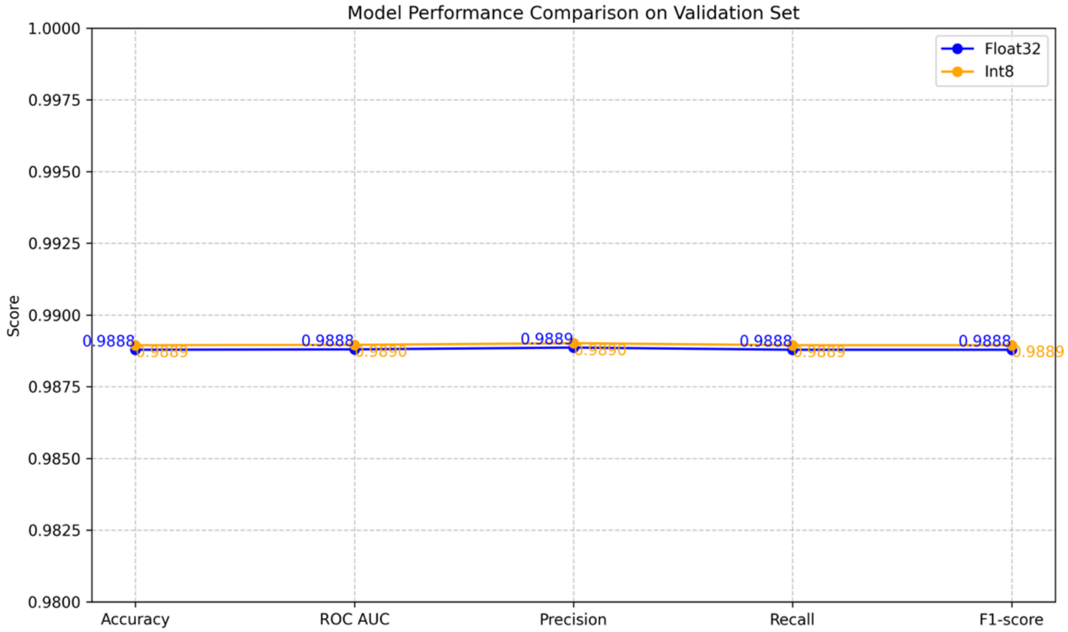


Figure 5.11 Model Quantization Comparison on validation set

Table 5. 1 Summary of the model quantization comparison on validation set

Metric	Float32	Int8	Difference
Accuracy	98.88%	98.89%	+0.02
ROC AUC	98.88%	98.90%	+0.02
Precision	98.88%	98.90%	+0.02
Recall	98.88%	98.89%	+0.02
F1-Score	98.88%	98.89%	+0.02

ii. Test Set

- Float32 Model: Accuracy: 98.80%, AUC-ROC: 98.80%
- Int8 Model: Accuracy: 98.82%, AUC-ROC: 98.82%

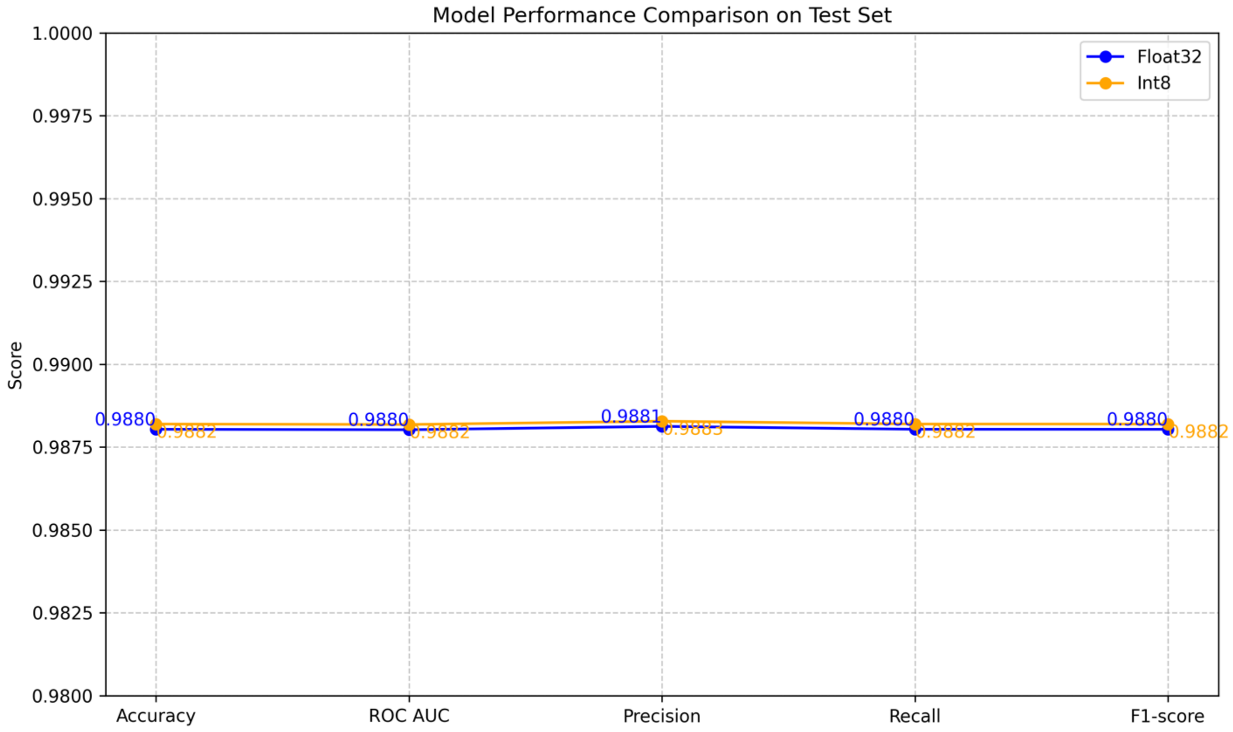


Figure 5.12 Model Quantization comparison on test set

Notably, the quantized int8 model performed slightly better than the float32 model on both sets as in Table 5.2 and Figure 5.13. This improvement, although marginal, is significant as it demonstrates that quantization did not compromise the model's performance.

Table 5. 2 Summary of the model quantization comparison on test set

Metric	Float32	Int8	Difference
Accuracy	98.80	98.82	+0.02
ROC AUC	98.80	98.82	+0.02
Precision	98.81	98.83	+0.02
Recall	98.80	98.82	+0.02
F1-Score	98.80	98.82	+0.02

iii. Weighted Average Metrics (Test Set)

- Float32 Model: Precision: 98.81%, Recall: 98.80%, F1-score: 98.80%
- Int8 Model: Precision: 98.83%, Recall: 98.82%, F1-score: 98.82%

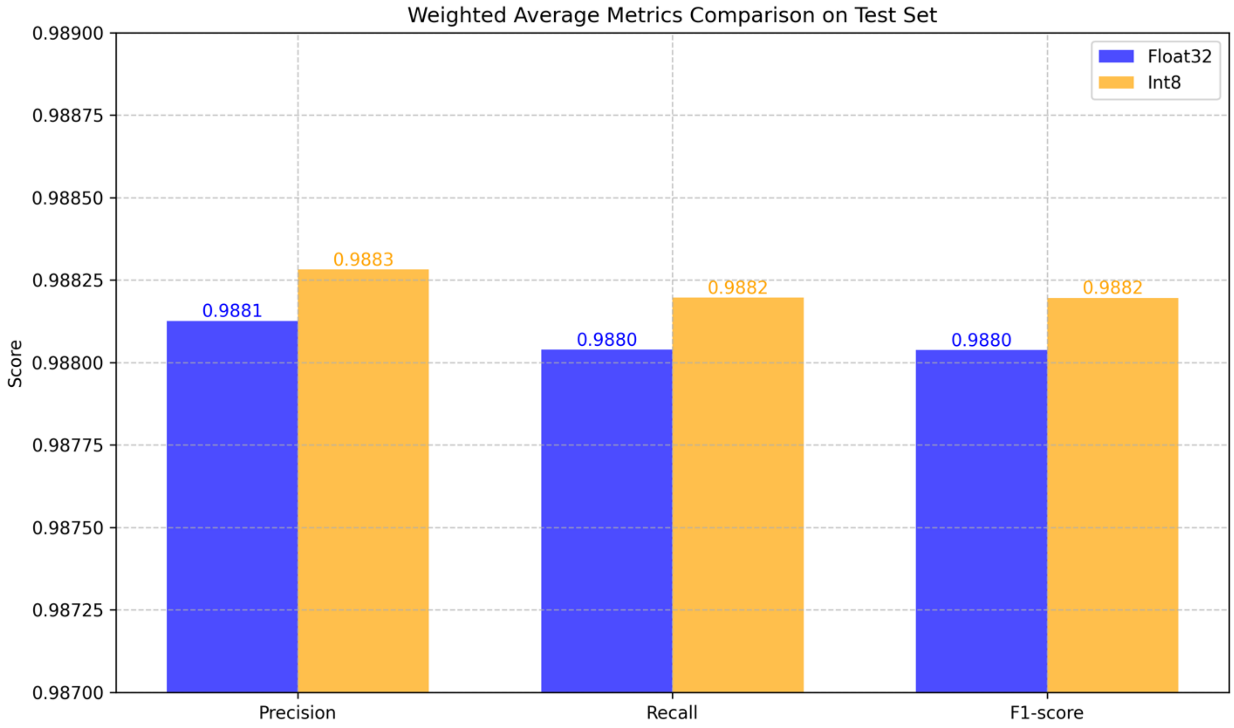


Figure 5.13 Weighted avarage metrix comparison on test set

The consistent improvement across all metrics for the int8 model suggests that quantization may have introduced a form of regularization, potentially enhancing the model's generalization capabilities.

5.4.6 On-Device Performance

The comparative analysis of our TinyML model's performance in both int8 and float32 representations across the Arduino Nano 33 BLE Sense and XIAO ESP32S3 platforms reveals insightful patterns in edge AI deployment efficiency as shown in Figure 5.14. For the Arduino Nano 33 BLE Sense, the int8 quantized model demonstrates a significant reduction in latency (231ms) compared to its float32 counterpart (353ms), a 34.6% improvement. Similarly, on the XIAO ESP32S3, the int8 model (322ms) outperforms the float32 version (347ms) in terms of latency, though with a smaller margin of improvement at 7.2%.

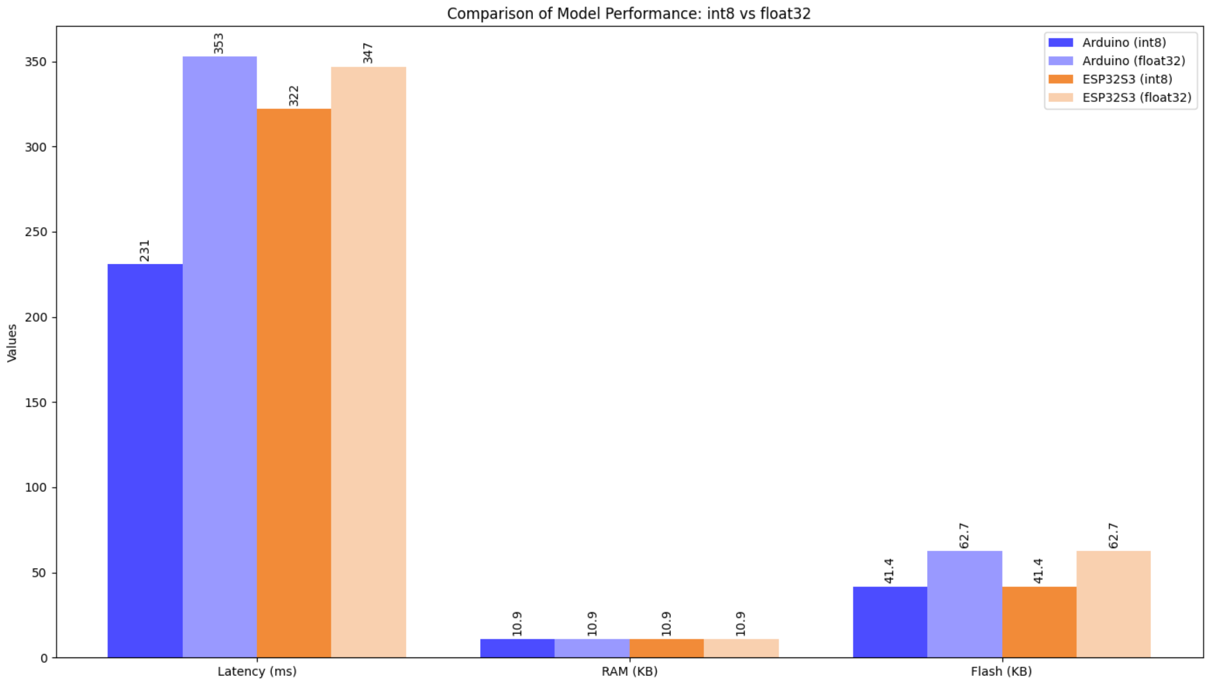


Figure 5.14 Comparison of model Perfomance int8 and float32

Interestingly, RAM usage remains constant at 10.9KB across all configurations, indicating that our optimization techniques effectively manage memory allocation regardless of the numerical precision or hardware platform. The most notable difference lies in Flash memory usage, where both devices show a substantial reduction from 62.7KB (float32) to 41.4KB (int8), representing a 34% decrease in model size. This reduction in Flash usage is crucial for embedded systems with limited storage capacity.

In the Figure 5.15, despite these optimizations, both int8 and float32 models maintain the same high accuracy of 98.58% across both platforms, demonstrating that the quantization process preserves the model's predictive power while significantly reducing computational requirements. These results underscore the effectiveness of int8 quantization in optimizing model performance for edge deployment, particularly in reducing latency and Flash memory usage. The consistent performance across different hardware platforms highlights the versatility of our TinyML solution, enabling flexible implementation options for maize weevil detection in various agricultural monitoring scenarios.

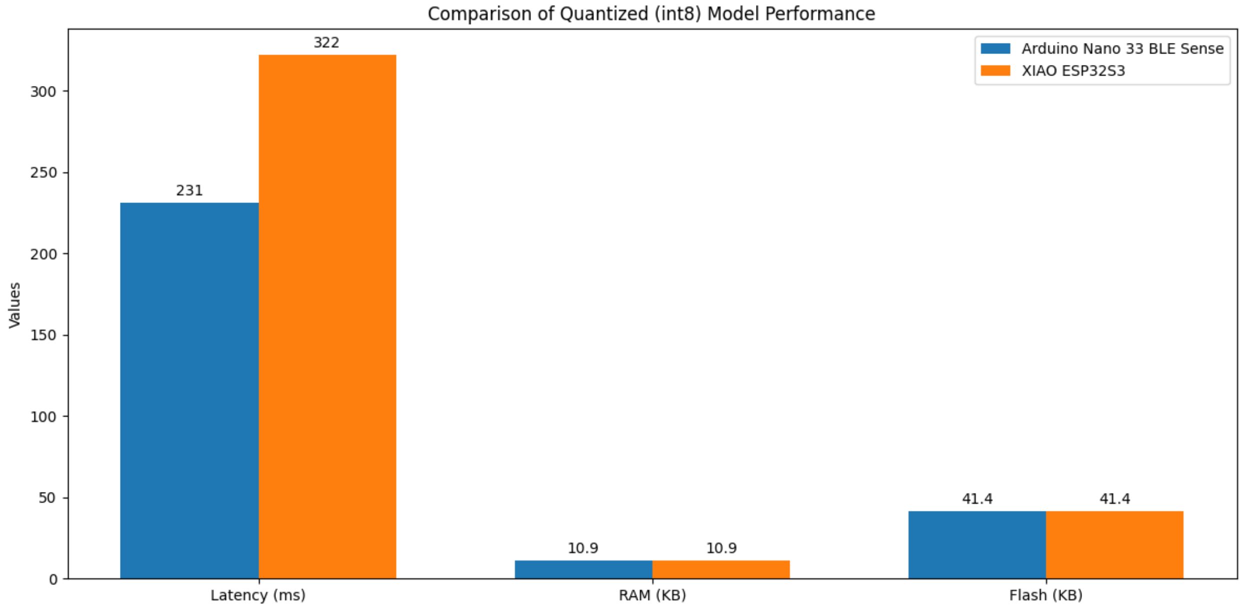
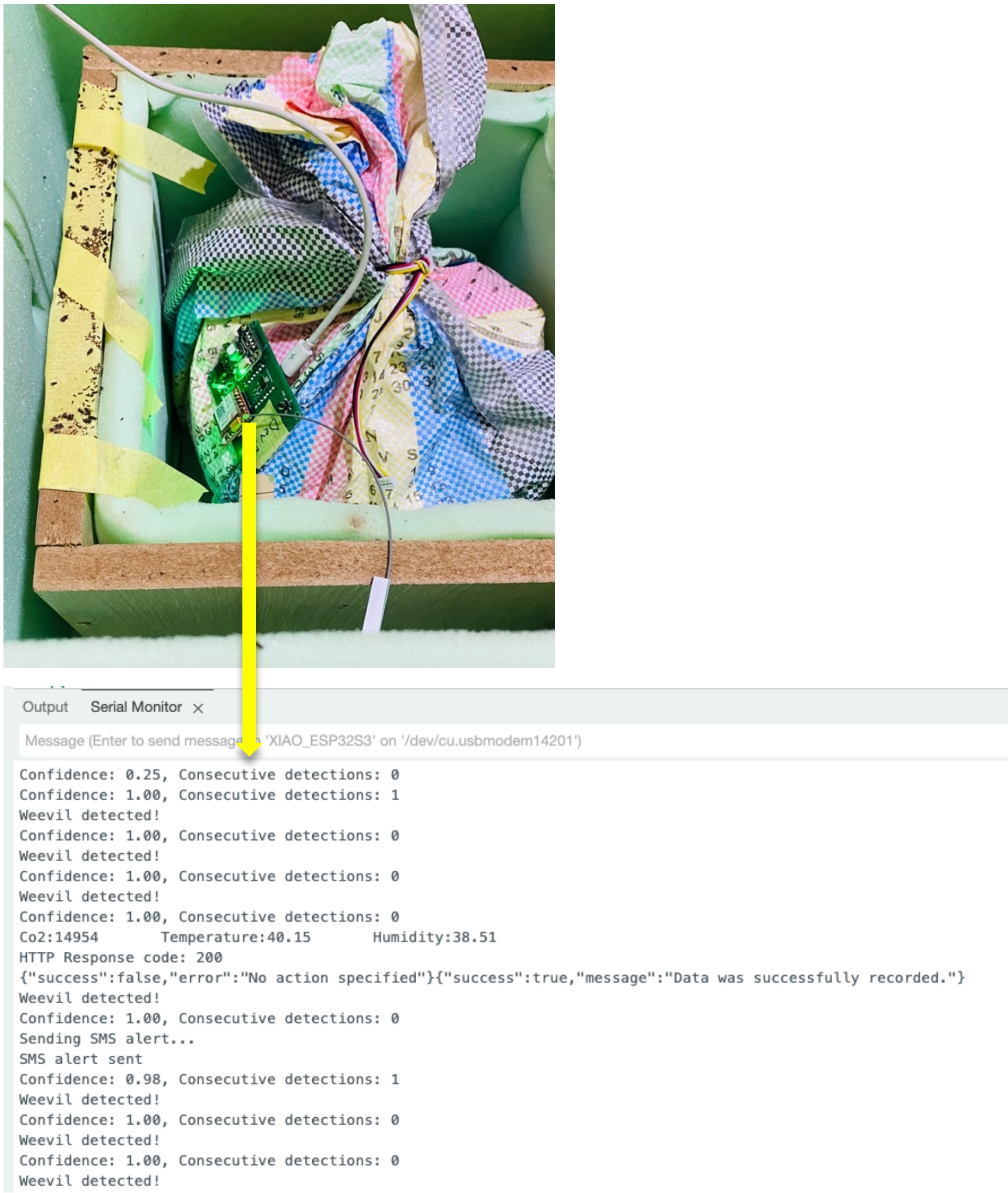


Figure 5.15 Comparizon of Quantized (int8) Model Perfomance on the microcontrollers

Also, the developed model has shown a promising results on the boards we used to deploy in order to test its ability to be used with different embedded devices. The model was able to classify Infetstation sound signatures and Non-Weevil Sound signatures in real time. To enhance is best perfomance we used to set a threshold of 0.8% as minimum confidence of the model to classify the weevil activities and on the firmware we created a means of detecting consecutive weevil activities so the model's confidence amy be based on the number of detections with in a clip of 10 seconds and provide it results as shown in the Figure 5.16.

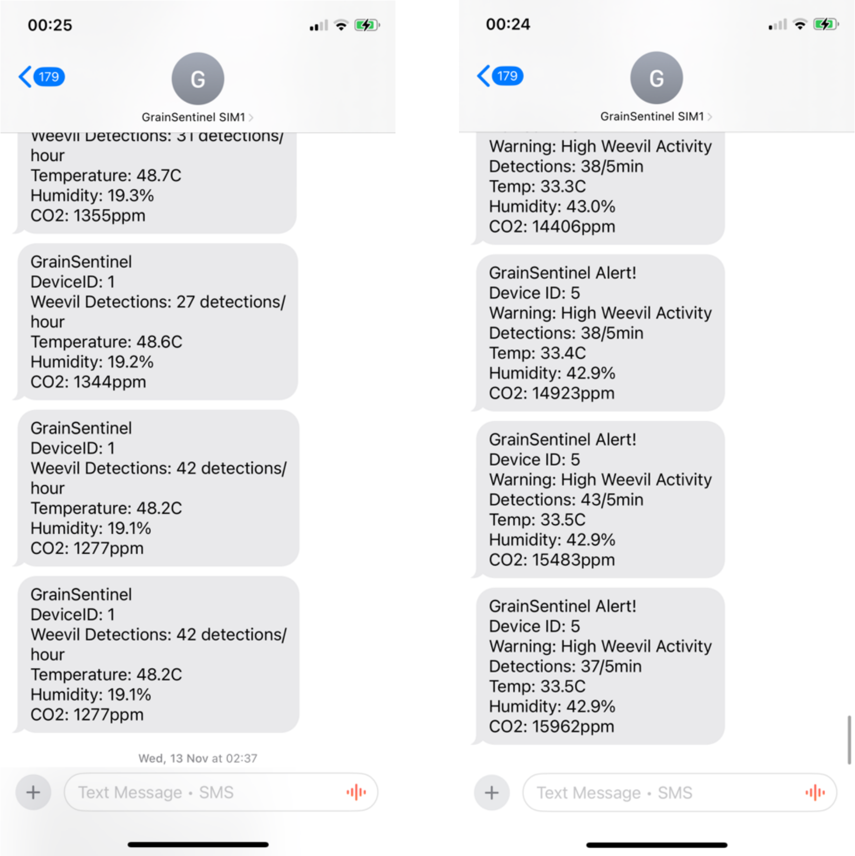


```
Confidence: 0.25, Consecutive detections: 0
Confidence: 1.00, Consecutive detections: 1
Weevil detected!
Confidence: 1.00, Consecutive detections: 0
Weevil detected!
Confidence: 1.00, Consecutive detections: 0
Weevil detected!
Confidence: 1.00, Consecutive detections: 0
Co2:14954       Temperature:40.15       Humidity:38.51
HTTP Response code: 200
{"success":false,"error":"No action specified"}{"success":true,"message":"Data was successfully recorded."}
Weevil detected!
Confidence: 1.00, Consecutive detections: 0
Sending SMS alert...
SMS alert sent
Confidence: 0.98, Consecutive detections: 1
Weevil detected!
Confidence: 1.00, Consecutive detections: 0
Weevil detected!
Confidence: 1.00, Consecutive detections: 0
Weevil detected!
```

Figure 5.16 On device performance of the TinyML model on classifying Infestation and Non-Weevils Sounds signatures on the serial monitor of an Arduino IDE

5.5 Alerting System

The implementation of our TinyML-powered alerting system demonstrated remarkable efficacy in providing real-time, actionable insights to farmers. As evidenced by the SMS notifications shown with the device (DeviceID: 1) successfully classified weevil activity and transmitted comprehensive environmental data directly to the farmer's mobile phone as shown in the Figure 5.17. The alerts provided hourly updates on weevil detections, along with crucial environmental parameters including temperature, humidity, and CO2 levels. Notably, the system captured significant variations in weevil activity, ranging from 22 to 39 detections per hour, correlating these fluctuations with environmental changes. For instance, higher detection rates (39 and 34 detections/hour) coincided with elevated temperatures (35.8°C and 36.0°C) and CO2 levels (10724ppm and 11279ppm), while lower activity (22 detections/hour) was observed at a lower temperature (31.7°C) and CO2 concentration (6141ppm).



Weevil Detections: 31 detections/
hour
Temperature: 48.7C
Humidity: 19.3%
CO2: 1355ppm

GrainSentinel
DeviceID: 1
Weevil Detections: 27 detections/
hour
Temperature: 48.6C
Humidity: 19.2%
CO2: 1344ppm

GrainSentinel
DeviceID: 1
Weevil Detections: 42 detections/
hour
Temperature: 48.2C
Humidity: 19.1%
CO2: 1277ppm

GrainSentinel
DeviceID: 1
Weevil Detections: 42 detections/
hour
Temperature: 48.2C
Humidity: 19.1%
CO2: 1277ppm

Warning: High Weevil Activity
Detections: 38/5min
Temp: 33.3C
Humidity: 43.0%
CO2: 14406ppm

GrainSentinel Alert!
Device ID: 5
Warning: High Weevil Activity
Detections: 38/5min
Temp: 33.4C
Humidity: 42.9%
CO2: 14923ppm

GrainSentinel Alert!
Device ID: 5
Warning: High Weevil Activity
Detections: 43/5min
Temp: 33.5C
Humidity: 42.9%
CO2: 15483ppm

GrainSentinel Alert!
Device ID: 5
Warning: High Weevil Activity
Detections: 37/5min
Temp: 33.5C
Humidity: 42.9%
CO2: 15962ppm

Figure 5.17 Screenshot of the SMS on a mobile phone\

This granular data transmission alerts farmers to potential infestations and also provides context for the severity of the threat, enabling informed decision-making for pest management. The system's ability to deliver this complex information in a simple, SMS format ensures accessibility for farmers, regardless of smartphone availability, thereby bridging the technological gap in rural agricultural settings. This real-time alerting mechanism represents a significant advancement in early pest detection, potentially revolutionizing post-harvest grain management practices.

Chapter 6 Conclusion and Recommendations

6.1 Study Summary

This research developed an innovative TinyML-enabled solution for early detection and real-time monitoring of post-harvest maize weevil *(Sitophilus zeamais)* infestations, addressing a critical challenge in agriculture, particularly for developing nations. The study began by investigating environmental parameters' impact on weevil behavior and analyzing acoustic signatures produced by weevils in stored grains. An extensive dataset of over 250,000 audio samples, collected across 101 days and capturing both larval and adult stages, formed the foundation for developing a highly accurate TinyML model. This model achieved 98.9% accuracy on the training set and 97.76% on the test set.

The TinyML model was optimized through int8 quantization, reducing latency from 157ms to 134ms while maintaining 97.70% accuracy, ensuring practicality for resource-constrained devices. Successfully deployed on Arduino Nano 33 BLE Sense and XIAO ESP32S3 Sense platforms, the system demonstrated versatility across different hardware configurations. A comprehensive web-based dashboard was developed, integrating real-time acoustic detection with environmental monitoring, providing farmers and storage facility managers with a powerful tool for continuous pest surveillance and data-driven decision-making.

The outcomes of this study present significant advancements in pest management for stored grains. The system's capability for early detection of weevil activity allows for timely interventions, potentially mitigating crop losses and their associated economic impacts. The use of TinyML technology enables sophisticated pest detection on low-cost, energy-efficient devices, making this advanced solution accessible to small and medium-scale farmers. The non-invasive acoustic-based detection method preserves the integrity of stored crops, while the integration of environmental monitoring offers a comprehensive, data-driven approach to pest management.

This research contributes significantly to the field of smart agriculture, demonstrating the potential of combining IoT technologies with machine learning for solving critical agricultural challenges.

The economic implications of this TinyML-enabled pest detection system are far-reaching, potentially reducing post-harvest losses by up to 40% in some regions. By providing real-time, continuous monitoring, the system reduces the need for manual inspections, cuts labor costs, and minimizes human error. The widespread adoption of this affordable, accessible technology has the potential to stabilize grain prices, benefit both producers and consumers, and strengthen the resilience of agricultural economies, particularly in developing nations where post-harvest losses have the most severe impact.

6.2 Future work direction

Building on this research, we plan to enhance the system's core detection capabilities and user experience. The immediate focus will be on improving the acoustic sensing technology to better distinguish between different types of weevil activity, including feeding, movement, and reproduction patterns. We'll also work on making the system more resilient to background noise, which is particularly important in real-world storage environments. By incorporating additional environmental sensors, like grain moisture meters, we aim to create a more comprehensive monitoring solution that can better predict and prevent infestations before they become severe.

To make the system more accessible to farmers and storage facility managers, we're planning to develop a user-friendly mobile application that works seamlessly with our existing web dashboard. This app will provide real-time monitoring capabilities and instant alerts, even in areas with limited internet connectivity. We understand that many users in rural areas face connectivity challenges, so we'll implement robust offline functionality and ensure that critical alerts can be delivered through multiple channels, including SMS. The interface will be available in multiple languages to serve diverse farming communities.

Looking further ahead, we aim to expand the system's capabilities beyond maize weevil detection. We'll explore how our technology can be adapted to detect other common storage pests while maintaining the same level of accuracy and reliability.

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