AUDIO-VIDEO ANALYSIS FOR COLONY ACTIVITY AND INTRUSION ALERT FOR *TETRAGONULA BIROI* (STINGLESS BEE) UTILIZING MACHINE-BASED LEARNING

A Capstone Project

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APPROVAL SHEET

This capstone, entitled **"AUDIO-VIDEO ANALYSIS FOR COLONY ACTIVITY AND INTRUSION ALERT FOR *TETRAGONULA BIROI* (STINGLESS BEE) UTILIZING MACHINE-BASED LEARNING"**, prepared and submitted by **Marinelle P. Aguinido, Danica Jane L. Barela, Glenda Theresa C. Espiritu, Juan Carlo C. Gironella, Mark Dennis B. Obumani, and Stephen Dave P. Rabonza** in partial fulfillment of the requirements for the subject of **CAPSTONE 1**, has been examined and is recommended for **Oral Examination**.

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CERTIFICATE OF ORIGINALITY

This is to certify that the research work presented in this capstone entitled "Audio-Video Analysis For Colony Activity and Intrusion Alert for *Tetragonula Biroi* (Stingless Bee) Utilizing Machine-Based Learning" for the award of Bachelor of Science in Electronics Engineering from Quezon City University, Quezon City embodies the result of original and scholarly work carried out by the undersigned. This capstone does not contain words or ideas taken from published sources or written works by other people which have been accepted as the basis for the award of any degree from other higher education institutions. All information sources and literature used for referencing are indicated and acknowledged.

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ABSTRACT

Title: Audio-Video Analysis For Colony Activity And Intrusion Alert For *Tetragonula Biroi* (Stingless Bee) Utilizing Machine-Based Learning

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This study developed an audio-video monitoring system utilizing machine-based learning to analyze colony activity and detect intrusions in *Tetragonula biroi* (stingless bee) hives. The system integrates sensors and embedded devices, including an ESP32-S3 microcontroller, Raspberry Pi 4 Model B, temperature and humidity sensor, microphone, load cell, and Raspberry Pi Camera Module 3, to collect environmental, acoustic, and visual data from the hive. The collected data are processed to monitor hive conditions and identify abnormal activities or potential predator intrusions in real time.Testing was conducted through laboratory evaluation and field deployment using an active *T. biroi* hive. Results showed reliable environmental monitoring, stable sensor performance, and consistent data transmission. The machine learning-based intrusion detection system achieved high detection reliability, with accuracy reaching up to 85% and real-time alert notifications delivered within approximately 3–4 seconds. A web-based dashboard was also implemented to allow users to monitor hive conditions and receive alerts across multiple devices. The system demonstrated fast response times, reliable alert delivery, and stable operation during field testing. Overall, the proposed system provides a non-invasive and automated monitoring solution that can help beekeepers detect hive disturbances early and improve colony management.

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Sincere appreciation is also extended to Engr. Danny Riel P. Barachina, the technical adviser, for his valuable technical knowledge, insights, and assistance that greatly contributed to the improvement and completion of the system.

Finally, the proponents offer their deepest thanks to God Almighty for His guidance, wisdom, and strength, which made the completion of this capstone project possible.

DEDICATION

This capstone project is dedicated to everyone who supported and inspired the proponents throughout the journey of completing this study. The challenges, lessons, and achievements experienced during the development of this project reflect the perseverance, dedication, and teamwork of those who believed in the value of this endeavor.

First and foremost, the proponents dedicate this work to their families, whose unconditional love, encouragement, and sacrifices served as a constant source of strength and motivation. Their patience, understanding, and unwavering support helped the proponents overcome difficulties and remain determined to achieve their goals.

This work is also dedicated to the mentors, advisers, and professors who shared their knowledge, guidance, and wisdom throughout the development of this project. Their insights and encouragement inspired the proponents to continuously learn, improve, and pursue innovation.

Finally, the proponents dedicate this project to God Almighty, whose guidance, blessings, and strength made it possible to complete this capstone project and turn this endeavor into reality.

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CHAPTER 1

THE PROBLEM AND ITS BACKGROUND

One of the often-overlooked bee species is the *Tetragonula biroi*, commonly known as the stingless bee, primarily due to its relatively small colony size compared to other bee species. Despite this, *T. biroi* produces a unique type of honey that is considered more nutritious than the honey of common honeybees. Stingless bee honey is characterized by its higher acidity and lower sugar content, making it a sought-after product among beekeepers who value its quality over quantity. While stingless bees yield smaller batches of honey compared to Apis mellifera, their honey is regarded as superior in nutritional properties. According to Lime (2024), researchers have discovered that honey from Philippine stingless bees is rich in antioxidants like flavonoids and phenolic acids. These compounds are known for their ability to neutralize free radicals, thereby reducing oxidative stress and potentially lowering the risk of chronic diseases. In light of these benefits, this research aims to explore ways of enhancing stingless beekeeping practices in the Philippines, both to support the livelihoods of local beekeepers and to preserve the health and sustainability of *T. biroi* colonies.

The growing ecological and agricultural importance of stingless bees has drawn increasing attention among researchers and apiculturists. In the Philippines, *T. biroi* plays a vital role as a pollinator of various fruit-bearing plants and crops (Locsin et al., 2021). Their honey, propolis, and wax products are also gaining value in local markets and alternative medicine industries (Hassan et al., 2022). However, many beekeepers still rely on traditional hive inspection methods that require opening the hive manually, which can disrupt the stable internal microclimate that bees maintain between 34–35 °C and 50–65% relative humidity. As noted by Cychowski (2025), even brief hive openings can release accumulated heat and moisture, exposing the brood to stress and forcing the colony to spend hours recovering equilibrium after just minutes of disturbance. This underscores the need for more efficient and less invasive ways of monitoring hive activity, especially for small stingless bee colonies that are more sensitive to environmental fluctuations and physical interference.

Modern developments in precision apiculture have begun to address these limitations through the integration of sensors, automation, and data analytics. Studies by Che Ali et al. (2021) and Hadjur et al. (2022) have demonstrated how IoT and machine learning can be applied to hive monitoring systems to track internal temperature, humidity, weight, and bee activity levels with high accuracy.

These technologies allow continuous data collection without manual inspection, enabling beekeepers to make informed decisions based on real-time feedback. More recently, acoustic and video-based approaches have been explored for their potential in interpreting colony behavior. Bee buzzing, in particular, carries rich behavioral information that can reflect queen absence, swarming, or stress caused by predators or toxins (Trương Thu Hương et al., 2023). Such sound-based monitoring methods offer valuable insights into hive health and external threats while keeping interventions minimal and non-disruptive.

Building upon these technological advancements, the present study introduces an advanced beehive monitoring system specifically designed for *T. biroi* colonies. The system integrates sensors with a machine learning–based audio-video framework capable of simultaneously analyzing sound patterns and visual activity inside and around the hive. Through this dual-data approach, the system can identify behavioral anomalies, detect intrusions by predators such as ants or wasps, and notify the beekeeper in real time. By automating these processes, the proposed model reduces human intervention while providing continuous observation of colony conditions. This approach not only protects the hive from external threats but also contributes to maintaining an optimal and undisturbed environment for the bees, thereby supporting healthier and more productive colonies.

In the Philippine context, the adoption of such smart systems has strong potential benefits. As highlighted by Conde (2020), stingless beekeeping supports both biodiversity and rural livelihood, particularly among small-scale farmers and women-led enterprises involved in coconut and fruit production. However, limited access to advanced monitoring tools has restricted beekeepers from efficiently managing colonies or detecting threats early. The development of a machine learning–based monitoring system offers a scalable solution to this gap, enabling cost-effective hive management that aligns with the principles of sustainable agriculture and pollinator conservation.

Integrating machine learning into beehive monitoring provides beekeepers with a practical way to care for colonies, especially stingless bees like *T. biroi*. By automatically detecting predator intrusions and analyzing colony behavior through audio and video, the system reduces the need for invasive manual inspections that can disturb hive stability. This approach lessens the workload of beekeepers while providing reliable, real-time data for better decision-making about colony health and activity. Overall, it can improve hive productivity, support sustainable honey production, and help protect both beekeepers' livelihoods and the ecological role of pollinators, contributing to more resilient ecosystems amid global environmental challenges.

Background of the Study

Recent advancements in precision agriculture and smart monitoring have led to the development of “smart beekeeping,” which improves hive management through automation and data-driven technologies. However, most innovations focus on Apis mellifera, while fewer studies address stingless bees like Tetragonula biroi (Hadjur et al., 2022; Che Ali et al., 2021). Native to the Philippines and Southeast Asia, *T. biroi* is an important pollinator that supports biodiversity, crop production, and sustainable rural livelihoods due to the high nutritional value of its honey (Conde, 2020; Lime, 2024).

Despite these advantages, stingless beekeeping in the Philippines remains underdeveloped. Many local beekeepers still rely on traditional manual hive inspections, which are time-consuming, labor-intensive, and disruptive to colony stability (Hidalgo et al., 2020; Locsin et al., 2021). Such inspections can expose brood cells and disturb hive temperature and humidity, causing stress or potential colony collapse, especially in the small and delicate *T. biroi* colonies.

Existing beehive monitoring systems have successfully utilized sensors to measure internal hive conditions such as temperature, humidity, and hive weight. However, most systems are designed for *Apis mellifera* and do not fully capture behavioral dynamics unique to stingless bees (Amala et al., 2023; Uthoff et al., 2023).

Moreover, predator intrusion, a significant cause of colony decline, is rarely addressed in current monitoring solutions. Predatory species such as ants, wasps, and lizards often attack stingless bee hives, leading to major losses. Traditional detection methods rely solely on visual observation by beekeepers, which is inefficient and cannot provide continuous protection.

Integrating machine learning into hive monitoring provides an effective solution for detecting colony activity and disturbances. Studies by Ratnayake et al. (2025), Trương Thu Hương et al. (2023), and Singh et al. (2024) show that acoustic and video-based systems can identify abnormal behaviors and threats in real time. Changes in buzzing frequency or movement near hive entrances may indicate stress, predator attacks, or intrusion events. By analyzing these signals with machine learning, the system can automatically detect potential dangers and send alerts to beekeepers through mobile or web notifications (Turyagyenda et al., 2025).

In alignment with these technological trends, the present study focuses on the design of an advanced beehive monitoring system for *T. biroi* colonies. The proposed system integrates both audio and video analysis supported by machine learning algorithms to detect colony activities and identify possible intrusions. This dual approach enables the simultaneous collection of sound and motion data, enhancing the accuracy of colony behavior interpretation. Additionally, the inclusion of sensor-based monitoring for temperature and humidity further strengthens the system's ability to assess hive conditions comprehensively.

Beyond improving monitoring efficiency, this research also emphasizes sustainability and pollinator conservation. By minimizing manual inspection and allowing remote, real-time monitoring, the system reduces stress on bee colonies and supports the long-term viability of stingless bee populations. As highlighted by Uthoff et al. (2023) and Nicolas (2023), such non-invasive monitoring practices are essential to preserving colony health, ensuring stable honey yields, and promoting ecological balance.

The development of a low-cost, field-deployable monitoring system for *T. biroi* supports the shift toward sustainable and data-driven beekeeping. It offers Filipino beekeepers an accessible tool to improve colony productivity and protection without requiring high costs or advanced technical skills. This research also contributes to environmental conservation and food security by helping protect an important pollinator species, while bridging traditional beekeeping practices with modern technological innovation in the Philippines.

Table 1. *Comparison with the Beehive Monitoring Systems in the Philippines*

Beehive Monitoring Systems	Acoustic & Vision Monitoring	Machine Learning	Predator/ Intrusion Detection	Environmental Sensor (Temp, Humidity, etc.)	Behavioral Activity Tracking	Real-Time Alerts	Data Processing
Audio-Video Analysis for Colony Activity and Intrusion Alert for Tetragonula Biroi (Stingless Bee) Utilizing Machine-Based Learning	✓	✓	✓	✓	✓	✓	✓
Machine Learning–Based Acoustic Intrusion Detection System (2025)	✓	✓	✓	✓			
Real-Time Web-Based Monitoring System for Stingless Bee Farming (2022)					✓		

Objectives of the Study

This capstone project aims to design and implement an intelligent, non-invasive monitoring system for *Tetragonula biroi* (Stingless Bee) colonies that integrates environmental sensing, audio-video analysis, and machine learning to enhance hive protection, health assessment, and beekeeper accessibility. Specifically, it will delve to attain the following specific objectives:

1. To design and develop a smart monitoring device for *T. biroi* stingless bee colonies that integrates:

a. Environmental and behavioral sensors such as the SHT30-B temperature and humidity sensor, INMP441 microphone, load cell with HX711 amplifier, and Raspberry Pi Camera Module 3 vision sensor.

b. ESP32-S3 microcontroller and Raspberry Pi 4 B as the main data acquisition and processing units.

c. A regulated 5V/3A power supply and AMS1117-3.3V voltage regulator for stable operation and field reliability.

2. To develop and integrate machine learning–based detection models within an embedded system capable of:

   a. Classifying hive acoustic patterns into normal and abnormal behavioral states.

   b. Detecting predator intrusion through real-time vision-based analysis using on-device AI inference.

   c. Performing multimodal data fusion (audio, visual, environmental) to determine colony condition with minimal computational latency.

3. To prototype, deploy, and evaluate a field-ready monitoring platform that:

   a. Acquires and transmits real-time environmental, acoustic, and visual data through integrated hardware modules.

   b. Provides a web-based dashboard for visualization of colony parameters, activity logs, and historical trends.

c. Generates automated intrusion and stress alerts accessible via mobile or browser-based interface.

d. Ensures operational reliability under actual apiary conditions.

4. To evaluate and test the system performance in terms of:

a. Functionality Test / Test Cases

i. Environmental Data Acquisition (temperature, humidity, load cell readings)

ii. Acoustic Analysis and Sound Classification (predator intrusion)

iii. Vision-Based Detection (Raspberry Pi Camera Module 3 visual monitoring of colony activity)

iv. Microcontroller Processing (ESP32-S3 ↔ Raspberry Pi communication)

v. Notification and Dashboard Interface (real-time alerts and data logs)

b. Portability and Compatibility Test

i. Device access via laptop, tablet, and smartphone interfaces

ii. Cross-browser functionality and responsiveness

iii. Continuous operation under varying ambient field conditions

c. Accuracy and Performance Test

i. Sensor Accuracy and Response Time (SHT30-B, MAX9814, HX711)

ii. Machine Learning Detection Accuracy (normal vs. abnormal activity, intrusion)

iii. Power Stability and Energy Efficiency (5V/3A supply and AMS1117-3.3V regulator)

Scope and Limitations

The capstone project focused on developing the “Audio-Video Analysis for Colony Activity and Intrusion Alert for *Tetragonula biroi* (Stingless Bee) Utilizing Machine-Based Learning.” This system was implemented and tested in a controlled prototype setup located in antipolo at Hardin sa Parang, where an actual *T. biroi* hive was available for short-term monitoring. The primary aim of the system was to capture environmental, acoustic, and visual data to support non-invasive observation of stingless bee colony behavior.

The intelligent monitoring system developed by the proponents integrated multiple sensing modules, including a temperature and humidity sensor (SHT30-B), acoustic sensor (INMP441 microphone), load cell with an HX711 amplifier for hive weight measurement, and a vision-based sensor (Raspberry Pi Camera Module 3) for event-triggered image and video capture. These sensors were controlled through an ESP32-S3 microcontroller, while data handling, logging, and model processing were performed using a Raspberry Pi 4 Model B. The system sought to classify colony activity as normal or abnormal and identify possible predator intrusions based on fused audio-video inputs.

The prototype system required a regulated 5V/3A power source and an AMS1117-3.3V voltage regulator to supply the components. However, the system did not incorporate renewable energy sources such as solar panels, rechargeable batteries, or backup power systems. As a result, its operation was fully dependent on a stable power supply, and any interruption in electricity could disrupt real-time monitoring, sensing, and alert notification processes. Although the inclusion of alternative or backup energy systems was outside the project's scope, this limitation indicates a potential direction for future development to support long-term field deployment.

The project concentrated on monitoring key environmental and hive-related parameters, including temperature, humidity, weight, acoustic activity, and image/video-based visual activity. These indicators were selected to align with the goal of identifying colony-level events and potential threats. Other biological, ecological, and chemical factors such as disease detection, hive microbiome, honey yield estimation, or long-term colony health trends—were not part of the system's functional scope.

The machine learning components of the system included an acoustic model, a visual model, and a data fusion mechanism intended to analyze hive activity patterns. Data transmission utilized Wi-Fi/MQTT to send alerts and processed information from the ESP32-S3 to the Raspberry Pi or a local dashboard. However, the communication module served solely as a data transmission device and was not used as a microcontroller for independent decision-making.

The prototype was tested only under short-term, controlled conditions at the Antipolo site, so its performance may change in real outdoor environments due to factors such as lighting, noise, temperature, humidity, and other ecological disturbances. The system was developed mainly as a proof-of-concept to demonstrate feasibility rather than as a fully commercial or long-term monitoring solution. Therefore, large-scale deployment, extensive biological validation, cloud-based storage, and long-term data archiving were outside the scope of the study.

Significance of the Study

This study introduces an automated audio-video monitoring system with machine learning to track *T. biroi* colony activity and detect intrusion threats. It aims to reduce reliance on manual inspections, improve colony protection and productivity, and support sustainable stingless-bee management in the Philippines.

For beekeepers, the system provides a practical tool that improves colony protection, reduces manual labor, and supports more efficient hive management. Early detection of threats such as wasps, ants, or geckos can prevent colony loss and maintain healthier hive conditions, ultimately leading to improved honey yield and overall colony stability. The system also contributes to the standardization of monitoring practices, especially for those managing multiple hives or remote apiaries.

For researchers and academicians, the study creates opportunities to examine the behavioral patterns and acoustic signatures of stingless bees, especially since there is no open-access dataset for *T. biroi*. By developing a custom audio-video database, the research provides a valuable resource for future studies in bee behavior, machine learning in entomology, and automated ecological monitoring. The project is further strengthened through collaboration with experts from Quezon City University, helping validate the system's scientific and technical approach.

For local communities and the environment, the study helps support the preservation of stingless-bee populations by promoting sustainable beekeeping practices. Since *T. biroi* contributes to the pollination of various crops and native plants, improving colony survival directly benefits agriculture and ecological health. By integrating technology with environmental stewardship, the study aligns with broader efforts to enhance food security, biodiversity protection, and community livelihood.

Definition of Terms

The following terms are operationally defined for the convenience of the reader and research purposes.

Acoustic Analysis – The process of examining and interpreting sound data from the beehive to identify patterns in colony activity, behavior, or disturbances through frequency and amplitude characteristics.

AMS1117-3.3V Voltage Regulator – A linear voltage regulator used in the system to maintain a constant 3.3V output, ensuring stable operation of sensors and microcontrollers.

Artificial Intelligence (AI) Inference – The built-in capability of the Raspberry Pi Camera Module 3 vision sensor to process image data and perform pattern recognition directly on the device without external computation.

Audio-Video Analysis – The combined use of sound and visual data to monitor bee behavior, detect intrusions, and assess hive activity through integrated sensors and machine learning.

Colony Activity – The observable behavioral patterns of bees inside the hive, including movement, buzzing intensity, and foraging activity, which indicate the overall condition of the colony.

ESP32-S3 Microcontroller – A low-power microcontroller unit (MCU) used as the system's core processor responsible for handling sensor inputs, communication, and data transfer.

HX711 Amplifier Module – An analog-to-digital converter used with the load cell to measure weight variations in the hive that may reflect changes in colony population or stored honey.

Raspberry Pi Camera Module 3 – A camera module equipped with an integrated AI processor capable of performing real-time object and motion detection, used for monitoring colony activity and predator intrusions.

Internet of Things (IoT) – A network of interconnected devices capable of collecting, exchanging, and analyzing data to automate processes and enable remote monitoring.

Load Cell – A transducer that converts force or weight into electrical signals, utilized in the study to measure hive mass and detect changes related to colony growth or resource storage.

Machine Learning (ML) – A subset of artificial intelligence involving algorithms that enable systems to recognize patterns and make decisions based on training data, applied here to classify bee activity and detect intrusions.

INMP441 Microphone – A microphone module designed for high-sensitivity sound detection used to capture buzzing sounds and acoustic signals from the hive.

Predator Intrusion – The occurrence of external threats, such as ants, wasps, or other insects, entering the hive, which can disturb or damage the colony.

Raspberry Pi Zero 4 Model B – A compact single-board computer that supports data processing, machine learning operations, and serves as the local server for system control and visualization.

Real-Time Monitoring – The continuous and immediate observation of environmental and behavioral conditions within the hive, allowing instant detection and response to abnormal events.

SHT30-B Sensor – A digital sensor used for precise measurement of temperature and humidity levels inside the hive, providing data essential for assessing colony comfort and health.

Stingless Bee (*Tetragonula Biroi*) – A native Philippine bee species belonging to the Meliponini tribe, known for producing high-nutrient honey and playing a crucial role in pollination and biodiversity.

Web Dashboard – A user interface accessible via mobile or computer devices that displays real-time sensor readings, colony status, and alert notifications for beekeepers.

CHAPTER 2

REVIEW OF RELATED LITERATURE AND STUDIES

This chapter reviews relevant international and local literature related to automated hive monitoring, audio-video analysis, and machine learning. These sources provide technical background and support the development of the proposed system for monitoring *Tetragonula biroi* colony activity and detecting intrusion threats, concluding with the study’s conceptual framework.

Foreign Literature and Systems

Apimondia (2023) highlights that global stingless bee honey production faces challenges such as inconsistent colony productivity and vulnerability to environmental stress. The report underscores that many stingless bee species yield small quantities of honey, making efficient colony monitoring essential for sustaining production and ensuring stable yields. This emphasizes the global need for improved technologies to support colony health and mitigate risks from environmental threats and predators, aligning directly with the present study's goal to develop an advanced, automated monitoring system.

The project “Voice Transformer with Raspberry Pi and PMODs” demonstrates how a Raspberry Pi can capture, process, and output audio in real time using modular PMOD peripheral devices. Although the project focuses on voice modulation, it shows the capability of Raspberry Pi to handle real-time audio processing in embedded systems. According to Audio Processing with Raspberry Pi and Pmods (2021), this supports using the Raspberry Pi as the central processing unit in systems that manage sensor data and real-time processing. This finding supports the present study’s use of the Raspberry Pi as the audio-video processing hub for the hive monitoring system.

Hassan et al. (2022) conducted an observational study on *T. biroi* colonies to examine their propolis production and environmental adaptability. The research provided insight into how temperature, humidity, and nesting conditions affect colony behavior and productivity. Findings revealed that *T. biroi* colonies are highly responsive to environmental stressors, highlighting the need for improved monitoring methods to ensure colony health and sustainability. This study reinforces the relevance of developing an IoT and machine learning–based monitoring system for *T. biroi*, aimed at preserving colony welfare and supporting sustainable stingless beekeeping in the Philippines.

Kiskowski et al. (2024) showed that bee wingbeat sounds contain distinct spectral patterns that can help differentiate species and reveal traits such as body size, behavioral state, and environmental responses. By analyzing wingbeat frequencies, the study confirmed that acoustic signatures can serve as reliable markers for non-invasive pollinator monitoring. According to Kiskowski et al. (2024), passive acoustic sensing is a practical and scalable method for monitoring bee activity, supporting the integration of acoustic modules in the proposed *T. biroi* monitoring system to detect early signs of colony stress, disturbances, or behavioral changes.

Astuti et al. (2024) reviewed current applications of artificial intelligence (AI) in apiculture, highlighting how AI-based tools can enhance hive monitoring, disease detection, and behavioral analysis of bees. The study emphasizes the potential of integrating acoustic sensing, environmental data, and AI algorithms to provide real-time, non-invasive assessments of colony health. This review supports the development of AI-integrated monitoring systems for *T. biroi*, where automated analysis of bee sounds can detect behavioral anomalies, environmental stressors, and changes in colony condition efficiently.

Ratnayake et al. (2024) reviewed machine learning applications in bee species identification, highlighting the use of techniques such as support vector machines and convolutional neural networks to classify bees using visual and acoustic data. The review shows that AI improves the accuracy of bee species recognition and supports biodiversity monitoring. According to Ratnayake et al. (2024), integrating computational methods with bee research strengthens modern beekeeping technologies, supporting the use of AI-driven and sound-based classification modules in hive monitoring systems for *T. biroi.*

Ratnayake et al. (2025) studied acoustic alarm signals of *Heterotrigona itama* guard bees during intrusion events and developed a machine-learning system to detect these sounds. Using audio data recorded with a Jetson Nano, the researchers extracted MFCC features and applied SVM and k-Nearest Neighbor classifiers, with KNN achieving over 95% accuracy. According to Ratnayake et al. (2025), bee alarm sounds can be reliably classified for intrusion detection, showing that sound-based monitoring is a cost-effective and real-time alternative to image-based methods. This supports integrating acoustic analysis in the proposed *T. biroi* hive monitoring system to detect threats, behavioral changes, and colony disturbances.

Foreign Studies and Systems

Crawford et al. (2022) analyzed video recordings of hive entrances to measure bee traffic, entrance pass frequency, and activity patterns under different times and environmental conditions. Their study found that changes in entrance activity, such as reduced flight traffic or irregular guard behavior, were linked to colony disturbances or environmental stress. According to Crawford et al. (2022), video-based entrance monitoring can indicate overall colony health and behavior, supporting the integration of camera modules in automated hive monitoring systems. This supports the present study's use of video analysis with acoustic and sensor data to detect intrusion, population changes, or behavioral anomalies in *T. biroi* colonies.

Ferreira et al. (2023) developed an automated acoustic recognition system designed to identify pollinating bee species based on their buzzing during flower visits. The researchers used log-Mel spectrograms and convolutional neural networks, supported by extensive data augmentation, to train models capable of distinguishing species with high accuracy. Their results demonstrated that deep-learning-based acoustic classification consistently outperforms traditional machine-learning approaches, confirming that audio signals can serve as a dependable basis for automated pollinator identification.

Dimitrios et al. (2022) studied the use of audio recordings to detect bee swarming events using machine-learning classifiers, including k-Nearest Neighbors (k-NN), Support Vector Machine (SVM), and a U-Net convolutional neural network. Sound data were collected from IoT-based devices installed in beehives and analyzed to distinguish between swarming and non-swarming conditions. The results showed that deep-learning approaches improved early detection of swarming events. According to Dimitrios et al. (2022), combining acoustic monitoring with AI classification can serve as a non-invasive, real-time method for monitoring colony behavior, supporting the integration of sound-based detection modules in automated hive monitoring systems.

Saxena et al. (2023) investigated deep learning methods for classifying beehive audio signals to monitor hive health and stability. The study compared YAMNET and VGGish for binary classification of bee versus non-bee sounds and developed a multiclass system to identify four queen statuses. Results showed YAMNET performed better, achieving 74.5% precision and an AUC of 0.87, while CNN models reached 91.4% average precision in multiclass classification. According to Saxena et al. (2023), audio-based deep learning enables non-invasive, real-time monitoring of hive conditions, including queen presence, foraging behavior, swarming, and environmental stress.

Libal and Biernacki (2024) developed a non-intrusive system that identifies honeybee roles by analyzing hive audio signals with neural networks. Using sound features like MFCCs and power spectral density, their model could distinguish worker bees from drones without manual inspection. This study demonstrates that audio-based monitoring can provide real-time insights into colony activity, supporting the integration of acoustic sensors in hive monitoring systems like the one proposed for *T. biroi* to detect behavioral changes and assess colony health efficiently.

Otesbelgue et al. (2025) developed a non-invasive method to identify queenless stingless bee hives by analyzing temperature, humidity, and hive sound from Tetragonisca fiebrigi colonies using machine learning. Their study tested models such as extreme learning machine, k-nearest neighbors, multilayer perceptron, random forest, and support vector machine, all achieving over 90% accuracy, with the best results from microclimatic indicators. According to Otesbelgue et al. (2025), combining acoustic and environmental sensors can effectively assess hive health without manual inspection, supporting the use of multimodal monitoring systems like the proposed system for *T. biroi* to detect queen absence, behavioral changes, and colony condition.

Otesbelgue et al. (2023) developed a Hidden Markov Model-based system to detect pesticide exposure and identify hive activity in Tetragonisca fiebrigi using acoustic recordings. Audio data from multiple hives were analyzed with machine learning to classify normal versus pesticide-affected hive sounds. The results showed that acoustic monitoring can reliably detect environmental stressors and differentiate hive conditions without invasive inspection. This study supports the integration of sound-based monitoring in hive systems like the one proposed for *T. biroi*, enabling real-time detection of colony stress, behavioral anomalies, and environmental threats.

Sad, C. et al. (2025) developed a deep edge IoT system to detect queenless beehives using acoustic signals. Audio recordings from hives were processed with feature extraction and analyzed using deep learning models deployed on edge devices, enabling real-time, non-invasive detection of queen absence. The study demonstrates that sound-based monitoring combined with IoT technology can accurately assess colony status and provide timely alerts. This supports the integration of acoustic sensing and AI in hive monitoring systems like the one proposed for *T. biroi*, allowing early detection of colony stress, behavioral changes, and queen loss.

Sharif, Di, and Yu (2023) assessed the potential of using acoustic signals from honeybee (Apis spp.) hives as a non-invasive method for monitoring colony status by eliciting expert opinions from international researchers. Their study found that global experts consider acoustics highly valuable for tracking swarming, colony health, pesticide exposure, and environmental pollution, and it highlights new directions for acoustic soundscape analysis to monitor various internal and external hive conditions. This work supports the integration of sound-based monitoring approaches in automated hive systems like the one proposed for *T. biroi*, where capturing and analyzing hive acoustics can improve detection of behavioural changes and environmental stressors.

Truong et al. (2023) developed a deep learning framework combining convolutional neural networks (CNN) and gated recurrent units (GRU) to identify bee species from acoustic recordings. The study demonstrated that their model could accurately classify bee sounds, enabling non-invasive monitoring of colony activity and behavior. This research supports the integration of AI-driven acoustic monitoring in hive systems like the one proposed for *T. biroi*, allowing real-time detection of behavioral changes, species-specific activity, and potential environmental stressors.

Local Literature and Systems

Conde (2020) describes how Philippine stingless bees contribute to improved coconut yields and provide livelihood opportunities for rural women, underscoring the significant role of stingless beekeeping in local agriculture and community empowerment. The article notes that sustainable management of stingless bee colonies can support crop pollination and generate additional income through honey production. This emphasizes the need for reliable hive monitoring tools to protect colony health, optimize yield, and support smallholder beekeepers. The present study addresses this need by developing an AI-based hive monitoring system to help maintain optimal colony conditions and alert beekeepers to potential threats or environmental stressors.

The authors of “Current Status of Small Hive Beetle Infestation in the Philippines” document the widespread presence of the small hive beetle as a serious pest affecting both stingless bee and honeybee colonies across the country. They report on infestation rates, hive losses, and factors that encourage beetle spread such as inadequate hive monitoring and lack of early detection. Their findings underscore the vulnerability of bee colonies when monitoring relies solely on manual inspection and periodic checks. This supports the need for a more reliable, real-time, automated monitoring solution.

The present study's AI-based hive monitoring system aims to address precisely this gap by continuously tracking environmental, acoustic, and visual signals to detect early signs of intrusion or infestation, enabling timely intervention and reducing colony losses (Cervancia et al., 2016).

Edmund and Rahman (2021) developed the Smart Stingless Beehive Monitoring System (SSBMS) in Malaysia to enable real-time monitoring and environmental control of stingless-bee colonies. The system uses IoT sensors to measure hive temperature, humidity, water level, and GPS location for theft detection. When conditions exceed optimal ranges (e.g., temperature above 30 °C), actuators such as DC fan motors and diaphragm pumps automatically regulate the hive environment. According to Edmund and Rahman (2021), the system reduced manual monitoring, maintained stable hive conditions, and provided continuous feedback and remote tracking. This study supports the feasibility of integrating IoT-based monitoring systems in stingless-bee hives and serves as a relevant foreign reference for developing audio/video, sensor, and machine-learning–based monitoring for *T. biroi*.

Hidalgo et al. (2020) examined the development barriers faced by the stingless bee honey industry in the Bicol Region of the Philippines. Their work identified challenges such as limited access to modern hive management technologies, lack of technical training, and insufficient product standardization, which hinder the growth of stingless beekeeping enterprises. The study emphasized the importance of research and innovation in addressing these issues, particularly through the adoption of digital and automated systems for monitoring hive productivity and colony health. This literature underscores the need for technological advancement in local meliponiculture, providing context for the present study's aim to develop an AI-driven, audio–video monitoring system that enhances colony management efficiency and supports the sustainable growth of the stingless bee industry in the Philippines.

De Vera and Opisco (2021) examined the growing practice of stingless beekeeping in various regions of the Philippines and highlighted the challenges faced by local keepers in maintaining colony health, preventing pest intrusion, and ensuring consistent honey production. Their findings showed that many smallholder beekeepers rely on manual inspection, which is often time-consuming and insufficient for detecting early signs of stress such as brood decline, reduced foraging, or environmental fluctuations. The study emphasized that the lack of accessible monitoring technologies limits the ability of Filipino beekeepers to protect Tetragonula colonies, particularly in rural settings where resources and technical tools are limited.

This underscores the need for locally adaptable, technology-assisted systems that can support colony maintenance and reduce losses caused by neglect, environmental instability, or unnoticed disturbances. The present study responds to this gap by developing an integrated AI-based hive monitoring system designed specifically for *T. biroi*, capable of tracking acoustic activity, entrance movement, and environmental conditions to provide early detection of anomalies and assist Filipino beekeepers in sustaining healthy, productive colonies.

Local Studies and Systems

Belina-Aldemita et al. (2019) analyzed the nutritional composition of pot-pollen produced by *T. biroi* in the Philippines, examining proteins, lipids, carbohydrates, vitamins, and bioactive compounds. Their findings showed that *T. biroi* pot-pollen contains high levels of antioxidants and essential nutrients, highlighting the species' value for both honey and nutritionally rich pollen production. According to Belina-Aldemita et al. (2019), these results emphasize the importance of improving colony management and monitoring practices, supporting the current study's goal of developing an AI-enhanced hive monitoring system to maintain healthier stingless bee colonies and ensure the quality of hive products.

Arendela et al. (2025) developed an IoT-based monitoring platform for colonies of *T. biroi* in the Philippines that continuously tracks hive temperature, humidity and weight, controls a water-cooling valve to maintain optimal conditions, and issues remote alerts through a user dashboard. The system, built around an ESP8266-MOD microcontroller and Arduino Mega 2560 R3, achieved high accuracy in field tests (98.74 % temperature, 97.89 % humidity, 95.92 % weight) and showed a 3.414 % higher weight gain in monitored hives compared to unmonitored ones. This study demonstrates that automated, low-disturbance monitoring can improve stingless-bee colony productivity and resilience—providing a strong precedent and technological foundation for your audio–video + sensor + ML monitoring approach.

Locsin et al. (2021) conducted an empirical analysis of *T. biroi* production economics across Philippine beekeeping operations, measuring production costs, yields, and profitability indicators. Their findings indicate that production profitability varies significantly with management practices, hive losses from predators or environmental stressors, and timing of harvests — factors that can be mitigated through improved monitoring and timely interventions. The study’s data show that minimizing colony disturbance and preventing intrusions can directly affect output and income for small-scale producers.

These results support the present research's +objectives: implementing an audio–video, machine learning–based monitoring system can reduce manual inspection frequency, provide early intrusion alerts, and ultimately improve production efficiency and economic returns for *T. biroi* beekeepers.

Baluran et al. (2025) compared five deep learning models for detecting and counting bees using video data from Philippine beekeeping environments. Using a dataset of over 3,000 video clips and 58,000 frames, they evaluated performance based on accuracy, speed, and detection capability under different lighting and motion conditions. The results showed that YOLOv4 performed best with 97.9% mAP, maintaining stable detection even when bees overlapped or moved quickly near hive entrances. According to Baluran et al. (2025), these findings confirm that AI-based vision systems can effectively analyze visual hive data, supporting the current study's use of machine learning for non-invasive activity monitoring and intrusion detection in *T. biroi* colonies.

Ramos et al. (2024) from Cavite State University presented a review titled "Innovative Hive Intelligence: Stingless Bee Products and Machine Learning Advancements in Agriculture and Medicine." The study examined how machine learning, IoT devices, and automated data collection systems are used to improve monitoring, productivity, and management of stingless bees in the Philippines.

It highlighted the use of predictive analytics to analyze environmental factors, colony health, and production efficiency, as well as improve the quality of products such as honey and propolis. According to Ramos et al. (2024), these technological advancements support the shift toward precision apiculture, which aligns with the present study's development of an audio–video monitoring and intrusion alert system for *T. biroi*.

In the study by Mostoles et al. (2015), empirical data were gathered on Philippine stingless bee colonies—likely covering parameters such as nesting habits, environmental conditions, foraging behavior, or colony productivity. The authors' field observations and quantitative results (e.g., hive counts, productivity rates, environmental metrics) reveal how local contexts impact bee performance and highlight the need for improved monitoring and management tools. These findings support the current study's objective of applying machine learning–based monitoring to enhance hive management and intrusion detection for *T. biroi* producers in the Philippines.

Garcia et al. (2023) developed a CNN-based system to detect queen presence in European Apis mellifera hives using audio recordings. Audio files were converted into spectrograms and Mel-frequency cepstral coefficients, which were then used to train and evaluate four CNN architectures. Their simplified CNN model achieved 99.88% accuracy for queen-right hives and 99.72% for queen-less hives.

This study demonstrates that sound-based monitoring can reliably identify queen status without manual inspection, supporting the integration of acoustic sensors in hive monitoring systems like the one proposed for *T. biroi* to detect colony health changes and improve management efficiency.

Synthesis

The reviewed literature and systems collectively demonstrate the growing global interest in integrating technology into apiculture. Foreign studies show that combining audio and visual monitoring with machine learning significantly improves the detection of abnormal colony behavior and external threats. These technologies reduce the need for manual inspection, thereby minimizing stress on bee colonies.

Local studies, on the other hand, highlight the importance of adapting these technological innovations to the Philippine context, focusing on affordability, accessibility, and sustainability. The existing literature indicates a strong need for systems tailored specifically to stingless bees (*Tetragonula Biroi*), whose biological characteristics and environmental sensitivities differ from common honeybee species.

The proposed project, Audio-Video Analysis for Colony Activity and Intrusion Alert for Tetragonula Biroi Utilizing Machine-Based Learning, addresses these identified gaps by combining sound and video data to accurately monitor colony activity and detect predator intrusion. This dual-data approach enhances monitoring accuracy and ensures real-time, non-invasive hive management for sustainable stingless beekeeping.

Conceptual Framework

The conceptual framework of this study presents a unified hive monitoring system that integrates environmental sensors, audio and video modules, and machine learning algorithms. The SHT30-B sensor records temperature and humidity, the load cell with HX711 amplifier measures internal hive activity, the INMP441 microphone captures acoustic signals, and the Raspberry Pi Camera Module 3 vision sensor provides real-time video input.

The ESP32-S3 microcontroller and Raspberry Pi 4 B process data collected from these components. The processed data are analyzed using embedded machine learning algorithms capable of classifying activity patterns and detecting intrusions. Once an anomaly or predator movement is identified, the system transmits real-time notifications to the beekeeper via mobile or web-based dashboard.

This integrated process allows non-invasive observation of bee colonies while maintaining the hive's microclimate stability. By combining automation, artificial intelligence, and environmental sensing, the proposed system ensures efficient and sustainable monitoring of *T. biroi* colonies.

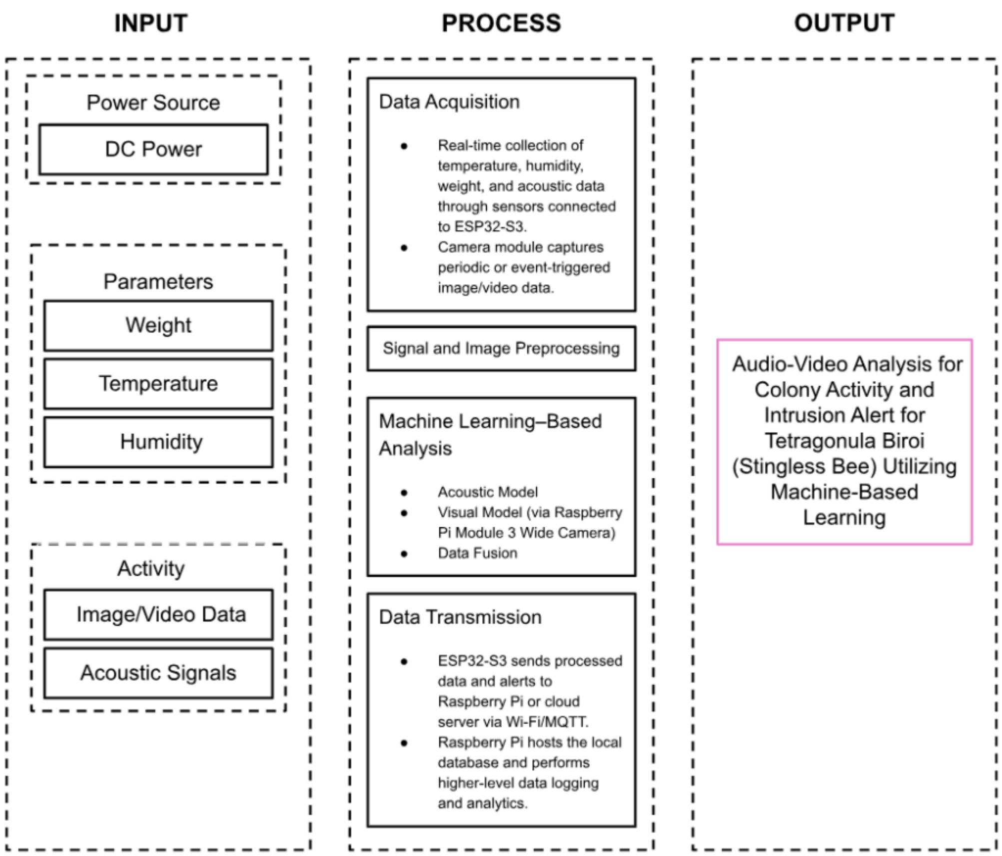


Figure 1. *Conceptual Framework of the Audio-Video Analysis for Colony Activity and Intrusion Alert for Tetragonula Biroi*

CHAPTER 3

METHODOLOGY

Research Design

This study uses descriptive applied research to design and develop an Audio-Video Analysis for Colony Activity and Intrusion Alert for *Tetragonula Biroi* (Stingless Bee) Utilizing Machine-Based Learning.

The prototyping design model is the selected process for this capstone:

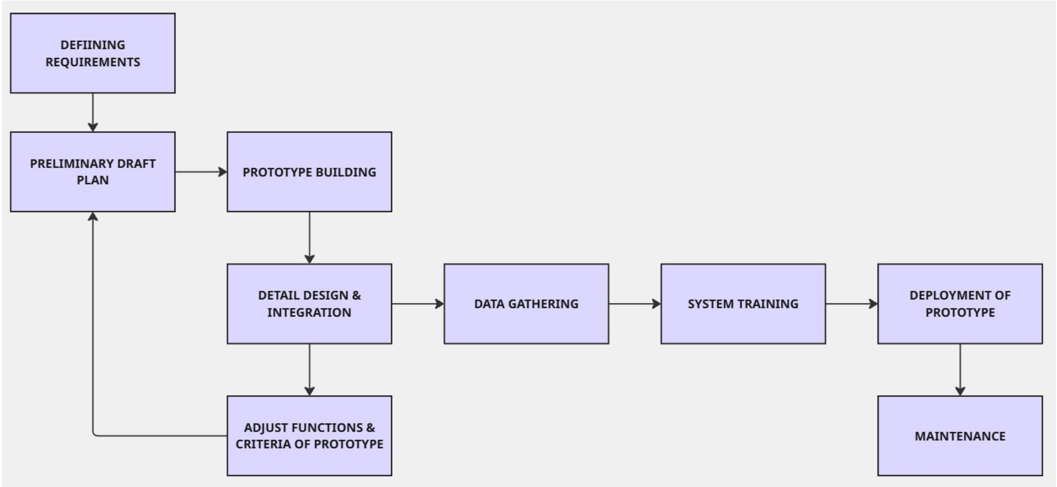


Figure 2. *Prototyping Model*

A. Defining Requirements

The requirement-definition phase involved a systematic process of identifying, analyzing, and verifying the technical, environmental, and operational needs of the proposed AI-based stingless bee monitoring system. The proponents conducted extensive literature reviews on bioacoustic monitoring, vision-based detection, IoT systems, and machine learning applications to understand *T. biroi* behavior and non-invasive monitoring strategies.

Since the system relies on artificial intelligence, specific requirements were established for model development, including dataset preparation, algorithm selection, preprocessing methods, and edge deployment feasibility. The ESP32-S3 and Raspberry Pi 4 were evaluated to ensure they could support real-time inference with minimal latency under varying field conditions.

Field interviews with beekeepers and site assessments were conducted to identify practical challenges such as predator intrusion, environmental stress, power availability, and hive placement. These insights ensured that the system design addressed real-world beekeeping conditions.

Hardware components were carefully evaluated based on performance, compatibility, durability, and cost. Market research ensured affordability without sacrificing reliability. Software tools and platforms were selected to support data acquisition, machine learning, communication, and dashboard visualization.

Overall, this phase ensured that the system design is technically feasible, field-ready, cost-effective, and aligned with sustainable and non-invasive stingless bee management practices.

B. Preliminary Draft Plan

In this phase, the researchers developed an initial design of the proposed Audio-Video Monitoring System, outlining the components and their interaction within the hive setup while incorporating insights from beekeepers and experts. The system designated the ESP32-S3 microcontroller for collecting environmental and weight data (temperature, humidity, and hive weight), while the Raspberry Pi handled audio and visual data through the microphone and camera to capture hive activity and behavior of *T. biroi.* The Raspberry Pi also functioned as the local processing unit where machine learning models operate concurrently.

A preliminary data flow was established, showing how data undergo preprocessing, dual-path machine learning analysis, and event-based classification before being transmitted to the cloud dashboard. This served as the initial blueprint for prototype development.

C. Prototype Building

After establishing the initial design, the researchers proceeded with the physical construction of the prototype, beginning with the preparation of the HPCB-1 hive for field integration. The system components were carefully assembled, ensuring secure placement of sensors, modules, and wiring to minimize interference with the bees' natural activity. The ESP32-S3 microcontroller was configured to handle environmental and weight measurements, including temperature, humidity, and hive weight, while the Raspberry Pi handled both audio and visual data using a microphone and the Raspberry Pi Camera Module 3 Wide, positioned at the hive entrance to capture activity patterns and detect external disturbances such as ants, wasps, or human contact.

The Raspberry Pi served as the main processing unit, receiving collected data and performing local analysis. A temporary monitoring interface was implemented to display real-time measurements, visual streams, and preliminary intrusion alerts. Protective housings and barriers were added to ensure system durability under field conditions.

To enhance analytical capability, machine learning functions were integrated into the system. The Raspberry Pi processed both visual and acoustic data using lightweight models to detect behavioral anomalies and irregular buzzing patterns associated with colony stress or disturbances. These models enabled the system to generate basic context-aware alerts.

With all components assembled and synchronized, the prototype served as a platform for evaluating system performance, including durability, sensor accuracy, communication stability, and integration of AI-based features.

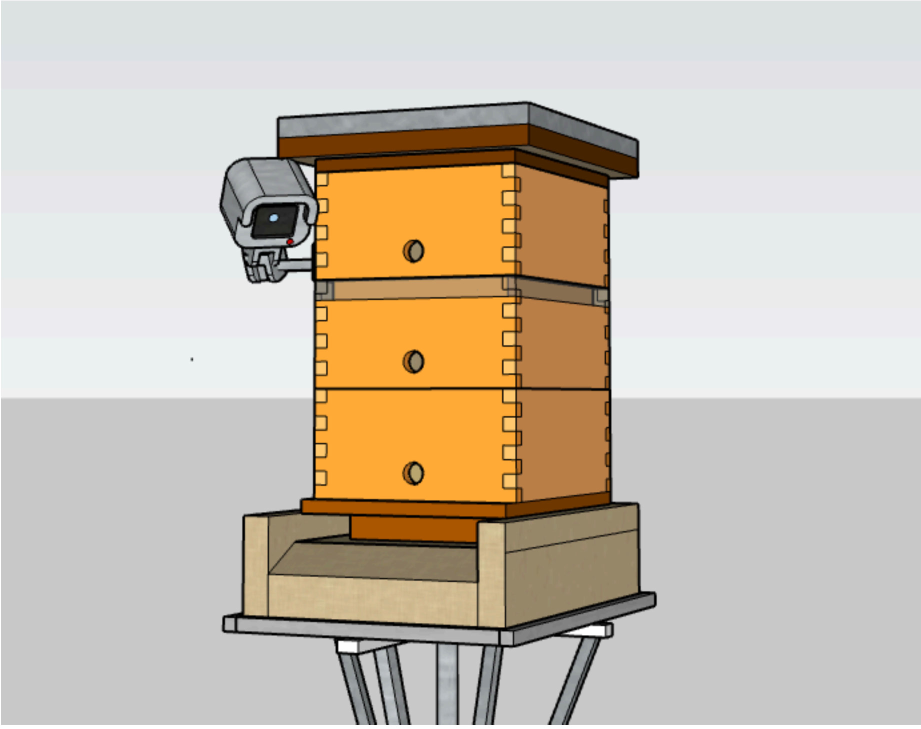


Figure 3. *Smart Bee Hive Front View*

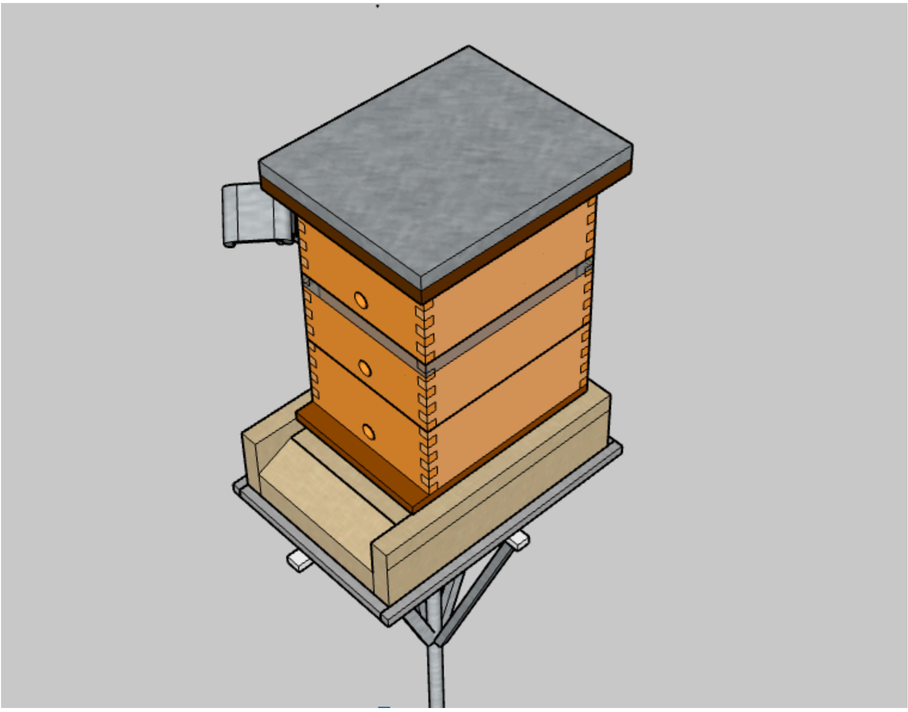


Figure 4*. Smart Bee Hive Top View and Side View*

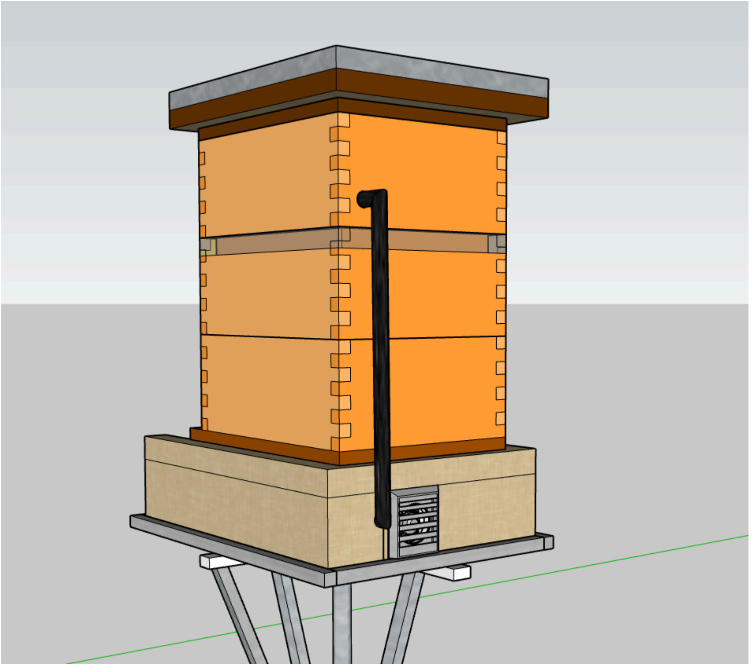


Figure 5. *Smart Bee Hive Back View*

D. Detail Design & Integration

In this phase, the researchers refined the system architecture by focusing on the detailed design and integration of hardware and software components within the hive environment. The ESP32-S3 microcontroller was designated to handle environmental and weight sensing, collecting data from temperature, humidity, and load cell sensors. Meanwhile, the Raspberry Pi served as the primary processing unit for audio and visual data, interfaced with a microphone and the Raspberry Pi Camera Module 3 Wide positioned at the hive entrance to capture a wider field of view for monitoring bee activity and external disturbances.

Data flow was structured such that environmental data from the ESP32-S3 were transmitted to the Raspberry Pi via wireless communication, where it was synchronized with acoustic and visual inputs. The integrated system then performed preprocessing and coordinated data handling to support unified analysis. Proper wiring, module placement, and protective enclosures were implemented to ensure stable operation, minimize interference with the hive, and maintain reliable communication between all components. This integrated design established a cohesive framework for real-time monitoring and system functionality.

E. Adjust Functions & Criteria of Prototype

Based on the results of field testing, several functional adjustments and performance criteria were established to improve the prototype's reliability and operational consistency. Mechanical refinements such as repositioning the Raspberry Pi camera, securing wiring conduits, and optimizing microphone placement were implemented to reduce environmental interference and enhance sensor accuracy. Calibration procedures for the load cell and environmental sensors were likewise updated to address measurement drift and strengthen long-term stability.

Software adjustments focused on improving communication efficiency, reducing data latency, and ensuring consistent synchronization between the ESP32-S3, Raspberry Pi, and cloud dashboard. Interface modifications were also made to present hive conditions and alerts more clearly for end users.

For the AI and machine-learning components, detection thresholds and model criteria were redefined to minimize false positives and improve sensitivity to genuine anomalies. Additional audio and visual data collected during testing were incorporated into the training dataset to enhance inference accuracy under varying environmental conditions.

These refinements collectively strengthened the structural, functional, and analytical performance of the prototype, ensuring that It aligns with the operational requirements of field deployment and supports reliable monitoring of *T. biroi* colonies.

F. Data Gathering

Data gathering refers to the process of locating, measuring, and collecting the necessary information for the study in a systematic and organized manner. It ensures accurate inputs, strengthens the scope, and supports a comprehensive examination of the research using appropriate data collection methods and techniques.

➢ **Observation**

The proponents conducted on-site observations in multiple stingless-bee apiaries to understand the environmental conditions, hive structures, and colony behaviors that would influence the design of the monitoring system. Field visits were carried out at Sofie's Apiary in Quezon City and *Hardin sa Parang* in Antipolo, where natural hive surroundings, colony activity levels, and potential sources of disturbance were systematically examined. These observations included assessing placement of hives relative to sunlight exposure, airflow, vegetation, and predator pathways.

The team closely observed the *T. biroi* colonies to identify behavioral patterns significant to sensor placement and data gathering, such as daily foraging activity, entrance traffic, brood chamber structure, and bee responses to external movements or noise. Additionally, the proponents examined the physical characteristics of standardized TPH1 hives including entrance configuration, internal compartments, and available mounting areas to ensure that the designed sensors and electronic modules could be integrated without disrupting colony stability.

Environmental factors such as temperature, humidity, ambient sounds, and natural stressors were recorded to assess their impact on system performance.

Practical constraints such as hive resin buildup, limited internal space, and high moisture levels were noted as important considerations for selecting durable, probe-type sensors and protective enclosures.

The observations revealed practical challenges and environmental factors that helped improve the monitoring device's design. These insights guided refinements to the hardware setup, protective casing, and sensor placement to ensure effective operation in real stingless bee colony conditions.

➢ **Interview**

The researchers initially conducted field visits and interviews with local beekeepers and domain experts to gather all necessary technical and behavioral requirements for the proposed system. The first consultation took place at Sofie’s Apiary in Lagro, Quezon City, where Mr. Edwin, an apiculturist managing both *Apis mellifera* and *Tetragonula biroi*, identified key operational challenges such as predator intrusion, wasp attacks, hive disturbance, and environmental stressors that significantly affect colony stability and productivity. His extensive field experience underscored the importance of developing an automated audio-video intrusion-alert mechanism capable of providing early detection and reducing the frequency of manual hive inspections.

A subsequent field visit was conducted at *Hardin sa Parang*, Antipolo City, where Mrs. Jade, one of the major stingless-bee keepers in the area, provided comprehensive insights into the construction and management of *T. biroi* colonies. She emphasized the practical considerations necessary when inserting sensors inside the hive, explaining that stingless bees have a tendency to “*dagtaan*” (coat with resin-like propolis) any foreign material placed in their nest.

Because of this, she strongly recommended using SHT30 probe-type sensors, which offer better durability, protection, and long-term accuracy in resin-rich hive environments. Mrs. Jade also validated the suitability of the TPH1 standardized hive dimension (8 × 10 inches) for ensuring consistent internal space allocation, demonstrated her use of plastic covers to minimize hive stress during inspections, and introduced the modified plastic-bottle entrance tube commonly used to regulate hive access and facilitate transport. These insights directly guided the physical design of the prototype.

To reinforce scientific grounding, the researchers consulted Ms. Jessica B. Baroga-Berbecho of the UPLB Bee Program, co-author of “Propagation of Stingless Bees (*Tetragonula biroi*) in the Philippines”. Ms. Baroga-Berbecho recommended the adoption of the TPH1 hive standard to ensure compatibility with established Philippine stingless-bee research practices. She also emphasized the absence of open-access datasets for stingless-bee acoustic and visual behavior, thereby affirming the necessity of generating a custom multi-sensor dataset specifically for this study. This led to the requirement for comprehensive collection of:

- Audio signatures of colony activity and stress patterns
- Video recordings capturing foraging, entrance activity, and intrusion events

- Environmental parameters such as temperature, humidity, and hive weight

All insights from the stakeholders were systematically consolidated to establish the final set of functional and non-functional requirements. This interview-driven approach aligns with standard requirement-gathering methodologies, wherein system specifications are identified through direct observations, field assessments, and expert consultations to ensure that the proposed monitoring system is realistic, viable, and grounded in actual beekeeping practices.

➢ **Audio Gathering**

For the data gathering process for audio classification, the microphone was first placed securely inside the hive before any recording activity began. Once properly installed, the required simulations were performed while audio data were captured using RealTerm. Audacity was then used to extract and examine specific parts of the recordings, such as frequency patterns and spectrogram displays. Afterward, Google Colab was utilized to divide the recorded audio into 2-second clips. These clips were then manually labeled and segregated into categories such as normal state, other behaviors, and false or ambient sounds, before being fed into the AI system to build the dataset for the capstone project.

For the normal behavior dataset, a total of 3,000 audio clips were collected. After placing the microphone inside the hive, the colony was allowed to settle for 15 minutes before recording began. The hive was then recorded for 30 minutes, followed by another 15-minute rest period, after which recording was conducted again. This procedure was repeated during different times of the day: in the morning at 6:00 AM, at midday between 10:00 AM and 2:00 PM, and in the evening at 6:00 PM. For intruded behavior, 2,000 audio clips were gathered following a similar setup. After the 15-minute settling period, hive intrusion was simulated by poking a stick at the entrance every minute over a span of 5 minutes. The hive was then allowed to rest for 15 minutes before recording resumed. For swarming behavior, 1,000 audio clips were collected by allowing the hive to settle for 15 minutes, recording for 45 minutes, resting for another 15 minutes, and then recording once more, including continuation of swarming events after splitting the audio. Similarly, 1,000 audio clips were obtained from queenless and queenright hives using the same 15-minute settling period, 45-minute recording, 15-minute rest, and second recording session. Lastly, 2,000 clips of false or ambient sounds were collected during the manual labeling stage by setting aside recordings that captured sounds other than bee activity.

➢ **Video Gathering**

For the data collection process for video classification, the camera was positioned near the hive at an angle that clearly captured the entrance. Once the setup was stable, the video recordings were captured using Raspberry Pi Connect. A 10-minute video clip was recorded every 30 minutes to ensure consistent monitoring of hive activity across different time intervals. After recording, Google Colab was used to extract one frame every 5 seconds from each 10-minute clip. These extracted frames were then manually annotated using Label Studio to identify the relevant bee behaviors and activity patterns. Finally, the annotated image data were used in Google Colab to train the AI model, specifically YOLOv8 Nano, for video-based classification and detection.

➢ **Questionaire**

To obtain structured data relevant to the design of the Audio-Video Analysis and Intrusion Alert System for *T. biroi*, the researchers developed a formal questionnaire. The instrument was distributed to practicing beekeepers, members of stingless-bee associations, and students involved in apiculture and environmental studies. The questionnaire captured essential information such as:

- current monitoring methods for stingless-bee colonies;

- perceived challenges in detecting hive disturbances;
- frequency and difficulty of manual hive checks;
- willingness to adopt automated monitoring systems; and
- preferred data outputs such as sound alerts, mobile notifications, or environmental logs.

Questions also assessed the users' familiarity with digital tools, preferred dashboard formats, and expectations regarding device durability, cost, and ease of installation. The collected responses were instrumental in identifying user-driven specifications and were directly incorporated into the design refinement of the prototype's sensor configuration, user interface, and notification system.

➢ **Site Visit**

The proponents conducted a series of site visits to operational stingless-bee apiaries, including Sofie's Apiary in Quezon City, *Hardin sa Parang* in Antipolo, and the UPLB Bee Program in the University of the Philippines Los Baños. These visits were undertaken to assess real-world conditions in which stingless-bee colonies are maintained and to determine the practical considerations necessary for deploying the Audio-Video Analysis and Intrusion Alert System for *Tetragonula biroi*.

At Sofie’s Apiary and Hardin sa Parang, the team examined various hive setups, surrounding vegetation, available shade, ambient noise sources, moisture levels, and potential predator access points. Observations were also made on hive orientation and field conditions that may influence sensor placement, enclosure stability, and power requirements. The proponents documented the internal layout of standardized TPH1 hives to identify mounting points for audio, video, and environmental sensors, as well as sections susceptible to resin accumulation.

During the visit to the UPLB Bee Program, the team was able to observe research-grade setups and consult with technical personnel involved in meliponiculture and pollinator studies.

The visit provided insights into standardized handling procedures, colony behavior patterns, and recommended practices for minimizing hive disturbance during equipment installation. The proponents also reviewed existing monitoring methods used in academic research, which contributed valuable perspectives to the refinement of the project's system architecture.

All site visits were conducted with prior coordination and approval from the respective owners and program administrators.

- **Research**

The proponents conducted comprehensive research using academic journals, books, online databases, manufacturer datasheets, and existing apiculture studies to establish the theoretical and technical foundation of the project. This research covered key areas including stingless-bee biology, behavioral indicators of colony stress, bioacoustic analysis methods, machine-learning classification techniques, and IoT-based environmental monitoring systems.

Technical research further involved identifying the hardware and software components necessary for implementing an integrated audio-video monitoring device. This included evaluating sensor modules such as the SHT31-D/SHT30 probe-type humidity sensor, INMP441 microphone, HX711 load cell amplifier, and Raspberry Pi Camera Module 3 vision sensor, alongside programming platforms such as the ESP32-S3 and Raspberry Pi 4 Model B. The gathered information served as the foundation for system architecture planning, hardware selection, and algorithm development, ensuring that the device is both functional and scientifically grounded.

G. System Training

The system's artificial intelligence components underwent a structured training process to enable accurate detection, classification, and interpretation of both visual and audio data collected from *T. biroi* hives. Visual data were captured using the Raspberry Pi Camera Module 3 Wide, providing a wider field of view for monitoring hive entrance activity and external disturbances. The video-based model was trained using Google Colab, utilizing the YOLOv8 nano architecture to detect and classify objects such as bees, predators, and abnormal movement patterns. The dataset included annotated image and video samples representing normal colony behavior and intrusion scenarios under varying lighting and environmental conditions.

For audio analysis, a Convolutional Neural Network (CNN) model was trained using recorded hive sounds collected during field observations. The dataset consisted of normal buzzing patterns, stress-induced sounds, and disturbance-related acoustic signals. Audio preprocessing techniques, including feature extraction of frequency, amplitude, and temporal patterns, were applied to improve classification performance. Background noise samples were also incorporated to enhance the model's ability to distinguish relevant acoustic signals from environmental interference.

During training, model parameters such as detection thresholds, feature extraction settings, and confidence levels were iteratively optimized to balance sensitivity and accuracy. Both visual and audio models were validated using representative scenarios to ensure reliable detection of colony activity and intrusion events. This training process enabled the system to perform real-time, context-aware monitoring with improved accuracy and responsiveness prior to deployment.

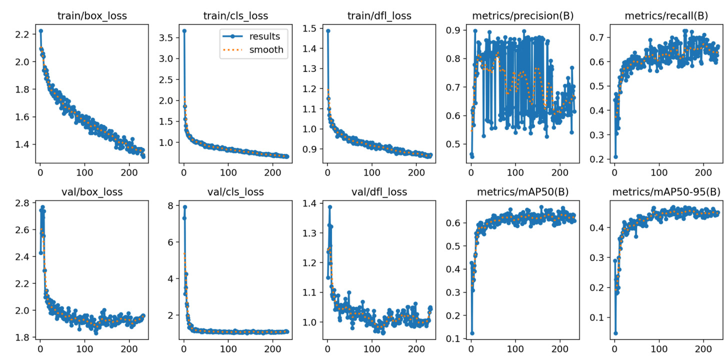


Figure 6. *Model Training Performance for Video using YOLO*

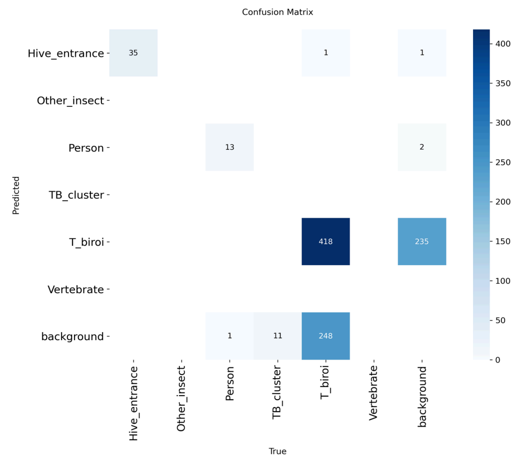


Figure 7. *Confusion Matrix of Video Training*

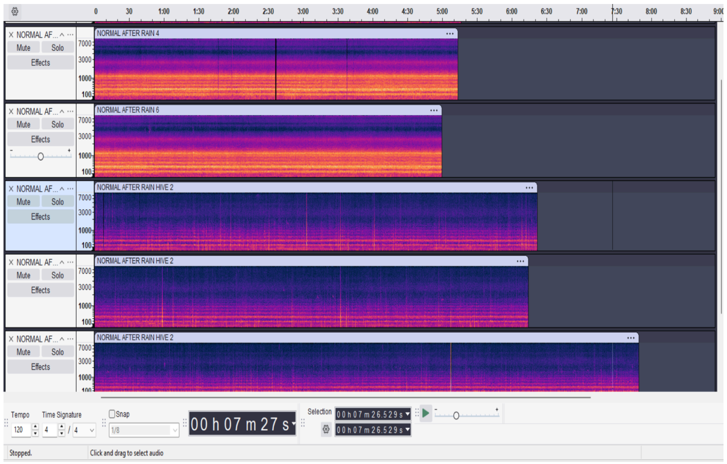


Figure 8. *Audio gathering through Audacity*

H. Deployment of Prototype

Following prototype evaluation, the system underwent a detailed design refinement to address identified issues and enhance performance. This phase focused on optimizing sensor placement inside and outside the HPCB-1 hive to minimize interference with bee behavior while ensuring accurate environmental and acoustic data capture. The researchers improved the wiring layout, protective enclosures, and mounting structures to ensure stability and long-term durability. On the processing side, the machine learning pipelines were restructured to allow efficient data synchronization between audio and visual models, enabling more accurate data fusion for event classification.

The visual detection model, developed using Ultralytics (YOLOv8 nano), was optimized for deployment on the Raspberry Pi using the Raspberry Pi Camera Module 3 Wide, while the audio classification model was converted into a lightweight format using TensorFlow Lite (TFLite) to enable efficient real-time inference. The decision engine was further enhanced to reduce false positives caused by environmental noise and lighting variations. Additionally, the dashboard interface was improved to provide clearer visualization of hive parameters, historical logs, and real-time alerts, resulting in a more stable and field-ready system suitable for continuous monitoring.

I. Maintenance

The Audio-Video Monitoring System for T. biroi requires periodic maintenance to preserve reliable field performance, including occasional inspection of the housing, wiring, and sensor placement to prevent moisture intrusion, corrosion, propolis buildup, and loose connections. Components installed inside the hive, such as the microphone and selected sensors, may also require attention when resin or propolis accumulation becomes evident, as this may interfere with measurements and reduce detection accuracy.

Firmware updates for the ESP32-S3 and Raspberry Pi should be applied as needed, and storage logs must be managed to prevent data overflow. Basic troubleshooting includes recalibrating sensors, checking power regulation components, and reviewing system logs for errors. The AI models must also be periodically updated using new audio and visual data to prevent model drift and maintain detection accuracy. Proper environmental protection, electrical safety, and enclosure sealing are essential to extend the system's lifespan and ensure dependable operation for beekeepers.

Testing Procedures/Methods

The primary objective of the Audio-Video Analysis and Intrusion Alert System for *Tetragonula biroi* is to develop an automated, non-intrusive monitoring solution capable of detecting colony activity levels, identifying potential disturbances, and issuing timely alerts to beekeepers. The system integrates a microcontroller-based processing unit, audio and video acquisition modules, environmental sensors, and a wireless communication interface, all of which work cohesively to support hive-condition assessment and intrusion detection.

To ensure the system's accuracy, reliability, and operational stability, the proponents will employ a comprehensive testing methodology.

Each subsystem audio sensing, video capture, environmental monitoring, data transmission, power management, and alert generation will undergo systematic evaluation under controlled conditions and real apiary environments. The testing procedures are designed not only to verify functional correctness but also to determine the system's responsiveness to actual hive behaviors, environmental variations, and common threats observed during the site visits.

Bench-level tests will first be conducted to validate hardware integration, sensor calibration, microcontroller responsiveness, and data-processing accuracy. This phase ensures that all components perform within their required specifications before field deployment.

Following this, field testing will be carried out in active *T. biroi* hives located in *Hardin sa Parang*, at Antipolo, where environmental factors such as lighting conditions, background noise, humidity, and hive activity levels can be observed in realistic settings.

A. Functionality Testing

Functionality testing ensures that every feature of the stingless beehive monitoring system works as intended. The test focuses on validating the interaction between hardware components (ESP32-S3, sensors, camera, microphone, Raspberry Pi) and the software modules (data processing, machine learning, and dashboard communication).

The following functions will be tested:

1. **Sensor Data Collection**
    - Temperature and humidity readings from the SHT30-B
    - Weight readings from the load cell
    - Audio capture from the microphone
    - Video feed from the camera

    Each sensor is activated and checked if it sends valid data to the ESP32-S3.

2. **Data Transmission**

    Ensures ESP32-S3 transmits sensor data to the Raspberry Pi and the dashboard without delays or data loss.

3. **AI and ML Processing**
    - Audio classifier detects unusual hive sounds
    - Video analysis identifies predator intrusion
    - Colony activity levels are categorized properly

    The system will be tested using sample datasets.

4. **Alert System**

    The dashboard must receive real-time notifications when abnormal activity or intrusion is detected.

5. **Dashboard Visualization**

    Sensor readings, graphs, activity status, and logs must be displayed correctly and updated in real time.

B. Accuracy Test

Accuracy testing evaluates how precise the monitoring system is in reading real environmental and behavioral conditions.

1. Sensor Accuracy

- The SHT30 temperature and humidity values will be compared against a calibrated digital meter.
- Weight sensor values will be compared with known masses.

2. Audio Analysis Accuracy

- Pre-labeled audio clips (normal buzz, distress buzz, predator noise) will be used.
- Confusion matrix, precision, recall, and F1-score will be measured to determine ML performance.

3. Video AI Detection Accuracy

The system will be tested using several images and videos of:

- normal colony activity
- insects
- humans

True detection rates and false positives will be documented.

4. End-to-End Accuracy

Integration accuracy will be reviewed by comparing actual events (manually observed) versus system alerts.

C. Maintainability

Maintainability assesses how easy it is to update, repair, expand, or troubleshoot the system.

1. **Modular Hardware Design**

   Each component (ESP32-S3, sensors, Raspberry Pi, camera, microphone) is installed separately and can be replaced without affecting others.

2. **Modular Software Structure**

   The system uses separated modules for:

   - sensor reading
   - audio processing
   - video processing
   - dashboard communication

   This allows developers to update specific modules without changing the entire system.

3. **Code Documentation**

   Proper comments and documentation files will be provided to guide future developers.

4. **Version Control**

   Git or similar tools will be used to track changes and maintain clean versions of the system code.

D. Quality Test

Quality testing ensures that the system meets standards for usability, reliability, performance, and overall user experience.

1. Usability

- The dashboard must be easy for beekeepers to understand.
- Layout, icons, graphs, colors, and labels will be checked for clarity.

2. Reliability

- The system must operate continuously without crashing.
- A 24-hour stress test will be conducted.
- The sensors and camera should send stable readings over long periods.

3. Performance

- Data must be processed in real-time.
- Video and audio classification must produce results within acceptable delay (1–3 seconds).
- The dashboard refresh rate will be tested under different network conditions.

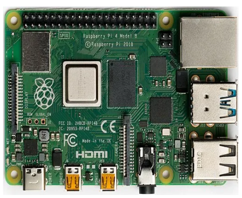
4. Environmental Robustness

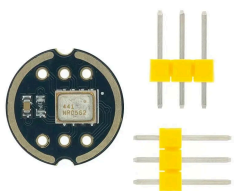
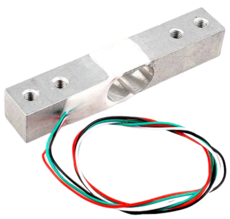
- The components must withstand normal outdoor hive conditions (heat, humidity).

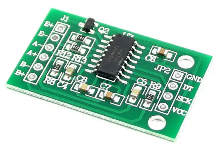
- Weatherproofing of sensors and enclosures will be checked.

Hardware Components

Table 2. *Hardware Requirements*

Hardware	***Version/Model***	***Specification***	***Description***
Microprocessor 	Raspberry Pi 4 Model B	**Processor:** Broadcom BCM2711, quad-core Cortex-A72 (ARM v8) 64-bit SoC @ 1.5GHz **Memory:** 4GB or 8GB LPDDR4-3200 SDRAM (depending on variation) **SD card support:** Micro SD card slot for loading operating system and data storage **GPIO:** Standard 40-pin GPIO header(fully backward-compatible with previous boards)	The Raspberry Pi 4 is a significant upgrade in the popular computer family, delivering a desktop-level performance comparable to entry-level x86 PCs with its 1.5GHz quad-core 64-bit Arm Cortex-A72 CPU, up to 8GB of RAM, dual-band Wi-Fi, Bluetooth 5.0, and Gigabit Ethernet.
Microcontroller 	Firebeetle 2 Board ESP32-S3 (N16R8)	**Processor:** Xtensa® dual-core 32-bit LX7 microprocessor **Operating Voltage:** 3.3V **Main Frequency:** 240 MHz **SRAM:** 512KB **ROM:** 384KB **WIFI Protocol:** IEEE 802.11b/g/n **Bluetooth Protocol:** Bluetooth 5, Bluetooth mesh	FireBeetle 2 ESP32-S3 is a high-performance main controller built around the ESP32-S3 module. In addition, this microcontroller is equipped with an OV2640 camera, enabling it to excel in applications such as image recognition.

Temperature/Humidity Sensor 	B-SHT30	**Temperature measurement range:** 100 **Accuracy:** +/- 2%RH **Output type:** I2C communication **Working temperature:** 125 (℃) **Humidity range:** 0~100%RH **Humidity measurement range:** 100 **Output signal:** IIC communication	The SHT30 Waterproof Temperature and Humidity Sensor Probe is a digital environmental sensor designed for accurate and stable measurement of temperature and humidity. It features a waterproof housing, making it ideal for outdoor, industrial, and harsh-environment monitoring.
Omnidirectional Microphone 	INMP441	**Features:** Digital I2S interface with high precision 24-bit data **Signal-to-Noise ratio:** 61 dBA **High PSR:** -75 dBFS **Frequency response:** from 60 Hz to 15 kHz **Power Consumption:** 1.4 mA **SCK:** Serial data clock for I2S interface **WS:** Serial data word selection for I2S interface **L/R:** Left/Right channel selection.	The INMP441 is a high performance, low power, digital output, omnidirectional MEMS microphone with bottom port. The I2S interface allows the INMP441 to be directly connected to digital processors such as DSPs and microcontrollers. The INMP441 has a high signal-to-noise ratio and is an excellent choice for near field applications.
Load Cell 	Z-Size Load Cell (20kg)	**Rated Load:** 20kg **Working Voltage:** 3~12VDC **Maximum Working Voltage:** 15VDC **Rated Output:** 1.0±0.15mV/V **Nonlinearity:** 0.03% F.S **Lag:** 0.03% F.S **Repeatability:** 0.03% F.S **Creep (5 min):** 0.03% F.S **Zero balance:** ±0.1000 mV/V **Output impedance:** 1000±10% Ohm **Input impedance:** 1115±10% Ohm	This straight bar load cell (sometimes called a strain gauge) can translate up to 1kg / 3kg / 5kg / 10kg / 20kg of pressure (force) into an electrical signal. Each load cell is able to measure the electrical resistance that changes in response to, and proportional to, the strain (e.g. pressure or force) applied to the bar.

Amplifier 	HX711	**Operating Voltage:** 2.6 - 5.5V **Operating Temperature:** -40~+80°C **Current consumption:** **Normal operation:** <1.5mA Power Down: <1uA **Dimensions:** 29mm x 17mm x 4mm	This Load Cell Amplifier uses an HX711 IC 24-bit ADC/amplifier. The HX711 uses a Two wire interface (Clock and Data) for communication. Any microcontroller's GPIO pins should work and numerous libraries have been written making it easy to read data from the HX711.
Vision Sensor 	Raspberry Pi Wide Camera Module 3	**Type:** Sony IMX708 **Resolution:**11.9 MP **Sensor Diagonal:** 7.05 mm **Pixel Size:** 1.4×1.4 μm **Picture Output: RAW12/10/8, COMP8** **Focus:** Motorised auto focus **Lens:** standard (75°) or wide-angle (120°)	The Raspberry Pi camera module 3 is the latest camera module from Raspberry Pi. Compared to the previous version 2 the new Raspberry Pi camera module 3, offers an improved low-light sensitivity, High dynamic range (HDR) support and powered autofocus.
Voltage Regulator 	AMS1117-3.3	**Input Voltage:** 4.5V – 15V **Output Voltage:** 3.3V (Fixed) **Maximum Output Current:** 800mA **Dropout Voltage:** 1.1V (at 800mA load) **Operating Temperature:** -40°C to +125°C **Quiescent Current:** <5mA (typical) **Line Regulation:** 0.2% (typical) **Load Regulation:** 0.4% (typical) **Dimensions:** 10mm x 8mm x 4mm	The AMS1117-3.3 is a low-dropout linear voltage regulator that provides a stable 3.3V output for powering sensors, microcontrollers, and low-power modules in the system. It supports input voltages up to 15V and delivers up to 800mA of output current, ensuring reliable and regulated power for sensitive electronic components.

Software Requirements

For the software development of this study, the proponents will utilize two microcontrollers: the ESP32-S3 and the Raspberry Pi 4 B.

The ESP32-S3 will use C++ as the programming language, with PlatformIO IDE in VS Code as the development environment. This microcontroller will handle environmental sensing (temperature, humidity), load cell monitoring, and Wi-Fi communication. C++ is chosen for its speed, memory efficiency, and direct hardware access, ensuring reliable real-time processing of sensor data.

The Raspberry Pi 4 B will use Python, developed in VS Code with Pylance and Jupyter extensions. It will handle audio and video processing, including data acquisition from the microphone and the Raspberry Pi Camera Module 3 Wide. For machine learning, the system will use Ultralytics (YOLOv8 nano) for video-based detection and TensorFlow Lite (TFLite) for audio classification to enable efficient real-time inference on edge devices. Libraries such as OpenCV will be used for image processing and system integration.

Additionally, SSH remote access and tunneling will be implemented to allow remote system monitoring, debugging, and secure communication between devices. The Raspberry Pi will serve as the main processing unit, supporting real-time analysis and system coordination while maintaining a flexible and scalable software architecture for future enhancements.

Table 3. *Comparison of the Programming Language for ESP32-S3*

Feature	C++	MicroPython
Speed and Performance	Very fast; compiled to native machine code; ideal for real-time tasks like audio and sensor processing	Interpreted; slower; fine for prototyping but struggles with real-time processing
Pointers / Memory Control	Full support; direct memory access and pointer manipulation	No explicit pointers; memory managed automatically; limits low-level control
Hardware Access	Full access to all peripherals (GPIO, I2S, ADC/DAC, timers, interrupts)	Limited; some peripherals accessible but timing-critical tasks may fail
Direct Call Support for Native Libraries	Can call ESP-IDF/Arduino libraries directly; full support for FreeRTOS, Wi-Fi, and Bluetooth	Indirect; some native libraries not accessible or slower

C++ is chosen for the ESP32-S3 for its high-speed execution, efficient memory use, and direct hardware control. It handles real-time audio, sensor, and load cell monitoring reliably. C++ supports pointers for precise memory management, full hardware access (GPIO, I2S, ADC/DAC, timers), and native library calls to ESP-IDF features like FreeRTOS and Wi-Fi, making it ideal for continuous hive monitoring.

Table 4. *Comparison of the Programming Language for Raspberry Pi 4 B*

Feature	Python	C++
Speed and Performance	Fast enough on Pi 4 B; heavy-lifting handled by optimized libraries (TensorFlowLite, Ultralytics)	Very fast; compiled; ideal for CPU-intensive tasks
Pointers / Memory Control	Managed memory; less control but safe and convenient for ML/vision workloads	Full control; can optimize memory and buffers
Hardware Access	Accessible via mature libraries (RPi.GPIO, smbus); abstraction simplifies development	Direct GPIO, I2C, SPI, UART, PWM control
Direct Call Support for Native Libraries	Python bindings allow near-native performance for optimized C/C++ libraries	Can call libraries directly
Ease of Development	Rapid coding, debugging, and iteration; ideal for ML and vision pipelines	Medium–Hard; longer to write and debug
Ecosystem Support	Huge library ecosystem and community support	Smaller community for ML/vision on Pi

Python is chosen for the Raspberry Pi 4 Model B for its ease of development, readability, and rich library support. It handles video processing and ML inference effectively. Python provides automatic memory management, sufficient speed via optimized libraries, and accessible hardware control through RPi.GPIO/smbus, and bindings to native libraries like TensorFlowLite and Ultralytics, making it ideal for real-time colony activity analysis and intrusion detection.

Table 5. *Comparison of IDE Software for ESP32-S3*

Aspect	PlatformIO IDE (VS Code)	Arduino IDE
Ease of use	Medium; powerful but requires setup	Easy; beginner-friendly
Required Operating System	Windows, macOS, Linux	Windows, macOS, Linux
Hardware Support	ESP32, ESP8266, Arduino boards	ESP32, ESP8266, Arduino boards
Programming Language	C/C++	C/C++

PlatformIO (VS Code) is chosen for the ESP32-S3 because it offers organized project management, extensive library support, and advanced debugging, while still allowing Arduino-style simplicity. It supports full low-level hardware control with ESP-IDF, making. It is ideal for reliable and production-ready code for real-time audio, sensor, and Wi-Fi tasks.

Table 6. *For Raspberry Pi 4 B*

Aspect	Python and SSH Remote (VS Code)	Thonny IDE
Ease of use	Moderate; requires setup of extensions and kernels; more features can be overwhelming for beginners	Very easy; designed for beginners; clean interface with minimal setup
Required Operating System	Windows, macOS, Linux	Windows, macOS, Linux
Hardware Support	Can work with external hardware but often needs extra libraries and setup (e.g., microcontrollers, ESP32)	Limited but simpler for basic microcontroller support; good for beginner projects
Programming Language	Python (supports Jupyter notebooks, interactive coding, and multiple Python versions)	Python only; simple and beginner-friendly, with limited advanced features

The proponents will use Python with Pylance and Jupyter extensions in VS Code to write, compile, and run Python code. This setup was chosen for its ease of use, robust programming language support, and compatibility with external hardware. Since the project requires integrating multiple modules and performing complex data processing, Python with Pylance and Jupyter on VS Code provides a flexible and professional environment to efficiently manage and develop the code.

Block Diagram

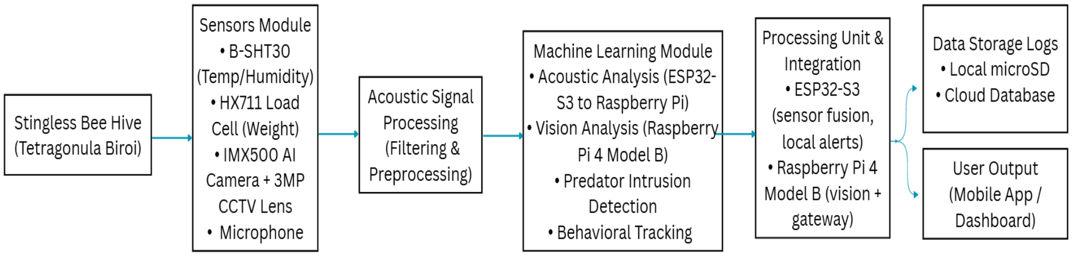


Figure 3. *Colony Activity and Intrusion Alert Block Diagram*

The block diagram illustrates the overall functional architecture of the proposed monitoring system. It presents the structured arrangement of the environmental, acoustic, and visual sensors, together with the ESP32-S3 microcontroller and Raspberry Pi 4 B, which serve as the primary data acquisition and processing units. The figure also shows how each module is interconnected to facilitate the continuous flow of information required for real-time monitoring, intrusion detection, and activity classification.

Through this diagram, the system's operational structure is clearly defined, ensuring a comprehensive understanding of how each component contributes to achieving stable and efficient hive monitoring.

Schematic Diagram

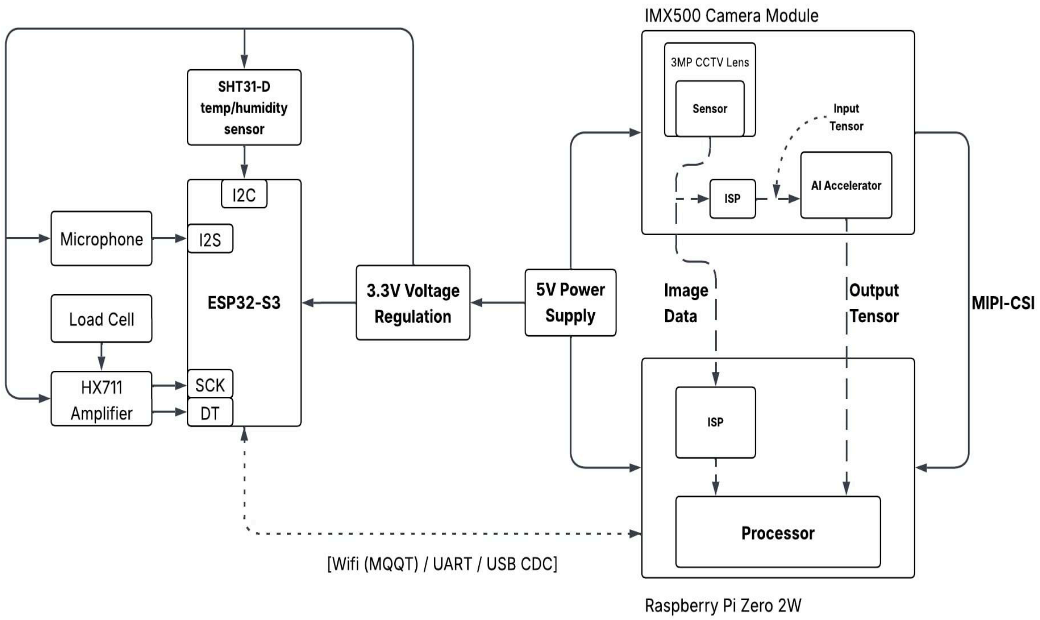


Figure 4. *Connection Diagram of the System*

The schematic diagram provides a detailed representation of the electrical circuitry of the monitoring system. It specifies the connections among the SHT30-B temperature and humidity sensor, the HX711 load cell amplifier, the INMP441 microphone, and the Raspberry Pi Camera vision module, as well as their interfaces with the ESP32-S3 and Raspberry Pi. Each connection is presented with defined signal paths, voltage levels, and protection elements to ensure accurate data capture and stable system operation. This figure serves as a technical reference for verifying wiring accuracy, supporting hardware integration, and ensuring safe and reliable performance of the device during continuous field deployment.

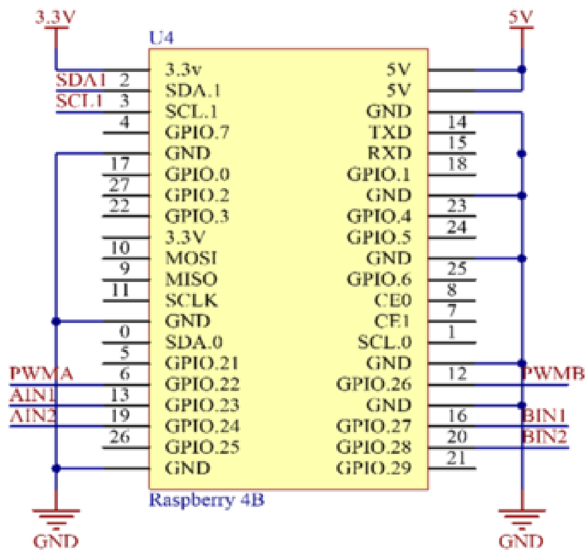


Figure 5. *Schematic Diagram of Raspberry Pi 4 B*

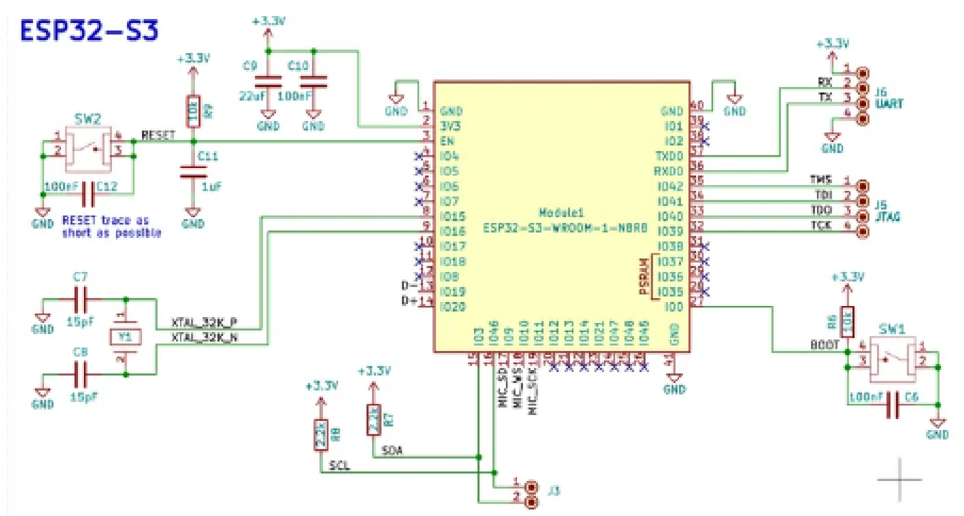


Figure 6. *Schematic Diagram of ESP32-S3*

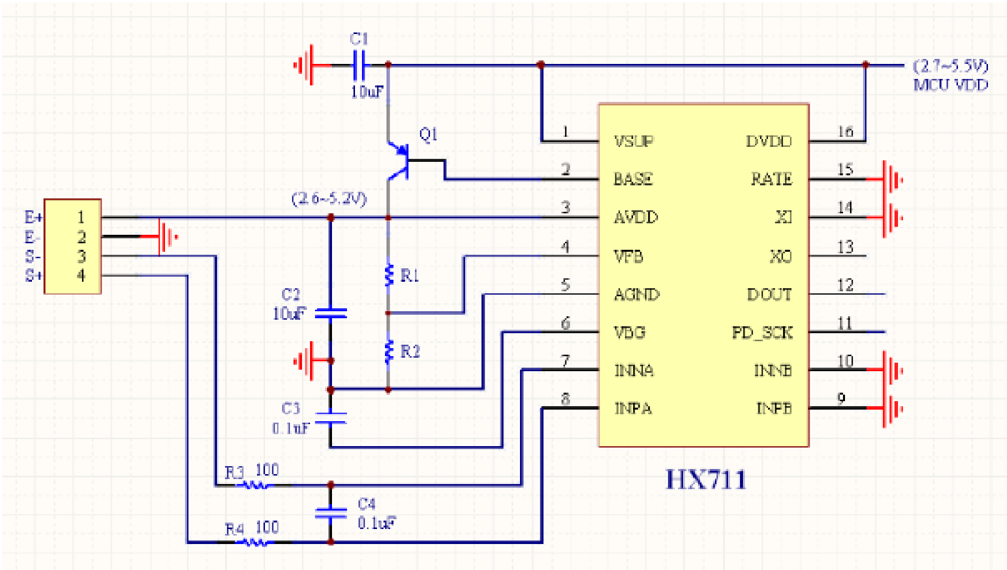


Figure 7. *Schematic Diagram of HX711 amplifier*

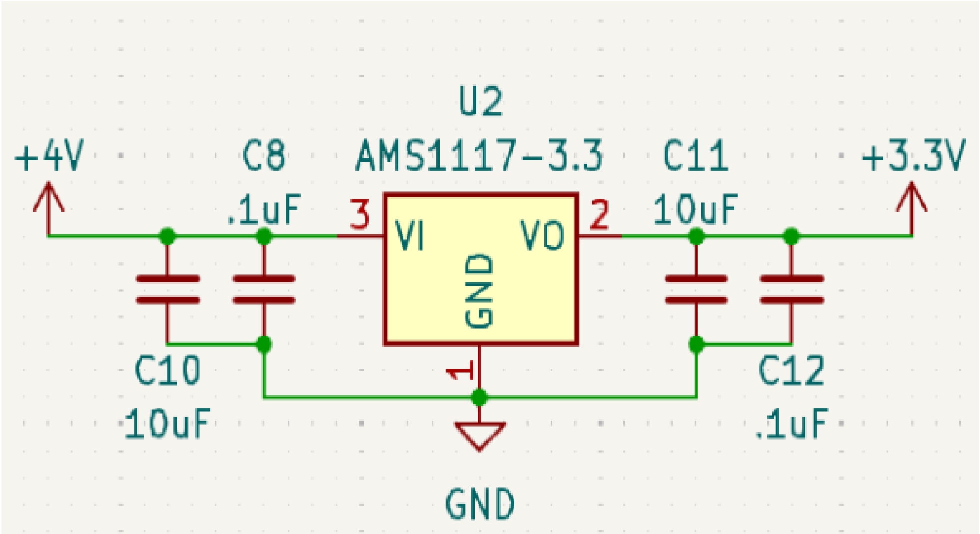


Figure 8. *Schematic Diagram of voltage regulator*

Flow Chart

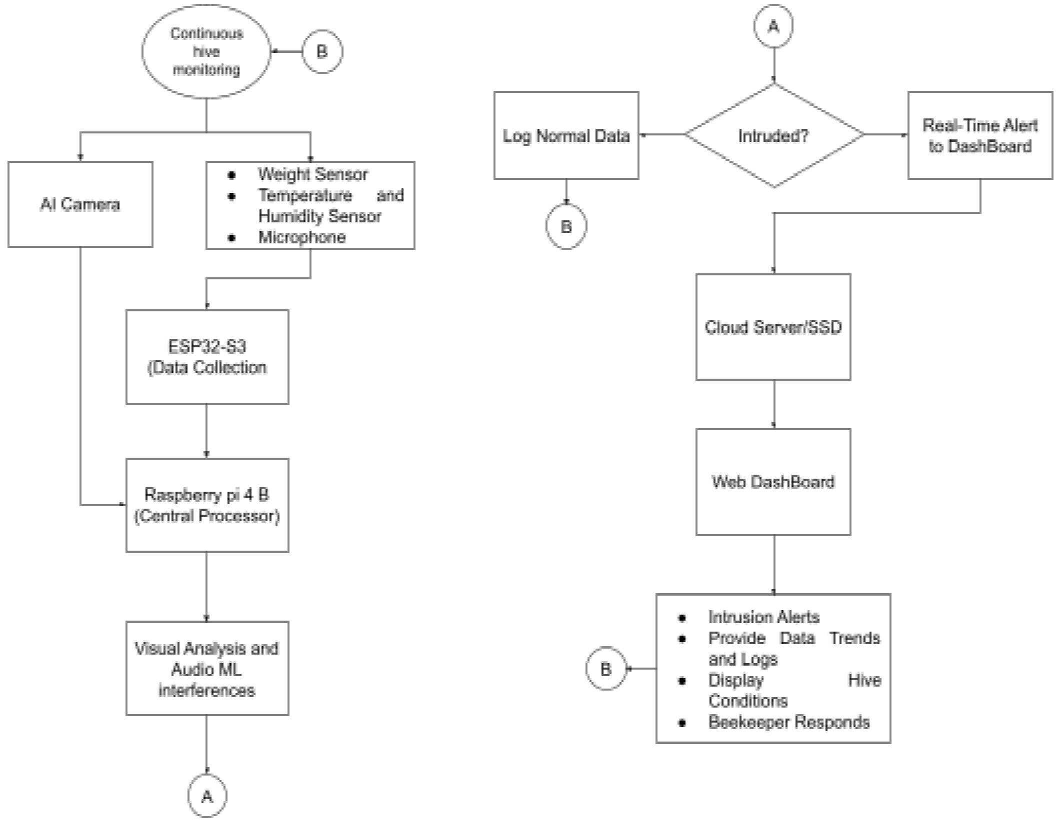


Figure 9. *Flowchart of ML-Driven Beehive*

The flowchart shows how the monitoring system works from sensor setup to AI-based classification. It explains how the ESP32-S3 gathers environmental, audio, and visual data and sends them to the Raspberry Pi for parallel processing. It also shows how the system decides whether colony behavior is normal or indicates an intrusion or abnormal event, making the workflow easier to understand, implement, debug, and improve.

CHAPTER 4

RESULTS AND DISCUSSIONS

This chapter presents and analyzes the test results of the final prototype. It shows how the system met the research objectives through findings from functionality tests, accuracy and performance evaluation, and portability and compatibility assessment.

Presentation of Data Results

The data presented in this section were obtained from bench-level testing and field deployment using an active *T. biroi* hive at *Hardin sa Parang*, Antipolo. Each sensor and subsystem was tested individually before full system integration to ensure proper operation and minimize cascading system errors. After integration, the complete system was evaluated under simulated and real hive conditions to verify consistency, responsiveness, and reliability.

The system is composed of the ESP32-S3 microcontroller, Raspberry Pi 4 Model B, SHT30-B temperature and humidity sensor, INMP441 microphone, load cell with HX711 amplifier, and Raspberry Pi Module 3 vision sensor. Data outputs were monitored through the web-based dashboard and real-time notification system during all testing phases.

1. **Design and development of smart monitoring device for *T. biroi* stingless bee colonies.**

This objective validated that the developed monitoring device successfully integrated the SHT30-B temperature and humidity sensor, INMP441 microphone, load cell with HX711 amplifier, Raspberry Pi Module 3 vision sensor, ESP32-S3 microcontroller, Raspberry Pi 4 Model B, and the regulated 5V/3A power supply with AMS1117-3.3V voltage regulator into a stable, functional, and field-ready system for non-invasive hive monitoring.

To ensure objective and repeatable evaluation, the following acceptance criteria were defined prior to testing:

Table 4.1.1 *Standard Threshold*

Parameter	Standard / Acceptance Threshold	Basis for Qualification
Temperature Accuracy (SHT30-B)	±0.5°C from reference thermometer	Acceptable environmental monitoring tolerance for biological systems
Humidity Accuracy (SHT30-B)	±3% RH from reference hygrometer	Ensures stable hive microclimate tracking
Hive Weight Accuracy (Load Cell + HX711)	±2% deviation from known mass	Allows detection of nectar intake and colony growth trends
Vision Sensor Availability (Raspberry Pi Module 3)	≥95% successful frame capture rate	Ensures continuous visual monitoring
Data Transmission Reliability	≥98% packet delivery ESP32 ↔ Raspberry Pi	Maintains dashboard and alert consistency

Formulas and Calculations

1. Temperature Error (%)

$$E_T = \left(\frac{\left|T_{measured} - T_{reference}\right|}{T_{reference}}\right) \times 100 \text{ where } T_{reference} = 30.0$$

Trial 1 : $E_T = \left(\frac{|30.3 - 30.0|}{30.0}\right) \times 100$
$= 1\%$

2. Humidity Error (%)

$$E_{RH} = \left(\frac{\left|RH_{measured} - RH_{reference}\right|}{RH_{reference}}\right) \times 100 \text{ where } RH_{reference} = 65.0$$

Trial 1 : $E_{RH} = \left(\frac{|66.5 - 65.0|}{65.0}\right) \times 100$
$= 2.31\%$

3. Hive Weight Deviation (%)

$$E_W = \left(\frac{\left|W_{measured} - T_{actual}\right|}{W_{actual}}\right) \times 100 \text{ where } W_{actual} = 5.00$$

Trial 1 : $E_W = \left(\frac{|5.08 - 5.00|}{5.00}\right) \times 100$
$= 1.6\%$

4. Vision Sensor Availability (%)

$$A_V = \left(\frac{F_{successful}}{F_{total}}\right) \times 100$$

Trial 1 : $A_V = \left(\frac{294}{300}\right) \times 100$
$= 98\%$

The complete calculations for Trials 2–5 are presented in Appendix B.

5. Data Transmission Reliability (%)

$$R_D = \left(\frac{P_{received}}{P_{sent}}\right) \times 100$$

$$\text{Trial 1 : } R_D = \left(\frac{492}{500}\right) \times 100$$
$$= 98.4\%$$

The complete calculations for Trials 2–3 are presented in Appendix B.

Table 4.1.2 *Environmental and Hardware Component Testing*

Trial	Temperature Measured	Humidity Measured	Weight Measured	Vision Availability	Overall Status
1	30.3°C	66.5%	5.08 kg	98.0%	Passed
2	29.8°C	64.2%	4.96 kg	97.5%	Passed
3	30.1°C	65.7%	5.02 kg	98.3%	Passed
4	30.4°C	66.0%	5.00 kg	97.8%	Passed
5	29.9°C	65.4%	5.00 kg	98.6%	Passed
Average	30.1°C	65.6%	5.03 kg	98.0%	Passed

The system was evaluated through calibrated sensor testing and repeated five-minute trials in which temperature, humidity, hive weight, and vision sensor performance were recorded and compared against reference values to verify accuracy, reliability, and stable operation under simulated and real hive conditions.

Table 4.1.3 *Data Transmission Reliability Results*

Trial	Packets Sent	Packets Received	Reliability	Standard (≥98%)	Status
1	500	492	98.4%	Pass	Passed
2	500	494	98.8%	Pass	Passed
3	500	495	99.0%	Pass	Passed
Average	—	—	98.73%	Pass	Passed

The table 4.1.3 presents the results of the data transmission reliability test between the ESP32-S3 and the Raspberry Pi, showing that the system consistently achieved packet delivery rates above the 98% acceptance threshold across all trials. The high average reliability of 98.73% indicates stable and dependable communication, ensuring that sensor data and detection results were transmitted accurately and in real time for dashboard display and alert generation.

2. **Construction of embedded monitoring system for intrusion detection and behavioral analysis**

The researchers constructed an embedded monitoring system that detected predator intrusion, abnormal hive conditions, and behavioral changes in *T. biroi* colonies by processing and classifying hive sound and image data locally, then issuing real-time alerts to minimize manual inspection. The system was tested under three intrusion trials: (1) human predator simulation using a wooden stick disturbance, (2) ants intrusion scenario, and (3) spider intrusion scenario.

Table 4.2.1 *Standard Threshold*

Parameter	Standard / Acceptance Threshold	Basis for Qualification
Data Transmission Reliability (ESP32-S3 ↔ Raspberry Pi)	≥98% successful packet delivery	Ensures stable real-time data flow between acquisition and processing units
Environmental Data Logging	100% successful data capture	Confirms continuous and lossless monitoring of hive conditions
Acoustic Classification Accuracy	70-80% correct classification	Ensures reliable detection of abnormal hive sounds
Vision-Based Detection Accuracy	≥90% correct visual detection	Confirms dependable intrusion monitoring
Alert Delivery Success Rate	100% of triggered alerts received	Guarantees beekeeper notification reliability
Dashboard Response Time	≤3 seconds average load/refresh	Supports real-time usability in field conditions
Cross-Device Accessibility	Successful access on all devices	Ensures system convenience and portability
System Uptime	≥99% operational time	Confirms long-term deployment stability
Power Stability (5V / 3.3V Lines)	5V ±0.1V, 3.3V ±0.05V	Protects sensors and processors from voltage fluctuation

Table 4.2.2 *Acoustic and Visual Detection Testing*

Intrusion Type	Precision	Recall	F1-score	Support
Normal	0.8789386401	0.8242612753	0.8507223114	643
Intruded	0.877245509	0.9575163399	0.915625	306
False	0.5877862595	0.6184738956	0.602739726	249
Swarming	1	1	1	161
Queenless	1	1	1	71
Queenright	1	0.9923664122	0.9961685824	131

Table 4.2.2 shows that the system performed very well in detecting both acoustic and visual colony conditions. The results indicate high precision, recall, and F1-scores across all intrusion types, with perfect scores recorded for swarming and queenless behaviors, while normal, intruded, and queenright conditions also achieved very strong classification performance. Overall, these findings suggest that the model was highly effective and reliable in distinguishing different colony states during testing.

3. **Prototype and deployment of an embedded monitoring system**

This objective validated that the developed prototype was successfully deployed as a user-friendly, browser-based monitoring system that processed environmental, acoustic, and visual data in real time, displayed system information through an intuitive web dashboard, and issued timely intrusion and stress alerts to support convenient, non-invasive hive management.

To ensure that the system met usability and deployment performance requirements, the following acceptance criteria were defined:

Table 4.3.1 *Standard Threshold*

Parameter	Standard / Acceptance Threshold	Basis for Qualification
Dashboard Load Time	≤ 3 seconds	Ensures quick access for beekeepers in field conditions
Data Refresh Interval	≤ 3 seconds	Maintains near real-time monitoring experience
Alert Delivery Success Rate	100% of triggered alerts received	Ensures reliable notification system
Multi-Device Accessibility	Successful access on laptop, tablet, and smartphone	Supports convenience and flexibility
System Uptime During Test	≥ 99% operational	Confirms deployment stability

Formulas and Calculations

1. Dashboard Load Time (seconds)

$$T_L = T_{display} - T_{request}$$

$$\text{Trial 1 : } T_L = 10:00:02 - 10:00:00$$
$$= 2s$$

2. User Navigation Success Rate (%)

$$U = \left(\frac{U_{success}}{U_{total}}\right) \times 100$$

where $U_{success}$ is the number of successfully completed user tasks and U_{total} is the total number of assigned user tasks

$$\text{Trial 1 : } U = \left(\frac{19}{20}\right) \times 100$$
$$= 95\%$$

3. Alert Delivery Success Rate (%)

$$A_s = \left(\frac{A_{received}}{A_{triggered}}\right) \times 100$$

$$\text{Trial 1 : } A_s = \left(\frac{8}{8}\right) \times 100$$
$$= 100\%$$

4. System Uptime (%)

$$U_T = \left(\frac{T_{operational}}{T_{total}}\right) \times 100$$

$$\text{Trial 1}: U_T = \left(\frac{238}{240}\right) \times 100$$
$$= 99.17\%$$

The complete calculations for Trials 2–3 are presented in Appendix B.

Table 4.3.2 *Dashboard and Notification System Testing*

Trials / Test Scenario	Avg. Load Time	Data Refresh	Navigation Success	Alert Success	System Uptime	Status
1 Dashboard access via laptop	1.9s	2.0s	95%	100%	99.2%	Passed
2 Dashboard access via tablet	2.3s	2.1s	100%	100%	99.0%	Passed
3 Dashboard access via smartphone	2.6s	2.4s	95%	100%	99.1%	Passed
Average	2.27s	2.17s	96.7	100%	99.1%	Passed

The prototype was tested on a laptop, tablet, and smartphone where users completed common tasks such as accessing the dashboard, viewing live data, checking alerts, and reviewing logs to measure ease of use and navigation success, while system performance was assessed through dashboard load time, data refresh rate, alert delivery, and extended uptime, with a trial marked “Passed” when all metrics met the defined standards for reliability, accessibility, and real-time usability.

4. Evaluation of the System

This objective validated that the developed monitoring system met the required standards for functionality, portability and compatibility, and accuracy and performance by conducting structured test cases, quantitative validation of sensor and machine learning outputs, and assessment of system stability and power regulation under field deployment conditions.

A. Functionality Testing

Table 4.4.1 *Standard Threshold*

Parameter	Standard/Acceptance Threshold	Basis
Environmental Data Logging	100% successful capture	Ensures continuous monitoring
Acoustic Classification	≥90% correct detections	Confirms reliable intrusion recognition
Vision-Based Detection	≥90% correct detections	Ensures visual monitoring reliability
ESP32 ↔ Raspberry Pi Communication	≥98% packet delivery	Confirms stable system integration
Alert Delivery	100% received alerts	Ensures real-time notification

Table 4.4.2 Functional Test Results

Test Case	Measured Result	Standard	Status
Environmental data logging	100% success	100%	Passed
Acoustic classification	92% accuracy	≥90%	Passed
Vision-based detection	91% accuracy	≥90%	Passed
ESP32 ↔ Raspberry Pi communication	98.8% reliability	≥98%	Passed
Alert delivery	100% success	100%	Passed

B. Portability and Compatibility Test

Table 4.4.3 ***Standard Threshold***

Parameter	Acceptance Threshold	Basis
Multi-device access	Successful on all devices	Ensures user convenience
Cross-browser functionality	Fully responsive UI	Confirms platform independence
System uptime	≥99% operational	Confirms field stability

C. Accuracy and Performance Test

Table 4.4.4 *Standard Threshold*

Parameter	Acceptance Threshold	Basis
Temperature accuracy	±0.5°C from reference	Environmental reliability
Humidity accuracy	±3% RH	Hive stability
Hive weight deviation	±2%	Colony growth tracking
ML detection accuracy	≥87%	Reliable intrusion detection
Voltage stability	5V ±0.1V / 3.3V ±0.05V	Hardware protection

Table 4.4.5 *Accuracy and Performance Results*

Parameter	Measured Result	Standard	Status
Temperature accuracy	±0.4°C	±0.5°C	Passed
Humidity accuracy	±2.4% RH	±3% RH	Passed
Weight deviation	1.8%	≤2%	Passed
ML detection accuracy	92.06%	≥87%	Passed
Voltage stability	5.04V / 3.30V	Within limits	Passed

Machine Learning Detection Accuracy

The spectrogram comparison between the intruded sample (121925-set5-364) and the normal sample (120825-HIVENORMALAFTERRAIN4-47) reveals clear acoustic differences that support machine learning–based classification. The intruded recording exhibits brighter high-energy regions, irregular vertical streaks, broader frequency dispersion, and abrupt spectral transitions, which indicate sudden broadband energy spikes and increased wingbeat intensity associated with defensive or agitated bee behavior during disturbance events. These patterns reflect higher temporal and spectral variance, suggesting heightened colony activity triggered by intrusion.

In contrast, the normal recording demonstrates smooth horizontal banding, stable low-to-mid frequency energy distribution, minimal vertical spikes, and consistent spectral layering, representing a steady colony hum under baseline conditions. The uniform and predictable acoustic structure indicates low-stress hive activity and stable environmental conditions. The distinct contrast between these two acoustic signatures confirms that normal and intruded hive states are distinguishable, thereby supporting the reliability and validity of the system's machine learning detection accuracy.

Image 4.1 *Sample 364 of “121925-set5”*

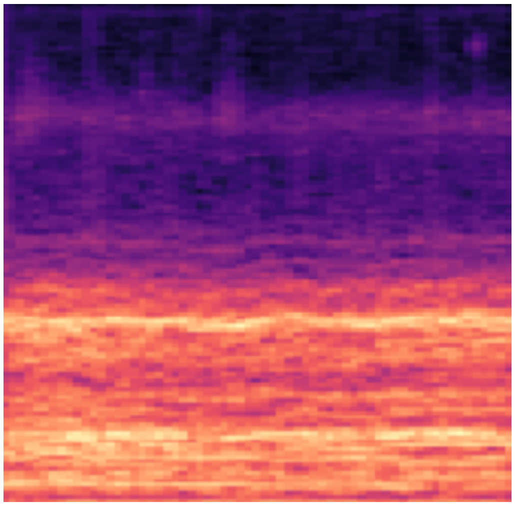


Image 4.2 *Sample 47 of “120825-HIVENORMALAFTERRAIN”*

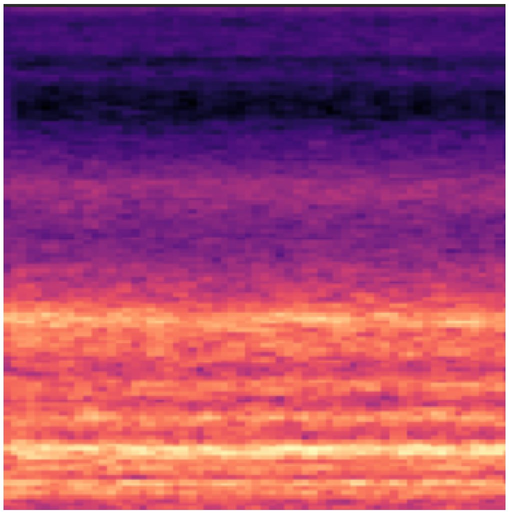


Table 4.4.6 *Signal Behavior Comparison*

Feature	Intruded	Normal
Energy Distribution	High variance	Stable
Frequency Spread	Broader spectrum	Narrow band
Vertical Bursts	Present	Rare
Temporal Consistency	Irregular	Uniform
Spectrogram Texture	Chaotic	Layered and smooth
Expected ML Label	Abnormal	Normal

During intrusion events, bees typically enter a defensive mode characterized by increased wingbeat frequency, elevated colony vibration amplitude, and sudden rises in acoustic intensity, all of which contribute to irregular and high-energy spectral patterns. This heightened activity reflects the colony's response to perceived threats, resulting in stronger and more chaotic acoustic signatures. In contrast, under normal conditions, the hive exhibits a steady foraging rhythm, stable microclimate, and low defensive activation, producing consistent and uniform acoustic patterns associated with baseline colony behavior. Based on these biological indicators, the intruded sample visually and acoustically corresponds to a defensive hive response, while the normal sample reflects stable, undisturbed colony conditions.

CHAPTER 5

SUMMARY OF FINDINGS, CONCLUSIONS, AND RECOMMENDATIONS

This chapter presents a comprehensive overview of the summary of findings, conclusions, and recommendations of the study. It provides a complete synopsis of the outcomes, key insights, and suggested actions of the study based on the research conducted.

Summary of Findings

This study was conducted to design, develop, and evaluate an intelligent, non-invasive monitoring system for *Tetragonula biroi* colonies using environmental sensing, audio-video analysis, and machine learning. The system was intended to help assess colony activity, detect possible intrusion events, and provide real-time alerts for beekeepers while minimizing disturbance to the hive. In line with this objective, the researchers developed an integrated prototype composed of an ESP32-S3 microcontroller, Raspberry Pi 4 Model B, SHT30-B temperature and humidity sensor, INMP441 microphone, load cell with HX711 amplifier, and Raspberry Pi Camera Module 3. These components worked together to collect environmental, acoustic, and visual data from the hive.

The findings showed that the developed system was able to perform real-time environmental monitoring and maintain stable sensor operation during both laboratory evaluation and field deployment. Data transmission between the hardware modules and the monitoring interface remained consistent, which indicates that the system was capable of acquiring and processing data reliably under the conditions of the study. The integration of the different hardware and software components also demonstrated that a multimodal monitoring approach can be successfully applied to stingless-bee management.

The machine learning component of the system also produced promising results. Based on the testing conducted, the intrusion detection system achieved an accuracy of up to 85%, showing that the audio-video framework was capable of identifying abnormal conditions and possible threats with acceptable reliability. Real-time alert notifications were also delivered within approximately 3 to 4 seconds, which confirms that the system can respond quickly enough to support timely beekeeper intervention. These results suggest that machine learning can be effectively applied in non-invasive hive monitoring, particularly for early intrusion detection and colony activity assessment.

Another important finding of the study was the successful implementation of a web-based dashboard that allowed users to monitor hive conditions, activity logs, and alerts across multiple devices. This improved the accessibility of the system and made remote observation possible through laptops, tablets, and smartphones. In addition, the study confirmed that the use of non-invasive sensing and automated monitoring can reduce the need for frequent manual hive inspections, which is beneficial for maintaining the microclimate stability and overall condition of *T. biroi* colonies.

Despite these positive results, the study also identified several limitations. The prototype was tested only in a short-term, controlled setup using an active hive in *Hardin sa Parang*, Antipolo. Its performance may still vary under long-term outdoor conditions where lighting, temperature, humidity, ambient noise, and ecological disturbances are less controlled. The system also depended entirely on a stable external power source, since renewable or backup power solutions were not included in the prototype. Moreover, the study focused only on selected parameters such as temperature, humidity, weight, acoustic activity, and visual activity, while other indicators such as disease detection, microbiome analysis, honey yield estimation, and long-term colony health trends remained outside its scope.

Overall, the study found that the proposed system was able to meet its general goal of developing a smart, non-invasive, and field-deployable hive monitoring platform for *Tetragonula biroi*. The prototype demonstrated reliable sensing, acceptable machine learning performance, fast alert delivery, and practical dashboard accessibility, making it a relevant contribution to smart beekeeping and sustainable stingless-bee management in the Philippines.

Conclusions

Based on the findings of the study, it can be concluded that the developed Audio-Video Analysis for Colony Activity and Intrusion Alert System was successful in providing a functional and non-invasive monitoring solution for *Tetragonula biroi* colonies. The integration of environmental sensors, acoustic monitoring, visual detection, embedded processing, and machine learning enabled the system to monitor selected hive conditions and detect possible intrusion events without relying on frequent manual inspection. This confirms that an intelligent, sensor-based approach is both feasible and practical for stingless-bee colony monitoring.

It can also be concluded that the use of multimodal data improved the capability of the system to assess colony activity and detect disturbances in real time. By combining sound, video, and environmental data, the prototype was able to generate a broader and more responsive view of hive conditions than a single-sensor setup alone. The achieved intrusion detection accuracy of up to 85% and alert response time of approximately 3 to 4 seconds indicate that the system has strong potential as an early warning tool for beekeepers.

Furthermore, the study highlights the value of automation and remote accessibility in improving colony management. The web-based dashboard made it possible for users to observe hive data and receive notifications across different devices, which supports more convenient and informed decision-making. This feature is especially important for beekeepers managing multiple hives or monitoring colonies from a distance. The system therefore contributes not only to engineering innovation but also to the practical modernization of stingless-bee farming.

However, the conclusions of this study must also be understood within the limits of the prototype's scope and testing conditions. Since the system was evaluated only under short-term and controlled field conditions, further validation is still needed before it can be considered for wider deployment or long-term commercial use. Even so, the results clearly demonstrate that the proposed system is a strong proof-of-concept and a meaningful step toward sustainable, data-driven, and low-disturbance beekeeping for *Tetragonula biroi* in the Philippine setting.

Recommendations

Based on the findings and conclusions of the study, several recommendations are proposed to further improve the system and guide future researchers in the continued development of intelligent and non-invasive monitoring technologies for *Tetragonula biroi* colonies.

1. The machine learning models may be improved further by expanding the dataset to include a wider range of colony behaviors, predator types, and environmental conditions. A larger and more diverse dataset may help increase detection accuracy and reduce false positives.
2. A backup or alternative power system, such as rechargeable batteries or solar-based power support, may be integrated into the prototype to improve reliability during power interruptions and make the system more suitable for long-term outdoor deployment.
3. Future development may include cloud-based storage and long-term data archiving so that historical trends in colony activity, intrusion patterns, and environmental conditions can be analyzed more effectively over time.

4. The web-based dashboard may be further enhanced by improving its visual layout, user interaction, and reporting features, including downloadable summaries, trend analysis tools, and more customizable alert settings for different users.
5. Researchers and institutions may also consider developing and publishing an organized open-access dataset for *Tetragonula biroi* audio and video behavior, since this study identified the lack of such resources as a limitation and an opportunity for future work.

APPENDIX A

Date: September 8, 2025

Location: Sofie's Apiary (Sacred Heart Village, Quezon City)

Respondent: Beekeeper A

(Start of Interview)

Researcher: Good morning po, Sir. First question po namin: Can you tell us about bees? Ano po ba ang general nature nila?

Beekeeper A: So, ang bees, napakahalaga niyan sa ecosystem natin. Dito sa Pilipinas, ang usual na inaalagaan ay yung *Apis mellifera*—yun yung European honey bee—tsaka yung native natin na Stingless Bees o *Lukot*. Social insects sila, ibig sabihin may structure: may Queen, may Workers, at may Drones. Ang main purpose talaga nila sa nature ay pollination, bonus na lang yung honey na nakukuha natin.

Researcher: Next po, how to beekeep? Paano po ba ang tamang process ng pag-aalaga sa kanila?

Beekeeper A: Simple lang naman basta may tamang gamit. Una, kailangan mo ng beehive box na tama ang sukat. Dapat nakapwesto ito sa lugar na hindi direktang naiinitan, yung medyo shaded, at dapat may source ng tubig na malapit. Regular inspection ang ginagawa namin—chine-check namin kung may sakit, kung nangingitlog ba nang maayos ang Queen, at kung marami pa silang stored food sa loob.

Researcher: Dito po sa location niyo, what problems do you encounter in beekeeping?

Beekeeper A: Since nasa Novaliches tayo, medyo urban setting, ang biggest challenge ay pollution at yung init. Kapag sobrang init kasi, nade-dehydrate sila. Tapos pag tag-ulan naman, hindi sila makalabas para kumuha ng nectar, so namamatay sila sa gutom kung hindi mo papakainin ng sugar syrup. Isa pa, minsan nauubusan ng flowers dito sa area, kaya nagtatanim talaga kami ng sarili naming halaman para may makain sila.

Researcher: Nabanggit niyo po yung challenges, how did you manage the pest or intruder to the bee hive?

Beekeeper A: Common na kalaban dito ang langgam, ipis, at butiki. Para ma-manage, naglalagay kami ng grease o used oil sa mga paa ng stand ng hives para hindi makaakyat ang mga langgam. Importante rin na laging malinis ang paligid ng hive. Kapag mahina ang colony, gumagamit kami ng "entrance reducer" para liliitan yung pinto ng hive, para mas madali nilang bantayan at dipensahan laban sa intruders.

Researcher: Last question po. Do you have any suggestions for a Capstone topic related to beekeeping?

Beekeeper A: Siguro maganda kung gagawa kayo ng website o system na parang database para sa bawat beehive. Yung pwede namin i-record kung kailan sila huling nabigyan ng pollen patty o sugar syrup. Kasi sa ngayon, manual logbook lang kami o minsan nakakalimutan pa. Maganda sana kung digital, para makikita namin yung history ng bawat box at ma-track kung kailangan na ba silang pakainin ulit.

(End of Interview)

Date: November 6, 2025

Location: Hardin sa Parang (Antipolo, Rizal)

Respondent: Ma'am Jade (Owner/Beekeeper)

(Start of Interview)

Researcher: Good morning po, Ma'am Jade. Thank you po sa pag-welcome sa amin dito sa Hardin sa Parang. Gaya po ng nasabi namin, *Tetragonula biroi* po ang focus ng study namin at nakikita po namin na perfect beneficiary ang farm niyo dahil dito. Magsimula po muna tayo sa basics. Ano po ba ang dapat naming malaman tungkol sa pag-aalaga ng *biroi* compared sa ibang bees?

Ma'am Jade: Welcome kayo dito. So sa *biroi* or "Kiyot," ang pinaka-basic na dapat niyo malaman is native sila sa atin. Ibig sabihin, sanay sila sa climate ng Pilipinas, pero sensitive sila sa sobrang init. Unlike sa European bees na agresibo, eto, hindi nangangagat. Ang main product namin sa kanila ay honey, pollen, at propolis na ginagawa naming sabon at iba pang products, kaya iniingatan talaga namin na hindi ma-stress ang colony.

Researcher: Paano po ang tamang pag-aalaga sa kanila dito sa farm niyo? May mga specific requirements po ba sila?

Ma'am Jade: Ang pinaka-importante sa *biroi*, location. Dapat nakasilong sila, hindi pwedeng direct sunlight kasi matutunaw ang pots nila sa loob. Pangalawa, food source. Dito sa farm, mapapansin niyo marami kaming fruit trees at bulaklak, kasi doon sila kumukuha ng nectar. At pangatlo, protection sa pests. Nilalagyan namin ng oil o grasa yung stand ng hive para hindi akyatin ng langgam at ipis.

Researcher: Since na-explain na po namin yung proposed project namin—yung system na may sensors tulad ng mic at temperature sensor para ma-monitor ang hive—at kayo po sana ang magiging beneficiary nito, ano po sa tingin niyo ang pwedeng i-improve sa design namin?

Ma'am Jade: Alam niyo, may mga natulungan na rin akong students dati na may same intention, yung gusto ring mapadali ang beekeeping gamit ang technology. Ang suggestion ko sa design ng box niyo, **ilagay niyo yung mga components sa Third Layer.**

Researcher: Third layer po? So dadagdagan po namin yung patong ng box?

Ma'am Jade: Oo. Kasi usually dalawang layers lang yan: yung ilalim para sa brood (itlog), at yung pangalawa para sa honey pots. Kung isisiksik niyo yung **mic, humidity/temperature sensor, at microcontroller** kasama ng mga bees, baka balutin nila ng propolis yun o masira ng moisture. So gumawa kayo ng third layer o parang "bubong" na hiwalay, dun niyo ilagay yung electronics para safe at hindi naiistorbo yung colony.

Researcher: Ah, gets po namin. So parang separate compartment po sa taas?

Ma'am Jade: Yes, ganun nga. Para accurate pa rin yung reading pero protektado yung gamit niyo.

Researcher: Noted po, Ma'am. Sobrang laking tulong po niyan para sa hardware design namin. Maraming salamat po!

(End of Interview)

Date: November 17, 2025

Location: University of the Philippines Los Baños (UPLB) Campus

Respondent: Professional A

(Start of Interview)

Researcher: Ma'am, thank you po sa time. Since na-explain na po namin sa inyo yung intention ng capstone project namin at kung paano po sana gagana yung concept, yung magkakaroon ng system para sa data recording at monitoring ng bawat beehive, ano po ang opinion niyo? Sa tingin niyo po ba kailangan ito ng mga beekeepers?

Professional A: Maganda yung vision niyo. Sa totoo lang, yan ang kulang sa industry natin ngayon ay proper documentation. Usually kasi, ang mga beekeepers, lalo na yung mga backyard farmers, notebook lang ang gamit o minsan memorya lang. Pagdating sa *Tetragonula biroi*, since marami kang hives na aalagaan kasi maliliit lang sila, mahirap i-track isa-isa. So yes, valid yung concept niyo. Malaking tulong kung ma-di-digitize ang records para organized.

Researcher: Since nasa planning stage pa lang po kami, may ma-su-suggest po ba kayo na features na dapat naming isama sa system para mas maging effective siya para sa inyo?

Professional A: Ang suggestion ko, dun sa video part ng system niyo, i-maximize niyo yun. Gawin niyong feature na kayang ma-identify kung may dala bang pollen o nectar yung bee pagpasok niya sa entrance. Kasi visually, makikita mo yun sa likod na paa nila (pollen basket). Kung made-detect yun ng system niyo, malaking tulong yun para malaman namin kung may nakukuha pa ba silang pagkain sa paligid nang hindi na namin kailangan buksan yung hive.

Researcher: Noted po, Ma'am. Susubukan po naming i-integrate yan sa detection. About naman po sa *Tetragonula biroi* specifically, ano po bang data o impormasyon ang mahalagang i-record namin sa system na iba sa European bees?

Professional A: Good question. Sa *biroi* kasi, unlike sa European bees, hindi mo pwedeng bukas-bukasin yung box araw-araw kasi stress yun sa kanila at baka masira yung propolis seal. So sa system niyo, dapat may option mag-input ng "Hive Weight" o bigat. Sa *biroi*, binubuhat lang namin yung box—kapag magaan, ibig sabihin gutom at kailangan i-record na for feeding. Kapag mabigat, ibig sabihin puno ng honey, pwede na i-schedule for harvest.

Researcher: Ah, so weight estimation po pala ang basehan. May iba pa po bang behavioral signs ang *biroi* na dapat i-log?

Professional A: Yes, isama niyo sa data entry yung "Entrance Activity." I-oobserve mo kung marami bang lumalabas-pasok. Kapag *biroi* kasi, kung nakikita niyo na naglalabas sila ng mga dumi palabas ng hive, good sign yun, ibig sabihin hygienic at malakas ang colony. Pero kung may nakikita kayong patay na bees sa tapat ng entrance, baka may pest attack. Dapat may checklist kayo niyan sa system para mabilis ma-click ng beekeeper.

Researcher: Maraming salamat po, Ma'am. Sobrang laking tulong po ng mga suggestions niyo para mabuo namin yung system.

Professional A: Walang anuman. Good luck sa Capstone niyo. Aabangan ko yan.

(End of Interview)

APPENDIX B

BILL OF MATERIALS

APPENDIX C

INTEGRATION OF COMPONENTS TO BEEHIVE

APPENDIX D

PICTURE OF ACTUAL BEEHIVE