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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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.

Bringing machine learning into beehive monitoring offers beekeepers a new and practical way to care for their colonies, especially for stingless bees like *T. biroi*. By automating the detection of predator intrusions and continuously analyzing colony behavior through audio and video cues, the system reduces dependence on invasive manual inspections that often disrupt hive stability. This not only lightens the workload of beekeepers but also improves decision-making by providing reliable, real-time data about colony health and activity. Ultimately, such an approach enhances hive productivity, supports sustainable honey production, and empowers beekeepers with innovative tools that protect both their livelihood and the ecological value of pollinators. As global challenges such as biodiversity loss and agricultural decline continue to emerge, projects like this contribute meaningfully to building resilient ecosystems through the technological advancement of small-scale apiculture.

Background of the Study

In recent years, advancements in precision agriculture and smart monitoring systems have expanded beyond crop production into apiculture, giving rise to the concept of “smart beekeeping.” This field focuses on improving hive management, monitoring, and productivity through automation and data-driven technologies. However, while numerous innovations have been developed for *Apis mellifera* (the common honeybee), far fewer studies have addressed the unique needs and biological behavior of stingless bees such as *Tetragonula biroi* (Hadjur et al., 2022; Che Ali et al., 2021). The *T. biroi* species, native to the Philippines and other Southeast Asian regions, represents a vital pollinator group with strong ecological and agricultural importance. Their contribution to biodiversity and local crop yields, coupled with the superior nutritional profile of their honey, makes them essential to sustainable rural livelihoods (Conde, 2020; Lime, 2024).

Despite these advantages, stingless beekeeping remains an underdeveloped industry in the Philippines. Studies by Hidalgo et al. (2020) and Locsin et al. (2021) reveal that many local beekeepers still rely on traditional and manual hive inspection methods. These approaches are time-consuming, labor-intensive, and can disrupt colony stability. Manual inspection often exposes brood cells and alters the hive’s temperature and humidity balance, leading to stress or even colony collapse. This challenge is intensified by the small size and delicate nature of *T. biroi* colonies, which makes them more vulnerable to frequent disturbances compared to larger honeybee species.

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.

The integration of machine learning into hive monitoring offers a transformative solution. Researchers such as Ratnayake et al. (2025), Trương Thu Hương et al. (2023), and Singh et al. (2024) have demonstrated the effectiveness of acoustic and video-based systems in identifying colony activity, disturbances, and anomalies in real time. Through these methods, it is possible to detect specific sound patterns or movement changes associated with threats or abnormal behaviors inside the hive. For example, changes in buzzing frequency can indicate stress or predator attacks, while sudden motion near hive entrances may signify intrusion events. By processing these signals through machine learning models, the system can automatically recognize potential dangers and alert beekeepers through mobile or web-based 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.

In the broader context, the development of a low-cost, field-deployable monitoring system for *T. biroi* aligns with the growing movement toward sustainable and data-driven beekeeping. It provides an accessible tool for Filipino beekeepers, enabling them to enhance productivity and protection of their colonies without heavy financial investment or advanced technical expertise. Furthermore, it contributes to national efforts in environmental conservation and food security by safeguarding a key pollinator species crucial to agricultural ecosystems. Through this research, a practical bridge is established between traditional beekeeping wisdom and modern technological innovation, one that strengthens both livelihoods and biodiversity 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 IMX500 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 prototype and deploy an embedded monitoring system that:

    a. Detects predator intrusion, abnormal hive conditions, and behavioral changes in *T. biroi* colonies.

    b. Processes and classifies hive sound and image data locally, utilizing the IMX500's on-chip AI inference to reduce external computation.

c. Minimizes manual inspections through automated colony activity tracking and real-time notifications to the beekeeper.

3. To prototype and deploy an embedded monitoring system that:

    a. Processes environmental, acoustic, and visual data in real time through integrated hardware and software modules.

    b. Displays collected information via web-based dashboard for ease of access by beekeepers.

    c. Issues alerts for intrusion or stress events to support non-invasive hive management practices.

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 (IMX500 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 (IMX500) 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 evaluated only under short-term and controlled testing conditions in the Antipolo site. Its performance may vary based on external elements such as lighting conditions, ambient noise, temperature fluctuations, humidity, and ecological disturbances present in real outdoor environments. The system was designed primarily as a proof-of-concept, aiming to demonstrate feasibility rather than establish a fully commercial or long-term monitoring solution. As such, large-scale deployment, extensive biological validation, cloud-based data storage, and long-term archiving were beyond the scope of this study.

Significance of the Study

This study is significant as it introduces an innovative approach to monitoring the colony activity and intrusion threats faced by *T. biroi* using an integrated audio-video system enhanced with machine-based learning. Stingless bees play an essential role in pollination, biodiversity maintenance, and local agricultural systems, and yet many beekeepers continue to depend on manual inspection, which may expose colonies to stress and increase vulnerability to predators and external disturbances. The development of an automated monitoring and alert system provides a meaningful contribution to improving colony protection, enhancing hive productivity, and supporting sustainable stingless-bee management practices 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 offers new opportunities to explore the behavioral patterns and acoustic signatures of stingless bees, particularly since there is currently no established, open-access dataset for *T. biroi*. The creation of a custom audio-video database serves as a foundational resource for future studies on bee behavior, machine-learning applications in entomology, and automated ecological monitoring systems. This development is further strengthened by the collaboration with experts and technical advisers from Quezon City University, whose insights help validate the scientific and technical direction of the system.

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 IMX500 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.

IMX500 Vision Sensor – 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 focuses on various research and literature from international and local authors to broaden the understanding of the study. It presents evidence, definitions, and technical data related to the systems, hardware, and components utilized in developing the proposed project. The gathered information was obtained from published theses, research papers, scientific journals, and credible online sources regarding automated hive monitoring, audio-video data analysis, and machine learning applications in apiculture. The discussions emphasize how these studies and systems contribute to the development of the Audio-Video Analysis for Colony Activity and Intrusion Alert for *Tetragonula biroi* Utilizing Machine-Based Learning. Finally, this chapter presents the conceptual framework of the study.

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 be interfaced with modular peripheral devices (PMODs) to capture, process, and output audio in real time. In that setup, the Raspberry Pi handles audio input and output while PMOD modules provide expansion interfaces for additional signal conditioning or input/output functions. Although the original article focuses on a voice-modulation application rather than beehive monitoring, it illustrates the feasibility of using Raspberry Pi as a central processing unit for real-time audio processing tasks in embedded systems. This supports the present study’s decision to employ the Raspberry Pi as an audio and video processing hub within the hive monitoring system, where it must handle sensor data, perform machine learning inference, and communicate real-time alerts without excessive latency or system overhead. (Audio Processing with Raspberry Pi and Pmods, 2021)

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) demonstrated that bee wingbeat acoustics carry distinct spectral patterns that can be used to differentiate species and assess individual traits such as body size, behavioural state, and responses to environmental conditions. By analyzing recorded wingbeat frequencies, the researchers showed that these acoustic signatures provide reliable biological markers for non-invasive pollinator monitoring. Their work highlights the viability of passive acoustic sensing as a practical and scalable tool for identifying bee activity and species presence in natural and agricultural settings. This supports the integration of acoustic modules in the proposed monitoring system for *Tetragonula biroi*, where subtle changes in buzz frequency or flight sound patterns can serve as early indicators of colony stress, environmental disturbances, or behavioural anomalies.

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 *Tetragonula biroi*, where automated analysis of bee sounds can detect behavioral anomalies, environmental stressors, and changes in colony condition efficiently.

Ratnayake et al. (2024) systematically reviewed machine learning applications in bee species identification, highlighting the growing use of both shallow and deep learning techniques—such as support vector machines and convolutional neural networks—for classifying bees using visual and acoustic data. The review underscores how advances in AI have enabled more accurate recognition of diverse bee species and emphasizes the importance of integrating computational methods with biodiversity monitoring. This literature supports the relevance of machine learning in beekeeping technologies and reinforces the rationale for incorporating sound-based and AI-driven classification modules in hive monitoring systems like the one proposed for Tetragonula biroi, enhancing automated detection of species-specific behaviours and colony health indicators.

Ratnayake et al. (2025) investigated acoustic signals produced by Heterotrigona itama guard bees during intrusion events and developed a machine-learning framework to detect these alarm sounds. Audio recordings were collected using a Jetson Nano setup, MFCC features were extracted, and dimensionality reduction was applied before training

Support Vector Machine and k-Nearest Neighbor classifiers, with KNN achieving over 95 % accuracy. The study demonstrates that distinct bee alarm sounds can be effectively classified for intrusion detection, suggesting that sound-based monitoring offers a cost-effective and real-time alternative to image-based approaches. This supports the integration of acoustic analysis in hive monitoring systems like the one proposed for Tetragonula biroi, where detecting abnormal acoustic cues can help identify threats, behavioral changes, and colony disturbances.

Foreign Studies and Systems

In their empirical study, Crawford et al. (2022) recorded and analyzed video footage of hive entrances over extended periods, quantifying bee traffic, entrance pass frequency, and variations related to time of day and environmental conditions. Their findings showed that changes in entrance activity (e.g., reduction in flight traffic or irregular guard behavior) correlated with known stressors such as colony disturbance or environmental shifts. This provides concrete evidence that video-based entrance monitoring can serve as a reliable proxy for overall colony health and behavior. These results justify integrating a camera module in the proposed monitoring system for *T. biroi*, where video analysis alongside acoustic and sensor data can improve detection of intrusion, population decline, or behavioral anomalies.

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) investigated the use of sound recordings to detect bee swarming events by comparing the performance of three machine-learning classifiers—k-Nearest Neighbors (k-NN), Support Vector Machine (SVM), and a U-Net convolutional neural network—on audio data captured from custom IoT sound devices installed in beehives. The study's experimental scenario involved collecting sound samples associated with swarming and non-swarming conditions and evaluating how effectively each algorithm could distinguish between these states, with results indicating that advanced deep-learning approaches can improve early and close-to-event detection of swarming. This research demonstrates that acoustic monitoring coupled with AI classification holds promise as a non-invasive tool for real-time monitoring of colony behaviours, reinforcing the case for incorporating sound-based detection modules in automated hive monitoring systems to identify anomalous activity such as swarming or other stress indicators in bee colonies.

Saxena et al. (2023) explored the use of deep learning techniques for classifying beehive audio signals to monitor hive stability and health. The study compared transfer learning models, YAMNET and VGGish, for binary classification of bee versus non-bee sounds and developed a multiclass framework to identify four distinct queen statuses within the hive. Results showed that YAMNET outperformed VGGish in the binary task, achieving a precision of 74.5% and an AUC of 0.87, while convolutional neural networks (CNN) in the multiclass setting reached an average precision of 91.4%. The findings demonstrate that audio-based deep learning can provide non-invasive, real-time insights into queen presence, foraging behavior, swarming events, and potential environmental stressors such as pesticide exposure. This research supports the integration of acoustic monitoring modules in automated hive systems, offering a scalable approach for detecting colony health anomalies and enhancing early intervention strategies in pollinator management.

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 monitoring temperature, humidity, and hive sound, using machine learning models to classify data from queenright and queenless Tetragonisca fiebrigi hives. Their results showed that algorithms such as extreme learning machine, k-nearest neighbors, multilayer perceptron, random forest, and support vector machine consistently achieved over 90 % accuracy, with the highest performance using microclimatic indicators. This study demonstrates that combining acoustic and environmental sensors can reliably assess hive health without manual inspection, supporting the integration of similar multimodal monitoring approaches in systems like the one proposed for *T. biroi* to detect queen absence, behavioural changes, and overall colony condition efficiently.

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) present the “Smart Stingless Beehive Monitoring System” (SSBMS) developed for stingless-bee colonies in Malaysia, focusing on real-time monitoring and environmental control. According to their abstract, the system utilises Internet-of-Things (IoT) sensors installed on stingless-bee hives to measure internal parameters such as temperature, humidity and water-level, as well as GPS location for theft detection. When hive internal temperature or water-supply levels deviate outside optimal ranges (e.g., exceeding 30 °C), the system automatically triggers actuators such as DC fan motors or diaphragm pumps to regulate conditions and ensure water supply. The authors report that this automated system helped reduce manual monitoring labour, maintain more stable environmental conditions inside hives, and provided continuous feedback and remote tracking. While the paper does not provide detailed numeric performance percentages (e.g., accuracy, error-rates) in the abstract, it emphasises that the SSBMS achieved the design goal of “automatically or based on beekeeper’s desire” regulation of temperature and water supply. For your project on *T. biroi*, Edmund & Rahman’s system provides a valuable foreign precedent: it validates that IoT sensor-based environmental monitoring and automatic controlled feedback are effective—and that integrating such monitoring into stingless-bee hives is feasible, thereby supporting your broader conceptual framework of audio/video + sensor + ML-based colony monitoring.

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) conducted an in-depth analysis of the nutritional composition of pot-pollen produced by *T. biroi* in the Philippines, providing one of the few scientific benchmarks on the biochemical quality of stingless bee products in the country. Their study examined nutrient profiles such as proteins, lipids, carbohydrates, vitamins, and bioactive compounds, confirming that *T. biroi* pot-pollen contains high levels of antioxidants and essential nutrients. These findings highlight the species' significant value not only for honey production but also for its nutritionally rich pollen stores, reinforcing the importance of improving management and monitoring practices to protect colony health. This supports the current study's objective of developing an AI-enhanced hive monitoring system that can help maintain healthier stingless bee colonies and ensure the quality of their 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.

In their empirical research, Baluran et al. (2025) conducted a performance comparison of five state-of-the-art deep learning models to detect and count bees from video data collected in Philippine beekeeping environments. Using a dataset of over 3,000 video clips and 58,000 frames, they measured model performance based on accuracy, speed, and object-detection capability under varying light and motion conditions.

Their results revealed that YOLOv4 achieved superior performance with 97.9% mAP and maintained detection stability even when bees overlapped or moved rapidly near hive entrances. These findings provide strong experimental evidence that machine learning models can accurately interpret visual data for hive monitoring applications. This study supports the current research by validating that AI-driven vision systems are viable for non-invasive activity tracking and intrusion detection in *T. biroi* colonies, aligning with the project's goal of integrating local AI innovation into sustainable meliponiculture practices.

Ramos et al. (2024) from Cavite State University developed a comprehensive review titled "Innovative Hive Intelligence: Stingless Bee Products and Machine Learning Advancements in Agriculture and Medicine." The study discussed how machine learning and smart technologies are being applied to enhance the monitoring, productivity, and utilization of stingless bees in the Philippines. It emphasized the integration of automated data collection systems, IoT devices, and predictive analytics for optimizing hive management and improving the quality of bee products such as honey and propolis. The review highlighted local innovations and research directions in meliponiculture, positioning machine learning as a key tool for analyzing environmental factors, colony health, and production efficiency. This supports the present study's development of an audio–video monitoring and intrusion alert system for *T. biroi*, aligning with the country's shift toward precision apiculture through technological adaptation.

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 illustrates the integration of environmental sensors, audio and video modules, and machine learning algorithms into a unified hive monitoring system. Environmental sensors such as the SHT30-B record temperature and humidity, while the load cell with HX711 amplifier measures internal hive activity. The INMP441 microphone captures acoustic signals, and the IMX500 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.

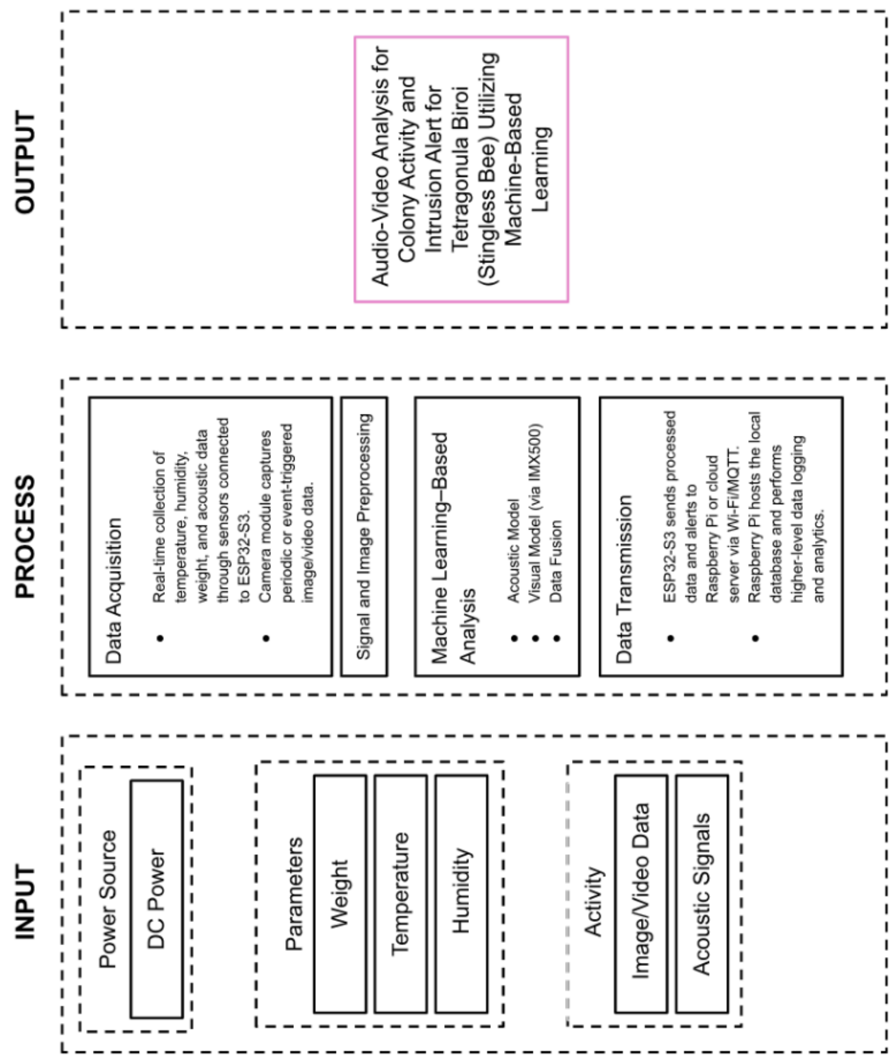


Figure 1. *Conceptual Framework of the Audio-Video Analysis for Colony Activity and Intrusion Alert for Tetragonula Biroi*

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:

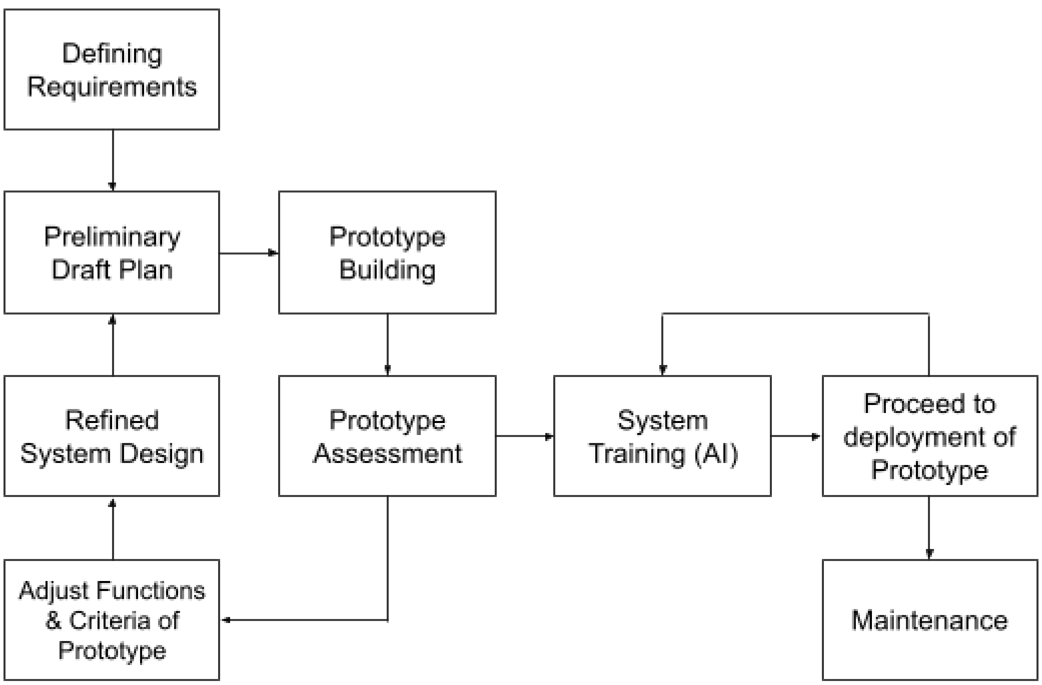


Figure 2. *Prototyping Model*

A. **Defining Requirements**

The development of this capstone project necessitated a systematic process of requirement identification, collection, analysis, and verification. All requirements essential to the creation of the system titled “Audio-Video Analysis for Colony Activity and Intrusion Alert for *Tetragonula biroi* (Stingless Bee) Utilizing Machine-Based Learning” were carefully specified and compiled to establish a strong foundation for its design and implementation. This process involved gathering technical, environmental, and operational information from multiple credible sources to determine the feasibility, scope, and necessary components of the proposed monitoring device.

The proponents conducted an extensive review of relevant literature and previous studies relating to bioacoustic monitoring, vision-based species detection, Internet of Things (IoT) systems, and machine-learning applications in agriculture and environmental conservation. These studies provided essential insights into the behavioral patterns of *T. biroi*, common stress indicators in stingless bee colonies, and effective strategies for non-invasive monitoring in real-world field conditions.

Because the system relies on AI-based analysis, additional requirements were defined specifically for machine learning. These included determining the volume and type of training data needed, selecting suitable algorithms for acoustic and visual classification, and identifying preprocessing techniques that would improve model accuracy. The team evaluated the feasibility of deploying ML models on edge devices, ensuring that the ESP32-S3 and Raspberry Pi 4 had sufficient computational resources for real-time inference. Considerations such as model optimization, latency, and reliability in field conditions were assessed to guarantee that the AI components could operate efficiently despite environmental noise, variable lighting, or intermittent connectivity.

To strengthen the contextual relevance of the system, the proponents gathered empirical information through interviews with local stingless beekeepers and practitioners. These discussions provided firsthand accounts of colony management challenges, predator threats, environmental stressors, and the limitations of traditional manual hive inspections. Additionally, site considerations such as ambient conditions, power availability, hive positioning, and common field constraints were assessed to determine the environmental requirements for successful device deployment. Understanding the needs of the primary beneficiaries small-scale and emerging beekeepers was crucial in shaping a system that is practical, sustainable, and responsive to the actual conditions encountered in local beekeeping operations.

The technical requirement analysis also involved identifying the specific roles of each hardware component within the system architecture. The SHT30-B temperature and humidity sensor, INMP441 microphone, load cell with HX711 amplifier, and Sony IMX500 AI camera module were evaluated based on their accuracy, reliability, interface compatibility, and suitability for continuous environmental monitoring. Microcontrollers such as the ESP32-S3 and processing platforms such as the Raspberry Pi 4 Model B were selected for their computational capabilities, wireless connectivity, and feasibility for real-time data processing and machine-learning inference at the edge.

Upon determining the essential hardware elements, the proponents conducted market research through both online platforms and physical electronic component suppliers. This allowed for the comparison of component specifications, pricing, durability, and availability to ensure that the selected materials met the functional requirements while remaining cost-efficient for field deployment. The resulting hardware configuration reflects a balanced selection of components optimized for performance, affordability, and long-term reliability.

In parallel with hardware evaluation, the proponents identified and examined the software requirements for system development.

Programming tools such as the Arduino IDE, ESP-IDF, and Python were selected for microcontroller programming and data handling. For machine-learning tasks, TensorFlow Lite, OpenCV, and the IMX500's on-chip AI pipeline were chosen to enable audio classification, visual detection, and local inference. Cloud platforms such as Firebase and ThingSpeak were assessed for their suitability in real-time data logging, alert notification, and remote dashboard access. These software tools collectively support data acquisition, processing, communication, visualization, and performance evaluation.

Through this extensive requirement-gathering phase, the proponents established a comprehensive understanding of the technical, environmental, and operational considerations necessary for developing a functional, field-ready stingless bee monitoring system. The analysis ensured that the finalized design is technically feasible, scientifically grounded, and aligned with the practical needs of beekeepers, thereby supporting the project's goal of promoting sustainable and non-invasive colony management practices in the Philippines.

B. Preliminary Draft Plan

In this phase, the researchers created an initial representation of the proposed Audio-Video Monitoring System by outlining the basic structure of the components and how they interact within the hive setup. The quick design integrated the insights gathered from beekeepers and experts, particularly the recommended TPH-1 hive dimensions and the importance of minimizing colony stress during monitoring. The system design identified the ESP32-S3 microcontroller as the main data acquisition unit for temperature, humidity, weight, and acoustic signals, while the IMX500 AI camera was designated for capturing entrance activity and visual behavior patterns of *T. biroi*. The Raspberry Pi served as the local data fusion and processing unit, where audio and visual machine-learning models would run concurrently. A preliminary data flow was drafted to illustrate how signals move from sensors to preprocessing, then to dual-path ML inference (audio and visual), proceeding to an event-decision module that classifies activity as normal or intrusion-related before presenting results to the cloud dashboard. At this stage, the design was intentionally broad, emphasizing conceptual integration rather than fine-grained detail, and served as an initial blueprint for prototype development.

C. Prototype Building

After establishing the initial design, the researchers moved forward with the physical construction of the prototype, beginning with the preparation of the HPCB-1 hive for field integration. The hardware components were methodically assembled, ensuring that each sensor, module, and cable pathway fit securely within the hive's modified layout. The team installed dedicated mounting points for the environmental sensors, the camera unit, and the necessary wiring conduits, all positioned to minimize any interference with the bees' natural activity. The ESP32-S3 microcontroller was configured to handle environmental readings and acoustic measurements, while the IMX500 vision sensor was placed at the hive entrance so it could capture clear activity patterns and detect external disturbances such as wasps, ants, or unauthorized human contact.

Alongside the structural assembly, the Raspberry Pi was prepared as the main processing board, receiving the collected data and executing local analysis routines. During this phase, the researchers set up a temporary monitoring interface that displayed real-time measurements, visual streams, and preliminary intrusion alerts. This ensured that each communication pathway from sensors to microcontroller to processor, was functioning correctly before field testing. Protective housings, moisture barriers, and vibration-reducing mounts were added to safeguard all components against weather changes and environmental stress.

To enhance the system's analytical capability, the researchers incorporated foundational AI and machine-learning functions during the build. Lightweight models were installed to allow the IMX500 to detect visual anomalies directly on the device, reducing the need for cloud computation. Meanwhile, the Raspberry Pi was equipped with an initial audio-classification model designed to recognize irregular buzzing patterns associated with colony stress or disturbance. Although these models were early-stage implementations, they enabled the prototype to generate intelligent, context-aware alerts rather than relying solely on raw sensor thresholds.

With all components assembled, protected, and synchronized, this initial prototype became the working platform for validating the system's durability, sensor accuracy, communication stability, and the functional integration of its early AI-driven features.

D. Prototype Assessment

The prototype underwent a thorough assessment to evaluate its functionality, detection accuracy, and overall performance in actual field conditions. Testing was carried out on active hives to observe how the system responded to natural variations in temperature, humidity, hive sound patterns, and normal bee movement. The IMX500 camera was examined for its ability to capture consistent visual data across changing daylight conditions and to identify incoming insects or irregular activity around the hive entrance. Simultaneously, the microphone module was assessed for its capability to register subtle fluctuations in colony buzzing that may signal agitation, environmental stress, or disturbance. The environmental sensors, including the load cell, were also checked for consistent readings, with particular focus on detecting small but meaningful weight changes that reflect nectar intake, honey buildup, or colony expansion.

An additional part of the assessment focused specifically on examining the behavior of the system's AI and machine-learning components. The researchers tested how reliably the IMX500's onboard models classified visual anomalies such as predator insects or sudden movement patterns. Likewise, the audio-anomaly model on the Raspberry Pi was monitored to determine whether it could correctly interpret shifts in hive acoustics and differentiate normal fluctuations from genuinely concerning patterns. These evaluations helped the team verify how well the AI features contributed to early warning detection and whether adjustments in training data, thresholds, or feature extraction were needed to improve model precision.

To further establish the prototype's effectiveness, the researchers performed controlled testing scenarios, including simulated threats like wasp approaches, deliberate tapping on the hive walls, and partial visual obstruction. These simulations enabled the team to check how quickly and accurately the system flagged abnormal conditions. Feedback from technical advisers and field specialists from Quezon City University, along with insights gathered from beekeepers during earlier visits, provided additional guidance on the prototype’s strengths and areas requiring enhancement. These combined assessments helped identify inconsistencies, refine system parameters, and outline the necessary adjustments for the next iteration of development.

E. System Training (AI)

The system’s AI components underwent a structured training process to ensure accurate detection, classification, and interpretation of both visual and audio data gathered from the hives. The IMX500’s built-in neural processing unit was trained using sample footage that included normal bee flight patterns, hive entrance activity, and various foreign insect approaches such as wasps and hornets. These datasets allowed the model to learn distinguishing features between regular foraging behavior and potential threats. To enhance reliability under real-world conditions, the training also incorporated clips taken at different times of day, accounting for shadows, low light, and fluctuating environmental brightness.

For audio analytics, the Raspberry Pi–based model was trained on recorded hive sounds captured during earlier field visits. These audio samples consisted of baseline colony buzzing, periods of mild agitation, and artificially induced disturbances such as tapping vibrations or hive movement. By analyzing variations in frequency, amplitude, and harmonic patterns, the model learned to identify acoustic anomalies that typically signal hive stress. Additional noise samples including wind, animal sounds, and environmental background hum, were included to help the system differentiate relevant signals from unrelated interference.

During training, the researchers iteratively adjusted parameters such as detection thresholds, feature extraction windows, and classification confidence levels to find the balance between sensitivity and false alarms. The performance of both visual and audio models was repeatedly validated through simulated scenarios similar to those used during prototype evaluation. These included staged predator approaches, controlled hive disturbances, and mock obstructions placed near the camera field of view. Feedback from technical advisers played an essential role in refining dataset composition and model behavior, ensuring that the AI components aligned with the project's monitoring objectives. Through this continuous learning cycle, the system's decision-making accuracy, responsiveness, and reliability were significantly improved prior to full field deployment.

F. Proceed to 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 brackets to ensure stability and long-term durability. On the processing side, the machine-learning pipelines were restructured to allow smoother data synchronization between the audio and visual models, enabling more accurate data fusion for event classification. The decision engine, which determines whether detected signals indicate normal behavior or an intrusion, was enhanced to reduce false positives triggered by wind, sudden lighting shifts, or background noise. The dashboard design was also updated to provide clearer visualization of hive parameters, historical logs, and real-time alerts. These improvements allowed the system to move from a general prototype toward a stable, field-ready design suitable for continuous monitoring.

G. Maintenance

The Audio-Video Monitoring System for *T. biroi* colonies requires regular maintenance to ensure consistent performance and long-term reliability in field conditions. Routine visual inspections of the housing, wiring, and sensor placements must be conducted to identify signs of moisture intrusion, corrosion, propolis buildup, or loose connections. The SHT30-B sensor, load cell, microphone, and IMX500 camera should be cleaned periodically to prevent debris, wax, or resin from obstructing measurements or visual detection.

Firmware updates for the ESP32-S3 and Raspberry Pi should be applied as needed to enhance system stability and detection capabilities. Storage logs on the Raspberry Pi must also be monitored and cleared to prevent data saturation. Basic troubleshooting includes checking sensor connections, recalibrating the load cell, examining power regulation components, and reviewing diagnostic logs for communication or inference errors.

Maintenance of the AI and machine-learning components is also essential. The visual and audio detection models should be periodically reviewed and updated to address model drift, seasonal changes, or newly observed hive behaviors. Incorporating new audio samples or intrusion footage into the training dataset ensures that detection accuracy remains reliable over time. Model performance can be verified through logged inference results to identify decreases in accuracy or increases in false alerts.

Adhering to proper electrical safety and environmental protection practices such as avoiding direct rain exposure, preventing overheating, and ensuring secure enclosure sealing, will further extend the system's operational lifespan and maintain dependable support for beekeepers.

H. Adjust Functions & Criteria for 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 IMX500 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.

I. Refined System Design

After completing the detailed design, the researchers revisited and reassessed the initial system requirements to determine whether adjustments were needed to enhance the system's performance and applicability in real hive conditions. Through continuous field testing and consultations with technical advisers from Quezon City University, several refinements were identified. One major requirement was the need to expand the dataset by collecting more audio and video samples from *T. biroi* colonies under various behavioral states, including foraging, guarding, agitation, and exposure to common predators such as wasps and ants. This ensured that the machine-learning models could distinguish normal patterns from true intrusion events with higher precision. The team also recognized the need for improved acoustic isolation around the microphone to minimize distortion from outdoor noise sources such as wind, passing vehicles, and environmental vibrations. Additionally, the camera configuration was refined to capture clearer entrance activity by adjusting the framing, height, shading, and angle of installation to ensure consistent visual data throughout different times of the day. Requirements related to sensor calibration intervals, data-logging frequency, and structural integration with the TPH-1 hive were also updated to ensure long-term stability and reduce colony disturbance. These redefined requirements allowed the system to evolve more accurately based on real-world observations, evaluation findings, and expert recommendations.

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 individual 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, 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 AI 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 or mobile app 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
    - ❖ ants
    - ❖ larger predators

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, AI camera) 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.

5. Scalability

   The system is designed so more sensors or additional beehives can be integrated later with minimal configuration.

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.
    - The sensors and camera should send stable readings over long periods.
    - A 24-hour stress test will be conducted.
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. Security
    - Communication between ESP32 → Raspberry Pi → dashboard must be protected.
    - Basic authentication and secure API endpoints will be assessed.

5. Environmental Robustness

- The components must withstand normal outdoor hive conditions (heat, humidity).
- Weatherproofing of sensors and enclosures will be checked.

Data Gathering Procedures

Data gathering refers to locating, measuring, and collecting the information needed for the study. It gives the proponent a clear process for securing the required data in an organized way. This strengthens the scope of the capstone and allows the proponent to work with more precise inputs. The process supports a wider examination of the topic and ensures that each part of the project is addressed with enough detail. The project will use the following data-collection methods and techniques.

a. **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 common 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 fluctuations, humidity levels around the hive, ambient sounds, and the presence of natural stressors (such as ants, wasps, or human disturbances) were also recorded to determine their impact on the system's 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.

Through these observations, the proponents identified real-world challenges and environmental influences essential to designing a reliable monitoring device. The collected insights supported the refinement of the system's hardware configuration, protective casing, and sensor placement strategy, ensuring that the proposed device would operate effectively in live stingless bee colony conditions.

b. 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 stingless bees, 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 and integration constraints 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.

c. **Survey**

A survey was conducted among local stingless-bee keepers, hobbyists, and agriculture-related practitioners to gather data on current colony monitoring practices, challenges, and technology adoption readiness. The survey focused on identifying common issues encountered in managing *T. biroi* colonies, including predator incidence, hive disturbance, environmental stress, and manual inspection frequency. Respondents were also asked about their familiarity with sensor-based monitoring systems, their perceived usefulness of automated alerts, and their interest in adopting machine-learning–based monitoring tools. The numerical results of the survey provided baseline insights into user needs and expectations, which directly influenced the development of the system's functional requirements, dashboard interface, and alert mechanisms.

d. 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.

e. Survey Validation

To ensure the credibility and accuracy of the survey instrument, the questionnaire underwent a formal validation process facilitated by faculty experts from the Electronics Engineering Department and research technical advisers from Quezon City University. The validation assessed the instrument's clarity, relevance, structure, and alignment with the study's objectives. Revisions were made based on comments regarding item phrasing, sequencing of questions, and appropriateness for both novice and experienced beekeepers. This validation process ensured that the collected data accurately reflected stakeholder needs and could be reliably used to inform the system's design and development.

f. 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. Formal letters were issued detailing the purpose of each visit, its relevance to the study, and the safety and ethical considerations observed to protect both the colonies and personnel involved.

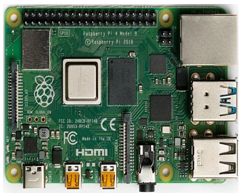
g. Research

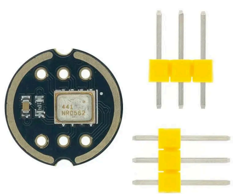
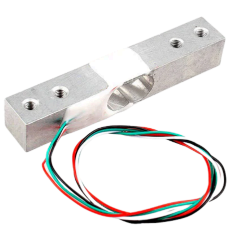
The proponents conducted comprehensive research using academic journals, books, online databases, manufacturer datasheets, and existing apiculture studies to establish the theoretical and technical foundation of the project. This research covered key areas including stingless-bee biology, behavioral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

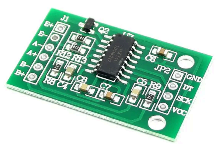
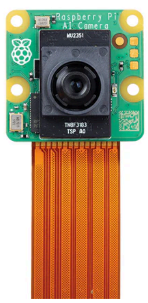
Technical research further involved identifying the hardware and software components necessary for implementing an integrated audio-video monitoring device. This included evaluating sensor modules such as the SHT31-D/SHT30 probe-type humidity sensor, INMP441 microphone, HX711 load cell amplifier, and IMX500 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.

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.
AI Camera Module 	IMX500	**Operating Voltage:** 3.3V **Sensor Resolution:** 12.3 Megapixels **AI Processing:** Integrated Edge-AI Processor (Sony AITRIOS) with on-sensor neural network acceleration **Frame Rate:** Up to 30 fps **Lens Mount / FOV:** Module-dependent **Interface:** MIPI-CSI2 **Supported Output:** AI metadata, bounding boxes, classification results, event flags **Dimensions:** Approximately 25mm x 25mm	AI Vision Sensor Module. Needs to be sourced from a specific AI hardware vendor. The Sony IMX500 is an AI-enabled image sensor that performs real-time object detection and classification directly on the chip, reducing latency and power use while providing fast, efficient visual analysis for embedded systems.
Voltage Regulation 	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.

3MP CCTV Lens 	CS-Mount Lens	**Lens Type:** CS-Mount CCTV Lens **Resolution:** 3 Megapixels **IR Compatibility:** Yes **Material:** Glass optics / Metal housing **Operating Temperature:** -20°C ~ +60°C **Optical Construction:** 12 elements in 10 groups **Focus Type:** Manual focus	Fixed-focus, low-light suitable lens compatible with the IMX500 module.

Software Requirements

For the software development of “Audio-Video Analysis for Colony Activity and Intrusion Alert for *Tetragonula Biroi* (Stingless Bee) Utilizing Machine-Based Learning”, 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 on VS Code as the development environment. This microcontroller will handle real-time audio acquisition, environmental sensing, load cell monitoring, and Wi-Fi communication. C++ is chosen for its speed, memory efficiency, and direct hardware access, which ensures reliable processing of sensor data and continuous 24/7 monitoring of the hive.

The Raspberry Pi 4 B will use Python, developed in VS Code with Python + Pylance + Jupyter extensions. Python is selected for its simplicity, readability, and extensive libraries for computer vision and machine learning, such as OpenCV, TensorFlow, and PyTorch. The Pi 4 B's processing power allows it to perform real-time video capture, colony activity analysis, and intrusion detection efficiently, while maintaining a maintainable and flexible code structure for future upgrades.

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 (OpenCV, TensorFlow, PyTorch)	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 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 OpenCV and TensorFlow, 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 and seamless integration with ESP-IDF, making It is ideal for reliable, maintainable, and production-ready code for real-time audio, sensor, and Wi-Fi tasks.

Table 6. *For Raspberry Pi 4 B*

Aspect	Python, Pylance, and Jupyter (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

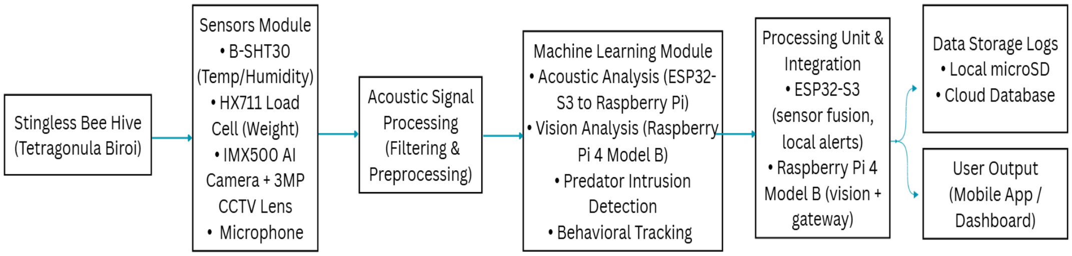


Figure 3. *Colony Activity and Intrusion Alert Block Diagram*

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

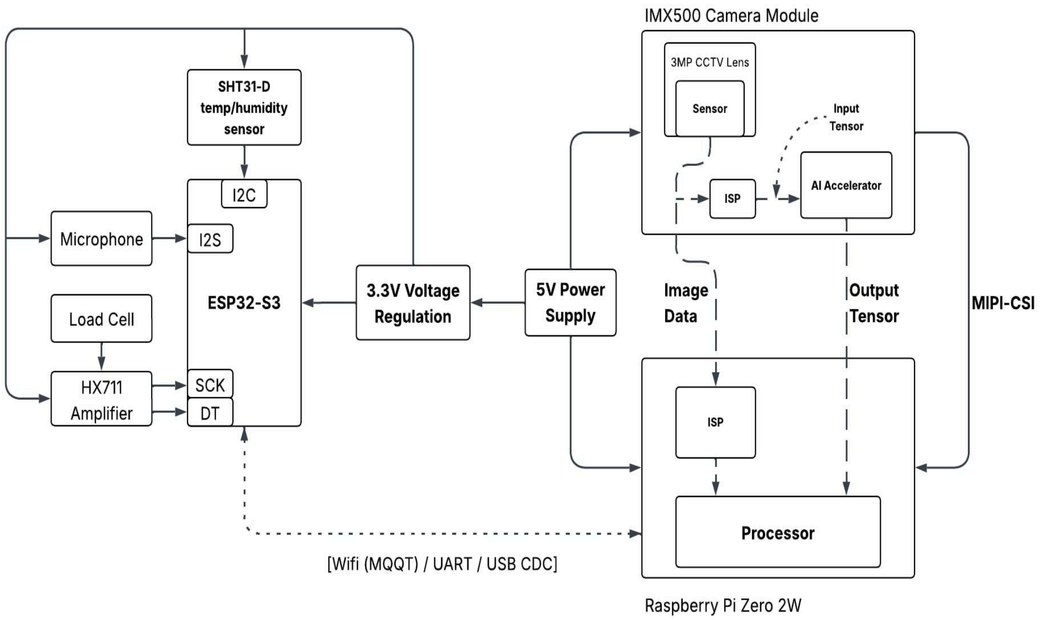


Figure 4. *Connection Diagram of the System*

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 IMX500 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.

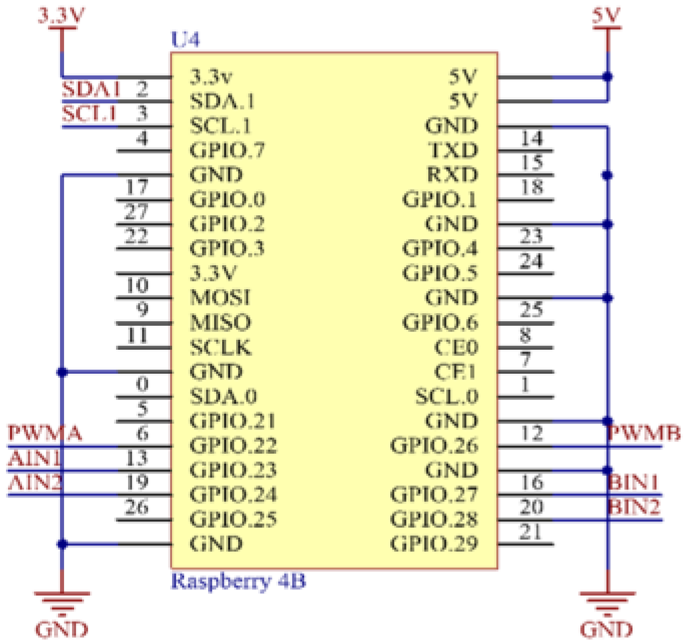


Figure 5. *Schematic Diagram of Raspberry Pi 4 B*

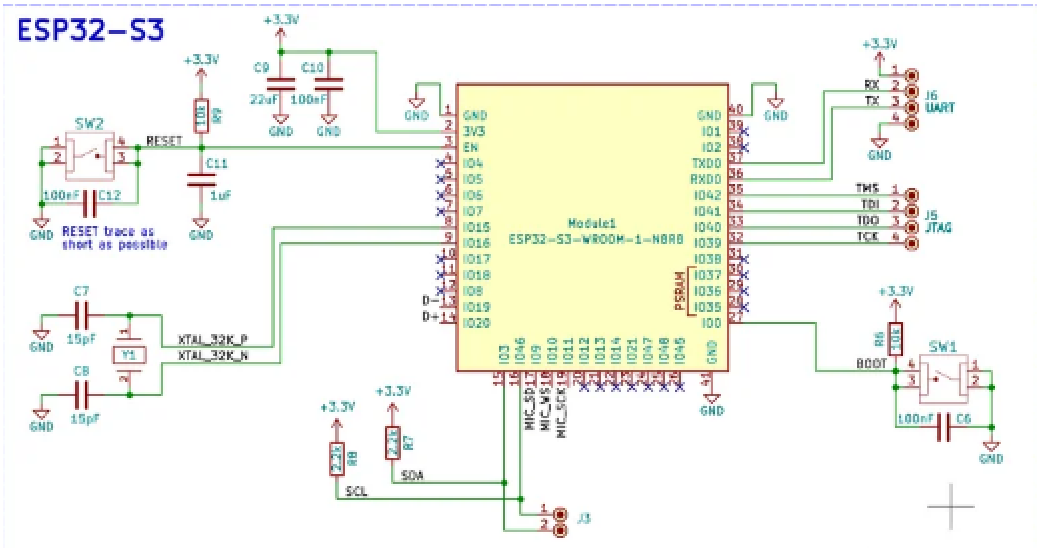


Figure 6. *Schematic Diagram of ESP32-S3*

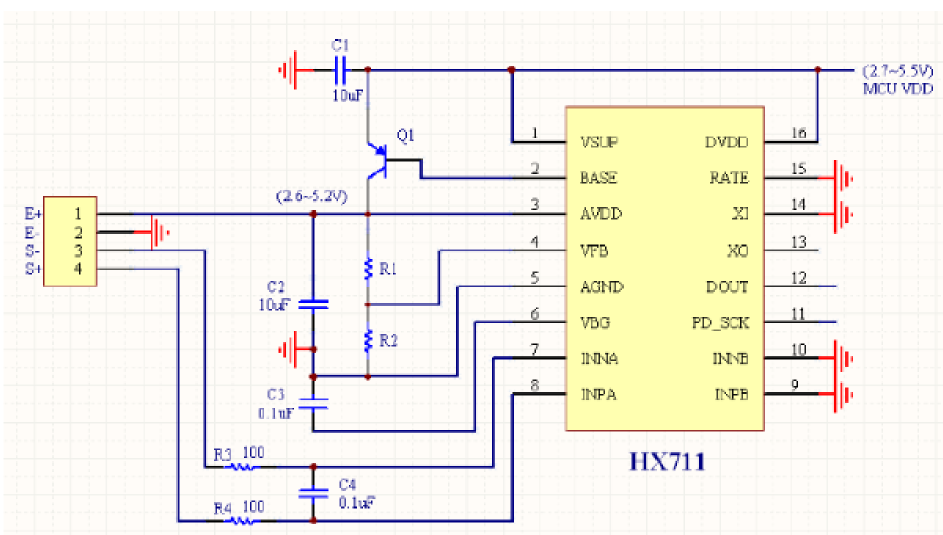


Figure 7. *Schematic Diagram of HX711 amplifier*

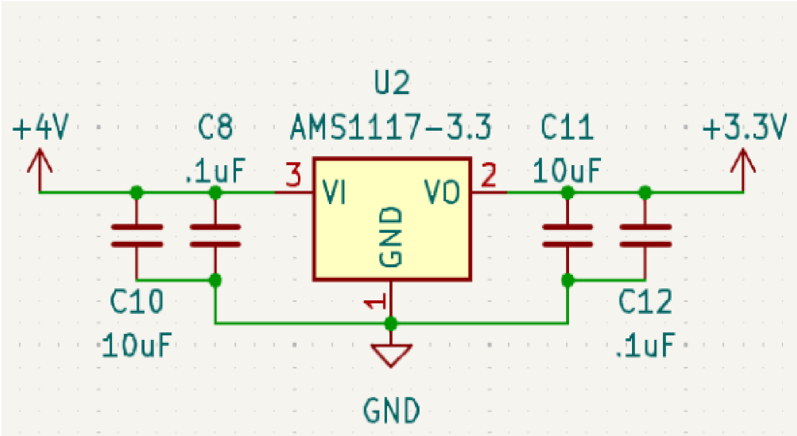


Figure 8. *Schematic Diagram of voltage regulator*

FLOW CHART

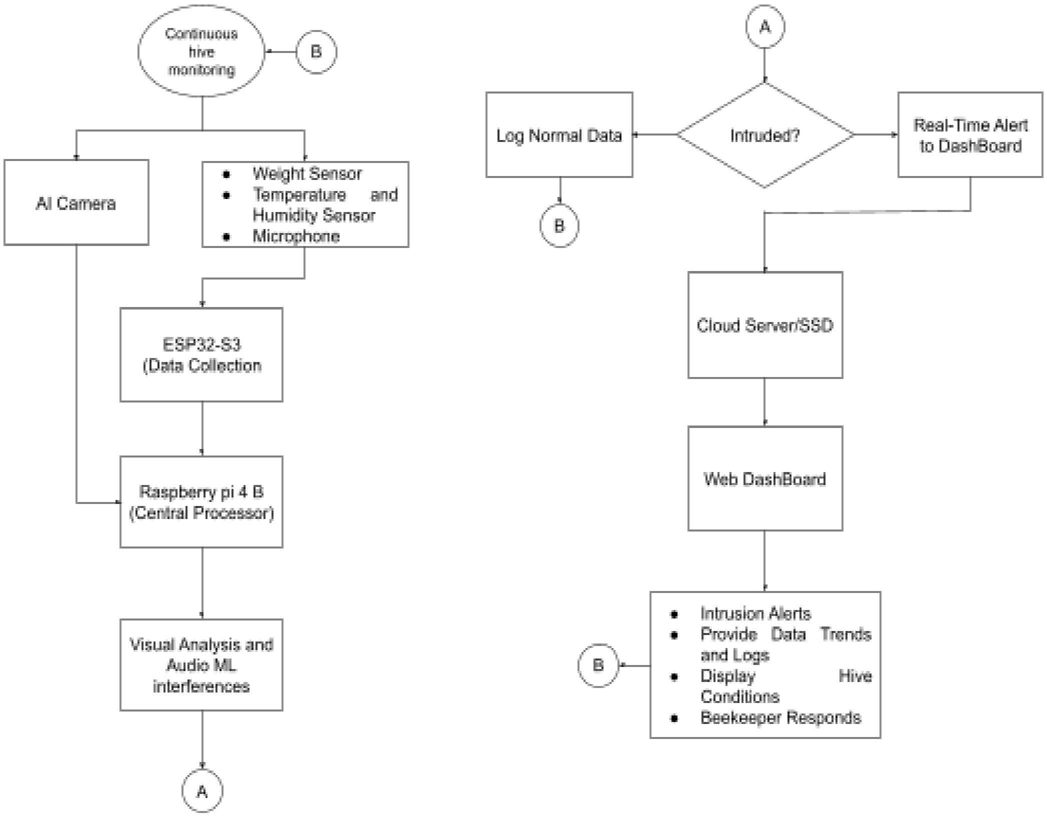


Figure 9. *Flowchart of ML-Driven Beehive*

The flowchart illustrates the operational workflow of the monitoring system by outlining the sequential processes from data acquisition to machine learning–based classification. It describes how the ESP32-S3 initializes each sensor, collects environmental, audio, and visual inputs, and transmits these to the Raspberry Pi for simultaneous processing. The diagram also presents the system's decision-making logic, identifying the conditions under which normal colony behavior transitions to an intrusion or abnormal event. This structured depiction ensures clarity in understanding the internal logic of the system and supports consistent implementation, debugging, and further enhancement of its functional processes.

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)

APPENDIX B

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)

APPENDIX C

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)