ENHANCING SUSTAINABLE COCONUT CROP PROTECTION THROUGH MACHINE LEARNING-DRIVEN INTEGRATED STRATEGIES

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Final Group Report

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We declare that this is our work, and this proposal does not incorporate without acknowledgmentany material previously submitted for a degree or diploma in any other university or Institute of higher learning, and to the best of our knowledge and belief, it does not contain any material previously published or written by another person except where the acknowledgment is made in the text.

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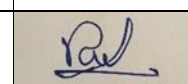
Senanayake P.M.	IT20606756	
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ABSTRACT

The challenges faced by agricultural communities worldwide, particularly in rural areas, are multifaceted, with pests posing a significant threat to crop cultivation and economic stability. Among these pests, macaque monkeys have emerged as a major concern due to their propensity for damaging various crops. The financial burden on farmers from pest control measures and crop damage is substantial and persistent, impacting both individual incomes and community-wide prosperity. In response, researchers are developing innovative solutions, such as automated pest detection and repulsion strategies, to mitigate these challenges and ensure long-term sustainability.

Specifically, a research project focuses on addressing the impact of macaque monkeys on crops in a rural village. By studying the behavior patterns of these pests, the research aims not only to provide immediate solutions but also to stimulate broader discussions within the farming community about land safeguarding practices. In another aspect of pest management, a study evaluates different convolutional neural network models to enhance coconut pest detection through a mobile app. MobileNetV2 emerges as the optimal choice due to its high accuracy, efficiency, and suitability for resource-constrained mobile devices. Future enhancements include expanding the pest species database, utilizing advanced techniques like transfer learning and data augmentation, and integrating IoT and cloud computing features to provide a robust tool for effective pest management in agricultural settings.

Keywords – Crop protection, Macaque monkey, Deep learning, Prevalence, Behavior patterns, Future prediction

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LIST OF THE ABBREVIATIONS

Abbreviation	Description
ML	Machine Learning
UI	User Interface
DB	Database
ARIMA	Autoregressive Integrated Moving Average
IDE	Integrated Development Environment
MSE	Mean Squared Error

Table 1 – List of abbreviations

1. INTRODUCTION

1.1. Background Study

Coconut palm (Cocos nucifera L.) is a crucial element of Sri Lanka's economy, contributing significantly through products like copra, coconut oil, and more. However, the cultivation of these palms is constantly challenged by various pests that threaten yield and economic stability. Among these pests, the red palm weevil (Rhynchophorus ferrugineus) is notably devastating, particularly for young coconut palms aged between 3-15 years. This beetle, recognized by its elongated snout and reddish-brown body, infiltrates the core of the palm, causing severe damage as the larvae tunnel through internal tissues, disrupting nutrient and water flow, leading to wilting and eventual death of the palm. Early detection is crucial, with signs such as oozing sap, a fermented odor, wilting fronds, and holes in the trunk or crown.

Another significant pest is the coconut leaf miner (Promecotheca spp.), a small beetle that burrows into leaves, disrupting photosynthesis and impeding the palm’s growth. Initially causing widespread damage upon its accidental introduction in 1970, the coconut leaf miner's impact was significantly mitigated through biological control. Scientists successfully introduced parasitic wasps like Dimmockia javanica, which predated on the leaf miner population, showcasing the effectiveness of sustainable pest management solutions.

In addition to these pests, coconut plantations in Sri Lanka also face threats from whiteflies, macaque monkeys, and coconut caterpillars. Traditional pest control methods, such as shooting or using scare tactics, are increasingly seen as ineffective and environmentally harmful. Thus, there is a pressing need for innovative and eco-friendly pest management strategies. Modern research aims to integrate advanced machine learning techniques with conventional agricultural practices to enhance pest and disease management in coconut farming.

This research proposes a cutting-edge pest control system that combines sensor technology with a mobile application to proactively address pest damage. This system is designed to detect the presence of pests early, ensuring accurate identification and understanding of pest behavior. Specifically, for macaque monkeys, the system employs strategically placed sensors equipped with image recognition technology to provide real-time updates on their presence. To reduce false alarms, the data is meticulously verified, and non-invasive sound techniques are used to humanely deter the monkeys. Pattern prediction algorithms are also utilized to detect early signs of pest presence, based on data analysis.

The mobile application associated with this system promptly alerts farmers upon pest detection, offering tailored pest management solutions that prioritize sustainability and eco-friendliness. This approach exemplifies the integration of agricultural expertise with technological advancements, aiming to develop sustainable pest management strategies that are urgently needed.

Beyond technological solutions, the research emphasizes understanding the broader impact of pests on rural agricultural communities. For instance, in one village, the persistent threat of pests, particularly macaque monkeys, poses significant challenges. These monkeys cause extensive damage to a variety of crops, leading to direct financial losses for farmers and broader economic repercussions for the community. The study of macaque behavior patterns aims to provide practical solutions for immediate pest control and to stimulate broader consideration among farmers about protecting their cultivated lands.

By equipping farmers with the insights and tools necessary to adapt and respond effectively to pest-related threats, the research aims to contribute to the long-term viability and sustainability of agricultural practices. This holistic approach underscores the importance of combining traditional agricultural knowledge with modern technology to address the complex challenges faced by coconut farmers in Sri Lanka and other tropical regions. Through early detection, precise identification, and sustainable pest management solutions, the research seeks to safeguard the coconut industry, ensuring its continued contribution to the economy and livelihoods of communities dependent on it.

1.2. Literature Review

Recent studies have explored various animal classification methods, particularly focusing on acoustic and visual techniques. Vithakshana L. G. C, Samankula W. G. D. M introduced an IoT-based animal classification system utilizing a convolutional neural network (CNN). Their hardware setup collected audio data, which was preprocessed using Mel-frequency Cepstral Coefficients (MFCC) and formatted using Audacity. The CNN, implemented with TensorFlow, trained on 400 sound clips, 40 from each of 10 animal species.

Che Yong Yeo, S. A. R. Al-Haddad, and C. K. Ng presented an animal identification system based on voice pattern recognition. Their approach integrated zero-cross-rate (ZCR), MFCC, and Dynamic Time Warping (DTW) algorithms to accurately identify animals by their vocal patterns, filtering out silence and extracting distinct voice features.

Additionally, authors proposed a bird classifier system using bird audio recordings and MFCC. They tested various algorithms such as Naïve Bayes, J4.8, and Multilayer Perceptron (MLP), with J4.8 achieving the highest accuracy of 78.40%. K.H. Frommolt and K.H. Tauchert researched bird call detection using two CNN approaches in bioacoustic monitoring systems.
In response to the persistent challenge of animal encroachment in agricultural fields, researchers have been developing innovative solutions to mitigate crop damage and protect farmers' livelihoods. Sheik Mohammed, Dr. T. Sheela, and Dr. T. Muthumanickam introduced a system that combines a modified CNN algorithm, thermal imaging, PIR sensors, GSM modules, and Raspberry Pi for real-time monitoring and alerts, effectively addressing wildlife intrusion.

Similarly, Manikandan et al. proposed a solution integrating Arduino, PIR motion sensors, Buzzer, LED lights, and GSM modules for rapid detection and response to animal intrusion, minimizing yield loss and enhancing crop protection.

In Indian farmlands, Shola Usharani et al. presented an IoT-based solution using Arduino, PIR, Ultrasonic sensors, GSM, and ESP32 Camera, which detects animal intrusion, alerts farmers, and provides real-time field images, ensuring efficient protection while considering animal welfare.

These studies highlight the significance of leveraging technological advancements like IoT, machine learning, and sensor networks to develop effective and humane solutions for mitigating crop damage caused by animal encroachment. By offering real-time monitoring, rapid detection, and timely alerts, these innovative systems hold promise for safeguarding farmers' livelihoods and promoting agricultural sustainability.

Agricultural pest infestation, particularly by macaque monkeys, poses a significant challenge to farming communities worldwide, leading to substantial economic losses. Researchers have begun focusing on innovative solutions to mitigate crop damage caused by animal encroachment. Studies have explored macaque monkeys' behavioral patterns, revealing insights into their foraging habits, movement dynamics, and interactions with humans. However, there's a gap in translating these insights into actionable information for farmers.

Several major studies delve into macaque behavior, covering topics such as social networks, abnormal behaviors, age-related tendencies, and disease ecology. While literature on applying data analysis to predict monkey incursions on cultivated fields is limited, there's research on the financial consequences of monkey damage on commercial agriculture and human-monkey interactions in various environments.

The collective research aims to better understand macaque behavior patterns, social dynamics, and implications for agricultural practices and welfare. While current literature provides valuable insights, future studies focusing on data analysis applications could further enhance understanding and aid in developing effective pest management strategies.

Several research studies have proposed innovative solutions for detecting and managing diseases, pests, and nutrient deficiencies in coconut plantations, leveraging deep learning techniques, image processing, and Internet of Things (IoT) technology.

Vidhanaarachchi et al. [1] introduce a smart solution utilizing deep neural networks (DNNs), image processing, and crowdsourcing to detect coconut diseases, pest infestations, and nutrient deficiencies. Their system achieves high accuracy rates and includes a bilingual mobile application for user-friendly disease identification and sharing of dispersion details, as well as a web application for disease monitoring and control measures.

Nesarajan et al. [2] present a system employing image processing and deep learning for identifying pest attacks, nutrient deficiencies, and diseases in coconut leaves. Their approach achieves high accuracy and focuses on rapid and non-destructive disease identification, particularly beneficial for large plantations where manual monitoring is challenging.

Banerjee et al. [3] propose a model combining Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) for detecting and classifying the severity levels of yellowing disease in coconut leaves. Their model demonstrates high effectiveness in disease severity assessment, incorporating a comprehensive four-phase methodology and achieving robust performance across different disease severity classes.

Ekanayaka et al. [4] introduce a unique approach to coconut pest detection by integrating IoT technology and deep learning, incorporating audio processing alongside visual data for more comprehensive pest identification. Their system enables real-time monitoring, knowledge dissemination to farmers, and achieves high accuracy rates in identifying specific coconut pest infestations.

Future developments in these research areas may include integrating environmental sensor data for predictive modeling, automating pest management recommendations, and conducting field trials to assess scalability and practical performance.

1.3. Research Problem

The primary issue in agricultural settings is detecting and repelling macaque monkeys, which can appear unpredictably at any time. Traditional methods like manual observation and physical barriers are labor-intensive, inefficient, and often fail to provide timely detection. This unpredictability causes significant problems for farmers who cannot constantly monitor their fields, highlighting the need for more effective solutions.

To address this, the study proposes an innovative solution using sound analysis, IoT devices, and deep learning algorithms. This approach aims to provide farmers with a more efficient way to detect and repel macaques, reducing labor and ecological impact. The key challenge is accurately confirming the presence of monkeys in real-time and developing effective, humane repelling methods while managing false alarms. The goal is to enhance detection accuracy and create robust systems that protect crops and consider animal welfare.

Additionally, there is a need for a comprehensive framework to predict macaque monkey arrivals, routes, and future presence. Current research lacks predictive models that collectively answer these critical questions. Existing visualization methods do not effectively translate monkey movement and behavior into actionable insights for farmers. The challenge is to develop predictive modeling and advanced data visualization techniques that provide farmers with holistic answers about when and where monkeys will arrive and their future impact.

Furthermore, there is a lack of integrated approaches to predict and mitigate future risks of macaque infestations in agriculture. While there is some understanding of macaque behavior and distribution, comprehensive predictive models that combine these patterns with ecological and environmental variables are missing. Effective data visualization techniques are also needed to accurately represent the complex movement dynamics and behavior of macaques in a way that is easy for farmers to understand and act upon.

In summary, the research seeks to develop innovative, tech-driven solutions for detecting and repelling macaque monkeys, improving prediction and visualization of their movements, and enhancing farmers' preparedness for managing these pests. This involves integrating advanced technologies like IoT, deep learning, and predictive modeling to create efficient, humane, and sustainable pest management strategies.

1.4. Research Gap

Detecting and managing pests, especially those with significant economic and ecological impacts, is a crucial area of research in agriculture and environmental science. However, a notable gap exists in the literature regarding the use of sound analysis for detecting macaque monkeys, which pose serious challenges to agriculture and human-wildlife coexistence.

Previous research has explored sound-based approaches for detecting pests like insects and birds but has not focused specifically on macaque monkeys. This gap highlights the novelty of using sound analysis to identify and track macaque monkey activity in agricultural settings. Moreover, while IoT devices and deep learning algorithms have been individually studied for pest detection, their integration, especially for macaque monkey detection, is lacking. Combining these technologies can significantly enhance the accuracy and efficiency of detecting and tracking macaques.

Another gap is the absence of real-time monitoring and location tracking in previous pest detection studies using sound analysis. Although some research has utilized sound analysis, the lack of real-time capabilities limits effective monitoring and response to pest activity.

Previous efforts have used computer vision and machine learning to tackle animal intrusion in agricultural fields, achieving accuracies below 94%. However, there remains a need for higher accuracy in detecting and alerting farmers to potential threats. Existing systems often alert farmers about animal presence without providing detailed information about the crop's condition. This highlights the need for research that not only improves detection accuracy but also incorporates real-time crop monitoring.

Addressing this gap involves developing advanced systems that surpass the 94% accuracy threshold and offer comprehensive alerts, including detailed insights into crop conditions. Such research would enhance crop protection and improve farmers' decision-making processes.

Furthermore, there is a need to integrate the analysis of macaque monkey presence and behavior patterns to predict future risks accurately. Some studies have examined macaque behavior and its impact on crops, but there is a lack of comprehensive predictive models that can translate these insights into actionable predictions for farmers. Additionally, data visualization techniques have not been effectively used to demonstrate macaque distribution and behavior. More sophisticated visual representations are needed to convey complex movement patterns and potential crop risk areas.

This gap presents an opportunity to develop integrated approaches that analyze macaque behavior and provide farmers with practical tools to proactively address agricultural pest threats. By leveraging sound analysis, IoT devices, deep learning algorithms, and advanced data visualization, researchers can create more effective and sustainable pest management strategies. These integrated systems would not only detect and repel macaques more accurately but also offer real-time monitoring and detailed alerts, significantly enhancing farmers' ability to protect their crops and improve their agricultural practices.

2. OBJECTIVES

2.1. Main Objectives

- The research aims to create an advanced system for detecting and repelling macaque monkeys in agricultural areas. Leveraging technologies like sound analysis, IoT devices, and deep learning algorithms, the system intends to offer farmers a highly efficient solution for managing macaque incursions.

- The primary goal of this research is to create dependable methods for confirming the presence of macaque monkeys in agricultural regions and to formulate efficient strategies for repelling them to mitigate crop damage. This involves enhancing the accuracy and speed of monkey detection, devising humane and effective repelling methods, and establishing robust systems for managing false alarms. Ultimately, the objective is to protect agricultural crops from monkey intrusion, promote sustainable farming practices, and ensure the welfare of both crops and animals.

- The objectives of the research include providing farmers with a comprehensive understanding of macaque monkey distribution through recent data analysis, clarifying spatial movement patterns, and distribution. Additionally, the study aims to determine if there's a discernible increase in macaque arrivals over time by scrutinizing historical data and employing statistical methods. Lastly, the research endeavors to predict future macaque threats by leveraging predictive modeling techniques, incorporating variables like historical data and environmental conditions. These insights empower farmers to proactively prepare for potential threats, adjust management strategies accordingly, and implement preemptive measures to minimize crop damage and financial losses.
- The research aims to develop a robust system to empower farmers in identifying pest infestations early on, utilizing convolutional neural networks (CNNs) and pretrained models. The goal is to create an intuitive and accessible solution capable of accurately detecting pests in coconut crops. Early pest detection is crucial for timely intervention and minimizing economic losses. The objective is to provide farmers with a user-friendly tool seamlessly integrated into existing agricultural practices, enabling informed decisions and proactive measures to protect crops. Through advanced technology, the research seeks to

enhance agricultural productivity, sustainability, and resilience, thereby benefiting farmers worldwide.

2.2. Specific Objectives

- The objectives of the research project include designing and implementing IoT devices equipped with sound sensors for automated macaque detection, developing deep learning algorithms to accurately identify macaque vocalizations from sound data, integrating GPS functionality into the IoT devices to track macaque movements, predicting future macaque behavior based on environmental factors, and creating a user-friendly mobile application for farmers to receive real-time detection alerts and intervention recommendations. These objectives aim to provide farmers with effective tools for monitoring and managing macaque incursions in agricultural fields, ultimately enhancing pest control strategies and mitigating crop damage.
- The primary objective is to develop a robust system for real-time detection of macaque monkeys in agricultural fields, utilizing both sound and visual cues. This involves designing and implementing hardware and software components capable of processing sound and visual data to identify macaque presence. Additionally, a reliable method for confirming the presence of monkeys through video analysis is to be established, with the development of algorithms or models for accurate detection. Furthermore, effective repelling strategies are to be designed and tested to deter macaque monkeys from agricultural areas while ensuring their welfare and minimizing crop harm, exploring methods such as auditory and visual deterrents or natural barriers.

- The process involves collecting and pre-processing data from sound sensors and cameras deployed in agricultural fields to accurately capture macaque monkey activity. Relevant information such as timestamps and sensor identifiers is extracted from the data. Subsequently, the collected data is analyzed to identify recurring patterns in macaque arrival, including preferred times, days, and locations. A machine learning module is then designed and implemented to utilize historical data for predicting future macaque arrivals and behavior. This module is trained to recognize patterns in past activities and forecast potential infestations during upcoming periods. Finally, the machine learning module is integrated with a user-friendly interface that provides farmers with predictions about upcoming macaque arrivals and behavior patterns, offering clear and actionable insights to empower farmers to take preventive measures in advance.

- The objective is to identify pests in their initial stages, enabling proactive pest management strategies. This involves providing the latest solutions for each identified pest.

3. METHODOLOGY

3.1. Research Area

Detection and Management of Macaque Monkeys Using Sound Analysis

To detect the presence of macaque monkeys in agricultural areas, a continuous monitoring system using a specialized device has been proposed. This device operates around the clock, filtering out background noise and detecting sounds that exceed a 50-decibel threshold. When such sounds are detected, the system records 4-second audio clips. These clips are then analyzed using Recurrent Neural Networks (RNN) LSTM algorithms, which are trained to distinguish macaque monkey sounds from other noises. The training dataset consists of 2100 audio recordings, split evenly between macaque sounds and ambient noises. To ensure the algorithm's accuracy, 75% of this data is used for training, and 25% for testing.

Upon detecting macaque sounds, additional data such as temperature, humidity, device ID, and location are also captured. This contextual information helps understand the environmental conditions associated with macaque activity. All data, including audio clips and supplementary information, is securely stored in the cloud for future analysis. This storage facilitates efficient data retrieval and system optimization.

The integration of advanced technologies like RNN algorithms and IoT devices aims to improve the accuracy and reliability of macaque detection. By leveraging a comprehensive dataset and cloud-based storage, the system provides a robust solution for managing macaque monkey presence in agricultural settings, enhancing pest management and agricultural sustainability.

Confirming Macaque Presence with Camera and Object Detection

After detecting macaque sounds, a camera trigger mechanism with real-time video input and object detection is employed to confirm their presence. The system activates a camera to capture video, which is processed using a YOLOV8 object detection model. This model, trained with 4400 video samples (95% for training and 5% for validation), ensures accurate identification of macaque monkeys.

Implemented on a Raspberry Pi board, the YOLOV8 model detects macaques in real-time video streams. Upon successful detection, the system triggers an alarm in Firebase and activates a buzzer to alert farmers. The system continues to monitor the area by capturing video footage every 10 seconds, allowing for timely detection of any subsequent macaque activity.

If no macaques are detected in the follow-up footage, indicating their departure, a false alarm node is activated in Firebase. The system preserves the image of the detected macaque and a post-departure frame for further analysis. This comprehensive system combines advanced technologies and real-time monitoring to provide an effective solution for confirming and managing macaque presence in agricultural areas, thereby protecting crops and enhancing productivity.

Repelling of Macaque Monkeys

In many villages, farmers struggle with macaque monkeys damaging their crops. The current method of shooting to drive them away is ineffective and poses risks to the animals. To address this, a humane and effective system using sound sensors and advanced algorithms has been proposed. Sound sensors are strategically placed to detect the distinct sounds of macaque monkeys. When their presence is confirmed, speakers emit high-frequency and high-decibel sounds to deter them from staying on the property.

Behavioral patterns identification

This system not only detects and repels macaques but also identifies patterns in their movement and entry points. By analyzing this data, preventive measures can be optimized. This proactive approach protects crops and offers a long-term solution to the macaque problem. The system also provides valuable insights into macaque behavior, helping to develop more effective strategies for crop protection.

This humane and effective method replaces harmful practices and ensures the safety of both crops and animals. By leveraging technology and data analysis, this system offers a sustainable solution to the challenges posed by macaque monkeys in agricultural areas.

Data Collection for Coconut Pest Detection

To protect Sri Lanka's coconut plantations from pests, a comprehensive dataset of coconut leaves has been collected. Leaves from various regions were gathered, representing the challenges faced by plantations, including damage from red palm weevils, coconut caterpillars, and coconut whiteflies. High-resolution images were taken with proper lighting to accurately capture the characteristics of healthy and pest-infested leaves. Detailed annotations were made to identify the presence and type of pest damage.

Focusing on the larval stage of coconut caterpillars, which is visible and causes significant damage, the dataset includes 990 images of leaves with clear signs of caterpillar activity. These images were meticulously annotated, identifying different developmental stages and feeding patterns. This comprehensive dataset is used to train a deep learning model to detect caterpillars in real-time.

Additionally, recognizing the impact of coconut whiteflies, 185 high-resolution images of the topside of leaves were collected. These images, along with a 5-minute video, showcase the characteristics of whitefly infestations. Detailed annotations identify the location and extent of damage, enabling the model to detect whiteflies and estimate infestation severity.

This meticulous data collection process ensures the development of a powerful deep learning model capable of accurately detecting coconut pests, ultimately protecting plantations and enhancing crop management.

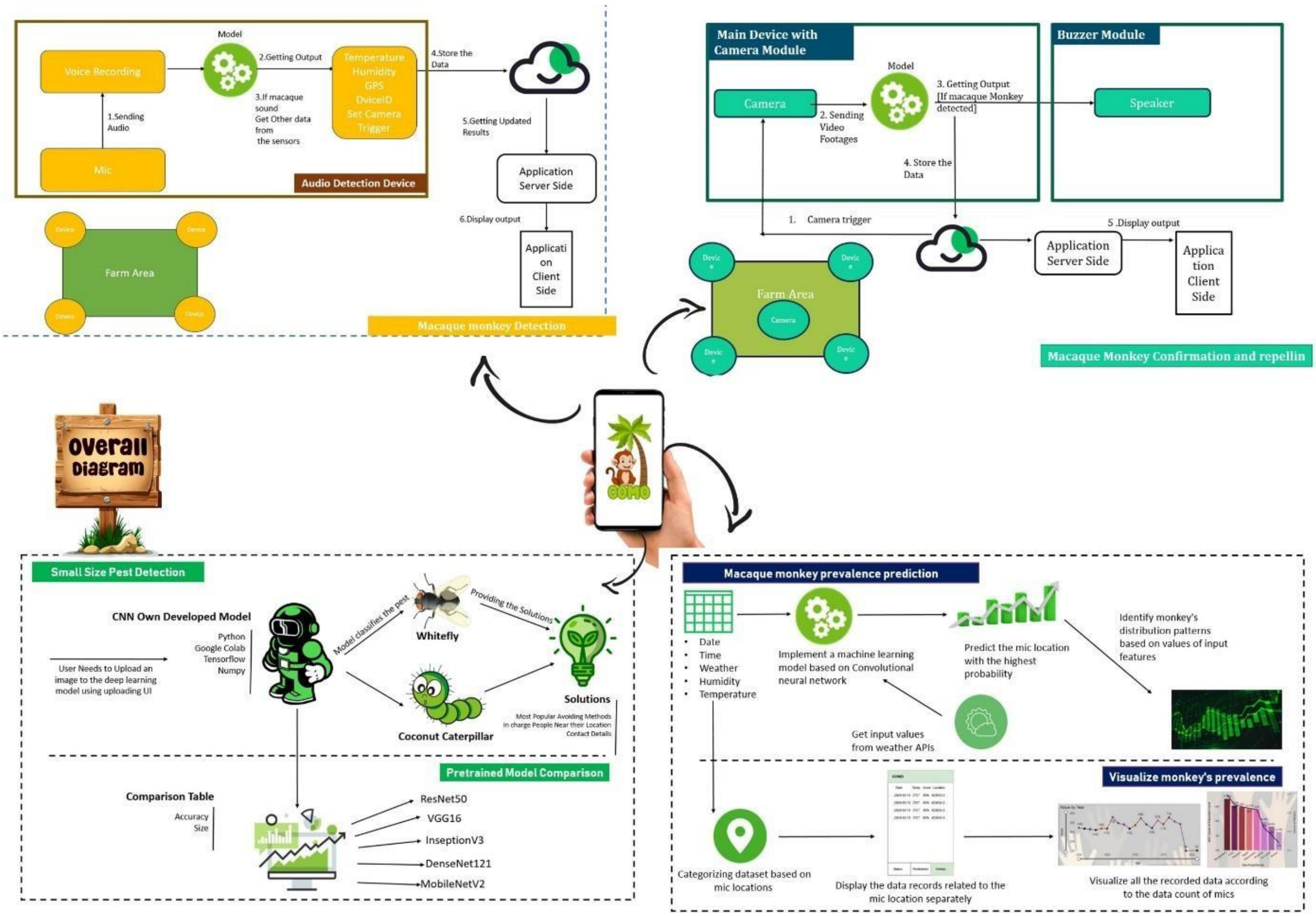


Figure 2. - Overall System Diagram

3.2. Data Collection

1. Detection: Collecting Sound Data

Data collection involved visiting various locations in Sri Lanka, including the Sri Lankan Zoo, Bisodola Falls, and Munangala Forest. Manual recordings of macaque sounds and ambient noises were conducted in these areas, along with visits to coconut farming lands. A total of 1040 macaque sound clips and 1040 ambient noise recordings were collected. This extensive dataset provides a comprehensive foundation for training and validating the sound classification algorithm, ensuring its accuracy and reliability in detecting macaque presence in agricultural settings.

2. Confirmation: Gathering Video Footage

To confirm macaque presence, multiple locations such as the Sri Lankan Zoo, Bisodola Falls, and Munangala Forest were visited again. An extensive dataset of approximately 4400 video footage samples was collected, with 95% used for training purposes. This dataset is crucial for training and validating the object detection model, ensuring its accuracy and reliability in confirming macaque presence in agricultural environments. This video data helps verify sound-based detections, providing visual confirmation of macaque activity.

3. Behavioral Patterns Identification: Using Environmental Data

Behavioral pattern identification involves deploying sound sensors and cameras in agricultural fields to capture audio and visual data. This data includes environmental factors such as temperature, humidity, time of day, weather conditions, and geographic location. By analyzing this data, researchers identified patterns in macaque behavior, including factors that affect their visits. Approximately 900 data points related to cultivated land were collected. This comprehensive dataset helps understand macaque movement patterns and improve detection and repelling strategies based on their behavior.

4. Small Pest Detection: Collecting Coconut Leaf Data

For small pest detection, data collection focused on protecting Sri Lanka's coconut plantations from pests like red palm weevils, coconut caterpillars, and whiteflies. A new dataset centered around coconut leaves was meticulously collected from various regions. High-resolution images of healthy and pest-infested leaves were taken with proper lighting and angles. Detailed annotations were made to identify the type and extent of pest damage on each leaf. This dataset ensures the creation of a rich and informative base for training a deep learning model. This model will accurately detect and manage coconut pests, enhancing crop protection and management.

3.3. Data Pre-processing and Storage

- In the data preprocessing stage for macaque sounds, several steps are typically undertaken to prepare the collected audio clips for further analysis and storage. Firstly, noise reduction techniques are applied using software like Audacity to remove any background noise or interference from the recordings, ensuring that only the macaque sounds are retained for analysis. Then, the audio clips are segmented into smaller segments of uniform duration to facilitate processing and analysis, which helps in standardizing the data and extracting relevant features for classification.

- Next, relevant features such as frequency components, amplitude variations, and spectral characteristics are extracted from the segmented audio clips. These features serve as input variables for the sound classification algorithm. Additionally, the extracted features are normalized to ensure consistency and comparability across different audio clips, removing biases and ensuring effective operation of the algorithm on the entire dataset.

- Finally, data augmentation techniques are applied to augment the dataset by applying transformations such as pitch shifting and time stretching. Data augmentation helps in improving the robustness and generalization ability of the sound classification algorithm. Overall, these preprocessing steps are essential for preparing the audio data for accurate analysis and classification of macaque sounds.

- In the labeling stage of preprocessing, appropriate labels are assigned to the preprocessed audio data, indicating whether each segment contains macaque sounds or ambient noise. Accurate labeling is crucial for training and validating the classification algorithm effectively.

- Once labeled, the preprocessed audio data, along with their corresponding labels and any additional metadata, are stored in a suitable data format. This may involve organizing the data into a structured database or storing it in a cloud-based storage system for easy access and retrieval during training and testing phases.

- By performing these preprocessing steps, the macaque sound data is transformed into a format that is suitable for training and testing the sound classification algorithm, ensuring accurate analysis and classification of macaque sounds.

3.4. Gantt Chart

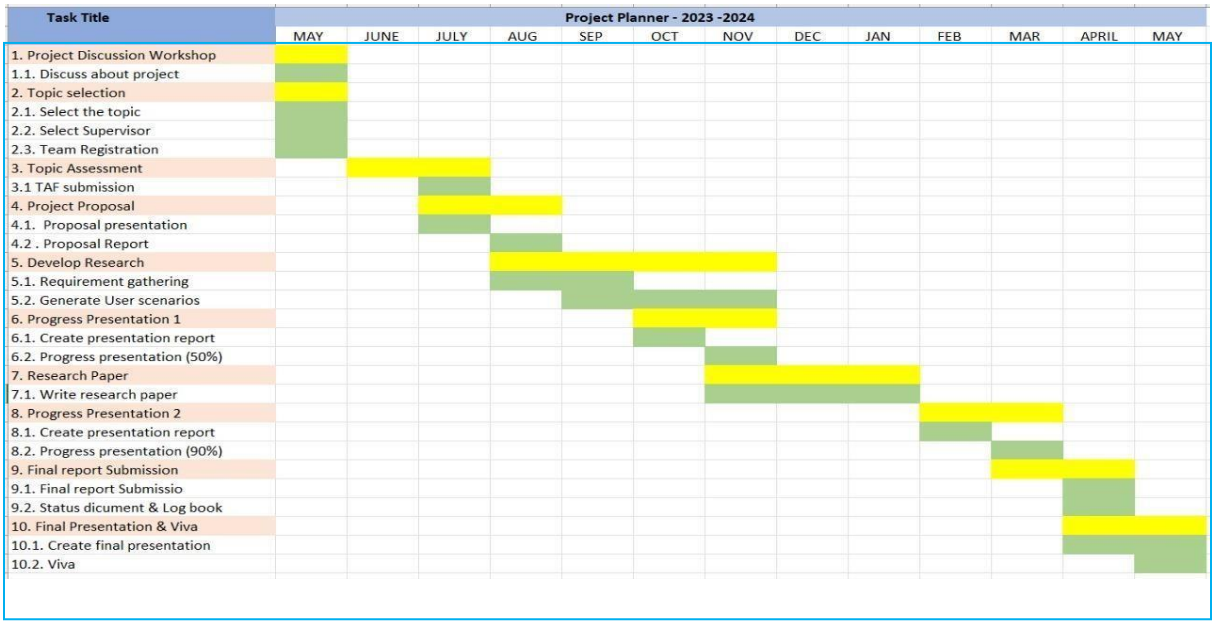


Figure 7. - Gantt Chart

3.5. Work Breakdown Structure

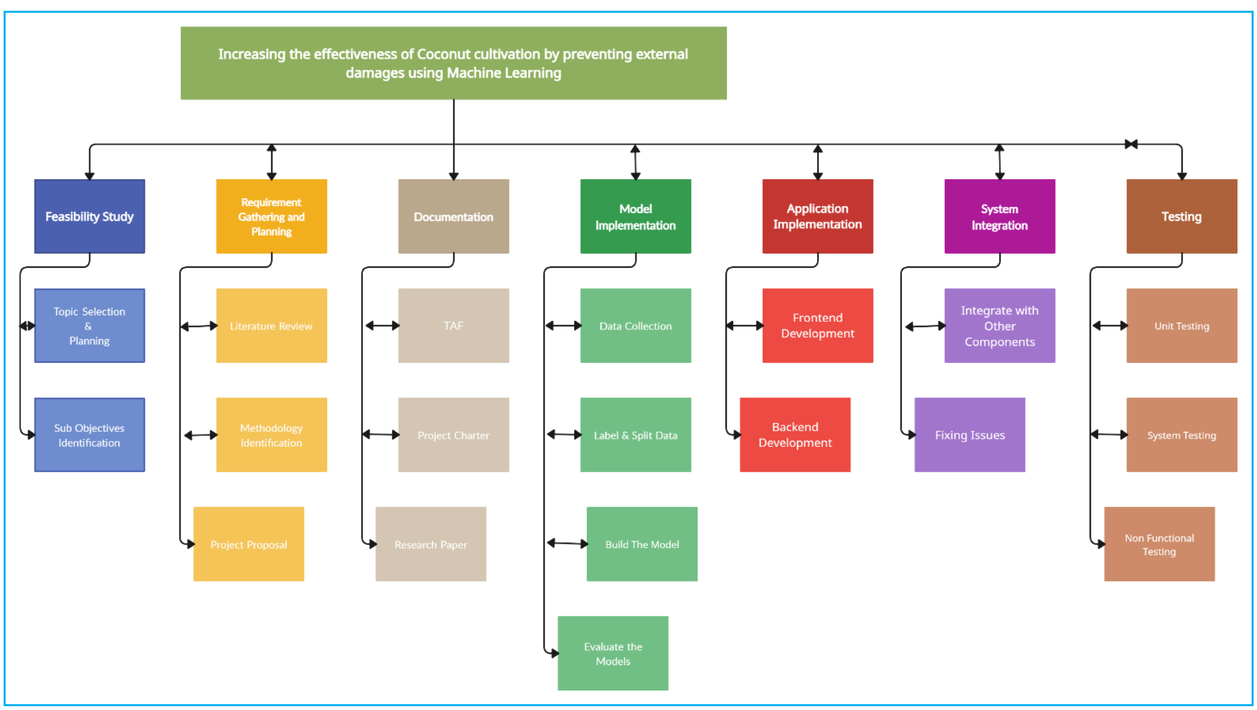


Figure 8. – Breakdown Chart

4. SOFTWARE SOLUTIONS

4.1. Functional Requirements

Accurate Detection Amidst Noise:

- The system must accurately detect macaque vocalizations amidst background noise and distinguish them from other environmental sounds.
- It should analyze audio signals in real-time to determine the presence of macaque monkeys.

Data Integration and Analysis:

- The system should process data from sound sensors, GPS sensors, and environmental sensors to identify patterns in macaque behavior.
- It must provide real-time monitoring of macaque activity, environmental conditions, and system status.

Hardware and Communication:

- All hardware components should be seamlessly integrated with the Raspberry Pi and communicate effectively using digital communication protocols.
- The system should be compatible with various environmental conditions and operate reliably outdoors.
- Efficient power management is necessary to ensure long-term operation without interruption, utilizing power-saving mechanisms and regulating voltage levels for optimal energy efficiency.

User Interface and Scalability:

- The system should provide a user-friendly interface for farmers to monitor macaque activity and access system data.
- It should be scalable to accommodate different farm sizes and configurations.
- Confirmation System Requirements

Camera Trigger Mechanism:

- The system must include a camera trigger mechanism to initiate video capture upon detecting macaque sounds or other relevant cues.

Object Detection Model:

- A robust object detection model, trained using YOLOV8, is required to process the video feed and accurately identify macaque monkeys within the captured footage.

Training Data:

- A comprehensive dataset of approximately 4400 footage samples should be collected and utilized for training the YOLOV8 object detection model, ensuring sufficient diversity and representation.
- The YOLOV8 model must be trained using 95% of the collected footage, with 5% reserved for testing and evaluation.

Implementation and Alert System:

- The trained YOLOV8 object detection model should be implemented on a Raspberry Pi board for efficient video data processing and real-time identification.
- Upon detection of macaque monkeys, the system should trigger an alarm node in Firebase and emit an audible alert through a buzzer.

Continuous Monitoring and False Alarm Management:

- The system should continue to monitor the area by capturing and analyzing video footage at regular intervals of every 10 seconds.
- If macaque monkeys are not detected after the alarm is triggered, a false alarm node should be activated in Firebase, saving the detected macaque's picture and a post-departure frame for further analysis and record-keeping.

Feature Extraction - Time domain extraction.

- Machine Learning Model - Implement a suitable machine learning algorithm or model.
- Behavior Prediction and Forecasting - Deploy the trained model to predict the macaque monkey behaviors based on their arrival patterns.
- Visual User Interface - Develop a user-friendly interface to interact with the system to obtain behavioral predictions and analysis results.
- Model Updates - Implement a mechanism to update and retrain the machine learning model periodically to accommodate changes in macaque monkey behavior patterns.

4.2. Non - Functional Requirements

- Accuracy: The system should achieve high accuracy in recognizing and classifying monkey behaviors based on their sounds to ensure reliable results.
- Real-time Responsiveness: For real-time applications, the system should respond quickly to new audio inputs and provide predictions promptly.
- Scalability: The system should be scalable to handle large volumes of macaque monkey arrivals data and accommodate behaviors in the future.
- Resource Efficiency: Optimize the system to use computational resources efficiently, especially if it's deployed on resource-constrained devices or in a real-time setting.
- Compatibility: The system should be compatible and support integration with different platforms or environments.
- Documentation and Maintainability: Provide comprehensive documentation and ensure that the codebase is maintainable and well-organized for future updates and enhancements.
- Ethical Considerations: Consider ethical aspects related to data collection, usage, and potential impact on wildlife conservation and research.

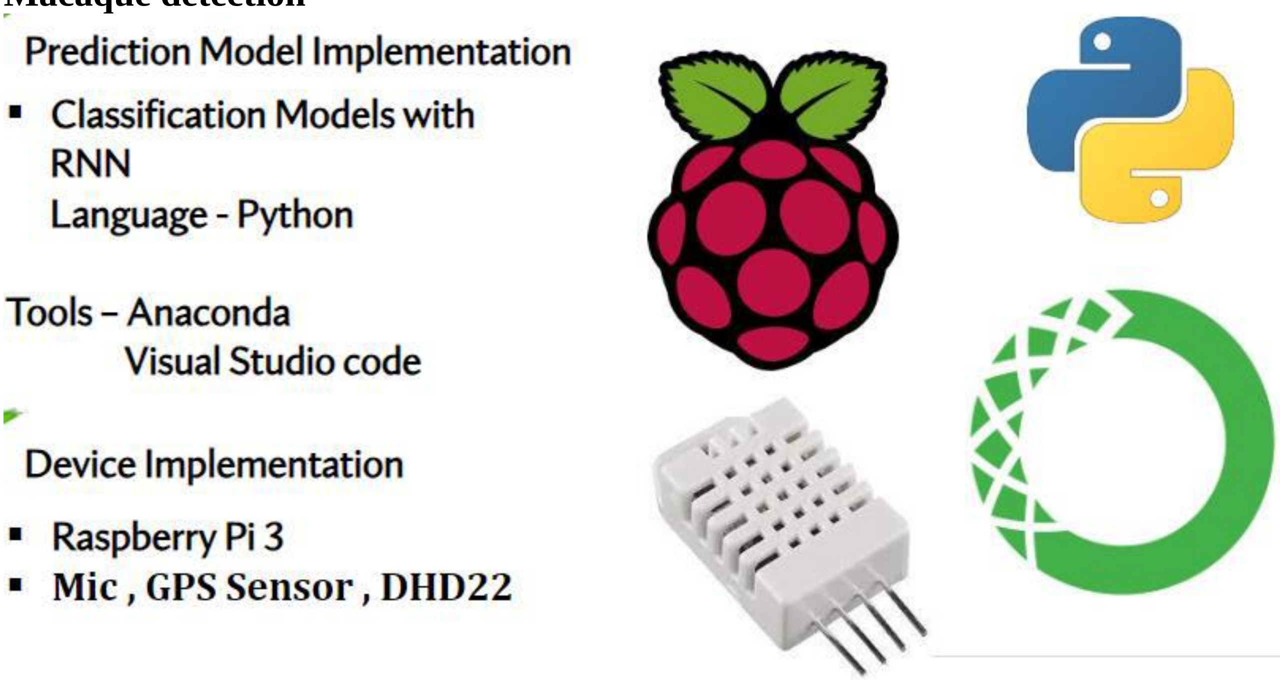
4.3. System Requirements

- Mobile device
- Internet Connection
- Database Connection

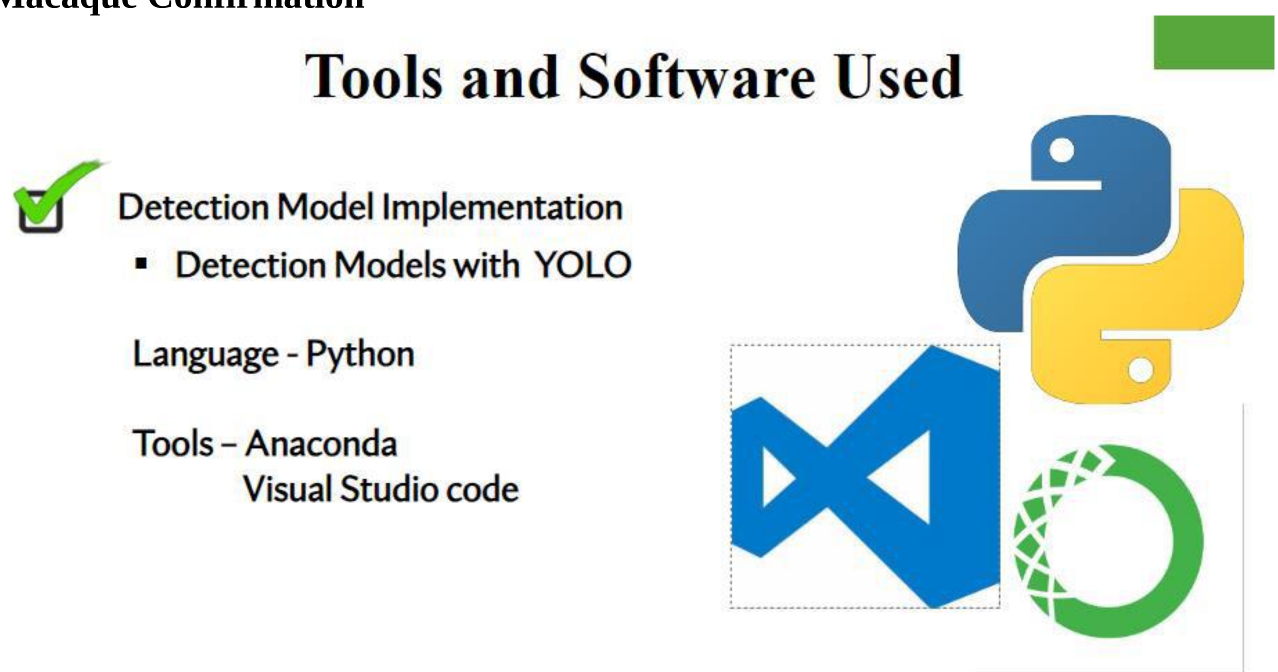
5. IMPLEMENTATION

5.1. Tools and Technologies

Macaque detection



Macaque Confirmation



Behavioral Pattern Analyzing

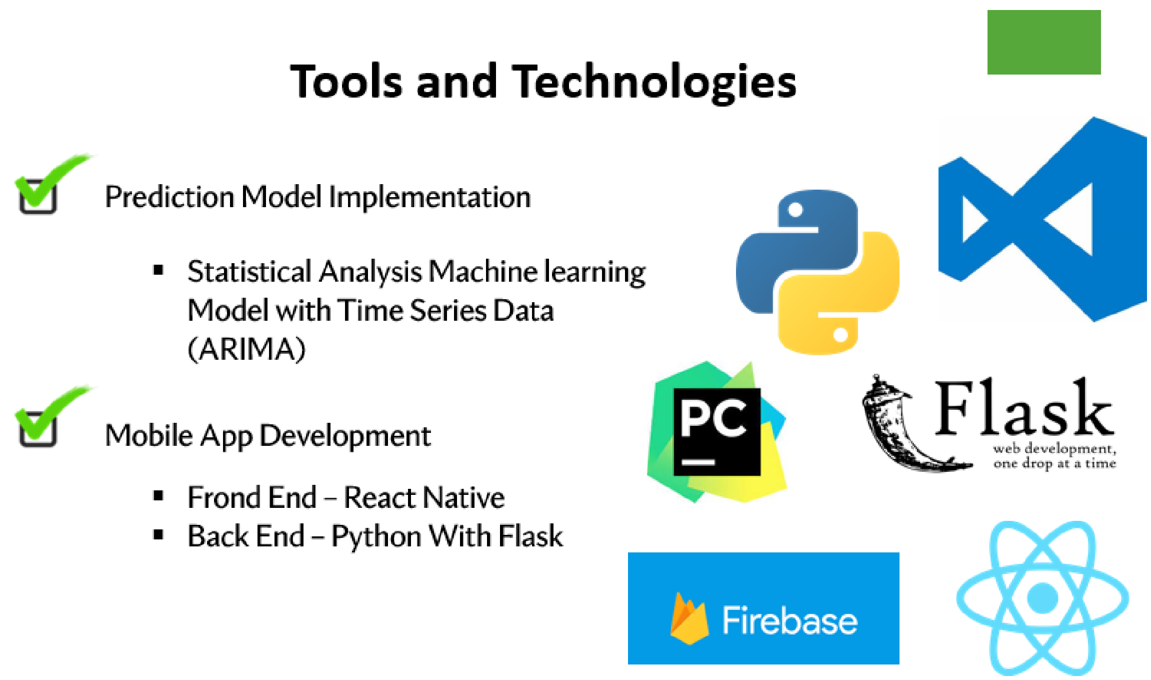


Figure 9. – Tools and Technologies

- PyCharm:

PyCharm is a powerful integrated development environment (IDE) specifically designed for Python programming. It offers a wide range of features such as code completion, debugging tools, and intelligent code analysis, making it an essential tool for Python developers to write, test, and debug their code efficiently.

- Python with Flask Backend:

Python with Flask is a popular combination for building web applications. Flask is a lightweight and flexible micro-framework that allows developers to quickly create web applications with Python. It provides essential tools for routing, request handling, and templating, making it ideal for developing backend services that power web applications.

- React Native Frontend:

React Native is a framework for building cross-platform mobile applications using JavaScript and React. It allows developers to write code once and deploy it on both iOS and Android platforms, saving time and effort. With its component-based architecture and hot reloading feature, React Native enables developers to create high-performance and visually appealing mobile apps.

- Firebase Database:

Firebase is a mobile and web application development platform that provides a variety of services, including a real-time NoSQL database. Firebase Database offers features like real-time synchronization, offline data support, and secure data storage, making it an excellent choice for building responsive and scalable applications. By integrating Firebase Database with Python, Flask, and React Native, developers can create dynamic and interactive applications with real-time data updates and seamless user experiences.

5.2. Model Implementation

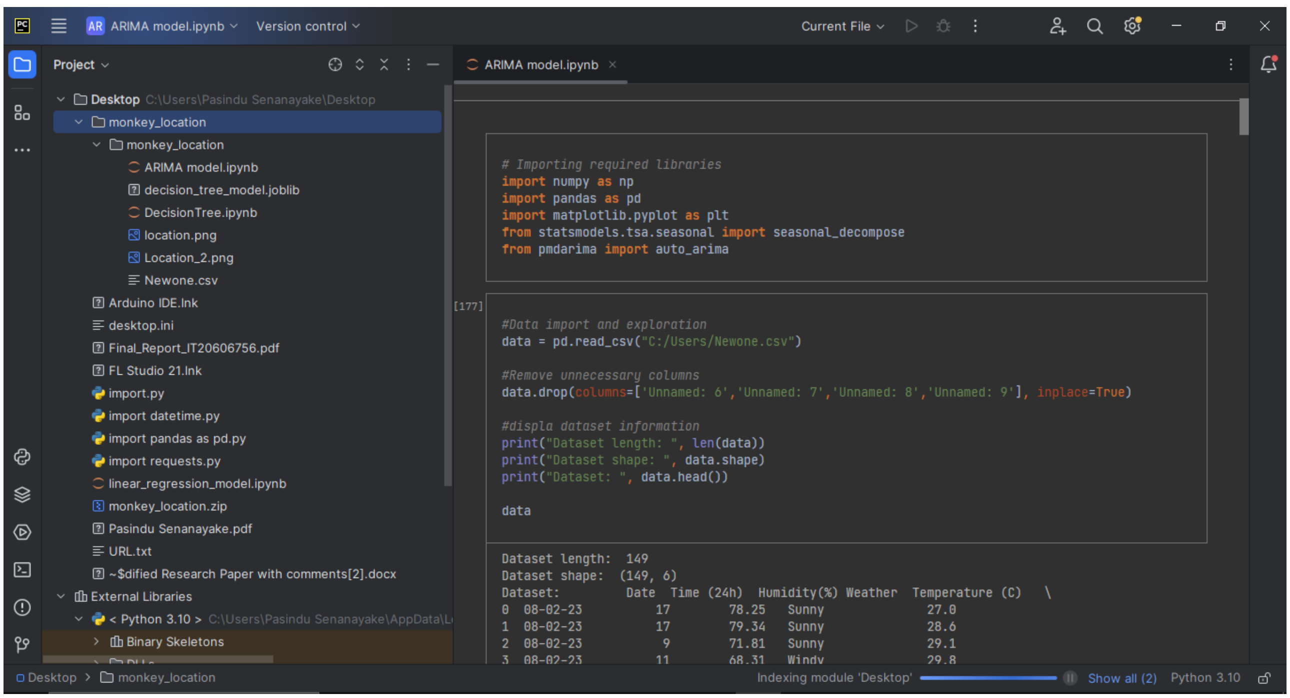


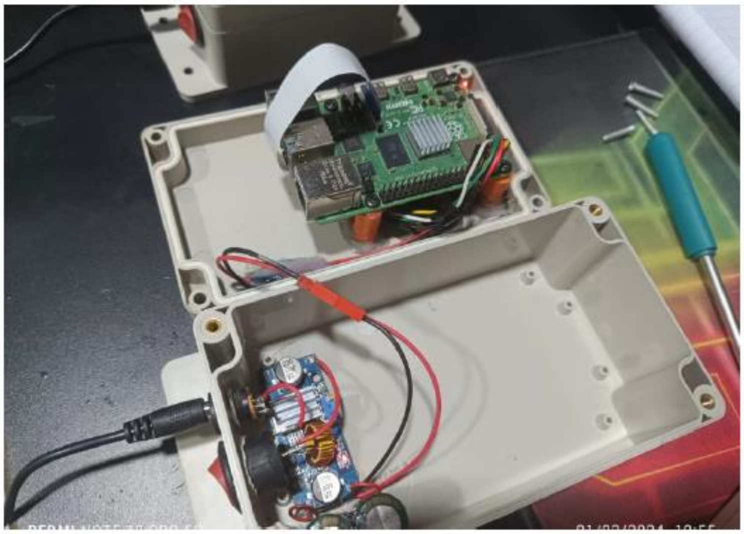
Figure 10. Model Implementations

5.3. Devices and Mobile Application Implementation

Detection device

The implemented device

Confirmation device



Mobile Application

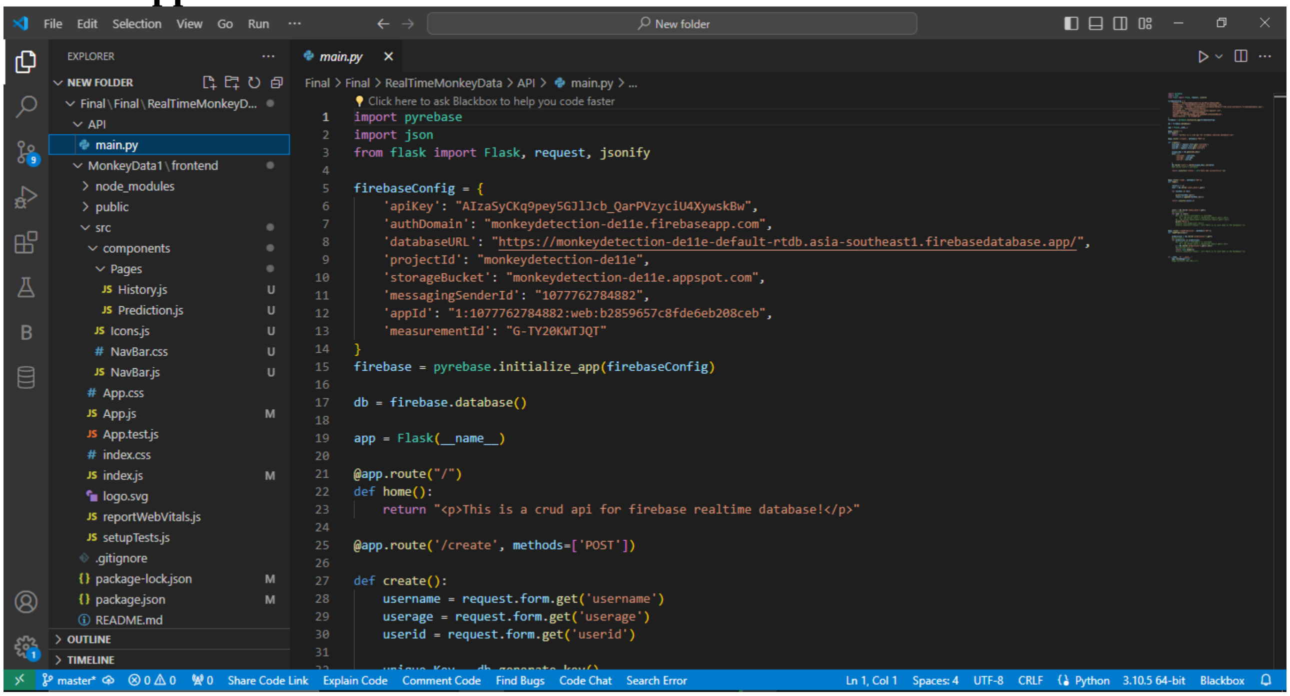


Figure 11. Backend Implementation

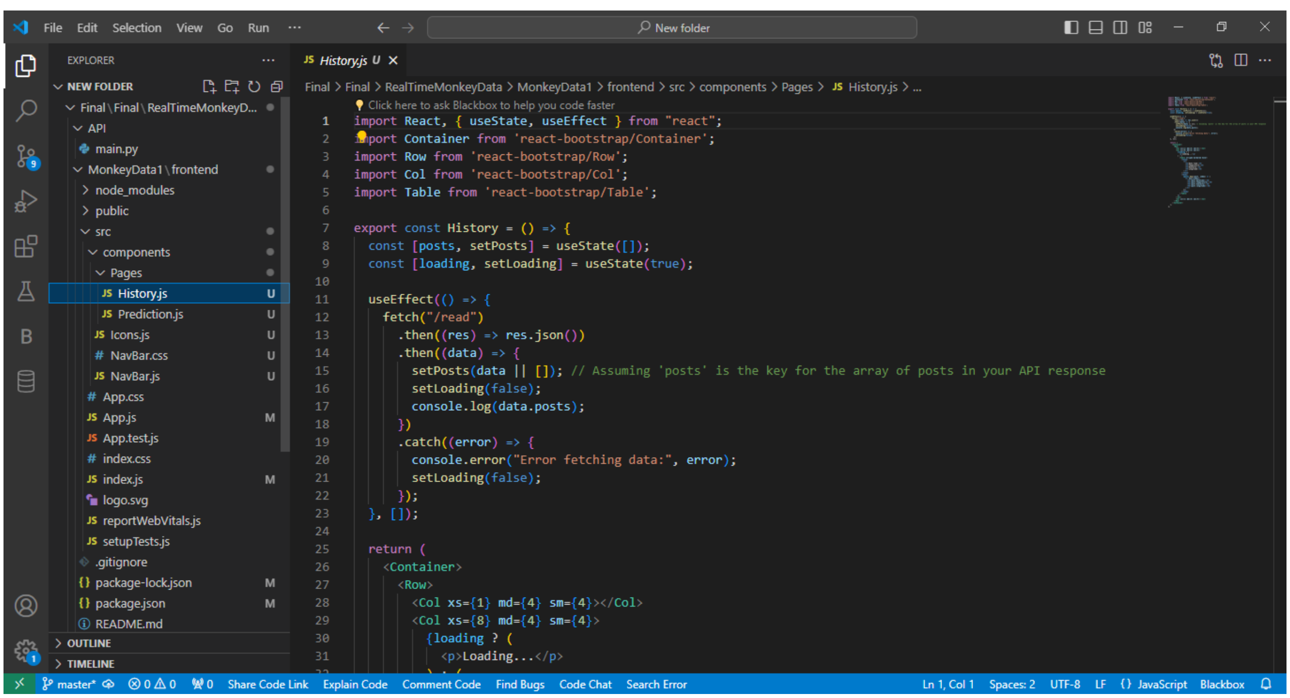


Figure 12. Frontend Implementation for History UI

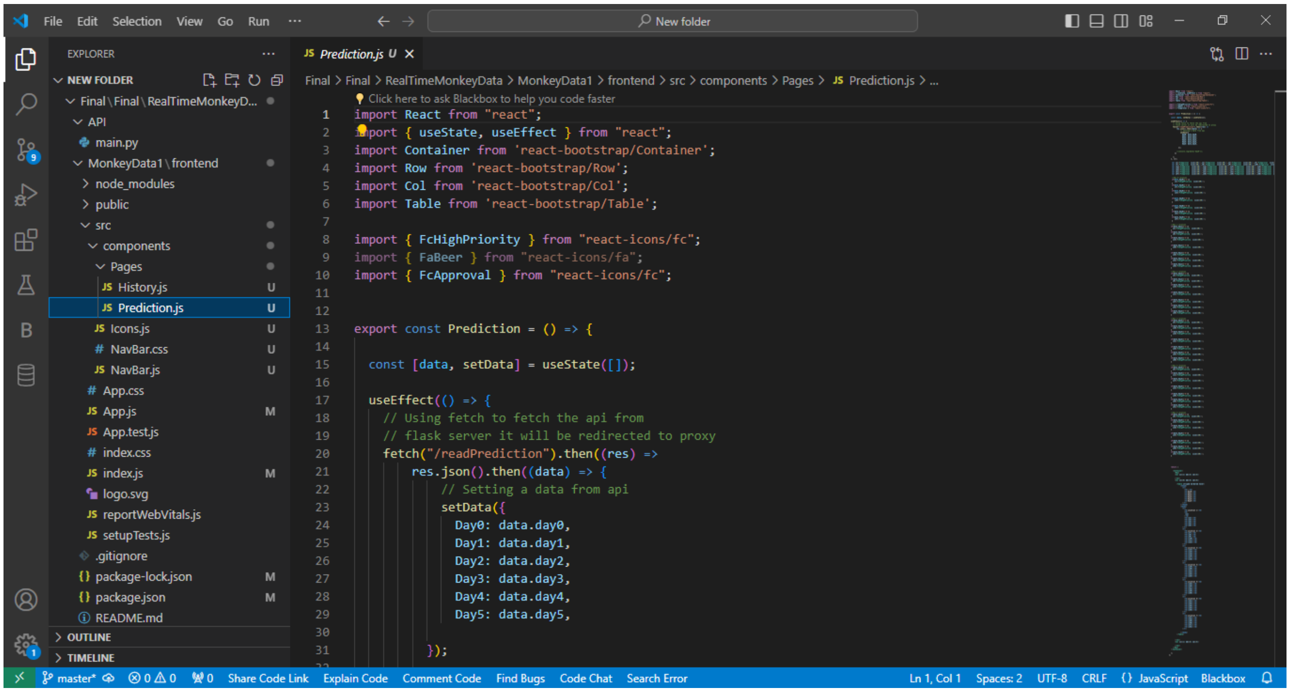


Figure 13. Frontend Implementation for Prediction UI

RESULTS AND DISCUSSION

After conducting a thorough evaluation, the Recurrent Neural Networks (RNN) was determined to be the optimal model for detecting macaque sounds while filtering out ambient noises. While the 1D Convolutional Neural Network (CNN1D) showed promising accuracy during manual testing, its implementation in the device did not yield satisfactory results. Consequently, the decision was made to opt for RNN.

In environments with high background noise levels and quieter surroundings, various macaque sounds were played, resulting in significantly different values. To address this, the sound detection threshold limit was increased in noisy backgrounds, and the recording time of the audio was reduced to 3 seconds. Subsequent tests showed improvements compared to previous iterations, indicating better performance.

The implemented system effectively detects macaque monkeys in agricultural areas through a camera trigger mechanism and real-time video input, utilizing object detection with the YOLOV8 model. It achieves high accuracy in identifying macaque presence in captured video feeds, promptly issuing alarms via Firebase and activating sound alerts with a buzzer upon detection. Efficient management of false alarms ensures continuous monitoring while minimizing unnecessary alerts. The system demonstrates robust performance across varying environmental conditions and prioritizes ethical and humane detection methods. These results underscore the system's potential to mitigate crop damage and support sustainable agriculture by providing farmers with timely notifications and surveillance capabilities in macaque-prone areas. Further refinement and field testing could enhance its effectiveness and adaptability to specific agricultural contexts.

Climate change poses a significant threat to primate species, including monkeys, apes, lemurs, lorises, and tarsiers. Studies indicate that these species will experience temperature increases higher than the global average, with some facing more than 1.5 degrees Celsius in annual average temperature for every degree of global warming. Hotspots, covering vast areas in Central America, the Amazon, southeastern Brazil, and parts of East and Southeast Asia, are expected to expose numerous species, including macaques, to the highest magnitude of climate change effects.

Under the Paris Agreement's 2-degree Celsius warming scenario, the ARIMA model predicts that a quarter of primate habitats will experience prolonged heat extremes, impacting foraging and mating activities due to dehydration and overheating. Regions such as the Brazilian Amazon, north coast of Venezuela, equatorial Africa, African east coast, and northwest coast of Madagascar are expected to be most affected.

Human activities, including habitat destruction, infrastructure development, hunting, and the illegal pet trade, exacerbate challenges faced by macaque populations, compounding the effects of climate change. Conservation efforts must consider habitat loss alongside other issues, as fixed borders of wildlife reserves may become unsuitable for primates due to temperature changes. Future primate conservation strategies should integrate predicted temperature changes with other conservation priorities to ensure the survival of these species.

After conducting a comprehensive evaluation of pretrained models for coconut pest detection, MobileNetV2 emerged as the most suitable choice due to its combination of high accuracy, minimal parameter count, and small model size. These characteristics make it ideal for deployment on mobile devices, ensuring both effectiveness and practical usability for farmers and agricultural workers. Future enhancements will focus on expanding the model's capabilities, improving accuracy, and integrating advanced technological features to create a robust and user-friendly tool. This research emphasizes the importance of selecting the right model to balance performance with efficiency, ultimately leading to better pest management and improved agricultural productivity.

6. COMMERCIALIZATION ASPECTS OF THE PRODUCT

6.1. Commercial Potential

- Market Analysis:

  Conduct thorough market research to understand the demand for agricultural pest management solutions.

  Identify target markets, such as regions with significant macaque monkey populations and reliance on agriculture.

  Analyze existing competitors and their offerings to identify unique selling points.

- Value Proposition:

  Clearly articulate the benefits of the system to potential customers, emphasizing accurate predictions, proactive pest management, and reduced crop losses.
  Highlight the user-friendly interface, real-time alerts, and data visualization capabilities that empower farmers.

- Product Positioning:

  Position the system as a comprehensive and intelligent solution that combines dataanalysis, machine learning, and predictive modeling for effective pest management.
  Differentiate the system from traditional methods by offering proactive insights and actionable recommendations.

6.2. Business Potential

- Market Demand:

  Agriculture remains a vital sector in many regions, making the demand for pest management solutions a constant requirement.
  The system caters to the demand for advanced, technology-driven tools that offer a comprehensive approach to pest management.

- App Licensing:

  Licensing Fees: Offer different tiers of licensing for the system, granting users access to its features based on their chosen plan.
  One-time Purchase: Farmers can opt for a one-time purchase of the app license, gaining access to the system's capabilities with a single payment.
  Feature Differentiation: Create tiered plans with varying features. For instance, a basic plan might provide predictive alerts, while a premium plan includes advanced data visualizations and historical trend analyses.

- Subscription Model:

  Recurring Revenue: Implement a subscription-based model where farmers pay a recurring fee to continue using the system.
  Tiered Subscription: Offer multiple subscription levels, each providing a different level of access and support.
  Benefits: Subscribers could enjoy benefits like automatic updates, priority customer support, and access to new features as they are developed.

- Pay-Per-Use Points:

  Usage-based Pricing: Introduce a pay-per-use model, where farmers are charged based on the frequency and extent of their system usage.
  Flexibility: This model accommodates users with varying needs. Farmers can pay only for the services they actively use.

Data Usage: Charge based on the amount of data processed, encouraging efficient use of the system's resources.

7. CONCLUSION

To enhance the protection of coconut crops and promote sustainability, understanding macaque monkey behavior and prevalence patterns is crucial. By leveraging machine learning algorithms and historical data analysis, researchers can identify behavioral patterns and predict macaque frequency in different regions. This knowledge empowers farmers to anticipate potential crop damage and implement proactive solutions.

Integrating machine learning algorithms with IoT sensors allows for real-time monitoring of macaque behavior and environmental factors affecting it, such as temperature changes and human activity. This information can inform the development of specialized crop protection techniques, including habitat modification, pesticide usage adjustments, or altered planting times.

Studying macaque behavior and prevalence patterns also guides conservation efforts by identifying high-risk areas where macaque-crop interactions are likely. Researchers can develop mitigation plans based on their understanding of macaque social behavior, such as habitat modification or deterrent use, to minimize crop damage.

In summary, advancing sustainable coconut crop security through integrated machine learning solutions requires a deep understanding of macaque behavior and prevalence patterns. Researchers can provide farmers with essential information for crop protection and conservation initiatives by harnessing machine learning algorithms and IoT devices.

The research aimed to develop an efficient coconut pest detection app by comparing various pretrained convolutional neural network (CNN) models, including ResNet50, VGG16, MobileNetV2, DenseNet121, and InceptionV3. While models like VGG16 and InceptionV3 exhibited high accuracy, their large parameter counts and model sizes were impractical for deployment on resource-constrained mobile devices. ResNet50 showed respectable accuracy but had limitations in computational efficiency and storage space. DenseNet121 offered a more balanced profile, but its higher prediction time made it less suitable for real-time detection scenarios. MobileNetV2 emerged as the optimal choice due to its high accuracy, low parameter count, and compact model size, making it suitable for mobile platforms with limited processing power and storage space.

The efficiency of MobileNetV2 is particularly beneficial for practical applications in agricultural fields, where timely and accurate pest detection is crucial. Future enhancements of the coconut pest detection app may involve expanding the training dataset to include a broader range of pest species, integrating advanced machine learning techniques like transfer learning and data augmentation to improve performance, and incorporating IoT devices and cloud computing capabilities for enhanced functionality, such as continuous monitoring and real-time alerts. Overall, the goal is to make advanced pest detection technology accessible and usable in real-world agricultural settings.

8. FUTURE WORK

Future research efforts should focus on analyzing data to better understand the prevalence and behavioral patterns of macaque monkeys. This could involve monitoring macaque populations in agricultural settings to identify patterns of arrival or prevalence, as well as informing farmers about regions at high risk and expected arrival periods. Additionally, to gain deeper insights into macaque social behaviors, studies should explore factors contributing to intra-specific behavioral variability and species-specific patterns of abnormal behavior, with a focus on animal welfare.

In conclusion, effective strategies for controlling macaque populations and ensuring their well-being depend on a thorough understanding of macaque behavior. Researchers can support farmers and animal welfare experts in making informed decisions by studying data on macaque behavior patterns. This collaborative effort aims to enhance the sustainability of agricultural practices while also promoting the well-being of macaques.

Future work on the coconut pest detection app will focus on several key enhancements to broaden its applicability and improve its performance. This includes expanding the app's database to include a wider variety of pests, which will involve collecting and annotating new image datasets and training models to accurately identify these additional species. To enhance detection accuracy, advanced machine learning techniques such as convolutional neural networks (CNNs), transfer learning, data augmentation, and ensemble methods will be utilized.

Integration of real-time detection capabilities, IoT devices, and cloud computing will elevate the app's technological sophistication, enabling more efficient and effective pest monitoring. Improvements in user experience will be made through the development of an intuitive interface, multilingual support, and interactive features such as tutorials and best practices.

Comprehensive field trials will be conducted to validate the app's performance in diverse agricultural conditions, while user training programs will ensure that farmers and agricultural workers can effectively utilize the app. These future enhancements aim to make the app a robust, accurate, and user-friendly tool, significantly contributing to better pest management and increased agricultural productivity.

9. REFERENCE LIST

[1] Corrine K. Lutz ; "A cross-species comparison of abnormal behavior in three species of singly-housed old world monkeys" ; Published online 2017 Oct 20. doi:10.1016/j.applanim.2017.10.010.

[2] Federica Amici, Anja Widdig, Lorenzo von Fersen, Alvaro Lopez Caicoya, Bonaventura Majolo; "Intra-specific Variation in the Social Behavior of Barbary macaques (Macaca sylvanus)"; Published - 13 October 2021; Volume 12 - 2021 | https://doi.org/10.3389/fpsyg.2021.666166.

[3] Tong Zhang, Shen-Qi Liu, Ying-Na Xia, Bo-Wen Li, Xi Wang, and Jin-Hua Li; "Aging-Related Behavioral Patterns in Tibetan Macaques"; Published online 2023 Oct 11. doi: 10.3390/biology12101325.

[4] Behavioural indicators – The macaque website; https://macaques.nc3rs.org.uk/welfare-assessment/behavioural-indicators.

[5] Benjamin Suarez-Jimenez, Amanda Hathaway, Carlos Waters, Kelli Vaughan, Stephen J. Suomi, Pamela L. Noble, Daniel S. Pine, Nathan A. Fox, And Eric E. Nelson; "Effect of Mother's Dominance Rank on Offspring Temperament in Infant Rhesus Monkeys (Macaca mulatta)" ; American Journal of Primatology 75:65–73 (2013).

[6] Darcy L Hannibal, Eliza Bliss-Moreau, Jessica Vandeleest, Brenda McCowan, and John Capitanio; "Laboratory Rhesus Macaque Social Housing and Social Changes: Implications for Research"; Published online 2016 Feb 5. doi: 10.1002/ajp.22528.

[7] Camille Testard, Sébastien Tremblay, Felipe Parodi, Ron W. DiTullio, Arianna Acevedo-Ithier, Kristin L. Gardiner, Konrad Kording, Michael L. Platt; "Neural signatures of natural behavior in socializing macaques"; Published - July 7, 2023; doi: https://doi.org/10.1101/2023.07.05.547833.

[8] Guarding crops from monkey troops: farmer-monkey interaction near a nature reserve in Guangxi, China. Wenxiu Li & Erica von Essen ; Pages 12-24 | Received 06 Apr 2020, Accepted 12 Aug 2020, Published online: 01 Sep 2020.

[9] Guarding crops from monkey troops: farmer-monkey interaction near a nature reserve in Guangxi, China. September 2020 ; Environmental Sociology.

[10] The economic impacts to commercial farms from invasive monkeys in Puerto Rico; Richard M. Engeman , José E. Laborde, Bernice U. Constantin , Stephanie Shwiff , Parker Hall , Anthony Duffiney , Freddie Luciano; Volume 29, Issue 4, April 2010, Pages 401-405.

[11] Primates on the farm – spatial patterns of human-wildlife conflict in forest-agricultural landscape mosaic in Taita Hills, Kenya; Mika Siljander a b, Toini Kuronen a, Tino Johansson a e, Martha Nzisa Munyao c d, Petri K.E. Pellikka ; Volume 117, April 2020, 102185.

[12] Extrapolating from Laboratory Behavioral Research on Non-human Primates is Unjustified Parker Crutchfield, PhD Western Michigan University Homer Stryker M.D. School of Medicine.

[13] Behavioral Profiles in Captive-Bred Cynomolgus Macaques: Towards Monkey Models of Mental Disorders? Sandrine M. J. Camus, Catherine Blois-Heulin, Qin Li, Martine Hausberger, Erwan Bezard Published: April 29, 2013

[14] [1] Export Development Board Sri Lanka "INDUSTRY CAPABILITY OF COCONUT AND COCONUT-BASED PRODUCT SECTOR IN SRI LANKA." Sri Lankan Export Development Board Sri Lanka. https://www.srilankabusiness.com/coconut/about/industry-capability.html (accessed Feb. 02, 2024).

[15] S. P Vidhanaarachchi, P.K.G.C. Akalanka, R.P.T.I. Gunasekara, H.M.U.D. Rajapaksha, N.S. Aratchige, Dilani Lunugalage, Janaka L. Wijekoon "Deep Learning-Based Surveillance System for Coconut Disease and Pest Infestation Identification" , 2021 IEEE Region 10 Conference (TENCON).

[16] Deepak Banerjee, Vinay Kukreja, Satvik Vats, Vishal Jain, Bhawna Goyal "Enhancing Accuracy of Yellowing Disease Severity Level Detection in Coconut Palms with SVM Regularization and CNN Feature Extraction" 2023 Third International Conference on Secure Cyber Computing and Communication (ICSCCC)

[17] Dhapitha Nesarajan, Lokini Kunalan, Mithun Logeswaran, Sanvitha Kasthuriarachchi, Dilani Lunugalage "Coconut Disease Prediction System Using Image Processing and Deep Learning Techniques" 2020 IEEE 4th International Conference on Image Processing, Applications and Systems (IPAS)

[18] Goodhands Sri Lanka "Damage by Coconut Caterpillar." Goodhands Sri Lanka. https://goodhands.lk/damages-by-coconut-caterpillar-opisina-arenosella/ (accessed Feb. 02, 2024).

[19] L. G. C. Vithakshana, W. G. D. M. Samankula," IoT based animal classification system using convolutional neural network", in 2020 International Research Conference on Smart Computing and Systems Engineering (SCSE), 2020

[20] Che Yong Yeo, S. A. R. Al-Haddad, and C. K. Ng, "Animal voice recognition for identification (ID) detection system," in 2011 IEEE 7th International Colloquium on Signal Processing and its Applications, 2011, pp. 198–201.

[21] A. E. Mehyadin, A. M. Abdulazeez, D. A. Hasan, and J. N. Saeed, "Birds Sound Classification Based on Machine Learning Algorithms," Asian Journal of Research in Computer Science, pp. 1– 11, Jun. 2021, doi: https://doi.org/10.9734/ajrcos/2021/v9i430227

[22] K.-H. Frommolt and K.-H. Tauchert, "Applying bioacoustic methods for long-term monitoring of a nocturnal wetland bird," Ecol. Inform., vol. 21, pp. 4–12, May 2014

[23] "Raspberry Pi Documentation," www.raspberrypi.com. https://www.raspberrypi.com/documentation/

[24] Sheik Mohammed.S, Dr.T.Sheela, Dr.T.Muthumanickam "Development of Animal-Detection System using Modified CNN Algorithm", Proceedings of the International Conference on Augmented Intelligence and Sustainable Systems (ICAISS-2022)

[25] P. Manikandan, A.Thenmozhi, G. Ramesh, T. Ravi Kiran Naidu, K. Vamsinath Reddy, K. BhanuPradeep Kumar Reddy "Crops Protection System from Animals using Arduino" 2021 3rd International Conference on Advances in Computing, Communication Control and Networking (ICACCCN)

[26] Shola Usharani, Gayathri, Rajarajeswari S, D. S. Kishore, Sivakumar Depuru "IoT based Animal Trespass Identification and Prevention System for Smart Agriculture" Proceedings of the 7th International Conference on Intelligent Computing and Control Systems (ICICCS2023)

Thank you!