Enhancing Sustainable Coconut Crop Protection through Machine Learning-Driven Integrated Strategies

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***Abstract*—The coconut industry faces challenges posed by pest attacks, particularly macaque monkeys, whiteflies, and caterpillars. This research addresses the critical need for effective mitigation strategies by introducing an integrated system for protecting coconut cultivations from pests. The study focuses on the development and implementation of a solution to detect the presence of macaque monkeys with mechanisms to humanely repel them and predict future incursions, along with identifying whitefly and caterpillar pest invasions in the early stages to protect the coconut crop. The proposed system offers a practical solution for safeguarding coconut plantations. By providing early warnings and actionable insights, this research aims to fortify the coconut industry against the detrimental impact of pests, ensuring the resilience and sustainable development of coconut cultivation. The findings derived from the implemented methodology for the detection, confirmation, prediction of macaque monkey behaviors, and identification of minuscule pests exhibit respectively 90%, 97%, 94%, and 98% accuracy levels.**

Keywords*— *Coconut Pest Control, Macaque monkey, Deep learning, CNN, Image Processing, Voice Recognition, Machine Learning, Agriculture, Pest Detection, Future Prediction, Behavior Patterns

I. INTRODUCTION

A crucial agricultural product, the coconut palm (*Cocos nucifera*) is important to the economy of many tropical regions. Coconut products, including coconut water, coconut oil, and desiccated coconut are vital resources for a variety of sectors and support international trade [1]. However, several obstacles must be overcome for coconut farming to remain sustainable, one of which is the negative effects of diseases and pests on crop quality and output.

To increase the protection of coconut farming, this research focuses on integrating cutting-edge machine-learning techniques with conventional agricultural methods. With its ability to provide predictive models, early detection systems, and intervention tactics, machine learning presents a viable path toward enhancing the control of pests and diseases. Our goal is to create a comprehensive and efficient strategy that minimizes the ecological imprint of coconut farming while optimizing crop output and quality by utilizing data-driven decision-making.

A multitude of pests that represent a danger to the health of commercial crops offer severe obstacles to agricultural output, especially in tropical settings [2]. Of them, whiteflies, macaque monkeys, and coconut caterpillars stand out as the most prominent threats that seriously affect coconut palms in Sri Lanka [3] - [4]. Because of the urgency with which these problems must be resolved, creative solutions combining agricultural knowledge and technological know-how are required to develop sustainable and efficient pest management plans.

Our study attempts to create a pest control system by utilizing state-of-the-art technology. The fundamental component of our novel strategy is the combination of sensors with the deployment of a mobile application. The system is designed to provide proactive measures against the damages caused by whiteflies and coconut caterpillars, while also emphasizing early detection, accurate identification, investigation into their behavior, and strategic rejection of macaque monkeys.

Sensors in our integrated system detect macaque monkeys in coconut farms using image recognition. These sensors provide real-time information, reducing false alarms and improving repulsion effectiveness. Non-invasive, unpleasant sound techniques encourage macaque aversion, encouraging them to seek alternative feeding areas.

Our approach uses pattern prediction algorithms to identify Macaque monkeys early on, analyzing coconut tree characteristics. The mobile app notifies farmers, facilitating prompt action and tailored pest management solutions. This sustainable approach minimizes ecosystem damage.

This study aims to enhance coconut farmers' sustainability by providing them with the necessary information and resources for sustainable crop preservation. Integrating ecological factors and machine learning ensures the sustained prosperity of countries that rely on coconuts in the agriculture industry.

II. LITERATURE REVIEW

Recent studies explored different animal classification strategies. Acoustic and visual methods are commonly employed for classification purposes. Vithakshana L. G. C, Samankula W. G. D. M [4] proposed an IoT-based animal classification system using a convolutional neural network. The hardware implementation was designed to collect the data. In the system, they got audio clips for 10 species. audio clips were preprocessed using the Mel-frequency Cepstral Coefficient (MFCC). A CNN architecture based on TensorFlow was used for the training process. 400 sound clips were used including 40 per each animal species. Audios are formatted using Audacity.

Che Yong Yeo, S. A. R. Al-Haddad, and C. K. Ng [5] present an animal identification system leveraging voice pattern recognition. It integrates zero-cross-rate (ZCR), Mel-Frequency Cepstral Coefficients, and Dynamic Time Warping (DTW) algorithms. ZCR detects voice endpoints, filtering out silence, while MFCC extracts compact, less redundant voice features. DTW handles voice pattern classification, finding the optimal path between input and reference voices in the database. Results affirm the system's effectiveness, showcasing its ability to accurately identify animals by their distinct vocal patterns.

Authors of [6] proposed a bird classifier system. They used bird audio recordings and bird species classification. They used the Mel-frequency cepstral coefficient (MFCC) and tested it through different algorithms, namely Naïve Bayes, J4.8, and Multilayer perceptron (MLP), to classify bird species. J4.8 has the highest accuracy (78.40%). K.H. Frommolt and K.H. Tauchert [7] researched birds using the bioacoustics monitoring system. The study presents two convolutional neural network approaches for bird call detection in audio recordings.

Sheik Mohammed, Dr. T. Sheela, and Dr. T. Muthumanickam [10] introduce an animal-detection system in their research. This system incorporates a modified CNN algorithm alongside thermal imaging, PIR sensors, GSM modules, and Raspberry Pi. By amalgamating these technologies, the system enables real-time monitoring and alerts, offering a comprehensive solution to counteract crop damage inflicted by animal encroachment in agricultural fields. This innovative approach represents a significant stride in safeguarding farmers' livelihoods and mitigating economic losses due to wildlife encroachment.

Addressing the challenge of farmers' inability to maintain constant oversight over their fields, Manikandan et al. [11] present a solution to mitigate crop damage caused by animal intrusion. Their innovative system, integrating Arduino, PIR motion sensor, Buzzer, LED lights, and GSM module, enables real-time detection and response. Upon detecting an animal, the system activates the Arduino, emits a buzzer sound, flashes LED lights, and promptly alerts the farmer within 10 seconds. This rapid response mechanism offers effective crop protection, ensuring minimal yield loss.

The study by Shola Usharani et al. [12] addresses the pressing issue of animal trespassing in Indian farmlands, causing significant losses to farmers, particularly those reliant on farming for income. Existing methods, such as government compensation, frequently fail to provide sufficient recompense for losses. Traditional deterrents like crackers and electrical fences are inefficient and harmful to animals. Leveraging IoT technology, the proposed system offers a cost-effective solution. Integrating Arduino, PIR, Ultrasonic sensors, GSM, and ESP32 Camera, the system detects animal intrusion, alerts farmers, and provides real-time field images. This innovative approach promises efficient protection, minimizing losses while ensuring animal welfare.

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Some information about the issue of applying data analysis to forecast monkey incursion on cultivated fields depending on environmental factors can be found in the search results. The literature, however, is scant and does not specifically address the subject. The interactions between farmers and monkeys, the financial effects of monkey damage to commercial agriculture, and the geographical patterns of conflict between humans and wildlife in forest-agricultural environments are the main topics of the studies. One study on the relationship between farmers and monkeys in Guangxi, China, for example, relied on farmers' and conservation workers' accounts of monkey crop raiding [13] – [14]. The financial consequences of monkey damage on Puerto Rico's commercial agriculture were measured in a different study. For example, the amount of crops lost by commercial farmers in southwest Puerto Rico between 2002 and 2006 because of monkey damage. Farmers moved from growing fruits and vegetables to hay and pastureland to prevent damage from monkeys, which reduced the value of losses [15].

Taita Hills, Kenya, is home to a variety of primate species, including Old World [16] monkeys, whose spatial patterns reveal a complex interaction in various environments, highlighting the diverse range of human-monkey interactions in the World. Research on macaques combines behavioral observations with data analysis to understand environmental elements like habitat, social structure, and resource availability [13]. This study examines macaque species' behavior in old-world monkey species and captive-bred cynomolgus [14] macaques. Research on Japanese macaques has revealed their behavior in both provisioned and nonprovisional wild environments [17]-[18]. A survey of literature on the relationship between environmental circumstances and monkey behavior can provide valuable insights into the behavior of these animals in various settings.

The literature provides important insights into the relationship between farmers and monkeys as well as the financial effects of monkey damage on commercial agriculture, even though it does not specifically address the use of data analysis to predict monkey attacks on cultivation fields based on environmental conditions. Additional relevant information might be found in future studies that focus especially on the application of data analysis for this purpose.

Authors of [21] proposed deep neural networks and image processing-based systems for identifying the Weligama coconut leaf wilt disease and coconut caterpillar infections. The method proposed has been performed with accuracies between 80% and 97% [21]. By using Google Maps and Expo, the proposed system shares real-time notifications among the stakeholders and researchers.

Banerjee et al. [22] proposed a system for identifying the coconut yellowing disease using a Support Vector Machine and CNN approach with an 88.02% accuracy rate. The proposed system performance had been evaluated using precision, recall, f1-Score, support, and accuracy rates. With the same approach, Natarajan et al. [23] proposed a system for identifying more than one disease. The system has compared EEfficientNetB0, ResNet50, and VGG 16 using average accuracy rates.

III. METHODOLOGY

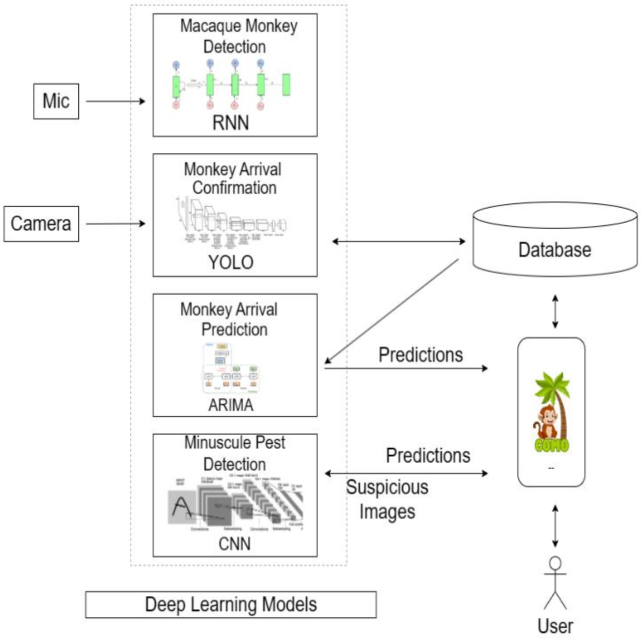

Fig. 1. Overall system diagram of the proposed solution

A. Macaque Monkey Detection

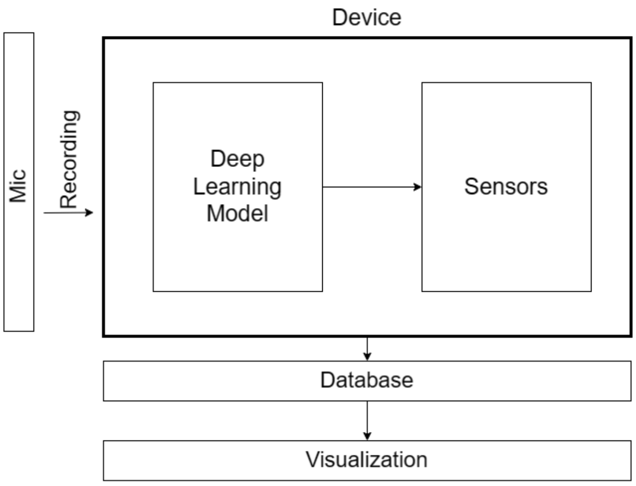

Fig. 2. System diagram of the macaque monkey detection

For the detection of the presence of macaque monkeys, the proposed device monitors the sounds of the environment, for 24 hours continuously. Natural environment noise is filtered by the volume threshold limit.

Detection is initiated when sounds surpassing the 30 thresholds are identified. The system continuously records 4-second audio clips and checks whether the recorded sound is macaque sound. If the system identifies the recorded sound belongs to a macaque monkey, along with the sound clip, the system also captures supplementary information including temperature, humidity, device ID, and location. The result of the audio, temperature, and contextual data are then stored in the cloud for subsequent confirmation processes.

To check whether a detected sound corresponds to a macaque monkey, a sound classification algorithm, specifically Recurrent Neural Networks (RNN) [9], is employed. The RNN algorithm is utilized for its effectiveness in distinguishing macaque monkey sounds from ambient noise. For the data set around 2100 audio data were collected including 1050 macaque sounds and 1050 ambient noises [27]. In the preprocessing stage, 75% of the entire data is separated into training data and 25% as test data. The selected dataset provides the foundation for training and validating the sound classification algorithm, thereby enhancing the reliability and accuracy of the overall system.

B. Macaque Monkey Arrival Confirmation

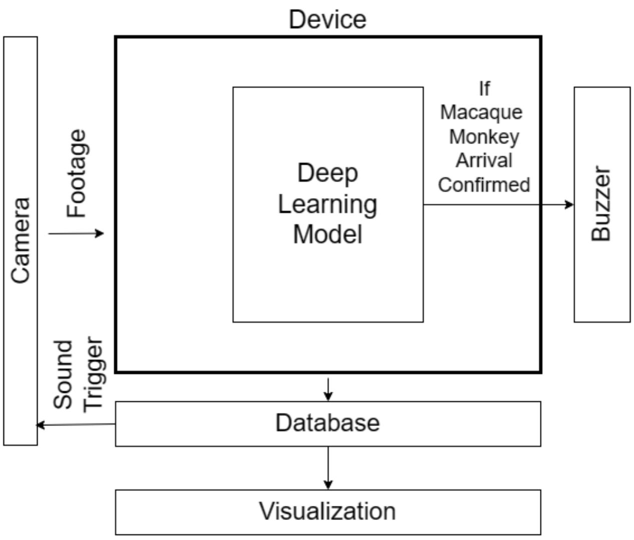

Fig. 3. System diagram of the macaque monkey arrival confirmation

To confirm the arrival of macaque monkeys after detection, the system utilizes a camera trigger mechanism coupled with real-time video input and object detection. Upon detecting macaque sounds, the camera is triggered to capture a video feed, which is then processed by an object detection model trained using YOLOV8. For the data set around 4400 footage were collected [26]. The YOLOV8 object detection model was trained using 95% of the collected footage. The remaining 5% of the collected footage was used to test the performance of the trained model. This model, implemented on a Raspberry Pi board, effectively identifies macaque monkeys within the video feed.

Upon detection of macaque monkeys by the model, the system triggers an alarm node in Firebase, and a buzzer is triggered to emit a sound alert signaling their presence.

Subsequently, the system continues to monitor the area by capturing and analyzing video footage every 10 seconds. If the monkeys are not detected thereafter, indicating their departure due to the alarm, a false alarm node is activated in Firebase. This includes saving the detected macaque monkey's picture and a post-departure frame picture.

C. Macaque Monkey Prevalence and Behaviour Patterns Identification

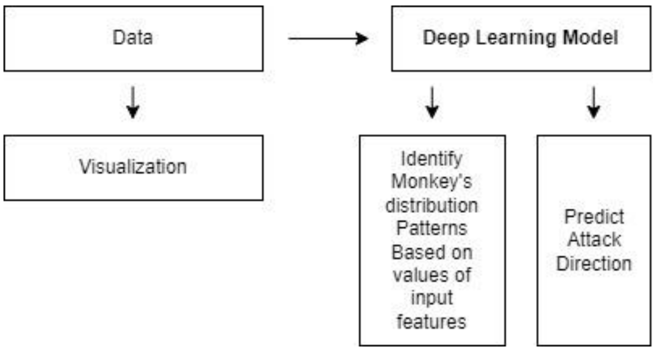

Fig. 4. System diagram of the future arrival of macaque monkey prediction

The implemented system's objective is to forecast the macaque's behavioral patterns and to predict future arrivals by using data from the above two components. Future arrival patterns of Macaque monkeys are predicted for the farmer through an analysis of their arrival patterns, an understanding of the effects of environmental factors, and other factors that influence them [13]-[14].

All the data that was identified as belonging to a Macaque monkey was used to create the module. During data preprocessing, roughly 900 data points are divided into 80% training data and 20% validation data. A statistical analysis technique used for time series forecasting is the Autoregressive Integrated Moving Average (ARIMA) model [25]. Auto-Regressive (AR) terms, Integration (I) or differencing terms, and Moving Average (MA) terms are its three main constituents. The AR portion creates equation terms using historical data points; the I portion uses differencing to account for data trends; and the MA portion handles error or noise terms using historical data points. These elements work together to create the AR-I-MA model, which enables time series data analysis and prediction. When data is gathered regularly and shows patterns rather than random occurrences, ARIMA models are useful for predicting future trends based on historical data.

To obtain more accurate predictions, feature extraction is used to identify the data features of the data collection. There, the temperature, humidity, and ambient conditions were confirmed, along with the time of their arrival [18]-[16].

It has also been investigated how the presence or absence of the crop at the time affects it, with a focus on other factors influencing macaque monkey arrival. There may be a pattern in their attendance, which has been attempted to be found by analyzing the data obtained over time [19].

The entire system is based on training and validating algorithms, as well as increasing reliability and accuracy.

D. Minuscule Pest Detection

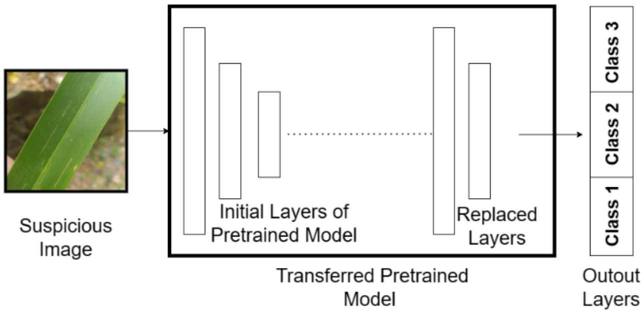

Fig. 5. System diagram of the minuscule pest detection

The proposed system offers a comprehensive approach to address not only the primary pest issue, which is the macaque monkey but also provides effective solutions for other pest-related concerns, particularly those impacting coconut leaves. To enhance the accuracy of pest detection, image classification models were employed, focusing on identifying White Fly Infection (WFI) on the front surface and Coconut Caterpillar Infection (CCI) on the lower surface of coconut leaves.

In this research, a dataset comprising 529 images belonging to WFI, CCI, and Not Infected classes underwent meticulous data preprocessing, including division into training (80%) and validation (20%) sets.

During the normalization phase, pixel values were appropriately scaled by dividing them by 255, thereby bringing the normalized values within the standardized range of 0 to 1. To select the optimal pre-trained model for minuscule pest detection, five pre-trained Convolutional Neural Network (CNN) architectures which are ResNet50, VGG16, MobileNetV2, DenseNet121, and InceptionV3 were compared. These architectures leveraged ImageNet weights and employed average pooling as a standard practice. During the compilation phase the SGD optimizer because of the ability to handle noisy data.

Evaluation of the models was conducted using the Average Accuracy Rate and size of the model. The primary architecture of all pre-trained models comprised convolutional layers, pooling layers, and fully connected layers [24].

IV. RESULTS AND DISCUSSION

A. Macaque Monkey Detection

Implemented system for the detection of macaque monkeys through macaque sounds, Recurrent Neural Networks (RNN) [9] model was implemented on the Raspberry Pi board.

TABLE I. MODEL COMPARISON FOR MACAQUE MONKEY DETECTION THROUGH AUDIO ANALYSIS

No	Model	Avg. Accuracy
1	RNN(LSTM)	0.90
2	CNN1D	0.94
3	Transformer	0.82

For prediction, after a comprehensive assessment, the Recurrent Neural Networks was used as the optimal model for the detection of the macaque sounds by filtering the ambient noises. While the 1D Convolutional Neural Network (CNN1D) displayed good accuracy in manual testing, CNN1D implementation in the device did not display good results. Consequently, RNN was chosen. In the highly noisy background and calm environments, different macaque sounds played and resulted in values differing in a wide range. In the noisy background, the sound detection threshold limit increased, and the recording time of the audio was decreased to 3 seconds and see the results. The results were better than the previous one.

B. *Macaque Monkey Arrival Confirmation*

TABLE II. TESTING ACCURACY FOR MACAQUE MONKEY ARRIVAL CONFIRMATION

Epoch No.	Testing Accuracy	Epoch No.	Testing Accuracy
1	0.78	6	0.81
2	0.80	7	0.84
3	0.79	8	0.86
4	0.82	9	0.90
5	0.85	10	0.89
Average Accuracy		**0.83**	

YOLOV8 was implemented for confirmation of the macaque monkey through video footage. Table 3 provides the testing accuracy for all 10 times the 10 epochs. All the time, the inputs, and the split for all the training, validation, and testing are random. The experimental results are taken into consideration because of the accuracy variations. The percentage values are rounded off to the nearest integer. The average value will be 83%, and the maximum and minimum will be 90% and 78% based on the detection.

C. *Macaque Monkey Prevalence and Behaviour Patterns Identification*

TABLE III. COMPARISON OF TIME SERIES FORECASTING MODELS FOR THE PREDICTION OF MACAQUE MONKEY ARRIVALS

No.	Model	Mean Squared Error
1	ARIMA	1.23
2	LSTM	1.41

TABLE IV. OTHER PREDICTIVE MODELS COMPARISON

No.	Model	Avg. Accuracy
1	Decision Tree	0.60
2	Random Forest	0.56

The aim was to select the most accurate model by evaluating several models. A comparison was made between average accuracy and mean squared error (MSE) values (Table 4). The MSE of approximately 1.239 indicates that, on average, the ARIMA model's predictions are around 1.239 units away from the actual values. This indicates a relatively small average error and good performance of the model.

Data analysis reveals interesting patterns of incidence and behavior in macaque monkey communities. According to our research, a few variables, such as climate change, natural humidity, human activities, and the suitability of the macaque's environment affect the prevalence of macaques. Climate change is altering macaque habitats, pushing them beyond thermal thresholds and potentially changing species distributions. This environmental shift is driving some macaque monkey species to spend more time on the ground, impacting their behavior and social structures. Human activities, such as habitat destruction and infrastructure development, further compound the challenges faced by macaque populations.

By using the ARIMA model to analyze historical data and make future predictions, we were able to better understand these complex interactions and macaque populations in the face of environmental change and human impacts.

D. *Minuscule Pest Detection*

TABLE V. PRETRAINED MODEL COMPARISON FOR MINUSCULE PEST DETECTION

No	**Pretrained Model Performance**				
	Pretrained Model	***Avg. Accuracy***	***Total Parameters***	***Avg Pred. Time(s)***	***Size (MB)***
1	ResNet50	0.62	24112513	1.2	91.92
2	VGG16	0.98	14846273	1.0	56.63
3	MobileNetV2	0.98	2652226	1.2	10.12
4	DenseNet121	0.78	7300161	3.2	27.85
5	InceptionV3	0.98	22327585	2.4	85.17

In the development of the mobile application, a meticulous evaluation was conducted among five pre-trained models to identify the optimal choice. The divergence in accuracy across these models for the same dataset stems from the inherent variances in their architectural complexities and task-specific capabilities. Each pre-trained model brings a unique set of features and optimizations, influencing its performance on the given dataset.

Following a thorough analysis, MobileNet emerged as the optimal pre-trained model, striking a balance between model size, total number of parameters, average prediction time, and accuracy. The selection of MobileNet was driven by a strategic comparison that considered both the efficiency of the model and its ability to deliver accurate results. This nuanced approach ensures that the mobile application benefits from a pre-trained model that not only meets the computational constraints inherent in mobile devices but also excels in accurately addressing the specific tasks associated with pest detection on coconut leaves.

In essence, the choice of MobileNet reflects a careful consideration of the trade-offs between model complexity and performance, aligning seamlessly with the objectives of the mobile application for effective pest management.

V. CONCLUSION AND FUTURE WORK

This paper identified coconut cultivation pests using ANN, CNN, ARIMA, and YOLO models with an overall accuracy between 88% and 99%. The proposed system consists of a mobile application for users to connect with hardware devices. Other than identifying Macaque monkeys, whiteflies, and coconut caterpillars, the mobile application provides predictions regarding future pest attacks. In the future, the system can be expanded by identifying other major pests related to coconut cultivation.

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