

AI Based System for Animal Detection and Classification

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Abstract—This paper presents an AI-based animal detection and classification system designed for real-time monitoring applications. The proposed system utilizes Raspberry Pi 5 integrated with a camera module, microphone sensor, PIR motion sensor, and buzzer for detecting and classifying wild, domestic, and farm animals. Image classification is performed using CNN and MobileNetV2 models, while audio analysis is carried out using YAMNet and MFCC feature extraction techniques. A custom dataset of animal images and sounds was used for training and testing. Experimental results demonstrated an overall classification accuracy of 83.33%, with successful real-time detection and alert generation. The developed system provides a low-cost, energy-efficient, and intelligent solution suitable for wildlife monitoring, smart agriculture, and rural safety applications.

Index Terms—Animal Detection, Raspberry Pi, CNN, MobileNetV2, YAMNet, MFCC, Edge AI.

I. INTRODUCTION

Animal intrusion in agricultural fields, forest-border areas, and rural regions has become a major concern due to crop damage, property loss, road accidents, and potential threats to human safety. Traditional monitoring methods rely heavily on human supervision, which is time-consuming, labor-intensive, and often ineffective in large or remote areas. Therefore, there is a growing need for intelligent and automated systems capable of continuously monitoring animal activity and providing timely alerts.

Recent advancements in Artificial Intelligence (AI), Deep Learning, Computer Vision, and Embedded Systems have enabled the development of smart monitoring solutions that can automatically detect and classify animals in real time. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated significant success in image classification and object recognition tasks. Similarly, audio-based classification techniques can be used to identify animals through their vocalizations, improving detection reliability under challenging environmental conditions.

In this work, an AI-based animal detection and classification system is proposed using Raspberry Pi 5 as the embedded processing platform. The system integrates a camera module, microphone sensor, PIR motion sensor, buzzer, and display unit to perform real-time monitoring. The PIR sensor detects movement and activates image and audio acquisition, thereby reducing unnecessary processing and power consumption.

The captured images are analyzed using CNN and MobileNetV2 models, while audio signals are processed using MFCC feature extraction and YAMNet-based sound classification techniques. The trained models are deployed on Raspberry Pi 5 using ONNX Runtime for efficient real-time inference. Whenever an animal is detected, the system displays the classification result and generates an alert through a buzzer.

The proposed system provides a low-cost, energy-efficient, and intelligent solution for detecting wild, domestic, and farm animals. The developed system can be effectively applied in wildlife monitoring, smart agriculture, crop protection, rural safety systems, and remote surveillance applications.

II. LITERATURE REVIEW

Several researchers have proposed various techniques for animal detection, monitoring, and classification using deep learning, computer vision, and embedded systems.

[1] Mai Ibraheem *et al.* developed an animal species detection system for embedded devices using YOLOv2 with Deformable Convolutional Layers (DCL). The proposed system achieved an mAP of 85.5

[2] J. Chappidi and D. Meena proposed a wildlife animal detection system based on cascaded YOLOv8 with adaptive preprocessing and feature extraction techniques. The system achieved high detection accuracy and improved robustness under varying environmental conditions.

[3] R. Sato *et al.* presented an energy-efficient wild animal detection system using MobileNet-v2 and PIR sensor tuning techniques. Their method achieved detection accuracies between 94

[4] Azraa Vally *et al.* introduced a multimodal sensor platform for remote animal motion capture in wildlife environments. The system utilized sensor fusion techniques for motion tracking and behavioral analysis of animals in natural habitats.

[5] Mai Ibraheem *et al.* proposed the MCFP-YOLO animal species detector for embedded systems. The method employed motion-compensated frame processing and parallel computation to achieve efficient real-time wildlife detection on resource-constrained platforms.

[6] Mindaugas Knyva *et al.* developed an IoT-based wildlife detection system using thermal imaging and sensor fusion

techniques. The system was designed to prevent animal-related road accidents and support environmental monitoring applications.

[7] Natarajan B *et al.* proposed a hybrid deep learning framework combining VGG-19 and Bi-LSTM networks for animal activity detection and alert generation. The proposed model achieved approximately 98

[8] J.P. Dominguez-Morales *et al.* evaluated embedded neural network controllers for wildlife monitoring applications. Their work demonstrated that edge AI devices can perform animal behavior classification with high accuracy while maintaining low power consumption.

A. Research Gap

From the literature survey, it is observed that most existing systems focus primarily on image-based detection, thermal imaging, motion sensing, or animal activity recognition. Many approaches require high computational resources, expensive hardware, or are limited to specific animal categories. Furthermore, only a few systems combine both image and audio analysis for real-time animal classification on low-cost embedded platforms.

Therefore, this work proposes an AI-Based Animal Detection and Classification System using Raspberry Pi 5, integrating image processing, audio analysis, motion sensing, and embedded AI techniques. The proposed system utilizes CNN, MobileNetV2, YAMNet, and MFCC-based feature extraction to provide accurate and efficient real-time animal detection and classification suitable for wildlife monitoring, smart agriculture, and rural safety applications.

III. METHODOLOGY

The proposed AI-based animal detection and classification system is designed to identify wild, domestic, and farm animals in real time using image and audio analysis. The system is built around a Raspberry Pi 5, which acts as the central processing unit and controls all sensing, processing, and output operations.

The camera module captures real-time images, while the microphone records environmental and animal sounds. A PIR motion sensor continuously monitors the surroundings and activates image and audio acquisition when motion is detected. This motion-triggered operation helps reduce unnecessary processing and improves energy efficiency.

The captured image and audio data are processed by the Raspberry Pi using deep learning models for animal classification. Image classification is performed using CNN and MobileNetV2-based models, while audio analysis is carried out using MFCC feature extraction and YAMNet-based sound classification techniques.

The trained models and collected data are stored in the storage unit for real-time inference and future analysis. After successful animal detection, the system generates outputs through connected devices. The detected animal information and confidence score are displayed on the monitor, while

the buzzer generates an alert signal whenever an animal is identified.

The built-in Wi-Fi functionality of Raspberry Pi 5 enables remote monitoring and system access through tools such as PuTTY and VNC Viewer. The power supply unit provides the required operating voltage to all system components and ensures reliable operation.

The proposed system provides a low-cost, energy-efficient, and intelligent solution for real-time animal detection and classification, making it suitable for wildlife monitoring, smart agriculture, rural safety systems, and remote surveillance applications.

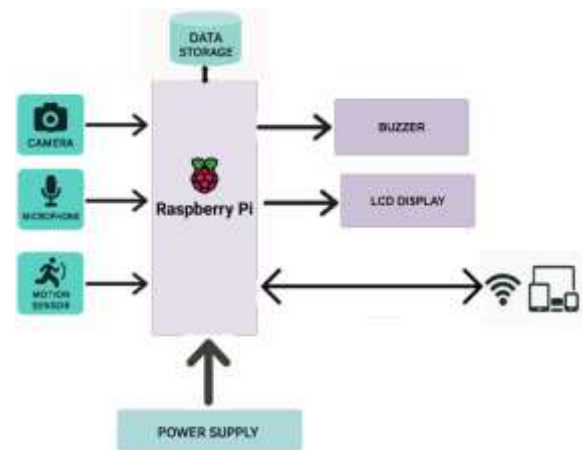


Fig. 1. Proposed AI-Based Animal Detection and Classification System

The overall working procedure of the proposed system is illustrated in Fig. 2. The system combines motion sensing, image acquisition, audio analysis, and deep learning techniques to perform real-time animal detection and classification.

Initially, the Raspberry Pi 5 initializes all connected hardware components and loads the trained AI models into memory. The PIR motion sensor continuously monitors the surrounding environment for movement. Whenever motion is detected, the camera and microphone are activated to capture image and audio data.

The captured image is preprocessed using resizing, normalization, and noise reduction techniques before being supplied to the classification model. Similarly, the captured audio signal is filtered and converted into MFCC features to extract important sound characteristics.

The processed image data is analyzed using CNN and MobileNetV2 models, while the audio data is analyzed using YAMNet. Based on the classification results, the detected animal is identified and assigned a confidence score.

If no animal is detected, the system returns to the monitoring stage and waits for the next motion event. If an animal is successfully detected, the detection result is displayed on the monitor and an alert is generated through the buzzer. The detection information is also stored for future analysis and monitoring purposes.

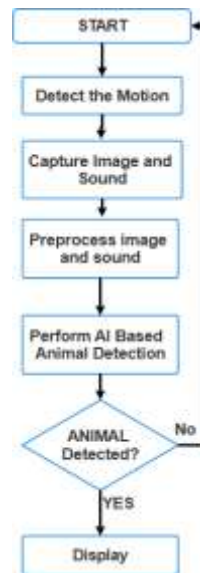


Fig. 2. Flowchart of the Proposed Methodology

A. Algorithms Used

The proposed system uses CNN, MobileNetV2, YAMNet, MFCC, OpenCV, and ONNX Runtime for image processing, audio analysis, and real-time animal classification.

1) *Convolutional Neural Network (CNN)*: CNN is used during the training phase for image and audio classification. It automatically extracts important features such as edges, shapes, textures, and frequency patterns from the dataset.

2) *MobileNetV2*: MobileNetV2 is a lightweight deep learning architecture optimized for embedded systems. It is used for real-time animal image classification on Raspberry Pi 5.

3) *YAMNet*: YAMNet is used for environmental sound and animal sound classification. It analyzes the audio signals captured by the microphone and identifies animal-related sounds.

4) *MFCC*: MFCC (Mel Frequency Cepstral Coefficients) is used for extracting meaningful frequency-domain features from animal sounds before classification.

5) *OpenCV*: OpenCV is used for image acquisition, preprocessing, and visualization of detection results.

6) *ONNX Runtime*: ONNX Runtime enables efficient deployment and execution of AI models on Raspberry Pi with reduced latency and improved real-time performance.

B. Flowchart of Working System

The AI-based animal detection system operates by continuously monitoring the environment using a combination of motion sensing, image capture, and audio analysis. It is capable of accurately identifying domestic, farm, and wild animals using AI algorithms designed for both visual and auditory classification. The working procedure of the system is described below.

AI-Based Animal Detection System – Overview

The system uses a Raspberry Pi 5 with a connected camera, microphone, PIR motion sensor, and Wi-Fi connectivity to

monitor the environment and detect animals through image and audio analysis.

1) System Initialization

At startup, all hardware components are initialized, and the trained AI models are loaded into memory for real-time operation.

2) Motion Detection

The PIR motion sensor continuously monitors the surrounding environment. When movement is detected, it triggers the camera and microphone to capture data only when required, thereby reducing unnecessary processing and power consumption.

3) Image and Sound Capture

- The camera captures real-time images or video frames.
- The microphone records environmental and animal sounds.

4) Preprocessing

- Captured images are resized, normalized, and de-noised before classification.
- Audio signals are filtered and converted into MFCC features for sound analysis.

5) AI-Based Detection

- Image classification is performed using CNN and MobileNetV2 models.
- Audio analysis is performed using YAMNet and MFCC feature extraction.
- The detected animal is identified based on image and sound analysis results.

6) Display and Alert Generation

The detected animal name and confidence score are displayed on the monitor. Whenever an animal is detected, the buzzer generates an alert notification. The system can also be monitored remotely using PuTTY and VNC Viewer through the built-in Wi-Fi connectivity of Raspberry Pi 5.

IV. MATHEMATICAL MODELING

Mathematical models are used in the proposed AI-based animal detection and classification system for probability estimation, feature extraction, and performance evaluation. These mathematical functions improve classification accuracy and enable efficient real-time inference on Raspberry Pi 5.

A. Softmax Probability Function

The Softmax function converts the output logits generated by the neural network into probability values for classification.

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^n e^{z_j}} \quad (1)$$

where,

- $P(y_i)$ = Probability of class i
- z_i = Output score (logit) of class i
- n = Total number of classes
- e = Exponential function

The class having the highest probability is selected as the detected animal category.

B. Accuracy Calculation

The classification accuracy of the proposed system is calculated using:

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions} \times 100 \quad (2)$$

where,

- Correct Predictions = Number of correctly classified samples
- Total Predictions = Total number of test samples

The obtained overall accuracy of the proposed system is 83.33%.

C. MFCC Feature Extraction

Mel Frequency Cepstral Coefficients (MFCC) are used to extract meaningful frequency-domain features from animal sounds before classification.

$$MFCC(n) = \frac{\sum_{k=1}^K \log(S_k)}{\cos \frac{\pi n(k-0.5)}{K}} \quad (3)$$

where,

- S_k = Mel-scaled filter bank energy
- K = Number of Mel filters
- n = Cepstral coefficient index

MFCC improves audio classification performance by extracting relevant sound characteristics from animal vocalizations.

V. HARDWARE AND SOFTWARE COMPONENTS

A. Hardware Components

The proposed AI-based animal detection and classification system consists of Raspberry Pi 5, USB camera, USB microphone, PIR motion sensor, active buzzer, HDMI monitor, Micro SD card, and power supply. These components work together to perform real-time animal monitoring and classification.

TABLE I
HARDWARE COMPONENTS USED

Component	Function
Raspberry Pi 5	Main processing unit
USB Camera	Image acquisition
USB Microphone	Audio acquisition
PIR Motion Sensor	Motion detection
Active Buzzer	Alert generation
HDMI Monitor	Display results
Micro SD Card	Data and model storage
Power Supply	System power source

B. Software Tools Used

Various software tools and frameworks are used for image processing, audio analysis, model training, and deployment.

TABLE II
SOFTWARE TOOLS USED

Software Tool	Purpose
Python	Programming language
OpenCV	Image processing
TensorFlow	Deep learning framework
TensorFlow Hub	YAMNet audio classification
ONNX Runtime	Embedded AI inference
NumPy	Numerical computation
Pandas	Dataset handling
Librosa	Audio preprocessing
VS Code	Development environment
Raspberry Pi OS	Operating system
PuTTY	Remote SSH access
VNC Viewer	Remote desktop monitoring

C. Communication Protocols

1) *SSH Communication Using PuTTY*: PuTTY is used for secure remote terminal access to Raspberry Pi 5 through SSH communication. It allows remote monitoring, code execution, and system configuration over a wireless network.

2) *VNC Viewer Communication*: VNC Viewer provides remote desktop access to the graphical interface of Raspberry Pi 5. It enables GUI monitoring, wireless desktop control, and real-time visualization of detection results.

D. Circuit Diagram

Fig. 3 shows the interfacing connections between Raspberry Pi 5 and external sensing and output devices used in the proposed system.

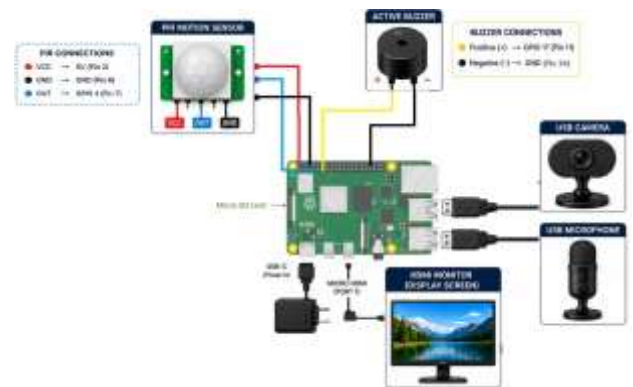


Fig. 3. Circuit Diagram of Proposed AI-Based Animal Detection and Classification System

E. Hardware Architecture

The hardware architecture of the proposed system consists of Raspberry Pi 5, USB camera, USB microphone, PIR motion sensor, active buzzer, HDMI monitor, Micro SD card, and regulated power supply.

Raspberry Pi 5 acts as the central processing unit responsible for image acquisition, audio processing, AI inference, and alert generation. The camera captures animal images, while the microphone records environmental sounds. The PIR sensor detects motion and activates the image and audio acquisition process. The buzzer provides alert notifications whenever

an animal is detected, and the HDMI monitor displays the detection results and confidence scores in real time.

The Micro SD card is used for storing the Raspberry Pi operating system, trained AI models, and application files. A regulated power supply provides stable operation to all hardware components.

VI. RESULTS AND DISCUSSION

The proposed AI-based animal detection and classification system was tested using different categories of wild, domestic, and farm animals. The system was evaluated based on the number of correctly classified animal samples and the overall classification accuracy.

A. Hardware Setup

The experimental hardware setup of the proposed AI-based animal detection and classification system is shown in Fig. 4. The setup consists of a Raspberry Pi 5, USB camera, USB microphone, PIR motion sensor, active buzzer, breadboard connections, and a regulated power supply.



Fig. 4. Experimental Hardware Setup of the Proposed AI-Based Animal Detection and Classification System

B. Animal Classification Results

Table III presents the classification performance of the proposed system for different animal categories.

TABLE III
ANIMAL CLASSIFICATION RESULTS

Animal	Test Samples	Correct Detection	Accuracy (%)
Lion	10	10	100
Tiger	10	9	90
Cheetah	10	9	90
Dog	10	9	90
Cat	10	7	70
Elephant	10	9	90
Cow	10	7	70
Horse	10	7	70
Pig	10	8	80

The results show that the proposed system achieved the highest accuracy of 100% for lion detection. Tiger, cheetah, dog, and elephant achieved 90% accuracy, while pig achieved 80% accuracy. Cat, cow, and horse achieved 70% accuracy. The overall system accuracy was found to be 83.33%.

C. Sample Detection Results

The proposed AI-based animal detection and classification system was tested using different categories of wild, domestic, and farm animals. Representative detection results obtained during experimental testing are shown in Fig. 5. The results demonstrate the capability of the proposed system to accurately identify different animal classes in real time.

D. Confusion Matrix Analysis

The confusion matrix obtained during testing is shown in Fig. 6.

The confusion matrix illustrates the classification performance of the proposed model. Higher values along the diagonal indicate correctly classified animal samples, while off-diagonal values represent misclassified samples. The results demonstrate that the proposed system is capable of accurately distinguishing between different animal categories.

E. Discussion

The experimental results demonstrate that the proposed AI-based animal detection and classification system can successfully identify wild, domestic, and farm animals in real time. The system achieved an overall classification accuracy of 83.33%, with the highest accuracy of 100% obtained for lion detection. The integration of image classification, audio analysis, and motion sensing improved the reliability of animal detection under different conditions. The use of Raspberry Pi 5 enabled efficient real-time processing while maintaining a low-cost and energy-efficient design. The obtained results confirm that the proposed system is suitable for wildlife monitoring, smart agriculture, and rural safety applications.

F. Communication Protocols

1) *SSH Communication Using PuTTY*: PuTTY is used for secure remote terminal access to Raspberry Pi 5 through SSH communication.

Functions:

- Remote monitoring
- Code execution
- Wireless system configuration
- Remote file management

2) *VNC Viewer Communication*: VNC Viewer provides wireless remote desktop access to the graphical user interface of Raspberry Pi 5.

Functions:

- GUI monitoring
- Wireless desktop control
- Remote visualization
- Real-time system monitoring



Fig. 5. Sample Animal Detection Results for Tiger, Lion, Cheetah, Dog, Cat, Elephant, Cow, Horse, and Pig

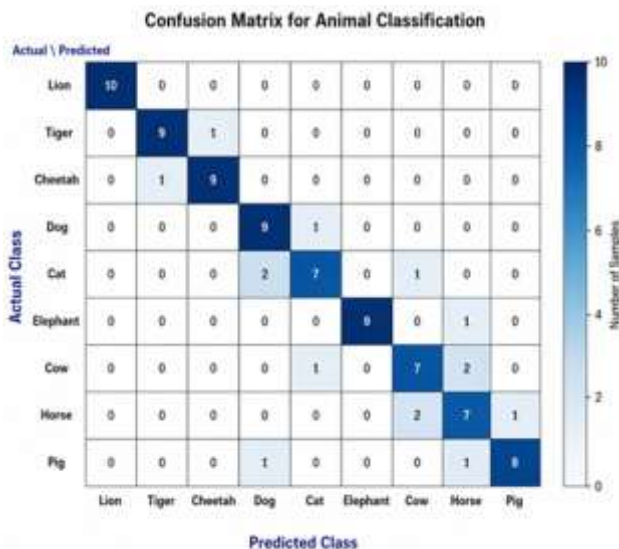


Fig. 6. Confusion Matrix of Animal Classification Results

This communication setup allows users to access and control the system remotely through a Wi-Fi network without requiring direct physical access to the Raspberry Pi.

VII. FUTURE SCOPE

Future enhancements may include the use of advanced edge-AI hardware such as NVIDIA Jetson Nano or Google Coral TPU for faster processing and improved performance. Night-vision and thermal cameras can be integrated to support animal detection in low-light and nighttime environments. Mobile applications and cloud-based monitoring platforms can be developed for remote access and alert management. The use of larger datasets and additional animal species can further

improve classification accuracy. GPS tracking and IoT-based monitoring systems can also be incorporated for large-scale wildlife surveillance and smart monitoring applications.

VIII. CONCLUSION

An AI-based animal detection and classification system was successfully developed using Raspberry Pi 5. The proposed system combines image processing, audio analysis, motion sensing, and deep learning techniques to perform real-time animal monitoring. Experimental testing achieved an overall classification accuracy of 83.33%, demonstrating the effectiveness of the proposed approach. The developed system provides a low-cost, energy-efficient, and intelligent solution suitable for wildlife monitoring, smart agriculture, and rural safety applications.

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