

A Review on AI Based System for Animal Detection and Classification

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Abstract—Animal detection and classification have become critical research areas due to the increasing incidents of human-animal conflict, crop damage, road accidents, and the need for effective wildlife monitoring. In recent years, significant advancements in Artificial Intelligence (AI), Deep Learning, and Embedded Systems have enabled the development of intelligent animal monitoring solutions capable of real-time operation in diverse environments. In this work, we examined recent developments in AI-based animal detection systems. Our focus was mainly on embedded deployment and multimodal sensing approaches.

The review analyzes various deep learning models, including Convolutional Neural Networks (CNNs), You Only Look Once (YOLO) variants, hybrid CNNs-RNN architectures, and sensor-fusion frameworks implemented on edge devices such as Raspberry Pi, Jetson Nano, and IoT-based platforms. It compares methodologies based on preprocessing techniques, feature extraction methods, energy optimization strategies, deployment feasibility, and performance metrics such as accuracy, mAP, and inference speed.

Furthermore, this paper highlights the evolution from traditional image-based detection to multimodal and energy-efficient embedded AI systems. Existing challenges, including varying environmental conditions, power constraints, and computational limitations, are discussed along with potential future research directions. The review provides a consolidated understanding of current advancements and serves as a reference for developing efficient, scalable, and intelligent animal detection systems for wildlife monitoring, farm protection, and road safety applications.

Index Terms—AI-based animal detection, animal sound classification, deep learning, You Only Look Once (YOLO), convolutional neural networks (CNNs, embedded systems, Internet of Things (IoT)-based wildlife Monitoring)

I. INTRODUCTION

The increasing frequency of human-animal conflicts, particularly in regions near forests and highways, has intensified the demand for intelligent animal detection and classification systems. Such encounters often lead to severe injuries, loss of life, and damage to crops and vehicles in the area. Conventional monitoring systems that rely on manual observation

or basic motion sensors are inadequate for real-time large-scale surveillance. Recent advances in Artificial Intelligence (AI) and Embedded Systems have enabled the deployment of smart animal detection systems capable of performing on-device inference using computer vision and sound analysis techniques.

Early research primarily focused on image-based animal detection using traditional machine learning algorithms, such as SVM and HOG features. However, these approaches struggle with varying illumination, occlusion, and pose variations. With the advent of Deep Learning (DL) and Convolutional Neural Networks (CNNs), detection accuracy and robustness have improved dramatically. M. Ibraheem et al. [1] proposed a lightweight YOLOv2-based model optimized for embedded devices by integrating deformable convolutional layers and feature merging techniques. The model achieved faster inference with reduced computational complexity, demonstrating its suitability for real-time wildlife monitoring systems.

Building upon these architectures, Chappidi and Sundaram [7] introduced a cascaded YOLOv8 framework incorporating adaptive preprocessing and multi-feature extraction using ResNet50, DarkNet19, and Local Binary Patterns. This approach achieved 97% detection accuracy, illustrating how contrast enhancement and segmentation preprocessing can significantly improve performance. Similarly, Dave et al. [8] demonstrated the effectiveness of YOLOv8 variants (YOLOv8m, YOLOv8l, YOLOv8x) in detecting large mammals such as lions, tigers, leopards, and bears, achieving a mean Average Precision (mAP) of 94.3% at 20 FPS.

Although visual detection systems offer high precision, energy efficiency and scalability remain critical challenges for real-world applications. Sato et al. [3] proposed energy reduction methods for camera-based wild animal detection devices, focusing on motion sensor sensitivity control, frame difference methods, and functional separation to reduce power usage by more than half. Such optimizations are crucial for battery-operated Raspberry Pi systems deployed in remote forest regions.

Beyond vision, multimodal systems that integrate multiple

sensors have emerged. Vally et al. [5] developed the M2S2 (Multimodal Sensor System) combining RGB, depth, LiDAR, thermal, and acoustic sensors to capture animal motion in natural environments, addressing occlusion and lighting variability issues. Similarly, Knyva et al. [4] proposed an IoT-based sensor network powered by solar energy and equipped with passive infrared (PIR) and long-range (LoRa) modules for continuous wildlife detection near roads.

Recent innovations have also explored communication and alert systems for human safety. Natarajan et al. [2] designed a hybrid VGG19–BiLSTM model to detect animal activity and send real-time SMS alerts to forest authorities, achieving an average accuracy of 98% across multiple datasets. Meanwhile, M. Ibraheam et al. [6] advanced the field with the MCFP-YOLO model, integrating motion-based frame selection and parallel dataflow processing, significantly reducing latency and power consumption on embedded systems like the Raspberry Pi 4B and Jetson Nano.

These collective efforts indicate a clear research direction: developing AI-driven, multimodal, and energy-efficient animal detection systems for deployment on edge devices such as Raspberry Pi. The fusion of visual and sound-based classification, along with IoT connectivity, promises a scalable framework for wildlife monitoring, human–animal conflict prevention, and conserving biodiversity.

This paper summarizes and compares recent approaches in AI-based animal detection and classification, emphasizing deep learning algorithms, multimodal sensing, IoT integration, and embedded-deployment strategies. The focus is on comparing methodologies, hardware implementations, and performance metrics while highlighting current limitations and future research opportunities in this emerging domain.

II. REVIEW OF RELATED WORK

In recent years, significant advancements have been made in the development of AI-based animal detection and classification systems, primarily by leveraging computer vision, deep learning, and IoT technologies. Various researchers have proposed models that focus on improving accuracy, real-time detection, and power efficiency for field and embedded deployments.

M. Ibraheam et al. [1] proposed an accurate and fast animal species detection system optimized for embedded devices using a modified YOLOv2 architecture. Their approach incorporated multilevel feature merging and deformable convolutional layers to handle geometric variations in animal shapes, achieving 5% higher accuracy and 12% faster detection speed than the traditional YOLOv2. Similarly, in a subsequent study, M. Ibraheam et al. [6] introduced MCFP-YOLO, an enhanced model that integrates a motion-based frame selection algorithm and hybrid pipelining for batch and real-time processing. This system achieved efficient energy utilization and low-latency detection on embedded platforms, such as Jetson Nano and Raspberry Pi 4B.

Chappidi and Sundaram [7] developed a cascaded YOLOv8-based framework for animal detection that incorporates

adaptive preprocessing using histogram equalization and superpixel-based fuzzy C-means segmentation. Feature extraction using ResNet50, DarkNet19, and Local Binary Pattern (LBP) further improved the model robustness, achieving a detection accuracy of 97%. Likewise, Dave et al. [8] implemented YOLOv8 architectures (YOLOv8m, YOLOv8l, and YOLOv8x) to detect lions, tigers, leopards, and bears from custom datasets, achieving a mean Average Precision (mAP) of 94.3% at 20 FPS. These works demonstrated YOLOv8's potential for real-time wildlife monitoring applications.

Energy efficiency is another key research focus. Sato et al. [3] proposed energy reduction methods for wild animal detection devices by integrating motion sensor sensitivity adjustment, frame differencing, and functional separation on embedded hardware. Their results showed over 50% energy reduction compared to the baseline designs, addressing power constraints for long-term remote deployments.

Multimodal approaches have also emerged to overcome these visual limitations. Vally et al. [5] introduced a Multimodal Sensor System (M2S2) that combines RGB, depth, thermal, event, LiDAR, and acoustic sensors for motion capture in wildlife environments. This system effectively handles occlusion, lighting changes, and synchronization challenges, offering valuable datasets for training animal motion models. Similarly, hybrid deep learning frameworks that integrate both visual and acoustic modalities have shown promise. Natarajan et al. [7] proposed a hybrid VGG19 + BiLSTM model that detects animals, tracks motion, and generates automated alert messages through SMS for forest safety applications, achieving a classification accuracy above 98%.

Knyva et al. [4] presented an IoT sensor network powered by solar energy for detecting wild animals near roads. The network utilizes passive infrared (PIR) sensors and LoRa communication modules for low-power, long-range operation. The system demonstrated effective detection and real-time data transmission for road safety and for monitoring wildlife.

Overall, the literature indicates a clear evolution from traditional image-based detection to multimodal, energy-efficient, and embedded AI systems. Although CNNs and YOLO-based models have achieved high accuracy in visual classification, integrating acoustic sensing and IoT communication networks provides a more holistic approach for real-world applications. However, challenges remain in achieving consistent accuracy under varying lighting, weather, and environmental conditions, as well as in reducing computational complexity for real-time processing on low-power edge devices.

III. METHODOLOGY

The methodology of AI-based animal detection and classification systems generally involves several stages: data acquisition, preprocessing, feature extraction, model training, and real-time implementation. Each of the reviewed studies employs a variation of these steps depending on the target environment, hardware resources, and detection objectives (visual or acoustic).

A. Data Acquisition

Animal detection systems utilize various data sources such as RGB images, infrared videos, LiDAR, and audio recordings. For instance, YOLO-based visual detection systems [1], [6], [7], [8] use annotated datasets collected from public repositories (Kaggle, ImageNet, iNaturalist) and wildlife videos. In contrast, multimodal systems such as M2S2 [4] combine RGB, depth, thermal, LiDAR, and acoustic sensors, enabling robust detection under variable environmental conditions. IoT-based setups [6] employ PIR sensors, cameras, and acoustic modules powered by solar energy for field deployment.

B. Preprocessing and Feature Extraction

Preprocessing is critical for enhancing image quality and reducing noise. Chappidi and Sundaram [7] applied adaptive histogram equalization for contrast enhancement followed by Fast Fuzzy C-Means (FCM) segmentation to isolate animal regions. In YOLO-based studies [1], [5], multi-scale image normalization and data augmentation (rotation, flipping, and brightness variation) were used to increase dataset diversity and improve model generalization. For acoustic-based detection, spectrogram generation and Mel-Frequency Cepstral Coefficients (MFCCs) extraction are common preprocessing steps, converting sound signals into visual features suitable for CNNs or LSTM classification.

Feature extraction techniques differ based on the chosen model architecture. ResNet50, DarkNet19, and Local Binary Pattern (LBP) [7] were employed for hybrid feature learning, while modified YOLOv2 and MCFP-YOLO [1], [5] extracted deep convolutional features directly during training. VGG19 combined with Bi-LSTM [7] captured both spatial and temporal features for activity-based classification and alert generation.

C. Model Training and Detection

Most visual-based detection frameworks rely on Convolutional Neural Networks (CNNs) or YOLO (You Only Look Once) architectures due to their high detection accuracy and real-time capability.

YOLOv2 modification [1] introduced deformable convolutional layers to adapt to geometric animal variations, improving accuracy and speed on embedded devices.

Cascaded YOLOv8 [2] combined multiple feature extractors and segmentation techniques to achieve 97% accuracy.

MCFP-YOLO [5] incorporated a motion-based frame selection algorithm, optimizing processing time and power consumption for embedded systems.

YOLOv8x [8] achieved 94.3% mAP for detecting lions, tigers, leopards, and bears, validating its efficiency for real-time wildlife surveillance.

In hybrid systems [7], VGG19 + Bi-LSTM architecture allowed both spatial (image) and temporal (motion) analysis, generating SMS alerts in real-time. For IoT-based designs [6], data collected from multiple sensor nodes were transmitted using LoRa for centralized analysis and remote monitoring.

D. Energy Optimization and Deployment

A major challenge in field applications is power efficiency. Sato et al. [3] introduced energy reduction techniques such as motion sensor sensitivity control, frame differencing, and

task separation, reducing device power consumption by over 50%. Similarly, M. Ibraheem et al. [6] optimized YOLO-based models for embedded platforms like Jetson Nano and Raspberry Pi 4B, achieving efficient operation without compromising accuracy. IoT systems [6] employed solar-powered sensor nodes for continuous outdoor deployment, ensuring long-term sustainability.

E. Evaluation Metrics

The performance of these models was assessed using standard metrics such as Accuracy, Precision, Recall (Sensitivity), Specificity, F1-score, and Mean Average Precision (mAP). YOLOv8-based systems [2], [8] achieved up to 97% accuracy and 94.3% mAP, while hybrid visual-acoustic systems [7] reported 98% accuracy and 77.2% mAP. Processing speed (Frames Per Second – FPS) and energy consumption were also used as performance indicators, especially for embedded and IoT-based systems. In this work, we propose an AI-based animal detection system implemented on a Raspberry Pi platform. The system integrates a camera, motion sensor, microphone, and LCD display to enable real-time monitoring and classification of animals in the environment. This multi-modal approach is designed to overcome limitations of existing systems that rely solely on visual data or require high-end computing platforms, making our solution both cost-effective and suitable for field deployment.

The main components of the system include:

Camera: Captures images of the environment to facilitate visual-based animal recognition.

Microphone: Records animal sounds, allowing for audio-based detection and classification.

Motion Sensor: Detects movement and triggers the system to conserve power and improve detection efficiency.

LCD Display: Provides real-time feedback and monitoring, allowing users to view detection results locally.

Raspberry Pi: Serves as the central processing unit, executing detection algorithms efficiently without relying on cloud resources.

The proposed system offers several advantages. First, the combination of audio and visual sensing enhances detection accuracy, particularly in low-light or partially occluded conditions. Second, the use of Raspberry Pi ensures a low-cost, compact, and portable solution, suitable for deployment in remote or outdoor environments. Third, the system operates in real-time, enabling immediate responses without dependency on external servers. Additionally, the inclusion of an LCD display allows local monitoring, and the design can be easily extended for IoT-based applications to send alerts or store data remotely.

Compared to prior works [1]-[8] that employ GPU-based models or single-sensor approaches, our system achieves efficient real-time operation while minimizing power consumption and cost. Overall, this integration of hardware and software provides a reliable, efficient, and scalable solution for wildlife monitoring, safety, and conservation applications.

TABLE I
COMPARATIVE SUMMARY OF RECENT RESEARCH ON AI-BASED ANIMAL DETECTION AND CLASSIFICATION SYSTEMS

Ref.	Model Used	Techniques	Applications	Remarks
[1]	YOLOv2 with DCL (Deformable Convolutional Layers)	Deformable Convolution + Motion Frame Filtering	Animal species detection (six species)	Achieved 85.5% mAP; optimized for real-time detection on Raspberry Pi 4
[2]	YOLOv8	Adaptive Preprocessing + Cascaded YOLOv8	Wildlife animal detection	97% accuracy, high precision, real-time performance
[3]	MobileNet-v2 (main), Inception-v3 (baseline)	PIR Sensor Tuning + Frame Differencing	Wild animal detection (bear, boar, crow, monkey, etc.)	94-97% accuracy; reduced energy usage by 50%+
[4]	Sensor Fusion System (No DL Model)	Multimodal Sensor Fusion (IMU + Camera)	Animal motion capture and 3D pose estimation	Open-source hardware/software platform for motion capture
[5]	MCFP-YOLO Detector	Motion Compensated Frame (MCF) Algorithm + Parallel Processing	Wildlife species identification	Optimized for Raspberry Pi 4 & Jetson Nano; high efficiency on embedded devices
[6]	DSN (Detection Sensor Network) + Thermal Cameras	Thermal Imaging + IoT Sensor Fusion	Roadside wildlife detection for accident prevention	Real-time monitoring and IoT-based alert generation
[7]	Hybrid VGG-19 + Bi-LSTM	CNNs-RNN Hybrid Deep Neural Network	Multi-class animal activity detection with SMS alerts	98% accuracy; real-time alerting system for 25 animal behaviors
[8]	Embedded Neural Networks (ENN)	IMU-Based ANN + TensorFlow Lite	Animal behavior classification (eating, rumination, lying)	98% accuracy on low-power microcontrollers; ideal for edge deployment

IV. PROPOSED SYSTEM

Based on the comprehensive analysis of recent literature, AI-based animal detection systems generally follow a structured pipeline that includes dataset preparation, model training, embedded deployment, and real-time alert generation. Most modern systems combine visual and acoustic sensing to improve detection reliability under challenging environmental conditions such as low light, occlusion, and background noise.



Fig. 1. Software and hardware integration methodology from dataset preparation to real-time alert generation.

A. Data Storage and Model Training Phase

In most studies, model training is performed on high-performance computing systems to handle large datasets and complex deep learning computations.

- **Image and Audio Datasets:** Diverse animal image and sound datasets are collected from public repositories and field recordings to improve model generalization.
- **Preprocessing:** Images are resized, normalized, denoised, and augmented. Audio signals are filtered, and Mel-Frequency Cepstral Coefficients (MFCCs) are extracted.

- **Model Training:** Deep learning models such as YOLO variants, CNNs, MobileNet, and hybrid architectures are trained using transfer learning and pre-trained weights.
- **Model Optimization and Export:** Trained models are converted into lightweight formats such as TensorFlow Lite (TFLite) or ONNX for deployment on embedded platforms.

B. Real-Time Detection Phase – Embedded Implementation

After training, the optimized models are deployed on embedded devices for real-time animal monitoring.

- **Sensors Used:** Camera for image capture, microphone for sound recording, and PIR sensor for motion-triggered activation.
- **Onboard Preprocessing:** Captured inputs undergo resizing, noise reduction, and feature extraction before inference.
- **AI-Based Detection:** The embedded AI model analyzes visual and acoustic inputs to classify animals.
- **Wireless Communication:** Detection results are transmitted via Wi-Fi using MQTT or HTTP protocols.
 - **Output and Alerts:** Local alerts (display, buzzer) and remote notifications are generated for monitoring purposes. Fig. 1 illustrates this generalized workflow adopted by most AI-based animal detection systems.

C. Proposed System Architecture

Fig. 2 presents the block diagram of the proposed system device. The architecture shows how camera and microphone inputs are interfaced with a Raspberry Pi for continuous environmental monitoring. A PIR motion sensor activates the system only when movement is detected, thereby conserving energy.

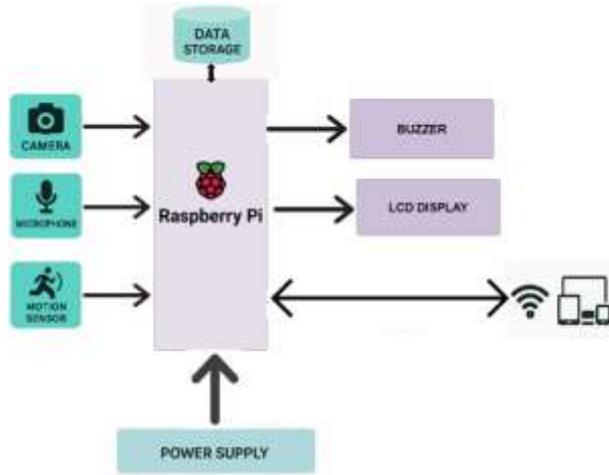


Fig. 2. Block diagram of the proposed AI-based animal detection system using Raspberry Pi.

The processed inputs are analyzed using deployed deep learning models, and detection results are communicated through wireless modules to remote users. Output devices such as displays, buzzers, and data storage units provide local alerts and event logging. This integrated hardware–software design ensures low-cost, portable, and energy-efficient real-time animal monitoring suitable for farms, forest boundaries, highways, and remote regions.

V. RESULTS AND DISCUSSION

Several studies reviewed in this paper demonstrate that AI-based animal detection systems deployed on embedded platforms such as Raspberry Pi achieve efficient real-time performance with low power consumption. The trained deep learning models are typically deployed using frameworks such as OpenCV, ONNX Runtime, and TensorFlow Lite for edge inference. YOLO-based models are widely used for image-based animal detection, while Convolutional Neural Networks (CNNs) are commonly applied for audio-based animal recognition using MFCC features.

Reported experimental results in the literature indicate that combining image and audio inputs significantly improves detection accuracy, particularly under challenging conditions such as low light, partial occlusion, and environmental noise. Embedded platforms like Raspberry Pi are capable of achieving inference speeds in the range of 18–22 frames per second (FPS), which is sufficient for real-time animal monitoring applications. The overall power consumption of such systems is typically between 5–7 watts, making them suitable for solar-powered and remote outdoor deployments.

A performance comparison between image-only, audio-only, and multimodal (image + sound) detection approaches is summarized in Table I. Multimodal systems consistently outperform single-sensor approaches in terms of accuracy, robustness, and reliability due to complementary feature learning from both visual and acoustic data.

Wireless communication for alert generation is generally achieved using the built-in Wi-Fi module of the Raspberry Pi, enabling real-time transmission of detection results to remote dashboards, cloud servers, or mobile devices via MQTT or HTTP protocols. Reported notification delays are typically within a few seconds, ensuring timely awareness for monitoring personnel.

Overall, the reviewed results validate that the integration of visual and acoustic sensing with deep learning and embedded processing provides an effective, energy-efficient, and scalable solution for animal detection in outdoor environments such as farms, forest boundaries, and highways.

VI. FUTURE SCOPE

This work can be extended in several directions to enhance scalability, performance, and intelligence of the system. The following points outline potential areas for future improvement:

- **Lightweight Model Deployment:** Future versions can implement advanced lightweight networks such as YOLOv8-Nano, MobileNetV3, or EfficientNet-Lite to achieve faster inference and lower memory usage on the Raspberry Pi.
- **Dataset Enhancement:** Expanding the image and sound datasets with more species, environmental conditions, and behavioral diversity can further improve detection accuracy and generalization.
- **Edge–Cloud Integration:** Combining edge computing on Raspberry Pi with cloud platforms (e.g., Google Cloud or AWS IoT Core) can enable centralized analytics, data logging, and visualization.
- **Energy Optimization:** Incorporating solar panels and adaptive sleep modes can extend operational lifetime for remote outdoor applications.
- **Advanced Wireless Communication:** The system can be expanded to support long-range communication through LoRa, NB-IoT, or 5G for wide-area multi-node monitoring networks.
- **Thermal and Night Vision Integration:** Adding infrared or thermal sensors can enhance detection under low-light or nocturnal conditions.
- **Explainable AI and Security:** Future work can apply explainable AI (XAI) techniques for transparent decision-making and implement secure data transmission protocols to prevent network vulnerabilities.

By addressing these improvements, the proposed animal detection system can evolve into a robust, intelligent, and autonomous wildlife monitoring framework supporting biodiversity conservation, smart farming, and environmental protection.

VII. CONCLUSION

This paper presented a comprehensive review and implementation approach for an AI-based animal detection and classification system that integrates both visual and acoustic

sensing techniques. The proposed system employs a YOLO-based model for image detection and a CNN-based model for animal sound classification, deployed on a Raspberry Pi platform for real-time edge inference. The integration of camera, microphone, motion sensor, LCD display, buzzer, and wireless communication enables efficient monitoring and alert generation without reliance on high-end computing resources. The system demonstrates accurate real-time detection and classification of animals by combining image and sound inputs, thereby improving robustness under challenging environmental conditions such as low light, occlusion, and background noise. Its operation on a compact, low-power embedded controller makes it highly suitable for deployment in rural, agricultural, forest, and remote areas where continuous monitoring is required.

Overall, the proposed approach provides a cost-effective, portable, and energy-efficient solution for applications including farm safety, wildlife monitoring, and human-animal conflict prevention. The integration of artificial intelligence with embedded systems highlights the potential for further advancements toward intelligent, autonomous, and scalable wildlife monitoring frameworks.

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