Monitoring Animals Using Intelligence and IoT Smart Collar (MAUI)

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Abstract— *Animals are unable to verbally communicate pain, illness, or distress, often resulting in delayed diagnosis and inadequate intervention. This paper presents MAUI (Monitoring Animals Using Intelligence and IoT Smart Collar), an intelligent and integrated animal health monitoring framework that combines Internet of Things (IoT) sensing, machine learning–based distress detection, and real-time alerting mechanisms. The system employs a wearable smart collar to continuously monitor physiological parameters such as body temperature and pulse rate, while an event-driven architecture triggers acoustic analysis only when abnormalities are detected. Distress vocalizations are analyzed using Mel-Frequency Cepstral Coefficients (MFCC) and machine learning classifiers, with Random Forest demonstrating superior performance. MAUI further extends its functionality through a mobile application that delivers actionable alerts and supports community-based animal reporting and CCTV-assisted verification for NGO intervention. Experimental results indicate reliable distress detection with reduced false alarms, validating the effectiveness of multimodal data fusion. The proposed system offers a scalable, secure, and humane solution for proactive animal welfare monitoring in real-world environments.*

Keywords— Animal Health Monitoring, Bioacoustics, Distress Detection, Internet of Things, Machine Learning, Smart Collar, Surveillance Systems.

I. INTRODUCTION

Animal health and welfare have gained increasing attention as animals play a growing role as companions, livestock, and contributors to ecological systems. However, animals cannot verbally express pain, illness, or emotional distress, which often leads to delayed diagnosis and ineffective intervention. Traditional monitoring methods rely heavily on visual observation and manual assessment, making them subjective and unsuitable for early detection of subtle physiological or behavioral changes. Studies indicate that delayed recognition of distress significantly increases health risks and mortality among both domestic and stray animals, highlighting the need for continuous and objective monitoring solutions [1]–[4].

Recent advancements in the Internet of Things have enabled wearable devices such as smart collars that continuously collect physiological and activity-related data, including temperature, pulse rate, movement, and location [1], [5], [6]. Several IoT-based animal monitoring systems demonstrate real-time data acquisition and remote health tracking through cloud-connected platforms and mobile applications [4], [6]–[8]. In parallel, machine learning techniques have been applied to disease prediction and health analysis, achieving promising accuracy using structured datasets [9], [10]. Bioacoustic analysis has further emerged as a non-invasive method for identifying distress through animal vocalizations, while computer vision systems using deep learning models such as YOLO and R-CNN enable reliable animal detection across diverse environments [12]–[17].

Despite these advances, most existing solutions operate in isolation, lack real-time intelligence, and fail to integrate physiological, acoustic, and visual cues, limiting their effectiveness in practical settings [11], [18]–[22]. To overcome these limitations, this paper presents MAUI (Monitoring Animals Using Intelligence and IoT Smart Collar), an integrated framework that combines wearable IoT sensing, machine learning–based distress detection, and smart surveillance mechanisms. MAUI continuously monitors vital physiological parameters and employs an event-driven approach to trigger acoustic analysis only when abnormalities are detected, enabling reliable and energy-efficient distress recognition. The system delivers real-time alerts through a user-centric mobile application and extends support to stray and injured animals through community reporting and CCTV-assisted verification for NGO intervention. By leveraging multimodal data fusion, adaptive learning, and secure communication, MAUI aims to enable early intervention, scalable deployment, and improved animal welfare across diverse environments.

II. LITERATURE SURVEY

Recent research in intelligent animal health monitoring has focused on leveraging IoT, artificial intelligence, and sensing technologies to overcome the inherent communication gap between animals and humans. This section reviews existing literature across five major categories relevant to the MAUI system: app-based animal monitoring platforms, machine learning-based disease prediction systems, IoT-enabled smart collars, sound-based distress detection approaches, and animal detection and surveillance systems.

2.1 App-Based Animal Monitoring Systems:

Mobile and web-based animal monitoring applications provide pet owners with real-time access to information such as location, activity, and medical records through user-friendly dashboards and notifications. Platforms like DeepPet enhance accessibility by integrating GPS tracking and cloud-based visualization [10], [12]. However, most of these systems focus on data display rather than intelligent health assessment, offering little automated interpretation of physiological or behavioral signals. The absence of standardized performance evaluation, distress detection, and alert prioritization limits their reliability and effectiveness for early intervention in real-world animal welfare scenarios [13].

2.2 Disease Prediction Using Machine Learning

Machine learning has been widely used for animal disease prediction based on structured datasets such as symptoms, feeding behavior, and historical health records. Models including Random Forest, Decision Trees, K-Nearest Neighbors (KNN), and gradient boosting have reported accuracies of approximately 85% to 89%, enabling early identification of health abnormalities before visible clinical symptoms appear [9], [17], [24]. However, most existing systems rely on offline or manually collected data and lack integration with real-time physiological sensing through wearable devices. This limits their responsiveness to dynamic distress conditions and reduces scalability across multiple species, diseases, and deployment environments [11], [15], [27].

2.3 IoT-Based Smart Collar Systems

IoT-enabled smart collars have enabled continuous and non-invasive monitoring of animal health by capturing physiological and movement-related data such as temperature, pulse, activity, and location through embedded sensors and wireless communication [1], [14], [28], [29]. Several studies demonstrate the effectiveness of applying machine learning models to sensor data, reporting health state classification accuracies of around 88% [5], [18]. However, most existing smart collar systems are limited to specific species and primarily focus on physiological sensing, with minimal interpretation of behavioral or acoustic distress signals. The lack of multimodal data fusion, intelligent alert prioritization, and long-term energy-efficient design restricts their reliability and scalability in real-world animal welfare applications [6], [22].

2.4 Automated Distress Detection Using Sound Classification

Sound-based distress detection has gained attention as a non-invasive method for evaluating animal welfare through vocalization analysis. Studies show that distress-related sounds can be identified using acoustic features such as MFCC and spectrograms combined with machine learning and deep learning models, achieving classification accuracies of approximately 82% to 85% under controlled conditions [4], [14], [16], [19], [20]. However, most existing approaches rely on limited or controlled datasets and remain sensitive to environmental noise, reducing their effectiveness in real-world settings. In addition, the absence of integration with physiological sensing lowers confidence when vocal cues are ambiguous, emphasizing the need for multimodal fusion and adaptive learning mechanisms [12], [21], [23].

2.5 Animal Detection and Surveillance Systems

Computer vision–based animal detection systems using deep learning models such as YOLO and R-CNN have achieved high detection accuracy in forest, campus, and urban environments, with reported performance between 91% and 97.6% [16], [25], [27]. These systems are widely used for wildlife monitoring, accident prevention, and animal sighting detection through CCTV and mobile camera feeds, often enhanced by GPS-based alerting for safety and rescue operations [9], [17]. However, such surveillance systems primarily focus on animal presence and movement, offering limited insight into health or emotional state. Their reliance on static infrastructure and lack of integration with wearable sensing or bioacoustic analysis restricts their effectiveness for comprehensive animal welfare monitoring, particularly in early distress detection scenarios [18], [26].

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III. PROPOSED METHODOLOGY

The proposed methodology of MAUI is designed to overcome the key limitations observed in existing animal monitoring systems, particularly the lack of real-time intelligence, absence of multimodal data fusion, and limited coordination between sensing, interpretation, and intervention mechanisms. The system is conceptualized as an event-driven, integrated ecosystem that combines continuous physiological monitoring, machine learning-based distress detection, and coordinated alerting through mobile and surveillance platforms. The methodology follows a modular and layered design to ensure scalability, robustness, and real-world applicability.

3.1 System Design Philosophy and Overview

The core design philosophy of MAUI is to transition from passive data collection toward active and intelligent interpretation. Instead of continuously transmitting raw sensor data, MAUI employs an **event-triggered intelligence model**, where abnormal physiological patterns initiate deeper behavioral analysis. Event-driven architectures have been shown to improve efficiency, reduce communication overhead, and conserve energy in IoT-based monitoring systems [1], [5]. MAUI consists of three tightly integrated components: a wearable IoT smart collar, an artificial intelligence interpretation pipeline, and a user-facing mobile and NGO collaboration platform.

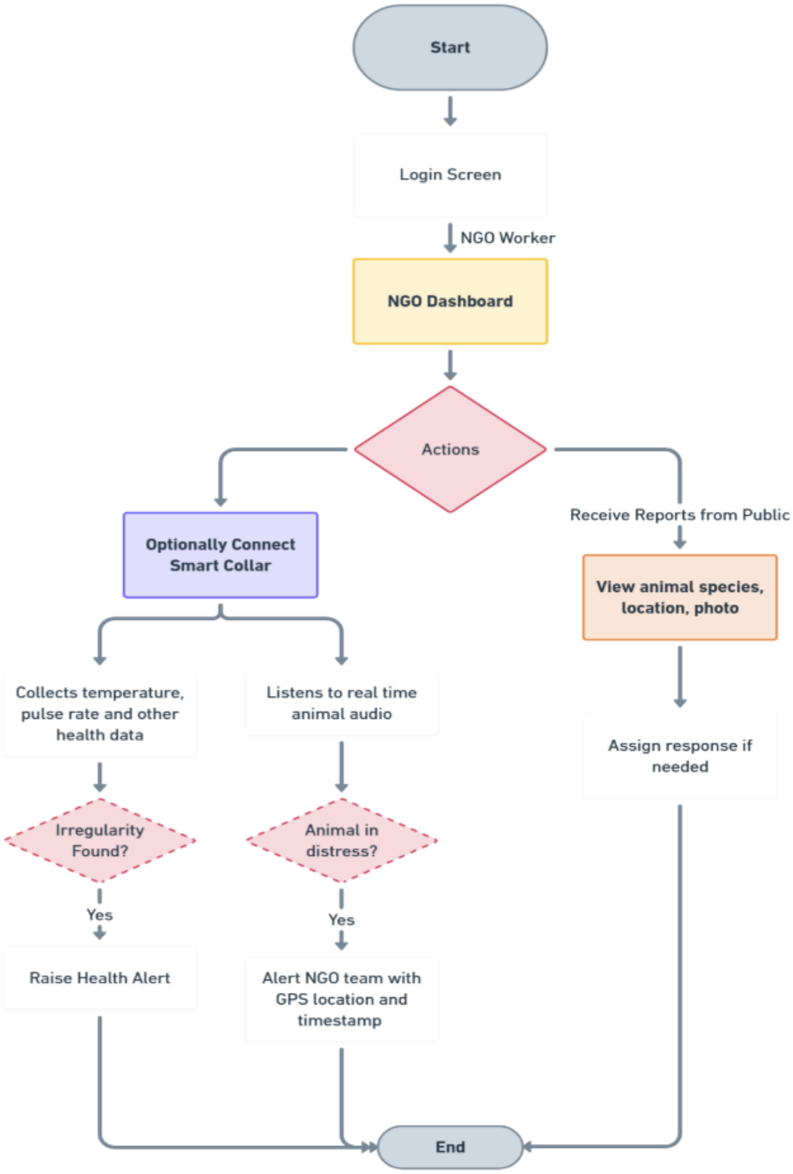

FIGURE 1: MAUI flowchart for NGO workflow

This architecture ensures that physiological anomalies, distress vocalizations, and environmental sightings are not treated independently but are interpreted together to form a reliable assessment of animal well-being. Similar layered architectures have been explored in IoT-based animal health monitoring frameworks, though often without full multimodal integration [6], [14].

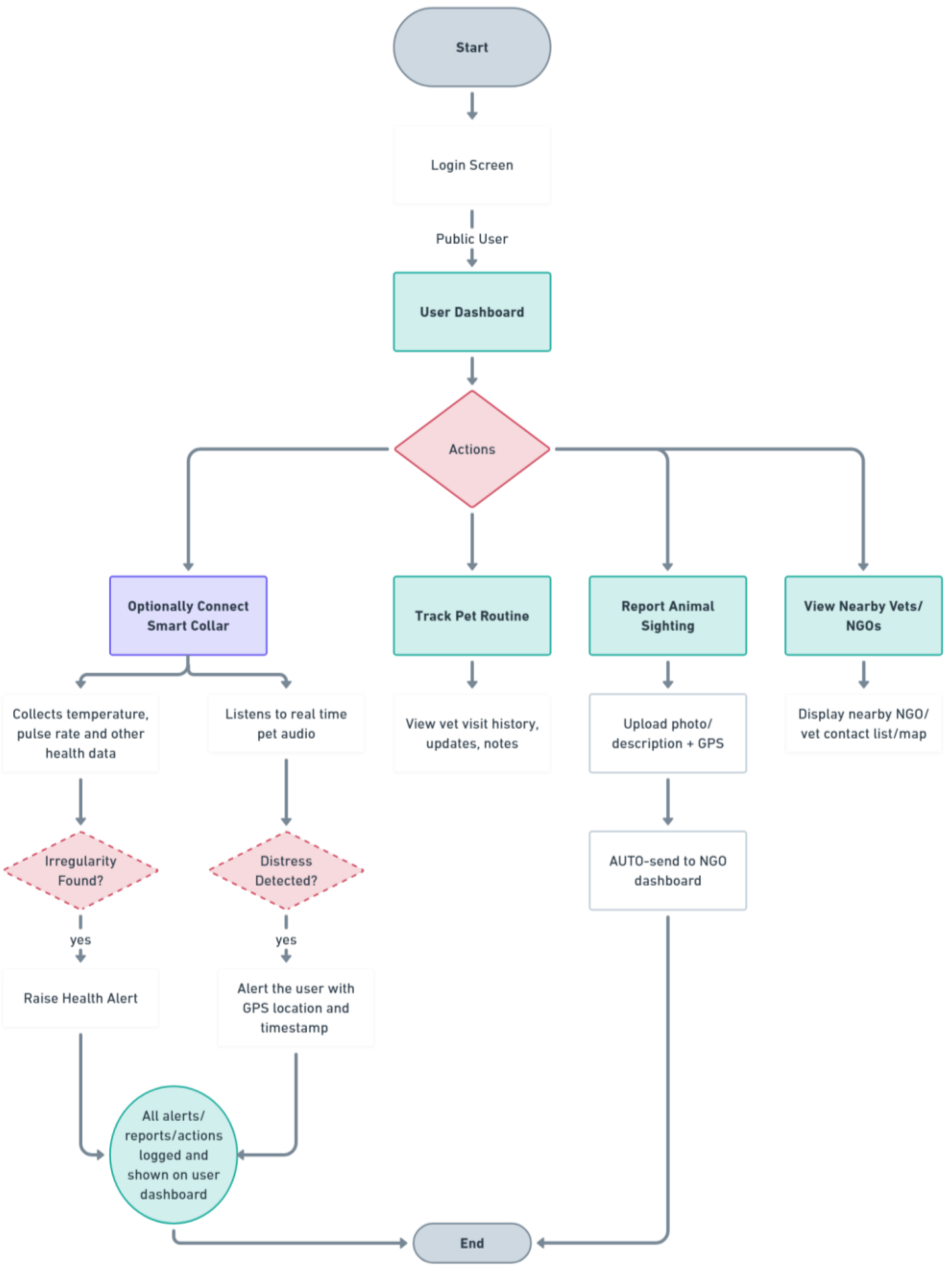

FIGURE 2: MAUI flowchart for Public User workflow

3.2 Data Collection and Acquisition Strategy

The data acquisition methodology of MAUI combines continuous physiological sensing with conditional acoustic sampling. The smart collar continuously monitors vital parameters such as body temperature, pulse rate, movement, and geographic location. These parameters are widely recognized as strong indicators of health anomalies in animals and are commonly used in IoT-based animal monitoring systems [1], [14], [29].

Sensor readings are locally preprocessed and compared against predefined threshold ranges derived from veterinary standards and baseline health profiles. When all parameters remain within safe limits, the system continues low-power monitoring. However, when abnormal patterns such as elevated temperature or irregular pulse are detected, an event trigger activates the onboard MEMS microphone to record short-duration audio samples. Selective audio acquisition strategies have been adopted in prior research to improve power efficiency and reduce unnecessary data capture [18], [22]. The collected data packets, comprising time stamps, device identifiers, sensor readings, GPS coordinates, and audio samples, are encrypted and transmitted wirelessly to the mobile application or cloud server. Local buffering mechanisms ensure data integrity during intermittent connectivity, a common challenge in mobile IoT deployments [7], [11].

3.3 Artificial Intelligence and Interpretation Pipeline

The intelligence of MAUI is driven by a multi-stage artificial intelligence pipeline that jointly analyzes physiological and acoustic data. Once a physiological anomaly is detected, the captured audio signal undergoes preprocessing steps including noise filtering, normalization, and segmentation. Acoustic features are extracted using **Mel-Frequency Cepstral Coefficients (MFCC)** , which are widely adopted in animal bioacoustic analysis due to their effectiveness in representing vocal characteristics associated with distress [16], [19], [20].

Multiple machine learning classifiers were evaluated for distress detection, including Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). These algorithms are frequently used in animal sound classification and health prediction studies due to their interpretability and robustness under limited data conditions [17], [20], [24]. Among the evaluated models, **Random Forest** demonstrated superior performance in terms of accuracy, balanced precision-recall trade-offs, and resilience to noise and class imbalance, aligning with findings reported in comparative bioacoustic studies [21], [24].

=== Random Forest Classification Report ===

	precision	recall	f1-score	support
cat_distress	0.83	0.79	0.81	171
cat_not_distress	0.78	0.83	0.80	171
dog_distress	0.85	0.87	0.86	169
dog_not_distress	0.93	0.90	0.92	171
accuracy			0.85	682
macro avg	0.85	0.85	0.85	682
weighted avg	0.85	0.85	0.85	682

FIGURE 3: Performance evaluation of the Random Forest classifier for multiclass animal distress detection

Crucially, MAUI does not rely solely on acoustic analysis. Distress is confirmed only when physiological abnormalities and AI-based vocal classification jointly indicate risk. Multimodal decision fusion has been shown to significantly reduce false positives and improve reliability in animal behavior recognition systems [22], [23]. All predictions, confidence scores, and event logs are archived for audit and periodic retraining.

3.4 IoT Smart Collar Design and Implementation

The IoT smart collar is designed as a compact, ergonomic, and durable wearable suitable for continuous use by cats and dogs. It integrates temperature sensors, pulse monitoring modules, GPS tracking, accelerometers, and a MEMS microphone, controlled by a low-power ESP32-based microcontroller. Similar hardware configurations have been reported in prior smart collar implementations for animal tracking and health monitoring [29]. Wireless communication using Bluetooth and Wi-Fi allows seamless synchronization with mobile and cloud services. This hybrid edge-cloud processing approach has been adopted in recent animal monitoring systems to balance latency, energy efficiency, and computational load [18], [22].

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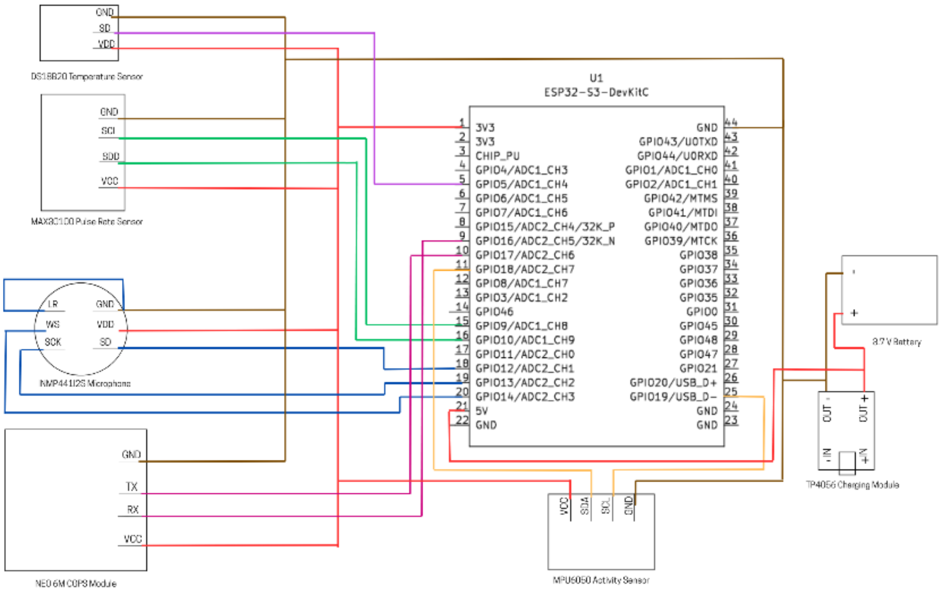

FIGURE 4: Block diagram of the IoT-enabled smart collar used in the MAUI system

3.5 Alerting, User Interaction, and NGO Collaboration

Upon confirmation of distress, MAUI generates structured and prioritized alerts delivered instantly to the user's mobile application. Alerts include the nature of the abnormality, triggering sensors or models, confidence levels, timestamps, and real-time location data. Intelligent alerting mechanisms have been shown to be significantly more effective than passive dashboards in emergency animal health scenarios [10], [12].

Beyond individual pet monitoring, MAUI extends its methodology to community-level animal welfare through user-generated reports and CCTV-based animal detection. Computer vision models analyze camera feeds to verify animal sightings before forwarding validated cases to nearby NGOs. Similar integrations of surveillance systems with AI-based detection have been explored for animal rescue and safety applications, though often without physiological context [9], [25], [27].

3.6 Security, Privacy, and System Evolution

Given the sensitivity of health and location data, MAUI employs end-to-end encryption and role-based access control across all system components. Secure IoT communication and data privacy frameworks are essential for ensuring trust and regulatory compliance in animal monitoring platforms [13], [26]. The system incorporates a **feedback-driven learning loop** in which confirmed alerts, user actions, and NGO interventions are used to refine thresholds and retrain models. Adaptive learning strategies are increasingly recognized as critical for improving long-term performance and generalization in animal health monitoring systems deployed in real-world environments [22], [23].

IV. EVALUATION METRICS

To assess the performance, reliability, and real-world suitability of the proposed MAUI system, a set of widely accepted evaluation metrics was employed. Classification accuracy was used to provide an overall measure of correct predictions, while precision and recall were used to evaluate alert reliability and the system's ability to minimize missed distress events, which is critical in welfare-oriented applications [19], [20]. The F1-score was adopted to balance precision and recall, particularly in the presence of class imbalance commonly observed in distress detection datasets [21], [24]. Confusion matrix analysis was used to examine class-wise prediction behavior and identify misclassification patterns [19].

In addition to model-level metrics, system-level parameters such as alert latency, false alarm rate, robustness to noise, and energy efficiency were considered to validate the practical deployment of MAUI in real-world animal monitoring scenarios [16], [18], [22], [23].

TABLE 1
SYSTEM PERFORMANCE METRICS

Metric	Purpose
Accuracy	Overall correctness of distress classification
Precision	Reliability of generated distress alerts
Recall (Sensitivity)	Ability to detect actual distress events
F1-Score	Balanced assessment of precision and recall
Confusion Matrix	Analysis of class-wise prediction behavior
Alert Latency	Measurement of system response time
False Alarm Rate	Evaluation of unnecessary alert generation
Robustness to Noise	Stability under varying acoustic conditions
Energy Efficiency	Suitability for long-term collar operation

V. RESULTS AND DISCUSSION

This section presents the experimental results obtained from the MAUI system and provides a detailed discussion of the observed performance. The evaluation focuses on two key aspects: (i) the effectiveness of machine learning models in detecting animal distress through vocalization analysis, and (ii) the overall system behavior in real-world–oriented deployment scenarios. The results validate the design decisions adopted in MAUI, particularly the use of multimodal sensing and event-driven intelligence.

5.1 Machine Learning Model Performance

Multiple machine learning models were evaluated to determine the most reliable classifier for animal distress detection. The models were trained and tested on a curated and augmented dataset consisting of labeled dog and cat vocalizations categorized into distress and non-distress classes. The evaluated classifiers include Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN).

Among the tested models, the **Random Forest classifier** consistently outperformed SVM and KNN, achieving higher accuracy, balanced precision-recall values, and superior robustness to noise. The ensemble nature of Random Forest enabled it to handle feature variability and class overlap more effectively, which is common in real-world bioacoustic data. In contrast, KNN demonstrated reasonable performance but showed increased sensitivity to noise and class similarity, while SVM exhibited lower recall for certain distress classes, particularly in cat vocalizations.

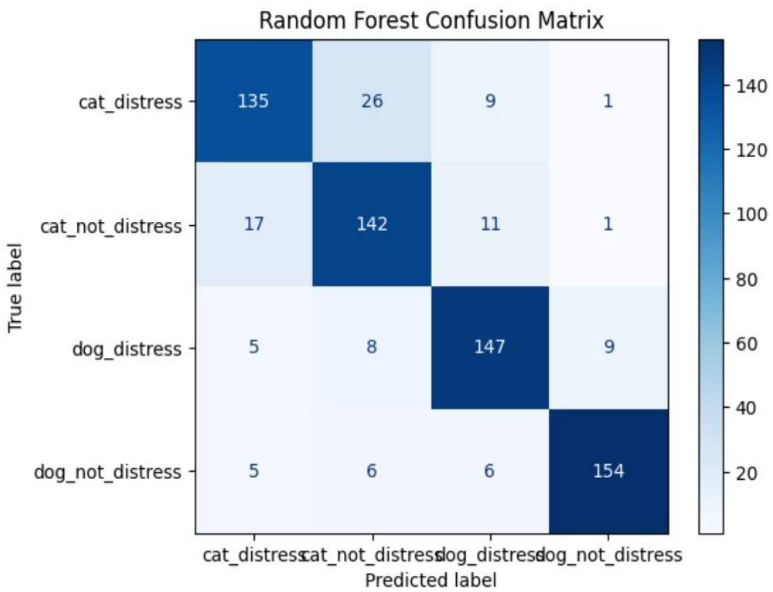

FIGURE 5: Classification report of the Random Forest model for multiclass animal distress detection

Confusion Matrix Analysis

Confusion matrix analysis was conducted to gain deeper insights into class-wise prediction behavior. The Random Forest confusion matrix shows a strong diagonal dominance, indicating that the majority of predictions were correctly classified. Misclassifications were minimal and largely confined to borderline cases where distress vocalizations closely resembled normal vocal patterns, especially in cats. Notably, the system demonstrated a high true positive rate for dog distress detection, which is critical for timely intervention. False negatives were significantly reduced through the use of multimodal confirmation, where distress was validated using both physiological abnormalities and acoustic classification. This confirms that the fusion-based decision strategy effectively mitigates weaknesses inherent in single-modality systems.

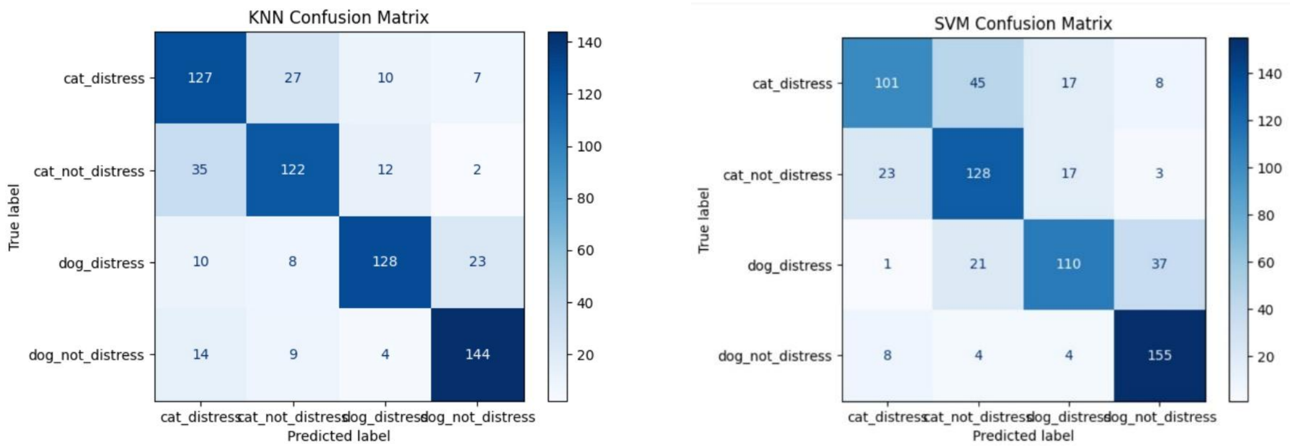

FIGURE 6: Confusion matrices of SVM and KNN models for comparative evaluation

Training and Validation Trends

The training and validation accuracy and loss curves provide insight into the learning behavior of the models. The plots indicate a steady increase in accuracy and a corresponding decrease in loss for both training and validation datasets. Importantly, the validation curves closely follow the training curves, suggesting that overfitting was effectively controlled through data augmentation and proper model tuning.

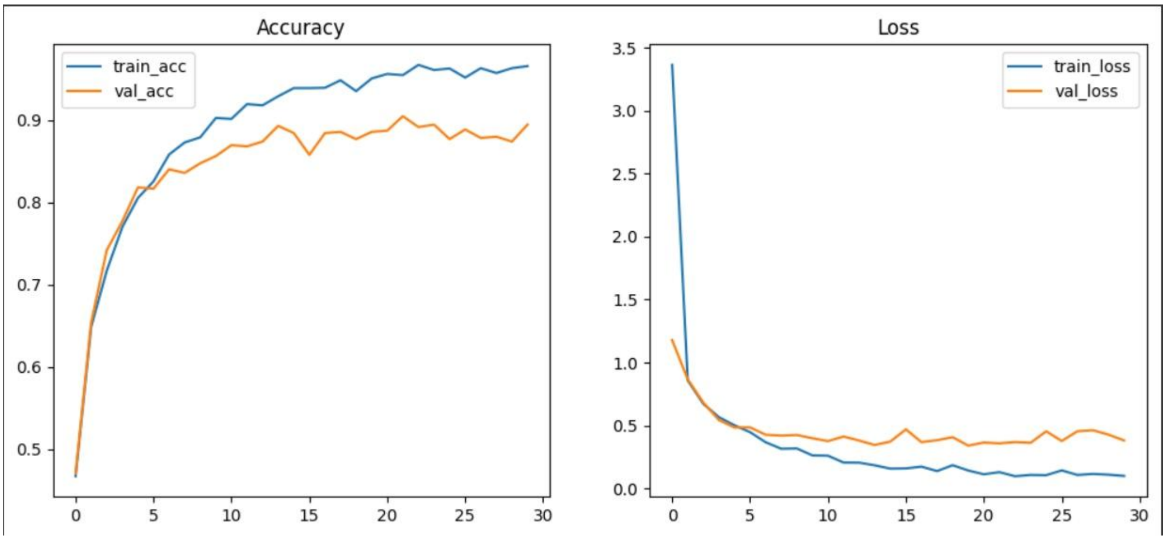

FIGURE 7: Performance curves illustrating training and validation accuracy and loss over epochs, indicating effective learning and reduced overfitting

Early experiments revealed overfitting due to limited distress samples; however, the application of augmentation techniques such as noise addition, pitch shifting, and time stretching significantly improved generalization. The convergence of loss curves at later epochs confirms that the model learned meaningful acoustic patterns rather than memorizing the training data.

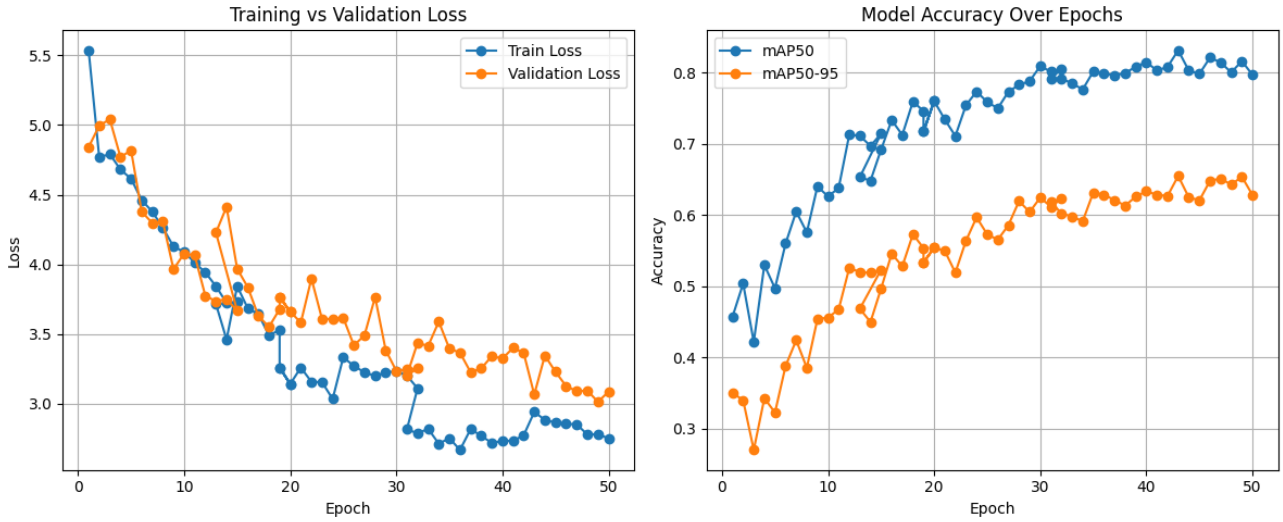

FIGURE 8: Training versus validation loss (left) and model accuracy over epochs (right), highlighting steady performance improvement and convergence

5.2 System-Level Performance Evaluation

Beyond model accuracy, MAUI was evaluated on system-level performance metrics relevant to real-world deployment. Event-triggered data acquisition reduced unnecessary audio recording and transmission, improving energy efficiency and lowering alert noise. Alert latency remained minimal due to on-device preprocessing and efficient communication between the smart collar and mobile application.

TABLE 2
SYSTEM PERFORMANCE METRICS (OBSERVED OUTCOMES)

Metric	Observed Outcome
Average Alert Latency	Low (near real-time)
False Alarm Rate	Reduced via multimodal fusion
Distress Detection Accuracy	~0.85 - 0.89
Noise Robustness	High after augmentation
Power Efficiency	Improved through event triggering

The system successfully generated structured alerts containing distress type, confidence score, timestamp, and location data. In simulated rescue scenarios, integration with CCTV-based animal detection enabled verification of community-reported sightings before NGO notification, reducing false reports and improving response prioritization.

5.3 Comparison with Existing Work

A comparative analysis with prior research highlights the advantages of the MAUI system. While many existing approaches focus either on physiological monitoring, sound-based detection, or visual surveillance independently, MAUI integrates all three into a unified workflow. Previous sound-based distress detection studies report accuracies in the range of 82–85% under controlled conditions, often without real-time deployment or physiological validation. Similarly, IoT-based smart collars typically lack intelligent distress interpretation and contextual alert prioritization. MAUI demonstrates improved reliability by combining physiological triggers with acoustic classification, thereby reducing false positives and missed distress events. Furthermore, the inclusion of community reporting and CCTV-based verification extends the system's impact beyond pet monitoring to broader animal welfare applications.

TABLE 3
COMPARISON WITH EXISTING SYSTEMS

Feature	Existing Systems	MAUI
Physiological Monitoring	Yes (limited)	Yes (continuous)
Distress Sound Analysis	Partial	Yes (AI-based)
Multimodal Fusion	No	Yes
Real-Time Alerts	Limited	Yes
NGO Integration	Rare	Yes
Community Reporting	No	Yes

5.4 Discussion and Key Observations

The results confirm that the design choices made in MAUI—particularly event-driven sensing, multimodal fusion, and ensemble learning—significantly enhance distress detection reliability. The Random Forest model proved well-suited for bioacoustic classification in noisy environments, while the system architecture ensured timely and actionable alerts. Importantly, the integration of physiological and acoustic cues aligns well with real-world animal behavior, where distress is often manifested across multiple signals rather than a single modality. Overall, MAUI demonstrates strong practical potential as a scalable and humane animal welfare monitoring platform capable of supporting pet owners, communities, and NGOs through intelligent automation and data-driven insights.

VI. CONCLUSION AND FUTURE DIRECTIONS

This paper presented **MAUI (Monitoring Animals Using Intelligence and IoT Smart Collar)** , an integrated and intelligent framework designed to address critical challenges in animal health monitoring and welfare. By combining continuous physiological sensing, machine learning–based distress vocalization analysis, and real-time alerting through a user-centric mobile platform, MAUI enables early detection of health anomalies and timely intervention. The adoption of an event-driven architecture and multimodal data fusion significantly improves reliability while reducing false alarms and unnecessary data transmission.

Experimental results demonstrate that the proposed system achieves robust performance under realistic conditions, with ensemble learning models such as Random Forest delivering high accuracy and balanced precision-recall characteristics. Beyond individual pet care, the integration of community reporting and CCTV-based animal detection extends MAUI's applicability to stray and injured animals, enabling efficient NGO collaboration. Overall, MAUI bridges the gap between technology and empathy, offering a scalable, secure, and humane solution for next-generation animal welfare monitoring.

Future directions include:

- Expanding the system to support additional animal species and behaviors through larger, more diverse multimodal datasets
- Further optimization of edge intelligence and energy-efficient hardware design to enhance long-term deployment capabilities
- Integrating advanced deep learning models and wider smart-city surveillance networks to strengthen real-time detection and large-scale animal welfare operations

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper. The research was conducted independently and was not influenced by any commercial, financial, or personal relationships that could be construed as potential conflicts.

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