Original Article

Ai-Iot Bioacoustics System for Animal Stress Monitoring

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Abstract

Bioacoustic sensing is a promising non-invasive method for monitoring livestock welfare, enabling continuous detection of health, behaviour, and emotional states from animal sounds. Advances in signal processing and machine-learning have improved feature extraction and classification for applications such as respiratory disease detection, behavioural monitoring, and stress identification. Although laboratory results are promising, practical deployment remains limited due to farm noise, overlapping calls, and lack of standardized validation. This paper reviews current bioacoustic technologies, highlights their strengths and challenges, and outlines key research gaps that must be addressed to develop scalable and reliable acoustic monitoring systems for precision livestock farming.

Keywords: *a iot systems, cyber-physical systems, smart farming technologies, digital animal health, automated decision support systems*

Introduction

The welfare and health monitoring of farm and domestic animals is a major challenge due to the lack of continuous, objective, and non-invasive assessment methods. Traditional observation-based techniques are labor-intensive, subjective, and often fail to detect early signs of stress or discomfort. To address this gap, this project proposes bioscout, a wearable throat-mounted vibration sensing system designed to monitor animal stress in real time.Bioscout uses a contact microphone or surface accelerometer to capture low-noise vocal-throat vibrations directly from the animal's laryngeal region. The acquired signal is digitized using an onboard microcontroller and processed through signal processing pipelines, including fft, autocorrelation, and spectral analysis. Extracted features such as dominant frequency, rms energy, zcr, and pitch are then evaluated to classify the animal's emotional state into normal, happy, or stressed. The system supports multiple species—including cows, dogs, pigs, poultry, sheep, horses, and elephants—through species-specific sampling and analysis methods. Processed data is transmitted wirelessly to an edge device and optionally to a cloud platform for visualization, storage, and alerts. Bio scout enables farmers, veterinarians, and wildlife managers to detect stress early.

Literature survey

Bioacoustics has emerged as a promising non-invasive approach for continuous monitoring of livestock welfare, enabling the detection of behaviour, health conditions, and affective states directly from vocal and non-vocal sounds. Recent advances in signal processing and machine-learning have significantly strengthened the ability to extract meaningful acoustic indicators related to physiology, emotional arousal, and disease progression in farm environments. Temporal, frequency-based, and spectral features such as call duration, fundamental frequency, formants, and entropy are commonly employed for analysis, while tools like fft, mfccs, praat, seewave, and deep learning models support automated classification and feature extraction. [1]

In poultry, acoustic markers have been used to differentiate healthy birds from those affected by infectious bronchitis, avian influenza, or digestive disorders, highlighting acoustics as an early-warning diagnostic tool. Behavioural monitoring, including detection of chewing, biting, and pecking, has also shown high accuracy with both barn-mounted and wearable microphones, though practical scalability is still limited by environmental variability. [1]

The reviewed work highlights how bio-inspired ant-system routing improves energy efficiency, reliability, and data delivery in iot networks. Its relevance to bioscout lies in optimizing wearable-to-edge communication, reducing transmission energy, and ensuring stable data flow from animal sensors to gateways—critical for long-term stress monitoring in distributed farm environments.[2] The assessment of affective states particularly stress, fear, and pain rely on measurable changes in vocal parameters, with strong evidence available for pigs and growing evidence for ruminants. However, detecting positive emotional states remains a developing area with limited cross-species generalization. The field overall faces methodological gaps, including inconsistent feature extraction methods, limited datasets, and a lack of standardized validation across farms. Addressing these challenges through open datasets, unified evaluation protocols, and real-farm testing is crucial for transitioning bioacoustic research into reliable, and real-farm testing is crucial for transitioning bioacoustic research into reliable, scalable welfare-monitoring tools. *[1]*

Methodology

The proposed Bio Scout system follows a multi-stage pipeline that integrates wearable sensing, embedded signal processing

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wireless communication, machine learning, and cloud-based monitoring. The complete methodology is divided into five major modules: **(1) Wearable Data Acquisition, (2) Signal Pre-Processing, (3) Feature Extraction, (4) Stress Classification, and (5) Data Transmission and Visualization**. Each stage is described below.

Wearable Sensor Data Acquisation

The system uses a **throat-mounted contact microphone or surface accelerometer** placed near the laryngeal region of the animal. Unlike air microphones, the contact sensor directly captures mechanical vibrations traveling through tissue, significantly reducing environmental noise and improving signal quality in open-field farming environments. The sensor output is fed into the onboard **Analog-to-Digital Converter (ADC)** of an ESP32-based wearable module. Species-specific sampling rates are configured, such as **8 kHz for cows**, **16 kHz for dogs and poultry**, **10 kHz for pigs and horses**, and **4 kHz for elephants**. This ensures accurate representation of vocal frequencies across different species.

Signal Pro- Processing

To prepare the raw vibration data for analysis, multiple DSP steps are applied locally on the microcontroller:

1. **DC Offset Removal:**The mean value of each sampled frame is subtracted to centre the signal.
2. **Band-PassFiltering:**
   Filters are set according to species-specific vocalranges(e.g., 80–1000 Hz for cows, 200–3000 Hz for poultry).
3. **Frame Segmentation:**The continuous signal is divided into small analysis windows(20–40 ms for most species, 500 ms for elephants).
4. **Windowing:**
   A Hamming window is applied to reduce spectral leakage during FFT computation.

A. Feature Extraction

Different species exhibit different vocalization characteristics; therefore, the system applies the most suitable acoustic analysis method for each animal.

B. Techniques

- **Fast Fourier Transform:** Used for cows, sheep, poultry, pigs, and horses.Computes dominant frequency peaks that correlate with stress-induced pitch changes.
- **Autocorrelation-Basedpitch Estimation:** Used for dogs and elephants.Autocorrelation is robust against noisy, broadband vocalizations such as barking and low-frequency rumbling.
- **Zero Crossing Rate:** Combined with FFT for poultry, where high-frequency distress chirps produce rapid zero-crossing fluctuations.

C. Stress Modulation

A rule-based or machine-learning-based classifier assigns a stress level (Normal, Happy, or Stressed) based on the extracted acoustic features.

Heuristic Threshold

Embedded decision rules compare measured frequency values with species-specific ranges derived from behavioral studies.
Example: For cows,

- <250 Hz → Normal
- 250–500 Hz → Relaxed/Happy
- 500 Hz → Stressed

Machine Learning

A supervised model (Random Forest/SVM/CNN) trained on labeled vocalizations enhances accuracy.Features or spectrograms are uploaded to an edge device or cloud server for inference

D. Wireless Transmission And Cloud Integration.

- The processed features or classified stress levels are transmitted over BLE, Wi-Fi, or LoRa, depending on range requirements. Data reaches an edge gateway (e.g., Raspberry Pi), which aggregates signals from multiple animals.

The Cloud Handles:

- Data storage
- Trend analysis
- Alert generation
- Dashboard visualization

E. Real Time Dashboard And Alerting System

This System Presents:

- Individual animal identity
- Live stress index
- Frequency and energy graphs
- Daily/weekly behaviour trends
- Alerts for high stress or abnormal vocalization

F. System Validation

The final stage includes laboratory testing, farm trials, and comparison against known behavioural states. Performance metrics include:

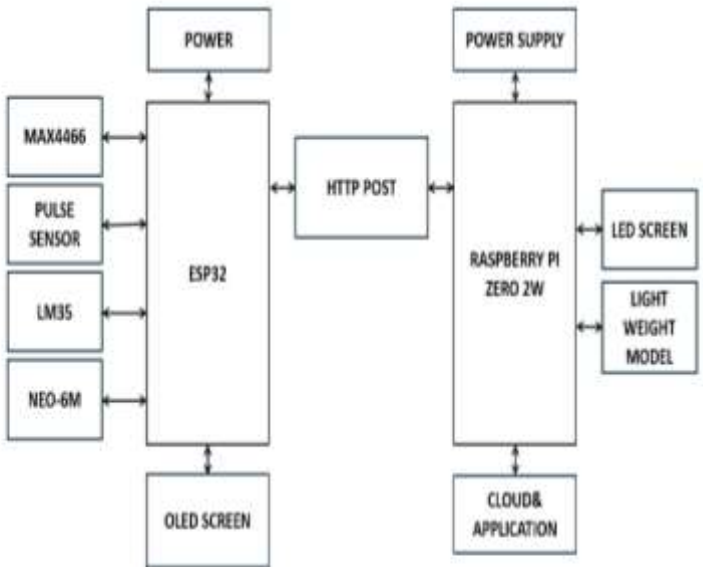
- Accuracy of stress detection
- False alarm rate
- Latency
- Battery endurance
- Wireless reliability

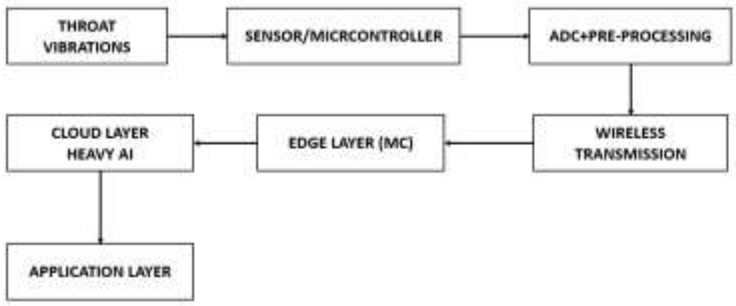
G. Testing And Validation

Bench testing: Sensor sensitivity calibration using controlled vibration input.
Animal testing: Field trials conducted across multiple species and environments.
Performance metrics:

- Precision, recall, F1-score for stress classification
- Latency from vibration detection to notification
- Battery endurance study under real workload

Comparison against **ground-truth behaviour logs** annotated by trainers or veterinarians.
Block Diagram



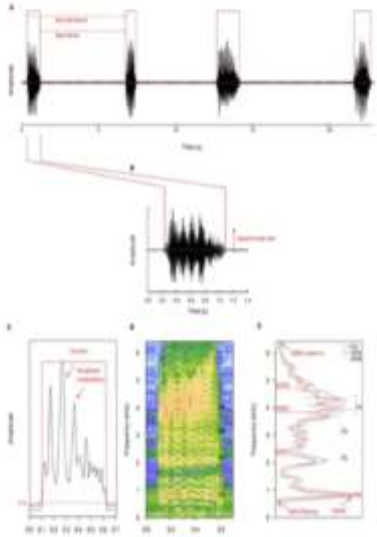


Vocal parameters recorded in farm animals

Before delving into how vocal indicators can inform about various aspects of farm animal health and welfare, this chapter aims to provide the reader with a brief summary of the mechanisms of vocal production in animals, the types of parameters that can be extracted from animal vocalizations, and the methods by which they can be analyzed and classified. Importantly, this section does not provide an in-depth guide to performing signal processing analyses leading to the extraction of quantitative parameters from vocalizations, but rather an overview of the general approach to acoustic analyses.

Classification Of Animal Signals

Non-human vocalizations can be broadly classified as calls, which are relatively short and simple (i.e. composed of one or a few sound units), and songs, which are longer and more complex **(i.e. composed of several sound units arranged following a particular syntax; Bradbury and Veh encamp, 2011).** Although songs received a great interest due to their complexity, they are produced in a limited number of contexts (**mostly territorial defense and mate attraction; Catchpole and Slater, 2008; Loning et al., 2023**). However, calls are more widespread and have multiple functions often their acoustic.



Proposed Scheme

1. Identification of a marker in the sounds

Performance of an explorative study showing that acoustic features of animals presenting the condition/performing the behaviour differ from sounds of control animals, ideally with validation within and across subjects.

2. Classification of a condition in the sounds (experimental set-up)

Development of an algorithm to automatically classify sounds as produced by individuals presenting the condition/performing the behaviour or control individuals. Usually performed in experimental settings.

3. Detection of a condition in the sounds (practical set-up)

Development of an algorithm to automatically detect the condition/behaviour in sounds of animals among a group of diverse individuals.
Usually performed in practical conditions.

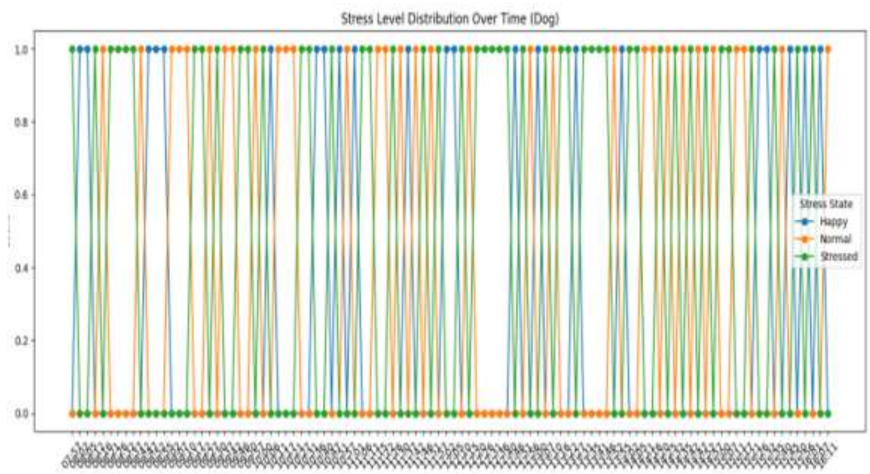
4. Validation of the detection across different contexts

Testing and refinement of the algorithm in practice, including farms characterized by various group size, age of animals, noise environment, etc.

5. Implementation

Development of a recording and analyzing device implementable in practice.

Stress Level Graphs



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Challenges And Limitations in Practical Deployment

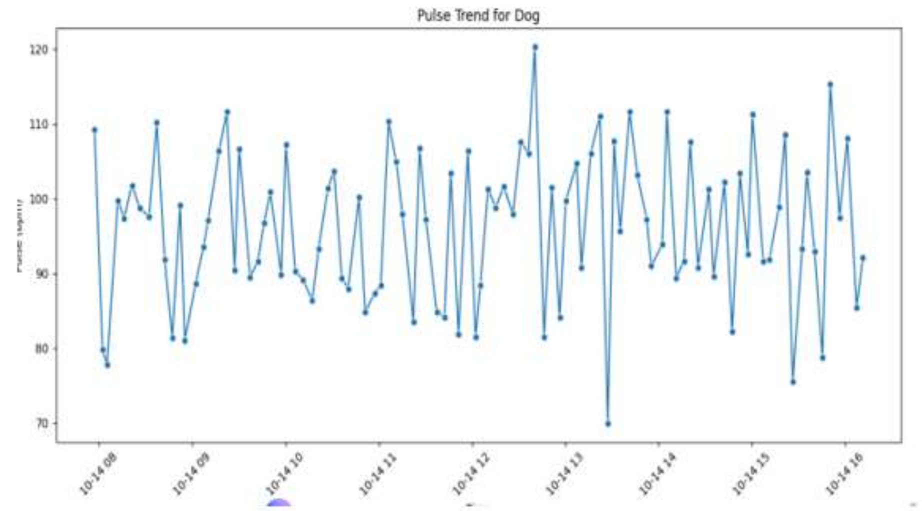
Noise and Cross-Interference

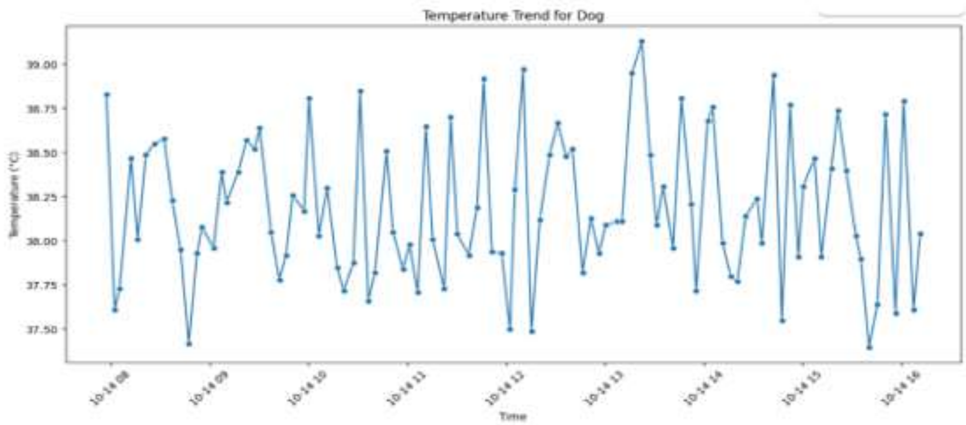
Traditional airborne microphones fail due to:

- Machinery sounds
- Wind
- Multiple animals vocalizing simultaneously

BioScout overcomes this using a contact sensor, but challenges still exist:

- Movement artefacts
- Collar misalignment
- Vibration interference during running or scratching





Dataset Limitations

Most bioacoustic datasets include very few animals. The base paper highlights that many algorithms were trained on <20 individuals, leading to overfitting.

BioScout addresses this by enabling on-farm incremental dataset expansion, allowing farmers to label events and build robust local models.

Interpretation Challenges

Machine learning systems may detect anomalies but not interpret why they occur. The base paper stresses the importance of linking acoustic markers to ground-truth biological meaning.

Thus, BioScout includes cross-verification with:

- Behaviour logs
- Environmental sensors
- Time-stamped activity cues

Species-Specific Acoustic Variability

The base paper highlights that each species has different vocal organs and spectral characteristics (larynx in mammals vs syrinx in birds)

This creates challenges for BioScout such as:

- Need for species-specific filters, sampling rates, and classification rules
- Difficulty in developing a universal ML model
- Increased storage requirements for multi-species datasets

Limited Availability of Large-Scale Labelled Datasets

The scoping review notes that most bioacoustic studies involve "very small groups of animals," often fewer than 20 subjects. This leads to:

- Overfitting of ML models
- Poor generalization when deployed on large farms
- Difficulty in validating stress vs. normal behaviour across breeds

Real-World Noise and Environmental Disturbances

Even though BioScout uses throat vibrations, environmental factors can still affect analysis:

- Dust accumulation on sensors
- Collar loosening on large animals
- Multiple animals rubbing or pushing against each other
- Weather influence on electronic components

Future scope

Multimodal Fusion

Combining vibration data with:

- Thermal cameras (heat stress detection)
- GPS collars (movement reduction)
- Environmental sensors (temperature, ammonia)

Cloud-Based Herd Analytics

Long-term modelling provides:

- Daily stress patterns
- Seasonal heat stress risk
- Prediction of respiratory outbreaks
- Behaviour deviation analytics

Integration With Veterinary Decision Systems

Future versions can offer:

- Early disease alerts
- Automated isolation recommendations

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Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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