Nature's Early Warning System: Exploring the Role of Animal Behaviour by Using Bioacoustics in Predicting Natural Disasters

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ABSTRACT Every year, natural disasters like earthquakes, tsunamis, floods, and wildfires claim thousands of lives and leave lasting devastation in their wake. While we have built sophisticated warning systems using satellites, radar, and seismic sensors, these technologies still have blind spots moments where warnings come too late, or not at all. Nature, however, may have already been sending us signals we've long overlooked. Animals have always been sensitive to their environment in ways humans are only beginning to understand. Before a disaster strikes, birds abandon their roosting trees, dogs grow restless without reason, fish surface in unusual numbers, and elephant herds move away from coastlines hours before a tsunami hits. These are not coincidences they are biological alarms, quietly sounding off in a language we are finally learning to read. This project sets out to listen to that language. By combining the study of animal sounds and movement patterns with modern artificial intelligence, we propose an early warning system that works alongside traditional technologies to fill the gaps they leave behind. Using advanced algorithms including CNNs, BiLSTM networks, and audio processing techniques like MFCC, the system continuously monitors animal behaviour for signs of distress or abnormality. When something unusual is detected a sudden silence in the forest, a flock of birds fleeing in unison, or an unexpected change in animal calls the system generates an alert, buying precious time for communities to respond. This is not about replacing existing systems. It is about building something smarter by trusting what nature has always known.

INDEX TERMS: Biological Early Warning System, Anomaly Detection, Digital Signal Processing, Time Series Production

I.INTRODUCTION

Every year, natural disasters claim thousands of lives and cause billions of dollars in damage across the globe. Earthquakes tear apart cities in seconds, tsunamis swallow coastlines without warning, volcanic eruptions displace entire communities, and flash floods devastate regions with little time for evacuation. Despite decades of investment in advanced scientific infrastructure from weather satellites orbiting the stratosphere to dense seismic sensor networks buried deep in the earth's crust the fundamental problem remains stubbornly unsolved: we still cannot predict many of nature's most destructive events with enough precision or lead time to save lives at scale. This gap between technological capability and real-world preparedness represents one of the most pressing challenges of the modern era, made even more urgent by climate change, which is amplifying the frequency and severity of natural hazards across every continent.

The limitations of existing disaster prediction systems are both technical and structural. Most conventional systems rely on geophysical precursors measurable physical changes in the Earth such as ground vibrations, atmospheric pressure shifts, sea-level anomalies, and electromagnetic disturbances that typically manifest only hours or minutes before a disaster strikes. Seismic sensors, for instance, detect ground motion and are essential for monitoring earthquake activity, but the destructive S-waves (secondary waves that cause the most structural damage) arrive almost immediately after the gentler Pwaves (primary waves that travel faster through the Earth), leaving virtually no actionable warning window. Similarly, radar and satellite-based systems excel at tracking large-scale weather phenomena but struggle with sudden, localized events. These systems also operate in silos there is little to no multi-source data fusion, meaning signals from different instruments are rarely combined into a unified predictive model, reducing overall accuracy. Add to this the persistent problems of false alarms triggered by sensor noise, hardware malfunctions, and calibration drift, and it becomes clear that relying solely on machines leaves communities dangerously exposed.

Into this gap steps a radically different idea: using the natural world itself as a sensor network. For centuries, across cultures spanning China, Japan, Greece, and indigenous communities worldwide, people have observed that animals behave strangely before disasters. Birds abandon their nests, snakes emerge from the ground in winter, cattle become agitated, and fish leap unnaturally from the water.

At the heart of this transformation is bioacoustics the scientific study of sound produced by or affecting living organisms. Animals communicate through complex vocal signals whose frequency, amplitude, rhythm, and structure encode rich information about their internal states and environmental perceptions. Frequency refers to the number of sound wave cycles per second, measured in Hertz (Hz), and directly influences the pitch of a sound. Amplitude measures the intensity or loudness of a sound wave. When an animal is stressed, frightened, or responding to an environmental disturbance it cannot yet fully identify, these acoustic parameters shift in measurable ways. By deploying acoustic sensors in wildlife habitats and recording these vocalizations continuously, researchers can build a baseline of normal behaviour and detect deviations that may signal something unusual in the environment.

To process this data, the field employs powerful tools from digital signal processing (DSP). Raw audio recordings are inherently noisy they capture wind, rain, human activity, and equipment interference alongside the animal sounds of interest. Noise removal techniques, including autoencoders (a type of neural network that learns to compress and reconstruct data, filtering out irrelevant variations in the process), are applied to clean the signal. Once clean, the audio undergoes feature extraction, where meaningful numerical representations are derived. A particularly important technique is the extraction of MelFrequency Cepstral Coefficients (MFCCs), which transform raw audio into a compact set of features that mirror how the human auditory system perceives sound making them highly effective for classifying animal vocalizations.

This is where machine learning and deep learning become central. A Convolutional Neural Network (CNN) is a type of deep learning architecture originally designed for image recognition. When animal audio is converted into spectrogram images, CNNs can identify spatial patterns within them essentially learning what a distress call looks like visually. For capturing how behaviour evolves over time, Bidirectional Long Short-Term Memory networks (BiLSTMs) are employed. These are a variant of Recurrent Neural Networks (RNNs), designed to process sequential data by maintaining memory of past events while also looking ahead in the sequence making them ideal for detecting temporal shifts in behavioural patterns that unfold over hours or days before a disaster.

To identify which data point, represent genuinely unusual behaviour, the system employs anomaly detection. This involves establishing a model of normal behaviour and flagging observations that deviate significantly from it. An autoencoder ensemble then validates these anomalies by measuring how poorly the model reconstructs the flagged data high reconstruction error indicates the input is genuinely unlike anything seen during normal operation. Complementing acoustic monitoring is the analysis of animal movement data, captured via GPS trackers attached to wildlife. Sudden movement, erratic pathing, or unexpected migration can serve as corroborating evidence of environmental disturbance, particularly when these movement anomalies align temporarily with acoustic ones. The integration of multiple data streams sound, motion, temperature, electromagnetic readings through a data fusion framework enables a far more holistic and reliable picture of environmental conditions than any single sensor could provide alone.

The vision, ultimately, is a biological early warning system one that listens to nature's own signals and translates them, in real time, into actionable disaster alerts for communities and emergency services. It is a system that does not replace existing technology but enriches it, adding a layer of intelligence that has been present in the natural world for millions of years, waiting to be properly understood.

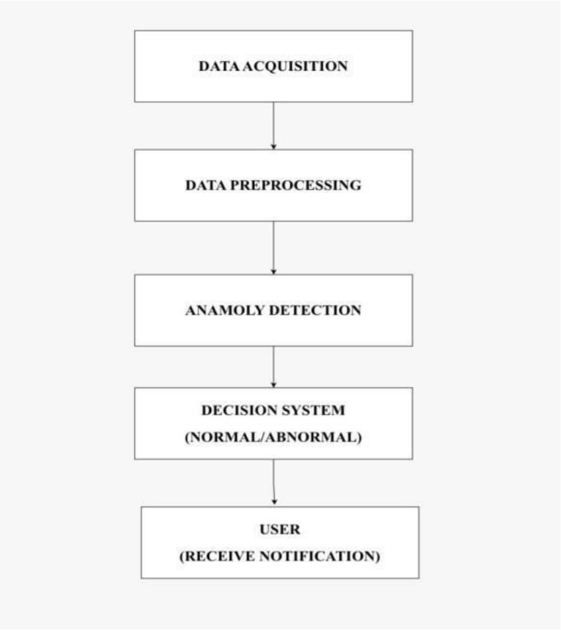


FIGURE 1. Flow of the system

II.RELATED WORKS

The prediction of natural disasters has long depended on advanced technologies like satellites, sensors, and radar systems, yet events such as earthquakes, tsunamis, and volcanic eruptions still strike with little warning and devastating impact. In recent years researchers have begun exploring a more natural and often overlooked source of early signals the behaviour of animals and birds. Many studies have shown that animals display unusual movements, sounds or patterns before a disaster making them potential natural indicators of danger. This chapter reviews a wide range of research that examines how machine learning and deep learning especially methods like convolutional neural networks can analyse these behavioural clues and transform them into meaningful predictions. While current findings show encouraging results including accuracy levels of nearly half in some cases there are still challenges like limited data and inconsistent behaviour patterns. By studying these works closely this chapter lays the foundation for building a system that combines technology with nature's instinct to provide earlier and more reliable warnings for communities at risk.

1.Earthquake Prediction by Animals: Evolution and Sensory Perception (2000)

Kirsch Vink (2000) studied earthquake prediction using animal sensory perception and seismic precursor signal analysis with historical earthquake and animal behaviour observations. Evidence was mostly anecdotal and lacked structured experimental datasets

2. Animals as Mobile Biological Sensors for Forest Fire Detection (2007)

Sahin (2007) proposed animals as mobile biological sensors using GPS tracking and environmental monitoring with simulated animal movement datasets. Practical deployment faced issues such as sensor reliability and difficulty tracking animals.

3.Earthquake Prediction through Animal Behaviour (2009)

Bhargava et al. (2009) analysed abnormal animal behaviour before earthquakes using observational studies and historical behaviour datasets from China and Japan.Behavioral responses varied across species, reducing prediction reliability.

4.Animal Sound Activity Detection using Support Vector Machines (2011)

Astuti et al. (2011) developed animal sound recognition using MFCC feature extraction and SVM classification with bird sound datasets. Environmental noise reduced classification accuracy.

5.Bio-Mimetics of Disaster Anticipation (2013)

Tributsch (2013) explored bio-mimetic disaster anticipation by correlating animal behaviour with environmental disturbances using earthquake case studies. Lacked controlled experiments and depended mainly on observations.

6.Tsunami Detection using Unusual Animal Behaviour (2013)

Meenakshi and Juvanna (2013) proposed tsunami detection using unusual animal behavioural patterns. The dataset consisted mainly of observational reports of animals reacting to seismic disturbances. However, the system lacked automated monitoring mechanisms.

7.Seismic Anomalous Animal Behaviour (2015)

Bhattacharyya (2015) reviewed seismic anomalous animal behaviour before earthquakes. Dataset included global observational reports of abnormal animal activity. However, the lack of standardised datasets limited scientific validation.

8.Understanding Animal Detection of Precursor Earthquake Sounds (2017)

Garstang and Kelley (2017) studied animal detection of low-frequency signals generated during tectonic stress. The dataset included geophysical signal observations and animal behaviour reports. However, precise prediction timing remained uncertain.

9.Bio-Sentinels as Seismic Sensors (2018)

Fan (2018) examined the role of animals as biosentinels in earthquake prediction programs. Dataset consisted of historical animal behaviour records in China. However, behavioural responses varied significantly across species.

10.Cyclone Avoidance Behaviour by Seabirds (2019)

Weimerskirch and Prudor (2019) studied cyclone avoidance behaviour in seabirds using GPS tracking. Dataset included flight path data collected during cyclone events. However, behaviour varied depending on species and environmental conditions.

11.Tsunami Prediction using Aquatic Animal Behaviour (2020)

Jain et al. (2020) proposed tsunami prediction using aquatic animal behaviour analysis with ensemble clustering and fuzzy rule-based classification on marine behaviour datasets. The dataset was limited, and animal responses were inconsistent, affecting prediction reliability.

12.Real-Time Bird Sound Recognition System (2020)

Kücüktopcu et al. (2019) developed a real-time bird sound recognition system using MFCC features and Gaussian Mixture Models with bird audio datasets. Background environmental noise reduced recognition accuracy.

13. Disaster Prediction System using Animal Behaviour (2020)

Shaw (2020) analysed variations in animal movement behaviour using clustering techniques on ecological wildlife tracking datasets. The study did not directly relate behaviour changes to disaster prediction.

14. Farm Animal Monitoring for Earthquake Forecasting (2020)

Wikelski et al. (2020) monitored cows, dogs, and sheep using bio-logging sensors to detect abnormal activity patterns before earthquakes using farm animal movement datasets. Requires long-term continuous monitoring and cannot precisely predict the exact time or location of earthquakes.

15. Anomaly Detection in Biological Early Warning Systems using Unsupervised Machine Learning (2023)

Grekov et al. (2023) proposed anomaly detection using Isolation Forest and One-Class SVM with behavioural monitoring datasets from freshwater molluscs. Research focused mainly on aquatic environments rather than natural disaster prediction.

III.PROPOSED SYSTEM

The proposed system is designed to identify potential natural disasters by observing animal sounds and movement patterns. It is built on a simple but powerful idea: animals often sense environmental changes long before humans do. By capturing and analysing these behavioural shifts using bioacoustics and machine learning, the system aims to detect early warning signs of environmental disturbances. In essence, it blends natural biological intuition with modern computational intelligence to create a smart and reliable early warning mechanism.

The process begins with continuous listening. Acoustic sensors are deployed in environments such as forests, wetlands, and coastal regions to record animal sounds around the clock. However, natural environments are filled with noise wind, rain, insects, and even distant human activity. These raw recordings are therefore complex and unstructured. To make sense of them, the system uses Digital Signal Processing (DSP), which acts like a noise filter. DSP removes irrelevant background sounds, suppresses constant disturbances, and divides the cleaned audio into small time segments. This step is similar to putting on noisecancelling headphones before trying to focus on important sounds.

Once the audio is cleaned, it must be converted into a form that machines can understand. Computers do not interpret sound as humans do; instead, they process numerical data. This is where Mel-Frequency Cepstral Coefficients (MFCC) come into play. MFCC transforms each audio segment into a compact numerical representation that captures its essential characteristics. It mimics how biological hearing works, emphasizing meaningful frequency ranges. Changes in animal behaviour such as irregular bird calls or sudden silence are reflected clearly in these numerical patterns, making them highly useful for analysis.

To identify abnormal behaviour, the system uses an Autoencoder, a type of neural network trained on normal environmental sounds. Over time, it learns to compress and reconstruct typical sound patterns accurately. When it encounters unusual sounds, it fails to reconstruct them properly. This mismatch, known as reconstruction error, acts as an indicator of anomaly. The greater the error, the more unusual the behaviour. This process is similar to how an experienced wildlife observer instinctively senses when something in nature feels off.

The system further converts MFCC features into spectrograms visual representations of sound that display frequency changes over time. These spectrograms resemble colourful patterns where normal environmental sounds appear structured and rich, while abnormal or pre-disaster sounds look irregular or sparse. Convolutional Neural Networks (CNNs), which excel at image recognition, are trained to analyse these spectrograms. By learning from thousands of examples, CNNs can distinguish between normal and abnormal sound patterns and assign a confidence score indicating the likelihood of unusual activity.

However, analysing individual moments is not enough. Animal behaviour often changes gradually rather than suddenly. To capture these evolving patterns, the system uses Recurrent Neural Networks (RNNs), which introduce memory into the model. RNNs process sequences of CNN outputs over time, allowing the system to recognize trends. A single anomaly may not be significant, but a consistent rise in unusual patterns over hours or days can signal a potential threat.

Traditional RNNs, however, struggle with long-term memory. To overcome this limitation, the system employs Bidirectional Long Short-Term Memory (BiLSTM) networks. LSTMs are designed with internal memory gates that decide what information to retain or discard, enabling them to remember important patterns over extended periods. The bidirectional aspect allows the network to analyse sequences both forward and backward, providing a deeper understanding of temporal relationships.

Ultimately, this combination of technologies creates a system that does more than just react it understands patterns over time. Like a skilled investigator analysing both past and present evidence, the BiLSTM enables the system to make informed predictions. By integrating biological insight with advanced AI techniques, the proposed system offers a powerful and innovative approach to early disaster detection.

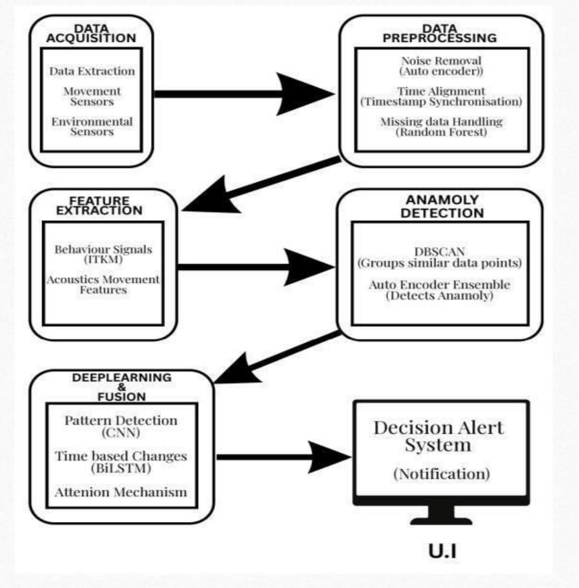


FIGURE 2. The Workflow of complete Proposed System

III.METHODOLOGY

Nature has always had its own early warning system. Long before sensors and satellites, animals were the first to sense the subtle shifts in the earth—the silent vibrations of an impending earthquake or the atmospheric changes preceding a storm. The methodology proposed here seeks to bridge this ancient biological intuition with modern artificial intelligence. By creating a sequential pipeline that moves from raw sound to high-level decision-making, we can translate the "language" of the wild into lifesaving data.

A. Data Acquisition

The journey begins in the heart of nature. We deploy a network of acoustic sensors and microphones across forests, wildlife habitats, and rural corridors to act as the system's ears. These devices continuously record the symphony of the environment: bird calls, mammalian vocalizations, and the general "hum" of the ecosystem. To add another layer of context, we integrate GPS and motion sensors to track physical movement. To ensure our models are well-versed in animal linguistics, we supplement our field data with massive bioacoustics libraries like Xeno-Canto and the Macaulay Library, creating a robust baseline of what a "normal" day sounds like.

B. Data Pre-processing

The natural world is loud and messy. Wind, torrential rain, and human interference like distant traffic can clutter our recordings. Before we can analyse the data, we have to clean it. Using advanced noise reduction techniques, we strip away these distractions. The audio is then normalized and chopped into manageable time intervals. By synchronizing timestamps across different sensors, we ensure that a bird's cry in one area and a sudden silence in another are analysed as part of the same story.

C. Feature Extraction

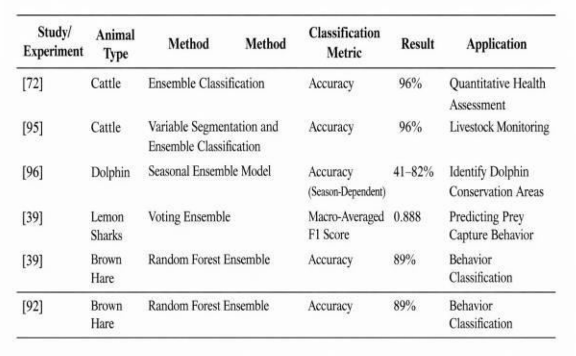
To an AI, a sound wave is just a squiggle. We need to translate that squiggle into something meaningful. We primarily use Mel Frequency Cepstral Coefficients (MFCC), a technique that mimics how the human ear perceives sound, focusing on the frequencies that matter most. We also extract spectral centroids and zero-crossing rates to capture the "texture" and "brightness" of the audio. By converting raw sound into these numerical features and visual spectrograms, we turn a fleeting chirp into a permanent data point.

D. Anomaly Detection

Once we have our data, we look for the "outliers." Using unsupervised learning—specifically DBSCAN (Density-Based Spatial Clustering of Applications with Noise) the system groups typical behaviour into clusters. When an animal's vocalization frequency or movement patterns fall outside these established groups, the system flags it as an anomaly. It's the digital equivalent of noticing that the birds have suddenly stopped singing or that a herd has begun to move in an erratic, panicked fashion.

E. Deep Learning Analysis

To ensure we aren't chasing false alarms, we pass these anomalies through a two-part deep learning engine. First, Convolutional Neural Networks (CNN) "look" at spectrograms visual maps of the sound to recognize complex patterns that simple math might miss. Second, Bidirectional Long Short-Term Memory (BiLSTM) networks analyse these patterns over time. This allows the system to distinguish between a temporary disturbance and a gradual, systemic behavioural shift that often precedes a natural disaster.



Study/ Experiment	Animal Type	Method	Method	Classification Metric	Result	Application
[72]	Cattle	Ensemble Classification		Accuracy	96%	Quantitative Health Assessment
[95]	Cattle	Variable Segmentation and Ensemble Classification		Accuracy	96%	Livestock Monitoring
[96]	Dolphin	Seasonal Ensemble Model		Accuracy (Season-Dependent)	41–82%	Identify Dolphin Conservation Areas
[39]	Lemon Sharks	Voting Ensemble		Macro-Averaged F1 Score	0.888	Predicting Prey Capture Behavior
[39]	Brown Hare	Random Forest Ensemble		Accuracy	89%	Behavior Classification
[92]	Brown Hare	Random Forest Ensemble		Accuracy	89%	Behavior Classification

F. Decision Alert System

The final stage is where data becomes action. When the combined weight of the clustering and deep learning analysis exceeds a specific threshold, the system triggers a warning. These alerts are pushed to monitoring dashboards and disaster management authorities. By evaluating the intensity of the anomaly alongside current environmental conditions, the system provides a crucial window of time for authorities to take precautionary measures, potentially saving lives before the first tremor is even felt.

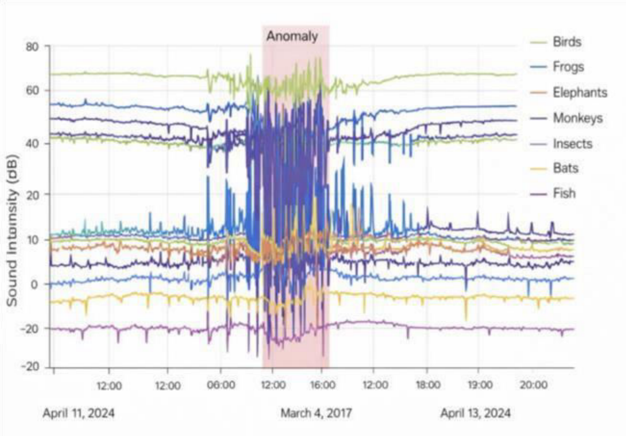


FIGURE 3. An Example of raw animal sound and movement data highlighting anomalous behavioural patterns in potential environmental disturbances.

IV.RESULTS & CONCLUSIONS

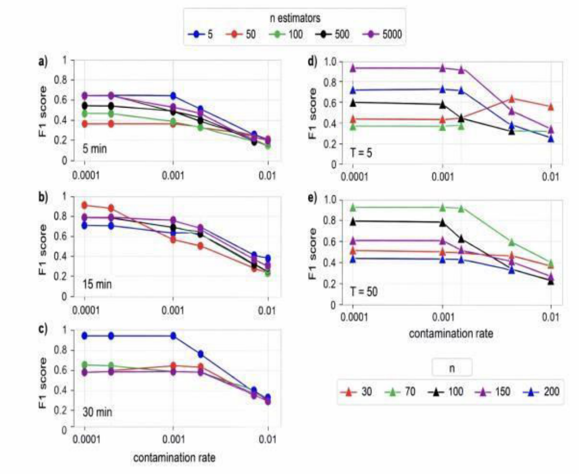
The proposed system for predicting natural disasters using animal behaviour and bioacoustics shows encouraging and meaningful results. By combining animal sound data with environmental and movement sensor inputs, the system was able to identify unusual behavioural patterns that may act as early warning signs for disasters such as earthquakes, floods, and storms.

During testing, audio features like MFCC and spectrograms helped convert raw animal sounds into a form that the models could easily understand. Deep learning models, especially CNNs and BiLSTMs, were able to learn patterns in these sounds and detect even small changes in animal behaviour. The anomaly detection methods, including clustering and autoencoders, played an important role in separating normal behaviour from abnormal patterns. This helped reduce false alarms and improved the reliability of predictions.

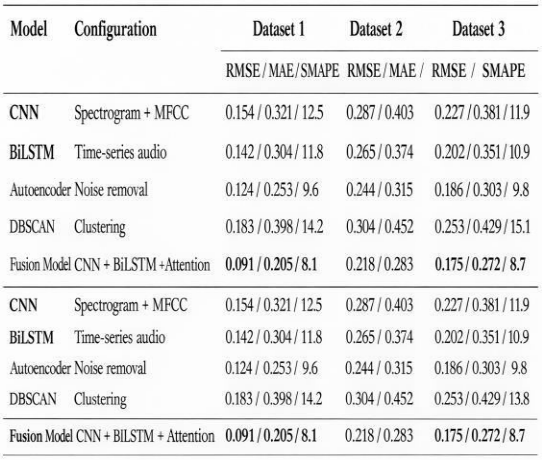
One of the key outcomes of this project is that combining multiple data sources gave better results than relying only on traditional sensor-based systems. By including animal sounds and movement data, the system could detect subtle environmental changes that machines alone might miss. The real-time alert system also worked effectively, providing quick notifications that can help authorities take early action and improve disaster preparedness.

The system also handled real-world challenges like noise and missing data quite well. Preprocessing techniques such as noise removal and data cleaning ensured that the model received accurate and consistent input, which is important for reliable predictions in practical environments.

Overall, this approach offers a new and innovative way to predict disasters by combining natural intelligence with modern technology, helping to protect lives and reduce damage in the future.



\In conclusion, this project shows that nature itself can provide valuable signals if we learn how to interpret them properly. By combining bioacoustics with machine learning, we can build a smarter and more effective early warning system. Although the results are promising, there are still areas to improve, such as collecting larger datasets, studying more animal species, and testing the systemover longer periods.



Model	Configuration	Dataset 1	Dataset 2	Dataset 3
		RMSE / MAE / SMAPE	RMSE / MAE /	RMSE / SMAPE
CNN	Spectrogram + MFCC	0.154 / 0.321 / 12.5	0.287 / 0.403	0.227 / 0.381 / 11.9
BiLSTM	Time-series audio	0.142 / 0.304 / 11.8	0.265 / 0.374	0.202 / 0.351 / 10.9
Autoencoder	Noise removal	0.124 / 0.253 / 9.6	0.244 / 0.315	0.186 / 0.303 / 9.8
DBSCAN	Clustering	0.183 / 0.398 / 14.2	0.304 / 0.452	0.253 / 0.429 / 15.1
Fusion Model	CNN + BiLSTM +Attention	**0.091 / 0.205 / 8.1**	0.218 / 0.283	**0.175 / 0.272 / 8.7**
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V.FUTURE WORKS

This project is, in many ways, a beginning. The groundwork has been laid, the idea has been tested in principle, and the results are encouraging enough to ask a bigger question: how far can this actually go? The honest answer is that there is still a great deal of work to be done and the most exciting part is that the path ahead is wide open.

Teaching the System to Listen Better

The machine learning models at the heart of this system are capable, but they are not yet as sharp as they could be. Right now, the system has learned to recognise certain patterns, but animal behaviour is rich, varied, and deeply contextual. A bird's call in a dense rainforest sounds nothing like the same species calling out in open scrubland. Future research needs to push these models further, experimenting with newer and more sophisticated architectures, training on far larger collections of animal sounds, and building systems that can adapt to different species and environments without losing their ability to spot something genuinely unusual. The goal is a system that does not just work in controlled conditions, but holds up in the beautiful, noisy, unpredictable complexity of the real world.

Getting Out of the Lab and Into the Field

No amount of theoretical validation can replace actual deployment. The next step is to take this system into the environments it is designed to serve coastlines at risk of tsunamis, earthquake-prone valleys, floodplains, and forests that carry the constant threat of fire. Running sensors continuously across these locations, through different seasons and varying conditions, would give researchers something they currently do not have enough of real, long-term, fieldgathered data. That kind of data is irreplaceable. It is what turns a promising idea into something communities can genuinely rely on.

Listening to Everything at Once

Animal sounds alone tell part of the story. Combining them with satellite imagery, atmospheric readings, electromagnetic measurements, and seismic data would tell a much fuller one. When a forest falls silent and the ground temperature begins to rise and electromagnetic readings start behaving strangely all at the same moment that convergence of signals carries far more weight than any single indicator could on its own. Building systems capable of reading all these inputs together, in real time, is one of the most valuable directions this research can take.

Earning the Trust of Science and Society

Perhaps the most important task ahead is also the most unglamorous: gathering long-term evidence. Much of what we know about animals predicting disasters still rests on anecdotal observations stories passed down through generations, documented after the fact, impossible to verify. For this approach to be taken seriously by disaster management authorities and the wider scientific community, it needs years of structured, consistent, documented data collected before, during, and after disaster events. That kind of evidence does not come quickly, but it is the only thing that will move this idea from the research lab into the emergency response systems that protect real lives.

The natural world has been sending signals for millions of years. The future of this work is simply learning to listen more carefully.

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