

Deep Learning-Based Behavioural Instability Analysis for Intelligent Environmental Monitoring

Dr. Anu Thomas ¹, Prajwal Adhav ²

Vice-principal ¹, Student ² Department of Information Technology
SIES College of Arts, Science and Commerce, Nerul, Navi Mumbai, India

Abstract

Environmental changes have become a growing concern in recent years, encouraging researchers to explore new ways of observing and understanding ecosystem behaviour. Among the many indicators present in nature, animal behaviour has attracted attention because animals often respond to changes in their surroundings through noticeable variations in movement and activity. Observing these behavioural patterns can provide useful insights into environmental conditions.

This study presents a behavioural instability analysis system that applies deep learning techniques to sequential animal activity data. An LSTM Autoencoder model was used to learn regular behavioural patterns and identify unusual deviations from normal activity. Instead of attempting to predict specific natural events, the system focuses on recognising behavioural irregularities and representing them through a stability index that is easy to understand.

To improve usability, the generated results are displayed through an interactive dashboard that allows continuous observation of behavioural trends. Different disturbance scenarios were simulated to evaluate system performance. The findings showed that the model was able to distinguish between stable and unstable behavioural conditions. The study suggests how artificial intelligence can be used as a supportive tool for behavioural monitoring and future environmental observation applications.

Keywords: Deep Learning, Behaviour Analysis, LSTM Autoencoder, Anomaly Detection, Environmental Monitoring, Time-Series Analysis, Artificial Intelligence

I. Introduction

Monitoring environmental conditions has become increasingly important due to the growing frequency of ecological and climate-related changes. Traditionally, environmental monitoring has relied on instruments such as weather stations, seismic sensors, and other measuring devices. While these technologies provide valuable information, biological responses within ecosystems can also offer meaningful observations that are often overlooked.

Animals are known to react to changes in their environment through modifications in movement patterns, activity levels, and other behavioural responses. Researchers have observed that unusual behaviour may occur before certain environmental disturbances, making animal activity an interesting area for further investigation. Although behavioural observations

alone cannot be considered a direct prediction method, they can contribute valuable information when analysed systematically.

Recent developments in machine learning and deep learning have made it possible to analyse large volumes of behavioural data efficiently. These technologies can identify hidden patterns within sequential data that may not be obvious through manual observation. As a result, behavioural monitoring has become an emerging research area within intelligent environmental analysis.

The advancement of deep learning has improved the ability to process large-scale behavioural datasets and identify hidden temporal patterns. Time-series learning models such as Long Short-Term Memory (LSTM) networks are particularly useful because they can capture long-term dependencies in sequential behavioural data. Such models are capable of learning normal behavioural activity and identifying deviations without requiring labelled abnormal events.

The primary objective of this research is to develop an intelligent behavioural analysis framework capable of detecting instability patterns from animal behavioural data. The system focuses on behavioural anomaly awareness rather than direct disaster prediction. By combining deep learning techniques with real-time visualization, the present study aims to improve interpretability and support future intelligent environmental monitoring applications.

II. Literature Review

Several researchers have explored the relationship between animal behaviour and environmental disturbances. Earlier ecological studies observed that animals often react differently under changing environmental conditions. These reactions may include changes in movement patterns, vocal behaviour, stress responses, and irregular activity levels.

Wikelski et al. [1] conducted an important study on farm animal behaviour before earthquake events. Their findings suggested that measurable behavioural irregularities were observed before seismic activity occurred. The study highlighted the potential of animal behaviour monitoring as a supportive environmental awareness mechanism.

Research related to anomaly detection has also expanded significantly within the field of Artificial Intelligence. Chandola et al. [2] described anomaly detection as the identification of patterns that differ considerably from expected behaviour. These approaches are commonly used in healthcare systems, cybersecurity monitoring, industrial fault detection, and intelligent surveillance systems.

Recent advancements in behavioural datasets and sensing technologies have further improved computational analysis. Lee et al. [3] introduced behavioural and physiological datasets for analysing animal activity patterns using advanced sensing systems. Such datasets enable researchers to apply machine learning techniques for behavioural pattern analysis and anomaly identification.

Deep learning models, especially LSTM networks, have shown strong performance in handling sequential datasets because of their ability to retain temporal information over long durations. Xu and Deng [4] discussed the growing importance of deep neural networks in sequence-based anomaly analysis and synthetic behavioural modelling.

Although previous studies provide significant contributions, many existing systems primarily focus on observational studies or isolated anomaly detection methods. Limited research combines deep learning-based behavioural analysis with interactive real-time visualization. The proposed research attempts to bridge this gap through an integrated behavioural instability monitoring framework.

III. Proposed Methodology

The proposed system consists of multiple stages including data preprocessing, sequence generation, model training, anomaly analysis, and dashboard visualization.

Initially, behavioural datasets are cleaned to remove inconsistent or missing values. Numerical normalization techniques are applied to ensure uniform feature scaling and improve model performance. After preprocessing, the dataset is converted into sequential windows suitable for time-series analysis.

The system uses an LSTM Autoencoder architecture for learning behavioural sequences. During training, the model learns normal behavioural patterns by reconstructing input sequences. During testing, reconstruction error is calculated between actual and predicted behavioural sequences.

The reconstruction error acts as an anomaly score. Higher reconstruction error indicates stronger behavioural deviation. These anomaly scores are further converted into a Stability Index ranging between 0 and 100 for easier interpretation and monitoring.

Figure 1: Proposed System Workflow

Behaviour Dataset



Data Preprocessing



Normalization & Sequence Generation



LSTM Autoencoder Training



Reconstruction Error Calculation



Stability Index Generation



Real-Time Dashboard Visualization

The above workflow illustrates the transformation of raw behavioural data into meaningful visual insights using deep learning techniques.

IV. Experimental Analysis

The developed system was tested using sequential behavioural datasets containing activity-based numerical features. Simulated disturbance conditions were introduced to analyse the system's response under different behavioural scenarios.

The generated stability values reflected visible fluctuations during disturbance simulations. Under stable conditions, the behavioural trend remained relatively smooth and consistent. However, moderate and severe disturbances produced significant behavioural instability and lower stability scores.

The dashboard successfully displayed behavioural variations through dynamic trend graphs and live monitoring tables. Real-time visualization improved the interpretability of behavioural instability and enabled continuous monitoring.

Table 1: Behavioural Stability Classification

Stability Range	Behaviour Status
90 – 100	Stable / Normal
80 – 89	Moderate Disturbance
Below 80	High Instability

The above classification scale was used to simplify anomaly interpretation within the monitoring dashboard.

Table 2: Distribution of Behaviour Categories

Behaviour Category	Percentage (%)
Normal	58
Moderate Disturbance	27
High Instability	15

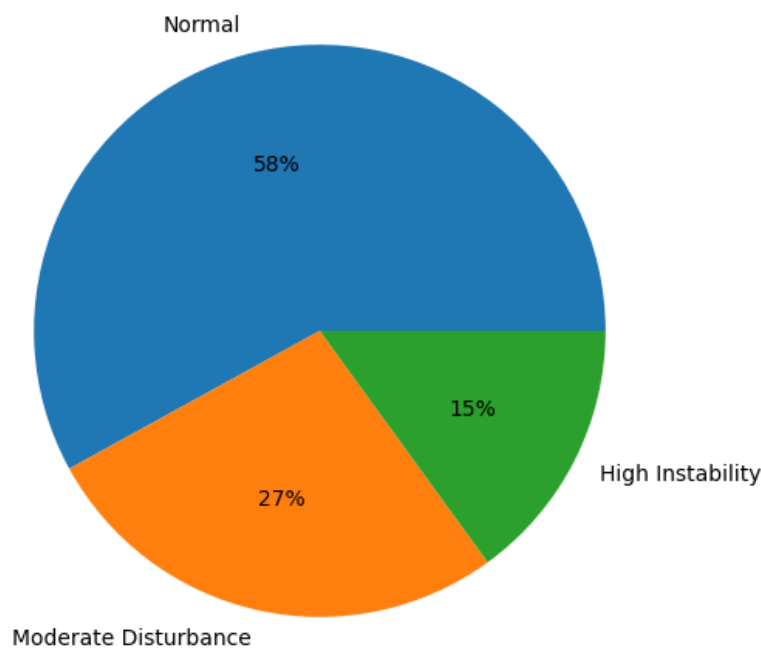
Figure 2: Distribution of Behaviour Categories

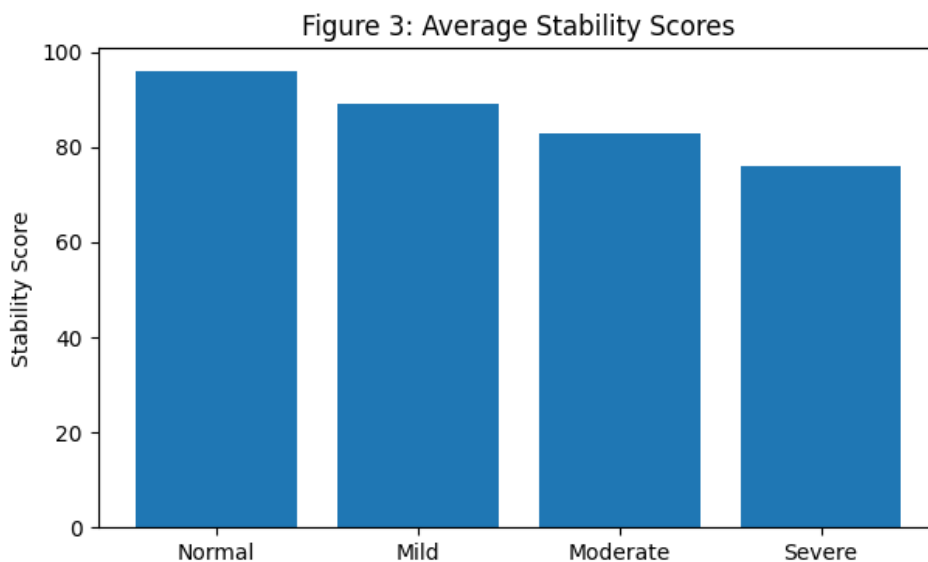
Figure 2 : Distribution of Behaviour Categories Generated by the implemented model

Explanation:

The behavioural observations generated during experimental evaluation were classified into three categories. A majority of observations were categorized as normal behaviour, indicating stable activity patterns. Moderate disturbances represented temporary fluctuations, while a smaller proportion exhibited significant instability. The distribution indicates the capability of the implemented model to distinguish between stable and unstable behavioural conditions.

Table 3: Stability Score Comparison

Environmental Condition	Stability Score
Normal Environment	96
Mild Disturbance	89
Moderate Disturbance	83
Severe Disturbance	76

Figure 3**Figure 3 : Average Stability Scores Under Different Environmental Conditions****Explanation:**

The bar chart illustrates the variation in behavioural stability under different simulated environmental conditions. A gradual decline in stability scores is observed as disturbance intensity increases. This trend confirms the effectiveness of the proposed anomaly detection framework in identifying behavioural irregularities.

V. Results and Discussion

The developed system was evaluated using behavioural datasets that included both normal activity patterns and simulated disturbance conditions. During testing, the LSTM Autoencoder learned common behavioural sequences and produced reconstruction errors whenever unusual activity was encountered. These reconstruction errors were then transformed into stability scores to provide a clearer representation of behavioural conditions.

The obtained results showed that stability values remained relatively high during normal conditions and decreased when behavioural disturbances were introduced. This behaviour indicates that the model was able to differentiate between regular and irregular activity patterns. The dashboard further improved result interpretation by presenting stability trends, classification tables, and graphical summaries in an easy-to-understand format.

The pie chart revealed that most observations belonged to the normal behavioural category, while a smaller percentage represented moderate and high instability conditions. Similarly, the bar chart demonstrated a gradual reduction in stability scores as disturbance intensity increased. These findings support the effectiveness of the developed approach for behavioural anomaly analysis.

Although the current implementation relies on simulated behavioural scenarios, the results suggest that deep learning can serve as a practical tool for analysing behavioural fluctuations. Future studies involving real-time behavioural datasets may provide additional insights and further validate the usefulness of the proposed monitoring approach.

VI. Conclusion

This research presents a deep learning–based behavioural instability analysis framework for intelligent environmental monitoring applications. The proposed system successfully applies LSTM Autoencoder techniques to analyse sequential behavioural data and identify unusual behavioural deviations.

The integration of anomaly detection with real-time dashboard visualization improves interpretability and enhances monitoring efficiency. Experimental results demonstrate that deep learning models are capable of identifying behavioural instability patterns effectively within time-series datasets.

Future improvements may include integration of IoT-based sensor systems, live environmental data streams, and advanced hybrid deep learning architectures for improving scalability and prediction capability. The developed system contributes toward the development of AI-assisted intelligent ecological monitoring systems.

References

- [1] M. Wikelski et al., “Potential short-term earthquake forecasting by farm animal monitoring,” *Ethology*, vol. 126, no. 10, pp. 931–940, 2020.
- [2] V. Chandola, A. Banerjee, and V. Kumar, “Anomaly detection: A survey,” *ACM Computing Surveys*, vol. 41, no. 3, pp. 1–58, 2009.
- [3] J. Lee et al., “A public dataset of dogs’ vital signs recorded using radar and reference sensors,” *Scientific Data*, vol. 11, no. 1, 2024.

[4] Y. Xu and Z. Deng, "Synthetic time-series data generation using deep models," *IEEE Transactions on Artificial Intelligence*, vol. 3, no. 2, pp. 145–156, 2022.

Bibliography

The development of this research was supported by several academic books, research publications, technical documentation sources, and machine learning references. These resources provided valuable insights into anomaly detection, deep learning architectures, behavioural monitoring systems, and environmental intelligence frameworks.

Bibliography Sources

- [1] Goodfellow, I., Bengio, Y., and Courville, A., *Deep Learning*, MIT Press, 2016.
- [2] Géron, A., *Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow*, O'Reilly Media, 2022.
- [3] Hastie, T., Tibshirani, R., and Friedman, J., *The Elements of Statistical Learning*, Springer, 2017.
- [4] TensorFlow Official Documentation.
- [5] Streamlit Official Documentation.
- [6] Scikit-Learn Official Documentation.
- [7] OpenWeather API Documentation.
- [8] Additional peer-reviewed research articles on behavioural monitoring, anomaly detection, and environmental intelligence systems.