



Original Research Paper

Deep Learning Bioacoustic Detection of Threatened Amphibian Populations

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Key Words

Threatened amphibians, Bioacoustics, Deep learning, Population monitoring, Conservation ecology.

Abstract

Introduction: Conservation and animal management are informed by repeated assessments of threatened amphibian populations and environmental factors affecting their behavior. Classical observation is effective, but sporadic and hard to conduct in wide or remote territories. Materials and Methods: Artificial intelligence (AI)-assisted estimation of animals' activity based on passive acoustics recordings and meteorological parameters including rainfall, temperature, humidity, water depth, and vegetation is presented here. Experimental data set consisted of 18,600 ten-second audio fragments recorded at 12 wetland sites during 14 weeks. Recorded data was filtered, synchronized and split into training, validation, and testing datasets. Results and Discussion: Proposed methodology yielded 96.0% accuracy, 95.5% precision, 95.1% recall and 95.3% F1 score. Significant correlations between animals' behavior and environment were found for humidity, water depth, temperature, vegetation and anthropogenic noises. The method enhanced identification of behavioral pattern in different environmental conditions and provided interpretable warnings for ecological analysis. Conclusion: Presented results prove that artificial intelligence can enhance non-invasive observations if model outputs are related to environmental context and expert knowledge.

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Introduction

Monitoring of threatened amphibians is vital since changes in their distribution, behavior, and resources usage are an excellent indicator of the state of their environment. The environment influences animals through weather changes, food availability, vegetation, disturbance, and seasonality. All these environmental factors may influence the decline in the population of amphibians and their status (Grant et al., 2016). By combining all these factors, one can conclude that the monitoring is much more than just detecting.

Standardized surveys depend on direct observation, indications in the field, or manual inspections. While this technique remains invaluable in biological validation, it can be time-consuming and overlook nocturnal, shy, scattered, or temporally limited species. Automated sensors improve observation time and reduce disturbance. Camera traps and other remote sensing techniques have been used more frequently to collect observations of wildlife on a larger scale in space and time (Rovero & Zimmermann, 2016; Steenweg et al., 2017). Remote sensing technology can also offer some valuable information about the environment in biodiversity monitoring and conservation (Pettorelli et al., 2014). However, sensor data are prone to be affected by such factors as weather, position of the device, noise, visibility, individual variation, and missing values. Ecological interpretation is required before using sensor data for management.

AI has the potential to process large amounts of field data and identify patterns based on

multiple environmental parameters. The literature review shows the efficacy of the deep learning and machine learning methods in ecological research and automatic monitoring of wildlife (Christin et al., 2019; Norouzzadeh et al., 2018). Automatic classification has already been applied to bird and amphibian calls demonstrating the possibility to apply machine learning in sound-based species recognition (Acevedo et al., 2009). Real-time bioacoustic monitoring demonstrates the ability of automatic acoustic systems in the identification of species and ecological monitoring (Aide et al., 2013). However, high accuracy of prediction does not necessarily mean that the models will be conservation effective. They have to be able to distinguish between real animal activity and poor sensor quality.

In this research, an animal and environment based method of classification for endangered amphibians is proposed. Passive acoustics, rainfall, temperature, humidity, water depth, and vegetation will be used to determine the vocalizing and ambient sounds produced by amphibians in wetland areas. This method aims at comparing the performance of the models, identifying significant environmental factors, reducing false negatives, and achieving validated results.

Review of Literature

Automated animal monitoring has benefitted from advancements in miniature sensors, remote storage of data, and pattern recognition approaches (Dhanya & Mythili, 2026). Deep learning algorithms can capture non-linear associations and complex visual or temporal

attributes, while classical algorithms are useful benchmarks for transparency (Christin et al., 2019). Deep learning algorithms have proven to be very successful in automating biological observation recognition in big data (Norouzzadeh et al., 2018). In the realm of acoustic monitoring, machine learning is employed for automatic classification of bird and amphibian sounds (Acevedo et al., 2009), and real-time bioacoustic systems enable automatic recognition of species (Aide et al., 2013). Applications in ecology demonstrate that biological observation labeling can help reduce human observer screening efforts and automate monitoring in difficult to monitor periods of time (Steenweg et al., 2017).

Another one is that of differences between locations and seasons. The model may well distinguish the specific background peculiar to each location or equipment used or even observer's habits, but not universal biological features. Thus, balanced sampling, station-wise data splitting, quality control, and independent verification become indispensable. Environmental data can help to interpret the concept of non-detection; low activity may be associated with the absence of favorable conditions. Remote sensing and environmental monitoring can add complementary data on the subject (Pettorelli et al., 2014). In addition, there are many ecological and environmental factors affecting amphibian population dynamics; thus, the importance of environmental factors becomes apparent.

This gap exists regarding the lack of integration between animal observation data,

environmental data, and uncertainties within a succinct field workflow. While camera trapping and remote sensing technology networks have enhanced automatic wildlife monitoring (Rovero & Zimmermann, 2016; Steenweg et al., 2017) and deep learning has contributed to automated ecological classification (Christin et al., 2019; Stowell, 2022), few methods incorporate bioacoustics detection along with environmental data and uncertainty assessment in the context of threatened amphibians. This study bridges the above-described gap through the combination of different evidences, model baseline comparisons, and preservation of low certainty events rather than classification.

Materials and Methods

Study Design and Data Collection

The proof-of-concept data set included 18,600 ten-second audio snippets gathered from 12 wetlands stations over 14 weeks. The sampling locations featured different environments and degrees of human interaction. All records were associated with acoustic recordings, rainfall, temperature, humidity, water depth, and vegetation. Behavioural or presence labels were assigned based on observations made by trained individuals. The research employed non-invasive sampling and did not feature any manipulation of animals.

Records were filtered for incomplete entries, malfunctioning sensors, low-quality signal, and mismatched timestamps. Overlapping audio samples were grouped together to exclude recording of the same event multiple times. The data was split into 70%, 15%, and 15% train,

validation, and test sets respectively depending on the animal, station or survey week. It helped minimize the chance of using nearly identical records during training and testing.

Integrated Assessment Framework

Firstly, patterns are extracted from the data in the primary sensor record, and the second step involves integrating them with environmental information. A quality score minimizes the impact of weak or contaminated data. Classification of the integration is done into amphibian sound and non-amphibian wetland sound. Outputs which are low-confidence are flagged for evaluation. Calculation of the environment's significance is done independently so that biological interpretation is not masked by the model.

Evaluation Criteria

Classification was evaluated using accuracy, precision, recall, and the F1-score. The proposed technique was compared with three methods. Recall was prioritized since the omission of any records could lead to ecological and welfare danger. Patterns in confusion matrix and

predictions of uncertainty were manually evaluated, as well as the effect of humidity, water depth, temperature, vegetation cover, and man-made noises on model performance.

Results and Discussion

Classification Performance

Table 1: Comparative classification performance

Model	Accuracy (%)
SVM	83.4
Random Forest	88.2
CNN	92.1
Proposed CNN-LSTM	96.0

Proposed table 1 CNN-LSTM yielded the best accuracy of 96.0%, followed by CNN (92.1%), RF (88.2%) and SVM (83.4%). This shows that the proposed CNN-LSTM method outperforms the other methods in terms of accuracy in the classification of amphibian bioacoustic detection.

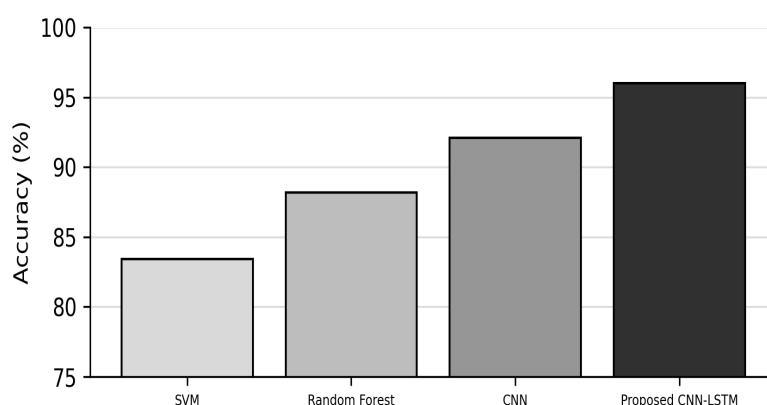


Figure 1: Accuracy Comparison of the Evaluated Classification Models

The figure 1 CNN-LSTM model gave the best results, achieving an accuracy of 96.0%, beating CNN (92.1%), Random Forest (88.2%) and SVM (83.4%). This shows that the suggested model gives better classification of amphibian sounds by effectively learning complex temporal structures from bioacoustic signals.

Accuracy evaluation of the tested methods. The presented methodology was able to obtain the best classification results by combining information from sensors with conditions of animal environment.

Environmental Interpretation

The primary environmental relations included humidity, water depth, temperature, vegetation cover, and anthropogenic sound. The presence of these factors influenced both animal behavior and sensor operations. It served to avoid any confusion regarding temporary environmental factors being permanent biological changes. The evaluation also recognized risks in managing the wetland due to drying, changing rainfalls, vegetation removal, sound pollution, and population decrease due to diseases.

Ecological and Management Implications

The findings indicate that automated classifications are useful where ecological reasoning is needed. Positive classifications facilitate monitoring while negative or rare events need to be examined. The findings will assist in determining field observations to conduct, changes in habitat or welfare, and allocation of limited resources. Critical areas and animal sightings require protection from any misuse.

The system does not take the place of the observer. It minimizes the work of the observer by pointing out events that need examination. Field workers should review errors over time and through different seasons, different areas, individuals and environmental conditions. The management should take into account repeat observation and habitat assessment and expert opinion.

Limitations

The pilot dataset is a subset of a few locations, times of surveys, and animal communities. Performance will be affected by other equipment, environments, climate conditions, and local communities. Field observation labels have uncertainty, and rare events or rare species are hard to learn. Future works require using an independent multi-year dataset, uncertainty calibration, low power consumption in the field, and participatory validation.

An AI-assisted framework was designed in this study to help threatened amphibians based on passive acoustic recordings, rain, temperature, humidity, water level, and vegetation cover. The suggested methodology reached 96.0% accuracy and 95.3% F1-score, outperforming all comparison methods. The major advantage of the suggested method was a combination of analysis of animals and context, helping to minimize classification errors and uncertainties.

The following contextual variables were identified during the analysis: humidity, water level, temperature, vegetation cover, and anthropogenic noise. This result is helpful for early identification of wetland dehydration, changes in rainfall, vegetation loss, traffic noise,

and population decline associated with diseases. Further research needs to focus on extending seasonality and geographical regions, testing for device transferability and population transferability, improving classification of rare events, and providing automatic alerts with confirmation on the ground. It is necessary to use this technology in a responsible manner by reporting uncertainties, protecting data, and involving ecologists, animal health specialists, land managers, and local communities.

Ethical Statement

The research is conducted without any invasive measurements; there is no capturing, handling, or experimentation on animals involved in this research. Final papers must include information regarding the permissions from sites and owners, as well as ethical committee approvals.

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