Leveraging Acoustic Monitoring and AI for Comprehensive Biodiversity Assessment in Zimbabwe

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1. Introduction

Biodiversity loss due to human activities, including deforestation and poaching, poses significant ecological threats. Traditional monitoring methods lack scalability and efficiency, necessitating novel approaches. We introduce the Acoustic Biodiversity Index (ABI), leveraging AI-driven acoustic monitoring for species detection and biodiversity assessment. This study was conducted under the My Trees initiative, covering 320,000 hectares of conservation forest in Zimbabwe.

Human activities such as illegal logging and poaching are driving deforestation and habitat loss in tropical forests, contributing to elevated CO_2 levels, biodiversity decline, and climate change [1]. Despite significant investments in wildlife conservation, many initiatives lack transparency and efficient impact measurement [2], hindering the assessment and improvement of conservation efforts critical to preserving biodiversity [3]. Addressing these challenges requires innovative technological solutions. Artificial intelligence (AI) and machine learning (ML) offer advanced capabilities for processing large ecological datasets more efficiently than traditional methods [4]. Techniques such as real-time monitoring and pattern recognition can accelerate data analysis, thereby enhancing conservation efforts. Acoustic monitoring has emerged as a valuable, non-invasive tool for biodiversity assessment, capable of collecting data over large spatial and temporal scales. Species diversity is typically quantified by species richness (the number of species) and evenness (the relative abundance of each) [5].

2. Methodology

This study was conducted in collaboration with the My Trees Trust, which manages a ~320,000-hectare conservation area in the Chirundu region of Zimbabwe [6]. The region suffers from severe deforestation—an estimated 330,000 hectares of natural woodland (about 10 million trees) are lost annually—resulting in the degradation of ecosystem services (e.g., erosion control, water regulation) [7] and the disruption of entire ecosystems.

We deployed a Wildlife Acoustics Song Meter SM4 recorder at a fixed location in the Chirundu forest for one month (December 2023) to continuously capture ambient wildlife sounds. This single acoustic sensor collected over 1.7 GB of audio data, including numerous bird, frog, and other animal vocalizations. No manual labeling of the recordings was performed on-site. Instead, to develop our species classification model, we utilized an open annotated audio dataset from the Rainforest Connection challenge. The dataset contains 1-minute .flac recordings of 24 distinct bird and frog species with strong labels (time-coded species presence annotations), providing 4,727 training samples and 1,992 test samples [8]. We trained a convolutional neural network classifier on this data to recognize species by their calls in the recordings. The trained model was then used to analyze our field recordings from Chirundu, producing a time series of species detection events. Finally, we formulated the Acoustic Biodiversity Index by integrating three components: (1) species richness, the number of unique species detected; (2) species evenness, the distribution of detection counts among species; and (3) temporal stability, the consistency of species detections over time. This composite index is designed to provide a single quantitative measure of biodiversity for the site [9].

Fig. 1: Acoustic sensor on the tree in MyTree reservation in Chirundu, Zimbabwe

Table. 1: Biodiversity statistics

Quantity	Value
Shannon Entropy	2.93
Normalized Shannon Entropy	0.95
Mean Coefficient of Variation (CV):	0.41
Acoustic Biodiversity Index (ABI):	0.67

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3. Results and discussions

- Model Performance: 85% accuracy across 24 species; F1-score stabilized at ~0.8 (Fig 2).
- Species Detection: Certain species were more frequently detected, while others had lower detection rates, suggesting data imbalance (Fig. 3).
- Comparison with Other Indices: Unlike Acoustic Complexity Index (ACI) or Bioacoustic Index (BI), ABI integrates species evenness and stability for a comprehensive biodiversity measure [10].
- Challenges & Future Work: Expanding datasets, improving species labeling, and addressing environmental noise challenges will enhance ABI accuracy.

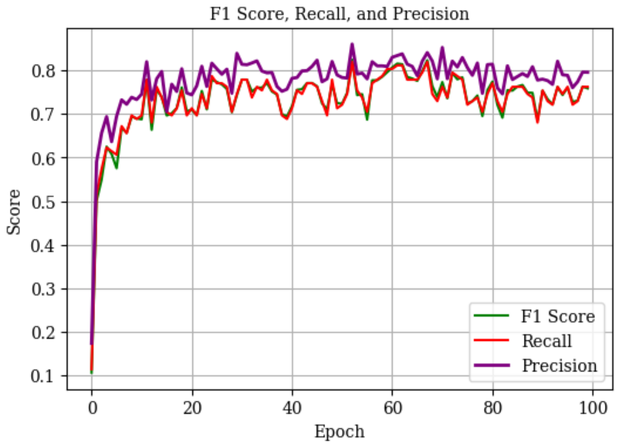

Fig. 2: Evolution of F1 Score, Recall, and Precision Over the Training Process

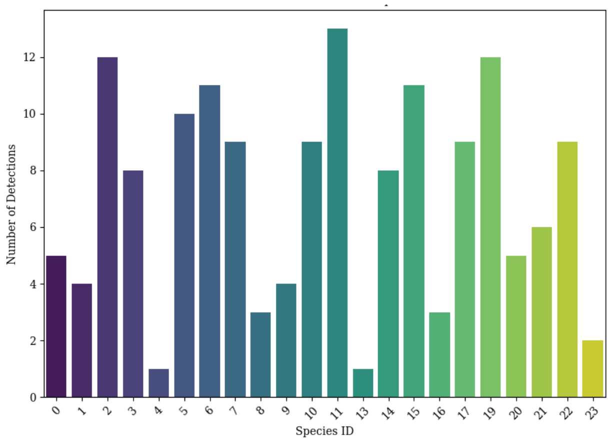

Fig. 3: Distribution of the detected species from the data from My Tree Project

4. conclusions

This study highlights the potential of AI-driven acoustic monitoring for biodiversity assessment. The ABI provides a scalable, non-invasive method for ecosystem analysis. Further research should focus on expanding sensor networks, refining classification models, and integrating real-time monitoring capabilities. With continued development, the ABI could serve as a global standard for conservation efforts.

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