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Fine-Grained Bioacoustics Species Recognition via Multi-Feature Synergy and Ensemble Decision Optimization

M. K. Chakravarthy[1*], Tulluri Santosh Ramana[2], Palasani Govardhan Reddy[2], Ponaka Vishnu[2], Shaik Dilavar Basha[2]

[1]Assistant Professor, [2]UG Student, [1,2]Department of Electronics and Communication Engineering

[1,2]Geethanjali Institute of Science and Technology, Nellore-Bombay Highway, S.P.S.R, Andhra Pradesh 524137, India

*Correspondence: M. K. Chakravarthy

ABSTRACT

Bioacoustics monitoring is vital for wildlife conservation, as over 60% of species rely on acoustic signals, yet manual surveys capture less than 40% of vocal activity. With endangered populations declining by 1–2% annually, the limitations of manual analysis being time-consuming, subjective, and prone to error necessitate scalable, automated solutions. This work proposes an Automated Animal Species Identification (AASI) system architecture using machine learning to monitor six target classes: lions, bears, dolphins, monkeys, donkeys, and elephants. The system utilizes a multi-spectral feature extraction framework to capture complex temporal and frequency-domain characteristics. Extracted features include Mel-frequency Cepstral Coefficients (MFCCs), Mel-Spectrograms, Chroma features, Spectral Contrast, Tonnetz, and various statistical descriptors like Zero-Crossing Rate (ZCR) and Spectral Centroid. This diverse feature set ensures robustness against background noise and overlapping calls. Following Exploratory Data Analysis (EDA) to assess class balance and feature distributions, the study evaluates traditional models such as Decision Tree, Nearest Centroid, and Gradient Boosting as baselines. To enhance performance, a Voting Ensemble Classifier (VEC) is proposed, integrating Support Vector Classifier (SVC) and Light Gradient Boosting Machine (LGBM). By employing a strategic voting mechanism, the AASI system achieves superior accuracy, stability, and generalization, providing a reliable framework for large-scale, real-time wildlife surveillance and biodiversity assessment.

Keywords: Bioacoustics Monitoring, Animal Species Identification, Feature Extraction, Ensemble Learning, Machine Learning, Acoustic Signal Processing.

1. Introduction

Acoustic communication plays a vital role in the lives of many animal species, serving functions like territory defense, warning signals, and social bonding. This communication has been in the topics of different studies in the last decades. The unique characteristics embedded in animal vocalizations provide a rich source of information about species identity, among others. Leveraging these signatures, sound-based classification methods have been increasingly proposed as non-invasive and efficient at monitoring wildlife populations. With recent advances in signal processing and machine learning, it has become feasible to automatically classify and identify animals based on their vocalizations with high efficiency. Other works have also been using modalities like vision. This capability holds great promise for applications in biodiversity conservation, ecological research, and behavioral studies. For instance, acoustic monitoring can facilitate long-term and large-scale surveys in remote or dense habitats where traditional visual methods are impractical. Despite significant progress, challenges remain. The variability in vocalizations due to environmental noise, individual differences, and contextual factors can complicate the

classification process. Furthermore, the development of generalizable models across species does not have a straightforward solution. Figure 1 shows the growth of the animal identification market in India from 2018 to 2030, highlighting a consistent upward trend in market size over the given period. The chart indicates that the market value increases steadily from approximately USD 110 million in 2018 to nearly USD 440 million by 2030. This gradual yet continuous growth reflects increasing adoption of animal identification technologies across sectors such as livestock management, wildlife monitoring, and animal health surveillance.

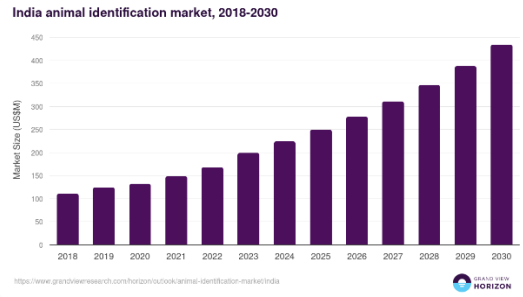


Figure. 1: Growth of the animal identification market in India

It also suggests that the growth rate accelerates after 2023, indicating rising investments and wider deployment of advanced identification and monitoring systems. Factors such as increased focus on animal welfare, disease control, conservation initiatives, and government-supported digitization programs contribute significantly to this expansion. Overall, the figure emphasizes the growing importance of animal identification solutions in India and provides strong motivation for developing automated, scalable, and efficient animal species identification systems. It emphasizes the growing importance of animal identification solutions in India and provides strong motivation for developing automated, scalable, and efficient animal species identification systems.

2. Literature Survey

Karim Youssef. et al. [1] addressed sound-based animal species classification method was presented using a biomimetic approach inspired by the human cochlea. Gammatone filter banks were employed to extract auditory features that captured distinctive animal vocalization characteristics, and four gammatone-based representations were evaluated using an artificial neural network. The method was tested on a dataset of 13 animal species with limited samples, and the results demonstrated that cochlear-inspired filtering combined with machine learning enabled reliable and robust species classification despite the small dataset size.

Chingiz Seyidbayli. et al. [2] presented a non-lethal acoustic monitoring system for real-time insect detection and classification based on sound signatures. A low-noise prototype suitable for autonomous field deployment was developed and validated through laboratory experiments and field testing in rapeseed fields over 25 days, collecting more than 3400 hours of acoustic data. The results emphasized the importance of minimizing system self-noise and highlighted challenges related to data handling and energy management in long-term IOT-based insect monitoring. amber Crittenden. et al. [3] examined acoustic identity in burr nan dolphins through the analysis of individual signature whistles used for social interaction. Researchers identified 22 unique signature whistles from recordings involving 57 dolphins, with whistles commonly associated with pairs or social clusters due to their highly social behavior. The findings showed that female dolphins and transient individuals exhibited very similar whistle patterns, and the study demonstrated that passive acoustic identification could support improved population monitoring and conservation efforts.

Vanessa Grundy. et al. [4] applied bioacoustics methods to analyze avian soundscapes and community composition in two forest types of Caparo national park, Brazil. Using song-meter

recordings and raven pro analysis, 98 bird species were identified, with higher species richness observed in semi-deciduous seasonal forests compared to ombrophiles montane forests. Although acoustic indices showed limited correlation with species richness, they successfully revealed differences in soundscape characteristics, demonstrating the usefulness of bioacoustics for bird monitoring and conservation planning. Vassilis Galanos. et al. [5] presented the design and field evaluation of a low-cost hydrophone system for passive acoustic monitoring of underwater soundscapes. The hydrophone was constructed using off-the-shelf components and validated through field experiments in different coastal environments, with recordings compared against a calibrated scientific hydrophone. Although the system showed limitations at low frequencies and mid-frequency resonance issues, it reliably detected major anthropogenic sounds, demonstrating its potential for large-scale, low-budget acoustic monitoring and citizen science applications.

Devin jean. et al. [6] proposed an adaptive animal-borne acoustic monitoring system aimed at long-term wildlife observation under power and storage constraints. The system combined low-power hardware with unsupervised machine learning, using a variational autoencoder and adaptive clustering to prioritize rare and novel acoustic events while reducing redundant data storage. Simulation and initial field deployments on species such as caribou, elephants, and bighorn sheep demonstrated effective retention of rare sounds, highlighting the potential of this approach for advanced wildlife monitoring despite remaining power optimization challenges. Jhoan Nicolas Ramos Niño. et al. [7] examined the use of environmental sounds and animal vocalizations as non-invasive indicators for welfare assessment in livestock systems. Following Prisma guidelines, 36 peer-reviewed studies were analyzed, highlighting approaches such as vocalization-based welfare indicators, acoustic source characterization, and animal responses to sound stimuli. The review reported recent advances in recording and signal processing techniques while identifying challenges related to metric standardization, physiological validation, and real-world farm deployment.

Tiago Garcia. et al. [8] investigated the integration of directional microphones with convolutional neural networks for long-range bird species identification. High-resolution directional audio recordings were processed using CNNs, enabling systematic species identification up to 150 m and, in some cases, up to 510 m for high-frequency and distinct vocalizations. Although the approach demonstrated improved performance over traditional methods, limitations in audio clarity and ambient noise indicated the need for further refinement in recording technology. Hiruni Dewmini. et al. [9] addressed elephant sound classification using raw audio processing with lightweight deep learning models suitable for resource-constrained edge devices. A novel model, elephant caller net, was proposed and achieved 89% classification accuracy without converting audio into spectrograms, outperforming spectrogram-based approaches. The model was optimized using Bayesian techniques and successfully classified three elephant caller types roar, rumble, and trumpet demonstrating improved effectiveness over existing binary or single-caller methods.

Mahmut Karaaslan. et al. [10] proposed an automated system for detecting and classifying animal vocalizations to overcome the limitations of manual bioacoustics analysis. The system segmented relevant sound regions, extracted features using STFT, MFCC, and LFCC, and evaluated multiple CNN models, including Alex net, dense net, efficient net, and res net variants. Experimental results demonstrated high accuracy in classifying vocal behaviors such as barking and howling, highlighting the effectiveness of deep learning–based approaches for animal behavior analysis. Venkatraman Manikandan. et al. [11] examined

the role of artificial intelligence and bioacoustics in non-invasive poultry welfare monitoring through vocalization analysis. It documented the evolution from traditional acoustic features such as MFCCs and spectrograms to advanced deep learning and self-supervised models, highlighting their suitability for edge and Tinyml deployment. The review identified key challenges related to dataset standardization, evaluation consistency, and model interpretability, and emphasized the need for explainable and scalable ai solutions for practical poultry welfare assessment.

Francesco di Nardo. et al. [12] proposed a convolutional neural network–based approach for classifying dolphin vocalizations from passive acoustic monitoring recordings. Four bottlenose dolphin vocalization types whistles, echolocation clicks, burst pulse sounds, and feeding buzzes were classified using spectrograms enhanced with edge-detection filters to reduce noise. Using nearly 10,000 samples, the model achieved high performance with an average accuracy of 95.2%, demonstrating the effectiveness of CNNs for dolphin monitoring and conservation applications. Jaeuk moon. et al. [13] addressed the limitations of few-shot animal sound classification methods by proposing a Task-Adaptive Parameter Transformation (TAPT) approach. Unlike model-agnostic meta-learning with static initialization, TAPT generated task-specific parameter transformations to improve adaptability and reduce overfitting in heterogeneous animal sound tasks. Experimental results on public datasets showed that TAPT significantly outperformed existing few-shot methods, achieving up to a 20.32% improvement in classification accuracy while maintaining robust and efficient training.

Giorgia Guglielmi. et al. [14] evaluated the effects of highway noise and vegetation structure on soundscape characteristics and avian distribution in the moraine oxbow lake, Italy, using eco-acoustic indices and vegetation surveys. Results showed that tree diversity, particularly the presence of Quercus Robur, significantly influenced the acoustic environment, while bird richness increased with vegetation biomass. The analysis also revealed that highway proximity strongly structured soundscape patterns, emphasizing the combined impact of anthropogenic noise and habitat features on biodiversity in modified landscapes.

Ashan Milinda Bandara Ratnayake. et al. [15] investigated the acoustic alarm signals produced by heterorganic Itama guard bees during colony intrusions to assess their suitability for sound-based intrusion detection. MFCC features combined with linear discriminant analysis were used to train machine learning classifiers, with the KNN model achieving the highest classification performance. The results confirmed that distinct alarm sounds could be reliably detected and classified, demonstrating the feasibility of a cost-effective, audio-based intrusion detection system for stingless bee colonies.

3. Proposed System

Figure 2 shows the system architecture of AASI on bioacoustics recordings. The system begins with a curated animal sound recordings dataset, which undergoes speech preprocessing to enhance signal quality and remove unwanted noise. EDA is then performed to understand feature distributions and class characteristics. An existing DTC model is used as a baseline classifier for performance benchmarking. To improve classification accuracy, a proposed multi spectral feature extraction approach is applied to capture comprehensive acoustic characteristics from the recordings. These features are then fed into a proposed VEC that combines SVC and LGBM models. The system evaluates and compares performance metrics across models, generates predictions on unseen test data, and integrates the final classification module with a Tkinter-based graphical user interface for user-friendly interaction. The system outputs predicted animal species such as

Lions, Bears, Dolphins, Monkeys, Donkeys, Elephants, and other classes, supporting efficient and automated wildlife monitoring.

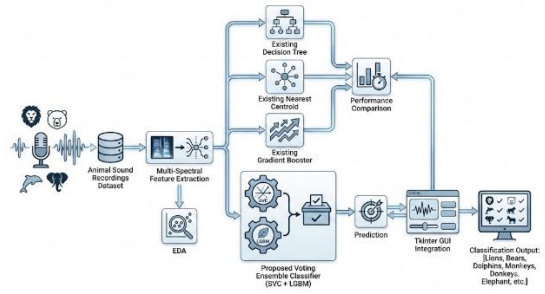


Figure. 2: System architecture of AASI on bioacoustics recordings.

Animal Sound Recordings Dataset: The methodology begins with the collection of an animal sound recordings dataset containing vocalizations from multiple species. The dataset includes diverse environmental conditions and recording variations to ensure robustness. Each audio sample is labeled according to its corresponding animal species for supervised learning.

Proposed Multi Spectral Feature Extraction: The proposed multi spectral feature extraction technique is applied to capture both temporal and spectral characteristics of animal sounds. Features such as MFCCs, Chroma, Mel-Spectrogram, Spectral Contrast, Tonnetz, ZCR, RMS Energy, Spectral Centroid, Spectral Bandwidth, and Spectral Flatness are extracted and combined to form a comprehensive feature vector.

EDA: EDA is conducted on the preprocessed data to examine class distribution, feature variability, and statistical patterns. Visualization and correlation analysis help identify dominant features, detect anomalies, and understand separability among animal species.

Existing Decision Tree: An existing DTC is implemented as a baseline model. The extracted features are used to train the model, and its performance is evaluated using standard metrics. This step provides a reference point for comparing the effectiveness of the proposed methods.

Existing Nearest Centroid: The NCC is implemented as another existing method. It classifies animal sounds based on the distance between feature vectors and class centroids. This simple and computationally efficient model helps evaluate the effectiveness of distance-based classification.

Existing Gradient Booster: An existing Gradient Booster model is trained to capture non-linear relationships between acoustic features and animal species. This ensemble-based approach improves learning capability compared to simple classifiers and serves as a stronger baseline for comparison.

Proposed VEC: The extracted feature vectors are used to train a VEC that integrates SVC and LGBM models. The ensemble leverages the strengths of both classifiers to improve generalization and robustness in species classification.

Performance Comparison: Performance evaluation is carried out by comparing the existing DTC model and the proposed ensemble classifier using metrics such as accuracy, precision, recall, and F1-score. This comparison demonstrates the effectiveness of the proposed approach over traditional methods.

Prediction from Test Data: The trained ensemble model is applied to unseen test data to generate species predictions using Proposed VEC. This step validates the model's ability to generalize and accurately classify animal species from new bioacoustics recordings.

3 Result Analysis

The results analysis section evaluates the performance and effectiveness of the proposed system in achieving accurate and reliable outcomes. It focuses on assessing the model using various evaluation metrics such as accuracy, precision, recall, and F1-score to ensure comprehensive performance

measurement. The analysis also compares the proposed approach with existing methods to highlight improvements and advantages. Graphical representations and visualizations are utilized to clearly interpret the results and identify patterns or trends. Additionally, the robustness and generalization capability of the model are examined using test datasets. This section provides critical insights into the strengths and limitations of the system, ensuring its suitability for real-world applications.

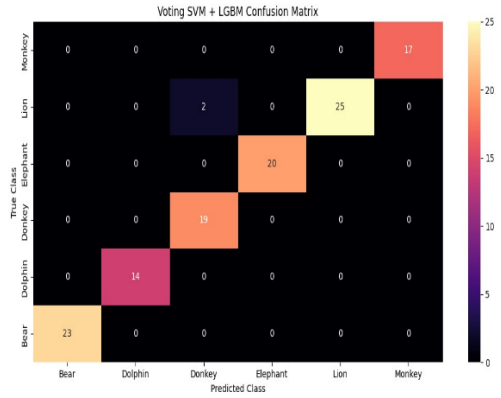


Figure. 3: Confusion Matrix obtained of voting VEC.

Figure 3 shows the confusion matrix of the proposed Voting SVM + LGBM hybrid model, highlighting its superior classification performance for AASI framework. The matrix exhibits very strong diagonal dominance, indicating highly accurate predictions across all classes, with 23 Bear samples correctly classified as Bear, 14 Dolphin samples correctly identified as Dolphin, 19 Donkey samples correctly predicted as Donkey, 20 Elephant samples accurately classified, 25 Lion samples correctly identified, and 17 Monkey samples correctly classified as Monkey. Only minimal misclassification is observed, where 2 Lion samples are incorrectly predicted as Donkey, while all other classes show zero or negligible off-diagonal errors. This near-perfect separation among classes demonstrates the effectiveness of combining margin-based learning from SVM with ensemble boosting from LGBM.

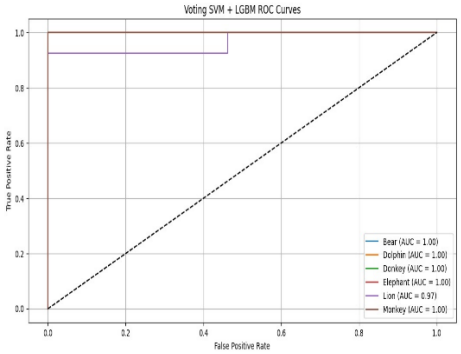


Figure. 4: ROC Curves obtained of voting VEC.

Figure 4 shows the ROC curves of the proposed Voting SVC + LGBM hybrid model for multi-class animal species identification. The ROC curves demonstrate outstanding discriminative performance, with Bear, Dolphin, Donkey, Elephant, and Monkey classes achieving perfect AUC values of 1.00, indicating complete separation between positive and negative samples. The Lion class also exhibits strong performance with an AUC value of 0.97, showing only minimal overlap with other classes. All ROC curves lie well above the diagonal dashed line representing random classification, confirming the model's superior ability to maximize true positive rates while minimizing false positive rates.

Table. 1: Overall Performance Comparison Table

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
NCC	46.67	41.86	44.05	42.63
GBC	96.67	97.10	97.10	97.10
DTC	91.67	91.84	92.53	91.62
VEC	98.33	98.41	98.77	98.53

Table 1 presents the overall performance comparison of different classification models used for AASI framework. The NCC model shows the weakest performance with an accuracy of 46.67%, precision of 41.86%, recall of 44.05%, and F1-score of 42.63%, indicating its inability to handle complex and overlapping bioacoustics feature distributions. The DTC model achieves improved performance with an accuracy of 91.67%, precision of 91.84%, recall of 92.53%, and F1-score of 91.62%, demonstrating its effectiveness in learning rule-based patterns from extracted features. The GBC model further enhances performance, achieving 96.67% accuracy and balanced precision, recall, and F1-score of 97.10%, reflecting the strength of ensemble learning in capturing non-linear relationships. The proposed VEC integrated with SVC and LGBM outperforms all existing approaches, achieving the highest accuracy of 98.33%, precision of 98.41%, recall of 98.77%, and F1-score of 98.53%, thereby confirming the effectiveness of combining margin-based classification with gradient boosting for robust and accurate bioacoustics animal species identification.

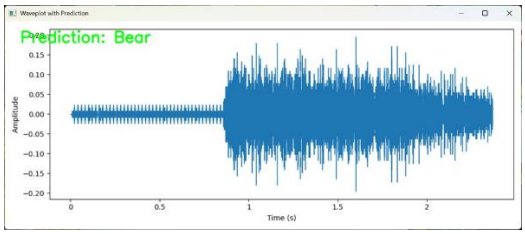


Figure. 5: Prediction results of bear class.

Figure 5 illustrates the waveform representation with prediction results for an in-vehicle audio event, highlighting the temporal variation of signal amplitude across the recorded duration. The plot depicts a distinct transition from low-amplitude steady patterns to high-intensity fluctuating signals, indicating the occurrence of a significant acoustic event. The model prediction labeled as “Bear” reflects the classification outcome derived from learned audio features and temporal characteristics. Visualization emphasizes variations in sound energy, signal density, and waveform irregularities, which contribute to accurate event identification. Figure 6 depicts the waveform visualization with prediction results for an acoustic event, demonstrating the variation of signal amplitude over time. The figure highlights two prominent high-energy segments separated by a low-amplitude interval, indicating distinct bursts of sound activity. The predicted label “Dolphin” signifies the classification outcome obtained from extracted temporal and spectral audio features. The waveform pattern reflects characteristic fluctuations, energy distribution, and signal intensity variations essential for accurate event recognition.

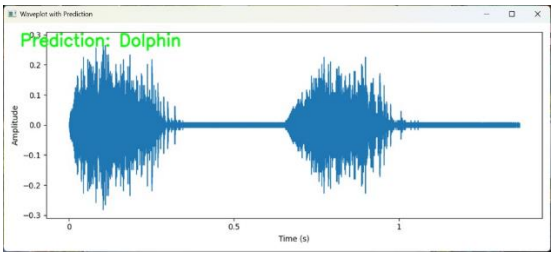


Figure. 6: Prediction results of dolphin class.

Conclusion

This research successfully demonstrates the efficacy of an AASI framework in addressing the critical limitations of manual bioacoustics monitoring. As wildlife populations face a steady decline, the transition from subjective, expert-dependent analysis to scalable machine learning solutions is no longer optional but essential for global conservation efforts. By leveraging a comprehensive multi-spectral feature extraction strategy—incorporating descriptors like MFCCs, Spectral Centroid, and Tonnetz, the system effectively captures the intricate nuances of vocalizations across diverse species, ensuring high discriminative power even in noise-heavy environments. The core contribution of this work lies in the implementation of the VEC. By synergizing the strengths of the SVC and LightGBM, the proposed ensemble significantly outperforms individual baseline models such as Decision Trees and Nearest Centroid Classifiers. This

approach provides a more stable, accurate, and generalized solution for multi-class animal sound classification.

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