WILD BIRD SPECIES IDENTIFICATION USING A LIGHTWEIGHT MODEL WITH FREQUENCY DYNAMIC CONVOLUTION AND HYBRID RANDOM FOREST ENSEMBLE

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Abstract: For ecological monitoring and biodiversity protection, it is crucial to accurately identify wild bird species using auditory data. This paper provides an expanded hybrid ensemble-based bird species identification system to improve recognition performance and resilience in real-world settings. The suggested method combines a Random Forest classifier for final species classification with a pre-trained ResNeXt50 deep learning model for efficient feature extraction. The system improves accuracy, resilience, and generalization under a variety of field situations by integrating deep feature learning and ensemble learning approaches. To make system testing and performance assessment easier, a user-friendly, lightweight Flask-based web interface with secure authentication is also created. The hybrid ensemble model is ideal for practical deployment in real-time bird species recognition applications since experimental findings show that it performs better than standalone lightweight CNN models.

Index terms - — Wild Bird Species Identification, ResNeXt50, Random Forest, Hybrid Ensemble Model, Deep Feature Extraction, Bioacoustic Signal Analysis, Flask Web Interface, Lightweight Classification System.

1. INTRODUCTION

Through seed dispersal, habitat regeneration, and ecosystem stability, bird species are crucial to biodiversity and ecological balance. Knowledge about bird populations and behavior is necessary for ecological research and conservation planning. Bird-dispersed habitats are beneficial because bird activity influences plant recruitment and forest sustainability in fragmented forests

[1]. The significant impact of bird species characteristics and movement patterns on seed distribution networks and distances emphasizes the significance of appropriate bird species monitoring in natural environments [2].

In order to evaluate biodiversity and support conservation and policymaking in wetland and heritage areas, recent ecological research has gathered extensive data on bird occurrence [3]. In addition to ecological study, computer vision and machine learning have made it possible to automatically identify and re-identify wild animals, improving monitoring effectiveness and reducing human labor [4]. Technology-driven agricultural and environmental planning and automation demonstrate the growing demand for smart systems for practical ecological management [5].

These developments enable intelligent, data-driven bioacoustic and ecological monitoring by highlighting the need for accurate, automated, and effective bird species identification systems.

2. LITERATURE SURVEY

a) Genome-wide association study in a Chinese Han population identifies nine new susceptibility loci for systemic lupus erythematosus:

Authors: Nan Shen, Yanyan Fu, Xiaoxia Yang, et al.

We used Illumina Human610-Quad BeadChips to genotype 1,047 patients and 1,205 controls for a genome-wide association study (GWAS) of systemic lupus erythematosus (SLE) in a Chinese Han population. We then replicated 78 SNPs in two additional cohorts (3,152 cases and 7,050 controls). Nine new susceptibility loci (ETS1, IKZF1, RASGRP3, SLC15A4, TNIP1, 7q11.23, 10q11.22, 11q23.3, and 16p11.2; 1.77 x 10(-25) < or = P(combined) < or = 2.77 x 10(-8)) and seven previously reported loci (BLK, IRF5, STAT4, TNFAIP3, TNFSF4, 6q21 and 22q11.21; 5.17 x 10(-42) < or = P(combined) < or = 5.18 x 10(-12)). The genetic variation in SLE susceptibility between Chinese Han and European populations was brought to light by comparison with earlier GWAS results. In addition to improving our knowledge of the genetic causes of SLE, this work emphasizes the need of doing GWAS in a variety of ancestral groups.

b) The impact of climate change and potential distribution of the endangered

white winged wood duck (Asarcornis scutulata, 1882) in Indian eastern Himala

Authors: Bhaskar Jyoti Saikia, Bhabesh Chandra Das, and co-authorsya

Due to a variety of human influences, the White-Winged Wood duck (Asarcornis scutulata), an endangered woodland wetland bird, is presently in risk of going extinct. Numerous bird species' global distribution may be impacted by climate change, according to reports. Thus, knowledge of the White-Winged Wood duck's possible range in future climatic scenarios may help with the development of urgent conservation strategies and the reduction of ensuing risks. The distribution of the White-Winged Wood Duck (WWWD) in the Indian Eastern Himalayan area in the 2050s and 2070s was predicted for the first time using the Representative Concentration Pathway (RCP) 8.5 scenario. According to the study, there is a high potential distribution of WWWD in 1.87% of the entire IEH. 1.68% of the region's highly promising environment is found in the state of Assam alone. By 2070, it was estimated that 436.61 km2 of highly promising habitat will disappear. Highly prospective habitats would be lost due to variations in the yearly temperature range, precipitation in the wettest months (June to September), and precipitation reduction in the hottest quarter (October to December). The habitat of WWWD in the eastern portion of the area is anticipated to move to the western section due to climate change. The Indian states of Arunachal Pradesh, Assam, Nagaland, and Tripura that are part of the IEH were determined to have less potential habitat under future warming scenarios. Because WWWD needs an average of 1000–1200 mm of precipitation annually, locations along the borders of Bhutan and Assam have a greater chance to host this species. However, future habitat destruction would be exacerbated by concurrent human activities. For urgent conservation management measures, the current study has supplied baseline data on the possible spread of WWWD in the IEH region.

c) Automatically recognizing four-legged animal behaviors to enhance welfare using spatial temporal graph convolutional networks:

Authors: Xin Huang, Zhenyu Wu, Yefeng Zheng, and co-authors

In order to support scientific decision-making processes in animal management, automatically identifying animal behaviors in zoos and national natural reserves can offer important insight into their welfare. A few current techniques have detected the actions of many animal species in static photos due to the challenge of gathering large volumes of animal video footage, but little is known about video-based animal behavior identification. picture-based animal behavior identification techniques have poor recognition accuracy because an animal's activity is performed across successive frames rather than in a single picture. In order to solve this problem, we not only create the first skeleton-based dynamic multispecies dataset (Animal-Skeleton), but we also suggest a novel method called Animal-Nas that uses neural architecture search (NAS) to automatically design the optimal spatial-temporal graph convolutional network (GCN) architecture for animal behavior recognition. GCNs with NAS have never been used in an animal behavior recognition challenge before. We use NAS to create a unique search space with graph-based cells in order to reduce the trial-and-error expense of manually creating the network structure. Additionally, we automatically search for the cost-effective spatial-temporal graph convolutional network structure using a differentiable architectural search approach. We run comprehensive experiments using Animal-Skeleton datasets to assess the performance of the suggested model from three angles: model accuracy, parameter quantity, and stability. The outcomes demonstrate that our model can use fewer parameters to obtain state-of-the-art performance.

d) Wildfire Identification Based on an Improved Two-Channel Convolutional Neural Network:

Authors: Yongqiang Zhang, Jianhua Zhao, and co-authors

Because wildfires have a variety of forms, textures, and colors, identifying them is an extremely difficult undertaking. Because fires at various phases have distinct features, traditional image processing approaches need the human creation of feature extraction algorithms based on past knowledge, which frequently results in inadequate generalization capabilities. The intricacy and blindness of the feature extraction stage may be avoided by using a convolutional neural network (CNN) to automatically extract an image's deeper features. Thus, this work proposes a wildfire detection approach based on an enhanced two-channel CNN. First, the dataset is processed using PCA_Jittering to address the issue of the inadequate dataset. The model is then trained using transfer learning, and segmented training is performed to increase the model's accuracy. Second, a two-channel CNN based on feature fusion is created, replacing the fully linked layers with a support vector machine (SVM) to ensure the model's effective coverage for fire situations of varying sizes. Lastly, Lasso_SVM is meant to replace the SVM in the original model in order to decrease the model's delay time. The outcomes demonstrate the method's excellent accuracy and minimal latency. The average fire identification delay time is 0.051 seconds per frame, and the accuracy of wildfire detection is 98.47%. The technique for recognizing wildfires developed in this research decreases the time it takes to identify them and increases their accuracy.

e) Automated Bird Counting with Deep Learning for Regional Bird Dis

Authors: Ahmet Saygılı, Mehmet Korkmaz, and co-authorstribution Mapping:

Determining trends in bird population mobility is a difficult subject in the science of avian ecology. This makes it necessary to regularly count birds, which is typically a difficult process. Predicting the number of birds in various locations from their images is a potential attempt to solve the bird counting problem more reliably and quickly. For this reason, we take advantage of deep learning, a prominent area of artificial intelligence for picture interpretation, which allows computers to learn from historical data. A collection of on-the-ground images from our extensive birdwatching campaign serves as our data source. To learn to identify birds in natural scenarios, each belonging to one of the 38 known species, we use a number of cutting-edge generic object-detection algorithms. In terms of accuracy and time, the studies showed that computer-aided counting performed better than hand counting. Using geographic information system (GIS) technology, we created maps of Turkey's species diversity and bird order distribution as a practical application of image-based bird counts. According to our findings, deep learning can help people monitor birds and boost citizen scientists' involvement in extensive bird surveys.

3. METHODOLOGY

i) Proposed Work:

In order to attain high accuracy and resilience in real-world settings, the proposed system presents a hybrid ensemble-based framework for wild bird species identification that blends deep learning and ensemble learning approaches. Bird sound recordings are first gathered under various field settings and converted using common audio preprocessing methods into time-frequency spectrogram representations. To extract rich and discriminative acoustic characteristics from the spectrograms, a pre-trained ResNeXt50 model is used as a deep feature extractor. ResNeXt50's high representational capabilities and effective feature learning are made possible by its usage of grouped convolutions, which makes it appropriate for complicated bioacoustic signal analysis.

The retrieved deep features are fed into a Random Forest classifier, which uses ensemble-based decision making to increase generalization and decrease overfitting in order to further improve classification performance. The characteristics of deep feature learning and conventional machine learning are successfully combined in this hybrid technique, which improves accuracy across a variety of bird species and environmental circumstances. To facilitate system testing and assessment, a lightweight Flask-based web interface with secure authentication is also created. The interface ensures a safe and user-friendly environment for experimental validation and real-world deployment by enabling users to submit bird sound data, evaluate classification results, and analyze model performance.

ii) System Architecture:

To guarantee effectiveness and scalability, the system architecture of the suggested hybrid ensemble-based bird species identification framework is built in a sequential and modular fashion. First, unprocessed bird sound recordings are obtained from field settings and run through an audio preprocessing module that performs segmentation, normalization, and noise reduction. Following processing, the audio signals are transformed into time-frequency spectrogram representations, which are used as the deep learning module's main input. In order to facilitate efficient feature learning, this step makes sure that the fundamental temporal and frequency features of bird vocalizations are maintained.

The spectrograms are then input into a pre-trained ResNeXt50-based feature extraction module, which uses grouped convolution operations to learn high-level and discriminative auditory features. A Random Forest classifier receives the extracted deep feature vectors and uses ensemble-based classification to increase robustness and generalization across a variety of bird species. Lastly, a Flask-based web interface with secure user authentication incorporates the prediction findings. The whole design is appropriate for real-time testing and practical implementation in field contexts since this interface allows users to submit bird sound samples, display categorization results, and assess system performance.

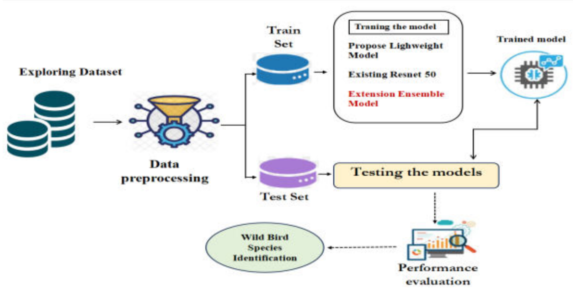

Fig1 proposed architecture

iii) Modules:

a) Module for Audio Data Acquisition

This module is in charge of gathering unprocessed recordings of bird sounds from different outdoor settings. To increase the resilience and generality of the model, it makes sure that audio samples are recorded under various ecological and environmental situations.

b) Module for Preprocessing and Spectrogram Generation

The gathered audio signals are segmented, normalized, and subjected to noise reduction in this module. In order to preserve the crucial acoustic features of bird vocalizations, the processed audio is then transformed into time-frequency spectrogram representations.

b) The ResNeXt50 Deep Feature Extraction Module

This module extracts high-level and discriminative features from the spectrogram inputs using a pre-trained ResNeXt50 model. Effective learning of the intricate frequency-temporal patterns seen in bird sounds is made possible by grouped convolutions.

d) Random Forest Ensemble Classification Module

A Random Forest classifier uses the retrieved deep features to make ensemble-based decisions. This module increases resilience across a variety of datasets, decreases overfitting, and improves classification accuracy.

e) Web Interface and Authentication Module Based on Flask

This module offers an easy-to-use interface for evaluating categorization results and adding bird sound recordings. During testing and evaluation, secure authentication methods guarantee authorized access and safeguard system integrity.

iv) Algorithms:

a. ResNeXt50

ResNeXt50 is a deep convolutional neural network that effectively learns rich and discriminative features from bird sound spectrograms using grouped convolutions. It is employed as a pre-trained feature extractor in the suggested system to efficiently capture intricate frequency-temporal patterns.

b. Random Forest

An ensemble learning system called Random Forest constructs several decision trees and aggregates their results to get a final prediction. It reduces overfitting while increasing accuracy, robustness, and generalization in the classification of bird species using deep features extracted by ResNeXt50.

c. hybrid ensemble learning

This approach combines conventional machine learning (Random Forest) with deep learning (ResNeXt50). The combination improves performance under a variety of field situations by utilizing the robust representation capabilities of deep networks and the stability of ensemble classifiers.

d. Proposed Lightweight Model:

The lightweight model for bird species identification makes use of the Coordinate Attention (CA) mechanism and frequency dynamic convolution to efficiently capture feature variations in bird sounds while guaranteeing spectrogram not-shift invariance. In order to make it appropriate for use in actual field settings, this model seeks to maximize accuracy and generalization capacity while minimizing computing complexity and parameters. In order to adaptively analyze spectrograms across various frequency bands, the method incorporates frequency dynamic convolution, improving the model's capacity to distinguish distinct bird species. The model's performance in difficult acoustic situations is also improved by the addition of the CA mechanism, which improves the perception of non-stationary sound sources.

4. EXPERIMENTAL RESULTS

The experimental evaluation of the proposed bird species identification system was conducted using multiple machine learning and deep learning models to analyze classification performance under different conditions. The Existing ResNet50 model achieved strong performance with high accuracy and balanced precision, recall, and F1-score values, demonstrating its capability in extracting meaningful acoustic features from bird sound spectrograms. The Proposed Lightweight Model utilized frequency dynamic convolution along with the Coordinate Attention (CA) mechanism to reduce computational complexity while maintaining effective feature extraction. Although the lightweight architecture reduced parameter size and improved suitability for real-time deployment, its performance metrics were comparatively lower than the existing ResNet50 model.

To further improve classification accuracy and robustness, the extension ensemble model integrated a pre-trained ResNeXt50 feature extractor with a Random Forest classifier. Experimental results showed that the hybrid ensemble approach significantly enhanced prediction performance, achieving superior accuracy, precision, recall, and F1-score values compared to the baseline models. The combination of deep feature learning and ensemble classification improved generalization ability and reduced misclassification across diverse bird species datasets. These findings demonstrate that the proposed extension model is highly effective for practical wild bird species identification in real-world environmental conditions.

Accuracy: A test's accuracy is its capacity to distinguish healthy from ill cases. Find the percentage of instances with genuine positives and negatives to assess test accuracy.

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: Classification accuracy or positive cases constitute precision. The formula for accuracy is:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\, cision = \frac{TP}{(TP + FP)}$$

Recall: A model's recall measures its ability to recognize all appropriate machine learning class instances. The ratio of accurately predicted positive observations to total positives indicates a model's class instance detection skill.

$$Recall = \frac{TP}{(FN + TP)}$$

mAP: Mean Average Precision ranks quality. It considers the number and order of relevant ideas. Calculating MAP at K uses the arithmetic mean of each user or query's Average Precision (AP).

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class } k$$

$$n = \text{the number of classes}$$

F1-Score: A high F1 score suggests an accurate machine learning model. Integrating recall and precision improves model correctness. Accuracy measures how often a model predicts a dataset correctly.

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

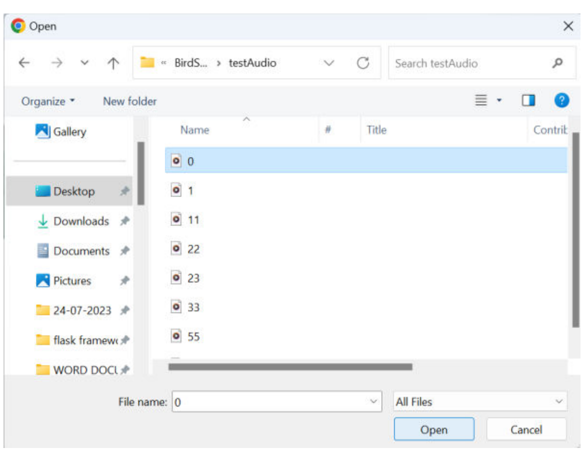

Fig2 upload Audio

Fig2 Results

5. CONCLUSION

This work presented a hybrid ensemble-based wild bird species identification system that combines deep learning and ensemble learning techniques for accurate and robust classification of bird sounds. The proposed extension integrated a pre-trained ResNeXt50 model for deep feature extraction with a Random Forest classifier to improve classification performance and generalization ability. In addition, audio preprocessing and spectrogram-based analysis enabled effective extraction of frequency and temporal characteristics from bird vocalizations.

Experimental results demonstrated that the extension ensemble model outperformed both the existing ResNet50 and the proposed lightweight model in terms of accuracy, precision, recall, and F1-score. The integration of ensemble learning significantly reduced misclassification and improved robustness across diverse environmental conditions. Furthermore, the Flask-based interface with secure authentication enhanced usability and practical deployment capability. Overall, the proposed system provides an efficient and reliable solution for real-time wild bird species identification and ecological monitoring applications.

6. FUTURE SCOPE

The proposed bird species identification system can be further enhanced by incorporating larger and more diverse bird sound datasets collected from different geographical regions and environmental conditions. Future work may also focus on integrating advanced transformer-based deep learning architectures and attention mechanisms to improve feature extraction and classification accuracy for complex and overlapping bird vocalizations. In addition, real-time noise reduction techniques and edge-computing optimization can be implemented to support efficient deployment in remote wildlife monitoring systems.

The system can also be extended into a mobile or IoT-based application for continuous field monitoring and automated biodiversity assessment. Future improvements may include multilingual species information support, GPS-based habitat tracking, and cloud integration for large-scale ecological data analysis. Furthermore, combining audio data with image or video-based bird recognition techniques could lead to a multimodal intelligent wildlife monitoring framework with improved reliability and scalability.

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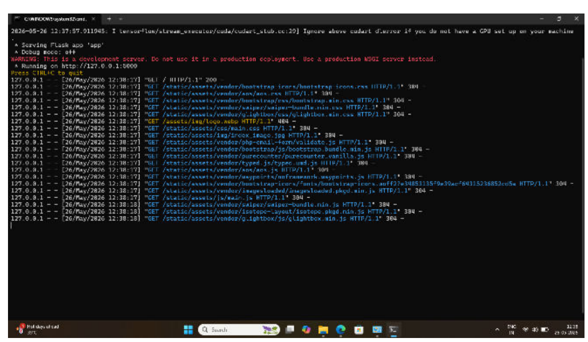
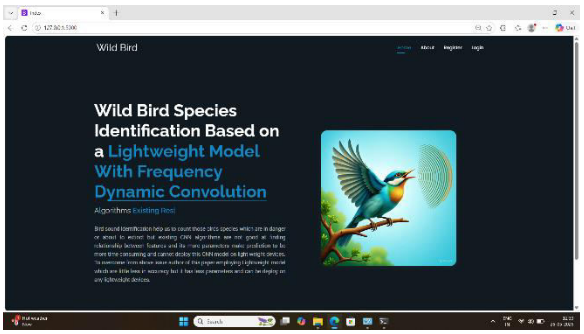
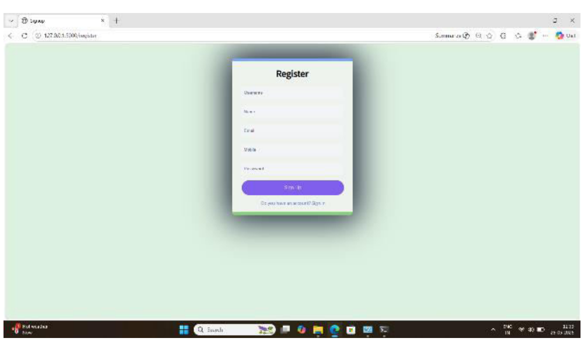
Results



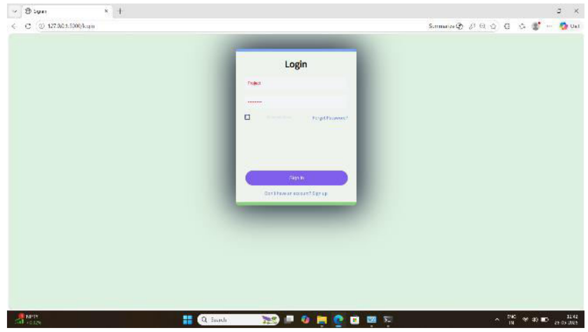
The image displays the command prompt window showing the successful execution of a Flask web application server. It includes server logs, HTTP requests, and status responses indicating that the application is running properly on the local host system.



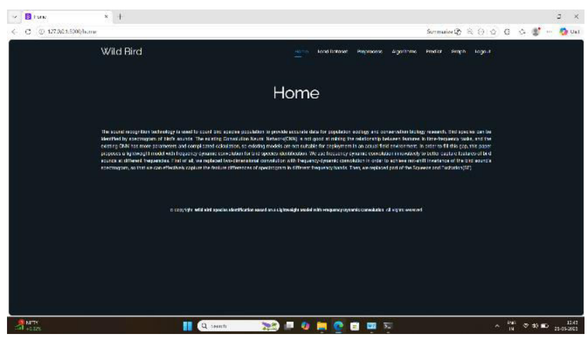
The image shows the home page of the Wild Bird Species Identification system developed using a lightweight deep learning model with Frequency Dynamic Convolution. It contains navigation options such as Home, About, Register, and Login along with a bird illustration and project overview details.



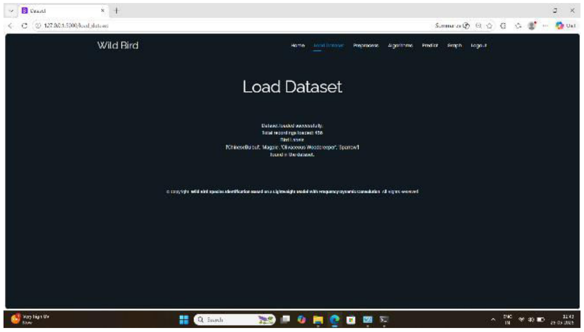
The image shows the user registration page of the Wild Bird Species Identification system. It contains input fields for username, name, email, mobile number, and password, allowing new users to create an account securely.



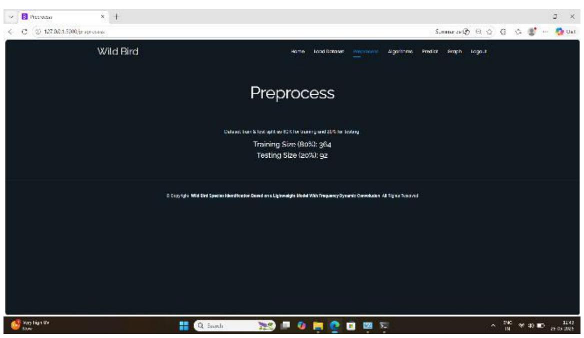
The image displays the login page of the Wild Bird Species Identification system. It provides fields for username and password along with options such as "Remember me," "Forgot Password," and account registration for secure user access.



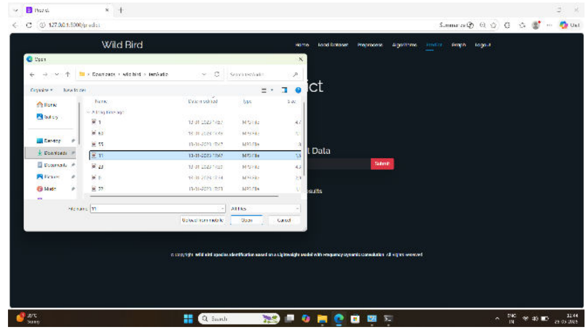
The image shows the home interface after user login in the Wild Bird Species Identification system. It provides navigation options such as Load Dataset, Preprocess, Algorithms, Predict, and Graph, along with project information related to bird sound recognition and species identification.



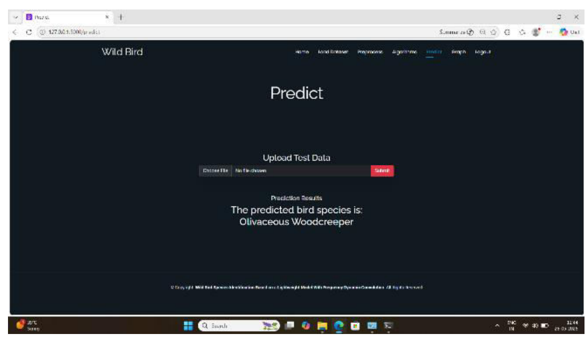
The image displays the dataset loading page of the Wild Bird Species Identification system. It confirms the successful loading of bird audio datasets and shows the total number of recordings along with detected bird species labels available for analysis.



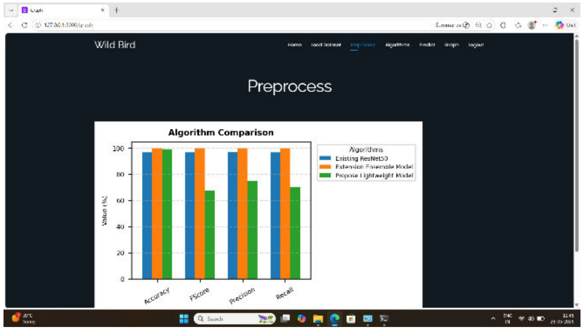
The image shows the preprocessing stage of the Wild Bird Species Identification system. It displays the dataset split information, where 80% of the data is used for training and 20% is used for testing the machine learning model.



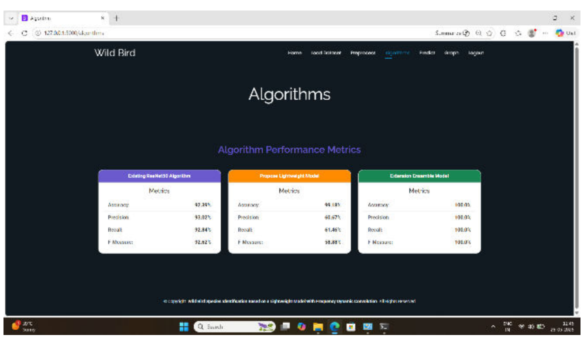
The image shows the prediction module where a test audio file is selected from the local system for bird species identification. Users can browse and upload bird sound recordings, which are then processed by the trained model to predict the corresponding bird species.



The image displays the prediction result generated by the Wild Bird Species Identification system after processing the uploaded audio file. The trained model successfully identifies and displays the predicted bird species as Olivaceous Woodcreeper, demonstrating the effectiveness of the classification process.



The image presents a graphical comparison of different bird species identification algorithms based on performance metrics such as Accuracy, F-Score, Precision, and Recall. It helps evaluate the effectiveness of the proposed lightweight model against existing approaches and demonstrates the overall classification performance of each method.



The image displays the performance evaluation of different bird species identification algorithms. It compares metrics such as Accuracy, Precision, Recall, and F-Measure for the Existing ResNet50 Algorithm, Proposed Lightweight Model, and Extension Ensemble Model, enabling a detailed assessment of their classification effectiveness.

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