BIRDS EMOTION CLASSIFICATION USING AI

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled "Birds Emotion Classification Using AI", submitted by Golam Faiyaz Rafid and Shreya Das to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 15-07-24

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We hereby declare that this project has been done by us under the supervision of **Prof. Dr. Syed Akhter Hossain, Dean and Professor of CSE, Faculty of Science and Information Technology, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

The recognition of emotions in animals, particularly birds, through vocalizations holds significant promise for understanding avian behavior and welfare. In this study, we propose a novel approach to classify bird species and their associated emotions using artificial intelligence (AI) techniques applied to vocalizations. Our research focuses on three commonly encountered species: Parrot, Pigeon, and Budgerigar. We begin by collecting a diverse dataset comprising vocalizations from various sources, which we subsequently convert to WAV format for analysis. To tackle the first task of species classification, we segment audio clips into manageable units and employ feature extraction methods such as Mel-frequency cepstral coefficients (MFCCs), root mean square energy (RMSE), chroma features, zero-crossing rate, rolloff, and spectral features. Additionally, we utilize visualization techniques such as spectrograms to enhance our understanding of frequency content over time. Employing a range of machine learning algorithms including Gradient Boosting Classifier, Random Forest Classifier, K-Nearest Neighbors, Decision Trees, Gaussian Naive Bayes, and XGBoost Classifier, we achieved a fair accuracy in classifying bird species. Furthermore, we address the challenging task of emotion classification in birds, focusing specifically on Budgerigars and their vocal expressions of Happiness and Anger. Utilizing the same AI framework, we have successfully implemented emotion classification, demonstrating the versatility and robustness of our approach. To the best of our knowledge, this study represents the first attempt to classify both species and emotions in birds using vocalizations, thus paving the way for further research in bird emotion recognition.

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LIST OF ACRONYMS

ML	Machine Learning
AI	Artificial Intelligence
MFCC	Mel-frequency Cepstral Coefficient
MLP	Multilayer Perceptron
STFT	Short-Time Fourier Transform
RMSE	Root, Mean, Square, Error
GBC	Gradient Boosting Classifier
RFC	Random Forest Classifier
KNN	K-Nearest Neighbors
DT	Decision Trees
GNB	Gaussian Naive Bayes
XGBC	XGBoost Classifier
LR	Logistic Regression

CHAPTER 1
Introduction

1.1 Overview

Birds are known for their complex vocalizations, which serve various communicative functions including signaling emotions, establishing territory, and attracting mates. While much research has focused on the acoustic properties of bird's vocalizations and their ecological significance, relatively little attention has been given to the emotional content encoded within these vocalizations. This study aims to bridge this gap by proposing a novel approach to classify bird species and bird emotion recognition using artificial intelligence (AI).

1.2 Background and Present State

The study of bird vocalizations plays a crucial role in understanding avian behavior and ecology. Researchers have employed various techniques to identify bird species based on their distinctive calls and songs, utilizing tools ranging from acoustic analysis software to machine learning algorithms like Random Forest and Naïve Bayes. While these methods have advanced species identification, research into decoding the emotional content of bird vocalizations remains underexplored.
Despite efforts to classify bird species accurately through sound analysis, there remains a significant gap in understanding how birds express and communicate emotions through their vocalizations. This gap limits our ability to fully comprehend avian welfare.

1.3 Problem Statement

In the field of avian research and welfare, there remains a need for an automated system that classifies the species as well as recognizes the emotion of a bird through vocalization. There are previous studies that classify the species of bird, but there has been no study that provides a solution to detect the emotion of a bird.

1.4 Objectives

Several studies have addressed the challenge of bird species identification using various approaches. Building upon existing research, this study adopts a data-driven approach to bird emotion recognition, employing machine learning algorithms to analyze and classify bird vocalizations. Specifically, we focus on three commonly encountered species: Parrot, Pigeon, and Budgerigar for species classification. For emotion classification, we concentrate on Budgerigars, aiming to distinguish between their happy and angry vocal expressions.

The ability to recognize emotions in animals has significant implications for both scientific research and practical applications. In the context of animal welfare, accurately identifying the emotional states of birds can help assess their well-being and inform management practices aimed at promoting positive welfare outcomes.

By collecting a diverse dataset incorporating both proprietary recordings and publicly available resources of bird vocalizations and extracting relevant acoustic features, we aim to develop robust models for both species and emotion classification. The use of feature extraction methods combined with machine learning algorithms enables us to achieve significant accuracy in these tasks. The integration of species classification and emotion recognition in one comprehensive system represents a novel approach in avian research. This dual focus not only contributes to the scientific understanding of bird behavior but also has practical benefits for bird conservation and management. The ability to automate and accurately classify bird species and their emotional states using AI can lead to more effective monitoring and conservation strategies, supporting the sustainability of bird populations.

1.5 Scope and Limitations

Scope

Understanding of bird behavior: Emotion classification can provide an insight on bird's emotional states under different circumstances.

Animal welfare and conservation: Enhance aviculture practices by providing insights into bird emotions.

Human-bird interaction: Mitigate the communication barrier with birds.

Overall, this study offers broad opportunities to deepen the understanding of avian behavior and improve their welfare as it bridges the field such as biology, psychology and computer science.

Limitations

Species and Emotion Coverage: The study is focused on a limited number of bird species (Parrot, Pigeon, Budgerigar) and emotional states (happiness and anger in Budgerigars), which may not be generalizable to other species or a wider range of emotions.

Ethical Considerations: Ensuring ethical guidelines are followed in the collection and use of bird vocalizations to minimize disturbance to the birds and their natural habitats.

1.6 Report Organization

Chapter 1: Introduction

The introductory chapter establishes the foundation for the study, outlining the significance of AI in avian research, particularly in species and emotion classification through vocalizations.

Chapter 2: Literature Review

A thorough review of existing literature and prior research is presented in this section. It delves into theoretical foundations, methodologies, and technological advancements relevant to bird species identification, and emotion recognition.

Chapter 3: Methodology

The research methodology chapter details the approach undertaken to conduct the study. It explains the data collection methods, algorithms and management of project.

Chapter 4: Implementation

The chapter discusses the models implemented, feature extraction techniques and machine learning algorithms employed for species and emotion classification.

Chapter 5: Result And Analysis

This chapter presents the experimental findings, provides comprehensive analyses of classification accuracies, and comparative evaluations between different machine learning algorithms.

Chapter 6: Impact On Society, Environment And Sustainability

The chapter on implications explores the broader impact of the research findings on aviculture practices and conservation strategies.

Chapter 7: Conclusion And Future Work

This concluding chapter reiterates the significance of AI-driven approaches in advancing avian research. Practical recommendations for future research directions are provided, emphasizing opportunities for further exploration and innovation.

1.7 Summary

In terms of communication, bird’s vocalization plays an important role. This study holds a novel approach for classifying bird species and recognizing bird emotions using AI. This project describes the importance for an automated system to mitigate the communication barrier between bird owners and birds, as well as improve bird's welfare. The research aims to develop machine-learning models for species and emotion classification by analyzing bird vocalizations.

CHAPTER 2
Literature Review

2.1 Overview

Bird species identification through audio analysis is a fundamental aspect of understanding birds' populations and their behaviors. The literature review explores advancements in bird species identification and emotion recognition through audio analysis. Existing studies have employed supervised and unsupervised approaches, utilizing algorithms such as Random Forest, Naïve Bayes, and Multi-layer Perceptron. However, limited research exists on bird emotion classification, presenting a significant gap in the literature.

2.2 Related Works

Neal et al. [1] have introduced a novel approach in their study, that employs supervised time-frequency audio segmentation using a Random Forest classifier. It enhances the ability to accurately segment and extract bird call syllables from noisy audio signals which improves the accuracy in species identification. The method that has been used in this study separates 93.6% of the acoustic energy of bird song with a false positive rate of 8.6%.

Graciarena et al. [2] have contributed in advancing the accuracy of bird species recognition by developing an unsupervised approach to generate note models from acoustic features and subsequently using phone n-gram statistical models originally designed for speaker recognition to recognize bird species. The importance of score-level combination to achieve better results has been highlighted in this study.

Jaddu et al. [3] explore the use of various vocal characteristics, such as tone, pitch, expression, and action, to identify human emotions conveyed through human language, contributing to improved communication between humans and computers. According to this research, animals such as dogs, elephants, and horses use a similar method to understand human emotions. The study utilizes samples to train and implement a speech emotion recognition classifier and examines a specific dataset, the Ryerson Audio-Visual Database of Emotional Speech and Song (RVDESS). Key features like the Mel frequency cepstrum coefficient (MFCC) are extracted to achieve the study's objectives. Multi-layer Perceptron Classifier Algorithm has been used in this study.

Hantke et al. [4] explores the interdisciplinary fields of evolutionary zoology, affective neuroscience, and comparative psychology, addressing the underexplored area of emotions' effects on the acoustic parameters of dogs. The findings of this research highlight notable results that demonstrate, machine learning-based acoustic analysis can outperform human-level performance when classifying the context of a dog bark.

Mehyadin et al. [5] explores machine learning methods to store and classify the calls of bird. The system used is this study is trained to classify and recognize the species and to filter out any undesirable noises using suppression filters, facilitating efficient processing. Mel-frequency cepstral coefficient (MFCC) is utilized along with machine learning algorithms like Naïve Bayes, J4.8, and Multilayer perceptron (MLP) to classify bird species. J4.8 provides the highest accuracy at 78.40% making it the optimal choice.

Jadhav et al. [6] utilizes machine learning algorithms to record and classify bird sounds. The system is trained to preprocess the data and filter out any unwanted noises. The framework also includes tools to translate annotations into training dataset. The algorithms used are KNN, Random Forest, Multi-layer perceptron, and Bayes with Support Vector machine producing the best accuracy of 96.7%.

Stastny et al. [7] investigates an automatic bird species recognition system based on bird vocalizations, analyzing 18 bird species across 6 families. Hidden Markov Models were trained for each species, resulting in an interspecific recognition success rate of 81.2% and a family-level classification accuracy of 90.45%.

Andono et al. [8] presents an innovative approach to recognizing bird sound patterns in open environments. The study employs the Mel Frequency Cepstral Coefficients and Gammatone Cepstral Coefficients methods for feature extraction, combined with k-Means clustering for data reduction and the k-Nearest Neighbor algorithm for classification. The proposed method achieved an accuracy of 78.11%, outperforming other feature extraction methods.

2.3 Comparison between existing works

Table 2.3.1. Comparative analysis of previous work

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	Briggs, L.N.F. et al. [1]	Random Forest classifier.	Random Forest Classifier = 93.6%
2.	Graciarena, M. et al. [2]	N-gram	______
3.	Jaddu, N.S. et al. [3]	Multi-layer Perceptron Classifier	______

4.	Hantke, S. et al. [4]	SVM SVR	______
5.	Mehyadin, A.E. et al [5]	Naïve Bayes, J4.8 Multilayer perceptron (MLP)	J4.8 = 78.40%
6.	Jadhav, Y. et al. [6]	Naive Bayes, Decision Tree, KNN, Neural Network	Neural Network=95%
7	Stastny, J. et al. [7]	Hidden Markov Model	Hidden Markov Model = 81.2%
8	Andono, P. N. [8]	KNN	KNN = 78.11%

2.4 Open Issues

Limited Research on Bird Emotion Classification: There is a notable gap in the existing literature concerning the application of AI for classifying and recognizing emotions in birds. While some studies have focused on bird species identification, there is a lack of research specifically addressing emotion recognition in bird vocalizations.

Suitable AI Algorithms: While some AI algorithms have been used for emotion recognition in humans and dogs, it is unclear which algorithms are most effective for classifying bird emotions.

Environmental and Species Variability: Bird vocalizations can vary significantly based on the species, environmental conditions, and context. Research should address the challenges that can handle diverse bird species and real-world recording conditions.

2.5 Summary

There exists a significant gap in current research regarding the application of AI for emotion classification in birds, with existing literature primarily focusing on species identification rather than emotion recognition through vocalizations. While AI algorithms have been successfully applied to emotion recognition in humans and dogs, their effectiveness in classifying bird emotions remains uncertain. Bird vocalizations exhibit considerable variability influenced by species diversity, environmental factors, and contextual nuances, posing challenges that necessitate research to develop robust algorithms capable of handling diverse species and real-world recording conditions effectively.

CHAPTER 3
Methodology

3.1 Overview

The methodology provides a structured framework for the research process, detailing the approaches and techniques employed in data collection, analysis, and experimentation.

Data Collection: Describing the sources, tools, and techniques used to collect data.

Analysis Techniques: Explaining how the features from the data were extracted and processed.

Experimental Procedures: Outlining the implementation of machine learning algorithms and evaluation of classification accuracy.

3.2 Proposed Methodology

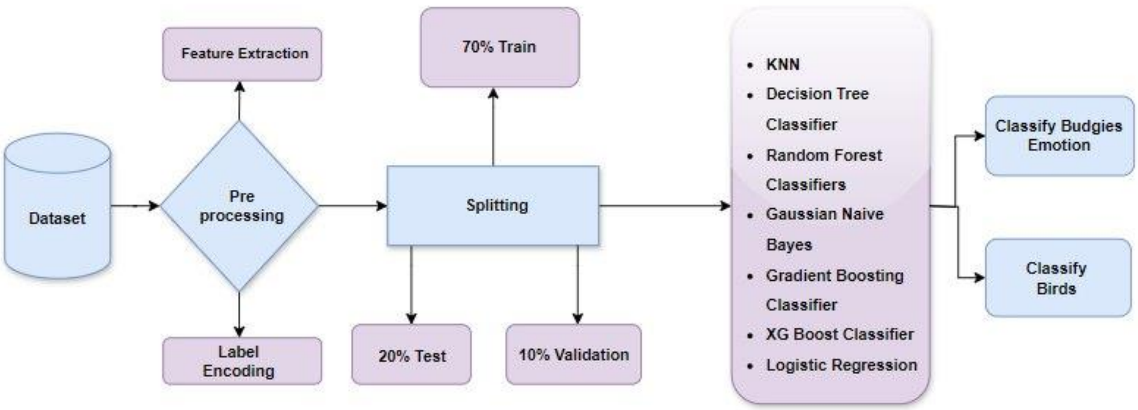

Figure 3.2.1. Proposed Methodology

1. Data Collection and Preprocessing

Acquire bird vocalization datasets online resources and through field recordings. Preprocess the audio data to extract relevant features such as spectrograms, Mel-frequency cepstral coefficients (MFCCs), chroma features, and statistical measures (e.g., RMS, zero crossing rate). Augment the dataset if necessary to enhance model robustness and generalization.

2. Model Development:

Design and implement machine learning for bird species classification and emotion classification. Experiment with various machine learning model architectures, including Decision tree classifiers, K-nearest neighbors, Gaussian Naive Bayes etc. to identify the most suitable approach. Optimize hyperparameters and regularization techniques to enhance model generalization.

3. Training and Evaluation:

Split the dataset into training, validation, and test sets using appropriate strategies (e.g., stratified sampling). Train the emotion classification model on the training data and validate its performance using the validation set. Evaluate the trained model on the test set to assess its accuracy, precision, recall, F1-score, and other relevant matrix. Perform cross-validation and hyperparameter tuning to ensure robustness and reliability of the results.

3.3 Hardware/ Software Requirement

1. Hardware Requirement:

i. High-Quality Microphones
ii. Digital Audio Recorders
iii. Cloud Storage Service for Data Storage and Backup
iv. Hardware Components (Monitor, RAM, SSD, Keyboard, Mouse, Motherboard, GPU, Cooling Fan, OS, PSU, UPS, Cables, Speakers, Headset, Casing)

2. Software Requirement:

i. Audio Editor
ii. MP3 to WAV Converter
iii. AudioMass for noise cancellation
iv. ChatGPT for literature review, and data interpretation
v. Google Scholar and Sci-Hub to access scientific articles and publications

3.4 Project Management and Financial Analysis

Project Management

Effective project management is essential for coordinating tasks, and managing risk to achieve project goals efficiently.

Risk Management: Identifying potential risks and implementing mitigation strategies to minimize disruptions to the research timeline and objectives is crucial. This involves a proactive approach to anticipate and address challenges that may arise during data collection, analysis, and implementation phases. Regular risk assessments and planning ensure that we remain agile in the face of unforeseen challenges, ultimately safeguarding the integrity and success of the research.

Communication Plan: Change Control Meetings.

Purpose: To review and approve modifications to the project scope or requirements.

Participants: Supervisor, and team members.
Frequency: Scheduled when change requests arise and to maintain oversight of progress.

Financial Analysis

Evaluating the financial aspects of the research, including budgeting, cost estimation, and financial projections is essential. Developing a budget involves outlining projected expenses for research activities, equipment, personnel, and overhead costs.

Table 3.4.1. Financial Analysis

SN	**Components/ Expenses**	**Estimated Cost (BDT)**
01.	Purchase of 8 Budgerigar birds	300*8 = 2400
02.	Expenses for bird care and habitat setup	10000
03.	Health Care of Birds	15000
04.	Purchase of a high-quality microphone(x3)	6000
05.	Documentation	1500
06.	Hardware Components (Monitor, RAM, SSD, Keyboard, Mouse, Motherboard, GPU, Cooling Fan, OS, PSU, UPS, Cables, Speakers, Headset, Casing)	150000

07.	Miscellaneous expenses / Contingency (10% of total)	18500
	Total Estimated Cost	203400

3.5 Summary

The methodology outlines the systematic approaches and techniques utilized in data collection, analysis, and experimentation. Various data collection methods were employed for various bird species, ensuring diverse and reliable datasets. Analysis techniques included preprocessing audio recordings and extracting relevant features crucial for emotion classification. Experimental procedures outlined the implementation of machine learning algorithms and evaluation of classification accuracy. Overall, the methodology provides a comprehensive framework for advancing the field of bird emotion classification using artificial intelligence.

CHAPTER 4
Implementation

4.1 Overview

The implementation of the bird species classification system involved several key steps: data collection, preprocessing, feature extraction, model training, and evaluation. The primary goal was to develop a robust model capable of accurately identifying bird species from their vocalizations. The species considered in this study were Parrot, Pigeon, and Budgerigar. The bird emotion classification system focused on identifying emotions in Budgerigars, specifically happy and angry states, from their vocalizations.

4.2 Train Model

Data Collection and Preprocessing

Dataset: The data collection process involved a systematic approach encompassing various sources, tools, and methods ensuring the acquisition of reliable data.
Audio recordings of bird vocalizations were collected, comprising 50 recordings each for Parrot, Pigeon, and Budgerigar. Among the three targeted species, for Pigeons and Parrots, data acquisition was facilitated through online sources hosting a variety of content creators' recordings of pet sounds. In the case of Budgerigars, a distinct approach was undertaken, data was gathered by subjecting them to varying circumstances, enabling the differentiation of their mood, followed by the recording of audio with 141 recordings labeled as "happy" and 271 as "angry." The recordings were stored in WAV format and organized into directories according to their respective categories.

Preprocessing

Conversion to Standard Format: The audio recordings were converted to a standardized format (WAV), to ensure compatibility and ease of processing.
Background Noise Removal: Background noise was removed using the website AudioMass.
Normalization: Audio levels were normalized to ensure consistency.
Segmentation: Audio clips were segmented into smaller, manageable units to ease focused analysis and feature extraction. Python code was employed to split the recordings into five-second segments.

Feature Extraction

Relevant features were extracted from audio signals, such as Mel-frequency cepstral coefficients (MFCCs), spectral features, and chroma features.

Mel-frequency cepstral coefficients (MFCCs) are a feature extraction technique widely used in tasks such as speech recognition, speaker identification, and audio classification.

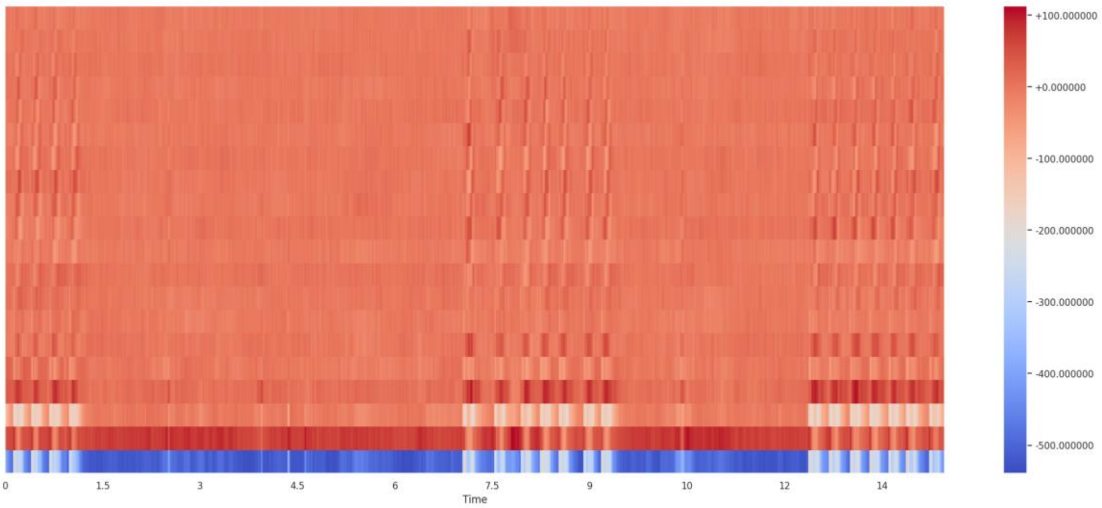

Figure 4.2.1. Visualization of MFCC for Species Classification

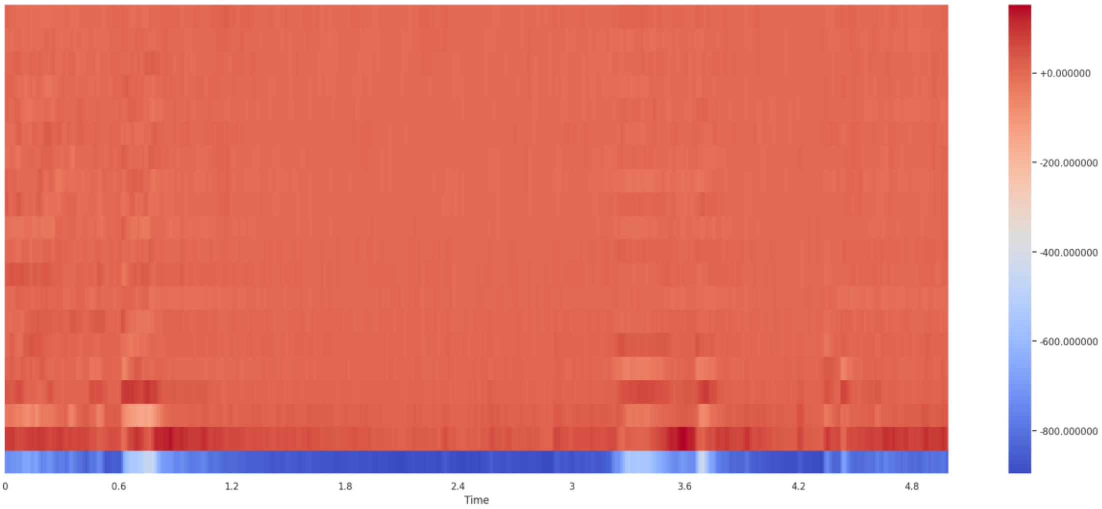

Figure 4.2.2. Visualization of MFCC for Emotion Classification

Chroma STFT (Short-Time Fourier Transform) helps analyze the changing pitch in a bird's song over short time intervals.

Spectral Centroid helps to figure out the average pitch of a sound, making it easier to understand the central frequency of a bird's vocalization.

Spectral Bandwidth measures of how spread out or concentrated the different pitches or frequencies are in a sound.

Zero-crossing rate measures of how frequently a sound wave changes direction.

RMSE refers to root, mean, square, error. It gives the average difference between the model predicted values and the actual observed values.

Spectrogram Visualization: Utilizing spectrograms, frequency content over time was visualized.

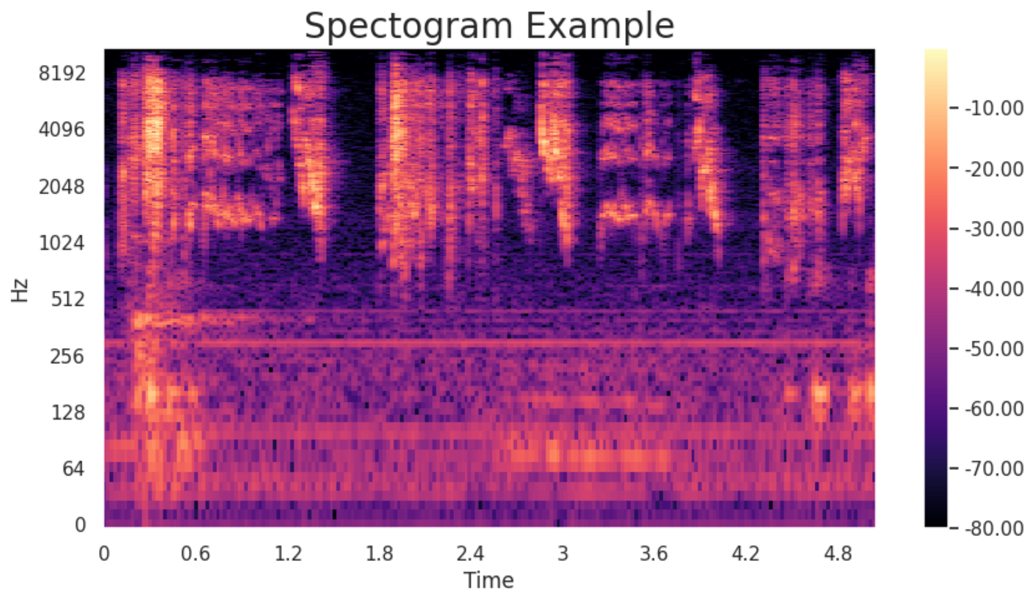

Figure 4.2.3. Spectrogram Visualization for Species Classification

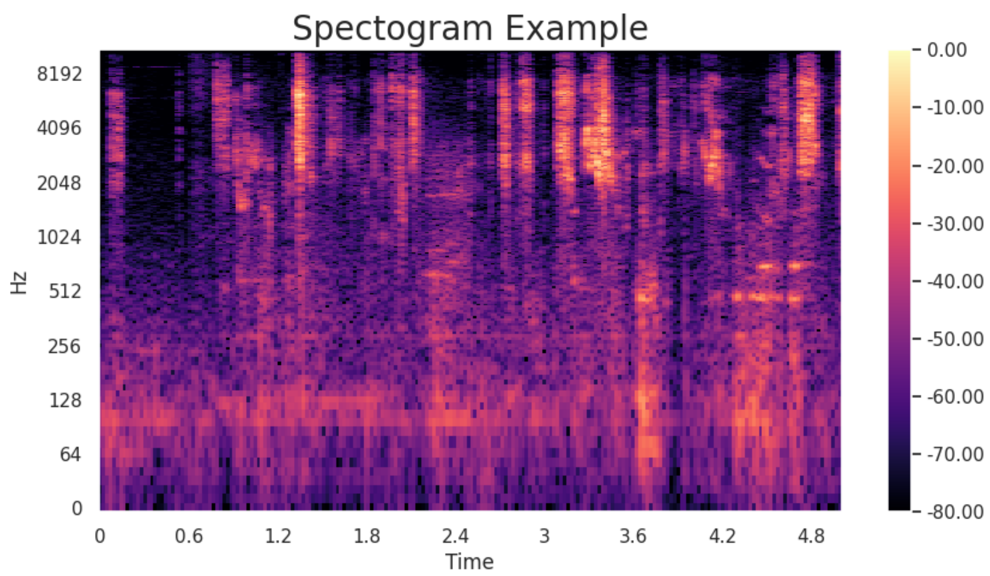

Figure 4.2.4. Spectrogram Visualization for Emotion Classification

Label Encoding: The species and emotion labels were encoded into numerical values. The mapping was as follows: Budgerigar: 0, Parrot: 1, Pigeon: 2 & Happy: 1, Angry: 0

Dataset Splitting: The dataset was divided into training, testing and validation sets using an 70-20-10 split to evaluate model performance.

Model Training:

Gradient Boosting Classifier: Builds an ensemble of decision trees in stages. Each tree focuses on correcting the errors made by the previous ones, leading to a more accurate overall model. In audio analysis, it can be used to classify audio data based on extracted features like pitch, loudness, or spectral patterns. For instance, it could distinguish between speech, music, and specific sound events.

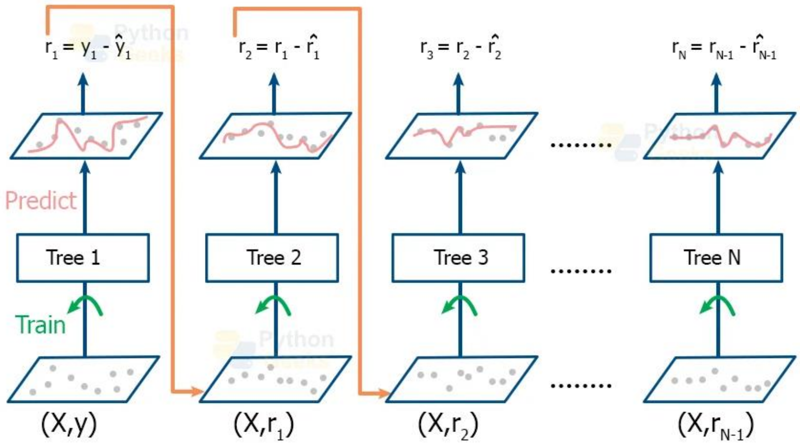

Figure 4.2.5. Architecture of GBC [12]

Random Forest Classifier: Builds a collection of independent decision trees. Each tree is trained on a random subset of features and data points. When making a prediction, the votes from all the trees are combined to determine the final classification.

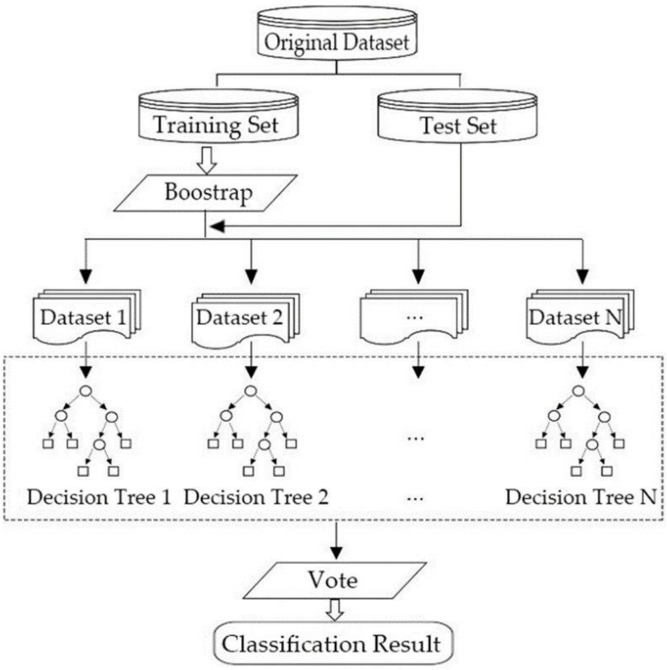

Figure 4.2.6. Architecture of RFC [13]

K-Nearest Neighbors: Classifies data points based on their similarity to their k nearest neighbors in the training data. To classify a new data point, the algorithm finds its k nearest neighbors in the training set and assigns the most frequent class label among those neighbors. KNN can also be used for genre classification by comparing a new audio sample to known genres in the training data.

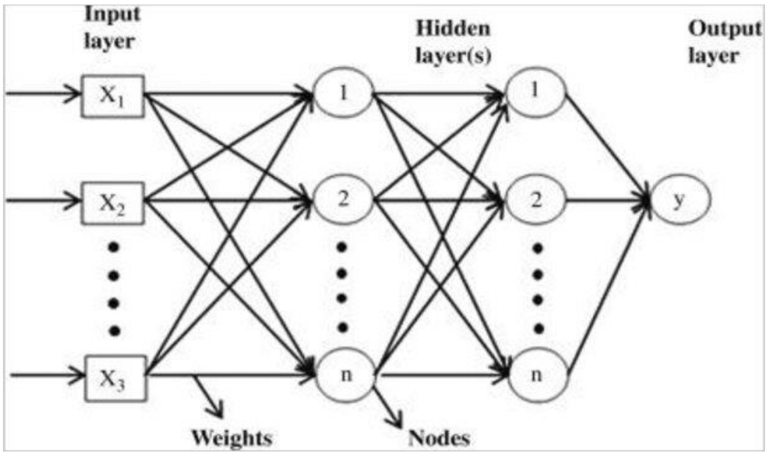

Figure 4.2.7. Architecture of KNN [12]

Decision Trees: These are tree-like structures where each node represents a decision rule based on a feature. The algorithm traverses the tree based on the feature values of the data point, reaching a leaf node that contains the final classification or prediction. Decision trees can be useful in audio analysis for understanding which audio features are most important for specific tasks.

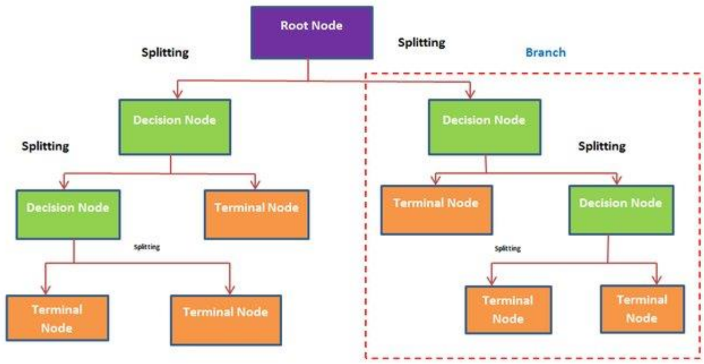

Figure 4.2.8. Architecture of DT [13]

Gaussian Naive Bayes: Estimates the probability of a data point belonging to a particular class based on the assumption that the features are independent of each other. GNB is used for classifying simple sounds with limited features.

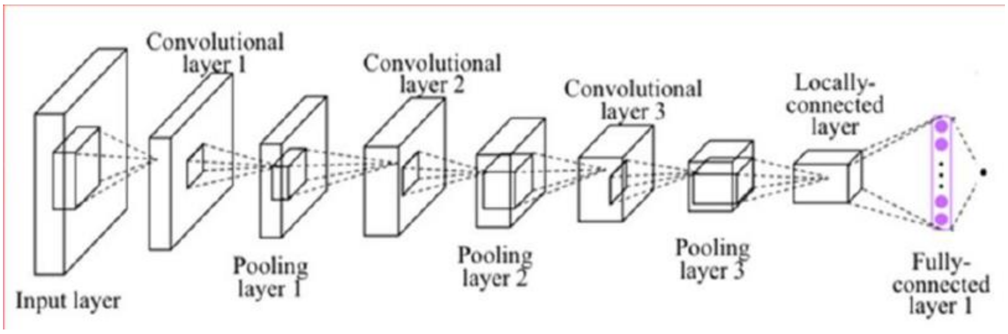

Figure 4.2.9. Architecture of GNB [14]

XGBoost Classifier: This is an optimized version of Gradient Boosting that is known for faster training times and improved performance, especially with complex datasets. XGBoost can be particularly valuable for audio analysis tasks involving large amounts of audio data or high-dimensional feature sets extracted from the audio.

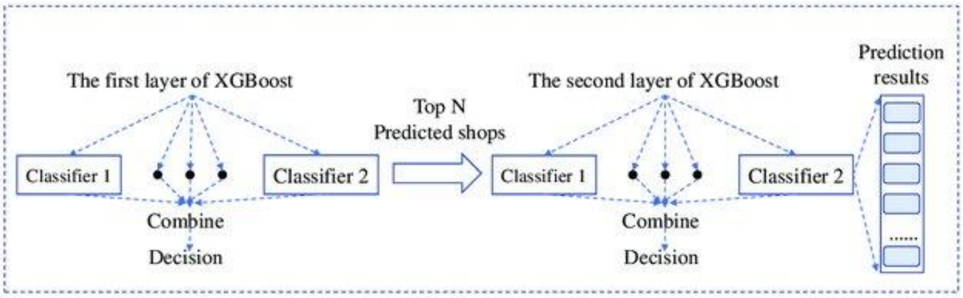

Figure 4.2.10. Architecture of XGBC [15]

Logistic Regression: Models the relationship between features and a binary classification outcome. It estimates the probability of a data point belonging to one of two classes.

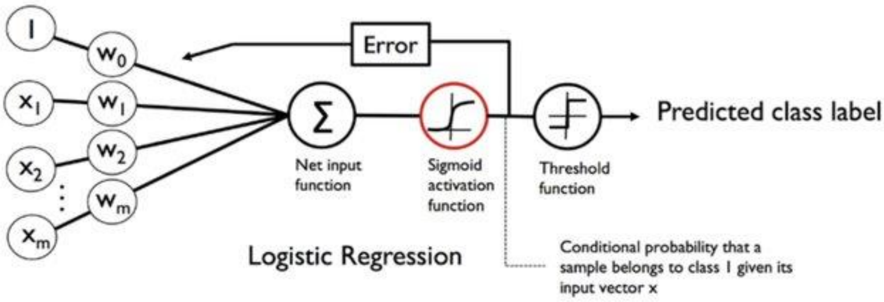

Figure 4.2.11. Architecture of LR [16]

4.3 Model Evaluation

Evaluation Matrix

For Species classification, among the algorithms, K-Nearest Neighbors achieved an accuracy of 96%. For, Emotion classification, Random Forest Classifier, Gaussian

Naive Bayes, XGBoost Classifier and Logistic Regression achieved 100% accuracy. These results highlight the effectiveness of the species recognition and emotion classification code, which utilizes features such as spectral and chroma extracted from audio signals, to precisely classify bird species and emotion based on their vocalizations.

Table 4.3.1. Bird Species Classification

Algorithm	**Train Accuracy**	**Test Accuracy**	**Validation Accuracy**
Gradient Boosting Classifier	100 %	100 %	100 %
Random Forest Classifier	100 %	100 %	100 %
K-Nearest Neighbors	95 %	86 %	96 %
Decision Trees	100 %	100 %	100 %
Gaussian Naive Bayes	100 %	100 %	100 %
XGBoost Classifier	100 %	100 %	100 %
Logistic Regression	100 %	100 %	100 %

Table 4.3.2. Emotion Classification of Budgerigars

Algorithm	**Train Accuracy**	**Test Accuracy**	**Validation Accuracy**
Gradient Boosting Classifier	100 %	97 %	95 %
Random Forest Classifier	100 %	100 %	100 %
K-Nearest Neighbors	92 %	95 %	90 %
Decision Trees	100 %	97 %	95 %
Gaussian Naive Bayes	98 %	97 %	100 %
XGBoost Classifier	100 %	100 %	100 %
Logistic Regression	100 %	100 %	100 %

4.4 Summary

The implementation of bird species and emotion classification systems demonstrated the effectiveness of machine learning algorithms in accurately classifying both bird species from vocalizations and emotions in Budgerigars. Both systems achieved high classification performance due to the crucial role played by extracted audio features, highlighting the importance of proper feature engineering in audio-based classification tasks.

CHAPTER 5
Result And Analysis

5.1 Overview

The study evaluates the effectiveness of various machine learning algorithms in classifying Parrot, Pigeon, and Budgerigar species based on vocalizations. Results indicate that models achieved high accuracy across all species. Furthermore, emotion classification experiments focused on detecting happiness and anger in Budgerigars. Results reveal robust accuracy rates with machine learning models like Random Forest Classifier and XGBoost Classifier demonstrating superior performance compared to others.

5.2 Experimental

The experimental process for this research was carried out in three phases.
Phase 1: Methodology, Data Collection, and Implementation of Initial Task

Data Collection: We gathered vocalizations from various sources, including proprietary recordings and publicly available datasets, for three species: Parrot, Pigeon, and Budgerigar.

Feature Extraction: Acoustic features such as MFCC, RMSE, Chroma features, Zero-crossing rate, Rolloff, and Spectral features were extracted from the audio clips.

Implementation: Various machine learning models were implemented for species classification, including GBC, RFC, KNN, DTC, GNB, and XGB.

Phase 2: Methodology, Data Collection for Budgerigar's emotion classification.

Data Collection: We gathered vocalizations from Budgerigars, focusing on two emotions: happy and angry. The dataset included 141 audio samples for happy and 271 audio samples for angry.

Feature Extraction: Acoustic features similar to the initial phase were extracted from the audio clips.

Phase 3: Methodology, Implementation of Budgerigar's emotion classification.

Implementation: Machine learning models similar to the initial phase were implemented for emotion classification. Precision, recall, F1-score, and accuracy were calculated for each model to provide a comprehensive evaluation of their performance.

5.3 Comparative Analysis

Bird Species Classification: The experiments on bird species classification were conducted to evaluate the effectiveness of various machine learning algorithms in classifying Parrot, Pigeon, and Budgerigar based on their vocalizations. The performance matrix for each algorithm were recorded, and a comparative analysis was performed to determine the best-performing model. The performance of each algorithm was evaluated using precision, recall, F1-score, and accuracy.

Table 5.3.1. Classification Report of Bird Species Classification

Algorithm	Precision	Recall	F-1 Score	Accuracy
Gradient Boosting Classifier	100 %	100 %	100 %	100 %
Random Forest Classifier	100 %	100 %	100 %	100 %
K-Nearest Neighbors	97 %	96 %	97 %	96 %
Decision Trees	100 %	100 %	100 %	100 %
Gaussian Naive Bayes	100 %	100 %	100 %	100 %
XGBoost Classifier	100 %	100 %	100 %	100 %
Logistic Regression	100 %	100 %	100 %	100 %

All the models demonstrated high accuracy with fast prediction time. Tree-based models, while highly accurate, required more computational resources. KNN had a faster prediction time but was less accurate.

Bird Emotion Classification: The bird emotion classification experiments aimed to identify emotions (happy and angry) in Budgerigars from their vocalizations. Similar to the species classification experiments, performance matrix were recorded and analyzed to assess the effectiveness of different models.

Table 5.3.2. Classification Report of Emotion Classification

Algorithm	Precision	Recall	F-1 Score	Accuracy
Gradient Boosting Classifier	93 %	96 %	95 %	95 %
Random Forest Classifier	100 %	100 %	100 %	100 %
K-Nearest Neighbors	94%	85 %	88 %	90 %
Decision Trees	93 %	96 %	95 %	95 %
Gaussian Naive Bayes	100 %	100 %	100 %	100 %
XGBoost Classifier	100 %	100 %	100 %	100 %
Logistic Regression	100 %	100 %	100 %	100 %

The training and prediction times were evaluated for each model. RFC and XGB, while highly accurate, required more computational resources. GBC, KNN, DTC were more efficient but less accurate compared to RFC and XGB.

Confusion Matrix

Confusion matrix are used to evaluate the accuracy of classification models, providing detailed breakdown of a model's performance beyond overall accuracy. [17]

True Positives (TP): Model correctly predicts a positive class.
False Positives (FP): Model incorrectly predicts a positive class.
True Negatives (TN): Model correctly predicts a negative class.
False Negatives (FN): Model incorrectly predicts a negative class.

Accuracy: The overall percentage of correctly classified instances.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \qquad (i)$$

Precision: The proportion of predicted positive cases that were actually correct.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \qquad (ii)$$

Recall: The proportion of actual positive cases that were correctly identified.

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

F1-Score: A harmonic mean of precision and recall, combining their importance into a single metric.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} \times \text{Recall}} \qquad (iv)$$

Confusion Matrix for Birds Species Classification:

Gradient Boosting Classifier: Accuracy 100%

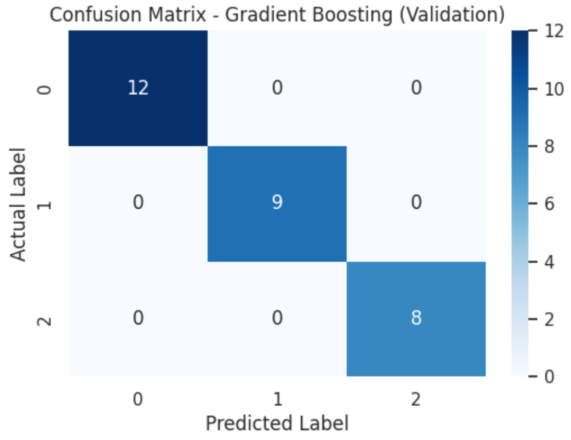

Figure: 5.3.1. Confusion Matrix for GBC

The model correctly predicted all 12 instances of class 0, 9 instances of class 1, and 8 instances of class 2 without any errors.

Random Forest Classifier: Accuracy 100%

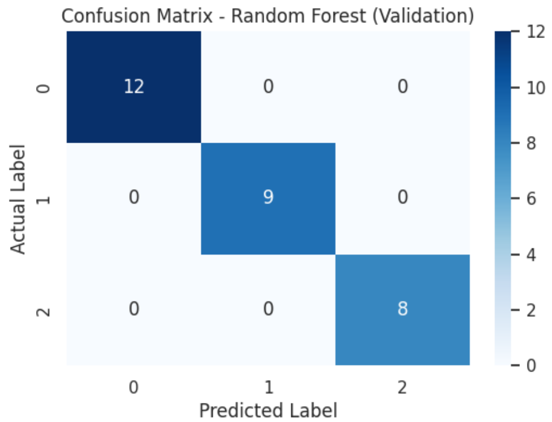

Figure: 5.3.2. Confusion Matrix for RFC

This model accurately identified all 12 samples of class 0, 9 samples of class 1, and 8 samples of class 2, with no errors.

K-Nearest Neighbor: Accuracy 96%

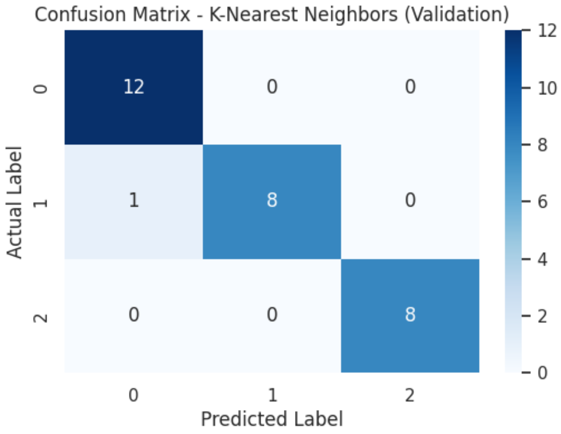

Figure: 5.3.3. Confusion Matrix for KNN

This model correctly classified 12 samples of class 0, 8 samples of class 1, and 8 samples of class 2, but it misclassified 1 instance of class 1 as class 0.

Decision Tree Classifier: Accuracy 100%

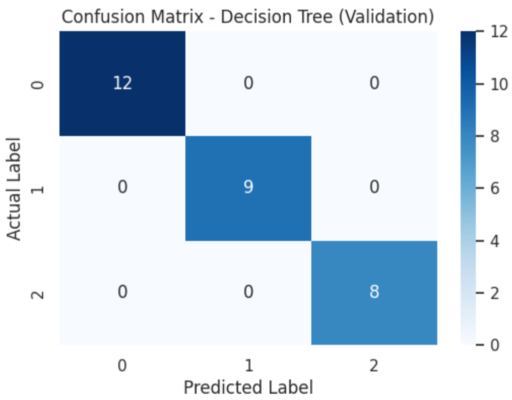

Figure: 5.3.4. Confusion Matrix for KNN

This model also achieves perfect accuracy. It correctly classified all 12 instances of class 0, all 9 instances of class 1, and all 8 instances of class 2.

Naive Bayes Classifier: Accuracy 100%

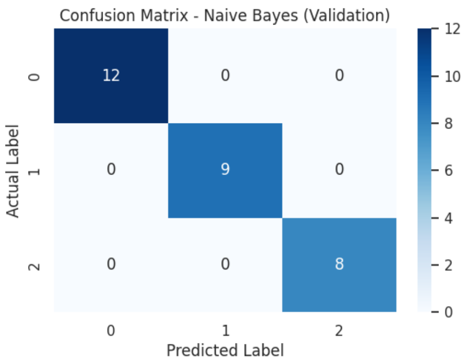

Figure: 5.3.5. Confusion Matrix for NBC

This shows proper classification with 12 instances correctly identified for class 0, 9 for class 1, and 8 for class 2.

XGBoost Classifier: Accuracy 100%

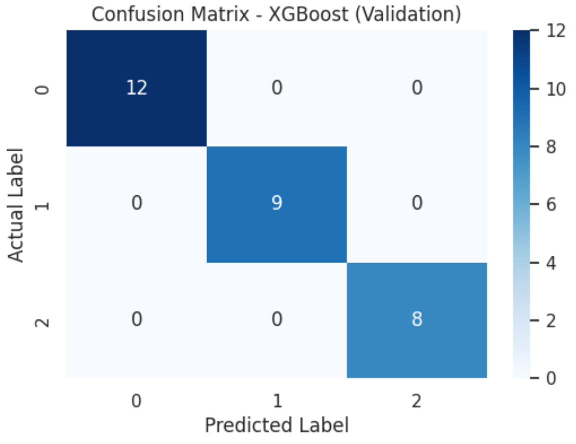

Figure: 5.3.6. Confusion Matrix for XGBC

This is indicating 12 correct predictions for class 0, 9 for class 1, and 8 for class 2.

Logistic Regression Classifier: Accuracy 100%

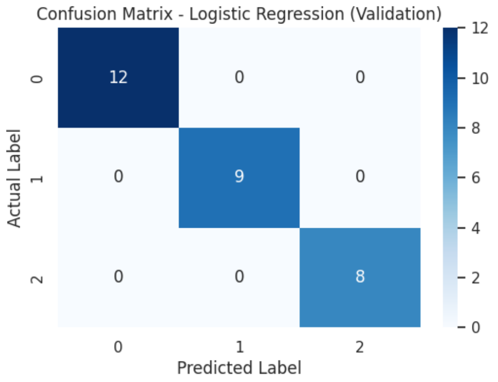

Figure: 5.3.7. Confusion Matrix for LRC

This model demonstrates 12 accurate classifications for class 0, 9 for class 1, and 8 for class 2.

Confusion Matrix for Birds Emotion Classification:

Gradient Boosting Classifier: Accuracy 95%

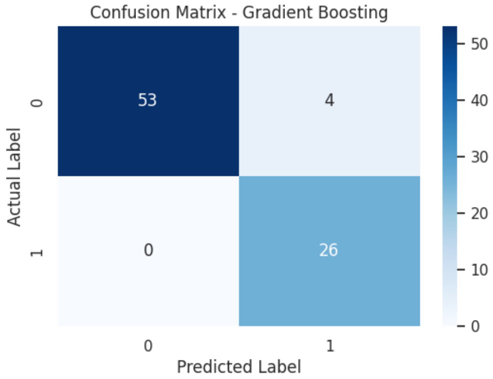

Figure: 5.3.8. Confusion Matrix for GBC

True Positives: 53, True Negatives: 26, False Positives: 4, False Negatives: 0

The model correctly identified 53 instances as angry(class 0) and 26 instances as happy (class 1). There are 4 instances where the model incorrectly predicted the positive class (1) for samples that actually belong to the negative class (0).

Random Forest Classifier: Accuracy 100%

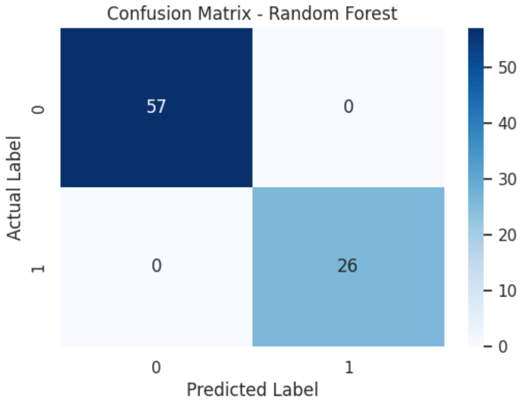

Figure: 5.3.9. Confusion Matrix for RFC

True Positives: 57, True Negatives: 26, False Positives: 0, False Negatives: 0

The model correctly predicted 57 instances as angry and 26 instances as happy.

K-Nearest Neighbors Classifier: Accuracy 90%

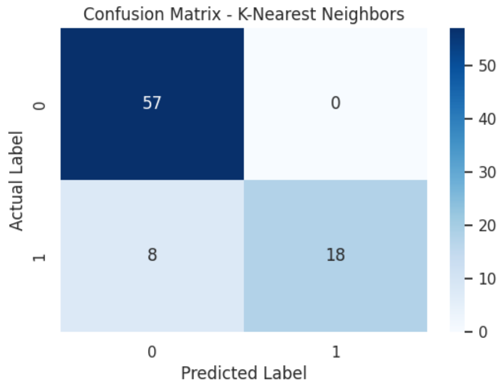

Figure: 5.3.10. Confusion Matrix for KNN

True Positives: 57, True Negatives: 18, False Positives: 0, False Negatives: 8
The model correctly predicted 57 positive instances and 18 negative instances, with no false positives and 8 false negatives.

Decision Tree Classifier: Accuracy 95%

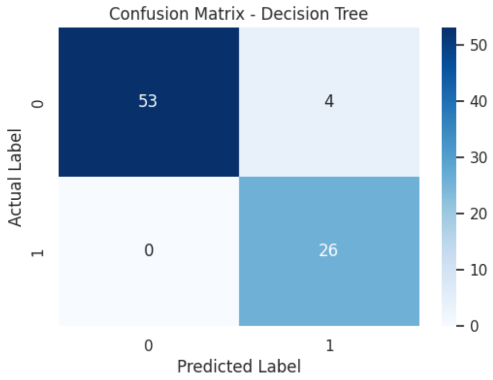

Figure: 5.3.11. Confusion Matrix for DTC

True Positives: 53, True Negatives: 26, False Positives: 4, False Negatives: 0
This means the model correctly predicted 53 positive instances and 26 negative instances, with only 4 false positives and no false negatives.

Naive Bayes Classifier: Accuracy 100%

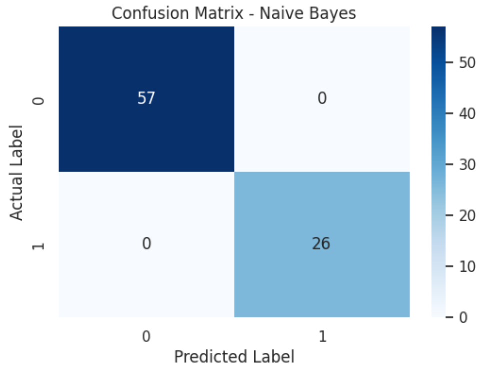

Figure: 5.3.12. Confusion Matrix for GNB

True Positives: 57, True Negatives: 26, False Positives: 0, False Negatives: 0
The model correctly predicted 57 instances as angry and 26 instances as happy.
XGBoost Classifier: Accuracy 100%

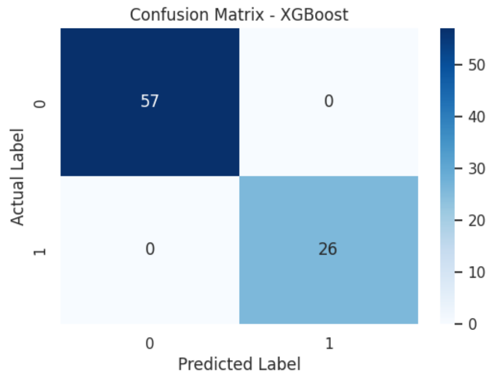

Figure: 5.3.13. Confusion Matrix for XGB

True Positives: 57, True Negatives: 26, False Positives: 0, False Negatives: 0

The model correctly predicted 57 positive instances and 26 negative instances, with no false positives and no false negatives.

Logistic Regression Classifier: Accuracy 100%

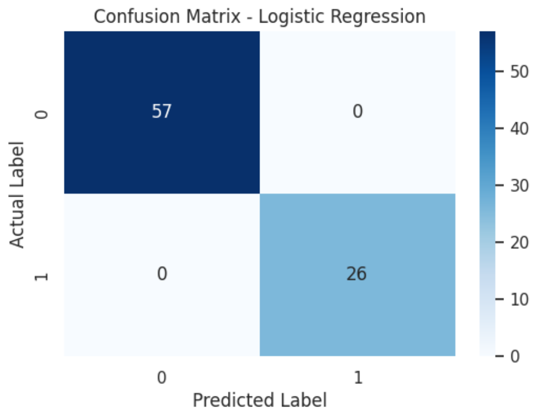

Figure: 5.3.14. Confusion Matrix for LRC

True Positives: 57, True Negatives: 26, False Positives: 0, False Negatives: 0

The model correctly identified 57 positive instances and 26 negative instances, with 0 false positives and 0 false negatives.

5.4 Summary

Machine learning models are highly effective in classifying species based on vocalizations. Tree-based models like Random Forest and XGBoost showed the best performance, achieving high accuracy and handling variations in the data well. Other models like KNN also performed well, offering a good balance between accuracy and efficiency. These findings suggest that machine learning is a valuable tool for understanding birds' communication and potentially even their emotions.

CHAPTER 6
Impact On Society, Environment And Sustainability

6.1 Impact on Life

The integration of AI-driven classification for bird species and emotions through vocalizations holds profound implications for understanding avian behavior and enhancing conservation efforts. By providing accurate methods to study and monitor bird populations, this technology supports biodiversity preservation and promotes sustainable practices across diverse ecosystems.

6.2 Impact on Society & Environment

This innovation empowers avian researchers, enthusiasts, and conservationists by providing precise methods for studying and monitoring bird populations, enhancing our ability to recognize species and emotional states in birds. By strengthening conservation efforts and promoting biodiversity preservation on a global scale, AI in avian research improves the accuracy of species identification and emotional recognition. This enables targeted conservation interventions, minimizes human impact on natural habitats, and fosters coexistence between wildlife and human communities. Moreover, promoting adaptive management strategies aids in mitigating threats to avian populations and their ecosystems. Beyond scientific communities, this research influences public engagement and environmental stewardship, fostering broader appreciation and conservation awareness among the general public. Ultimately, integrating AI into avian research not only advances scientific knowledge but also promotes sustainable coexistence with avian species, contributing significantly to global biodiversity conservation and environmental sustainability efforts.

6.3 Ethical Aspects

Ethical considerations in this study encompass several key principles to ensure responsible research and conservation practices. Central to these considerations is the principle of wildlife welfare, ensuring that research practices prioritize the well-being and minimal disturbance of avian subjects during data collection and analysis. This includes adhering to ethical guidelines that advocate for non-invasive monitoring techniques and respectful interactions with bird populations in their natural habitats.

Transparency in data handling is another critical aspect of ethical avian research. It is mandatory to ensure clear documentation and disclosure of data sources, methodologies, and analytical techniques used in AI models. This transparency not only supports scientific rigor but also promotes accountability and reproducibility in avian research practices.

6.4 Sustainability Plan

The sustainability plan for this research focuses on maximizing environmental responsibility and long-term societal benefits. Key components of this plan include:

Data Privacy: Ensuring severe data management protocols to protect sensitive information.
Collaboration: Fostering partnerships with avian experts, and communities for knowledge sharing and capacity building.
Public Awareness: Developing educational programs to promote avian conservation awareness.
Adaptability: Continuously improving AI models to meet evolving conservation challenges.
Ethical Guidelines: Advocating for ethical standards in AI-driven wildlife research and conservation.
By integrating these strategies into the implementation of AI-driven avian research, the sustainability plan aims to maximize positive environmental and societal impacts while advancing scientific knowledge and conservation efforts for avian species globally.

6.5 Summary

This research represents a significant advancement in the classification of bird species and emotions using AI-driven vocalization analysis. By achieving accurate species identification and emotion recognition, the study contributes to enhancing avian welfare, conservation practices, and sustainable management of avian populations worldwide.

CHAPTER 7

Conclusion And Future Work

7.1 Conclusions

To conclude, this study highlights significant advancements made in the research of bird emotion classification using artificial intelligence. The completion of data collection involves a diverse dataset comprising vocalizations from three distinct bird species: Parrots, Pigeons, and Budgerigars, crucial for both species and emotion classification. Specifically, we gathered extensive recordings of Budgerigars expressing happiness and anger, enabling comprehensive emotion classification for this species.

The successful implementation of various machine learning algorithms has produced promising results. Specifically, several of these models have achieved exceptional accuracy rates, reaching up to 100% in accurately classifying different bird species based solely on their vocalizations. This remarkable achievement underscores the robustness and reliability of our approach in distinguishing subtle acoustic differences that define each species.

Moreover, they have shown robust performance in accurately recognizing emotional states in birds. The algorithms have demonstrated strong performance in emotional classification of budgerigars, accurately identifying whether these birds' express happiness or anger through their vocal signals. This capability is crucial for understanding avian behavior and emotions, providing valuable insights into how birds communicate their emotional states through vocalizations.

These accomplishments represent a significant advancement in avian research, where the precise classification of species and emotions through AI-driven methods opens new avenues for studying and monitoring bird populations.

7.2 Further Suggested Works

Building on the achievements of this research, several avenues emerge for further exploration and advancement in the field of bird emotion and species classification using artificial intelligence.

Expanding the Species: Broadening the scope beyond parrots, pigeons, and budgerigars to encompass a wider array of avian species would enrich our dataset and enhance the robustness of our models. By including a diverse range of bird vocalizations from various taxonomic groups and habitats, future studies can ensure more comprehensive and representative species classification.

Enhancing Emotional Recognition: Further refining emotion recognition algorithms to detect a broader spectrum of emotional states in birds is crucial. While our current focus has successfully distinguished between happiness and anger in Budgerigars, exploring nuanced emotions like fear, distress, or contentment would provide deeper insights into avian behavior and welfare dynamics.

Investigating Environmental Influences: Exploring how environmental factors such as habitat types, climate variations, and human disturbances influence bird vocalizations and emotional expressions is essential.

Developing Real-time Monitoring Systems: Advancing towards real-time monitoring and automated detection systems powered by AI could revolutionize field research. Developing portable AI models capable of operating in diverse field conditions would enable continuous data collection and analysis, facilitating more proactive conservation efforts and adaptive management strategies.

7.3 Limitations

While this study represents a significant step forward in AI-driven avian research by advancing species and emotion classification through vocalizations, several limitations must be acknowledged. Despite the potential importance of bird emotion classification, no studies have attempted to classify the emotional content of bird vocalizations. This could be due to the challenges associated with interpreting the complex acoustic signals produced by birds and the lack of standardize methodologies for emotion classification.

Data Collection: During the data collection phase, one of the main challenges encountered was ensuring the acquisition of high-quality audio recordings of bird vocalizations. Background noise interference and variability in recording conditions posed significant obstacles to obtaining clean and reliable data. Additionally, capturing a sufficient number of samples for each bird species proved to be challenging, particularly given the need for diversity within the dataset.

Algorithm Selection: The absence of previous work on emotion detection and limited research on species detection presented challenges in selecting appropriate machine learning algorithms. Without established benchmarks or baseline models to guide algorithm selection, it was difficult to determine the most effective approaches for our specific tasks.

Model Overfitting: Due to the limited amount of collected data, considering the challenges of data collection, there is a possibility of models being overfitted.

References

[1] Neal, L., Briggs, F., Raich, R., & Fern, X. Z. (2011, May). Time-frequency segmentation of bird song in noisy acoustic environments. In 2011 ieee international conference on acoustics, speech and signal processing (icassp) (pp. 2012-2015). IEEE.
[2] Graciarena, M., Delplanche, M., Shriberg, E., & Stolcke, A. (2011, May). Bird species recognition combining acoustic and sequence modeling. In 2011 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 341-344). IEEE.
[3] Jaddu, N. S., Shashank, S. R. S., & Suresh, A. (2022, November). Voice Emotion Detection: Acoustic Features Extraction Using Multi-layer Perceptron Classifier Algorithm. In International Conference on Innovative Computing and Communications: Proceedings of ICICC 2022, Volume 3 (pp. 593-602). Singapore: Springer Nature Singapore
[4] Hantke, S., Cummins, N., & Schuller, B. (2018, April). What is my dog trying to tell me? The automatic recognition of the context and perceived emotion of dog barks. In 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 5134- 5138). IEEE.
[5] Mehyadin, A. E., Abdulazeez, A. M., Hasan, D. A., & Saeed, J. N. (2021). Birds sound classification based on machine learning algorithms. Asian Journal of Research in Computer Science, 9(4), 1-11.
[6] Jadhav, Y., Patil, V., & Parasar, D. (2020, February). Machine learning approach to classify birds on the basis of their sound. In 2020 International Conference on Inventive Computation Technologies (ICICT) (pp. 69-73). IEEE.
[7] Stastny, J., Munk, M., & Juranek, L. (2018). Automatic bird species recognition based on birds vocalization. EURASIP Journal on Audio, Speech, and Music Processing, 2018(1), 1-7.
[8] Andono, P. N., Shidik, G. F., Prabowo, D. P., Pergiwati, D., & Pramunendar, R. A. (2022). Bird Voice Classification Based on Combination Feature Extraction and Reduction Dimension with the K-Nearest Neighbor. International Journal of Intelligent Engineering & Systems, 15(1).
[9] Rabiner, L. R., & Schafer, R. W. (2007). Introduction to digital speech processing. Foundations and Trends® in Signal Processing, 1(1–2), 1-194.
[10] Gradient Boosting Algorithm in Machine Learning, Python Geeks. Available At: https://pythongeeks.org/gradient-boosting-algorithm-in-machine-learning/ (accessed Jun. 20, 2024).
[11] Chen, J., Yu, J., Wen, J., Zhang, C., Yin, Z. E., Wu, J., & Yao, S. (2019). Pre-evacuation time estimation-based emergency evacuation simulation in urban residential communities. International journal of environmental research and public health, 16(23), 4599.

[12] Kumari, B., & Swarnkar, T. (2021). Stock movement prediction using hybrid normalization technique and artificial neural network. International Journal of Advanced Technology and Engineering Exploration, 8(83), 1336.
[13] Mishra, A., & Vats, A. (2021). Supervised machine learning classification algorithms for detection of fracture location in dissimilar friction stir welded joints. Frattura ed Integrità Strutturale, 15(58), 242-253.
[14] milaan9. Machine_Learning_Algorithms_from_Scratch. GitHub repository. (accessed Jun. 20, 2024).
[15] Jiang, H., He, M., Xi, Y., & Zeng, J. (2021). Machine-learning-based user position prediction and behavior analysis for location services. Information, 12(5), 180.
[16] Torres, R., Ohashi, O., & Pessin, G. (2019). A machine-learning approach to distinguish passengers and drivers reading while driving. Sensors, 19(14), 3174.
[17] B, H.N. (2020) Confusion matrix, accuracy, precision, recall, F1 score, Medium. Available at: https://medium.com/analytics-vidhya/confusion-matrix-accuracy-precision-recall-f1-score-ade299cf63cd (Accessed: 18 May 2024).
[18] Rabiner, L. R., & Schafer, R. W. (2007). Introduction to digital speech processing. Foundations and Trends® in Signal Processing, 1(1–2), 1-194.
[19] Rabiner, L., & Schafer, R. (2010). Theory and applications of digital speech processing. Prentice Hall Press.
[20] Beckers, G. J. (2011). Bird speech perception and vocal production: a comparison with humans. Human Biology, 83(2), 191-212.
[21] Rong, F. (2016, December). Audio classification method based on machine learning. In 2016 International conference on intelligent transportation, big data & smart city (ICITBS) (pp. 81-84). IEEE.
[22] Wu, D. (2019, January). An audio classification approach based on machine learning. In 2019 International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS) (pp. 626-629). IEEE.
[23] Street, C. (2023). "How Many Hours a Day Should I Spend with My Budgie?", My Bird Garden, 2024. [Online]. Available: https://mybirdgarden.com/how-many-hours-a-day-should-i-spend-with-my-budgie/. [Accessed: 14-May-2024].
[24] A. Lad, "Signs Your Budgie is Happy", Bird Feeder Hub, 2024. [Online]. Available: https://birdfeederhub.com/signs-your-budgie-is-happy/. [Accessed: 14-May-2024].

Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title: Birds Emotion Classification Using AI.

Student ID: 203-15-14509 and 203-15-14489

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **bird's species and emotion classification** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish these goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**

CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates **fundamental engineering (K3)** principles by employing machine learning based models, data augmentation techniques and implementation of various algorithms for audio classification tasks. The project demonstrates **specialist knowledge (K4)** by conducting machine learning algorithms like RFC, XGB to predict birds species and emotion which is crucial for birds welfare.	**Page no:** [11-13] **Section:** [4.2] **Page no:** [14-18] **Section:** [4.3]

				The project applies **engineering practice & design (K5)** by the figure of process of experiments. The project addresses **engineering practice & technology (K6)** by employing machine learning models.	**Page no:** [17-18] **Section:** [4.3] **Page no:** [7-8] **Section:** [3.2]
				This project ensures to **K8 (Research Literature)** by synthesizing insights from previous studies related to birds species classification showcasing a comprehensive understanding of methodologies.	**Page no:** [4-5] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses **EP-2** by recognizing the hurdles in bird's species classification and emotion classification, including limitations of traditional methods and the complexities of integrating machine learning. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining classifications.	**Page no:** [6] **Section:** [2.4]

3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting Machine Learning as the chosen significant solution for enhancing species classification and emotion classification amidst multiple potential approaches.	**Page no:** [18-20] **Section:** [5.2, 5.3]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science and engineering, impacting social and environmental aspects contributing to the advancements in animal welfare which indicates **EP-4**.	**Page no:** [4-6] **Section:** [2.2, 2.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, ensuring a holistic solution to complex challenges in animal emotion classification which ensures **EP-7**.	**Page no:** [7-8, 11, 16-17] **Section:** [3.2, 4.2, 4.3]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, machine learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in bird's species detection through machine learning.	**Page no:** [8-9] **Section:** [3.3, 3.4]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		This project contributes to society by improving animal welfare through emotion detection, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines.	**Page no:** [27-28] **Section:** [6.1, 6.2, 6.4]

5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in birds species and emotion classification through machine learning, demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [4-5] **Section:** [2.2, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [8-9] **Section:** [3.4]
2	CO9	Yes	The project demonstrates adherence to ethical principles by prioritizing birds health and environmental safety ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced animal welfare technologies which comply with **CO9**.	**Page no:** [27] **Section:** [6.3]
3	CO10	No	N/A	N/A

4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [7-8, 18] **Section:** [3.2, 5.2]

Birds Emotion Classification Using AI

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