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Birds Sound Classification Based on Machine Learning Algorithms

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Authors' contributions

This work was carried out in collaboration among all authors. Author AMA designed the study, performed the statistical analysis. Author AEM wrote the protocol and wrote the first draft of the manuscript. Author DAH managed the analyses of the study. Author JNS managed the literature searches. All authors read and approved the final manuscript.

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ABSTRACT

The bird classifier is a system that is equipped with an area machine learning technology and uses a machine learning method to store and classify bird calls. Bird species can be known by recording only the sound of the bird, which will make it easier for the system to manage. The system also provides species classification resources to allow automated species detection from observations that can teach a machine how to recognize whether or classify the species. Non-undesirable noises are filtered out of and sorted into data sets, where each sound is run via a noise suppression filter and a separate classification procedure so that the most useful data set can be easily processed. Mel-frequency cepstral coefficient (MFCC) is used and tested through different algorithms, namely Naïve Bayes, J4.8 and Multilayer perceptron (MLP), to classify bird species. J4.8 has the highest accuracy (78.40%) and is the best. Accuracy and elapsed time are (39.4 seconds).

Keywords: Machine learning; classification; bird sound classification; MFCC.

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1. INTRODUCTION

Recently, technology has developed a lot, especially in the field of Machine Learning (ML), which is useful for reducing human work. In the field of artificial intelligence, ML integrates statistics and computer science to build algorithms that get more efficient when they are subject to relevant data rather than being given specific instructions [1][2][3].

Machine learning is commonly used in diverse fields to solve difficult problems that cannot be readily solved based on computer approaches [4][5][6].

Recently, these advances in machine learning have helped a lot with sound classification, and sound recognition has shown to be a strong value in automating these tasks [7]. To say it another way, birds can make two basic sounds: Call and song [8][9]. While this approach is time-consuming, machine learning approaches may also be useful in establishing differentiating between the different species, even after that since it is done on a species of birds that are still not thought to be discernable [10]. However, machine learning's usage of bird classification has only been examined for a small number of species or mannequin processing on the assumption that it can be applied in the real world only through numerical simulation or hand recordings [11]. The results have proven unpractical for ecologists but can be useful for many people of a wide variety of professions [12]. When the classification rate study is extended to more organisms that are currently existing, the findings may vary greatly [13][14]. The features used to identify and classify birds can be organized in two ways: First, bird species can be compared, and second, all birds can be identified based on a handful of specific features. In the sound classification of birds, the static noise is removed because it makes it difficult to hear the bird calls until the signal is filtered and boost the volume. The study of the bird's specific sound categories such as joyful, sad, gentle, grating, and quiet to discover a lot of additional information about it. Machine learning algorithms, examine them to decide which strategies are the most effective at identifying birds [15-20]. The more often used audio feature— (MFCC). Mel-frequency cepstral coefficients (MFCCs), MFC is composed of individual values that add up to a unit vector. The form of the vocal tract expresses itself in the time-band continuum, and the function of (MFCCs) is to faithfully capture it. The organization of this paper is as follows: Section 2 we review the related work, section 3 is the methodology of the proposed approach, section 4 is Performance Evaluation, section 5 gives results-discussions and conclusions are made in Section 6.

2. RELATED WORK

V. Morfi et al. [21] presented NIPS4Bplus which is the first annotated, typographically enriched bird song dataset. The NIPS4Bplus dataset and tags used for the 2013 bird song classification challenge, as well as newly acquired temporal annotations, make up NIPS4Bplus. They have comparative data on the recordings, as well as their species-specific tags and temporal annotations.

A. Pareta et al. [22] The MC-LS-VM classifier was calculated with an RBF kernel function with seven input parameters given a class accuracy features a rating of 85.43% According to them, their claims have had the best results to date and are therefore more successful to date.

K. Ko et al. [23] utilized the pre-trained neural network offers innovative solutions for fine categorization of animal species based on their sound signals using pre-trained CNNs, and a new self-attention model well-suited for acoustics.

I. Lezhenin et al. [24] proposed the LSTM model outperforms a range of current implementations and is more accurate and reliable than the previous model CNN.

L. Nanni et al. [25] analyzed CNN model using two collections of animal data: one on the feline audio files and the other on bird recordings. They also devised a way to locate the centers of the spectra through their analysis of their pre-exposed dots. When experimenting with their proposal, results show that it outperforms other approaches on other types of data as well Since the use of LSTM networks is highly effective in learning temporal dependencies

W. Xu et al. [26] implemented a CNN design, in which three convolutions had to be done in parallel using three different filter lengths Observation showed that their method was successful, obtaining a high degree of accuracy in real-world environments.

Erhan Akbal [27] achieved a 90.25% prediction accuracy rate with his proposed system. In his study, he suggests a cognitive, lightweight, highly reliable, and low bandwidth form of online expansion. By the end of the experiment, it was shown that this approach works.

M. M. M. Sukri et al. [28] used the bird's sound classification system employs artificial neural networks (ANN). This work has been completed and can provide useful information on the different bird types. Using the automated environmental sound classification (or, ESC) it is possible to foresee the kind of sounds that will be made.

C. Chalmers et al. [29] obtained bird songs are sampled with a Mel-band filter bank cephalometer to collect their vocal parameters analyzed with a multilayer perceptron to determine whether they belong to one species or another. Their proposed approach yielded positive results with a sensitivity of 0.74.
H. Xu et al. [30] believed that the birds found produced a noise filter sound and future testing should conduct tests to examine the effectiveness of this method. The approach used in the MICV and MIC-MFT is better than other selection approaches in terms of how well it classifies features.

3. MATERIALS AND METHODS

The proposed work is divided into four main stages as shown in Fig. 1. The first step is the process of collecting the bird sound data. Then, the collected data should be pre-processed to increase the efficiency of the playback. The next processes are features extraction and classification operations of sound patterns using machine learning algorithms based on derived features [31].

3.1 Data Collection

The (Female Feature MFCC) dataset was used in this work. It is an open-source dataset published on kaggle.com. This dataset created with the aim to predict female's emotions based on MFCCs values. With this setup (58 values for each emotion) we were been able to get a good 94% accuracy on the female emotions. The mean for a data set is termed as the arithmetic mean [32]. In this paper, the mean of MFCCs is taken to reduce the huge set of values that are obtained from MFCC [33]. When 'x'= {x1, x2, x3, ,xn} represents MFCC values and total number of MFCC is n then the arithmetic mean is taken as

$$X= \frac{x1+x2+x3+\cdots.+xn}{n}$$

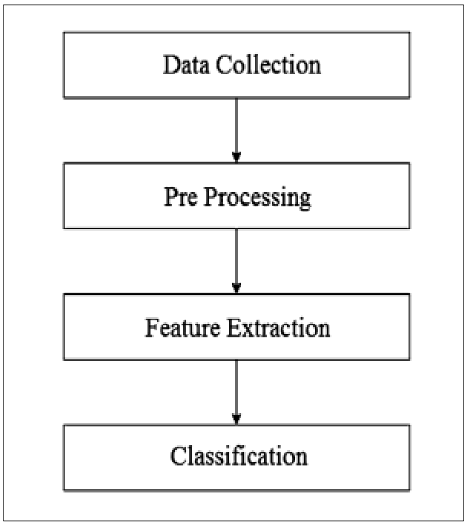

Fig. 1. General stages in automatic bird identification process

3.2 Pre-Processing

A natural recording has a lot of background noise in it, so there is no way to clean up the audio clips prior to use [34]. Also, unwanted sounds have been used in the original sound recordings. it is essential to eliminate or minimize the noise from the desired sound, particularly when you are trying to hear the call of a wild bird Pre-processing of the sound recordings is needed to ensure reasonable device efficiency [35]. noise reduction methods (like filtering) must be applied to the recorded signals in order to take out unnecessary noise components that can, in turn, enhance the sound quality of the resulting recordings A frequency-based pass band-pass filter (Butter) is used to get rid of unwanted background noise as it filters out a frequency spectrum and has a very flat frequency response in the passband [36]. For records of many species to have been discovered, it's found that overlapping sounds can be heard [37]. Nevertheless, we will conclude that there is only one dominant species of bird species this time around which is making the sounds from the tape [38]. The other sections of the audio signal, except the required ones, must be removed from the signal. To receive a known-requirements query that yields focused results, or tuned results, unbind the query so that it can return a single type of signal that has the results. in the way that the mean pitch is calculated using the harmonic continuum analysis [39]. From this, the preceding material, the Butterworth filter is manually calibrated, and a spectrogram is used to ensure that the waveforms have been recovered [40]. While the accuracy is increased, a downside of this approach is that other birds might still be making the same signal, which is when used alongside it [41]. But in this case, bird species have frequencies that are close to one another and appear to possess identical characteristics separating the various recordings of birds' calls to increase the success of single-label methods results would be very impractical so doing so would only make the success of the results of each form of detection less likely [42]. The instances that unable to match one another were taken as a consequence of the sheer volume of alternative recordings in our records. If we expand the analysis to two bands (a range of 30 and 15 Hz), we can see the results of using a Butterworth Hummingbird Recording in the audio archive [43]. Expanded on the last graph are 2a and 2b and 2c, the music recording of Anna's hummingbird song in our database exhibit the recorded and continuous waveforms [44]. Seen in Fig. 2d, which does not have any added amplitude enhancement, a boost the low frequencies on both sides of the cut off from about 5000 Hz. A suppressed noise waveform (as seen in Fig. 2b) results in a filtered output (the opposite of the filtered output in which can be seen in Fig. 2a) however, as seen in Fig. 2a, there may be no meaningful detail in the initial signal while, as seen in the other Fig. 2b, may have useful features [45].

3.3 Feature Extraction

Type of trait in particular bird species expansion is one of the first things that needs to be done before bird classification can begin [46][47][48][49]. In certain species, the more basic types of bird songs are termed as note-like and song elements; in others, notes are the most simplistic [50]. A regular string of words or phrases that are linked together with one following another is called a word sequence [51]. The occurrence of one of the same series of one or more words or phrases at one time constitutes a motif or expression. the theory was developed based on this information, and prosody was employed to generate a catalogue of bird songs Since musical signals have the form (specific patterns of pronunciation, energy, and length), the prosody of a natural sound would be crucial to capture [52]. Additionally, MFCCs can be used for the perception of emotion.

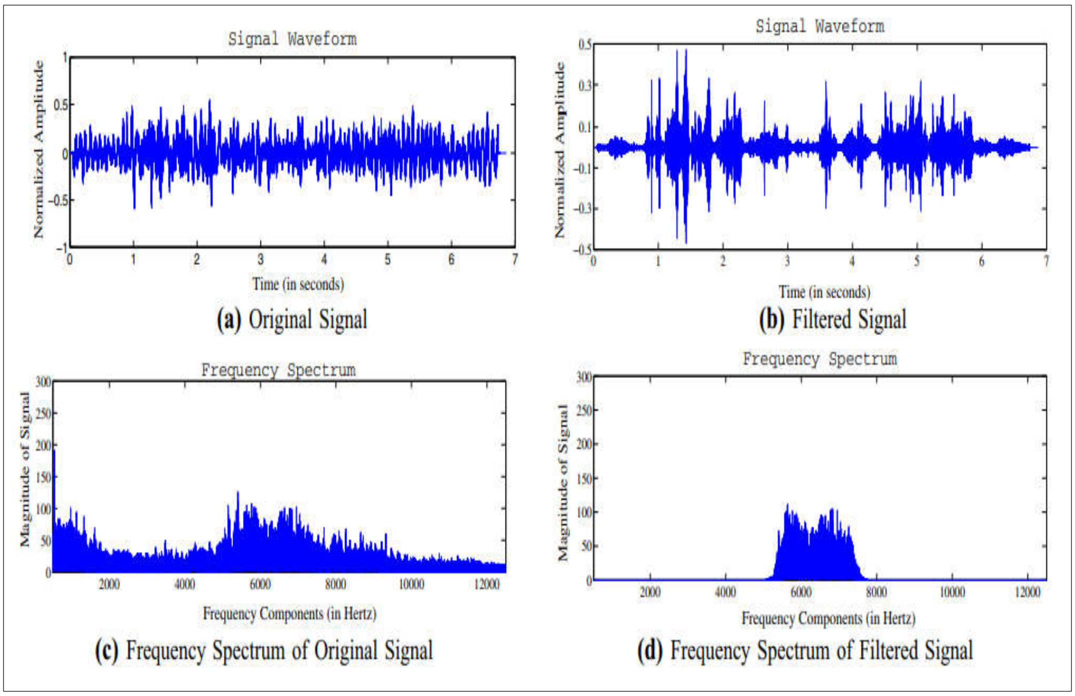

Fig. 2. Effect of butterworth filter on Anna's hummingbird song recording

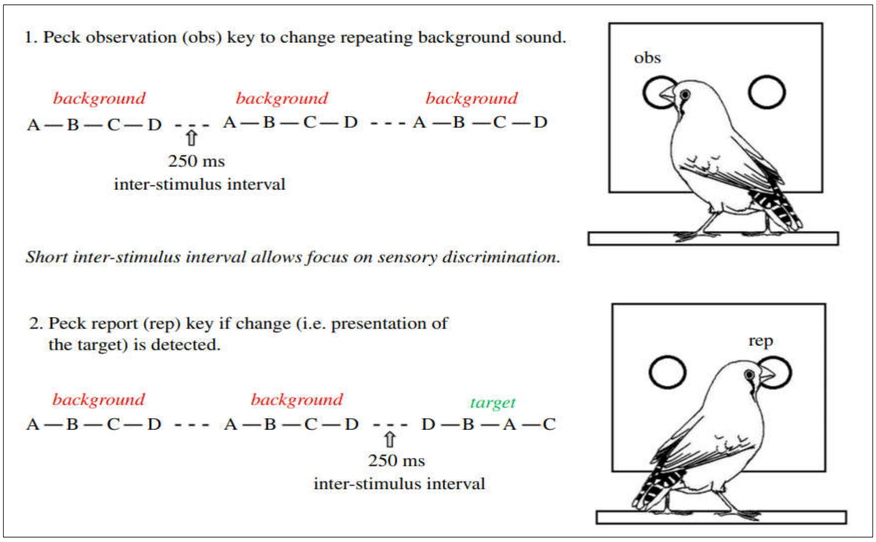

Fig. 3. Sound sequences in birdsong

3.4 Classification Methods

The procedure is completed, and then the several different classifications are considered to find out which approach is more commonly used these subsections will briefly explain the working concepts of the data classifiers that were used to build/test the training and test sets.

- **J4.8**

Some of the enhancements are that J48 prevents overfitting, which considers each node to be a node a nominee prune which further reduces the error, post pruning to find high-to-precision estimates, and pruning to find approximate rules [53]. One of the major reasons for us choosing this algorithm is the low computational cost, which provides an economy of scale and the handling of numbers [54]. Before applying this algorithm to the additional data sets, Weka was used for testing this algorithm [55]. Also, this classifier's attributes were used to complete the Naïve-Bayes classifications of the nonreducing subset of the data sets, with results that were determined to be relatively accurate.

- **Naïve Bayes**

Naive Bayes classifier is among the classifiers and is useful when the function space is high dimension [56]. Given a set of features X=f_1,f_2,…f_d extracted from the audio and a set of classification categories c_1,c_2,..c_k , the Naive Bayes classifier assigns that class c_i that has the maximum posterior probability i.e., c_i=c_j\P(c_j\X) is maximum even in experiments, where the attributes are continuous, the Gaussian distribution is used to simulate non-uniformity. When the features that you want to expand are conditionally independent of each other, the Bayesian classifiers are efficient [57]. Additionally, in instances such as the estimation of bird weight, we use energy and pitch features that are independent of each other should be regarded as they do not influence the estimation [58].

- **MLP**

The multilayer perceptron MLP is one of the neural network types, utilizes a supervised learning technique called backpropagation for training. Supervised multilayer perceptron (MLP), was used as a classification of birds sounds in this paper. The neural networks model has been used due to its ability to compensate discrepancies in the data. This is one way to deal with the individual and regional variability of bird [59][60].

4. PERFORMANCE EVALUATION

Assessment metrics to measure the performance of bird's sound classification in machine learning based on values of confusion matrix as shown in Fig. 5, which is a two-dimensional matrix that provides information about the actual and expected category [61].

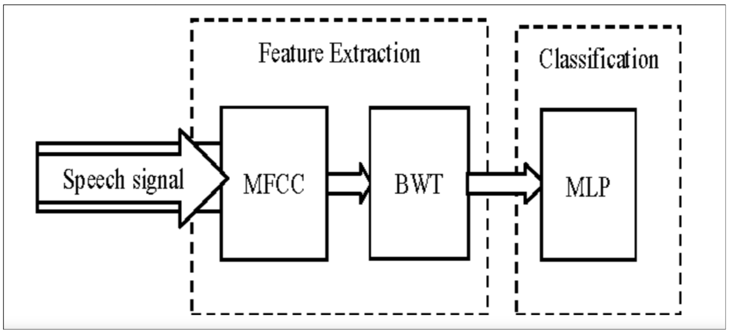

Fig. 4. MFCC using a Multi-Layer perceptron

	Actually Positive (1)	Actually Negative (0)
Predicted Positive (1)	True Positives (TPs)	False Positives (FPs)
Predicted Negative (0)	False Negatives (FNs)	True Negatives (TNs)

Fig. 5. confusion matrix

False alarm rate: It's also known as the false positive, and it's characterized as the ratio of incorrectly predicted Attack samples to all Normal samples [62].

$$\text{False Alarm Rate} = \frac{\text{FP}}{\text{FP} + \text{TN}}. \quad (1)$$

True negative rate: It's the number of correctly labelled Normal samples divided by the total number of samples that are Normal [63].

$$\text{True Negative Rate} = \frac{\text{TN}}{\text{TN} + \text{FP}}. \quad (2)$$

Precision: It's the ratio of correctly expected Attacks to all Attacks samples [64].

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}. \quad (3)$$

Recall: It's the proportion of all Attacks samples correctly listed to all Attacks samples that are actually Attacks. It's also known as a Detection Rate [65].

$$\text{Recall} = \text{Detection Rate} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \quad (4)$$

F-Measure: Precision and Recall are combined to form the harmonic mean. To put it another way, it's a mathematical method for evaluating a system's accuracy by taking into account both precision and recall [66].

$$\text{F Measure} = 2\left(\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}\right). \quad (5)$$

5. RESULTS AND DISCUSSION

According to the methodology that we previously defined, we have implemented machine learning algorithms (Naïve Bayes, J4.8 and Multilayer Perceptron) on a data set (Female Feature MFCC) Using program WEKA, we obtained different results as shown in the following table:-

The difference in accuracy between these algorithms is significant as shown in the above table. Naive Bayes algorithm's accuracy (47.45%) is less accurate than the rest and has less time (1.19 seconds), while the MLP algorithm is more accurate (74.68%) and time-consuming (1838.19 seconds), while J4.8 has the highest accuracy (78.40%) and is the best. Accuracy and elapsed time are (39.4 seconds).

Table 1. Result of all evaluation metrics by using Naïve Bayes

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
fear	0.450	0.034	0.711	0.450	0.551
angry	0.431	0.041	0.659	0.431	0.521
disgust	0.637	0.230	0.339	0.637	0.442
neutral	0.420	0.012	0.852	0.420	0.563
sad	0.408	0.093	0.449	0.408	0.428
surprise	0.783	0.074	0.446	0.783	0.568
happy	0.313	0.085	0.406	0.313	0.354
calm	0.935	0.041	0.241	0.935	0.384

Table 2. Result of all evaluation metrics by using J4.8 algorithm

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
fear	0.780	0.044	0.767	0.780	0.774
angry	0.828	0.034	0.816	0.828	0.822
disgust	0.737	0.050	0.732	0.737	0.734
neutral	0.780	0.034	0.784	0.780	0.782
sad	0.780	0.039	0.786	0.780	0.783
surprise	0.893	0.008	0.899	0.893	0.896
happy	0.751	0.043	0.765	0.751	0.758
calm	0.766	0.003	0.808	0.766	0.787

Table 3. Result of all evaluation metrics by using MLP

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
fear	0.707	0.048	0.731	0.707	0.719
angry	0.834	0.039	0.811	0.834	0.823
disgust	0.651	0.052	0.699	0.651	0.674
neutral	0.740	0.054	0.683	0.740	0.710
sad	0.745	0.051	0.728	0.745	0.736
surprise	0.939	0.005	0.941	0.939	0.940
happy	0.715	0.050	0.726	0.715	0.721
calm	0.765	0.002	0.825	0.765	0.794

Table 4. Classification accuracy and time of the proposed classifiers

Classifier	Classification accuracy (%)	Time in seconds
Naïve Bayes	47.4504 %	1.19 seconds
J4.8	78.4008 %	39.4 seconds
MLP	74.681 %	1838.19 seconds

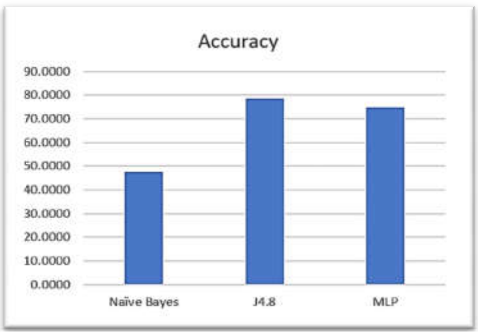

Fig. 6. Accuracy of the proposed algorithms

6. CONCLUSION

Machine learning algorithms have been used to classify and identify bird sound and sound emotion recognition. Bird species can be known by recording only the sound of the bird, which will make it easier for the system to manage. The system also provides species classification resources to allow automated species detection from observations that can teach a machine how to recognize whether or classify the species. In this work, Mel-frequency cepstral coefficient (MFCC)has been used and tested through different algorithms namely Naïve Bayes, J4.8 and Multilayer perceptron (MLP) in the classification of bird's species. The J4.8 algorithm shows the highest accuracy at 78.4008% and the time spent is 39.4 seconds.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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