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Content-based Audio Classification System for Bird Sounds

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ABSTRACT

Birds are very important to the ecosystem and an agent in promoting biodiversity. Their vocalizations consist of songs and calls, and are used to communicate, i.e., mating calls, warning calls, etc. This paper aims to automatically classify bird sounds from five native Malaysian birds – the Rhinoceros Hornbill, the Black and Yellow Broadbill, the Common Myna, the Malayan Banded Pitta, and the Crested Serpent Eagle. In the initial experiment, the factors that affect the classification accuracy was studied. Results from the initial became the basis of the development of the MyBird5ounds system, a PC-based standalone system that was build using MATLAB. By applying different features combinations, the classification results differed, and the combination that resulted in the improvement of the classification results were identified. The contribution of this paper lies in the small-scale study that compares the performance of manual bird sounds classification by humans and the automatic classification from MyBird5ounds. 80% classification accuracy was achieved when the optimized parameters were applied – almost twice that achieved in manual classification by trained humans with no prior background in bird watching. This suggests that such a system is beneficial in aiding classification of birds using content-based audio classification methods.

1. Introduction

Birds are very important to ecosystem and biodiversity – their roles are crucial in regulating the insect population, enabling plant-seed dispersal, aiding plant pollinations by moving the pollen from flower to flower to help fertilize the sex cells and create new plants [1-3].

Different birds have different sound patterns. Birds produce sounds through an organ called syrinx. Air passes through this vessel at the base of a bird's trachea and vibrations of the wall of the syrinx and the pessulus produce the sound (Figure 1). The oscillations of air pressure then hit the ear drum, stimulating the auditory nerves, sending signals the brain of birds (and other animals, including humans) to which bird vocalization, or birdcalls and bird songs are heard.

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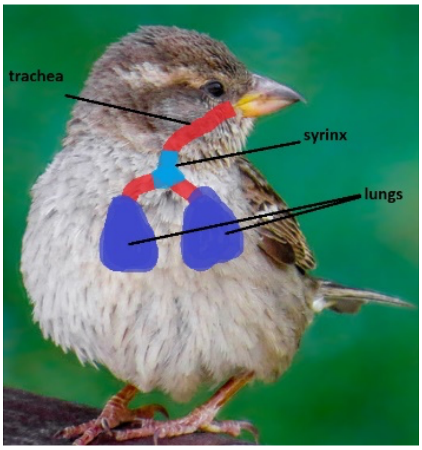

Fig. 1. General bird sound mechanism through the use of syrinx

Bird calls and bird songs form combinations of complex and sometimes melodious sounds that act as means of communication for the birds. Variations of sounds are produced from one species to another, and can communicate different circumstances such as warning calls, contact calls, cry for help calls, threat and defense calls, territorial calls, parent-offspring interaction calls (during food foraging in the forest), social flock calls, as well as mating calls [4-7]. In general, calls are composed of simple sounds that can be produced by both male and female, while songs are commonly produced by male songbirds and are known to be longer and more harmonious. Both birdcalls and bird songs can be used as a mean to classify birds according to their species.

1.1 Ornithology in Malaysia

Analyzing the sound of birds are part of the important tasks which are carried out by ornithologists. Ornithologists study aspect of birds, including bird songs, flight patterns, physical appearance, and migration patterns. In addition, collecting data through tagging and bird watching, ornithologists rely on bird sounds to obtain crucial information on the distribution patterns and biodiversity changes of an area [8]. These changes could be a result of climate change or habitat loss, making their presence or absence an excellent indicator of whether they are environmental threats in local areas where they are typically found. In addition, bird sounds are also used to help zoologists understand birds' behavioral and studies relating to the birds' ecology, as each bird's species has its own type of vocalizations [9].

In Malaysia, there are over 700 species of birds. It is therefore very difficult to identify the sounds of these birds physically, without having invested years in understanding the subject. Very few Malaysians can recognize the bird by their sounds only, as compared classification by the color or size of the birds. Moreover, birds can be further classified into different kingdom, phylum, and class, some of which may have the same pattern of sounds with only slightly different pitch and range. Currently, there is not much of research in Malaysia about classifying birds' sounds. The number of elderly natives who can classify the birds the sounds they make are slowly diminishing. Without any intervention, this birds' sounds classification skills will not get passed on to the next generation of Malaysians due to the change of lifestyle and pastime interests.

The current practice of performing manual observations has several disadvantages, such as being more time consuming, expensive, and more laborious. Another challenge with manual classification is that it relies on ideal weather conditions to visually classify using of telescopes. Thus, using technology to promote and facilitate automatic birds' sounds classification is timely and anticipated.

The main aim of this study is to automatically classify several types of rare birds in Malaysia based on the audio files of birds' sounds. Five species of birds, namely the Rhinoceros Hornbill (*Buceros rhinoceros*), the Black and Yellow Broadbill (*Eurylaimus ochromalus*), the Common Myna (*Acridotheres tristis*), the Malayan Banded Pitta (*Hydrornis irena*) and the Crested Serpent Eagle (*Spilornis cheela malayensis*) are included in this study as they are birds that are becoming scarce and facing extinction in Malaysia (Figure 2). For the classification to take place, this study will have to first determine the factors affecting the classification of birds' sounds and the optimum parameter that increases the accuracy of result – including the determining the best suited audio features to be extracted between zero crossing rates, energy, pitch, harmonic ratio, spectral centroid, and spectral spread features. Finally, this study will present a fully working system developed based on these specifications that can classify the birds' sounds with satisfactory results.

Fig. 2. From top left, clockwise - Rhinoceros Hornbill, Black and Yellow Broadbill, Common Myna, Crested Serpent Eagle, and Malayan Banded Pitta

1.2 Audio Features for Bird Sounds Classification

Bird sounds can be complex and varied as any group of non-human animals. Sound analysis is applied in order to understand and extract the characteristics of the acoustic signals [10-12]. This extracted information provides meaning from audio signals for analysis, classification, storage, retrieval, and synthesis. In the case of a birds' sounds analysis, the first step is to procure the sound data of the birds to be identified. The data consisting of birdcalls or bird songs need to be matched the correct types of birds as different birds have different song and calls. Although the waveform, spectrum, and spectrogram of the sound files all provide some form of information that can be used to help distinguish the bird' species, the most important step in process of sound recognition is signal detection and signal characterization. Signal detection is used to measure the ability to differentiate between information-bearing patterns and random patterns. Information-bearing patterns are stimulus in living organisms and signal in machines, while random patterns are called noise and other background stimuli. Typically, a noise filtering mechanism is added to the process to clear the data from unwanted background noises which may be present. This is then followed by the classification of the extracted signals using some form of machine learning algorithm. From here, the expected output which is the bird's species is suggested based on the data supplemented.

As most classification steps, the data must undergo some form of pre-processing, which includes segmenting the data into specific lengths. Noise filtering is also a similarly important step where common filtering techniques such as low-pass filter high-pass filter and bad-pass filter were applied to the bird sound dataset by Qian *et al*., [8] and Venier *et al*., [13]. Extracted audio features in bird sounds classification system can include features such as zero crossing rate (ZCR), energy, pitch, harmonic ratio, spectra centroid, spectral spread, and others. Closely linked, the time-based audio feature energy also provides the information on the magnitude of the spectrum, which is useful in differentiating low and high voice for the audio. Qian *et al*., [8] and Mporas *et al*., [14] both utilized the ZCR and energy features to measure change in polarity of signals over time. This particularly useful in determining if there are certain rhythms to the bird sounds.

Pitch is another important feature in bird sounds classification – it is the attribute that is used to determine the tone in a musical scale (the first harmonics). Another feature which is closely related to pitch is the harmonic ratio (HR). HR is derived from the Fourier analysis acceleration and is used to measure the dominant frequency and the harmonicity. Again, in the case of bird sounds classification, pitch and harmonicity can help differentiate the different tones that are vocalized by birds, which are then heard by humans [8,9,13].

Other common features which are used in classifying bird sounds are spectral centroid and spectral spreads. As the names suggest, these features can be displayed in a spectrogram and they describe the distribution of frequencies in the signal. Spectral features can be used to measure the bandwidth of a sound signal. This can be used to differentiate between different classes of birds, particularly if they have varying vocal range between one species to another [13].

1.3 Existing Applications for Bird Sounds Classification

Examples of existing bird sounds classification system are the Song Sleuth, the ChirpOMatic and the Bird Song ID system. All three systems are built on the iOS platform and can be used to identify and learn basic knowledge about birds including the sounds the birds make, their location and habitat, etc. Song Sleuth can immediately record the sound of birds in the wild upon initiation of the app, and classify the sounds in real time. Users can then edit, export, and share the classification result to another platform. However, the limitations of this app are the price and the unnecessary editing process can sometimes complicate and deter users from the actual classification process.

The second application is ChirpOMatic, which makes best guesses of the bird sounds queried through its automatic analysis. It remains relevant as it regularly updates its database with new bird sounds. However, its limitations are that it only allows a maximum length of 12 seconds per recording, and its real-time analysis means that users need to have good phone signal for further analysis. In addition, it also does not have much information about birds and are limited to bird only such as the Red-winged Blackbird, Yellow-rumped Warbler, Mourning Dove, American Robin, American Crow, and House Sparrow, which are not commonly found in Malaysia.

The Bird Song ID application is also used to recognize bird sounds. Out of the three apps compared, it is the only app that provides detail such as confidence score for each classification. It also allows users to train newer dataset of birds. However, it has the least friendly user interface, and achieved the lowest classification result compared to the other two apps.

Thus, from the comparison of existing systems, for this study, bird sounds classification that is uniquely dedicated to local birds is to be designed. Different parametric factors that affect the classification result of the bird sounds are also investigated, particularly the effect of different audio features such as spectral centroid, pitch, and harmonicity. The overall performance will then be compared between random, human, and automated classification.

2. Methodology

The design and development of the bird sounds classification system follows the general mechanism for any sound classification which typically consist of a training module and a testing module. All dataset is pre-processed at the beginning and then undergo processes starting from features extraction, followed by classification (Figure 3).

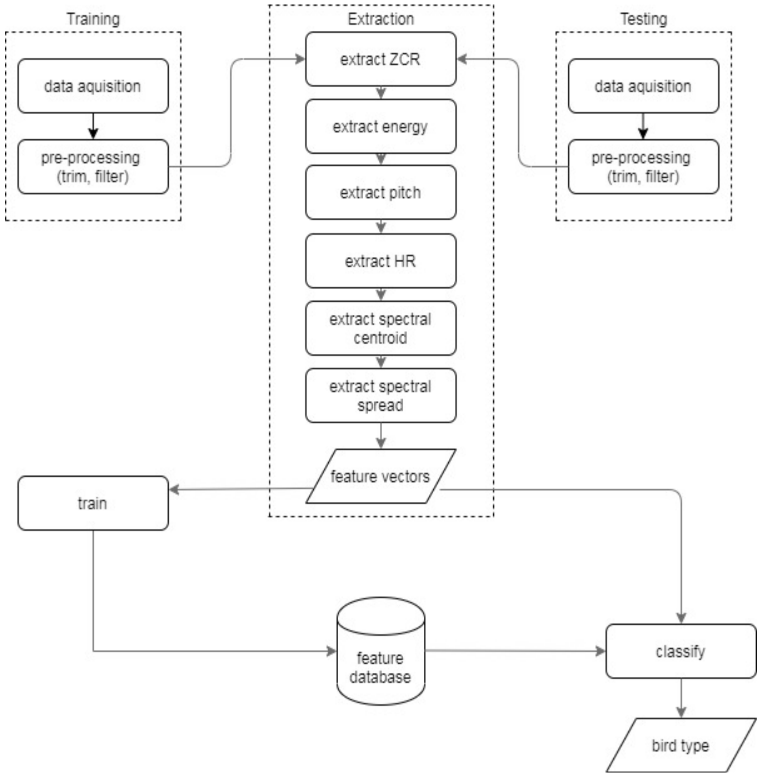

Fig. 3. The general mechanism for bird sound classification system

2.1 Pre-processing

It starts with dataset training, where acquired bird sounds are pre-processed. The dataset is first converted into a .wav file format before being segmented into smaller sound units. The minimum dataset duration needs to be above 9 seconds in order to produce acceptable analysis results. Next, band-pass filter is applied to all sound units in the dataset. Band-pass filter passes frequencies within a certain range and rejects frequencies outside of that range. This allows signals within a selected range of frequencies to be heard or decoded, while preventing signals at unwanted frequencies from getting through. The differences between filtered and unfiltered sound waves of the bird sounds dataset are shown in Figure 4. As can be seen, the sound wave is smoother and the noise is reduced.

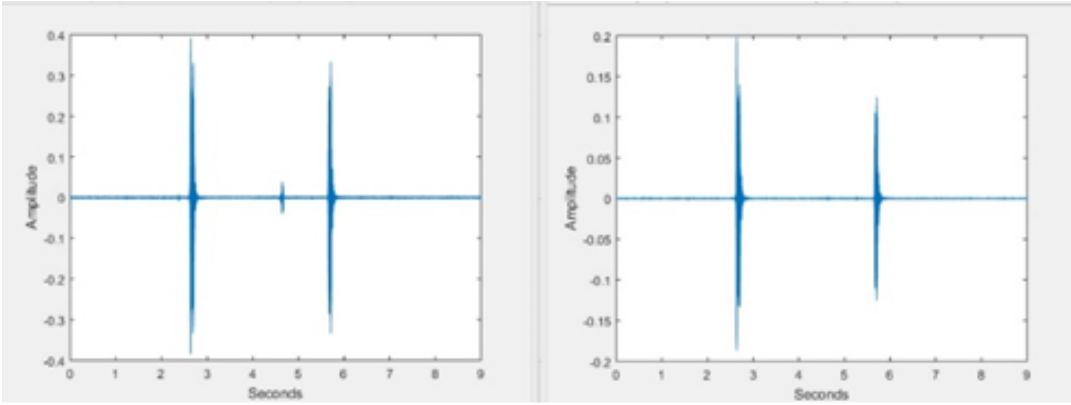

Fig. 4. Left – noisy, unfiltered sound file. Right – smooth, cleaner, filtered sound file

2.2 Feature extraction and Classification

Following this, the bird sounds dataset then undergoes through the extraction process. The feature extracted are as zero crossing rate, energy, pitch, harmonic ratio, spectral centroid, and spectral spread. Once extraction is completed, the feature vectors that are produced are saved and stored in the audio features database.

The same steps are repeated when a classification task is to be carried with a testing dataset. Once the feature vectors of the testing dataset have been generated, it will be compared in the classification process. As different classifiers will result in different classification results, four different classifiers are programmed in this system, namely Support Vector Machine (SVM), Decision Tree J48, k-Nearest Neighbor (kNN) and Naïve Bayes. When J48 is selected, it produces a set of rules and the birds are classified based on these rules.

2.3 MyBird5ounds System

MyBird5ounds is the name dubbed for the classification system that is developed specifically for the five types of Malaysian birds included in this study. The MATLAB scripting language is used to develop the extraction engine. Using the GUIDE functions in MATLAB also, the basic the GUI interface is created and linked to the database. Classification of the bird sounds is conducted using WEKA. The accuracy of the classification will be display at the classifier output along with other information once analysis is completed. The typical length of time that it takes to complete the classification process is less than 5 seconds.

Figure 5 shows the interface of the main classification page, while Figure 6 shows the updated interface once a classification has been performed. Users can also choose to view the spectrum or spectrogram of the original bird sound seed unit (query) if needed. (Figure 7)

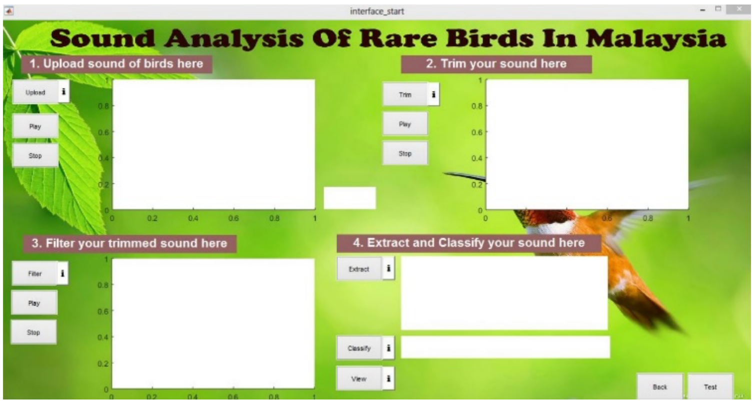

Fig. 5. MyBird5ounds system main page

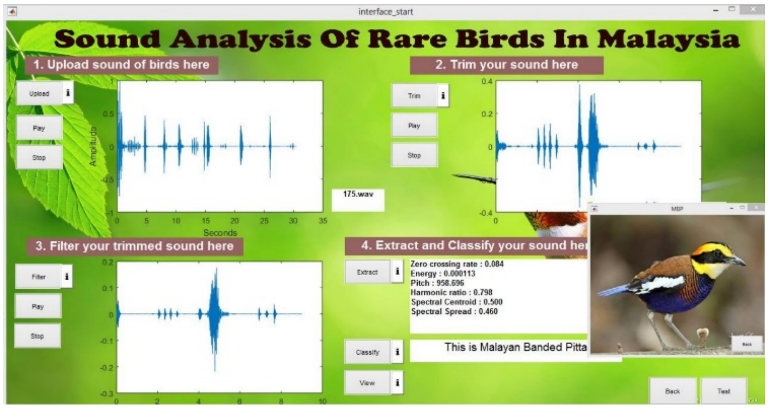

Fig. 6. MyBird5ounds system page displaying classification results

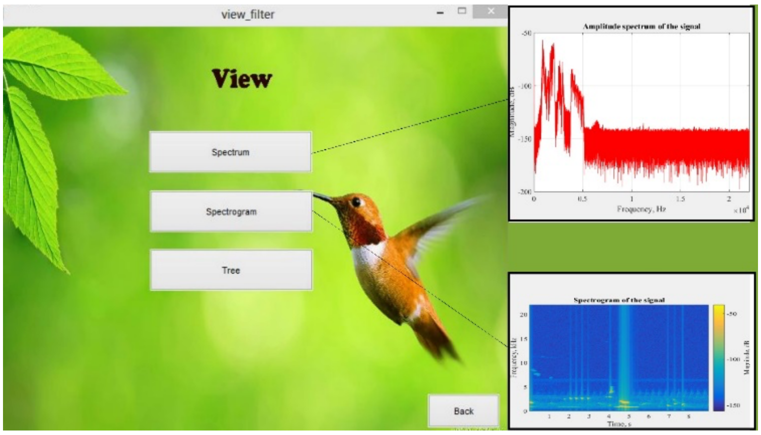

Fig. 7. MyBird5ounds system displaying the spectrum and spectrogram of the seed sound file

3. Results

The purpose of the experiment was to determine the optimum parameters used for the bird sounds classification in order to achieve results with the highest accuracy. The audio features investigated were zero crossing rate, energy, pitch, harmonic ratio, spectral centroid, and spectral spread. The effect of four different classifiers were also studied, i.e., SVM, kNN, J48 and naïve Bayes. The overall classification performance between MyBird5ounds system, humans, and random were also compared.

3.1 Experimental Setup

Five species of Malaysian birds were involved in this study, namely the Rhinoceros Hornbill, the Black and Yellow Broadbill, the Common Myna, the Malayan Banded Pitta, and the Crested Serpent Eagle. For each of category, a total of fifty files were obtained as the training dataset, giving a total of 250 sounds. All sound files had a duration of ten seconds or longer. For the testing dataset, another set of ten,10-seconds long sounds were provided for each bird types (50 sound files, ~ 8 minutes duration in total). This means that the training / testing ratio is the common 80/20 split. Overall, the total duration for the entire training and testing dataset was over an hour long. The sounds for the five birds were collected from an open-sourced website dedicated to sharing bird sounds from all over the world with research scientists, or bird enthusiasts (https://www.xeno-canto.org). A band-pass filter was applied to remove unwanted noise in the dataset.

3.2 Effect of Audio Features on Bird Sounds Classification Using MyBird5ounds

Figure 8 shows the graph of comparison of accuracy between all six features individually and when all the features were combined, and J48 was used as the constant classifier. Individually, the pitch feature returned the highest accuracy at 42.4%. However, when all the features were extracted and used together to classify, the accuracy increased to 56%. Although this was a relatively low classification result, it fared better than randomly guessing the bird class (20%). Generally, the higher the number of features included, the better the result of the classification. However, after some time, the inclusion of more features may not increase the performance anymore (glass ceiling effect). Moreover, including more features typically result in an increase processing time. Thus, performance of single features served as a benchmark to the rest of the feature sets used in this study. In this experiment, no significant delay was seen in the classification performance, and the entire process was within than ten seconds – as had been the case with single feature extraction. Therefore, it was deduced that for MyBird5ounds to classify well, ideally all six features needed to be extracted.

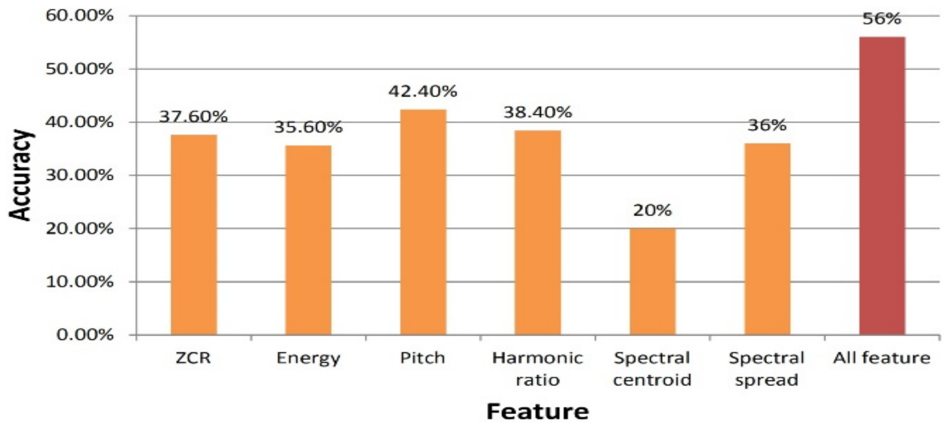

Fig. 8. Classification results of MyBird5ounds across different audio features

3.3 Effect of Audio Features on Bird Sounds Classification Using MyBird5ounds

Following this result, all six features were included in the extraction of the next part of the study – which was to investigate the effect of classifiers on the performance of bird sounds classification using MyBird5ounds. It was found that out of the four classifiers, J48 returned the highest classification result at 84.8% compared to classification results of k-NN, SVM and naïve Bayes classifiers at 66.4%, 57.2% and 56% respectively (Figure 9). The significant difference in the classification result of the J48 classifier may be because as a decision tree classifier that uses a predictive machine-learning model which could calculate the resultant value of a new sample based on various attribute values of available data. Hence, for MyBird5ounds system, the combination of all six audio features and J48 classifier were found to be the most efficient. The use of the C5.0 classifier was not compared in this study, as it had many similar traits to C4.5. Technically, C5.0 may perform more accurately and faster.

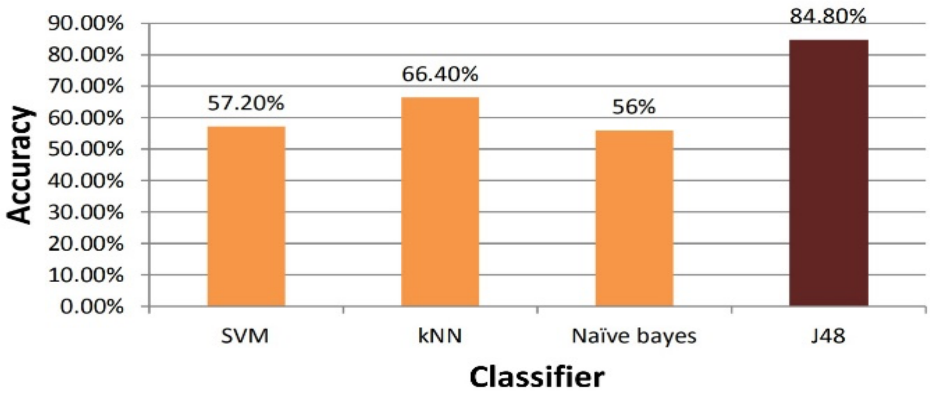

Fig. 9. Classification results of MyBird5ounds across different audio features

3.3 Classification Performance - Human versus MyBird5ounds

To highlight the importance of such app, a small-scale experiment was carried out to compare the bird sounds classification performances between humans and the automated system, MyBird5ounds. A group of ten undergraduate students between the ages of 18-25 were recruited, of which two were males and eight were females. The test required that the participants answered a short background questionnaire on their level of interests in bird watching and their perceived level of knowledge on the subject. 50% of the participants admitted that they were not familiar with the different types of bird sounds in general, while 20% were confident of the subjects, and another 30% replied that they were unsure. Each participant was given a brief training on the sounds made by each of the five types of birds (Rhinoceros Hornbill, Black and Yellow Broadbill, Common Myna, Malayan Banded Pitta, and Crested Serpent Eagle). This process is to expose and familiarize the participants to the unique bird sounds. When the training was complete, the participants sat through a listening test where the participants listened to ten sound files of the birds, and were asked to identify them. Their answers were recorded and were then analyzed to determine their average classification accuracy.

Table 1 shows the result of the classification from the listening test. Less than half (47%) of the listening test participants had correctly identified the bird sounds - the Common Myna and the Rhinoceros Hornbill were among the greatest number of correctly classified instances, while the Malayan Banded Pitta had the least number of correctly classified instances. This could be due to the nature of the calls the birds made. For instance, the Rhinoceros Hornbills mostly made single, bass calls, instead of a myriad of sounds that Malayan Banded Pittas made, i.e., purr-like sounds, trills, caw-like calls, which might have confused the participants. In addition, although noise-removal filter was applied to the dataset, it was not able to separate and single out the sounds cleanly where more than one bird sounds were present in the data.

Table 1
Number of correctly classified instances by listening test participants

Sound	Correct Answer	Accuracy by Humans
Sound 1	Rhinoceros Hornbill	0.9
Sound 2	Crested Serpent Eagle	0.3
Sound 3	Malayan Banded Pitta	0.2
Sound 4	Malayan Banded Pitta	0.5
Sound 5	Rhinoceros Hornbill	0.2
Sound 6	Black and Yellow Broadbill	0.4
Sound 7	Common Myna	0.7
Sound 8	Black and Yellow Broadbill	0.4
Sound 9	Common Myna	0.5
Sound 10	Crested Serpent Eagle	0.6
Average Accuracy		**0.47**

Despite this, interestingly, when the same dataset was classified by MyBird5ounds system, the system achieved 80% correct classification of the same instances - almost doubled that of humans' achievement. Figure 10 shows the result of classification of the same instances between humans, the system and random classification.

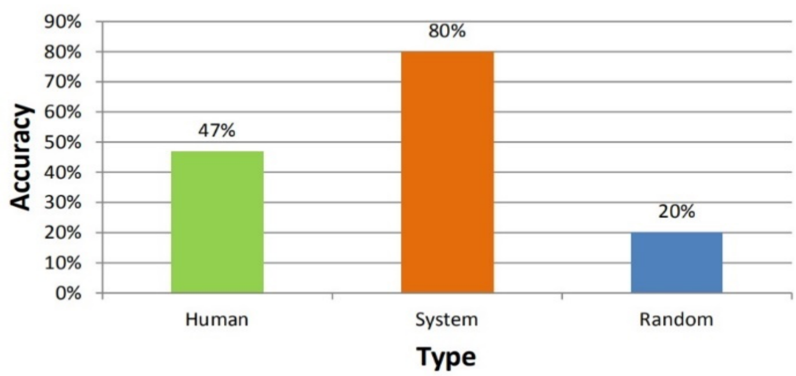

Fig. 10. Comparison of classification performance between humans, MyBird5ounds and random

Although the results can not directly be compared, as the human listeners were not expert ornithologists, they had been given an intensive listening briefing on the different sounds of the five birds tested prior to the test, simulating the training session of the system. The result further highlights that the MyBird5ounds system is a useful system to facilitate in the classifying bird sounds, particularly those which are native to Malaysia, as no such system has been developed specifically for birds in this geographical area, and because it exceeds the performance of average non-expert, Malaysian bird sound listeners.

4. Conclusions

Birds' sounds are unique and can be used to aid species recognition, which have been mostly relying on visual data (images, videos). In this paper, the birds studied were the Rhinoceros Hornbill, the Black and Yellow Broadbill, the Common Myna, the Malayan Banded Pitta, and the Crested

Serpent Eagle - all natives to Malaysia. Despite this, very few Malaysians are familiar with the bird sounds to be able to make correct classifications based on the birdcalls or bird songs alone. Several systems have been compared in this study; however, these systems were mostly focused on birds originating from the West, which does not support the sounds made by the birds in this study in their databases.

The factors affecting bird sounds classification was studied and the optimum parameters for a bird sounds classification system were identified in this paper. The factors include audio features and classifiers, which in this case, were ZCR, energy, pitch, harmonic ratio, spectral centroid, and spectral spread for the features, and J48 for the classifier. For the dataset used in this study, it was found that the most useful audio between all six that were extracted, was pitch. This primarily separates the calls made by the birds into high-pitched (i.e., Crested Serpent Eagle and the Common Myna, which made shrilly calls). The Rhinoceros Hornbill was at the other end of the spectrum, where its growling sound was classified as low pitch and low energy. The harmonicity ratio was found to be a good feature for classifying calls of melodious and sing song birds such as Malayan Banded Pitta and the Black and Yellow Broadbill. A full system has been developed from the initial findings and a satisfactory result have been achieved my MyBird5ounds using these parameters. The result achieved by the system was also almost twice as accurate as the humans had managed to achieve, suggesting that such a system is needed to aid classification of Malaysian birds in the future.

The purpose of this study is to illustrate the potential of content-based audio classification, specifically on the dataset of bird calls of native birds in Malaysia. In Malaysia, several other similar classification works has been carried out to classify uniquely Malaysian animals using either sounds and images such as bird calls [15], marine invertebrates [16] fish eggs [17], rodent pests in paddy field [18], tuberculosis diseases [19], and even Malay musical genres [20]. In addition, the system itself can be exploited as a mean to spread the knowledge on the native birds of Malaysia, especially to the younger generation. This will hopefully be beneficial as it has been found that students learn better about biological control and environment conservation in the form of a non-traditional teaching and learning setup [21].

Future work includes adding, training, and testing more species and sounds of birds in the database. The accuracy of the classification needs to also be improved, perhaps through optimization of the parameters involved. Transforming the system into a portable and lightweight app that works on mobile phones, with a more user-friendly interface, is another work-in-progress that is hoped to benefit more users too.

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