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Dual Tree Complex Wavelet Cepstral Coefficient–based Bat Classification in Kalakad Mundanthurai Tiger Reserve.

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Abstract— **Bats, the only flying mammalian species, play a vital role in maintaining eco-balance and pest-management. Bats are bio-indicators and key informers of climate change. Insectivorous bats produce echolocation calls, that vary from species to species and hence the echolocation calls can be used to identify the different bat species. Bat detectors help in recording the echolocation calls which are ultrasonic. The bat detectors convert the ultrasonic signals of bats into audio signals. This audio signal is pre-emphasized and pre-processed and then features are extracted. In this article, we propose a bat classification scheme with Dual Tree Complex Wavelet Cepstral Coefficient for bats in Kalakad Mundanthurai Tiger Reserve, which lies in the Southern Western Ghats, South India, declared as the World Heritage Centre by UNESCO. On classifying the bats calls with k-NN, Bayes and SVM classifiers, SVM was found to outperform others.**

Keywords— **insectivores, echolocation call, feature extraction, cepstral features, wavelet, classifiers.**

I. INTRODUCTION

India has a vast diversity of bats consisting of one hundred and twenty bat species. Bats are important keystone members of ecosystem. They serve as pest managers and bio-indicators of the condition of the ecosystem and its degradation. Bats are mammals with webbed wings which are are found all over the world, performing different ecological functions such as pollination and seed dispersal. Nearly seventy percent of bats are insectivores and the rest are fruit eaters and vampires. One hundred and twenty species of bats are seen in India, showing a vast diversity. This study has been restricted to only sixteen species which are found in Kalakad Mundanthurai Tiger Reserve [KMTR] situated in Tirunelveli District, Southern Tamil Nadu, in the Western Ghats which is a biodiversity hotspot.

Some bat species can be distinguished by unique echolocation call characteristics. The ultrasonic echolocation calls are produced by insectivorous bats which vary from species to species. Artificial Neural Networks and Voice Recognition techniques are used to analyse the echolocation calls acoustically. Bat detectors convert the ultrasonic calls into audible frequencies and help detect the presence of bats. Anabat SD1, Petterson D240X and Wildlife Acoustics Echometer EM3+ were the bat detectors used in this research.

Bio-sonar or Echolocation is a principle[1] used by bats and many other animals. Echolocation calls are ultrasonic sounds emitted into the environment and bats listen to the echoes of these calls which return from hitting any obstruction or objects in their path. These echoes are used to locate the objects. Echolocation is used for navigation and for foraging [2] (hunting, resting, feeding etc.) in various environments. Only insectivorous [3,4] bats use echolocation. Bats produce these ultrasonic sounds, that is, echolocation calls, for the purpose of moving about in darkness.

Acoustic classification is recently evolving in the field of acoustic signal analysis[5]. Acoustic survey is one of the research methods of gathering information about the abundance of a species.

Acoustic surveys are carried out in a wide range of habitats to detect large number of species.Species identification is necessary to survey and monitor bat activity [6]. The echolocation calls of bats are recorded through bat detectors and are used for identification of species. The echolocation calls of bats (call structure and shape of calls) [7] differ from species to species, that is, the echolocation calls are species-specific [8]. This facilitates acoustic identification of bat species. However, call structures, shapes and frequencies within species can be extremely flexible and depend on factors including habitat, age, sex and the presence of conspecifics.[9,10]

Quian Quiroga et al. [11] proposed the application of the Wavelet Transform to the study of evoked potentials. Wavelet Transform gives an optimal time-dependent frequency decomposition of evoked responses which is difficult to be achieved with earlier methods such as Fourier

Transform. They proposed the protocol for implementing the decomposition based on the Wavelet Transform and applied it to two different types of evoked potentials. They showed examples of the better performance of the wavelet decomposition in comparison with Fourier-based methods.

Ranjan [12] explored Discrete Wavelet Transform [DWT] as a tool for Hindi Speech Recognition. The author proposed a scheme for recognition of isolated words in Hindi Language Speech. Discrete Wavelet Transform Coefficients of the speech signal was first computed and then, Linear Predictive Coding Coefficients of the Discrete Wavelet Transform Coefficients were calculated. Then, K-means algorithm was used on the obtained Linear Predictive Coding Coefficients to form a Vector Quantized Codebook. Recognition of a spoken Hindi word is done by deciding in favour of the Hindi word whose corresponding centroid in the Vector Quantized codebook gives a minimum squared Euclidean distance error with respect to the word under test.

Trivedi et al. [13] described automatic classification of various speech signals using Discrete Wavelet Transform [DWT] and compared using different wavelets. They investigated wavelet-based feature extraction system and its performance on an isolated word recognition problem. They used a three-layer feed forward network for the classification of words.

JiZhong and Scalzo [14] performed automatic heart sound signal analysis with reused multi-scale wavelet transform. The heart sound signal recorded from normal adults usually contains two distinct tones that occur in each heartbeat. Their respective and relative time latencies are important parameters for the monitoring of cardiac functions, diagnosis, and improved treatment. The authors proposed a method to locate heart sound features by feature-extraction using a multi-scale wavelet transform and a threshold decision to increase the precision of the detection process. The effectiveness of the framework to extract the features was evaluated in experiments on thirty five patients presenting various cardiac conditions. The proposed algorithm reaches an accuracy of about 92% on abnormal heart sounds.

Gamulkiewicz and Weeks [15] illustrated how wavelets can be used for better accuracy in speech recognition. The problem of speech recognition was addressed using the wavelet transform as a means to help match phonemes from a speech signal. They used a template of pre-recorded, wavelet-transformed phonemes, as a basis for comparison. The authors used the wavelet transform to extract coefficients from phonemes and used cross-correlation to classify the phoneme. Cross-correlation measures the similarities between two signals. Normalisation of amplitudes and frequencies was done. Silence was eliminated from the signal. A Daubechies eight wavelet is used to obtain five octaves of each signal. The results show that using the wavelet transform improved the accuracy in correctly identifying the phonemes. The results also show that using the approximate coefficients to generate octaves in the wavelet transform, give better accuracy than using the detail coefficients.

DWT is a shift-variant transform which makes it difficult to use with transient signal analysis and pattern recognition applications. Hence Ahmad et al. [16] have proposed a shift-invariant analysis scheme which is non-redundant. The scheme combined minimum-phase [MP] reconstruction with the DWT so that the resultant scheme provided a shift-invariant transform. The scheme could be used for the analysis-synthesis, classification and compression of transient sound signals.

The Dual Tree Complex Wavelet Transform (DT-CWT) [17] is an enhancement to the Discrete Wavelet Transform (DWT) to handle the issues such as oscillations, shift variance, aliasing, lack of directionality etc.

Wang et al. [18] demonstrated that Dual-Tree Complex Wavelet Transform [DTCWT] has better shift-invariance and reduced spectral aliasing than Second-Generation Wavelet Transform [SGWT]. They also proposed empirical mode decomposition by means of numerical simulations. These advantages of the DTCWT arise from the relationship between the two dual-tree wavelet basis functions, instead of the matching of the used single wavelet basis function to the signal being analysed. Since noise inevitably exists in the measured signals, they also developed an enhanced vibrations signals denoising algorithm incorporating DTCWT. The results confirmed that DTCWT-based method is a powerful and versatile tool and consistently outperforms SGWT and has good robustness.

Chen and Xie [19] proposed a descriptor for pattern recognition by using dual-tree complex wavelet features and SVM. The dual-tree complex wavelet has the approximate shift-invariant property and it has good directional selectivity in 2D. SVM and dual-tree complex wavelet are combined. They achieved highest rates when they used dual-tree complex wavelet features with the Gaussian radial basis function kernel and the wavelet kernel for recognizing similar hand written numerals. The authors found out that the dual-tree complex wavelets are better than the scalar wavelet for pattern recognition, when SVM is used. Among many frequently used SVM kernels, the Gaussian radial basis function and the wavelet kernel are best suited for pattern recognition applications.

Wongso and Santika [20] have proposed a method for automatic music genre classification using Dual-Tree Complex Wavelet Transform [DTCWT] –based features and Support Vector Machine [SVM] as classifier. The authors classified the four genres of music namely pop, classical, jazz and rock by using features such as mean, standard deviation, variance and entropy. This proposed approach produced an accuracy of 88.33%.

II. Background Study

1) *Cepstral Coefficients*

The name "cepstrum" was derived by reversing the first four letters of "spectrum". Operations on cepstra are labeled quefrency analysis, liftering, or cepstral analysis. A cepstrum is the result of taking the Inverse Fourier Transform (IFT) of the logarithm of the estimated spectrum of a signal.

The MFCCs-Mel-Frequency Cepstral Coefficients. From the FFT power coefficients, MFCCs are computed. A triangular bandpass filter bank is used to filter the power coefficients. The filter bank consists of K = 19 triangular filters. They have a constant mel-frequency interval, and covers the frequency range of 0Hz-4000Hz. Denoting the output of the filter bank by Sk (k = 1, 2, …., K), the MFCCs are calculated as,

$$c_n = \sqrt{(2/k)} \sum_{k=1}^{k} (\log S_k) \cos\ [n\ (k-0.5)\pi/K] \quad (1)$$

n=1,2,3,…..,L, where L is the order of the cepstrum.

A 38+Cdur+2L –dimensional feature vector is formed when the means and standard deviations of the FFT and MFCC features are computed over the non-silent frames, where 38 represents the means and standard deviations of all the FFT features, Cd represents the Call Duration and 2Lrepresents that for the Cepstral coefficients. The means and standard deviations of the L MFCCs are also calculated over the non-silent frames, giving a 2L -dimensional Cepstral feature vector.

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2) Wavelet Cepstral Coefficients

Adam et al. [21] proposes an improved feature extraction method that is called Wavelet Cepstral Coefficients [WCC]. In traditional cepstral analysis, the cepstrums are calculated with the use of the Discrete Fourier Transform [DFT]. Since the DFT calculation assumes 'signal stationary' between frames, which in practice, is not quite true, the WCC replaces the DFT block in the traditional cepstrum calculation with the Discrete Wavelet Transform [DWT] [22] hence producing the WCC. It is found that the WCCs showed remarkable results when compared to the MFCCs, considering the WCCs' small vector dimension. Feature extraction is one of the most significant phases and plays a major role in the accuracy of audio signal classification scheme.

A set of features called Wavelet Cepstral Coefficients (WCC) were proposed for isolated spoken English alphabet recognition, to remedy the issues posed by MFCCs.

DWT were also used by Gowdy and Tufekci [23] to obtain a new feature vector called Mel-Frequency Discrete Wavelet Coefficients (MFDWC). The MFDWC were obtained by applying DWT to the Mel-scaled log filter bank energies of a speech frame. Results showed that the MFDWC performed better in terms of recognition over other features that were used for the test.

Several authors have used wavelets for computing the cepstrum, like Pavez and Silva [24], Kinney A and Stevens J [25] and Sanchez et al. [26]. The paper by Kinney proposed decomposing the speech signal using Wavelet Packet Transform (WPT) and then calculating the real cepstrum for the coefficients or atoms obtained from that decomposition. Promising results were obtained for text-dependent speaker recognition considering the methods few feature coefficients. It was shown that 90% of speakers were recognized when using 9 training vectors.

Wavelet-based cepstrum calculation was proposed by Sanchez et.al. [26] in 2009. The wavelet-based calculation was used for pitch extraction in speech signals. Different types of wavelet family were used to find the optimal accuracy for pitch extraction. Pavez and Silva [24] proposed the Wavelet Packet Cepstral Coefficients (WPCC) as an alternative to filter-bank energy based feature extraction. In their work, detailed filter design were presented to obtain the WPCC as an alternative to the widely used MFCCs. Results show that the WPCC are better than MFCCs and has the ability to retain more phone discriminating information in the speech signal at lower frequency ranges.

2) a) Estimation of Wavelet Cepstral Coefficients[WCC]

First the speech signal is decomposed with the help of Discrete Wavelet Transform. The coefficients from the DWT of the speech signal are then subjected to log power spectrum and DCT. The final output is what we call Wavelet Cepstral Coefficient (WCC). Figure1 shows the process flow diagram for wavelet cepstrum calculation from audio signal. Figure2 shows the process of obtaining wavelet cepstral coefficients from 3-level DWT coefficients.

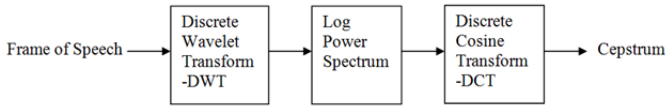

Fig. 1 Wavelet Cepstrum of Audio Signal

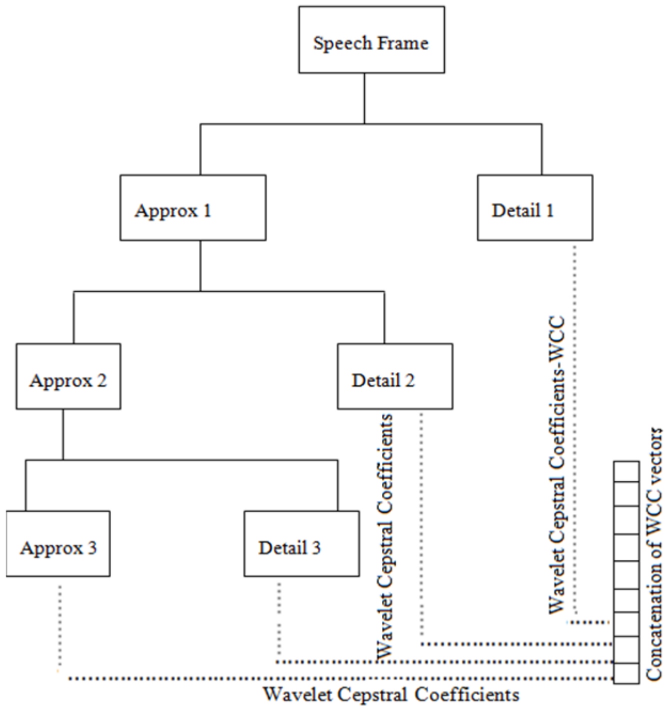

Fig. 2 Process of obtaining WCC from 3 level DWT coefficients

The audio signal is passed through Approximation 1 and Detail 1. Then we obtain wavelet cepstral coefficients in the size of ten, from Detail 1. From Approximation 1, the signal is again passed through Approximation 2 and Detail

2. Then we obtain another set of wavelet cepstral coefficients from Detail 2. From Approximation 2, the signal is again passed through Approximation 3 and Detail 3. Then we obtain further wavelet cepstral coefficients from Approximation 3 as well as from Detail 3. Then all the coefficients are concatenated to form WCC vectors. After the Cepstrum is obtained, we can classify it using a suitable classifier.

3) *Dual Tree Complex Wavelet Transform*

Prof. Nick Kingsbury of Cambridge university generalised the use of Complex Wavelets in 1997. The Dual Tree Complex Wavelet Transform (DT-CWT) is an enhancement to the Discrete Wavelet Transform (DWT). The wavelet transform suffers from the following four fundamental shortcomings.

1. Oscillations
2. Shift Variance
3. Aliasing
4. Lack of Directionality

The DT-CWT provides solution to these four DWT shortcomings. Because the DWT is based on real-valued oscillating wavelets, where in DT-CWT the Fourier transform is based on complex-valued oscillating sinusoids. The Fourier transform does not suffer from these problems. First, the magnitude of the Fourier transform does not oscillate positive and negative but rather provides a smooth positive envelope in the Fourier domain. Second, the magnitude of the Fourier transform is perfectly shifting invariant, with a simple linear phase offset encoding the shift. Third, the Fourier coefficients are not aliased and do not rely on a complicated aliasing cancellation property to reconstruct the signal; and fourth, the sinusoids of the M-D Fourier basis are highly directional plane waves.

Fortunately, there is a simple solution to these four shortcomings of DWT. Complex wavelets can be used to analyse and represent both real-valued signals and complex-valued signals. In both cases, the CWT enables new coherent multi-scale signal processing algorithms that exploit the complex magnitude and phase. The design of complex analytic wavelets raises several unique and nontrivial challenges that do not arise with the real DWT.

The Dual-Tree Complex Wavelet Transform (DTCWT) is a relatively recent enhancement to the Discrete Wavelet Transform (DWT) with additional properties: it is nearly shift-invariant and directionally selective in two and higher dimensions. The Dual-Tree CWT is a valuable enhancement of the traditional real wavelet transform. As the real and imaginary part of the dual-tree CWT are, conventional real wavelet transforms, the CWT benefits from the vast theoretical, practical and computational resources that have been developed for the standard DWT. The magnitude and phase of CWT coefficients can be exploited to develop new effective wavelet-based algorithms, especially for applications for which the DWT is unsuitable.

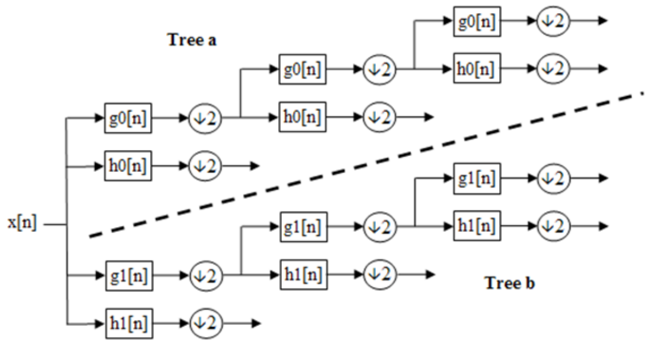

Fig. 3 Block Diagram for a 3-level DTCWT

The dual tree complex DWT of a signal ‘x’ is implemented using two critically-sampled DWTs in parallel on the same data, as shown in Figure 3.

The filters in the upper (tree a) and lower (tree b) DWTs are not in the same model. They are designed in a specific way [27] to achieve shift invariant property. Then the subband signals of the upper DWT can be interpreted as the real part of a complex wavelet transform, and subband signals of the lower DWT can be interpreted as the imaginary part. Equivalently, for specially designed sets of filters, the wavelet associated with the upper DWT can be an approximate Hilbert transform of the wavelet associated with the lower DWT. When designed in this way, the dual-tree complex DWT is nearly shift-invariant, in contrast with the critically-sampled DWT. Moreover, the dual-tree complex DWT can be used to implement 2D wavelet transforms where each wavelet is oriented, which is especially useful for image processing.

The properties of the DT-CWT can be summarized as

a. Approximate shift invariance.
b. Good directional selectivity in 2 dimensions.
c. Phase information.
d. Perfect reconstruction using short linear-phase filters.
e. Limited redundancy, independent of the number of scales, 2 : 1 for 1D (2m : 1 for mD).
f. Efficient order-N computation—only twice the simple DWT for 1D (2m times for mD).

The dual-tree complex wavelet transform is suitable for many applications of interest in image communication such as coding [28], denoising [29], motion estimation [30], quality measures [31] and image retrieval [32]. Each pair of complex filters has the Hilbert transform relationship. In spatial domain, the real part of the complex filter is symmetric while the imaginary part is anti-symmetric.

C. *Methodology*

Bats emit calls from about 12 kHz to 160 kHz, but the upper frequencies in this range are rapidly absorbed in air. Many bat detectors are limited to around 15 kHz to 125 kHz at best. Bat detectors are available commercially and also can be self-built. Some early bat detectors used ex-Navy, low frequency radio sets, simply replacing the aerial with a microphone and pre-amplifier. It is also possible to modify a portable Long Wave radio to be a bat detector by adjusting the tuning frequencies and replacing the ferrite rod aerial with a microphone and pre-amplifier.

A bat detector is a device used to detect the presence of bats by converting their echolocation ultrasonic signals (as they are emitted by the bats), into audible frequencies, usually about 300 Hz to 5 kHz.

Audio signals are generally referred to as signals that are audible to humans. Audio signals usually come from a sound source which vibrates in the audible frequency range. There are many ways to classify audio signals. Acoustics is the interdisciplinary science that deals with the study of all mechanical waves including vibration, sound, ultrasound and infrasound.

Audio data is an integral part of many computer applications and audio recordings are dealt with in audio and multimedia applications. The effectiveness of their deployment is dependent on the ability to classify and retrieve the audio files in terms of their sound properties. Rapid increase in the amount of audio data demands for a computerized method which allows efficient and automated content-based audio classification.

1) *Proposed Dual Tree Complex Wavelet Cepstral Coefficient [DTCWCC] – based Bat Classification*

In this approach we use the Dual Tree Complex Wavelet Transform [DT-CWT] because of the advantages of the complex wavelet transform. The coefficients from the DT-CWT of the audio signal are then subjected to log power spectrum and Discrete Cosine Transform [DCT]. The final output is called the Dual Tree Complex Wavelet Cepstral Coefficient [DTCWCC].

The corresponding Process Flow Diagram for the estimation of Dual Tree Complex Wavelet Cepstral Coefficients is shown in the Figure4 which is given below.

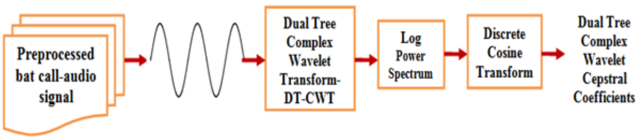

Fig. 4 Computation of Dual Tree Complex Wavelet Cepstral Coefficients

2) *Statistical Features*

Each sample is divided into coefficients of hundred and the following features are calculated for each.

F1: Skewness
F2: Entropy :
F3: Kurtosis :
F4: Moment
F5: Mean
F6: Standard Deviation
F7: Variance

The statistical features, DT-CWT coefficients and Cepstral coefficients together form the overall feature vector of the DTCWCC.

The block diagram of the proposed approach, namely, Dual Tree Complex Wavelet Cepstral Coefficients, is shown in the following Figure5.

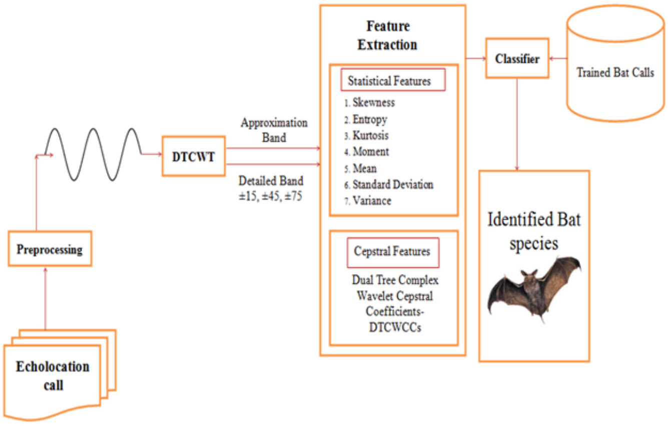

Fig. 5 Modules description Block Diagram

D. Experimental Results and Analysis

The DTCWT, Statistical features and Cepstral features are used in this bat classification scheme. The scheme is implemented with three types of classifiers, namely, Bayes classifier, Support Vector Machine (SVM) classifier and k-NN classifier.

1) *Data Set*

The Megabats or the fruit-eating bats do not echolocate but the micro bats or the insect-eating bats use echolocation much. There are six families of insectivorous bats(microchiroptera)[3,4] which are found in the KMTR region. They are i) Rhinopomatidae ii) Emballonuridae iii) Megadermatidae iv) Rhinolophidae v) Hipposideridae vi) Vespertilionidae[33]. In the family Rhinopomatidae, one genus by name Rhinopoma is found. The name of the species found is *Rhinopoma hardwickii*. In the family Emballonuridae, one genus by name Taphozus is found. The name of the species found is *Taphozus melanopogon*. In the family Megadermatidae, one genus by name Megaderma is found. The two species found are *Megaderma lyra* and *Megaderma spasma*. In the family Rhinolophidae, one genus by name Rhinolophus is found. The four species found are *Rhinolophus rouxii*, *Rhinolophus pusillus*, *Rhinolophus lepidus* and *Rhinolophus beddomei*. In the family Hipposideridae, one genus by name Hipposideros is found. The four species found are *Hipposideros ater*,*Hipposideros pomona*, *Hipposideros fulvus* and *Hipposideros speoris*. In the family Vespertilionidae, three genii namely Myotis, Pipistrellus and Miniopterus are found. In the genus Myotis, the species *Myotis montivagus* is found. In the genus, Pipistrellus, two species namely, *Pipistrellus coromandra* and *Pipistrellus tenuis* are found. In the genus Miniopterus, the species *Miniopterus pusillus* is found.

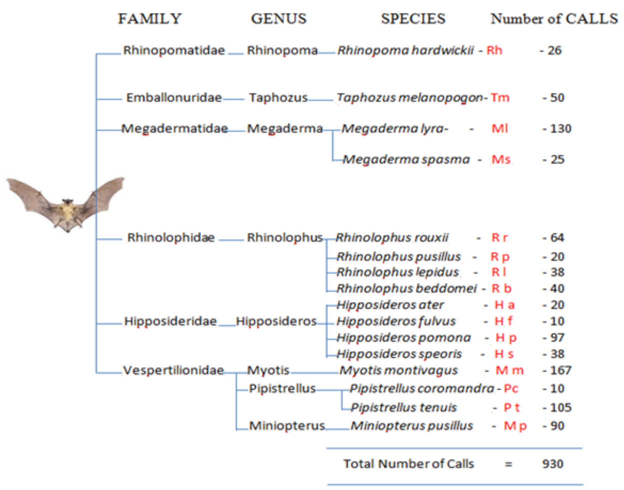

Fig.6. Data Set

2) *Analysis Metrics*

In this experiment the analysis metrics such as True Positive (TP), False Positive (FP), Sensitivity, Specificity and Accuracy were used.

Table 1 shows the Sensitivity, Specificity and Accuracy calculated for each of the sixteen bat species under consideration, with the approach namely, DTCWCC-based bat classification with k-NN classifier.

Table 2 shows the Sensitivity, Specificity and Accuracy, calculated for each of the sixteen bat species under consideration, with the approach namely, DTCWCC–based bat classification scheme, with Bayes classifier.

TABLE 1 DTCWCC-BASED BAT CLASSIFICATION WITH K-NN CLASSIFIER

	Bat Species	Sensitivity%	Specificity%	Accuracy%
1	*Rhinopoma hardwickii*	92.3077	80	88.8889
2	*Taphozus melanopogon*	83.871	85.7143	84.2105
3	*Megaderma lyra*	76.6667	66.6667	76.0417
4	*Megaderma spasma*	76.9231	80	77.7778
5	*Rhinolophus rouxii*	64.7059	66.6667	65
6	*Rhinolophus pusillus*	80	80	80
7	*Rhinolophus Lepidus*	82.6087	71.4286	80
8	*Rhinolophus beddomei*	70	66.6667	69.2308
9	*Hipposideros ater*	80	80	80
10	*Hipposideros fulvus*	80	83.3333	81.8182
11	*Hipposideros pomona*	82.4561	80	82.0896
12	*Hipposideros speoris*	78.2609	66.6667	75.8621
13	*Myotis montivagus*	71.9626	70	71.7949
14	*Pipistrellus coromandra*	80	80	80
15	*Pipistrellus tenuis*	75.3846	80	76
16	*Miniopterus pusillus*	78.1818	72.7273	77.2727
	Average Accuracy			**77.8742**

TABLE 2 DTCWCC-BASED BAT CLASSIFICATION WITH BAYES CLASSIFIER

	Bat Species	Sensitivity%	Specificity%	Accuracy%
1	*Rhinopoma hardwickii*	84.6154	80	83.3333
2	*Taphozus melanopogon*	87.0968	85.7143	86.8421
3	*Megaderma lyra*	81.1111	83.3333	81.25
4	*Megaderma spasma*	84.6154	80	83.3333
5	*Rhinolophus rouxii*	73.5294	83.3333	75
6	*Rhinolophus pusillus*	90	60	80
7	*Rhinolophus Lepidus*	82.6087	71.4286	80
8	*Rhinolophus beddomei*	75	83.3333	76.9231
9	*Hipposideros ater*	80	80	80
10	*Hipposideros fulvus*	60	80	70
11	*Hipposideros pomona*	87.2727	70	84.6154
12	*Hipposideros speoris*	91.3043	66.6667	86.2069
13	*Myotis montivagus*	75.4545	80	75.8333
14	*Pipistrellus coromandra*	60	66.6667	63.6364
15	*Pipistrellus tenuis*	77.2727	80	77.6316
16	*Miniopterus pusillus*	81.8182	72.7273	80.303
	Average Accuracy			**79.0568**

TABLE 3 DTCWCC-BASED BAT CLASSIFICATION WITH SVM CLASSIFIER

	Bat Species	Sensitivity%	Specificity%	Accuracy%
1	*Rhinopoma hardwickii*	92.3077	80	88.8889
2	*Taphozus melanopogon*	90.3226	85.7143	89.4737
3	*Megaderma lyra*	85.5556	83.3333	85.4167
4	*Megaderma spasma*	92.3077	80	88.8889
5	*Rhinolophus rouxii*	85.2941	83.3333	85
6	*Rhinolophus pusillus*	90	60	80
7	*Rhinolophus lepidus*	91.3043	71.4286	86.6667
8	*Rhinolophus beddomei*	80	83.3333	80.7692
9	*Hipposideros ater*	80	80	80
10	*Hipposideros fulvus*	60	80	70
11	*Hipposideros pomona*	90.9091	70	87.6923
12	*Hipposideros speoris*	95.6522	66.6667	89.6552
13	*Myotis montivagus*	76.3636	80	76.6667
14	*Pipistrellus coromandra*	100	66.6667	81.8182
15	*Pipistrellus tenuis*	83.0769	80	82.6667
16	*Miniopterus pusillus*	89.0909	72.7273	86.3636
	Average Accuracy			**83.7479**

Table 3 shows the Sensitivity, Specificity and Accuracy, calculated for each of the sixteen bat species taken into consideration, with the approach namely, DTCWCC–based bat classification scheme, with SVM classifier.

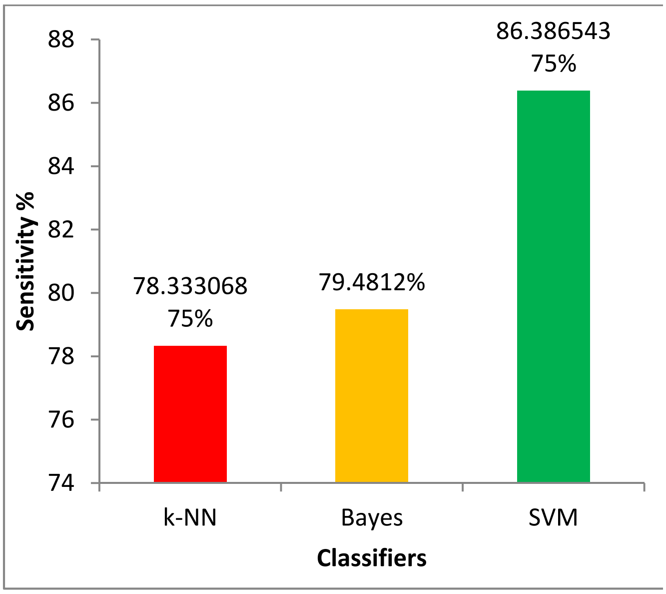

Fig. 7. Sensitivity of DTCWCC

The above graph Figure 7 shows the Sensitivity of the DTCWCC-based Bat Classification approach with k-NN, Bayes and SVM classifiers. The graph shows that Bayes classifier outperforms k-NN classifier by 1.14813125%. The SVM classifier outperforms Bayes classifier by 6.90534375%. The SVM classifier outperforms k-NN classifier by 8.053475%.

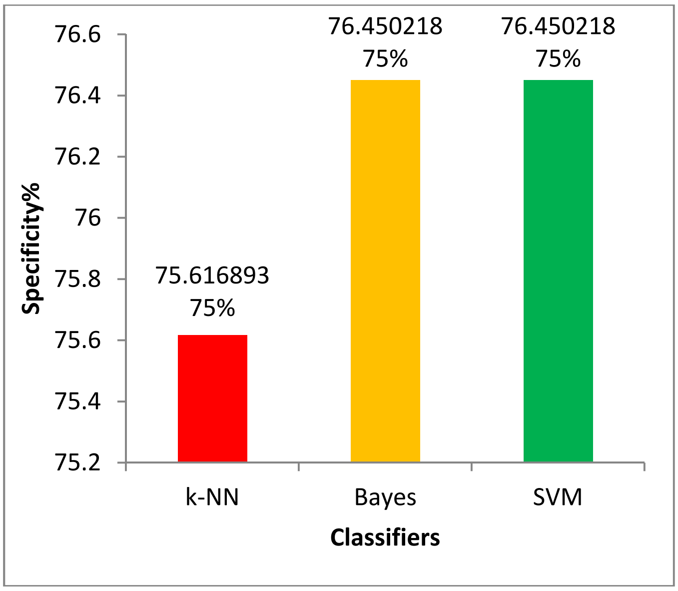

Fig.8. Specificity of DTCWCC

The above graph Figure8 shows the Specificity of the DTCWCC Feature-based Bat Classification approach with k-NN, Bayes and SVM classifiers. The graph shows that Bayes and SVM classifiers outperform k-NN classifier by 0.833325%.

Figure9. shows the Accuracy of the DTCWCC Feature-based Bat Classification approach with k-NN, Bayes and SVM classifiers. The graph shows that Bayes classifier outperforms k-NN classifier by 1.18258%. The SVM classifier outperforms Bayes classifier by 4.69115%. The SVM classifier outperforms k-NN classifier by 5.87373%.

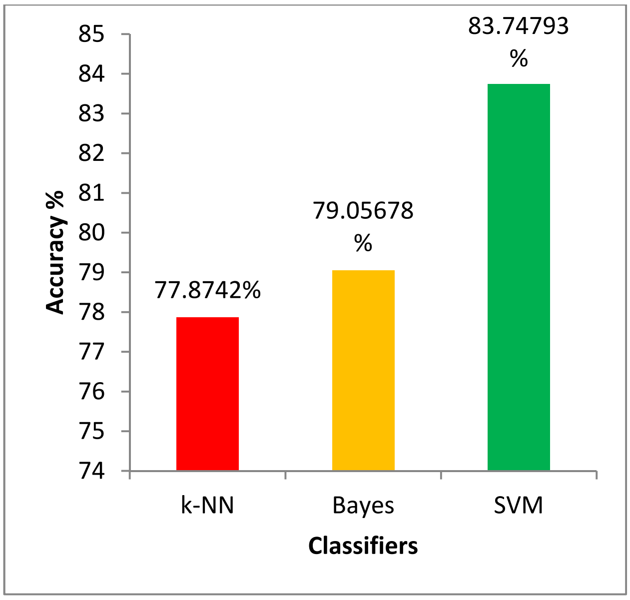

Fig. 9. Accuracy of DTCWCC

Perceptual, Spectral and Cepstral Feature [PSCF]-based Bat Classification was proposed in [34]. Here we compare PSCF and DTCWCC.

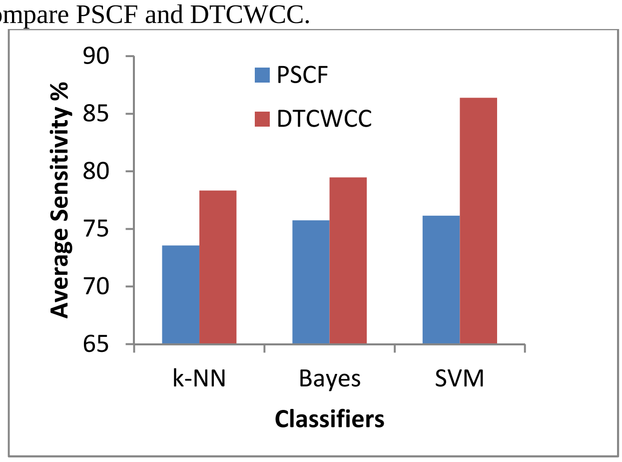

Fig. 10. Sensitivity: PSCF vs DTCWCC & k-NN vs Bayes vs SVM classifiers

From the above graph Figure10. it is evident that the Sensitivity of DTCWCC exceeds PSCF by 4.77% for k-NN classifier, 3.73% for Bayes classifier and 10.23% for SVM classifier.

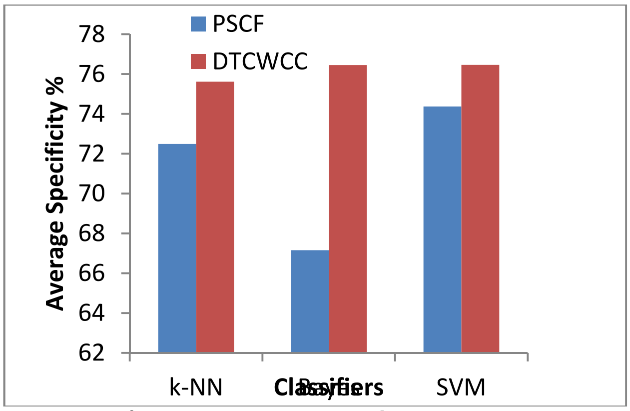

Fig. 11. Specificity: PSCF vs DTCWCC & k-NN vs Bayes vs SVM classifiers

From the Figure11 it is evident that the Specificity of DTCWCC exceeds PSCF by 3.125% for k-NN classifier, 9.299% for Bayes classifier and 2.093% for SVM classifier.

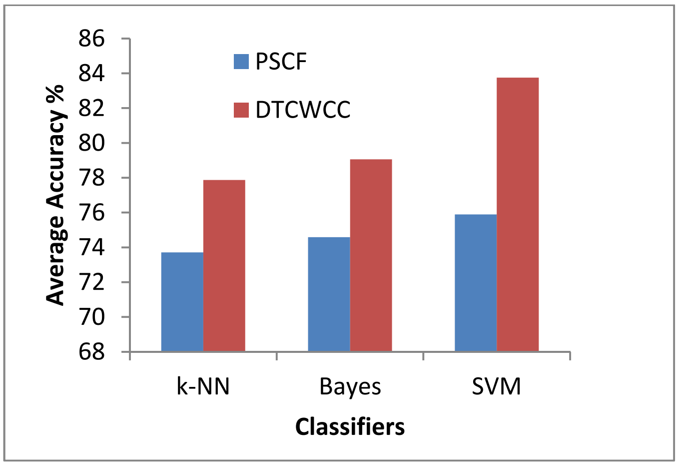

Fig. 12. Accuracy: DTT vs DTCWCC & k-NN vs Bayes vs SVM classifiers

From the above graph Figure12 it is evident that the Accuracy of DTCWCC exceeds PSCF by 4.158% for k-NN classifier, 4.4668% for Bayes classifier and 7.855% for SVM classifier.

E. Conclusion

Acoustic monitoring of bats enables the collection of important biological data over a long period of time which allows conservation management decisions. Using acoustics to track changes in indicator species, may serve as an efficient way to measure habitat quality and the health of the ecosystem. Bats' echolocation signals are classified using classification schemes. In this paper, a classification scheme based on Dual Tree Complex Wavelet Cepstral Coefficients was proposed. It was carried out with k-nn, Bayes and SVM classifiers. It was found that SVM classifier outperforms the k-NN and Bayes classifiers and shows more accuracy.

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