CHAPTER 2
REVIEW OF LITERATURE

Echolocation is considered as an ‘active orientation system’ because the carrier signal for information is produced by the animal itself. Bats produce ultrasonic sounds for the purpose of moving about in the darkness. They send the ultrasonic sound as an echo which may hit any obstruction and return back to the bat, implying that there is an obstruction ahead. This is called echolocation call. Through this system, bats have succeeded in becoming independent of sunlight as a medium for perceiving their world [14]. Echolocation [66], also called bio sonar, is the biological sonar used by several kinds of animals including bats. Echolocating animals emit calls out to the environment and listen to the echoes of those calls that return from various objects near them. They use these echoes to locate and identify the objects. Echolocation is used for navigation and for foraging [67] (hunting, resting, feeding etc.) in various environments. Only insectivorous [68, 69] bats use echolocation.

Blumstein et al. [59] have studied that animals produce sounds for diverse biological functions such as defending territories, attracting mates, deterring predators, navigation, finding food and maintaining contact with members of their social group. Biologists can take advantage of these acoustic behaviours to gain valuable insights into the spatial and temporal scales over which individuals and populations interact. They used spatially dispersed groups of microphones (arrays) to enable users to study signal directionality on a small scale or to locate animals and track their movements on a larger scale.

Vaughan et al. [70] have assessed the habitat use by Chiroptera (bats) by means of a broad-band acoustic method. Bat habitat use is difficult to study directly, because bats are nocturnal, usually volent when feeding and their echolocation calls are ultrasonic. With the use of bat detectors, it has been possible to survey bats acoustically. Bat detectors are receivers which transform bat calls into the human hearing range. On a detector, a series of clicks is heard as a bat flies within range. This is defined as a bat pass. Bat species can be identified from their calls with varying degrees of certainty. However,
levels of activity of different bat species cannot be compared easily or interpreted as population estimates, because some species have more intense calls than others and are more easily heard on a detector. Bat detector studies generally confirm predictions derived from echolocation call structure and wing morphology, of resource partitioning through bats’ hunting behavior and habitat use. Some dietary and habitat use studies suggest that bats are, to a certain extent, opportunistic in their foraging habits. The authors have quantified bat foraging activity by using broad-band acoustic method in south-west England. From multivariate analysis of parameters of echolocation calls, 83% of bat passes could be identified to species level with quantified degrees of certainty. The remaining 17% could be identified to species group.

Gareth Jones [71] has investigated the scaling of echolocation call parameters namely, frequency, duration and repetition rate, in bats, in a functional context. Scaling is a powerful tool in understanding why animals function or behave in the ways they do. Echolocation is used to some extent by all bats in the suborder Microchiroptera which is more than seven hundred and fifty species in the sub order. Jones G found that echolocation calls are often Quasi Constant Frequency [QCF] in structure so that energy is focused into a narrow bandwidth to maximize ranging and so that detection is enhanced. Low duty cycle bats emit Frequency Modulation [FM] calls for orientation. FM bats produce short calls and have the lowest duty cycles. Constant Frequency [CF] bats such as rhinolophids emit the longest pulses and have the highest duty cycles. Bats that hunt in clutter usually produce calls of low intensity, presumably to minimize the return of clutter echoes in complex habitats. Many gleaning bats produce more than one call per predicted wingbeat.

Bogdanowicz et al. [72] explored the quantitative relationships between the size of bats, the frequencies in their echolocation calls and the incidence of moths and beetles in their diets. Microchiropteran bats are specialized for echolocation which involves broadcasting intense pulses of sound and receiving the much fainter echoes that return from objects, such as prey, in their path. Insects with ears sensitive to the echolocation calls of bats hear some frequencies better than others. They conducted morphological analyses on a sample of 728 skins and skulls of 62 species from the families Rhinolophidae,
Hipposideridae, Vespertilionidae and Molossidae. They examined at least five males and five females of each species. They measured forearm length, condylocanine length and condylobasal length. They found that morphology and echolocation can be highly intercorrelated. They showed evidence that there is highly significant association between the frequencies dominating the echolocation calls and morphological parameters of both high duty cycle (Rhinolophidae and Hipposideridae) and low duty cycle echolocating bats (Vespertilionidae and Molossidae). In both groups, lower echolocation call frequencies tend to be linearly associated with larger species, as showed by different indicators of body size, namely forearm length, condylocanine and condylobasal lengths and lengths of upper toothrow and mandible.

Gareth Jones et al. [1] have studied the importance of bats as bioindicators. Bats have enormous potential as bioindicators. Insectivorous bats occupy high trophic levels and are sensitive to accumulations of pesticides and other toxins. Changes in their abundance may reflect changes in populations of arthropod prey species. Bats provide several ecosystem services and hence reflect the status of the plant populations on which they feed and pollinate as well as the productivity of insect communities. Bats are ideal indicators of human-induced climate change and habitat quality. Bats can also be important environmental indicators because they are sensitive to a wide range of environmental stresses. Bats are also sensitive to human-induced changes to ecosystems. Insectivorous bats occupy higher trophic levels and would be excellent indicators owing to the relationship between contaminant and/or environmental disturbance and trophic levels. Dietary accumulation and metabolic capacity increases at higher positions in the food chain and insectivorous bats are likely to show the consequences of pollutants before organisms at lower trophic levels such as herbivorous insects or birds. Bat populations can be monitored directly to assess long-term population changes, short-term impacts on insectivorous bats can be quantified by monitoring ‘feeding buzzes’ – increases in the rate of emission of echolocation calls as bats home in on insect prey. Methods for surveying many bat species involve low-cost trapping methods such as the use of mist-nets and harp traps. Powered flight sets bats apart from other mammals and this most likely has been an important factor contributing to their widespread distribution and diversity. Bats fill such a wide array of ecological niches.
Sound event classification is attracting a growing attention recently in the field of acoustic signal analysis [70]. An *acoustic survey* is one of the research methods of gathering information on the abundance of a species and detecting their presence using acoustic detectors. Acoustic surveys are carried out in a wide range of habitats to detect large number of species. To survey and monitor bat activity [73], species identification is necessary. 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) [74] differ from species to species, that is, species-specific [75]. This facilitates acoustic identification of bat species. However, call structures within species can be extremely flexible and depend on factors including habitat, age, sex and the presence of conspecifics [76, 60].

Methods of identifying bat calls involve researchers listening to calls [77] and taking account of the echolocation call structure [74]. These methods require that the researcher has to get a good site (a suitable habitat) in which they can see the bats and record the echolocation calls. Hence the observer must wait for the opportunity to identify a bat and identify its staying place which is called the roost [78]. The researcher must follow the bats along flight paths to roosts where bats can be captured. These methods require several field visits and a lot of time; multiple observers may need to survey multiple sites simultaneously. These methods rely heavily on observer experience.

Denny M [79] has found that several groups of animals have evolved a method of navigation in the dark and the ability to locate and identify prey, based on the interpretation of sound waves that they transmit and that are reflected back to them from their environment. The 813 species of small nocturnal bats echolocate, making use of structured tonal signals. They have developed many varied echolocation adaptations and have brains that are adapted for processing acoustic signals. Bats transmit two types of acoustic signals: either Constant Frequency [CF] or Frequency Modulated [FM]. Some bats transmit CF only and some both.

Schnitzler and Kalko [80] have described the echolocation behavior of insect-eating bats and have shown that bats belonging to the same guild share many
similarities in echolocation behavior, especially in the structure of search signals, which are intimately linked to habitat type and foraging mode. Search signals are emitted when bats are searching for prey, or when they commute from one place to another and do not approach a specific target. Bats gleaning their prey from surfaces of vegetation or the ground forage in highly cluttered space. Echolocation is used by gleaning insectivorous bats for orientation in space and to guide the bat to the site with prey.

Yovel et al. [81] have taken up a study of active control of acoustic field-of-view in a biosonar system. Echolocation system in bats or the biosonar is an active sensing system. Echolocating bats actively emit the energy with which they probe their surroundings, and they can control many aspects of sensory acquisition, such as the temporal or spectral resolution of their signals. The importance of “active sensing,” by which an animal actively interacts with the environment to adaptively control the acquisition of sensory information, is fundamental to perception across sensory modalities. Bat echolocation, an active sensory system, enables an acoustic representation of the environment through precise control of outgoing sonar signals.

Ahlen [82] has put forth the idea that the heterodyne system is sensitive and enables long-range detection of bats. The narrow frequency band that is transposed to audible sound, must be tuned to the sounds made by the bat. Careful tuning will allow an observer to determine whether there is a constant frequency in the sound. The heterodyne system enables sampling of long sequences of pulses which, when displayed as oscillograms, allow analysis of pulse repetition or rhythm.

Jones G et al. [83] have put forth that time-expanded recordings and direct sampling of sound can be used to identify some bat species from their vocalizations and that such methods may be applied to field surveys of bat activity. Some species emit distinctive social calls that permit identification, and social calls may be individually distinctive within species. Analysis of echolocation calls can identify cryptic species that are very similar in appearance, but differ in echolocation calls. Species identification from echolocation calls is best approached by quantitative analysis, such as discriminant function analysis (DFA) based on several measurements taken from calls. DFA gives an
objective measure of confidence in species identification, and can be applied to surveys of habitat use.

Jones G [84] has proposed that echolocating bats normally emit one call per wingbeat when searching for prey. The coupling of sound production with flapping makes the production of intense sound pulses cost no more in energetic terms than beating the wings and not calling, whereas calling without flapping would be energetically expensive. Calling and flapping are coupled in echolocating bats. Aerial feeding bats typically emit intense search phase calls. Such bats normally produce one or fewer pulses per wing beat during search phase, as predicted by the coupling hypothesis.

Ahlen and Baggoe [85] have examined the use of ultrasound detectors for bat studies in Europe with their experiences from field identification, surveys and monitoring. No single variable of bat sound can be used to separate all species. Identification of bat species is based on a number of characters in combination. They used ultrasound detectors equipped with heterodyne and time expansion systems in combination. This combination has many advantages for instant identification as well as subsequent analysis.

Jung K and Kalko EKV [86] have put forth how anthropogenic factors affect species-presence and activity and consequently how well species tolerate or adapt to anthropogenically altered environments. Acoustic monitoring is used to investigate habitat use in a tropical forest-town interface. Aerial insectivorous bats were present in town and regularly foraged around streetlights, suggesting a species-specific tolerance for habitat alteration. Bats foraging at streetlights used microhabitats and some species even changed micro habitats, according to season or moon phase. This indicates species-specific requirements for microhabitats and the importance of preserving habitat heterogeneity.

Tressler et al. [87] have studied the regulation of bat echolocation pulse acoustics by striatal dopamine. The ability to control the bandwidth, amplitude and duration of echolocation pulses is a crucial aspect of echolocation performance. Echolocating bats precisely regulate the acoustic properties of their echolocating pulses to maximize the efficiency of their sonar behavior. The vocal plasticity displayed by
echolocating bats is uncommon among mammals because it represents a cognitive rather than limbic control of the vocal motor circuitry.

Adams A M [88] analysed the bat activity with acoustic monitoring. There was difference in the results by comparing the detection of bats by using various commonly available bat detectors. The variation resulting from the differences between bat detectors used was put forth by analyzing the variation in the detection of echolocation pulses and found significant differences in distance and angle of detection.

Sun et al. [89] have studied the geographic variation in the acoustic traits of greater horseshoe bats, testing the importance of drift and ecological selection in evolutionary processes. Intraspecific geographic variation of signaling systems provide insight into the micro-evolutionary processes driving phenotypic divergence. The acoustic calls of bats are sensitive to diverse evolutionary forces. They found that in China, *Rhinolophus ferrumequinum* displays a diverse call frequency and inhabits a heterogeneous landscape. They quantified geographic variation in resting frequency (RF) of echolocation calls, estimated genetic structure and phylogeny of *R. ferrumequinum* populations, and combined this with climatic factors to explain acoustic variation in genetic drift, cultural drift, and local adaptation.

Miller et al. [90] studied the acoustic behavior of four species of vespertilionid bats in the field using high speed tape recorders and ultrasonic detectors. The bats can be identified solely on the basis of their cries when using a ‘divide-by-ten’ detector. Several aspects of the cry repertoire can be correlated with the bats’ activities and acoustic environment. During aerial chases and when circling the roost, *Eptesicus serotinus, Nyctalus noctula, and Pipistrellus pipistrellus* emit ultrasound that is distinctly different from their orientational cries. They found that such ultrasound may have a social function.

Airas M [91] has put forth his findings regarding acoustical properties such as the temporal and frequency domain qualities of echolocation signals. He studied the echolocation voice production and perception capabilities of Chiroptera including the vocal organs and ear anatomy, voice control capabilities and neurological aspects.
Ghose and Moss [92] have done research on the direction of the ultrasonic beam produced by the bat and the direction in which it moves in flight. Bat is an acoustically guided animal and not a visually guided animal. There is an anticipatory relationship between the direction of the sonar beam and the locomotory flight plan as the bat searches for and intercepts insect prey. Echolocating bats emit brief, intermittent ultrasonic pulses. Each pulse forms a beam of sound that echoes off objects in its path. Bats compute the direction and distance to obstacles and prey, from a spectrotemporal analysis of the returning echoes. Auditory directional information, however, requires a complex mapping of binaural spectrotemporal information into spatial location. The ability to localize objects and navigate via echolocation is very well developed in bats, and the distinctive aspects of echolocation as a sensory system suggest that the study of auditory guided locomotion in bats offers a valuable complement to similar studies in visually guided animals.

Jakobsen et al. [93] have studied the convergent acoustic field of view in echolocating bats. Most echolocating bats exhibit a strong correlation between body size and the frequency of maximum energy in their echolocation calls that is, the peak frequency. The smaller species use signals of higher frequency and the larger species use signals of lower frequency. They found that smaller bats emit higher frequencies to achieve directional sonar beams and that variable beam width is critical for bats. Bats that emit their calls through their mouths show a relationship between mouth size and wavelength, driving smaller bats to signals of higher frequency.

Vaughan et al. [94] have used multivariate discriminant functions to identify calls of bats recorded in south–east England and Italy for habitat-use assessment [95]. They have presented a method for the identification of bat species from time-expanded broadband recordings of their echolocation calls. Due to interspecific variation in the echolocation calls produced by bats, multivariate analysis of call parameters is a possible technique for species identification. Variation in echolocation call structure was investigated using multivariate analysis and correlation. Parameters from calls of individual species conform to multivariate quadratic discriminant functions and are quite robust to departures from normality. Recordings were made of echolocation calls produced by 536
bats of known species identity, belonging to 15 species found in Great Britain. One call was analysed per individual and sonograms and descriptive statistics of six, time and frequency variables of calls are presented. British bats can be placed in three groups according to the structure of their calls: High duty cycle Frequency Modulation [FM] / Constant Frequency [CF] / Frequency Modulation [FM] bats, that is, FM/CF/FM bats, low duty cycle FM bats and intermediate duty cycle FM/CF bats. FM/CF/FM bats could be identified from the peak frequency of their calls. Two separate quadratic multivariate discriminant analysis were carried out on the time and frequency parameters of calls produced by FM bats and FM/CF bats. Unknown calls of 67% of FM bats and 89% of FM/CF bats were classified to species.

Herr et al. [96] proposed a decision tree-based approach to classify zero-crossed echolocation call recordings from eight Australian species. They have used search phase calls of free-flying bats in their natural environment. The ANABAT system was used for bat detection and as recording equipment. The stored calls were analysed. Calls from each sex were used in the identification of all species with one exception of F. tasmaniensis. Such recordings are typically used in identifying calls from bats in surveys using remote sensing techniques. The identification of ultrasonic calls uses short sequences of pulses, as the shape of each pulse (frequency change over time) becomes more important for identification. The automated identification of bat calls using a decision tree based classification led to good results for species with distinct mathematical differences in call parameters. The advantage of using a decision tree classification system over statistical approaches is that, each single pulse is analysed and outliers and variation of each pulse are included in the analysis system of a decision tree. This enhances the discrimination between pulses as it does not rely on a single analysis step, but includes testing of already defined groups against the newly formed groups, in addition to optimizing the separation. The decision tree classification procedure creates a set of rules that optimizes the discrimination between the species using all available information from the extracted variables. Using a decision tree classification system, the automated identification of pulse parameters led to good results for species with distinct differences in calls, with four out of eight species classified correctly in 95% of the attempts.
Machine learning techniques which are used in automated (human) speech recognition [97-102] have been used to detect and classify calls from five North American bat species. These methods allow satisfactory identification of several species.

Briggs et al. [103] have attempted to automatically identify which species of bird is present in an audio recording using supervised learning. They devised effective algorithms for bird species classification. They proposed a probabilistic model for audio features within a short interval of time. They proposed the use of another approximation to the Fischer information metric, namely the Hellinger metric. They followed a Bayesian approach to classification. Then they introduced the interval IID model to describe the distribution of feature vectors within an interval consisting of frames and derived the corresponding MAP classifier. The MAP classifier suggests aggregating features into histograms and using KL nearest neighbor to classify. This connection to nearest neighbor classification on statistical manifolds, led them to extend the classifier by proposing different metrics like Hellinger. To use the MAP classifier with high-dimensional frame-level features, they employed codebook histograms. The classifiers made predictions from intervals based on the collection of frames within the interval. The classifiers achieved over 90% accuracy on a data set containing six species of birds and outperformed support vector machines.

Aggarwal et al. [104] have used audio mining to extract audio signals for indicating patterns and features of audio data. Audio content had to be indexed to enable searching, because audio content in binary format is not readily searchable. Audio content in PCM format is suitable for processing of audio data as it contains only audio data and no header information is added to it. They used various audio features like Mel-Frequency Cepstral Coefficient (MFCC), Linear Predictive Coefficient (LPC), Compactness, Spectral Flux (SF), Band Periodicity (BP), Zero Crossing Rate (ZCR) etc. are used to classify audio data into various classes. Various classification algorithms such as Naïve Bayes, FT, J48, ID3 and LibSVM were used to classify audio data into defined classes. The results of various classification algorithms were compared using performance parameters such as True Positive (TP) Rate, False Positive(FP) Rate etc.
Redgwell et al. [105] have tested the ability of two classifiers, Support Vector Machines (SVM) and Ensembles of Artificial Neural Networks (ENN), to classify the echolocation calls of bats and compared with Discriminant Function Analysis (DFA) was used as a benchmark. SVMs [46] work by creating separation boundaries between classes by training iteratively on a dataset. The bat calls were categorized into one of three previously described types: constant frequency (CF), frequency modulated (FM), quasi-constant frequency (QCF) and kinked (K). Kinked calls were characterized by having a sudden decrease in frequency in the final quarter of the call. The call parameters were classified into genus and species using three classification algorithms, DFA (quadratic with cross-validation), SVM and ENN. DFA was carried out using SPSS which is a package for statistical analysis and calls classified to genus and species. In this approach, two types of ENNs were generated. The first utilized the top performing 21 neural networks (of the 50 retrained networks) trained to classify calls to species. The second type used a hierarchy of neural networks. DFA classified calls to genus with an overall accuracy of 81%. They correctly classified 73% of the calls to species. The optimal i.e. achieving the highest correct identification rate of SVM for classifying calls to genus had a correct classification rate of 93%. The best SVM for classifying calls to species achieved an 87% correct classification rate. All ENNs consisted of 21 neural networks as there were sufficient networks that classified with greater than 50% accuracy. The ENN trained to classify calls to genus yielded a 98% correct classification rate. Classification of calls to species achieved 98% accuracy. The hierarchical ensemble of the best performing neural networks achieved an overall accuracy of 98%.

Walters et al. [60] have proposed that Artificial Neural Networks (ANN) are machine-learning methods to classify input data into particular output categories. They developed classifiers using reference search-phase echolocation calls from EchoBank to train ensembles of artificial neural networks (eANNs) to distinguish calls from 34 European bat species. They developed a pan-European acoustic identification tool, iBatsID for consistent identification of full-spectrum bat echolocation calls recorded throughout Europe. This tool can be used for standardized continent-wide acoustic bat survey and monitoring programmes. They used the commercially available sound analysis software SONOBAT version3 to automatically find and measure calls in the recorded sequences.
SONOBAT uses amplitude threshold filters and recognition of smooth frequency changes over time to find calls and to fit a frequency-time trend line to the shape of the call, from which a number of measurements are extracted. Automatic feature extraction removes operator measurement bias from call parameters. All calls located by SONOBAT were visually inspected and calls where the measurement line did not fit the call accurately (i.e. the fitted line included background noise or echo) were rejected, using a customized accept/reject button in SONOBAT. They measured 15,858 search-phase calls in 1259 sequences, with each sequence assumed to be from a different individual. Twenty-four parameters describing the frequency and time course of the call were automatically extracted by SONOBAT. Species were grouped according to echolocation call type, reflecting either phylogenetic constraints or convergence. Parameters were compared within each group to determine which are most useful in distinguishing species, as the most useful parameters may differ depending on the type of call used. They compared the variance within each species (F-ration of univariate ANOVA. As F-ratios > 1 suggests that inter-specific call variation is greater than intraspecific variation, they assumed that the parameters with higher F-ratios would be more useful in distinguishing between species. A k-means cluster analysis was used with each call-type group to separate parameters into two clusters based on the F-ratios and those in the high mean cluster were selected. Parameters selected as important for any group were then used to build each stage of the neural networks. Ensembles of artificial neural networks were trained and tested using a custom-written Java application. Half of the data were used to train the networks and half used as an independent testing data set to assess accuracy. Ensembles of artificial neural networks achieved an overall median correct classification rate of 83.7% across the hierarchy for all 34 species.

Parsons S and Jones G [106] recorded echolocation calls from fourteen sympatric species of bats in Britain. The calls were digitized and one temporal and four spectral features were measured from each call. The frequency-time course of each call was approximated by fitting eight mathematical functions and the goodness of fit, represented by the mean-squared error, was calculated. Measurements were taken using an automated process that extracted a single call from background noise and measured all variables without intervention. Two species of *Rhinolophus* were easily identified from call duration
and spectral measurements. For the remaining twelve species, Discriminant Function Analysis [DFA] and multilayer back-propagation perceptrons were used to classify calls to species level. It was clear that the success of a hierarchical classification system of DFAs is dependent on the species to be analysed and the nature of any misclassifications. The use of hierarchical ANNs was much more effective. Identification rates increased or stayed the same for most of the species. This highlights the power of ANNs because the pattern of misclassifications from the all-species analysis was very similar to that of the all-species DFA. At every systematic level, the ANNs outperformed their equivalent DFA. DFA uses series of functions that best separate the groups and then classifies each data point in turn. Discriminant function analysis achieved an overall correct classification rate of 79% while an artificial neural network achieved 87%.

Jennings, Parsons and Pocock [77] used a data set of echolocation calls made by known species of bat to compare the ability of human experts and a hierarchy of artificial neural networks (ANNs) to identify species of bats from short sequences of echolocation calls. Call sequences consisted of only a few calls and were selected independent of their quality so that they represented recordings typically obtained in the field and were a realistic challenge to both ANNs and human participants. The null hypothesis was tested, that there was no difference in the ability of ANNs and humans to identify these recordings correctly. Another null hypothesis was tested, that there humans’ length of experience in analysis of echolocation calls had no effect on their ability to identify calls correctly. They used 45 time-expanded recordings of search-phase echolocation calls used in free flight rather than in insect capture. Each recording consisted of 1-4 calls and 14 of the 16 species occurring in the United Kingdom were represented. The 45 recordings were submitted to ANNs which had been trained and developed with an independent set of high-quality recordings of the same species of bats. The ANNs employed a hierarchical design: calls were first identified to genus by one network and then were submitted to another network trained to identify calls from that genus to species. Humans correctly classified 86% of recordings to genus and 56% to species. ANNs correctly identified 92% and 62% respectively. ANNs outperformed humans by 75%.
Obrist, Boesch and Fluckiger [107] used synergetic pattern recognition to classify bats. The synergetic algorithm emphasizes unique pattern content of training signals and diminishes of pattern contents common to all others. They tested the hypothesis that a pattern recognition approach based on a synergetic algorithm will outperform classical statistical analysis of parametric measurements even for larger species assemblages. All bat call recordings were done with a Pettersson D980 bat detector. Digital recordings of 26 bat species’ echolocation calls were acquired, mostly releasing identified bats rarely in front of previously inspected roosts of known species occupancy. 643 sequences (3.6 hours), containing calls of 362 hand-identified specimens were recorded. Prior to analysis, high-pass filtering (7.5 kHz) was applied and single echolocation calls (26ms = 8192 data points) were cut from sequences. They performed three selections of learning calls and tested each training set against three other selections of classification calls. The classification of bat calls is achieved with an algorithm termed SC-MELT which combines several training patterns per class into one feature vector, which has the same dimension as the training vectors. This ability enables the synergetic algorithm to handle big dimensions in contrast to Artificial Neural Networks (ANN). They have explored with Discriminant Function Analyses (DFA), the classification power of parametric measurements to be able to compare against the power of the pattern recognition approach. Increasing the number of calls to calculate the function did result in a general increase of the percentage of correctly reclassified calls from 68% to 75%.

Neural networks have also been used to identify species of British bats flying over organic and conventional farms. Although these previous studies accurately classify many of the species on which they are trained and prove the concept and value of quantitative call identification, they have not been made publicly accessible and are restricted to a regional (often national) level (eg. Venezuela [74]; Greece [106]; Switzerland [107]; Italy [108]; Mediterranean area [109]; UK [110]; USA). Therefore, they cannot be used to generate comparable classifications at a continental scale [60]. For continent-wide survey and monitoring programmes that aim to assess changes in activity over time or between sites, a method of identification that is objective, standardized and repeatable is essential.
Bohn *et al.* [111] have studied syllable acoustics and temporal patterns and have found that call composition vary with behavioural context. A syllable is the smallest acoustic unit of a vocalization of bat and equivalent to one continuous emission surrounded by silence. Call is the simplest emission of a vocalization. Calls can be composed of single syllables or groups of syllables. If syllables are emitted singly, then each syllable is a monosyllabic call. If multiple syllables are always emitted together, then the group of syllables, is a multi-syllabic call. The authors have put forth a vocal repertoire of Mexican free-tailed bats, *T. brasiliensis*. They found that some syllables are unique to specific calls while othersyllables are shared among different calls. The entire calls associated with one behavior can be embedded into more complex vocalizations used in entirely different behavioural contexts. The vocalizations were recorded using a 1/4in microphone and a custom-made amplifier. Earlier in 2003, signals were recorded into a custom-made digital time expander. The time expander recorded a maximum of 10s at 16bits that was played onto a computer at a sample rate of 44.1kHz. Later on in 2004-5, calls were recorded directly onto a computer at a sample rate of 300kHz using a high speed data acquisition card. If vocalizations are correlated with different behavioural contexts, they are likely to have different meanings that should be reflected in their acoustics. Calls are usually identified and described by the acoustic features of individual elements. Syllable acoustics can also vary with different bats and provide information on the identity of the individual bat. The authors determine whether different calls are distinguishable based on syllable acoustics, temporal emission patterns, or call composition features. When different calls are composed of similar syllables, distinctive temporal emission pattern may facilitate call recognition. These results indicate that syllable acoustics alone do not provide enough information for call recognition; rather, the acoustic context and temporal emission patterns of vocalisations may affect meaning.

A call library [60] contains recordings from a variety of methods and surroundings providing confidence to classify the variations represented in the calls. To ensure correct classification, the best quality calls within a recorded sequence can be taken into account.
A bat call library is a database in which there are acoustic details of all species of bats in a region, specifying the frequency range of the calls, shape of the calls etc. There are call libraries for European bats [60] and in other continents too. But there are not any for Indian bats. Hence in our research area of KMTR we propose to build classification schemes for the various bat species present in the KMTR region using Echolocation call.