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North Indian Classical Instrumental Raga Music: Multifractal Parameters Analysis and Raga Recognition System

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ABSTRACT

Introduction: The foundation of Indian classical music is the raga. Ancient music literature describes raga as a collection of particular arrangement of musical notes, that turns into soothing music. According to basic music theory, the raga segments have fractal properties. In fractal theory, the scale of the music note (signal) can be altered while maintaining its shape

Objectives: This enhances musical quality with improved raga note. In the proposed work, Codebook of Feature (CoF) model is used to recognize 12 Indian classical ragas. The application considered is north Indian classical instrumental raga music. The multifractal parameter analysis of musical segments is done, based on fractal theory.

Methods: The proposed work recognizes raga without note detection, hence reducing the complexity of the raga recognition system. The training and testing datasets considered are 60 % – 40 % and 90 % – 10 % respectively.

Results: The accuracy obtained is 98.94 % and 99.01 % respectively. The accuracy calculated based on F1 – score for the mentioned datasets is 98.93 % and 99.06 % respectively.

Conclusions: The proposed system is also compared with the recognition of raga using previous work on the same dataset that was implemented with variants of Mel Frequency Cepstral Coefficients (MFCC) features and the ensemble bagged tree as a classifier, which gives 96.32% accuracy. The proposed system's accuracy has increased by 3% compared to MFCC features.
Keywords: North Indian Music, Raga identification, Multifractal Analysis, Hurst Parameters, Code of Feature model.

1. INTRODUCTION

Music recognition has applications in music indexing, audio recommendation systems, audio performance evaluation, and music education. Listeners can now choose from a wide range of music genres in the digital age. Indian classical music is one such genre. Indian classical music is made up of a specific sequence of notes known as raga, which can be sung or played on a musical instrument. For music experts, identifying these ragas involves longer period of training. People unfamiliar with this music genre, on the other hand, may struggle to recognize and differentiate these ragas. Attempts have previously been made to develop a recognition system of software tools that can assist ordinary people in recognizing a raga from an input track that they provide. As a result, a novel recognition system for identifying Hindustani classical music ragas was proposed. Information is required for recommendation systems to retrieve musical content. For information retrieval, other researchers have used the Mel frequency cepstral coefficient (MFCC), pitch distribution of musical scale, chromatogram, spectral components, and linear prediction coefficient. This study employed a system that proposes the use of feature extraction via the fusion of parameters derived from the wavelet leader and the wavelet transform modulus maxima method to retrieve musical information for use in the recognition system.

The researchers used a background of the existing literature that is published on the topic of a raga recognition system, which is mentioned in the Literature Survey, for this research. The following section is Material and Methods, which describes the fundamentals of Indian classical music, the inspiration for using multifractal theory on the music database, and the proposed recognition system. This also includes a description of the dataset as well as the feature extraction method used with the proposed system. In the section Result and Discussion, the results of the raga recognition experiments are discussed. Finally, the paper concludes with suggestions for future work on the recognition system.

2. LITERATURE REVIEW

McDonough et al. (2023) study suggests using the self-similarity of melodic lines that recur at different temporal scales to comprehend the complexity of musical compositions. This approach doesn't use time-window averaging. It defines the fractal dimension in terms of the tonal contours of musical motifs and the temporal scaling hierarchy. The concepts are tested on musical "renditions" like the Cantor Set and Koch Curve, and applied to masterful compositions over five centuries.

A study of existing raga recognition systems and their musical information retrieval approaches is carried out. Gowrishankar, B. S., & Nagappa, U. B. (2021) discussed the proposed models for automatic raga recognition using a pitch detection algorithm, finding the tuning offset, and Note Segmentation process. The team concludes that using this process achieves an accuracy of more than 96 % which is better than the existing convolutional neural network (CNN) with 94% accuracy and the Gaussian Mixture Model (GMM) with an accuracy of 95 %. Sinith et al. (2020) used a Pitch distribution contour based on the Fibonacci series for 17 ragas and achieved a 95.3 % raga recognition rate. Each raga segment pitch was mapped with states, and the decision output was generated using a pre-trained HMM model. It was concluded that the recognition rates were higher than in previous studies on raga recognition systems. Ranjani et al. (2019) used a data-driven approach to discover structural similarities between different ragas through density-based parametric quantization of each segment. Using the comp-music dataset, the stochastics model generated discrete note series from the melody contour. After clustering the data, M skip-N-grams dictionaries were used to identify raga. The researchers discovered similarities in low-dimensional embedded space between ragas. It was concluded that using knowledge of Hindustani and Carnatic music, it was possible to understand the relationships and distances between ragas in the embedded space. With different techniques, recall accuracy ranges from 90% to 60% for the Hindustani music dataset and from 75% to 32% for the Carnatic music dataset. Kumaraswamy et al. (2020) investigated recognizing ragas without using notes. In their experiment, they used a raga recognition system model with an adaptive classifier based on a neural network. For the input audio signal, the team extracted STFT, NMF, and pitch features. They classified ten ragas with 77 % accuracy. Sarkar et al. (2019) attempted to group north Indian music based on energy distribution and the occurrence of notes generated by the pitch-based Swara profile. Swara is a musical note, according to music theory. The note sequence is essential for understanding raga composition. As a result, a raga note co-occurrence matrix was created, and support vector classification was used. For 17 ragas, the instrumental dataset had an accuracy of 84.6 % and the vocal dataset had an accuracy of 70.5 %. Farishta et al. (2020) used ANN to identify a Swara sequence combination of 12 Carnatic ragas, and feature extraction was done using a digital signal processing technique.

Dodia et al. (2020) identified two North Indian classical ragas with 92 % accuracy using the KNN classifier and 91 % accuracy using the SVM classifier. They used the music segment's chromogram as a feature. Joseph et al. (2017) researched Carnatic raga recognition. Every pitch in the song was given a note mapping. For recognition, the Nave Bayes and Bayes net classifiers were used, with 95.76 % and 95 % accuracy, respectively. Alekh, Sanchit (2017) experimented with raga recognition in Hindustani classical music. Raga recognition was performed with tonic estimation and pitch movements using Bhattacharya Distance in neural network classifiers. Experiments were conducted on 127 samples of 31 different ragas, with an error rate of 8.5 % in raga recognition. Acharya et al. (2016) attempted the Swara sequence and chromograms as a feature on the Swar-Sudha dataset of 48 concert recordings and 78 short-duration recordings from Jodhpur. Swara recognition of raga played on the harmonium was performed by Pendekar et al. (2013). For onset detection, two methods for segmentation were tested: spectral flux and fundamental frequency estimation. Eight ragas were considered for testing, and four of them achieved 100 percent accuracy. Anand (2019) demonstrated a convolutional network with the song's major pitch as input. The generated model identified 5 ragas with 96.7 % accuracy and 11 ragas with 85.6 % accuracy from the Comp-Music dataset. Lele and Abhyankar (2019) extracted notes from ragas played on santoor using the Praat tool. The chromogram was also extracted with 70-80% accuracy. Shridharn (2018) proposed a method for predicting music genres based on pitch, midi value, interval, contour, and duration parameters using a similarity measure. They tested 476 jazz and Western music files and achieved 95.8% accuracy. Three ragas from 68 files of Indian Classical Carnatic music were tested with different N-grams with 90.14% accuracy.

Ross et al. (2017) attempted to develop a framework for identifying melodic similarities between ragas. To learn distributed representations of notes in raga notations, they used a deep recursive neural network with bidirectional long short-term memory units. Multilevel clustering was performed on 144 raga bandish collected from Swarganag.org, and an accuracy level of around 90% was achieved using different N-grams. Kumar et al. (2014) attempted to solve the raga classification problem using a non-linear SVM with two kernels. As a result, similarities between pitch class profile and note N-gram distribution were discovered. Carnatic music was used to recognize ragas with 97 % accuracy. Katte and Tiple (2014) surveyed the recognition system and used a chromogram of the raga segment to identify the raga using HMM (Hidden Markov model) and HMM with N-gram pakad (Musical phrase that encapsulates the essence of a particular raga) matching, GMM (Gaussian Mixture Model) and GMM with N-gram pakad matching with accuracy of 93.63%, 95.75%. Dighe et al. (2013) experimented with a chromogram of musical note sequence and classification using GMM-based HMM in conjunction with MFCC and Timbers. They achieved a maximum accuracy of 97 % for four ragas. Qin et al. (2013) proposed a bag of tones model with a Mel frequency (MFCC) feature for music genre classification. The codebook was generated for 13 MFCC values using k means and achieved an accuracy of 61% on the BUAA5 and GTZAN datasets. Krasseret et al. (2012) used GMM and SVM classifiers with MFCC tones to estimate music similarity and achieved an accuracy of 86%. Muflikhah et al. (2009) use cosine similarity for document clustering using the latent specific index, achieving an F-measure of 0.91. Schluter's Unsupervised KNN model with mean covariance Boltzmann machine on spectrogram feature was used to assess music similarity (2011). Jensen et al. (2006) classified 729 songs into six genres using MFCC and FFT features and a GMM-based classifier. West et al. (2006) estimate music similarity using a feature of Mel frequency spectral irregularities. They created a template and employed a regression tree and likelihood profile. Bag of words was used by Lee et al. (2015) for modulation spectral analysis of spectral and cepstral features. For analysis, 1458 tracks are used. The accuracy of music classification is 89.16 %.

Bhat et al. (2020) compared classification models for 15 ragas of Carnatic instrumental audio and achieved an accuracy rate of 97 %. The researchers employed spectral centroid, spectral bandwidth, spectral roll-off, chroma features, and Mel Frequency Cepstral Coefficients as features (MFCC). The system is tested with artificial neural networks, XGboost, and convolutional neural network classifiers. West et al. (2006) estimate music similarity using a feature of Mel frequency spectral irregularities. They created a template and employed a regression tree and likelihood profile. Pendekar et al. (2013) performed Swara recognition of ragas played on the harmonium. For segmentation, two methods were tested: spectral flux estimation and fundamental frequency estimation for onset detection. Eight ragas were considered for testing, and four of them achieved 100% accuracy. S. Gulati et al. (2016) tested 40 different raga clips, totaling 480 recordings, for automatic raga recognition in Carnatic music. They used a melodic phrase-pattern-matching technique that employs audio recording and a predictive vector space model. The researchers achieved 70% accuracy with 40 raga collections and 92 % accuracy for raga identification accuracy with a subset of 10 ragas. In another work Gulati S. et al. (2016) achieved 98% accuracy with 300 recordings and 30 ragas in a Hindustani music dataset and with 480 recordings and 40 ragas in a Carnatic music dataset, they achieved 87% accuracy. Using only an estimated predominant pitch, the time-delayed melody surface (TDMS) feature specifies a melody's temporal and tonal qualities. A raga's melodic contour is captured via delay coordinates. For raga recognition, a basic k-nearest neighbor classifier is used. To summarize, MFCC features, chromogram, and note transcription were used to classify the music pitch class profile or pitch contour. SVM, KNN, GMM, and HMM-based classifiers were all implemented. For note recognition, chromograms or pitch class profiles must examine each frequency. Previous research was either done on a small sample of ragas or on Carnatic ragas, which provided a reasonable level of accuracy in recognizing ragas.

In the literature, each musical note is recognized firstly and then the analysis is carried out. Similarly, consideration of musical instrument recognition is commonly followed by many researchers. The recognition of mentioned entities may not be an essential process to identify raga because raga can be generated from different sources. Hence, raga identification can be instrument free process. In the proposed work, novel approach based on multifractal analysis is implemented to identify raga. In this approach, the musical notes emphasizing raga are directly identified without considering all the musical notes and the instruments played.

3. MATERIAL AND METHODS

3.1 Basics of Indian Music Theory

Indian classical music has its own set of rules for performing a raga. Like Western music, Indian classical music has 12 notes as well. A note is known as Swara in Indian music. As per the music theory, any raga should have a sequence of 5 to 8 notes. These sequences have been specified in ancient literature (Dr. Vasantrao Rajopddhye (2002) “Sangeet Shastra” Gandharv mahavidyalaya Publication. & Pandit Vishnu Narayan Bhatkhande (January 1675) “Hindustani Sangeet Paddhati” Sangeet Karyalaya, Hathras(U. P.) Publication). Raga is made up of ascending or descending notes. A performer explores the raga based on the rules of this mentioned structure known as the gamak of the raga. The variations in the musical piece of the raga are dependent on the presenter as there are no fixed rules in exploration; except that the gamak property should be constant. A raga can be presented in the sequence of an alap, jod, and jhala. An alap is an exploration of notes in a slow rhythm whereas a jod does have a faster rhythm than an alap. Like jod jhala is expressed faster but may be accompanied by other musical instruments like tabla (Indian Musical Instrument) or similar instrument. During the presentation, a drone of fixed note or tanpura is played tuned to the basic tone of the raga. Due to these alterations and flexibility in the performance art of raga, it is very challenging to implement a machine learning system to identify the raga.

3.2 Motivation to use a Multifractal Theory

As per Espen A. F. Ihlen (2012), the multifractal singularity spectrum pinpoints the variations in fractal formation within the time duration with small and large oscillations. As per the fractal theory, the scale can be changed but the shape remains the same. Studying basic music theory, this research assumes that the raga segment possesses the fractal property since the sequence of notes in a fast rhythm as taan of a classical raga segment will be repeated in alap with a slow rhythm. Thus, an attempt is given a thought to use multifractal analysis for this work. Figure 1 shows the time-domain nature of one audio clip played by all musical instruments.

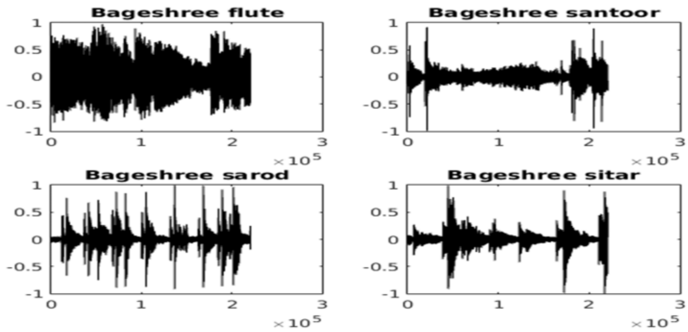

Figure 1: Time series of Bageshree Sample

The researcher attempted experiments based on the tutorial by Espen A. F. Ihlen (2012) to confirm the multifractal theory applies to music signals. The Multifractal Detrended Fluctuation Analysis (MFDFA) algorithm works as follows:

1. Input time series
2. Convert a noise-like time series into a random walk-like time series.
3. Compute the average variation i.e. root-mean-square (RMS) value
4. Computation of local fluctuation in the time series as RMS of the time series within non-overlapping segments
5. The q-order RMS can distinguish between segments with small and large fluctuations. The power-law relation between the q-order RMS is numerically identified as the q-order Hurst exponent.

6. Several multifractal spectra are computed from the q-order Hurst exponent.

Holder exponent or Hurst component α gives self-similarity in multifractal. The singularity spectrum can be plotted by f(α) with variations in α. MFDFA is the identification of scaling of qth order of moments. The singularity spectrum of the Holder exponents f(α) is obtained from the generalized Hurst exponents by,

$$\alpha = h(q) + qh'(q),\ f(\alpha) = q(\alpha - h(q)) + 1.$$

As per Multifractality theory, whether the time series is multifractal or not; can be confirmed from the following points:

i. Fluctuation function spreads for smaller scales and converges for higher scales for all values of q

ii. Hq decreases as q increases

iii. Tau_q deviates from linearity, i.e., a slope for negative and positive q differs

iv. Multifractal spectrum has a concave shape with finite width

The audio dataset is tested and observed that the multifractal theory can be applied to music data files and the above-mentioned definitions of multifractality are satisfied. Figure 2 shows a multifractal spectrum of the Bageshree flute signal.

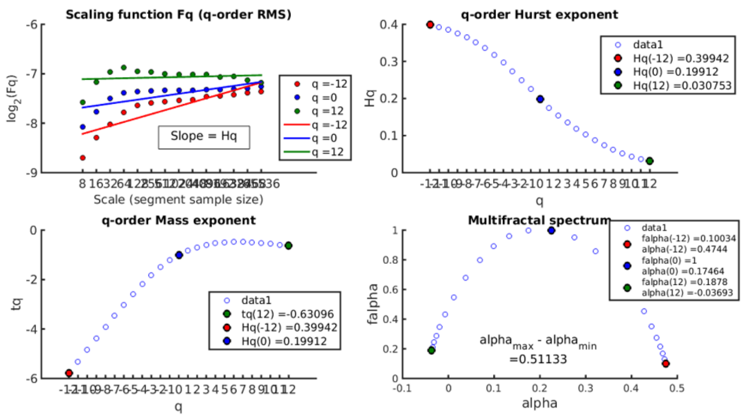

Figure 2: Bageshree Flute sample

With the above discussion the researcher concludes that for the database of Indian music, multifractal theory can be applied. Related to multifractal analysis and application the study states that, Zhi-Yuan Sua , Tzuyin Wu (2006) applied the study of the fractal property of music for the melody and rhythm of the musical piece into distributed points along one-dimensional lines. Local holder exponent and multifractal spectrum curve mapping to point sequences converted two-dimensional graph. Sanyal, S., Banerjee et al. (2016) 3 min alap portion of six conventional ragas of Hindustani classical music namely, Darbari Kanada, Yaman, Mian ki Malhar, Durga, Jay Jayanti, and Hamswadhani played in three different musical instruments were analyzed using Multifractal Detrended Fluctuation Analysis. Emotional music segments can be identified using flute and sitar signals and complexity still exists with sarod signal. Sanyal S., et al. (2016) identified the improvisational cues in the performance using the multifractal detrended fluctuation analysis (MFDFA) technique as by far the most suitable method wherein the measurement of the multifractal spectral width (‘w’) worked on 4 samples of the same raga.

Multifractal spectrum width and MFDFA is used to study

- The variation in gharana (style) of north Indian classical music by Banerjee, A. (2016),
- Classification of different performers playing the same melodies in the same manner for Western music by Reljin, N., & Pokrajac, D. (2017)
- To understand the bird song rhythm by Roeske, T. C., Kelty-Stephen, D., & Wallot, S. (2018).
- Differentiate the speech and music by Bhaduri, S., & Ghosh, D. (2016).

Thus in this research, an attempt to use multifractal parameters for the North Indian classical music raga recognition system is implemented.

3.3 Proposed Research Methodology

Through this research, the researcher attempted to implement the raga recognition system using the novel use of multifractal features and the generation of a Codebook of feature (CoF) dictionary. The system architecture is shown in Figure 3, which indicates that the training set and testing data set are separated. The dataset generated by the researcher is explained in the following section. Signal processing is done for feature extraction which is explained in the feature extraction. Once the dictionary is created Test data sample is compared with the dictionary to recognize the raga class. This is done using cosine similarity measurement. Cosine similarity is the ratio of the dot product of two vectors to the product of their magnitudes. It measures the angle between two vectors and a smaller angle means higher similarity. The output raga class is recognized.

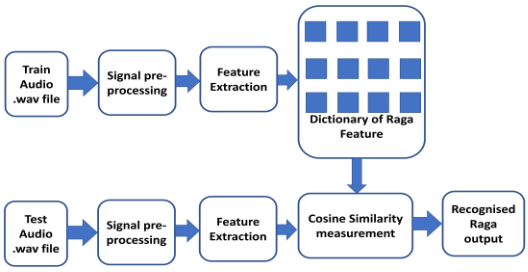

Figure 3: The Block Schematic of Proposed System

3.3.1 Dataset Information

The researcher created a database of ragas played by 4 different musical instruments sitar, sarod, santoor, and flute. Generally, ragas will be recognized by a trained skilled expert within a few seconds of the initial phrase of alap or sometimes from a segment of a taan. For machine learning, it is a very challenging task. This research generated the database in discussion with a music expert. Ragas used for experimentation are of Hindustani or North Indian classical music. Twelve ragas were selected as Ahir Bhairav (279 files), Bageshree (364 files), Bhiarav (247 files), Bihag (358 files), Bhimpalas (429 files), Lalit (313 files), Madhuwanti (294 files), Malkauns (316 files), Pooriya Kalyan (273 files), Sarang (238 files), Todi (255 files), Yaman (449 files). The duration of each audio piece was 20 seconds. The database generated consisted of all variations of the performance of a raga. A total of 3815 '.wav' audio files were used for examining the performance of the system.

3.3.2 Feature Extraction

The audio files have a standard 44100 kHz sampling frequency. This signal was decimated by 4, and then the signal was converted into a mono channel. The randomization of the signal was done by random walk which is the requirement of Multifractal analysis.

Algorithm for feature extraction

Input time series of .wav file, signal converted to mono channel and down sampled to 11025 samples.

Convert a noise-like time series into a random walk-like time series by taking the cumulative sum of the difference of signal and the mean of the signal.

Power spectral density using the Welch method is calculated, and the mean is plotted, for that slope is calculated as one feature.

Using dwtleader, multifractal singularity spectrum is plotted and global holder exponent, wavelet leader estimate, wavelet transform modulus maxima, first cumulant of wavelet leader from the singularity spectrum, the width of the spectrum, and scaling exponent are selected as features.

Feature normalization was done, and a unique feature set was saved in the Dictionary of CoF.

The feature set using the parameter of wavelet leader and wavelet transform modulus maxima was defined for the basic theory of multifractal. The researcher has considered (power spectral density -PSD) PSD mean, the slope of the log of the PSD curve. PSD has a power-law process of C|ω|-α where C is some constant and α is some exponent. This exponent can be calculated to fit the least square line of the log-log of PSD and from this curve, the slope can be estimated. The PSD curve is shown in Figure 4.

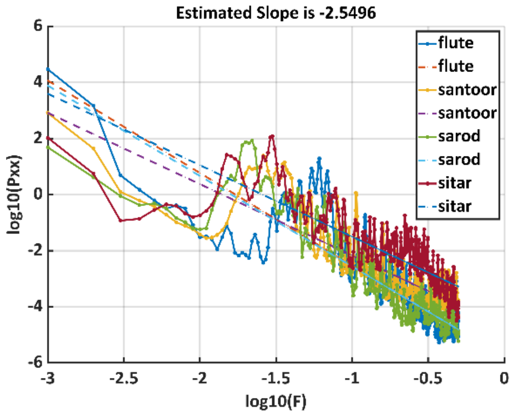

Figure 4: PSD Curve

The next feature was considered as H as holder exponent returned by dwtleader of MATLAB 2020 and the Wavelets Transform Modulus Maxima (WTMM) are estimated by relation α = 2H +1, thus fractal dimension can be detected. This will detect the scaling of maxima. Wavelet leader is used to estimate the multifractal spectrum and self-similarity. Get DH and h values whose multifractal spectrum plot is shown are Figure 5. From this graph, the first cumulant will be derived at maximum and tq is the scaling component, also width can be calculated from the graph. The scaling exponent will vary from -5 to +5, One sample of each instrument of raga Bhimpalas is plotted in Figure 6. These features are then processed for the recognition system.

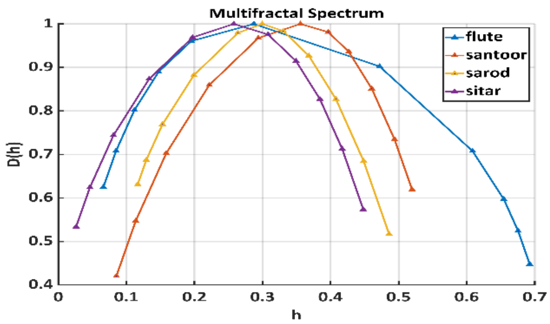

Figure 5: Multifractal Spectrum

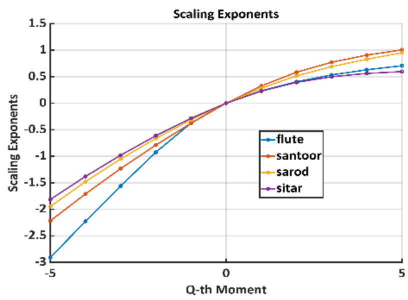

Figure 6: Scaling Exponent

4. RESULTS AND DISCUSSION

Results were generated by different training and testing data split trials. Experimentation was done on 50 % training – 50 % testing to 90 % training – 10 % testing sample splitting of data. Extracted testing features were compared with the dictionary of features of training samples using cosine similarity measure and output ragas were identified.

After generating the feature set, features were tested using SVM i.e., support vector machine classifier of the MATLAB classifier app, where an average accuracy of 58.7% was achieved. The researcher discovered that the data was excessively nonlinear by creating a scatter plot of the features, making it challenging to create a line equation that showed a noticeable difference. To improve this, the researcher tried a different approach which was using the CoF dictionary.

Results were generated for different training and testing splitting of data with 5-fold cross-validation. Attributes were mean of power spectral density (PSD mean), the estimated slope of power spectral density (b), global holder exponent (h), wavelet leader estimate (WTE), WTMM, first cumulant of wavelet leader from the singularity spectrum (cp), the width of the spectrum (w) and scaling exponent, tq. A dictionary was generated for these features as well a Codebook of Features and cosine similarity was used to generate the output raga class. The researcher found that these features were more robust and due to that the accuracy of the recognition system was increased.

Thus, feature dictionaries were generated based on the unique value of features. The testing result was generated by computing the cosine similarity with each sample in the dictionary of features CoF. Table 1 indicates the accuracy achieved for the different train and test splits.

The accuracy was calculated by three different measures as follows:

Accuracy A1 is calculated from (1) as the number of predicted classes to the actual class of the test file.

$$A1 = \frac{Number\ of\ Predicted\ Class}{Total\ Number\ of\ Actual\ Class} * 100 \tag{1}$$

Accuracy A2 is calculated from the confusion matrix given by equation (2)

$$A2 = \frac{TP+TN}{\mathrm{TP+TN+FP+FN}} * 100 \tag{2}$$

Where TP is a True Positive value i.e. predicted class, TN is a True Negative value that indicates negative prediction, FP is a false positive, and FN is a false negative value.

Accuracy A3 was achieved for the different train and test splits using F1- Score which is a measure of recall and precision. F1 -Score is evaluated as equation (3)

$$A3\ by\ F1\_Score = 2 * \frac{\mathrm{Recall} * \mathrm{Precision}}{\mathrm{Recall} + \mathrm{Precision}} \tag{3}$$

From the comparative accuracy chart mentioned in Table 1, it is observed that for a given data set accuracy for Ahir Bhairav, Bageshree, Todi, Pooriyakalyan and Sarang is the same which is equal to 100 %.

Table 1. Chart for Training & Testing Data % Split Accuracy

% Split	**Training Data 50 % - Testing Data 50 %**			**Training Data 60 % - Testing Data 40 %**			**Training Data 70 % - Testing Data 30 %**			**Training Data 80 % - Testing Data 20 %**			**Training Data 90 % - Testing Data 10 %**		
Raga name	A1	A2	A3	A1	A2	A3	A1	A2	A3	A1	A2	A3	A1	A2	A3
AhirBhiarav	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Bageshree	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Bhirav	100	100	100	100	100	100	100	100	100	97.87	99.87	98.92	100	100	100
Bhimpalas	99.53	99.90	99.53	100	100	100	100	100	100	98.80	99.73	98.80	100	100	100
Bihag	98.31	99.79	98.86	100	100	100	98.18	99.82	99.08	97.14	99.60	97.84	100	100	100
Lalit	99.35	99.79	98.72	99.19	99.87	98.79	100	99.82	98.92	100	99.46	96.83	100	100	100

Madhuwanti	97.28	99.74	98.28	97.41	99.83	98.26	97.67	99.64	97.67	96.49	99.73	98.21	100	100	100
Malkauns	98.73	99.69	98.11	100	99.91	99.21	98.94	99.82	98.94	98.41	99.87	99.20	96.77	99.72	98.36
PooriyaKalyan	97.79	99.37	95.68	97.22	99.74	97.22	100	100	100	98.11	99.73	98.11	100	99.72	98.11
Sarang	92.44	99.32	94.42	99.57	99.74	99.68	100	100	100	100	99.73	97.87	95.45	99.45	95.45
Todi	93.65	98.33	88.06	95.00	99.66	95.96	92.11	99.38	95.24	92.00	98.79	91.09	95.83	99.72	97.87
Yaman	90.53	98.43	93.62	98.88	99.70	98.05	99.25	99.38	97.42	94.44	98.93	95.51	100	99.72	98.88
Overall accuracy	97.30	99.53	97.11	98.94	99.87	98.93	98.85	99.82	98.94	97.77	99.62	97.70	99.01	99.86	99.06

	Ahir-Bhiarav	Bage-shree	Bhirav	Bhim-palas	Bihag	Lalit	Madhu-wanti	Mal-kauns	Pooriya Kalyan	Sarang	Todi	Yaman
Ahir-Bhiarav	82	0	0	0	0	0	0	0	0	0	0	0
Bage-shree	0	107	0	0	0	0	0	0	0	0	0	0
Bhirav	0	0	71	0	0	0	0	0	0	0	0	0
Bhim-palas	0	0	0	126	0	0	0	0	0	0	0	0
Bihag	0	0	0	0	108	1	1	0	0	0	0	0
Lalit	0	0	0	0	0	92	0	0	0	0	0	0
Madhu-wanti	0	0	0	0	0	1	84	1	0	0	0	0
Mal-kauns	0	0	0	0	0	0	1	93	0	0	0	0
Pooriya Kalyan	0	0	0	0	0	0	0	0	80	0	0	0
Sarang	0	0	0	0	0	0	0	0	0	63	0	0
Todi	0	0	0	0	0	0	0	0	0	0	70	6
Yaman	0	0	0	0	0	0	0	0	0	0	1	132

Figure 7: Confusion Matrix for 70-30 percentage split

From the confusion matrix, it is observed that misclassification has fallen in the nearby class. The overall accuracy achieved was around 98. 94 %, with confusion matrix accuracy, is 99.87% and with F1-score attained as 98.03 % for 60-40 training and testing split. For Ahir Bhairav, Bageshree, Bhairav, and Bhimpalas it is observed that the accuracy gained is 100%. For the remaining raga, for a given dataset accuracy calculated using confusion parameters is around 99.53 %to 99.87 % which is acceptable.

One more experiment is done with the same model and dataset. For this, the conventional spectral features extracted Bidkar et. al.(2021) were pitch, centroid, kurtosis, and Mel Frequency Cepstral Coefficients (MFCC) with their variants. Pitch is the fundamental note frequency of that segment, a centroid is the center of the audio segment, and kurtosis indicates the density of transients; pitch, centroid, and kurtosis have one value for each audio file. MFCC describes a spectral envelope which is 13 values in the vector. MFCC delta and MFCC delta are variants of MFCC derived by differentiation and double differentiation of MFCC respectively. For these variants mean value is considered a feature. This feature set of pitch, centroid, kurtosis, MFCC mean, MFCC delta mean and MFCC delta-delta mean is considered. With this experimentation, the accuracy variation from 87 % to 89 % is gained which is plotted in Figure 8 along with the novel features. Feature Set 1 is Spectral MFCC features and Feature Set 2 is derived multifractal features. From this result, the proposed system proves better justified. Table 2 mentions the accuracy gained with other techniques and can be understood that the proposed method is giving satisfactory performance about the accuracy achieved.

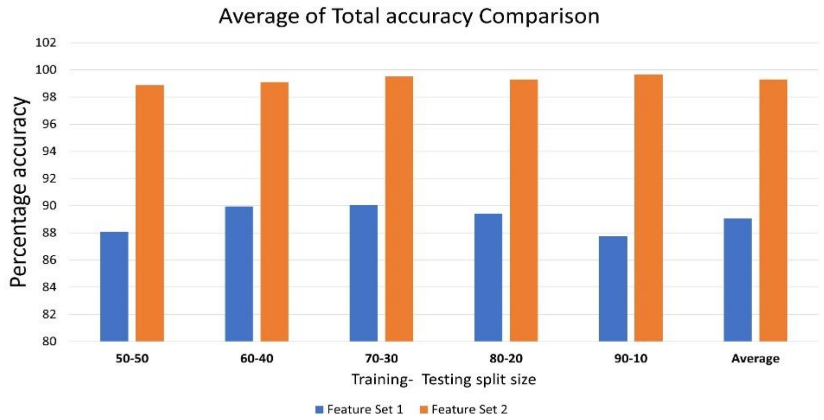

Figure 8: Accuracy Comparison with Spectral MFCC Features (Feature Set 1) and Multifractal Features (Feature Set 2)

Table 2. Comparative Accuracy summary of previous work and the proposed method

Researcher	Dataset	Accuracy achieved
Gowrishankar, B. S. & Nagappa, U. B. (2021)	CompMusic dataset	98%
Sinith et al. (2020)	17 ragas	95.3 %
Ranjani et al. (2019)	CompMusic 40 ragas of carantic music and 30 ragas of Hindustani raga music	Recall accuracy: 90 % for Hindustani music and 75 % for Carnatic music
Kumaraswamy et al. (2020)	10 ragas	77 %
Sarkar (2017)	North Indian music 17 ragas	84.6 % accuracy for the instrumental dataset, 70.5 % for the vocal dataset
Dodia et al. (2020)	2 North Indian classical ragas	92% accuracy with the KNN classifier and 91% accuracy with the SVM classifier
Joseph et al. (2017)	Carnatic raga	95.76% using Naïve Bayes classifier and 95 % Bayes net classifiers
Alekh (2017)	Hindustani classical music raga 127 samples of 31 different ragas	An error rate of 8.5 % Accuracy 91.5 %
Lee et al. (2015)	1458 tracks ISMIR2004 Audio Contest music dataset	89.16 %
Qin et al. (2013)	dataset of BUAA5 and GTZAN	61 %
Bidkar et al. (2021)	12 ragas, 4 musical instruments 3815 audio clips of 20 sec	ensemble bagged tree classifier 96.32% and ensemble subspace KNN classifier 95.83%
Proposed System	12 ragas, 4 musical instruments 3815 audio clips of 20 sec	99.87 % using confusion matrix parameters

5. CONCLUSIONS

The novel approach of applying multifractal analysis is implemented for North Indian raga recognition. The researcher attempted the Indian classical music raga recognition of 12 ragas generated by four musical instruments consisting of a total of 3815 '.wav' files. Most of the work of raga recognition was based on note transcription or musical instrument detection. The novelty of the result was that irrespective of instrument identification, regardless of realizing rhythm and note transcription; the researcher could achieve an accuracy of 98.94 % for the generated database using the feature of wavelet leaders and multifractal analysis with cosine similarity measure. For this experiment, the novel use of the concept of multifractal analysis and a set of its derived parameters such as the mean of power spectral density, estimated slope of power spectral density, global holder exponent, wavelet leader estimate, wavelet transform modulus maxima, first cumulate of wavelet leader from the singularity spectrum, the width of the spectrum, and scaling exponent are used as a feature input. The accuracy is also compared with the accuracy using F1-Score is 98.93 % and the form confusion matrix 99.87 %. The accuracy is consistent in all conditions. The misclassification was very small at around 0.004 as observed from the confusion matrix that is also in the nearby class.

This work can be extended to a greater number of ragas in the future and variants of multifractal analysis. Analysis of ragas as per music theory can also be explored further. Deep learning approach can be experimented by augmentation of dataset.

DECLARATIONS:

Ethical Approval

Institutional Review Board approval was not required.

Consent for Participate

All contributors agreed and given consent to participate.

Conflict of Interest

On behalf of all authors, the corresponding author states that they have no conflict of interest.

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Data availability

No data, models, or code were generated or used during the study

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