Identification of Raga by Machine Learning with Chromagram

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Abstract - *Music is one of the fast-growing industries in today's world and faces many difficulties. Indian Classical music, too, is different from other western music patterns and difficult to learn or identify. A lot of work has been done before using traditional approaches and expertise to identify ragas with the help of standard features such as arohana, avarohana, pakad, gamak, vaadi, savandi etc. but with the help of new features such as chromagrams, we have tried a new approach. After extraction, storage and data training with the help of a Machine Learning algorithm and a classifier such as SVM, KNN and CNN. We selected two ragas from Indian classical music, named Bhimpalasi and Yaman. The complete workflow and the features extracted are discussed here. The average accuracy of the K-NN classifier is 92 per cent and for SVM we achieved 91 per cent accuracy for raga specified with the graphical visualization of each feature. We used the python core and its various modules for a variety of purposes.*

Key Words: Raga, ML, Indian classical music, SVM, KNN, Chromagrams.

1. INTRODUCTION

Indian classical music is different from that of western music. Raga plays an important role in classical Indian music. Raga consists of different characteristics that are not easy to extract or mine by applying an approach that is used to identify western music. Some properties of raga may be lost by this. There is therefore a need for different data mining techniques to identify raga. So, apart from the traditional approach of collecting different notes that have some special properties (e.g. arohana, avarohana, pakad, taal, etc.), we have tried to use different techniques and different features. Raga is divided into two systems of Hindustani (North Indian) music, Carnatic (South Indian) music[1]. Both systems differ in their characteristics and performance. Raga is having special characteristics of their timing, that depending on their nature they can be played in different timeslots of the day. Notes of a raga arranged in an ascending order forms arohana of that raga and notes of a raga arranged in a descending order forms avarohana of that raga. In Indian classical music, different notes are called swaras. Raga identification consists of techniques that identify different notes from a piece of music and therefore classify it as appropriate raga. By using our different features discussed further, we have tried to achieve new heights.

1.1. LITERATURE SURVEY

In existing systems, work to date has been done on the basis of a static level using the characteristics of raga. Raga is identified on the basis of its fundamental characteristics: Arohana-Avarohana, Pakad, Gamakas, Swara Choice, Vadi, Time and Season, etc. These characteristics help to analyze and frame different computational techniques for the identification of raga. Pandey et.a.[2]. It provides approximately 70 percent-80 percent accuracy with respect to the ML algorithm data set. Also, these methods are not real tome methods.

A brief introduction to raga is being discussed. Characteristics of raga that make them sufficient to be distinguishable from each other. Different techniques are better than other techniques depending on the input parameters and the restriction on the input and the method. Limited database containing a limited number of ragas. Incorrect extraction of pitch. Manual detection of tonic. Assumption has been made for different algorithm parameters. Various restrictions on inputs, such as limitation on singers, number of swaras, length of time, monophonic type. No machine learning techniques have been used[1]. Note on this Prefer method, which is independent of input parameters. Provide a large amount of dataset to obtain a better and more accurate result.

Try to combine 2 techniques, n-gram & pitch-class profiles in order to get a better result than other classical methods. Comp-Music dataset and our own dataset show that the combination of pitch-class profiles and n-gram histograms actually improves performance. The best accuracy of our approach is 83.39 per cent. It is limited to only 4 to 5 ragas. There are problems with the classifiers and the pitch profile class. The combination of male and female voice as well as many other instruments may affect the accuracy of the result[2]. Remark on this paper uses combinations of techniques that provide better results and accuracy than conventional methods. The combination of different voices and instruments may lead to a wrong result.

Incorrect extraction of pitch. Manual detection of tonic. Assumption has been made for different algorithm parameters. Various restrictions on inputs, such as limitation on singers, number of swaras, length of time, monophonic type. There are no machine learning techniques used. Only the static work is done through identification[3]. Remark on this paper is the lack of a database and the incorrect extraction of features results in an incorrect result. Machine learning is going to provide a better result. Assumption could go wrong.

Using a classifier, we can identify raga, so that we can correlate this raga with its respective rasa to identify emotions in music. For a better result, more comprehensive dataset is needed for the K-NN classifier. We can only get approximate values by using soft computing techniques such as fuzzy logic. The SVM classifier is difficult to handle scale and multiple instruments. K-NN may cause problems with gammakas and pitch extraction. Classifier of Naïve Bayes, the identification of raga is very difficult and gives less accuracy[7]. Remark on this paper is that soft computing techniques are used to archive results. The classifiers used have limitations on the results and the extracting features.

The algorithms used give the most accurate result for two types of ragas. The system needs to be improved with the Hidden Markov model. Based approach where we combine the features of low levels. And HMM for better and more accurate identification. Singers and audios are only specific and limited. Limited test data may lead to a misleading decision. This one. The basic disadvantage of the system is the assumption of the fundamental frequency and therefore the determination of the fundamental frequency is our next task[8]. Review of this paper is a new "Hidden Markov" method used to improve the outcome. The result is limited by different singers and styles. Fundamental frequencies are considered as one of the disadvantages due to inaccuracy.

1.2. PROBLEM DEFINITION

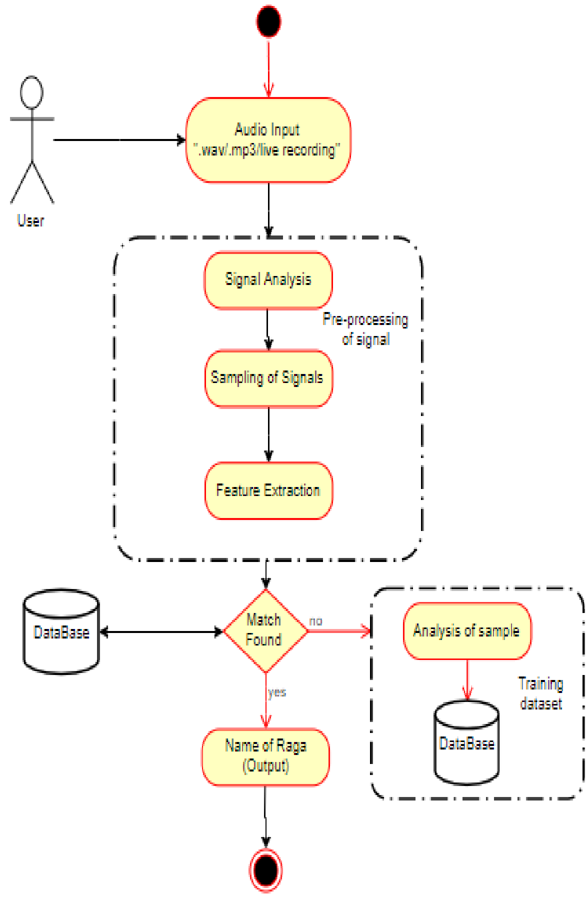
It is quite difficult to identify ragas in Indian classical music. Since it has several features and parameters, it is not easy to recognize ragas in music. The identity of each raga varies, and each has its own speciality that needs to be maintained. In addition, Hindustani music is highly improvised as a performer enjoys full freedom for any raga movement that leads to misclassification errors.

2. PROPOSED SYSTEM

We have proposed a system where we use one supervised and one unsupervised algorithm for more accuracy. In music, chroma features or chromagrams are closely related to the twelve different pitch classes. It is also referred to as "pitch class profiles" which is a powerful tool for analyzing music, the pitches of which can be meaningfully categorized and the tuning of which is approximate to an equal-tempered scale. We also chose chroma features due to its properties of capturing harmonic and melodic characteristics while being robust to changes in timbre and instrumentation.

2.1. WORKFLOW

Fig. 2.1: workflow of proposed system



2.2. IMPLEMENTATION METHODS

As discussed in Fig. 2.1. Methodology will also be applied in the same way. The same approach will be taken to complete the project.

1. First, we will create an input module, which will accept approximately. 30s input audio file of the ".wav" format.
2. Signal pre-processing: The input accepted by the user will be pre-processed in this block.
a. Signal analysis: In this step, the input signal will be analyzed. Signal analysis will be done using Librosa.
b. Signal sampling: during sampling, the signal is divided into segments and the study of each sample will be performed for the extraction of the feature.
c. Feature extraction: Extraction of features means that the specialty or pattern that is repeated in that signal

will be observed and extracted as a feature. It will help to distinguish between different ragas, as each raga has its own characteristics and the pattern through which it is identified.

3. After extracting the features, each feature is stored as a database.
4. Created Convolutional Neural Network for Machine Training.
5. Then we'll send this database to the machine learning algorithm. Until now, we're working on the K-NN classifier. The SVM algorithm letter will be programmed.

A database will be created to train and test algorithms and to test the work of the classifier. Of which 80 percent is for training and 20 percent is for testing. And on the basis of that, the prediction will be made.

2.3. RESULT AND DISCUSSION

As we extracted various input signal features, which are stored in.csv file format using python with the help of pandas. In this project, we used two different types of ragas: Bhimpalasi and Yaman. The result of the features is shown in the graphs below, which work as indicated in the fourth chapter of this report. This feature provides time vs. frequency graph and provides data. The results of all the extracted features are shown below:

Chroma_cens: This feature sets the frame for twelve chorma bands. It is closely related to the melodic and harmonic progression. This progression is often similar for different recordings of the same piece of music and makes it suitable for matching tasks.

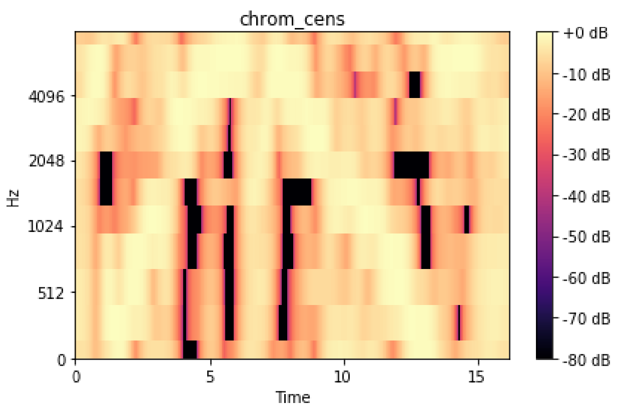


Fig. 2.3.1: Result of chroma_cens

Chroma_cqt: This feature converts a data series to a frequency domain. It is related to the fourier transformation and very closely related to the complex transformation of the Morlet wavelet. And transform is the fk series of filters, logarithmically spaced in frequency, with the k-th filter having spectral width equal to a multiple of the width of the previous filter.

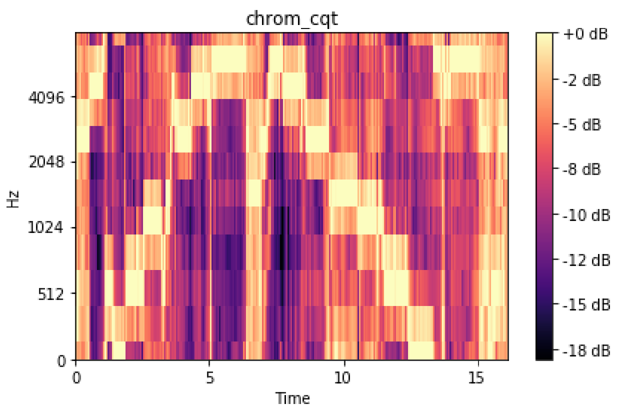


Fig: 2.3.2: Result of chroma_cqt

Chroma_stft: This feature is a Fourier-related transform used to determine the sinusoidal frequency and phase content of the local signal sections as it changes over time, in support of previously extracted features for more accurate data file details (i.e. audio time series).

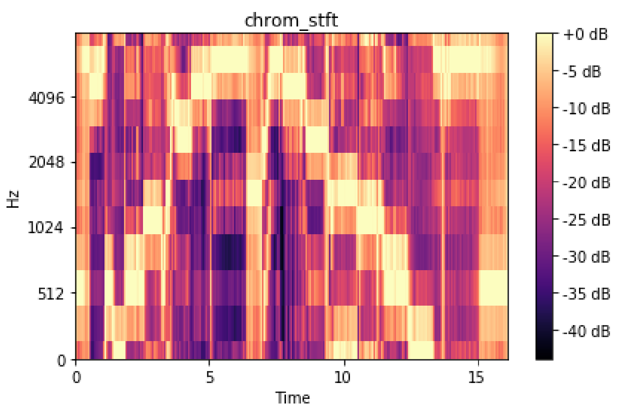


Fig. 2.3.3: Result of chroma_stft

Mel Spectrogram: This feature is used for frequencies where the frequency is converted to the mel scale. It is used to support the MFCC feature and also to visualize 3D wave frequencies at different times.

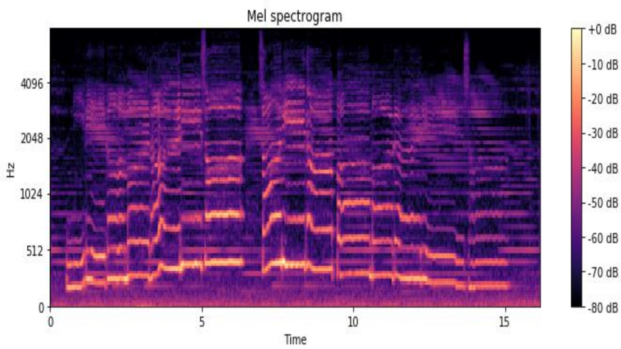


Fig. 2.3.4: Result of Mel Spectrum

Mfcc: This feature is used for frequencies where the frequency is converted to the mel scale. It is used to support the MFCC feature and also to visualize 3D wave frequencies at different times.

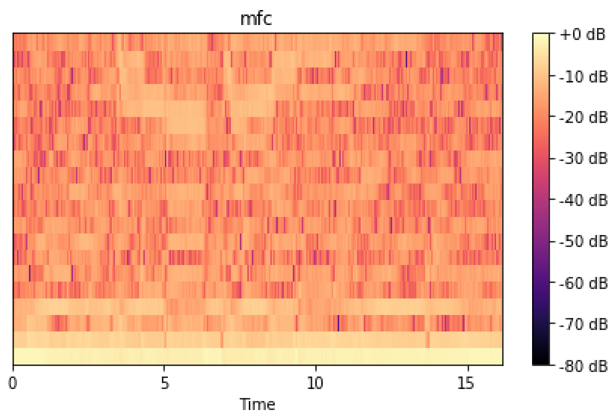


Fig. 2.3.5 Result of Mfcc

Zero Crossing: It is a point where the sign of a mathematical function changes (e.g. from positive to negative), represented by an axis intercept (zero value) in the function graph. It is a term commonly used in electronics, mathematics, acoustics and image processing. Used for music recognition and retrieval of information.

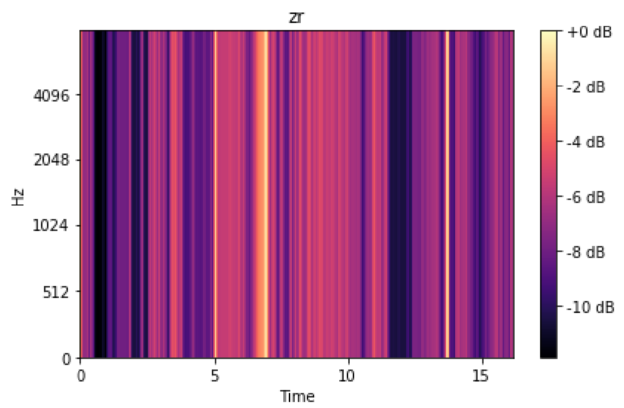


Fig. 2.3.6: Result of Zero Crossing

After the feature extraction has been completed, these features are stored in the "features.csv" file for the K-NN and SVM algorithms with the help of CNN. The result of the train and test set of both algorithms is shown in the following graphs:

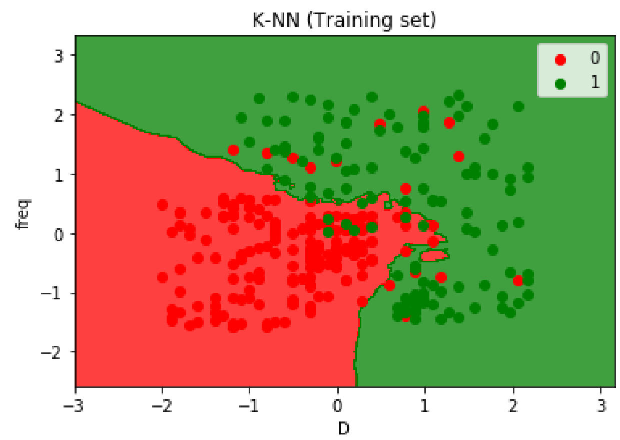


Fig. 2.3.7(a): Result of K-NN Training Set

The same is true for the test, as in the graph, with 89 percent accuracy. As shown in the graph shown here:

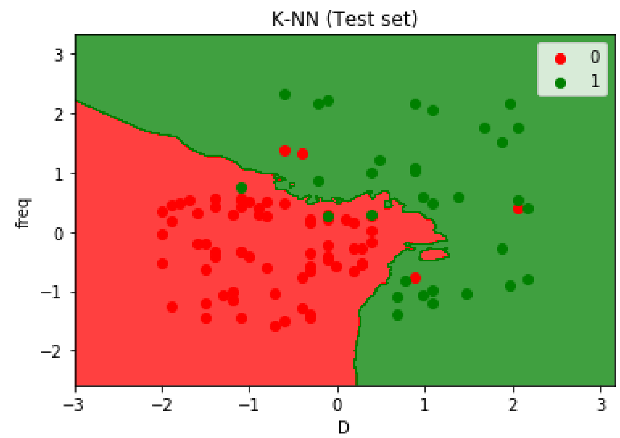


Fig. 2.3.7(b): Result of K-NN Test Set

So we can conclude that avg as a result. The accuracy of the model is 90% for this K-NN algorithm with Bhimpalasa raga.

For raga Yaman, the result of the SVM algorithm is represented in the graph as shown below with 92 percent accuracy:

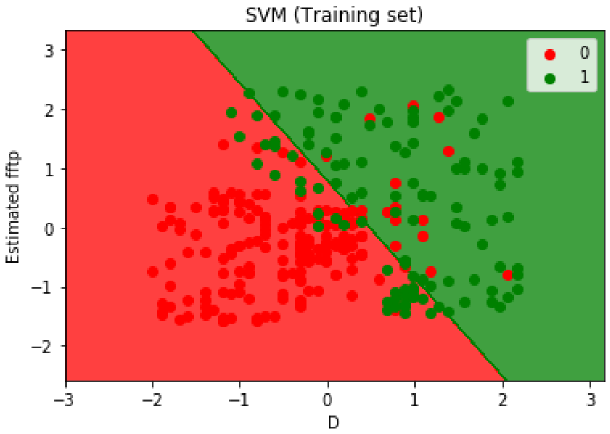


Fig. 2.3.8(a): Result of SVM Training Set

And the same was true for the test, as in the graph, with 94 percent accuracy. As shown in the graph shown here:

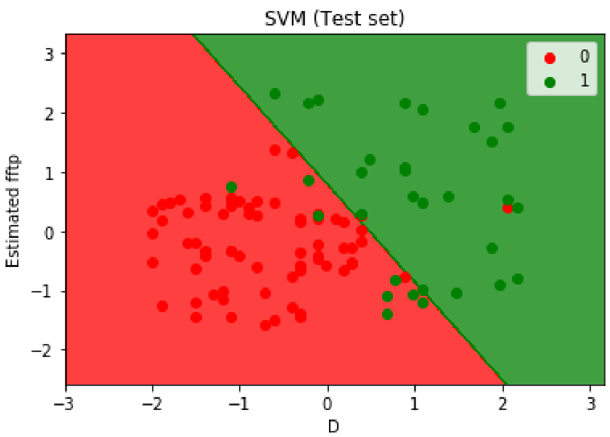


Fig. 2.3.8(b): Result of SVM Test Set

So we can conclude that avg as a result. Model accuracy is 93 percent for this K-NN algorithm with Yaman raga.

We discussed the result of both the different ragas algorithm and future work can be done. As we all know, the future is about advanced technology, and the need for software and technology will be higher for automation. Music business has also begun to use technology to provide user suggestions based on their mood, etc. Our project will help to distinguish between different types of music between different instruments / vocals, which will help people to identify and easily analyze new music areas.

3. CONCLUSION

A brief introduction to raga and its characteristics is discussed. Previous techniques for the identification of raga are investigated with their data set, details of the implementation method, accuracy and issues. Techniques differ from one another with differences in their data set, method of implementation, parameters, accuracy and limitations. Different techniques are better than other techniques depending on the input parameters and the restriction on the input and the method. We assessed and compared two machine learning classifiers on the standardized ragas dataset, namely SVM & KNN, with 93 percent accuracy. Well-defined rules, a musician, whether a vocal or an instrumental performer, never follows these rules exactly. In addition, Hindustani music is highly improvised as a performer enjoys full freedom for any raga movement that leads to misclassification errors. Fluctuations in human voice while performing live are taken into account and this has affected the accuracy of our work.

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