Taal Recognition of North Indian Classical Music: A Data Mining Approach

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***Abstract*—Computational musicology is an interdisciplinary area in which computational methods are used to analyze musical structures: notes, chords, rhythms, and patterns thereof. While western classical music is extensively explored, North Indian classical music still remains to be explored computationally. Recognition of their rhythmic structures is important as it serves in a multitude of applications e.g., intelligent music archival, enhanced navigation and retrieval of music, and informed music listening. Rhythm in North Indian classical music revolves around the theme of *Taal* - the cycle of beats of specific syllables and beats. The main aim of the proposed study is to apply data mining for the recognition of *Taal* in North Indian classical music. In this study, acoustic features pertaining to rhythm were extracted using MATLAB MIRToolbox. Support Vector Machine, Naive Bayes, Decision Tree, Random Forest and k-Nearest Neighbor classifiers were applied on extracted features. Among these classifiers, Decision Tree obtained an accuracy of 51.61% and Naïve Bayes obtained an accuracy of 64.16% with cross-validation. The findings of the study are limited by the consideration of a smaller dataset, but the study would make a promising contribution through computationally exploring rhythmic patterns of a great music tradition.**

Keywords—Taal Recognition, Computational Musicology, North Indian Music

I. Introduction

Music plays a vital role in our day-to-day life especially in today's digital age. With music going digital, there are large and growing collections of music available to users on demand, requiring novel ways for structuring these collections automatically using different dimensions of music. Recognition of rhythmic structures and patterns of North Indian classical music is important hence it has a large audience and significant musicological literature [5].

Rhythm in North Indian classical music revolves around the theme of *Taal* - the cycle of beats of specific syllables and beats. *Taal* is the most basic information for listeners to follow the rhythmic structure of music [6]. A *Taal* has fixed-length cycles, each of which is called an *avar*t. An *avart* is divided into equal basic time units called *matra*. The *matras* of a *taal* are grouped into sections, sometimes with unequal time-spans, called the *vibhags*. *Vibhags* are indicated through the hand gestures of a *thali* (clap) and a *khali* (wave). The first *matra* of an *avart* (the downbeat) is referred to as *sam*, marking the end of the previous cycle and the beginning of the next cycle [3].

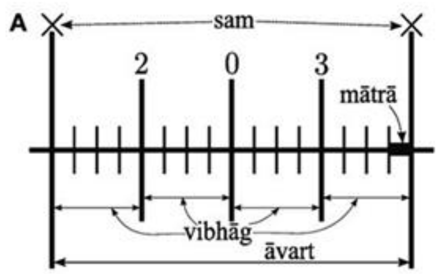

Fig. 1. An avart of a popular tal, showing the matras(all time ticks),

There are over 70 different Hindustani *Taals* defined, but in this study, we mainly focus on only 4 *Taals.* They are *teentaal*, *ektaal*, *jhaptaal*, and *rupak.*

Table 1: Matra, Vibhag, and Matra Grouping of the Four Taals considered in the Study

Taal	Matras	Vibhag	Matra Grouping
Teentaal	16	4	4+4+4+4
Ektaal	12	6	2+2+2+2+2+2
Jhaptaal	10	4	2+3+2+3
Rupak	7	3	3+2+2

Major Research Questions

a) What are the frequently used data mining algorithms for *Taal* recognition?

b) What are the most effective acoustic features pertaining to rhythm in *Taal* recognition?

c) How to develop a data mining-based model for *Taal* recognition with a higher accuracy compared to the existing models?

Rhythmic analysis is the study of how music works andhow it is structured organized and generated in time. It is the study of the most fundamental aspects of music, and tells us not only about the music but about the culture which produces that music, about the importance of universal and culturally specific factors in music, and ultimately about how music may represent our knowledge of the world.

II. Objectives

North Indian classical music has evolved into a complex but established music system over the years and it is one of the most rhythmically sophisticated in the world. Even though various attempts are made to computationally analyze its rhythmic structure, this sophistication calls further

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advanced methods. Hindustani music therefore can be considered as an ideal subject for computational analysis. Accordingly, the main objective of this research was to present a data mining approach for *Taal* recognition of North Indian classical music. The specific objectives were to review the frequently used data mining algorithms for *Taal* recognition, to review the most effective acoustic features pertaining to rhythm in *Taal* recognition, and to develop a data mining model for *Taal* recognition with an improved accuracy over the existing models.

III. METHODOLOGY

A. *Tools and Resources*

The literature reveals that there are number of audio feature extraction tools that have been used in previous music classification studies. Among them, MIRtoolbox, marsyasand psySound are the most commonly used tools [1,2]. This study employed the Matlab MIRtoolbox version 1.7.2 to extract the rhythmic acoustic features. For the scientific calculation process Jupyter Notebook development environments were used with python language to train and test the classifiers.

A dataset consisting of 151 excerpts (2mins; 44.1 kHz; stereo; .wav) obtained from CompMusic Hindustani test corpus, operated by the Music Technology Group of the Universitat Pompeu Fabra (UPF) in Barcelona, Spain[4] was used in the study. belonging to four popular *Taals*: namely *Tintal, Ektal, Jhaptal, Rupak Tal.* For each *Taal*, there are excerpts in three *Layas* namely Vilambit (slow), Madhya (Medium), Drut (Fast).

B. *Feature Extraction (Using Matlab MIRToolbox)*

Music acoustic feature extraction is the most important part in this study to influence the rest of the experiments. In order to train the machine classifier by supervised learning, eight rhythmic acoustic features were obtained from MATLAB MIRToolbox by using various dimensional features methods that are already defined by the toolbox.

Table 2: Extracted Features were Used in This Work; STD = Standard Deviation, M = Mean

Features	**Used Method(MIRtoolbox)**
Tempo M	*mirtempo()*
Fluctuation M	*mirfluctuation()*
Onsetcurve(Envelope)_PeakPos M	*mironsets()*
Onsetcurve(Envelope)_PeakMag M	*mironsets()*
Event density M	*mireventdensity()*
Metrical Centroid M	*mirmetroid()*
Metrical Centroid STD	*mirmetroid()*
Pulse clarity M	*mirpulseclarity()*

C. *Rhythmic Analysis (Taal Recognition)*

As shown in Figure 2, the initial stage describes the process of audio preprocessing. Under this stage another process was carried out and known as music feature engineering, which includes acoustic feature extraction from music segments using the MIRtoolbox mirexport method. In the next Stage, training and testing data were formed from the major dataset in order to train and test classifiers. Five standard classifiers were used for experiments which were identified as frequently used classifiers in previous studies which were Support Vector Machine (SVM), k-Nearest Neighbor, Naïve Baise, Decision Tree and Random Forest. Supervised learning is usually done with independent training and testing datasets and therefore the dataset (151 music excerpts) was split as 80% for training and 20% for testing. Then the classifiers were evaluated by its corresponding testing data set and the best classifiers were identified based on the measurements:precision, recall, and f-measure.

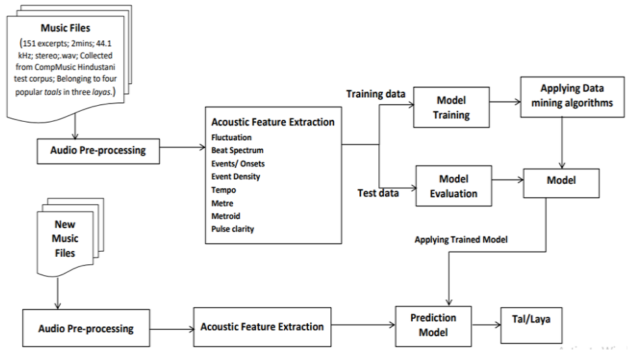

Fig. 2: Overall Taal Recognition Process

IV. RESULTS AND DISCUSSION

The following results were obtained from the classifiers as shown in Table 3.

Table 3: Results of the Taal Recognition (SVM-Support Vector Machine, NB-Naïve Baise, KNN-K-Nearest Neighbour, DT-Decision Tree, RF-Random Forest,

Classification Algorithms	Evaluation Metrics			Accuracy
	Precision	Recall	F1-Score	
SVM	50%	48%	49%	48.38%
NB	43%	48%	43%	48.38%
RF	44%	35%	35%	35.48%
DT	51%	52%	51%	51.61%
KNN	42%	39%	38%	38.70%

Decision Tree (DT) classifier achieved the best results yielding precision, recall, and F-measure values of 51%, 52%, and 51% respectively. Further the results shows that Naïve Bayes (NB) and Support Vector Machine (SVM) classifiers yield the next highest accuracy value which is 48.38% However, comparing the ultimate results of the Taal recognition , DT was identified to be outperforming the other classifiers yielding an accuracy of 51.61%.

The experiment was continued to evaluate the performance of classification using 5-fold cross validation. Apart from the conventional training and testing approach, cross validation randomly partitions the dataset into 5 (5-fold) equal sized subsamples. Thereafter each fold splits the dataset in training and testing with randomly selected data. After the training, the testing is performed using test data. Likewise, the training and testing processes are repeated until every 5-fold serves as the test data. The accuracy is returned for five folds and finally the averages of all 5 accuracies are calculated in each and every iteration. Table 4 shows the performance of classifiers with cross validation. According to the previous approach DT was identified as the best classifier. However, after the cross validation, NB was returned as the classifier with highest accuracy (64.16%). Therefore, the final prediction model was developed using the NB classification algorithm.

Table 4: Cross validation result of Classifiers ((SVM-Support Vector Machine, NB-Naïve Baise, KNN-KNearest Neighbour, DT-Decision Tree, RF-Random Forest))

	SVM	KNN	NB	DT	RF
1st	58.33%	37.50%	45.83%	41.66%	26.66%
2nd	66.66%	54.16%	70.83%	54.16%	60.80%
3rd	58.33%	41.66%	70.83%	41.66%	48.09%
4th	45.83%	54.16%	62.50%	50.00%	75.78%
5th	70.83%	62.50%	70.83%	50.00%	61.51%
Mean	60.00%	50%	64.16%	47.50%	43.90%

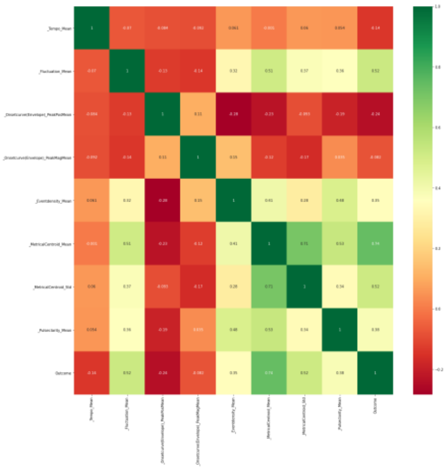

Fig. 3: Correlation Metrics Among all the features

In order to further enhance the accuracy of the prediction model, the study used correlation metrics method and the statistical relationship between the selected 8 features were identified as shown in Figure 3. Accordingly, the top six highly correlated features (Fluctuation, Onset curve (Envelope) PeakPos, Event density, Metrical Centroid, Metrical Centroid STD, Pulse clarity) were considered which led to an enhanced classification performance of60.83% with both SVM and NB classifiers.

V. CONCLUSION

Summing up the results of literature review, computational analysis of rhythm in North Indian Classical music warrants further attention and existing research can be further improved to enhance the classification accuracy. Accordingly, the ultimate goal of this study was to classify and verify the rhythmic structure of music associated with Taal in North Indian Classical Music. An evaluation of five supervised learning classification algorithms was made on a collection of 151 music stimuli which belongs to four popular Hindustani Taals namely,Teentaal, Ektaal, Jhaptaal and Rupak. Among them five classifiers, Decision Tree yielded the highest accuracy. However after cross validation, a higher accuracy could be obtained using NB classifier. The performance of this classifier could be further improved when considered only the six most influential features from among the initial eight features. The resulting improvements in the accuracy levels indicates that we can consider those features for the final prediction model. Even though the findings of the study are limited by the consideration of a smaller dataset, it is believed that the study would make a significant contribution through attempting to computationally explore rhythmic patterns of a great music tradition.

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