A COMPARATIVE STUDY OF INDIAN AND WESTERN MUSIC FORMS

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ABSTRACT

Music in India has very ancient roots. Indian classical music is considered to be one of the oldest musical traditions in the world but compared to Western music very little work has been done in the areas of genre recognition, classification, automatic tagging, comparative studies etc. In this work, we investigate the structural differences between Indian and Western music forms and compare the two forms of music in terms of harmony, rhythm, microtones, timbre and other spectral features. To capture the temporal and static structure of the spectrogram, we form a set of global and local frame-wise features for 5- genres of each music form. We then apply Adaboost classification and GMM based Hidden Markov Models for four types of feature sets and observe that Indian Music performs better as compared to Western Music. We have achieved a best accuracy of 98.0% and 77.5% for Indian and Western musical genres respectively. Our comparative analysis indicates that features that work well with one form of music may not necessarily perform well with the other form. The results obtained on Indian Music Genres are better than the previous state-of-the-art.

1. INTRODUCTION

Due to technology advances the size of digital music collections have increased making it difficult to navigate such collections. Music content is very often described by its genre [1], though the definition of genre may differ based on culture, musicians and other factors. Considerable analysis has been done on western music for genre classification [2] [3] and content analysis [4].

Although, Indian music, especially classical music, is considered to be one of the oldest musical traditions in the world, not much computational analytical work has been done in this area. Indian music can be divided into two broad categories *classical* and *popular*. Classical music has two main variants *Hindustani classical* prevalent largely in north and central India and *Carnatic classical* prevalent largely in the south of India. Each variety has multiple genres. For example *Hindustani* music has *Dhrupad, Khayal, Tarana* as classical genres and *Thumri, Dadra, Tappa, Bhajan* as semi-classical genres - amongst others. Popular music has multiple folk genres based on region, film music and *adhunik* or modern music which is influenced by multiple Indian and western genres.

At the base of classical and semi-classical Indian music is a *raga(s)* which is described as a mood or sentiment expressed by a microtonal scale form [28]. A *raga* can be sung in many Indian genres like Dhrupad, Khayal, Thumri etc with its corresponding microtonal scale based on a natural harmonic series. Popular Indian music, on the other hand, is not necessarily based on *ragas* and can have tonal elements that can differ from the traditionally accepted classical norms. Almost all Indian music is based on melody - single notes played in a given order. Western music has strong harmonic content i.e. a group of notes called chords played simultaneously. Unlike Indian tonal system, the Western tonal system is divided into twelve equal intervals. Each Indian genre has its own well-defined structure which makes it different from other forms of music. To capture the inherent structure of Indian music and use it for genre classification is a challenging problem. Through our work we try to explore this area and focus on the following research questions:

- What are the structural differences between Indian and Western musical forms?
- How well can the audio features used for genre classification in Western music, capture the characteristics of Indian genres?
- Is there a feature set that can be used for cross-cultural music genre classification? In this case, for Indian and Western music.

2. RELEVANT WORK

2.1 Study on Genre classification by humans

Research has been done on the human ability to classify music genres. Perrot et al. [16](1999) reported that humans with little musical training were able to classify genres with an accuracy of about 72% on a ten-genre dataset of a music company, based on only 300 milliseconds of audio. Soltau (1997) conducted a Turing-test in which he trained 37 people to distinguish rock from pop music and found

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that his automatic music classifier was similar to their performance on the same dataset. Lippens et al. [15](2004) conducted an experiment with six genres and observed that people were able to classify with an accuracy of around 90%. Considerable work has been done in the area of automatic music genre classification and with increasing improvement in classification methods there is a distinct possibility that they may outperform humans in the near future.

2.2 Genre classification of Western Music

Many supervised and unsupervised methods have been used to automatically classify recordings into genres. Commonly used supervised classification methods are k-nearest Neighbours (KNN) [5] [17], Support Vector Machines (SVMs) [19] [17], Gaussian Mixture Models (GMMs) [5] [20] [17], Linear Discriminant Analysis (LDA) [17] [18], non-negative Matrix Factorization (NMF) [2], Artificial Neural Networks (ANNs) and Hidden Markov Models (HMMs). In the unsupervised domain, there is work using the k-means approach and hierarchical clustering.

To the best of our knowledge, there is no work in the literature that analyses which features are best for music genre classification. There is work using Fourier analysis, cepstral analysis and wavelet analysis [17] [24]. Li et al. [17] and J. Bergstra et al. [3] worked with a set of parameters like spectral centroid, spectral rolloff, spectral flux, zero crossings and low energy. Y.Panagakis et al. [25] used sparse representation-based classifiers on audio temporal modulations of songs for genre classification. Salamon et al. [26] used a combination of low level features with high level melodic features derived from pitch contours and showed that the combination outperforms the results from using only low level features.

Tzanetakis et al. [5] proposed to classify musical genres using K -Nearest Neighbours and GMMs based on timbral texture and rhythmic features. E. Benetos et al. [2] used non-negative tensor factorization (NTF) with GTZAN data set [5]. J. Bergstra et al. [3] used GMM based Adaboost classification with aggregate features dividing frames into segments. Hidden Markov Models were used by T. Langlois et al. [10] for genre classification based on timbre information.

2.3 Genre classification of Indian Music

Compared to western music very little work has been done in Indian musical genre classification. S.Jothilakshmi et al. [12] used kNN and GMM on spectral and perceptual features and achieved an accuracy of 91.23% with 5 Indian genres- Hindustani, Carnatic, Ghazal, Folk and Indian western. P. Chordia et al. [13] used pitch profiles and Pitch-Class Distributions for *raga* identification. A. Vidwans et al. [14] extracted melodic contours to classify Indian classical vocals. They also performed a listening test in which around 85% samples were correctly identified by people without any training.

2.4 Contributions of the paper

There is no study, to the best of our knowledge, that compares classification of Indian musical genres with Western musical genres. Our work makes the following contributions: first, this paper introduces a new research problem on cross-cultural music genre classification by doing a comparative study on Indian and Western musical forms in terms of their structure and characteristics. Second, while there are many standard datasets on genre classification available for Western music like GTZAN dataset [5], 2005 MIREX dataset, Magnatune [21], USPOP [22] etc. There is no standard dataset for Indian genre classification. For our study, we built a dataset of 5 Indian genres- Dhrupad, Thumri, Carnatic, Punjabi and Ghazals. There are 100 samples in each genre where each sample is an audio clip of 30 seconds length. This dataset can be used for future work on Indian music genre classification. Third, we have incorporated short-time and long-time features to capture the static and temporal structure of the spectrogram and have analysed both cultural forms. Fourth, we propose a novel approach of using timbre and chromagram features with Gaussian Mixture Models(GMM) based Hidden Markov Models to identify the patterns in Indian music which gave an overall accuracy of 98.0%, which is better than the previous state-of-the-art [12] which also worked with 5-genres.

2.5 Outline of Paper

In section 3 we discuss the dataset used for the experiments and the structure and characteristics that make an Indian genre distinct from other genres. Sections 4 and 5 give a detailed explanation of the features chosen and classifiers used. Section 6 discusses the experimental results. Section 7 outlines possible future work.

3. DATASET

In this section, we look at the structural differences between Indian and Western music forms and discuss the characteristic features of the Indian genres used in the experiment.

3.1 Indian Music

For the experiments we have considered five popular genres - Hindustani (Dhrupad + Thumri), Carnatic, Folk (Punjabi) and Ghazal. We constructed our own dataset because no standard dataset is available. Each genre contains 100 audio recordings each 30 seconds long extracted randomly from recordings available on-line. All samples are vocals.

3.1.1 Indian classical Music

Indian classical music is based on melody without the presence of any major harmonic structure. It has seven basic notes with five interspersed half- notes, resulting in a 12-note scale. In Indian music any frequency can be set as the base frequency, known as *swara*(note) 'Sa' with other notes taking frequency values following their fixed ratios with respect to Sa. Indian classical music has three important characteristics- *raga* (melodic aspect of music) and *taal* (cycle of fixed number of beats repeated over and over as shown in Figure 1) and a *drone*(a sustained note). Indian popular music have the the melodic (though not *raga*) and *taal/beat* components but do not usually have the *drone*.

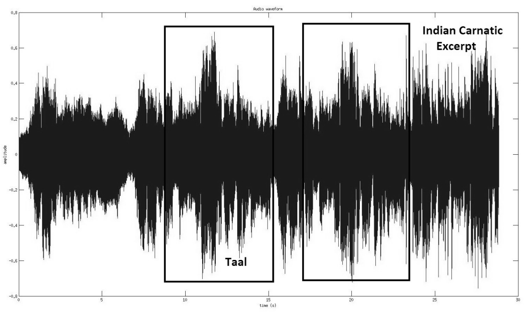

Figure 1. Repetition of beats *(taal)* in Indian Classical

Dhrupad: Dhrupad is a very old form of Hindustani music that is primarily devotional in content. It has two major parts- Alap (sung without words) and Dhrupad (fixed composition part) accompanied by Pakhawaj, a two headed barrel drum. A performance begins slowly with alap where usually the syllables of the following mantra is recited: *"Om Anant tam Taran Tarini Twam Hari Om Narayan Anant Hari Om Narayan"*. In alap an artist develops each note and uncovers the personality of the chosen raga. The tempo gradually increases and an alap ends after exploring three octaves. Then begins the dhrupad in which the artist is joined by the Pakhawaj. It is usually set to the following *talas/taal*: tala chautal (12 beats), tivra (7 beats), sulfak (10 beats), matt (9 beats), or farodast (14 beats). In the dataset samples were extracted from dhrupad performances where about 25% of them were by female artists.

Thumri: Thumri is a semi-classical form of Hindustani music which is romantic and devotional in nature. The text revolves around a girl's love for Lord Krishna. The lyrics are written in dialects of Hindi called Awadhi and Brij Bhasha. Thumri has greater flexibility and more liberties are taken with the raga as compared to Dhrupad or Khayal. The compositions are usually of 8 beats (*kaherava*), 14 beats (*dipchandi*) or of 16 beats (*addha tala*). Samples were extracted from 10 Thumri performances where 3 were by female artists.

Carnatic: Carnatic music is the classical music of Southern India. Like Hindustani music, it is based on ragas and *taals*. Performances in Carnatic music are divided into a number of sections. It starts with a *varanam*, literally meaning "a description", which unfolds the important features of the raga being performed. Then comes the fixed composition in the raga, known as *kritis*. The main composition is *alapana*, which explores the raga and uses the sounds like aa, ri, na, ta etc to elaborate the notes. This starts slowly and finally builds a complicated exposition of the raga without any rhythmic accompaniment. There are *niruval* and *kalpana* swara(notes) that provide opportunities to improvise. In the dataset, about 55% of the samples are sung by female singers.

Hindustani and Carnatic music differs mainly in the following characteristics-

- Hindustani music like Dhrupad gradually builds up tempo from very slow to very fast while in Carnatic music there is a constant and fairly fast tempo throughout.
- In Hindustani music notes are held longer and are mostly approached and released by ornaments or small ornamental phrases whereas in Carnatic music notes are not held for long and usually released by a characteristic oscillation using indeterminate pitch.
- Hindustani music has more improvisation around the *raga* unlike Carnatic which has a some what more rigid structure and is composition based.

3.1.2 Folk- Punjabi

Punjabi music has a smaller range which seldom extends beyond an octave. It is accompanied by a lively rhythm (*chaal*) and is usually based on *kaherava taal*, a cycle of eight beats. Greater emphasis of the music is on the lyrical nature of the songs. The characteristic which makes it different from other music forms is the use of *Dhol*- a barrel shaped drum that gives a bass sound. Samples are taken from *Folk N Duet 2010* Album contributed by 16 singers which includes 3 female singers.

3.1.3 Ghazal

Ghazal is defined as a poetic genre and consists of a series of rhymed verses, each symmetrically divided into two half-verses. The structure of a Ghazal is defined by its metre and rhyme which are maintained throughout the poem. Samples were extracted from ghazal performances where 19% of total pieces were sung by female singers.

3.2 Western Music

For western music we considered the GTZAN dataset [5]. It consists of 10 distinct genres- Blues, Classical, Country, Disco, Hip hop, Jazz, Metal, Pop, Reggae and Rock. Each genre is represented by 100 samples of 30 seconds length each. Since we have 5 genres for the Indian music, we considered only top 5 genres (Classical, Hiphop, Jazz, Pop and Reggae) from the GTZAN dataset based on the results of [5].

4. FEATURE EXTRACTION

For feature extraction, we used the MIRToolbox [27], an open source toolbox for musical feature extraction. For the experimental set-up we used three types of feature sets as described below:

4.1 Feature set 1- Frequency of chromagram notes

A chromagram is a redistribution of the spectrum energy along the different pitch levels (or chromas). We have considered 12 pitch classes- C, C#, D, D#, E, F, F#, G, G#, A, A# and B. We used a framesize of 100 milli-seconds with 50% overlap. The choice of a large framesize is to cover for the semitone energies in lower frequencies. For each frame, we assigned the note that has the maximum energy in the frame's 12-dimensional chromagram vector; we call this the "dominant note". The use of the dominant note in each frame captures the melodic information as the melody note is the one that typically dominates the feature. Concatenating the dominant note in each frame gave us a note sequence representing the sample. We then formed a 12-dimensional vector of the normalized frequencies (counts) of the notes in the note sequence. This feature set is motivated by the repetition of notes in Indian music and the use of chromagrams in [6] and [7].

4.2 Feature set 2- Global features

We extract a set of global features based on the main dimensions of music which includes melody, rhythm, timbre and spatial features as described in [8] [9] and [10]. We used the following features to form a vector of 86 global features-

- **Energy features**- mean and variance of the energy envelope, Root Mean Square (RMS) energy, low-energy rate(percentage of frames having less than average energy).
- **Rhythm features**- mean and variance of notes onset time (successive bursts of energy indicating estimated positions of the notes), event density (average frequency of events, i.e., the number of note onsets per second), tempo, pulse clarity [11](strength of beats).
- **Pitch features**- mean and variance of pitch.
- **Tonality features**- 12-chromagram pitch class energies, 24- key strength major and minor (cross correlation of the chromagram), 6- dimensional tonal centroid vector from the chromagram (corresponds to projection of the chords along circles of fifths, of minor thirds, and of major thirds).
- **Timbre features**- mean and variance of attack time of notes onset, rolloff frequency, brightness (percentage of energy above 1500Hz), 13 Mel-Frequency Cepstral Coefficients (MFCCs), roughness(sensory dissonance), irregularity (degree of variation of the successive peaks of the spectrum)
- **Spectral-shape features**- zero-crossing rate, spread, centroid, skewness, kurtosis, mean and variance of Inverse Fourier Transform of logarithm of spectrum, flatness, mean and variance of spectrum, mean and variance of spectral flux, mean and variance of spectrum peaks.

These features are taken to capture the static structure of the spectrogram.

4.3 Feature set 3- Frame-wise features

We analyse each song using a framesize of 100 milli seconds with 50% overlap and extract the following features: 12-chromagram features, 13 MFCC, 13 delta- MFCC, 13 delta-delta-MFCC, 11 spectral features (zero-crossing rate, rolloff, brightness, centroid, spread, skewness, kurtosis, flatness, entropy, roughness and irregularity). For the chromagram features, we first perform a logarithm transform and then a discrete cosine transform (DCT) which essentially decorrelates the features. We use these modified chromagram features with the above mentioned features to get a vector of 62 features for each frame. A sample is now represented by a 2-D matrix of size $62 \times frames$, where *frames* are the number of frames in the sample. These features carry the temporal information of the spectrogram.

5. EXPERIMENTAL RESULTS

We performed four experiments based on the above three feature sets. For each run, we randomly divided the dataset into 80% train and 20% test.

5.1 Experiment 1: Adaboost on Feature set 1

We train One-Vs-One Adaboost classifiers. A sample is assigned the class which gets the maximum votes. In case of a tie, the class with the lower index is the predicted label. Table 1 shows the confusion matrix for 10 runs of the experiment for Indian Music and Western Music. Overall the accuracies obtained for Indian Music and Western Music are 58.70% and 46.90% respectively.

Table 1. Confusion Matrix (in %) for Exp 1

(a) Indian Music

	Ca	Dh	Gh	Pu	Th
Ca	**66.50**	9.00	5.50	6.50	12.50
Dh	10.50	**64.00**	6.00	9.00	10.50
Gh	16.50	6.50	**64.50**	7.00	5.50
Pu	18.50	12.50	14.00	**47.50**	7.50
Th	19.50	6.50	13.00	10.00	**51.00**

Legend: Ca:Carnatic, Dh:Dhrupad, Gh:Ghazal, Pu:Punjabi, Th:Thumri

(b)Western Music

	Cl	Hi	Ja	Po	Re
Cl	**60.00**	8.00	13.50	12.50	6.00
Hi	3.50	**58.50**	12.00	14.00	12.00
Ja	8.50	21.00	**48.00**	13.00	9.50
Po	9.50	18.50	22.00	**32.00**	18.00
Re	14.00	17.50	16.50	16.00	**36.00**

Legend: Cl:Classical, Hi:Hip-hop, Ja:Jazz, Po:Pop, Re:Reggae

5.2 Experiment 2: Adaboost on Feature set 2

The Adaboost classification technique is used in a manner similar to Experiment 1. The confusion matrices for Indian music and Western music are shown in Table 2. The overall accuracies obtained are: Indian music- 87.30%, Western music- 74.50%.

5.3 Experiment 3: Adaboost on Feature set 1+2

Adaboost classification technique is used similar to Experiment 1. Here we take a combination of feature set 1 and feature set 2 for the training and testing. Table 3 shows the confusion matrices. The overall accuracies achieved are: Indian music- 87.80% , Western music- 77.50%.

Table 2. Confusion Matrix (in %) for Exp 2

(a) Indian Music

	Ca	Dh	Gh	Pu	Th
Ca	**89.50**	1.50	5.00	0.50	3.50
Dh	5.00	**90.00**	2.50	0	2.50
Gh	5.50	6.50	**81.00**	1.50	5.50
Pu	3.00	0	2.00	**95.00**	0
Th	10.50	5.00	3.50	0	**81.00**

Legend: Ca:Carnatic, Dh:Dhrupad, Gh:Ghazal, Pu:Punjabi, Th:Thumri

(b)Western Music

	Cl	Hi	Ja	Po	Re
Cl	**87.50**	0	10.50	0	2.00
Hi	0.50	**69.50**	0.50	14.00	15.50
Ja	9.00	2.00	**78.50**	0	10.50
Po	1.50	10.50	3.00	**74.50**	10.50
Re	4.50	18.50	4.00	10.50	**62.50**

Legend: Cl:Classical, Hi:Hip-hop, Ja:Jazz, Po:Pop, Re:Reggae

Table 3. Confusion Matrix (in %) for Exp 3

(a) Indian Music

	Ca	Dh	Gh	Pu	Th
Ca	**90.00**	1.50	4.00	0.50	4.00
Dh	4.50	**91.00**	2.00	0	2.50
Gh	6.50	5.50	**81.50**	2.00	4.50
Pu	3.00	0	2.00	**95.00**	0
Th	7.50	3.50	7.50	0	**81.50**

Legend: Ca:Carnatic, Dh:Dhrupad, Gh:Ghazal, Pu:Punjabi, Th:Thumri

(b)Western Music

	Cl	Hi	Ja	Po	Re
Cl	**90.50**	0	9.00	0.50	0
Hi	0.50	**79.00**	1.00	12.50	7.00
Ja	10.50	2.00	**78.00**	0.50	9.00
Po	0.50	15.00	1.50	**72.50**	10.50
Re	3.50	11.50	9.50	8.00	**67.50**

Legend: Cl:Classical, Hi:Hip-hop, Ja:Jazz, Po:Pop, Re:Reggae

5.4 Experiment 4: HMM with GMM based on Feature set 3

We train Hidden Markov Models on Feature set 3 with 62 hidden states and full covariance matrix. The emissions of all states were randomly initialized and the states need not represent exactly the underlying feature. The algorithms uses maximum likelihood parameter estimation using Expectation Maximization. The state emissions were 62 dimensional chroma and timbre data modelled by Gaussian mixtures with 8 Gaussians. We used the Hidden Markov Model Toolbox of Matlab by [23] for the same. The confusion matrix for Indian music and Western music are shown in Table 4. Overall accuracies of 98.00% and 67.00% were obtained for Indian and Western music respectively.

6. DISCUSSION

Our experiments performed better on Indian music than on Western music for given classification techniques and sets of features (Figure 2). The differences in performance of the two cultural forms of music can perhaps be traced to the more well-defined structural form and strong melodic content of Indian Music. In Indian music, melody and rhythm

Table 4. Confusion Matrix (in %) for Exp 4

(a) Indian Music

	Ca	Dh	Gh	Pu	Th
Ca	**95.00**	0	3.00	2.00	0
Dh	0	**99.00**	1.00	0	0
Gh	1.00	0	**98.50**	0.50	0
Pu	0	0.500	0	**99.50**	0
Th	1.00	0	1.00	0	**98.00**

Legend: Ca:Carnatic, Dh:Dhrupad, Gh:Ghazal, Pu:Punjabi, Th:Thumri

(b)Western Music

	Cl	Hi	Ja	Po	Re
Cl	**85.00**	0	10.00	0	5.00
Hi	0	**75.00**	5.00	15.00	5.00
Ja	25.00	15.00	**55.00**	5.00	0
Po	0	20.00	5.00	**65.00**	10.00
Re	0	15.00	0	30.00	**55.00**

Legend: Cl:Classical, Hi:Hip-hop, Ja:Jazz, Po:Pop, Re:Reggae

offer a variety of cues that do not seem to be present in Western music.

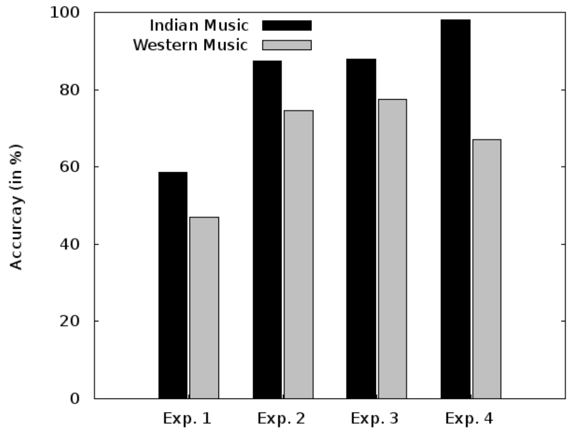

Figure 2. Comparison of performance of Indian and Western Genres on four experiments

The better performance of Indian music over Western music on similar experiments answers the second question of our research problem which suggests that the state-of-the-art features (spectral, timbre, harmony etc) used for Western music genre classification can be applied to Indian music where they show higher accuracies.

In Indian music, the classical forms (Carnatic and Dhrupad) performed better than Ghazal. This is may be because the Indian classical music is more structured as it has 3 components of *raga* (melody), *taal* (rhythm) and *drone* (sustained note) and has a strong melodic structure. In last three experiments Punjabi music has lowest confusion because its two characteristics features: lively rhythm and distinct timbre due to bass sound produced by *Dhol*; are accounted for in features used. In Western music, Classical and Jazz performed better than other genres, with Reggae performing the worst. These results are consistent with G.Tzanetakis et al. [5].

Performance on Feature set 1 (which is just based on the frequency of chromagram notes) for Indian music and

Western music is about 59% and 47% respectively. This is expected as the Indian music is based on melody, i.e. a sequence of notes played in a given order. Whereas, the Western music is more harmonic in nature, i.e. group of notes played simultaneously, which is not captured by a single dominant note in Feature set 1.

In Feature set 2 we have used the 12-chromagram pitch class energies which tries to capture the dominance order of notes. The dominance order of notes is also represented by the frequency of chromagram notes in Feature set 1. Thus, there is no significant difference in accuracies of Experiment 2 (using Feature set 2) and Experiment 3 (using Feature set 1+2).

The highest accuracy of 98.0% for Indian music genres in Experiment 4 is better than S.Jothilakshmi et al. [12] and the state-of-the-art to the best of our knowledge. The major difference in accuracies between local frame-wise features and global features in case of Indian music may be because the local frame-wise features are better in capturing the characteristics of Indian music like raga notes and *taal* (repetition of beats) which require small size windows to be analysed. An accuracy of 77.5% for Western music genres in Experiment 3 is better than G.Tzanetakis et al. [5] on the same dataset of five genres (Classical, Hiphop, Jazz, Pop and Reggae).

7. FUTURE WORK

This work can be extended in various ways: forming a 'golden-set' of features that are genre-specific like rhyme in Ghazal, beats in Folk Punjabi etc.; recognition of patterns like *taal* in Indian music and *chords* in Western music; expansion of classes in terms of genres and sub-genres so that we can work with more classes in both datasets (GTZAN has 10-genres); studying music forms of other cultures for example Chinese and Japanese and comparing them with Indian and Western genres.

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