Abstract

Tabla is a North Indian percussion instrument used as an accompaniment and an exclusive instrument for solo performances. Tabla solo is intricate and elaborate, exhibiting rhythmic evolution through a sequence of homogeneous sections marked by shared rhythmic characteristics. Each section has a specific structure and name associated with it. Tabla learning and performance in the Indian subcontinent is based on stylistic schools called gharānā-s. Several compositions by various composers from different gharānā-s are played in each section. This paper addresses the task of segmenting the tabla solo concert into musically meaningful sections. We then assign suitable section labels and recognize gharānā-s from the sections. We present a diverse collection of over 38 hours of solo tabla recordings for the task. We motivate the problem and present different challenges and facets of the tasks. Inspired by the distinct musical properties of tabla solo, we compute several rhythmic and timbral features for the segmentation task. This work explores the approach of automatically locating the significant changes in the rhythmic structure by analyzing local self-similarity in an unsupervised manner. We also explore supervised random forest and a convolutional neural network trained on hand-crafted features. Both supervised and unsupervised approaches are also tested on a set of held-out recordings. Segmentation of an audio piece into its structural components and labeling is crucial to many music information retrieval applications like repetitive structure finding, audio summarization, and fast music navigation. This work helps us obtain a comprehensive musical description of the tabla solo concert.

Keywords: Gharānā, Pēśkār; Kāyadā; Gaṭ; Tukdā; Chakradhār.

1 Introduction

With the availability of varied music collections on digital platforms and widespread use of personal digital devices, there is a growing interest in accessing music based on its various characteristics. Metadata supplied with the audio recordings of concert performances that are available online contain information about the musicians and the performance duration. But, the information relating to the section boundaries and other annotations are rarely provided, irrespective of whether it is vocal, accompaniment or percussion, especially in the
context of Indian art music. The limited availability of editorial metadata and annotations led to the need for music information retrieval (MIR) to automatically extract characteristic properties of music from the audio recordings.

From the MIR perspective, analyzing the rhythm structure of tabla performances is vital. Automatic segmentation of concert audios offers a variety of MIR applications, including quick navigation Cooper and Foote (2003); Peeters (2003), detection of repeating structure in music, and meaningful transcription of music Klapuri, Virtanen, Eronen, and Seppänen (2001). The tasks such as audio thumbnailing Bartsch and Wakefield (2005), auto-tagging, music summarization and description, similarity measurements, as well as informed and enhanced music listening, training and computational musicology, are all made easier by automatic metadata identification. Identifying metadata from audio-like, stylistic school recognition—especially in the same genre—is a difficult process for humans.

This paper addresses the structural segmentation and labeling of tabla solo concerts. Tabla solo is intricate, with a variety of precomposed compositions with further elaborations based on the player’s stylistic schools called gharānā-s\(^1\) Bagchee (1998); Gowriprasad, Venkatesh, Murthy, Aravind, and Murty (2021). Figure 1 shows the overall tasks focused in the paper. Segmentation of a tabla solo performance involves finding the boundaries that mark the transition between segments with different rhythmic structures. Other important tasks are labeling the segments and the identification of tabla gharānā-s on the segmented audio clips. The paper addresses three tasks: 1. Concert segmentation, 2. Segment classification and labeling, 3. Gharānā recognition and labeling of each segment. We perform genre/culture-specific analyses since tabla solo performances are distinct from other genres. The paper explores techniques used in other well-researched genres of music, with culture-specific changes for both supervised and unsupervised structural segmentation and labeling methods.

\(^{1}\)The word gharānā literally means house and implies the house of the teacher.
The rest of the paper is structured as follows. In the following part of the current section, we discuss an overview of tabla solo performances and tabla gharānā-s, followed by a literature review. The challenging factors influencing each task are categorically mentioned motivating the experiment. Section 2 describes the dataset collected as well as the ground truth annotation procedure. Section 3 discusses the pre-processing and feature extraction steps, inspired by the characteristics of the music tradition. The proposed segmentation methods, and models are explained in Section 4. Section labeling and gharānā recognition tasks are described in Section 5. Multiple experiments addressing various facets of the task are described. The experimental results are analyzed and discussed in Section 6. Finally, Section 7 summarizes the work mentioning the key takeaways.

1.1 Structure of Tabla Solo Concert and Gharānā-s

Tabla solo is entirely independent of the Hindustani vocal or other instrumental concerts.Tabla is the main instrument, and the instruments like Sarangi, Harmonium, or sometimes Violin are used for Lehra accompaniment. The purpose of lehra is to indicate the reference metric tempo Bagchee (1998) while providing a background melody.Tabla solo is intricate, with a variety of pre-composed forms within the rhythmic framework called tāl. Further elaborations are based on the player’s school of practice called gharānā.

Tabla solo consists of different compositions such as ṭhēkā, uthān, pēśkār, kāyadā, rēlā, rau, gaṭ, paran, tukdā, chakradhār Pradhan (2011). Each composition has different functional and aesthetic roles in a solo performance. The structural framework of a tabla solo is generally as follows: The lehra accompaniment plays an alāp initially for a few minutes. Then the tabla player starts with the initial uthān or directly pēśkār. Pēśkār rendition can go from five minutes to more than 15-20 mins depending on the overall concert duration. Next to pēśkār, various kāyadā compositions from different gharānā-s are played one after the other. Further, the compositions such as rēlā, rau are presented. Later on, the metric tempo increases and the fixed compositions such as gaṭ-s, stuti paran-s, tukdā and mukhdā-s are played. In the end, the chakradhār-s are played, which are essentially long-term mukhdā-s. Therefore, the sequence of these pieces would broadly be as follows: pēśkār/uthān → kāydhā → rēlā → gaṭ → tukdā/chakradhār

It is necessary to point out the role that is played by the ṭhēkā2 in the context of solo tabla recitals. The basic ṭhēkā is usually played in between adjacent compositions, marking the start and end of the item Pradhan (2011). This indicates the basic tempo (the barābar laya) on which the repertoire and subsequent improvisation are built. This is the metric tempo as indicated and maintained by lehra accompaniment. After establishing the metric tempo by playing ṭhēkā, the player can perform further elaborations as the performance

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2ṭhēkā is the basic stroke pattern associated with a particular rhythm cycle “tāl”
progresses. The thekā thus provides the standard for improvisations Bagchee (1998). Another aspect is that the choice of metric tempo is highly flexible, and the artiste decides it on stage. The metric tempo changes across the concerts, as well as for different compositions within the concert. The tempo is measured in beats per minute (bpm).

1.1.1 Major sections in tabla solo

Based on the item/compositions’ structure and their position in the recital, one can find three major sections in the tabla solo concert. They are pēśkār (Pe), kāyadā (Ka), and gat.–tukdā–chakradhār (GTC) sections, each of these sections have a specific meaning as indicated below.

Pe: The word pēśkār means ”to present” and is played at the beginning of the concert. Through the pēśkār, the performer establishes the basic structure of the tāl that is being presented. It sets the mood of the tāl and of the performance itself. Many tabla players liken it to the alāp in vocal and instrumental recitals. Pēśkār is an extempore rendition played at a slower metric tempo (40-45bpm). It is usually the single longest section in the concert.

Ka: The kāyadā, meaning ”rule,” follows a theme and consists of a pattern of variations, where the variations use syllables from the theme. Thus, the structure is restrictive and demands that the tabla player works within bounds. Kāyadha-s are usually played in a medium metric tempo (55-65bpm). Each kāyadā ends with a tihāyi which is essentially a small phrase that is repeated thrice. Each kāyadā rendition usually lasts for two to five minutes.

GTC: The gat is a short and pithy composition, which generally employs loud and heavy strokes influenced by the Pakhāwaj vocabulary. The tukdā, and chakradhār are non-extendable pre-conceived compositions played towards the end of a solo recital. The chakradhār structure involves a short passage followed by a tihāyi, but the entire unit has to be repeated thrice for it to resolve on the first beat of the approaching cycle called as ”sam”. The GTC are examples of fixed compositions played at a fast metric tempo (100-130bpm).

1.1.2 Tabla Gharānā-s

Teacher-student lineage gave rise to six different gharānā-s namely Delhi (D), Ajrada (A), Lucknow (L), Banaras (B), Farukhabad (F), and Punjab (P). Each gharānā is characterized by its unique style of playing Pradhan (2011), strokes, improvisations, and pre-composed patterns. Each stylistic school also has differences in elaboration and dynamics of tabla phrases and specific compositional patterns (signature patterns). Compositions are the heart of tabla’s repertoire. These compositions are usually from different gharānā-s. Thus we

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3A double barrel drum used as rhythm accompaniment in Hindustani music.
consider the aspect of repertoire, in so far as it has a bearing on the gharānā distinctions Bagchee (1998). For more details of tabla solo and gharānā-s, refer to Bagchee (1998); Gottlieb (1993); of Primary and Education (2002); Pradhan (2011); Saxena (2006). Figure 2 illustrates the overall objective of the paper. It depicts the segmentation boundaries, section labels along with gharānā annotations.

1.2 Related works

Musical attributes like timbre, melody, rhythm, or harmony represent the musical structure differently. Different acoustic and temporal parameters capture these musical characteristics and are used to determine the structural boundaries in music. In Western music, many researchers have used timbre features as harmony-based features for music segmentation into intro-chorus-verse-outro sections Dannenberg and Goto (2008); Paulus, Müller, and Klapuri (2010). Grosche, Müller, and Kurth (2010) used Low dimensional tempo features for segmentation tasks in Western classical music. Several inherent challenges in the structural segmentation of classical sonata music were reviewed by Allegraud et al. (2019). The authors used melodic, harmonic, and rhythmic features that characterized the evolving structure and formulated them as a sequence of recurring states.

There are many different approaches to music segmentation. A few approaches exploit the homogeneity of the sections in some musical aspects. A few novelty-based approaches are based on detecting a sudden change in the musical properties, and the recursion-based approaches detect the repeating structure in the music. Different unsupervised approaches were reviewed by grouping similar sections using structural analysis Paulus et al. (2010). Foote (2000) proposed a method that uses a self-distance matrix (SDM) to determine the boundary between contrasting musical characteristics. Turnbull, Lanckriet, Pampalk, and
Goto (2007) characterize the changes in musical features like melody, harmony, timbre, and rhythm in Pop and Rock music to train the boosted decision stump (BDS) supervised classifier for predicting boundary frames. Lately, Ullrich, Schlüter, and Grill (2014) explored the mel-scaled spectrograms in training the convolutional neural networks (CNN) for the structural segmentation on the SALAMI dataset that spans a large variety of genres Smith, Burgoyne, Fujinaga, De Roure, and Downie (2011).

In the context of Indian music, different approaches were explored for the segmentation task, addressing both the Hindustani and Carnatic music traditions. Padi and Murthy (2018) identified the applause instances between adjacent compositions in live recordings of the Carnatic music as a cue for segmentation. In Indian art music owing to its improvisational nature, it is common to hear applause intra item. Nevertheless, melodies are defined by ragas, and the same melody will not be used in adjacent items. This property is exploited in this work to segment continuous recordings of concerts into items. The authors used tonic normalized timbre features (cent filterbank cepstral coefficients - CFCC) and the pitch histograms in merging the adjacent sections. PV, Sankaran, and Murthy (2016) addresses the segmentation of carnatic music items into alapana and kriti using GMMs and energy features. Sankaran, Krishnaraj Sekhar, and Hema (2015) also used CFCC feature templates to segment the compositions in Carnatic music automatically. Verma, Vinutha, Pandit, and Rao (2015) explored the structural segmentation of Hindustani instrumental and Dhrupad concert recordings Rohit and Rao (2020). In the case of instrumental concerts, Vinutha et al. Vinutha, Sankagiri, Ganguli, and Rao (2016) considered the segmentation of sitar and sarod concerts using reliable tempo detection Vinutha, Sankagiri, and Rao (2016). In the case of Dhrupad vocal concerts, Rao, Vinutha, and Rohit (2020) performed the segmentation of alap, jod, and jhala in dhrupad vocal concerts. They have also segmented Dhrupad bandish using the tempo MA, TP, and Rao (2020). Ranjani and Sreenivas (2013) considered the aspects of rhythmicity and percussiveness, strongly signaled by the accompanying percussion instrument’s onsets and low frequency content to classify the concert sections in Carnatic music. Thoshkahna, Müller, Kulkarni, and Jiang (2015) exploited the salience of the estimated tempo to distinguish sections with ambiguous tempo (alapana) from the later concerts sections with clear rhythmic properties in Carnatic music concerts.

Indian percussion research has mainly focused on stroke transcription Chordia (2005); Gillet and Richard (October 2003) and sequence modeling Chordia, Sastry, Mallikarjuna, and Albin (2010); Chordia, Sastry, and Şentürk (2011) of tabla strokes. The stroke transcription task was developed using hidden Markov models Samudravijaya, Shah, and Pandya (2004), followed by percussion pattern identification Gupta, Srinivasamurthy, Kumar, Murthy, and Serra (2015). Recently, A., Bhattacharjee, and Rao (2021) performed four-way classification of tabla strokes using the models adapted from automatic drum transcription. In case of mridangam, stroke transcription can be found in Anantapadmanabhan, Bellur,
and Murthy (2013); Kuriakose, Kumar, Sarala, Murthy, and Sivaraman (2015). Srinivasamurthy, Holzapfel, and Serra (2014) explored the rhythmic analysis of Indian and Turkish music where the authors addressed the meter tracking and beat tracking tasks.

The works on music style and classification are as follows. Melodic contours were used to classify vocal style Vidwans, Ganguli, and Rao (2012), and the melodic features for classifying cultural music Vidwans, Verma, and Rao (2020). In case of percussion, the task of mridangam artiste identification from mridangam tani-avartanam audio was attempted Gogineni, Kuriakose, and Murthy (2018). Recently, tabla gharānā recognition from the solo tabla performance audios was addressed in Gowriprasad et al. (2021); Gowriprasad, Venkatesh, and Murty K (2022).

1.3 Motivation and challenges

We motivate the task of segmentation and labeling by getting insights into the factors influencing each sub-tasks. The factors include both the supporting and challenging aspects. We consulted four tabla maestros to get expert advice on the factors influencing the task. Based on the discussion and the artists’ common opinions, we formulate the challenging factors for each of the sub-tasks.

**Structural Segmentation:** Tabla solo is a structured rendition of numerous compositions played one after the other. The number of compositions played and the duration of each composition is also not fixed. Thus the number of segments in each performance varies. There exist some instances of spoken recitation of the compositions before being played. Each composition has its own rhythmic structure and is presented at multiple speeds. This is reflected in the boundary within a single composition itself due to sudden changes in tempo or the rhythmic structure. The rendition also has pauses, which may be part of the composition itself or due to the artiste’s presentation style. Thus the tabla solo segmentation task poses new challenges to the existing audio segmentation methods. Listening to the entire audio carefully to mark the segment boundaries is time-consuming. This also motivates us to build systems for automatic segmentation and annotations.

**Section labeling and Gharānā recognition:** Artistes nowadays would have learned from several teachers from different gharānā-s. Different gharānā styles will also influence their playing style Bagchee (1998). Thus the structure of the tabla solo and its components have also evolved. There is no specific rule governing a certain composition’s position in the concert. As mentioned in Section 1.1.1, the tabla solo concerts consist of three kinds of renditions: mostly extempore and extempore nuances upon a theme and fixed compositions. It is hard to label the rendition just by stroke patterns and structures.

Tabla is a pitched harmonic percussive instrument tuned to a specific tonic in a concert Anantapadmanabhan, Bello, Krishnan, and Murthy (2014); Saxena (2006). As the tonic
varies, the properties of the sound, like harmonics, timbre, tone, etc., also vary. Thus the feature vectors representing the same stroke with different tonic will also change, challenging the system performance. In an ideal scenario, the metadata is independent of tonic variability. Gottlieb (1993) mentions three factors for comparing the similarities and differences in playing: (1) Sound production, that is, quality and the technique used, (2) Repertoires, and (3) Rhythmic practices. The technique and the rhythmic practices differ from artiste to artiste. Compositions bearing the gharānā distinctions are based on the repertoires of each gharānā-s Gowriprasad et al. (2021). The challenges involved in each task motivate addressing the unexplored problem of segmentation and labeling tabla solo recordings.

2 Dataset Description

Since there was no tabla solo dataset available, we collected tabla solo recordings from commercial audio CDs, live recordings from the artistes’ archives, and online sources. This corpus consists of tabla solos played in 5 different tāl-s by 25 artistes. All the artistes are senior exponents from different tabla gharānā-s with at least 20 years of tabla playing experience. A concert’s duration varies from 15 minutes to 80 minutes. Concert audios were annotated for the major structural boundaries. The overall dataset comprises 55 solo tabla audios with a total duration of around 38 hours, having more than 2000 segment boundaries.

2.1 Labeling the raw data

The rhythm structure and tempo are the most distinctive properties of a segment within a concert, and the relative change in tempo and rhythmic structures serves as cues for segment boundary detection. A few cycles of thēkā are played in between adjacent compositions, marking the start and end of a composition Pradhan (2011). Each compositional theme is played initially at a speed of or double the speed of the original tempo (metric tempo) for one or two cycles and is then played at four times the original tempo Pradhan (2011). A step increase in surface tempo is observed at the initial stages of the compositions. The sharp decrease in the stroke density (indicator of surface tempo) is usually observed at the end of each composition to thēkā. This is depicted in the Figure 7 and 8.

Professional performers were employed to listen and extract the kāyadā, gat, and chakradhār sections from the audio by marking the start and endpoints. The ground truth annotations relied on various culture-specific cues mentioned above. The aspect of tempo change is recognized immediately by the listeners; the section boundaries at the end of the composition transiting from the higher speed to the lower speed thēkā are marked consistently. This ensured the reliability of the labeling. Then four tabla maestros from different gharānā-s were
requested to listen to these audio segments and give the ground truth labels for the section name as well as the gharānā. Manual annotations are subjective due to the multiple musical cues. We discussed with four tabla maestros and followed a consensus-based approach in deciding the boundary annotations. It is to be mentioned that the performers had to listen to the entire audio carefully to mark the segment boundaries, which was time-consuming. This also motivates us to build systems for automatic segmentation and annotations.

Structural segmentation in the context of tabla solo involves the detection of start and end instances of compositions. The task is not addressed at the metrical time scale, or stroke level but at a larger time scale. Thus the tolerance duration is not in milliseconds as in the case of stroke onset detection Bello et al. (2005); Gowriprasad and Murty (2020) but in a larger time scale in “seconds”. For completeness, the segmented portion is expected to contain the full composition. The start marking needs to be before the composition starts, and the end markings need to be after the composition ends. Marking the segment boundaries precisely on the first beat of the tāl cycle where the compositions start and end will affect the completeness for the listeners. Usually, in practice, the artists will play a few cycles of thēka before the start of any composition (kāydha, GTC). This establishes the tāl structure and the metric tempo for the composition to be played. Thus the smaller segments in between the compositions where thēka is played for a few cycles are included with the following segment.

2.2 Statistical analysis of the annotated data

Plots in Figure 3 show the various statistics of three sections of tabla solo computed from the entire dataset. The first plot (A) showcases the duration ratio of each section in the concert. The average duration ratio Pe-Ka-GTC is 0.3, 0.48, 0.28, respectively. The second plot (B) showcases the average number of individual compositions in each section in a concert. The pēśkār is one single section which is extempore. The number of kāyadā-s, gāṭ, tukdā, and chakradhār compositions varies across the concert. The mean average number of kāydha-s and GTCs are 4 − 5 and 8, respectively. One can observe a large variance in the number of individual compositions in the GTC section and a relatively smaller variance in the number of kāydha-s. This essentially depends on which gharānā the artiste belongs. Some gharānā players give more emphasis on kāydha-s and some on GTC. The third plot (C) shows the average section length in each composition. Since pēśkār is one single composition and spans nearly 30% of the entire concert, the mean average length of pēśkār is large compared to the other two sections. The mean average lengths of individual kāydha-s, and GTCs are around 210s and 60s, respectively. The larger variance in the length of pēśkār in plot (C) and the number of kāydha-s, and GTCs in plot (B) also depends on the overall duration of the concert. The duration of the concert is not fixed. As
3 Audio processing and Features

The raw concert audios have to be pre-processed for further analysis. Since each concert is unique in the choice of metric tempo, tabla tonic, and compositional structure, the feature representation need to handle concert specific characteristics as well as scale to multiple concerts. We addressed the tasks by computing relevant features considering the culture-specific musicological perspectives.

3.1 Audio Pre-Processing and Onset Detection

From Section 1.1, we know that there may exist an initial introductory speech in the case of a live concert. Mel-frequency cepstral coefficients (MFCC) are used to localize the vocal parts in the entire recording. We check for the presence of vocals only in the initial section and discard them if any. The short vocal passages in the middle of the recordings are retained as they are the instances of spoken recitation which are common in tabla solo concerts.

Initially, the raw audio is pre-processed by computing the Hilbert envelop of the linear prediction residual on the raw audio as described in Gowriprasad and Murty (2020). Then the onset detection function (ODF) is computed using spectral flux method Dixon (2006). The quality of the onset detection function is crucial for the analysis of tempo and rhythm. The performance of onset detection was evaluated independently on the onset annotated tabla solo audio datasets from Gowriprasad and Murty (2020); Gupta et al. (2015); Rohit
and Rao (2018). The best performing peak-picking threshold gave an F-score of 0.96. The computed onset locations with this threshold are considered for further analysis.

3.2 Feature computation

The change in the rhythm structure or the tempo is a prominent indicator of the transition between sections. We present rhythm-based and other related features motivated by observations on the tabla solo concert audios for our segmentation task. The following feature vectors are computed for every frame, where the frame rate is two-frames/second.

3.2.1 Rhythmogram

Rhythm is a fundamental dimension of music, and each rhythm pattern has its own time signature. In the case of percussion instruments like tabla, rhythm pattern refers to the aspects of stroke patterns. Changes in rhythm can come about from a difference in the manifestation of tāl, tempo, or even a change in the surface stroke pattern. A rhythm representation of a tabla solo audio can be obtained by considering the stroke ODF (sampled at 10 ms) over a suitably long window. The inherent periodicity in the ODF is captured by the auto-correlation function (ACF). The ACF obtains the correlation between an ODF and its time-shifted version (where the shift is measured in seconds and termed the ‘lag’). The local tempo and rhythmic structure are obtained by periodicity estimation to a fixed length window over the ODF centered at the time instant of interest. The periodicity analysis using the auto-correlation function on the ODF gives a nice rhythmic representation of the audio called rhythmogram Jensen (2006). Rhythmogram is essentially short-time ACF strength versus time and lag axes. The ACF on the ODF is computed frame-wise with a frame length of 4 seconds and a frameshift of 0.5 seconds up to a lag of 2 seconds. Figure 2 shows the rhythmogram representation of a full concert spanning 70 minutes as it varies in time.

In the alāp section, we can see that there is no periodic structure. In the remaining sections, the horizontal striations along the lag axis (y-axis) suggest the stroke periodicity. The decreasing distance between striations implies a faster rate of stroke onsets, i.e., faster tempo. The rhythmogram clearly depicts the boundaries between the segments. Thus the rhythmogram can be used as a potential feature for segmentation.

3.2.2 Tempo — Average stroke density (ASD)

Different compositions in tabla solos are performed at different speeds though the underlying metric tempo may remain constant. Here the metric tempo refers to the tempo of underlying lehra. The ODF captures the stroke onsets and not the lehra variations. It
is not straightforward to get the metric tempo information from the stroke onset information. The different tabla compositions have different stroke patterns and often have unequal stroke distribution across the mātras, and getting the surface tempo is not possible unless we know the stroke pattern and the speed. The tempo estimation by using the product of ACF-DFT or by counting the number of peaks along the lag axis of ACF is often prone to tempo octave errors due to uneven distribution of strokes. Thus, we compute the average stroke density (ASD) instead of computing the surface tempo.

The ASD is computed on a frame-by-frame basis by counting the number of onsets in each frame. Frame size and frameshift are the same as ACF computation 4 and 0.5 seconds. This gives the ASD per 4 seconds for every 0.5 seconds. The values in each frame are divided by four to get the ASD per second. The ASD is robust to tempo octave errors and is a nice representative of surface tempo in the case of percussive audio. Figure 4 shows the histogram depicting the statistical estimate of stroke density per second for different concerts (A to E) and over the entire dataset (F). The subplots (A) and (B) are from the same artist (A-1) for two different concerts (C-1, C-2). The subplots (C) to (E) are from three different artistes (A-2, A-3, A-4). We can observe that the ASD is not consistent across the concerts, even for the same artiste. This is essentially due to the fact that ASD inherently depends on the compositions played. The mean and median of stroke density per second, as obtained in the entire dataset (F), are found to be 10.62 and 10.38, respectively. The spread of ASD also depicts the vast diversity of the dataset. We can observe the evolution of ASD over time in Figures 7, and 8.

### 3.2.3 Rhythm Posteriors

Transforming the feature vectors into a vector of class-conditional probabilities, the posteriors are shown to improve the homogeneity within the segment Verma et al. (2015). Since segmentation is based on the change in rhythmic structure and tempo, modeling the rhythm-
mogram vectors to get the class-conditional posteriors helps model each section differently from adjacent sections. The intuition behind using rhythmogram features is as follows. The high dimensional rhythmogram clearly represents the homogeneity within the section and the changes between the adjacent sections. The peaks along the lag axis of the rhythmogram depicts the periodicity of the surface rhythm indicate the surface tempo Vinutha, Sankagiri, Ganguli, and Rao (2016). This allows us to use Gaussian mixture models (GMM) to model the section’s homogeneity and tempo.

Each feature vector of the rhythmogram \( \mathbf{X}_i \) is transformed to a vector \( \mathbf{q}_i \). The dimension of \( \mathbf{q}_i \) is the number of different possible speeds. The feature vectors are clustered in an unsupervised manner using a Gaussian mixture model with \( k \) Gaussians representing different ACF speeds. The posterior is computed from each of the \( k \) Gaussians and stacked to form a vector.

\[
\mathbf{q}_i = (P(C_1 \mid \mathbf{X}_i), P(C_2 \mid \mathbf{X}_i), \ldots, P(C_k \mid \mathbf{X}_i)) \tag{1}
\]

In Equation 1, the \( k \)th dimension of \( \mathbf{q}_i \) represents the posterior probability \( P \) given the frame vector \( \mathbf{X}_i \), of the \( k \)th Gaussian component. The GMM is trained with maximum likelihood across all the rhythmogram frames in a given concert. Posteriors for each concert feature vector are computed from the GMMs trained individually for each concert. The noisy features affecting the homogeneity of the segment are expected to have low probability values in the mapped posterior vector.

The major empirical parameter in modeling the GMM is the number of Gaussians. We did two tests to decide the number of Gaussians. At first, K-means clustering is performed on the feature vectors with a different number of clusters \( M \) to initialize the means of GMMs. The task is to choose an optimal value of \( M \) such that the total intra-cluster variation (known as a total within-cluster variation) \( \text{Var} = \sum_{m=1}^{M} \sum_{x_i \in C_m} (x_i - \mu_m)^2 \) is minimized. \( x_i \)s are the data points from the cluster \( C_m \), and \( \mu_m \) is the mean of the cluster \( C_m \). The total within-cluster variation is computed for different values of \( M \) and plotted. The number of Gaussians \( (k) \) are chosen as the value of \( M \) around the elbow point on the curve.

We quantized the ASD starting from 3 levels to 7 levels (value of \( k \) around the elbow point) of quantization. It was found that 5 to 6 quantization levels were sufficient to quantize ASD with a minimum difference of 5 strokes per second. Thus we fixed the number of Gaussians to be 5. The GMM is fit only on the ACF vectors from a particular concert. Therefore, a single Gaussian is used to model one specific speed. One Gaussian for alap where ASD is nearly zero. The 2nd Gaussian corresponds to the first speed w.r.t metric tempo. 3rd Gaussian corresponds to the second speed, 4th one for fourth speed rendition. 5th one for any other speed. Thus each Gaussian depicts a different speed.

As mentioned in Section 1.1.1, the metric tempo varies across the concerts. From
Section 3.2.2, and Figure 4, we can also observe the variability of the ASD (indicator of surface tempo) across concerts. Considering these variables, we built the GMMs and computed the rhythm posterior features on each concerts separately.

### 3.3 Timbre Features

The stroke density and the stroke combinations change from composition to composition. As the energy in a frame is proportional to the number of strokes in the frame, the short time energy evolves as the ASD changes. Different strokes have a different timbre, so as the combination of strokes. As the stroke combinations change, the timbre feature characteristics also change. Thus we explore the use of MFCCs and short-time energy (STE) as the timbral features.

MFCC + derivatives (MFCC $\Delta$) + double derivatives (MFCC $\Delta\Delta$) features and the short term energy (STE) features are extracted with a window size of 25 ms and a frameshift of 5 ms. Each MFCC $\Delta\Delta$ feature vector is of dimension $d = 57$. It is the sum of MFCC (19) + $\Delta$ + $\Delta\Delta$ ($d=19+19+19=57$). The features vectors are then averaged over a 2s window with 0.5 s frameshift. Averaging over longer window filters out the noisy fluctuations at the larger timescale. We fixed the frameshift consistent with that of the rhythmogram.

### 4 Structural Segmentation of Tabla Solo

In the context of tabla solo, structural segmentation is the task of detecting the start and end instances of compositions in a rendition that mark segment boundaries as indicated by several musical attributes. In this work, we consider music segmentation based on locating boundaries by detecting changes in the local rhythmic structure of segments at the highest timescale, that is, concert segments marked by prominent changes in rhythmic structure. The segmentation task can also be seen as a boundary detection task. A frame is classified as either a boundary or non-boundary frame based on whether a transition between segments occurs over the frame duration.

We propose two approaches for the segmentation task. The first is an unsupervised signal processing-based approach, and the second is based on supervised machine learning. The unsupervised framework involves the similarity measures and kernel correlation, and the supervised approach involves a random forest and a deep-learning CNN classifier that classifies the boundary and non-boundary frames.

#### 4.1 Unsupervised signal processing approach

Given different sets of feature vectors, the self-similarity matrices (SSM) are computed on each of them using $L_2$ distance measure Paulus et al. (2010). The homogeneous segments
of length $L$ frames possibly appear as $(L \times L)$ blocks having lower distance scores. The SSM obtained on the rhythmogram, posteriors, and MFCCs are displayed in Figure 5. The section change points with high contrast in SSM are captured by convolving a checkerboard kernel of the desired size of interest along the diagonal of SSM (Foote 2000). The minimum segment duration is at least 10-15 seconds, as known from the annotation process (see Section 2.2). The frame resolution of the feature vectors and SSM is 0.5 s. Thus, we examine $(50 \times 50)$ kernel size corresponding to $(25s \times 25s)$.

The 1D output obtained from the convolution is called a novelty function (NF). The peaks of the NF indicate the section boundary instances having high contrast in SSM. The aim is to get an NF whose peaks indicate the desired segment boundaries. We compute six different novelty functions from different features, as mentioned in Table 1.

The steps involved in feature extraction and computing novelty functions are shown in Figure 6. The 1st difference of ASD (ASD-D), rhythmogram flux (NF-RF), and 1st difference of STE (STE-D) captures the sudden change in tempo, rhythm, and energy, respectively, which can serve as a potential novelty function for the segmentation task. We compute the Hilbert envelope on the difference signal and use it as NF. Hilbert envelope is the magnitude function of complex time function and hence it is unipolar in nature. Figure 7 and 8 shows different NFs obtained for two different concerts. The ASD-D, NF-RF, and
STE-D are observed to be noisy. This is so because the differentiation is a highpass filter, and even the small changes in the features are enhanced in the derivative. The NF-P, NF-R, and NF-M obtained by SSM-kernel convolution are relatively less noisy. This confirms the property of SSM in capturing the homogeneity Verma et al. (2015). The homogeneity of the sections is clearly seen in NF-P as well. We can observe that the NF-P is flat around the frames where ASD is not changing much. This verifies that NF-P is indeed capturing the underlying tempo information.

Due to local tempo and timbre variations, peaks are observed around the boundary instances with other spurious peaks. Peak picking is performed on the NF of each feature by maintaining the minimum inter-peak interval of 10 s. Initially, the peaks are picked on individual NFs and considered as boundary instances. We further explore two different ways of getting the boundary instances. The first one is to combine the individual NFs by computing the average and peak picking. The second is to fuse the boundary information from each NFs after the peak picking, which is more flexible in performance tuning.

Each of the novelty functions works well in certain situations. Averaging out different novelty functions worked very well for most concerts. For fusing the detected peaks, NF-P is taken as the reference as it is less noisy. Boundary candidates picked from each rhythm-
Figure 7: Rhythmogram, Average Stroke Density (ASD), and different Novelty Functions (NF) Representation for Concert-1. The ground truth segment boundaries are marked by vertical dotted lines.

Alt-Text: Figure shows the Rhythmogram, Average Stroke Density (ASD), and different Novelty Functions (NF) Representation for Concert-1. The ground truth segment boundaries are marked by vertical dotted lines.

based NFs (ASD-D, NF-RF, NF-R, NF-P) are fused using a majority decision rule (i.e., the peaks from two or more NFs out of three are examined for coincidence with NF-P as reference).

4.2 Supervised approaches

The supervised classifier models are trained on the original and augmented dataset, which includes speed perturbation (see Section 6.1). All the frames in ±5 seconds about the manually labelled boundaries are labelled as boundary frames Ullrich et al. (2014). This accounts for the ambiguities in the manual boundary annotation. The number of non-boundary frames is very high compared to boundary frames. Thus to balance the ratio of boundary and non-boundary frames, only the boundary frames from the augmented audios are retained, along with all of the frames from the original dataset (Data augmentation is explained in Section 6.1).

Since the segment boundaries are depicted by a sudden change in the tempo and rhythmic structures, the task benefits from the use of context frames. Thus by keeping the current frame at the center, ±C adjacent feature frames are included as the context frames forming
Figure 8: Rhythmogram, Average Stroke Density (ASD), and different Novelty Functions (NF) Representation for Concert-2. The ground truth segment boundaries are marked by vertical dotted lines.

A window. The target corresponding to each window is a label that indicates if the central frame is a manually labelled boundary frame or not. The probability of the central frame in a window being a boundary frame is estimated at the output of the classifier. Since segment boundary cues can be spread over several frames, predictions within a 5s window are replaced by a single prediction on the frame having the highest probability.

4.2.1 Random Forest Classifier

A random forest (RF) is an ensemble of decision trees. The RF classifier outputs the class labels with the majority voting rule on each decision tree prediction. The feature vectors with the current and context frames are fed as the input. Each of the training vectors is assigned the target 1 or 0, indicating if the current frame is a manually labelled boundary or not. The classifier is trained independently on rhythmogram and posterior features. We experimented with and tuned the model hyperparameters, such as the number of trees, and the maximum number of levels in a tree, with and without bootstrap aggregation. The number of decision trees is varied between 10 and 50 in steps of 5, while the context duration (C) is varied from ±5 to ±20 seconds in step 5s. The maximum number of levels
in the tree is 5 for the rhythmogram and 3 for posteriors inputs.

4.2.2 CNN Classifier

The rhythmogram is split into smaller overlapping chunks having $\pm C$ context frames and used as the input to the network. All the input data chunks are normalized to have zero mean and unit variance in a single input chunk. The network is trained to learn the frame-level targets. Each target output is 1 or 0, indicating if the center frame has the labelled boundary or not. The boundary predictions are at the frame resolution of 0.5 s.

The CNN network architecture is adapted from Ullrich et al. (2014) network with modifications. The model has three convolutional layers and two fully connected layers. Each CNN layer is followed by BatchNormalization Ioffe and Szegedy (2015) and ReLU activation Nair and Hinton (2010). The horizontal Sobel kernels are used in convolutional layers Sobel (2014). The kernel size, number of kernels, and padding of each convolution layer are (100 x 10, 256, 3), (256 x 8, 128, 2), (128 x 4, 64, 1), respectively. This 1D-CNN component configuration is adapted from Oord, Li, and Vinyals (2018). The model further consists of two fully connected layers with 256 and 2 hidden units, respectively. Sigmoid and softmax activations are used for fully connected layers. The model is trained using Adam optimizer Kingma and Ba (2014) and binary cross-entropy loss on mini-batches of a size of 32 and a learning rate of 0.01. We have used a learning schedule of dropping the learning rate to half of the current whenever the validation loss doesn’t decrease Audhkhasi, Rosenberg, Sethy, Ramabhadran, and Kingsbury (2017). We experimented with different kernels sizes and other activation function combinations — sigmoid for the convolutional layers and ReLU and with 5% dropout.

4.3 Post processing – merging the segments

As mentioned in the challenges, small pauses may exist within the rendition of the same compositions. This causes a change in rhythm and tempo structure in those instances. Since our segmentation models inherently depend on sudden tempo and rhythm changes to predict the segment boundaries, these small pauses cause false positives. Thus, we try to look for the tempo and posterior information in the adjacent segments and merge adjacent rhythmically similar segments with the same tempo.

After we get the hypothesized segment boundaries from segmentation systems (Section 4), we compute the mean value of ASD (M-ASD) in each segment. In Figure 9, ASD and M-ASD are plotted using green and black solid curves respectively, for three different concerts. If the M-ASD difference between the adjacent segment is less than three strokes per second, then the posteriors from these segments are considered to decide whether these segments can be merged. The posterior class for each frame of the two segments is checked.
The two segments are merged if both the segments have the same posterior classes in the majority of the frames. This also helped in merging smaller ṭhēkā segments between the compositions.

5 Section Classification and Labeling

Once the local segment boundary results are obtained from the segmentation models, the next task is to classify and label the segments appropriately. Segment classification and labeling is the task consisting of: (1) Classifying the concert segments into high-level sections such as alāp, pēśkār (Pe), kāyadā (Ka), and gaṭ-tukdā-chakradhār (GTC). (2) Gharānā labeling the individual segments (compositions).

5.1 Section classification

Each of these four sections alāp, Pe, Ka, and GTC have unique structural, positional, and duration characteristics which are common across the concerts. We consider these characteristic cues for initial section markings and updates. The characteristic cues for each section are described in Section 1.1. Since the alāp section does not have percussive strokes and is always present at the start of the concert, the initial segments are checked for the percussive onsets, and the segments which do not contain percussion onsets, are classified as alāp section. The timbre information is very helpful in classifying the percussion and non-percussion (alāp in this case). Thus we also use the MFCC features for verifying the alāp boundary.

Labeling the next three sections involves initialization and re-estimation of the label boundaries. Figure 9 illustrates the initial and updated section boundaries for three different tabla solo concerts having different lengths. The pēśkār section always occurs at the start of the concert, and the average duration ratio is one-third the length of the concert (Figure 3). Thus the Pe-Ka boundary is initialized at the instance that is 0.3 times the length of the concert by taking the ratio of the length of the pēśkār section. The kāyadā section is the middle larger section and it occurs after pēśkār and before GTC (see Section 2). The ratio of the average duration of the Ka section to the whole concert is found to be 0.42. The initial Ka-GTC boundary is fixed at the instance of \(0.3 + 0.42 = 0.72\) times the length of the concert. The initialized Pe-Ka, and Ka-GTC boundaries are marked using vertical dotted red lines for all the three concerts in Figure 9.

The boundary between alāp and pēśkār is accurate in the initial markings itself due to the difference in the timbre and the absence of percussion onsets in alāp. The Pe-Ka and the Ka-GTC boundaries need to be re-aligned considering the cues and musical characteristics. The duration of each segment in GTC sections is very small compared to others (Figure 3.
Figure 9: Section Classification update depiction for three different concerts. 
Green dotted lines: Segmentation boundaries. Black solid curves: mean value of ASD (M-ASD) in each segment. Blue E1: Ground truth Pe-Ka boundary. E2: Start of multiple small segments. 
Alt-Text: Figure shows the Section Classification update depiction for three different concerts. 
Green dotted lines: Segmentation boundaries. Black solid curves: mean value of ASD (M-ASD) in each segment. Blue E1: Ground truth Pe-Ka boundary. E2: Start of multiple small segments.

We check for the repeated smaller segments having a duration of fewer than 50 seconds, and the Ka-GTC boundary is shifted to the start of these smaller segments. These repeated smaller segments are depicted by ellipse E-2, and the updated Pe-Ka boundaries are depicted by vertical blue dotted lines for all the three concerts in Figure 9. Each composition is developed and played at a higher speed towards end, followed by a few cycles of ṭhēkā at the basic tempo before starting the next composition as described in Section 1.1. Thus, the ASD increases and decreases, indicating the end of the composition. This sudden drop in ASD followed by ṭhēkā in a slower tempo is also seen during the transition from pēskār to kāyadā. We check for this change in ASD around the initially assigned Pe-Ka boundary and update the Pe-Ka boundary as the end of pēskār. The updated Pe-Ka boundaries are depicted by blue vertical dotted lines in Figure 9.

5.2 Gharānā Recognition

Tabla gharānā recognition is a task of identifying the stylistic schools of tabla from tabla recordings. As described in Section 2, the tabla solo concert consists of several compositions played one after the other. Each composition may be from different gharānā-s. Given
Table 2: Dataset information of gharānā labels.

| Gharānā Name (ID) | No. of segments | Durations hh:mm:ss |
|-------------------|-----------------|--------------------|
| Ajrada (A)        | 73              | 2:23:58            |
| Banaras (B)       | 76              | 3:09:01            |
| Delhi (D)         | 84              | 2:32:11            |
| Farrukhabad (F)   | 96              | 2:36:50            |
| Lucknow (L)       | 83              | 2:34:52            |
| Punjab (P)        | 79              | 2:53:27            |

the section information such as segment boundaries and section labels (kāyadā, pēśkār, GTC), gharānā recognition is task is performed only on the kāyadā and GTC sections of the concert, primarily because the ground truth is available only for these two sections. Recognizing the gharānā from the pēśkār section is not straightforward as it is extempore and the improvisations are usually artiste specific. Table 2 shows the details of the annotated data used for gharānā recognition task.

Thus, given the segment boundaries, recognizing tabla gharānā for each segment (composition) is the third task.Tabla solos are developed, improvised, and elaborated upon a theme through a series of variations according to rhythmic practices Pradhan (2011). Thus some strokes co-occur more often than others in the tabla compositions. Hence it is essential to train the models by encoding the sequence information. The rhythmogram features only have tempo-related information but not sequence-specific language information. Thus we cannot use the ACF features directly for the gharānā recognition work. We used the CNN-LSTM model for gharānā recognition described in Gowriprasad et al. (2021). The CNN architecture extracts the raw audio’s local discriminate features on different stroke sounds. The LSTM networks are trained to classify the gharānā-s by processing the sequence of extracted features from CNNs.

6 Experiments and Results

Different experiments are performed addressing different challenges for the three tasks mentioned above.

6.1 Train-Test sets and evaluation criteria

The overall dataset consists of 50 concert recordings with around 2000 ground-truth annotated boundary instances marked as described in Section 2. We split the 50 concerts into 40-5-5 as train-development-test respectively. The supervised segmentation system evaluation is performed with 10-fold cross-validation. Since different artists use different tonics
to perform each concert, we tried to make train-test tonic and artiste mutually exclusive. The train-test tonic is different in each of the seven folds, and the artiste is different in 8 folds. In each fold, the 45 concerts form the train-dev set. Data augmentation is performed to increase the training data diversity. Speed perturbation with the factor of 0.9X and 1.1X (10% variation) without altering the pitch is done on the entire data using the HPSS-TSM method Driedger, Müller, and Ewert (2014); Yong, Choi, and Nam (2020). The speed perturbation essentially changes the speed and, in turn, changes the rhythmogram structure, thus resulting in a variation in features for training. Each fold has \(5 \times 3 = 15\) test concerts, and the final performance is averaged over ten folds (150 concerts). In the case of an unsupervised approach, the validation set is used to tune the hyperparameters, such as the kernel width, and peak picking thresholds. In the case of supervised, it is used to tune the network-related hyperparameters such as number of trees, context window, number of CNN layers, etc.

### 6.2 Structural segmentation (Results)

Structural segmentation in the context of tabla solo involves the detection of start and end instances of composition. Approaching the segmentation task as the boundary detection task, we inspect the presence or absence of a boundary in the uniformly spaced audio frame intervals of 0.5 s. The task is not addressed at the metrical time scale, stroke level but at a larger time scale. Thus the tolerance duration is not in milliseconds as in the case of stroke onset detection Bello et al. (2005); Gowriprasad and Murty (2020) but in a larger time scale in “seconds”. A detected boundary is considered true-positive if the prediction is within the tolerance of \(\pm 5\) seconds of ground truth (GT) boundary; otherwise, it is treated as false-positive. The performance is evaluated using the measures of precision, recall, and weighted-F1 scores.

#### 6.2.1 Unsupervised Segmentation

The segmentation evaluation scores like precision, recall, and F-measure for individual novelty functions and their combinations are tabulated in Table 3. NFs are computed by convolving \((50 \times 50)\) kernel with SSM of different features. Peak picking is performed with an adequate threshold, with a minimum distance between adjacent peaks as 10s. Combo-1 is obtained by averaging the rhythm-based NFs (ASD-D, NF-R, NF-P) by excluding NF-RF, as it found to have larger variance in F-measure. Combo-2 results are obtained by fusing the results of individual NFs after peak picking.

We experimented with smaller kernel sizes such as \((10 \times 10), (20 \times 20)\), resulting in noisy NFs. This decreased the precision as a lot of false positives were reported. Though much larger kernel sizes, such as \((100 \times 100)\), made the NFs smoother, they compromised
Table 3: Performance of Unsupervised Segmentation using different feature subsets.

| Features set | Precision | Recall | F-measure |
|--------------|-----------|--------|-----------|
| NF-M         | 0.86      | 0.55   | 0.63      |
| STE-D        | 0.77      | 0.81   | 0.78      |
| ASD-D        | 0.78      | 0.87   | 0.82      |
| NF-RF        | 0.76      | 0.86   | 0.79      |
| NF-R         | 0.83      | 0.90   | 0.86      |
| NF-P         | 0.80      | 0.91   | 0.85      |
| Combo-1      | 0.86      | 0.90   | **0.88**  |
| Combo-2      | **0.87**  | 0.90   | **0.88**  |

in resolving the closer boundaries. Thus we used \((50 \times 50)\) kernel owing to the reasons mentioned in Section 4.1. It is found to produce considerably smooth NFs that result in higher F-measure.

Timbre feature MFCC is performing very poorly compared to the rhythm-based features. Since a single tabla is used throughout the concert, the timbre of the tabla does not change throughout. Though the timbre of each stroke is different, the short-term averaging eliminates the stroke combination information within the context window. Even though the stroke combinations vary across the compositions, the stroke set remains the same. We can observe good precision but very poor recall (a lot of false-negative). This indicates that MFCC does not capture the change in rhythm structure. The timbre structure remains more or less the same throughout, making it hard to distinguish between adjacent compositions. Another important factor is that it is common to recite the face theme of the composition often before playing. These are especially seen in the GTC section. This switching between oral recitation and playing causes a drastic switch in timbre features. These drastic changes mask the other timbre changes due to rhythm variations during playing. This resulted in a very low recall.

We can observe that the precision is consistently less than recall in all the other cases, indicating false positives. The change in local rhythm structure, which may be both gradual and abrupt, causes peaks in the novelty function. The gradual change in rhythm structure can be seen often in the pēśkār section as it is extempore, and the tempo increases gradually. The abrupt changes due to pauses or inherent compositional characteristics can be seen throughout the concert.

NF-R and NF-P performed better than the rest NFs individually. The NF-R has the highest precision and lowest variance in F-measure while considering individual NF. In the case of NF-R, the entire rhythmogram is used to compute the SSM. The gradual tempo evolution and small pauses are less emphasized than larger changes in rhythmic structure across different compositions. This helped in reducing the false positives. In the case of
Table 4: Segmentation Performance of RF Classifier using different feature subset.

| Features set  | Parameters # trees | Performance Precision | Recall | F-measure |
|---------------|--------------------|-----------------------|--------|-----------|
| MFCC          | 25                 | 0.37                  | 0.59   | 0.45      |
| Rhythmogram   | 25                 | 0.85                  | 0.88   | 0.87      |
| Posteriors    | 30                 | 0.85                  | 0.84   | 0.84      |

NF-P, the posteriors are only dimension five, and each dimension captures a different set of tempo-rhythm structures. The gradual change in rhythm structure changes the posteriors at some point. This causes a few false positives in NF-P compared to NF-R.

Combining the NFs yielded slightly better results compared to the individual NFs. We can observe the increase in precision when the NFs are combined. Each NF highlights the actual boundary instances along with the spurious false positives. One of the advantages was that the spurious peaks are found at different instances in different NFs. Thus, these spurious peaks are de-emphasized, and the actual boundary peak instances common across the NFs are emphasized by taking the ensemble average of NFs (Combo-1). This increased the precision and the overall performance.

A similar behaviour is observed while fusing the information from different novelty functions. The common peaks are picked on the majority voting across the NFs. This helped retain most of the boundary peaks while eliminating the spurious ones, thus increasing the precision. We can observe that the recall is not compromised by these combinations of NFs, which indicates that each considered NF emphasizes the actual boundary instances correctly.

6.2.2 Random Forest Classifier

Table 4 presents the segmentation performance for different feature sets using random forest classifier. All the results are reported for the context duration of 10s, which was found to perform best. The performance of MFCC is clearly bad, indicating the inadequacy of timbre features for rhythm-based analysis. It can be observed that the rhythmogram feature alone performs better than the other features. This verifies the consistency of the rhythmogram feature performance as observed in the unsupervised approach.

6.2.3 CNN - Classifier

Since rhythmogram features worked best in both the unsupervised and RF methods, we also used the same features for the CNN classifier. We started with the architecture as described in Section 4.2.2. We experimented with different kernel sizes for convolution as well as max-pooling layers. We increased the number of convolutional layers, but the performance
did not improve, indicating the overfitting of the model. When used in the fully-connected layer, we found that the Relu activation function fetched 1.5% less training loss than the sigmoid. The use of additional max-pooling layers did not affect the performance. The final model architecture fetched the best results and has three convolutional layers and two fully connected layers.

Table 5: Segmentation Performance of CNN Classifier on Rhythmogram features.

| Model         | Context window C(s) | Performance |       |       |
|---------------|---------------------|-------------|-------|-------|
|               |                     | Precision   | Recall| F-measure |
| CNN-Classifier| 5                   | 0.86        | 0.87  | 0.86   |
|               | 10                  | 0.9         | 0.89  | **0.89** |
|               | 20                  | 0.84        | 0.81  | 0.83   |

Table 5 shows the performance results obtained for different context durations. The context duration values are motivated by the results from the RF classifier. It is evident from the results that increasing the context duration beyond 10s affected the performance as a larger context window contains multiple boundaries. This indicates that the larger context window contains multiple changes in rhythmic structure. The context window of 10s performed best in this case.

### 6.2.4 Structural Segmentation (Discussion)

Figure 10 depicts the performances of different approaches for tabla solo segmentation. Rhythmogram features alone proved to be more efficient in both the supervised and unsupervised approaches. Both the CNN and RF trained on rhythmogram features performed equally well. In the unsupervised approach, combining the peak information and NF-R performed competitively with supervised approach. As mentioned in the challenges section, the short pauses and vocal recitation in the middle of the rendition cause sudden changes in the feature vectors. These cause false positives during segment boundary detection. Thus we can observe that the precision is consistently less than recall almost in all the cases. Merging similar adjacent segments in the post-processing step increased the precision without compromising the recall. Adjacent segments are merged only if they have the same posteriors. Since a single composition is played at multiple speeds, the adjacent segments within the composition do not have the same posteriors, failing to merge and leading to false positives. The precision is relatively less than recall.

Table 6 presents the best performing unsupervised and supervised results for the individual sections separately. We can observe that all the models’ performance is high on kāyadā sections and low in the GTC section. This is evident as the kāyadā-s are the elaborate compositions explored on a theme and played longer than the GTC compositions. In the case of GTC, the compositions are smaller in length, and the rhythm structure changes
Figure 10: Comparative results for Segmentation task.
Alt-Text: Figure shows the comparative results for Segmentation task across both supervised and unsupervised methods via boxplots.

Table 6: Segmentation performance evaluated on individual section.

| Section | Unsup Combo-2 | CNN |
|---------|---------------|-----|
|         | Precision     | Recall | F-measure | Precision | Recall | F-measure |
| pēśkār  | 0.69          | 1      | 0.81      | 0.71      | 1      | 0.83      |
| kāyadā  | 0.94          | 0.98   | 0.96      | 0.94      | 0.95   | 0.94      |
| GTC     | 0.84          | 0.81   | 0.82      | 0.85      | 0.80   | 0.82      |

rapidly over time, causing false positives. There are many instances where the multiple gat-śs and tukdā-śs are played continuously without any gaps. This causes false negatives. In the case of pēśkār section, the tempo, and the rhythmic evolution are gradual. This change also evokes false positives in certain instances, even in the case of posterior features. This can be visualized in Figure 7 and Figure 8.

6.2.5 Out-of-Domain test data evaluation

The best performing supervised, and unsupervised systems are further evaluated on five new live concert recordings. These five concerts are considered the out-of-domain test data and, therefore, not used in systems’ hyperparameter tuning. Each of these five concerts is about 40-45 minutes in duration and contains more than a hundred annotated boundaries in total. These five concerts are from three different artistes who are distinct from the fifty concert artiste from the in-domain data. Thus the approach and the sequence of compositions played are reasonably different in these five concerts. These five concerts have only segment boundary and Pe-Ka-GTC annotations and do not have gharānā labels.

Table 7 presents the performance of supervised and unsupervised models on the five out-of-domain test concerts. The Combo-2 in the unsupervised approach performed slightly better than the supervised approach. Despite concert and artiste-specific variations, the
Table 7: Segmentation performance on out-of-domain test data (five unseen test concerts).

| Methods | Performance |
|---------|-------------|
|         | Precision  | Recall | F-measure |
| UnSup   |             |        |           |
| NF-R    | 0.81        | 0.86   | 0.84      |
| NF-P    | 0.80        | 0.86   | 0.83      |
| Combo-1 | 0.85        | 0.86   | 0.85      |
| Combo-2 | 0.85        | 0.86   | 0.86      |
| Sup     |             |        |           |
| Random Forest | 0.79 | 0.87 | 0.83 |
| CNN     | 0.80        | 0.88   | 0.845     |

CNN and RF performance did not degrade much. This indicates the models are not overfitting. The performance on the out-of-domain data validates the efficiency of rhythmogram features. The advantage of rhythmogram features is that it is independent of the different tonic values in the concert, as it is computed only on the onset instances of the strokes. Thus the variations of the concert-specific parameters such as lehra (sarangi/harmonium) and tabla tonic variations do not affect the structure of the rhythmogram. We can also observe that only precision degraded while the recall did not. These five recordings are from live concert renditions and have many pauses and vocal recitations in the middle. These characteristic fluctuations resulted in false positives, which in turn decreased the precision.

6.3 Section classification

Section classification does not require training, as the algorithm for the task is a set of rules that makes the decision. Thus the classification performance evaluation is done on the entire data. Considering the ground truth annotations, we quantify the performance of section classification by calculating the number of miss-classified frames in the whole recording. We present the evaluation in terms of accuracy: the ratio of the number of frames correctly classified to the total number of frames in the concert. The weighted average of accuracy considering the length of the concert is 92%. That is, given one hour of segmented concert details, around 55 minutes of the concert frames are correctly labeled as pēskār – kāyadā – GTC. The ground truth location for Pe-Ka boundary is marked by ellipse E-1 in Figure 9. In the case of concerts (A) and (B), the final Pe-Ka boundary is found to coincide with the E-1. In the case of concert (C), an error in the final Pe-Ka boundary is observed, which is not coinciding with E-1. The frames belonging to Ka, which are misclassified, are also marked in Figure 9-C. The section classification accuracy in the case of out-of-domain test concerts is found to be 86%. This is because the sequence of compositions in the five concerts is slightly different. There were a few instances of gaṭ-s and tukdā-s in between the kāyadā-s which is significantly different from that present in the training data.
6.4 Gharānā recognition

The task of gharānā recognition is performed using the CNN-LSTM model described in Gowriprasad et al. (2021). The train-test data split is the same as the segmentation task. The audios from the Ka and GTC sections of the 45 concert audios are used for training, and five concert audios for testing. The section audios are segmented into fifteen seconds smaller chunks with a five seconds overlap. Each fifteen-second chunk is treated as an individual data point for training the network.

During testing, gharānā prediction is made independently on each of the fifteen-second chunks in a particular segment. The number of chunks predicted for each gharānā in the segment is counted. The final gharānā label for a segment is assigned according to the majority vote. The gharānā for the whole segment is labelled by the voting rule, i.e., the gharānā to which a maximum number of chunks are predicted. The experiment is 5-fold cross-validated, and the average performance results are tabulated in Table 8. One can observe that the performance is better when evaluated segment-wise. Though a few chunks in a segment confused and miss-classified, most of the chunks in the segment were classified correctly, making the gharānā recognition better segment-wise. The gharānā recognition task is performed by labeling the automatically segmented audios in this work. The train-

| Performance | Experiment | Weighted F1 | Accuracy |
|-------------|------------|-------------|----------|
| Chunk wise  | 0.72       | 0.71        |
| Section wise| 0.78       | 0.79        |

Figure 11: (a) Gharānā Recognition Confusion Matrix, (b) t-SNE visualization of test data embedding extracted from CNN-LSTM Model.

Alt-Text: Figure shows (a) Gharānā Recognition Confusion Matrix, (b) t-SNE visualization of test data embedding extracted from CNN-LSTM Model.
split task was kept the same as before (segmentation task). Since the train and test concerts are different in each fold of evaluation, the tonic and artiste of the train-test were maintained distinct. Thus the gharānā recognition results are in the context of inter-artiste and inter-tonic conditions as mentioned in Gowriprasad et al. (2021).

The confusion matrix depicting the gharānā recognition performance and the t-SNE visualization of the test data embeddings from the penultimate layer of the CNN-LSTM network for fifteen seconds chunk duration are shown in Figure 11. Different clusters are marked for the benefit of reference. We can observe confusion between Ajrada-Delhi ($C_1$), as well Lucknow-Farrukhabad ($C_2$). This confusion is defensible as the Farrukhabad and Ajrada gharānā-s are developed from Lucknow and Delhi gharānā-s respectively Gottlieb (1993). Less confusion and high recognition accuracy are observed in the case of Banaras ($C_3$) and Punjab gharānā ($C_4$) embeddings. This is apparent as the Punjab gharānā has had an individual existence and is distinctive compared to the other ones Pradhan (2011). Pakhāwaj syllables highly influence the Banaras gharānā Gottlieb (1993), and the technique of playing the bass drum is also unique in Banaras gharānā Pradhan (2011). Thus one can verify some of the traditional similarities and differences across the gharānā-s as portrayed and described in the sources Gottlieb (1993); Pradhan (2011); Saxena (2006) from the obtained results.

7 Conclusions

This work has addressed an unexplored problem, structural segmentation and labeling of tabla solo concerts. We described the different sections of tabla solo concerts and analyzed their diversity using various statistical parameters. The major contributions of this work are as follows: (i) curating a diverse dataset of tabla solo recordings having section boundary information along with gharānā annotated section labels, (ii) evaluating the existing MIR techniques for a musicologically important task segmentation and labeling of tabla solo concert, (iii) formulating Average Stroke Density ASD feature (a representative of surface tempo), which is robust to tempo octave errors, (iv) formulating the class-conditional probability features from the rhythmogram, and (v) exploring the combination of different NFs obtained from different features.

We described the challenges that are unique to the above tasks. We evaluated the performance of unsupervised and supervised methods for the structural segmentation task. The CNN classifier trained on hand-crafted rhythm features performed well on the in-domain dataset with an F-measure of 0.89 and 0.845 on the out-of-domain test data. The unsupervised approach based on rhythm features performed competitively on in-domain and out-of-domain datasets, achieving F-measures of 0.88 and 0.86, respectively. We found that the rhythmogram is robust to concert and artiste variations. By choosing a suitable
combination of hand-crafted features, it appears that the unsupervised approach performs on par with the supervised machine learning approaches.

The labeling task consists of classifying the segments into high-level sections and recognizing the gharānā-s of each segment. As shown in the Section 6, the results of segment classification and gharānā recognition tasks are reliable with the performance accuracies of 92% and 79%, respectively. The outcome of the tasks, such as section boundaries, section-specific, and gharānā specific labeling, are vital metadata for analysis of tabla solo performances.

8 Data Availability

Manually annotated metadata of all the audio files and the information about the audios sources in the dataset will be provided upon request.

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Glossary

tāl The rhythmic framework of Hindustani music.
alāp An unmetered melodic improvisation.
ṭhēkā The basic stroke pattern associated with a tāl.
gharānā The stylistic schools of Hindustani music.
mātra The lowest defined metrical pulse in Hindustani music (equivalent to a beat).
sam The first mātra of rhythm cycle.
pakhāwaj A double barrel drum used as rhythm accompaniment in Hindustani music.
lehra Melodic accompaniment in tabla solo performances which keeps track of the metric tempo.
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Structural Segmentation and Annotation of Tabla solo performances
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1 Introduction

With the vast availability of varied music collections on the digital platform and widespread use of personal digital devices, there is a growing interest in accessing music based on its various characteristics. Metadata supplied with commercial CDs or performance audios on the internet provides information about the musicians and, possibly, about the number and duration of the constituent music tracks. However, section boundary information among the tracks and other annotations is rarely specified. The limited availability of editorial metadata and annotations led to the need for music information retrieval to automatically extract music’s characteristic properties from the audio recordings.

This paper addresses the structural segmentation and annotation of tabla solo concert recordings. Tabla solo is intricate and elaborate, with a variety of precomposed forms used for developing further elaborations based on the player’s stylistic schools called gharānā-s. Segmentation of the tabla solo performance into different sections involves finding the boundaries that mark the transition between two structural segments. This paper further the automatic labeling and identification of tabla gharānā-s on the segmented audio clips. Thus the paper addresses three tasks: 1. Concert segmentation by detecting the segment boundaries. 2. Segment classification and labeling. 3. Gharānā recognition and annotation for each segment. Identifying the section labels and the gharānā specific information from a tabla performance provides valuable editorial metadata, which helps characterize performance and further musicological analysis.

Music structure analysis of tabla performance is vital from Music Information Retrieval (MIR) standpoint. Audio segmentation is crucial for MIR applications like fast navigation (Cooper and Foote, 2003; Peeters, 2003), finding repetitive structure in music, or even for music transcription (Klapuri et al., 2001). The automatic metadata identification facilitates complicated tasks like section labeling, audio thumbnailing (Bartsch and Wakefield, 2005), music summarization and description, auto-tagging, similarity measures, and discovery, and informed and enhanced music listening training and computational musicology. Automatic metadata identification from audio-like, stylistic school recognition- especially in the same genre- is a tough task, even for humans.
The present work is intended to explore the existing potential MIR techniques to a musicologically interesting task in an under-researched genre. Since much of the MIR research has focused on Western and other popular music cultures, we test existing Unsupervised and supervised methods for structural segmentation and annotation by exploring new approaches and features motivated by the characteristics of the music tradition. The system design involving the culture-specific musicological perspectives can also provide new insights about performance practice over that possible with purely data-driven methods (Serra, 2011).

The rest of the paper is structured as follows. We discuss an overview of tabla solo performances and tabla gharānā-s, followed by a literature review. The challenging factors influencing the task are categorically mentioned motivating the experiment. The dataset collected for the task and the annotation procedure is described in Section 2. Various acoustic and rhythmic features inspired by the characteristics of the music tradition are discussed in Section 3. Segmentation approaches, experiment conditions, and models are explained in Section 4 and the section classification and labeling in Section 5. Multiple experiments addressing various facets of the task are described. The experimental results are analyzed and discussed in Section 6. Finally, Section 7 summarizes the work and points to some future tasks.

After we get the hypothesized boundaries, we compute the median value of ASD (M-ASD) in each section as depicted in Figure ??.

The steps followed for the Unsupervised approach:

- Audio pre-processing and onset detection
- ACF, rhythmogram computation.
- Compute self similarity matrix and foote’s novelty function (FNF).
- Compute rhythmogram posteriors.
- Compute rhythmogram flux (NF-RF).
- Compute average stroke density (ASD), and get the first difference of ASD to get 1D-ASD.
- Add FNF, NF-RF, and 1D-ASD to get the novelty function.
- Perform peak picking to get the segment boundaries.
Table 1: Segmentation performance of the different methods on test concerts.

| Methods | Models          | In-domain test data 5-fold |          | Out of domain test data |          |
|---------|-----------------|----------------------------|----------|-------------------------|----------|
|         |                 | Precision | Recall | Weighted F1 | Precision | Recall | Weighted F1 |
|         |                 | 0.73      | 0.69   | 0.71        | 0.74      | 0.76   | 0.75        |
| Unsupervised | ACF       | 0.78      | 0.76   | 0.77        | 0.81      | 0.86   | 0.84        |
|         | Postiors       | 0.84      | 0.85   | 0.85        | 0.84      | 0.89   | 0.87        |
| Supervised | RF          | 0.86      | 0.89   | 0.88        | 0.88      | 0.92   | 0.9         |
|         | CNN            | 0.84      | 0.83   | 0.83        | 0.80      | 0.78   | 0.79        |
|         | CNN-LSTM       |           |        |             |           |        |             |