Signal-Based Characterisation of Stylistic Variation Across Tabla Gharanas

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Independent Research

Abstract

The gharana system of North Indian classical music represents one of the most formalised traditions of stylistic transmission in the world, yet remains almost entirely unexamined from a computational perspective. A corpus-based, signal-level investigation of stylistic variation across four tabla gharanas (Delhi, Lucknow, Benares, and Punjab) is presented, using onset-derived and spectral features extracted from solo concert recordings. Four acoustically robust metrics are proposed and evaluated: the Normalised Pairwise Variability Index (nPVI), a normalised low-frequency energy ratio, a burst density coefficient, and the coefficient of variation of per-onset spectral centroid. Each metric is theoretically motivated by documented properties of gharana style, with predictions derived from ethnomusicological literature prior to analysis. To our knowledge, this constitutes the first signal-level computational study of tabla gharana stylistics, and a methodological framework is proposed to support future work in this domain.

Keywords: tabla, gharana, computational musicology, music information retrieval, Hindustani music, onset analysis, rhythmic style, timbral analysis

1. Introduction

The tabla is the principal percussion instrument of Hindustani classical music. It is a pair of hand drums capable of an exceptional range of timbres and rhythmic expression, performed both in ensemble and as a solo instrument in its own right. Solo tabla performance is organised through a system of hereditary schools known as gharanas, each originating in a particular region of North India and transmitting its own heritage of technique, sound, and aesthetic values from teacher to student across generations.

Six such schools are formally recognised: Delhi, Ajrada, Lucknow, Farrukhabad, Benares, and Punjab. The stylistic differences between them, documented extensively in the ethnomusicological literature [1, 2], are the product of centuries of geographic isolation and lineage-based transmission, and remain a central concern for performers and scholars of Hindustani music.

Despite this richness, the tabla gharana system has received almost no attention from the computational musicology community. To our knowledge, no prior study has attempted to characterise inter-gharana stylistic differences from audio signals. This paper addresses that gap. A signal-based analysis of four gharanas, namely Delhi, Lucknow, Benares, and Punjab, is presented using onset-derived and spectral features extracted from solo concert recordings, without stroke-level transcription or section labelling. Four metrics are proposed, each grounded in a specific musicological prediction. Results show ordering patterns consistent with predictions across all four metrics, with large and statistically significant effects for two.

2. Background

2.1 The Tabla and Its Compositional Vocabulary

The tabla consists of two drums: the dayan, a small conical treble drum played with the dominant hand, and the bayan, a kettle-shaped bass drum played with the non-dominant. Each produces its characteristic sounds through a system of syllables called bols, such as na, ti, and tun on the dayan; ge and ka on the bayan; and compound strokes such as dha and dhin engaging both simultaneously. These syllables are the basis of the grammar of tabla: compositions are conceived as a sequence of bols, and their oral recitation is itself a performance art [1].

Taal is a cyclically repeating time cycle of a fixed number of beats (matras). The subdivision of each beat is described by the concept of jati: groups of four (chatusra), three (tishra), five (khand), seven (misra), or nine (sankirna) per beat. For instance, teentaal is the 16-beat taal can be treated as 4 bars of 4 beats (4/4 time), and tishra jati is equivalent to playing triplets in this time signature. Deliberate play between jatis is a primary tool of rhythmic elaboration and a key axis on which gharanas differ [3].

A tabla solo follows a broadly understood structural arc. The peshkar is a slow, improvisatory introduction. The kayda is the central form: a composed theme elaborated through a series of variations (paltas) using only the theme's bol vocabulary. The rela is a fast, continuous section. Shorter fixed compositions such as tukra, chakradhar, and paran are performed in sequence towards the close of the concert, typically ending with a tihai, a phrase repeated exactly three times resolving onto the first beat (sam) of the cycle. Between compositions, the player returns to the theka, the fundamental bol pattern marking the taal, often embellishing it with melodic elaborations (rao) [4].

2.2 The Gharana System

The most fundamental stylistic distinction in tabla is between band baaj (closed style) and khula baaj (open style). In band baaj, strokes are played on the chaati (inner rim) of the dayan with the hand remaining close to the drumhead, producing a controlled, less resonant sound. In khula baaj, the hand lifts freely after each stroke, allowing resonance to sustain and ring. These two approaches reflect different aesthetic philosophies: band baaj values clarity and precise articulation; khula baaj values tonal richness and expressive weight [5].

The tabla is generally dated to the mid-to-late 18th century, when Siddhar Khan Dhadi formalised its technique in Delhi [6]. Delhi is the oldest school and its band baaj kayda repertoire became the foundation all subsequent gharanas either adopted or innovated upon. Delhi is also called do ungliyon ka baaj (two-finger style): most dayan strokes use only the index and middle fingers on the outer rim, producing controlled clarity with limited resonance and deliberate restraint in bayan use [4].

Lucknow developed in close contact with kathak dance, producing a khula baaj style that prioritises tonal beauty, full-hand strokes on the bayan maidan, and compositional forms such as gat, toda, and paran derived from dance accompaniment [2].

Benares was founded by Pandit Ram Sahai (1780-1826), who trained in Lucknow before developing an independent style characterised by full-palm pakhawaj-derived strokes, strong meend on the bayan, and a dramatic concert aesthetic [7].

Punjab has no lineage connection to Delhi and originates instead in the pakhawaj tradition of the Punjab region [8]. Its compositional priorities are gat, paran, and chakradhar, and in the modern era, the lineage of Ustad Alla Rakha and Ustad Zakir Hussain made jati variety the most internationally recognisable signature of Punjab tabla [9].

2.3 Related Computational Work

MIR work on Indian classical music has focused primarily on melodic analysis (raga recognition) and beat tracking rather than percussion style. The CompMusic project [10] identified beat tracking as particularly difficult in this domain; Gowriprasad and Aravind (2022) [11] address structural segmentation of tabla solos, directly relevant to the section-type confounding problem identified here; and Bhattacharjee and Rao (2021) [12] demonstrate four-way stroke classification, reporting that recording quality variation remains a significant obstacle, a constraint this study explicitly designs around.

Onset-based rhythm features draw on Bello et al. (2005) [13] and Dixon (2006) [14] for detection methodology, Senn et al. (2017) [15] for density-based descriptors, and Grabe and Low (2002) [16] and Patel (2008) [17] for the nPVI. Standard timbral features such as MFCCs and raw spectral centroid were evaluated and found unsuitable for a percussive corpus with high recording quality variation; the dimensionless, within-clip normalised measures adopted here represent a methodological adaptation to these constraints.

3. Corpus and Data Preparation

3.1 Recording Selection

The corpus comprises publicly available solo tabla concert recordings spanning four gharanas: Delhi, Lucknow, Benares, and Punjab. For each gharana, recordings from two to three performing artists were selected, prioritising artists whose gharana affiliation is explicitly documented in the musicological literature or confirmed by lineage. All recordings are solo performances in Teentaal, chosen to minimise variation arising from differences in tala structure. No recordings were sourced from controlled studio environments, reflecting the realistic constraint that professional studio-quality tabla recordings with verified gharana provenance are not systematically available, and is a limitation shared by most computational work on
Indian classical music [18].

3.2 Audio Preprocessing and Clip Extraction

Each recording was loaded as a mono signal at its native sample rate using LIBROSA [19] and segmented into non-overlapping clips of four minutes (240 seconds). Two exclusion criteria were applied after feature extraction. Clips in which the mean per-onset low-frequency energy ratio exceeded 0.50 were flagged as likely contaminated by drone or severe bass equalisation and excluded from all analyses. Clips yielding fewer than 30 detected onsets were also excluded as degenerate. Table 1 reports the final corpus composition.

Table 1. Corpus Summary After Exclusion.

Gharana	Artists	Total Clips	Flagged	N_{clips}
Delhi	Ustad Inam Ali Khan, Babar Latif	38	4	34
Lucknow	Pandit Swapan Chaudhuri, Ustad Ilmas Hussain Khan	54	11	43
Benares	Pandit Kumar Bose, Pandit Sanju Sahai	40	2	38
Punjab	Ustad Zakir Hussain, Ustad Miyan Shaukat Hussain, Pandit Yogesh Samsi	52	7	45

Total		**184**	**24**	**160**

4. Methodology

4.1 Design Principle

A fundamental constraint of this corpus is the substantial variation in recording quality across artists, decades, and source types: differences in microphone placement, dynamic compression, and EQ that are irreducible in an archival corpus of this kind. Any feature sensitive to absolute amplitude or spectral balance is therefore unreliable as a stylistic signal. All features are computed as dimensionless ratios or normalised measures designed to be invariant to recording level, following Grosche and Müller (2011) [20], who demonstrate that density-based measures require local rate normalisation to remain interpretable across different performance contexts.

4.2 Onset Detection

The tabla produces a wide variety of stroke timbres, and the long decay tails of resonant strokes can generate spurious onset detections if detection sensitivity is not carefully managed. This is a known challenge: Gowriprasad and Aravind (2022) [11] identify onset detection as a primary bottleneck in tabla analysis. Onset detection was performed using LIBROSA [19], following the spectral flux pipeline described by Bello et al. (2005) [13] and evaluated for percussive audio by Dixon (2006) [14]. The onset strength envelope was computed using median rather than mean spectral flux aggregation, which reduces sensitivity to sustained low-frequency resonance. Peak-picking used a relative onset strength threshold ($\delta = 0.06$) and a minimum inter-onset wait of four frames (approximately 40ms at hop length 512), with a post-processing filter discarding any pair of onsets separated by fewer than 25ms.

4.3 Feature Extraction

Four metrics are computed per clip. Each is designed to capture a distinct dimension of the acoustic differences described in the gharana literature.

4.3.1 Normalised Pairwise Variability Index (nPVI)

Let $\{\delta_1, ..., \delta_N\}$ be the sequence of inter-onset intervals (IOIs) in seconds. The nPVI is:

$$\mathrm{nPVI} = \frac{100}{N-1}\sum_{k=1}^{N-1}\left|\frac{\delta_k - \delta_{k+1}}{(\delta_k + \delta_{k+1})/2}\right|$$

This measures the mean normalised contrast between each successive pair of IOIs. It is dimensionless and tempo-invariant. High nPVI indicates that adjacent strokes tend to differ markedly in duration; low nPVI indicates even, isochronous subdivision. Originally developed for cross-linguistic speech rhythm comparison [16], its application here is motivated by the contrast between Delhi's traditional usage of chatusra jati and Punjab's exploration of odd-metered phrases through tishra and khanda jati, a practice that by definition produces large pairwise IOI contrasts.

4.3.2 Bayan Mean (Low-Frequency Energy Ratio)

For each detected onset, a short STFT window is extracted and the per-onset low-frequency energy ratio computed as:

$$r_t = \frac{\sum_{f \le 300\text{Hz}} |S_t(f)|^2}{\sum_f \quad |S_t(f)|^2}$$

The clip-level Bayan Mean is the mean of r_t across all onset frames, given by
$\overline{r} = \frac{1}{|T|} \sum_{t \in T} r_t$.
The 300 Hz cutoff captures the fundamental frequency range of the bayan drum, typically tuned between 60 and 200 Hz [21], while excluding the primary resonant register of the dayan. Delhi's tradition values restraint in bayan use [1]; Benares is defined in part by strong bayan emphasis [2]. Gowriprasad and Aravind (2025) [22] demonstrate that low-frequency energy content is among the most discriminative acoustic features for separating bass-register from treble-register strokes.

4.3.3 Burst Coefficient

Local onset density r(t) is the number of onsets in a 2.5-second sliding window centred at t, divided by the window width, evaluated at 0.5-second hops. The Burst Coefficient (b) is:

$$b = \frac{P_{95}(r(t))}{P_{50}(r(t))},$$

where P_n is the nth percentile. A value of 1 indicates uniform density; higher values indicate that a performance's densest moments are dramatically more intense than its typical texture. The use of P_{95} rather than the maximum follows the robust percentile approach recommended by Lartillot et al. (2008) [23].

4.3.4 Spectral Centroid Coefficient of Variation (Centroid CV)

The spectral centroid at onset frame t is the frequency-weighted centre of gravity of the spectrum:

$$C_t = \frac{\sum_f f \cdot |S_t(f)|^2}{\sum_f |S_t(f)|^2}$$

The Centroid CV, the coefficient of variation of per-onset centroid values C_T, is given by:

$$c_v = \frac{\sigma(C_T)}{\mu(C_T)}$$

This measures how dramatically the spectral centre of gravity shifts between strokes, capturing timbral variety rather than timbral register. The CV formulation removes dependence on absolute tonal register, which varies with recording equalisation. The khula baaj traditions (Lucknow, Benares, Punjab) involve deliberate alternation between resonant bass-heavy bayan strokes and bright dayan strokes, producing large swing in centroid value. Delhi's band baaj two-finger technique produces tonally more homogeneous strokes, predicting the lowest Centroid CV. The spectral centroid is a well-established proxy for the brightness of a sound [24], and its per-onset computation for percussive instruments follows Bello et al. (2005) [13].

4.4 Metrics Considered but Excluded

A larger set of twenty candidate metrics was evaluated prior to the selection of the four reported above.
IOI Coefficient of Variation [14]: Produced clear separation of Benares from the other groups but failed to distinguish Delhi from Lucknow (means of 0.89 and 0.87 respectively), likely due to section-type

confounding: both styles produce moderate global timing variability when kayda, rela, and theka sections are averaged together.

ISME Slope (multi-scale IOI entropy slope): Showed directional signals consistent with predictions in early runs but became positive and undifferentiated across all gharanas in the full corpus, suggesting the early signal was driven by a single artist group rather than a stable cross-gharana dimension.

Stroke stream separation: Attempted via a logistic regression classifier trained on manually labelled dayan and bayan onsets. The classifier achieved only 31% cross-validated accuracy against a 33% chance baseline. Gowriprasad and Aravind (2025) [22] note that reliable cross-recording stroke classification requires either recording-matched training data or tonic normalisation; neither was feasible within this corpus.

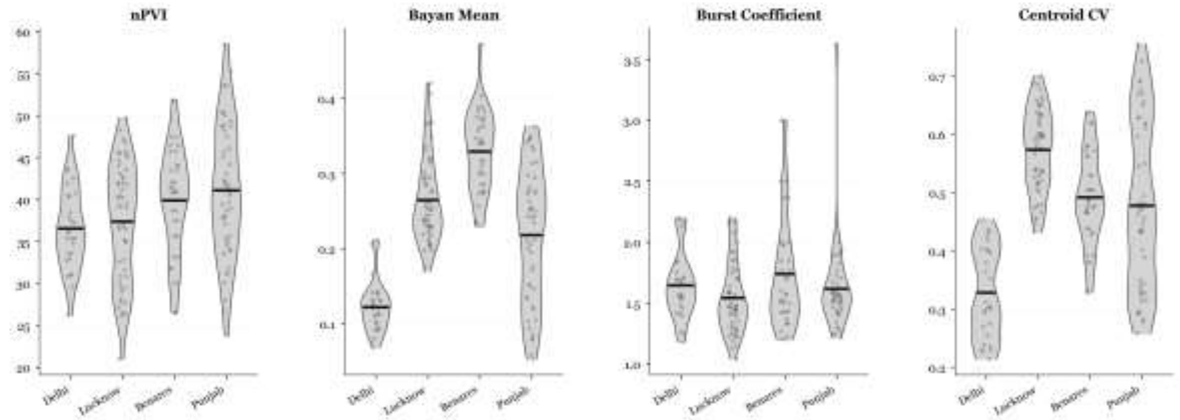
5. Results

Table 2 reports the mean and standard deviation of each metric per gharana across all clean clips. Figure 1 shows the full distributions as violin plots and Figure 2 presents the group ranking and spread for each metric as ranked dot plots.

Table 2. Mean (Plus or Minus SD) of Each Metric Per Gharana.

Gharana	nPVI	Bayan Mean	Burst Coefficient	Centroid CV
Delhi	36.550 +/- 4.972	0.122 +/- 0.034	1.646 +/- 0.277	0.328 +/- 0.078
Lucknow	37.374 +/- 7.039	0.265 +/- 0.057	1.541 +/- 0.294	0.573 +/- 0.070
Benares	39.877 +/- 6.464	0.329 +/- 0.054	1.739 +/- 0.472	0.492 +/- 0.081
Punjab	41.080 +/- 7.990	0.218 +/- 0.090	1.617 +/- 0.364	0.477 +/- 0.146

Figure 1: Per-clip distributions of all four metrics across gharanas. Violin width reflects kernel density. Horizontal bars indicate group means.



5.1 Statistical Validation

To assess whether the observed group mean differences are likely to reflect genuine gharana-level stylistic patterns rather than chance variation, a permutation-based one-way F-test was conducted for each metric (5,000 permutations). The observed F-statistic was compared against a null distribution constructed by randomly reassigning gharana labels across clips, providing a test of the null hypothesis that gharana identity carries no information about metric values. Because four tests are conducted simultaneously, Bonferroni correction is applied by multiplying each p-value by four, controlling the family-wise error rate at $\alpha = 0.05$. Effect size is reported as η^2, the proportion of total variance in each metric accounted for by gharana identity [25]. Conventional benchmarks are: small $\eta^2 >= 0.01$, medium $\eta^2 >= 0.06$, large $\eta^2 >= 0.14$.

Table 3. Permutation F-Test Results (5,000 Permutations).

Metric	F	p (corrected)	η^2	Effect Size
nPVI	3.687	0.050	0.065	Medium
Bayan Mean	56.413	< 0.001	0.516	Large
Burst Coefficient	2.226	0.334	0.040	Small
Centroid CV	35.332	< 0.001	0.400	Large

6. Discussion

6.1 Interpretation of Findings

Across all four metrics, the observed group mean orderings are consistent with predictions derived from the gharana literature prior to analysis. Figure 2 represents the group ranking and spread for each metric individually as dot plots. Table 4 summarises the comparison of predicted to observed ordering.

Figure 2. Gharana rankings on each metric.

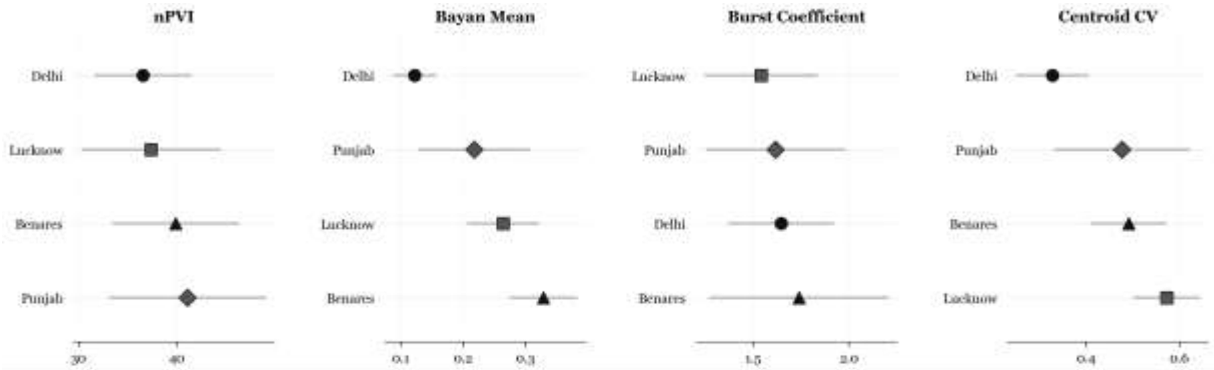


Table 4. Predicted Versus Observed Group Orderings.

Metric	Predicted Ordering	Consistent?
nPVI	Punjab > Benares > Lucknow > Delhi	Yes
Bayan Mean	Benares > Lucknow > Punjab > Delhi	Yes
Burst Coefficient	Benares > {Lucknow, Punjab} > Delhi	Partial
Centroid CV	Lucknow > Benares > Punjab > Delhi	Yes

The strongest and most statistically robust findings concern the two spectral metrics. With Benares highest, Delhi lowest, and an effect size accounting for over half the total variance in the measure, the Bayan Mean result provides direct computational evidence that the documented difference in bayan register emphasis between the khula baaj and band baaj traditions is acoustically realised in modern performance at a level detectable from undifferentiated audio. The Centroid CV result is equally clear: Delhi's two-finger technique produces tonally homogeneous strokes (low centroid variance) while all three khula baaj traditions alternate more freely between bass-heavy and bright strokes, producing higher centroid variance. Delhi sitting substantially below the other three on both spectral metrics, by margins that exceed within-group spread, is the most consistent finding in the dataset.

The nPVI result, while modest in effect size, aligns with the single most specific prediction in the study: that Punjab's tradition of jati exploration would produce the highest pairwise IOI contrast in the corpus. The modest effect size reflects the sensitivity of this metric to section-type composition within clips: dense rela sections are inherently isochronous regardless of gharana, and clips containing more rela material will produce lower nPVI independently of style.

The Burst Coefficient does not reach significance after correction, but its directional consistency is preserved. Benares highest and Lucknow lowest are both predicted, and Delhi's second-place position is interpretable through the structure of the Delhi concert tradition. The plain, unembellished theka sections characteristic of Delhi performance create a sparse floor density that immediately precedes and follows denser compositions, producing sharp local density contrasts that inflate the Burst Coefficient independently of the dramatic energy shaping that drives Benares's high value. This interpretation is post-hoc and would require section-annotated data to confirm but is consistent with the concert structure documented by Mativetsky (2023) [7].

Taken together, the results suggest that the band baaj versus khula baaj distinction is the dimension most reliably detectable from undifferentiated audio at this corpus size. Rhythmic surface features such as nPVI carry genuine signal but require section conditioning to express it cleanly.

6.2 Limitations

The most significant methodological limitation is section-type confounding. Clips contain undifferentiated mixtures of kayda, rela, theka, and transitional passages. Because these section types have systematically different acoustic properties independent of gharana, the composition of sections within a clip affects all metrics as a nuisance variable. A corpus with section-level annotations would allow conditioning before metric computation, and is predicted to substantially improve sensitivity, particularly for nPVI and Burst Coefficient.

A further structural limitation is the erosion of gharana boundaries in modern performance. As Neuman (1980) [26] documents, the regional isolation that allowed distinct styles to crystallise has given way to cross-gharana learning, recorded transmission, and deliberate synthesis. The effect sizes observed for Bayan Mean and Centroid CV are notable for persisting despite this convergence, but the modest nPVI effect and non-significant Burst Coefficient may partly reflect genuine stylistic homogenisation. Finally, the corpus comprises two to three artists per gharana, which limits statistical power and means effect size estimates are imprecise. The findings should be understood as exploratory and directional rather than confirmatory.

7. Conclusion

A signal-based computational analysis of stylistic variation across four tabla gharanas is presented, using four onset-derived and spectral metrics extracted from solo concert recordings without stroke-level transcription or section labelling. Across all four metrics, group mean orderings were consistent with predictions derived from musicological literature prior to analysis. Two metrics, Bayan Mean and Centroid CV, showed large effect sizes ($\eta^2 = 0.516$ and 0.400 respectively) with statistically significant gharana-level separation after Bonferroni correction, providing robust computational evidence that the band baaj versus khula baaj distinction is acoustically realised in modern performance at a level detectable from undifferentiated audio.

The principal methodological contribution is the identification of section-type confounding as a binding constraint for computational analysis of this repertoire, and the proposal of recording-robust, within-clip-normalised features as a design principle for working within it. Future work with section-annotated corpora is expected to recover substantially cleaner separation on the remaining metrics.

Data Availability

Feature extraction code and computed metric CSVs are available from the author on request. Raw audio recordings were sourced from publicly available concert documentation and used solely for non-commercial academic feature extraction.

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References

1. Gottlieb R.S. (1993), Solo Tabla Drumming of North India. Motilal Banarsidass, Delhi.
2. Kippen J. (1988), The Tabla of Lucknow: A Cultural Analysis of a Musical Tradition. Cambridge University Press, Cambridge.
3. Clayton M. (2000), Time in Indian Music: Rhythm, Metre, and Form in North Indian Rag Performance. Oxford University Press.
4. Varma S.K. (2019), The Art of Tabla Playing. https://tablaabhi.com/wp-content/uploads/2019/05/219921265-the-art-of-tabla-playing-prof-sudhir-k-varma.pdf
5. DigiTabla (2024), Tabla Baj. https://digitabla.com/tabla-tradition/baj/
6. Delaram Music (2026), The Tabla: A Comprehensive Historical Overview. https://www.delaramm.com/the-tabla-a-comprehensive-historical-overview/
7. Mativetsky S. (2023), The Art of Tabla Solo in the Benares Gharana. https://shawnmativetsky.com/the-art-of-tabla-solo-in-the-benares-gharana
8. TablaSpark (2018), Tabla Gharanas and Baaj. https://tablaspark.wordpress.com/2018/11/24/tabla-gharanas-and-baaj/
9. Burhoe T. (2024), Tabla Gharanas. https://www.tyburhoe.com/gharanas
10. Srinivasamurthy A., Holzapfel A., Serra X. (2014), In Search of Automatic Rhythm Analysis Methods for Turkish and Indian Art Music. Journal of New Music Research, 43(1), 94-114.

11. Gowriprasad R., Aravind R. (2022), Structural Segmentation and Labeling of Tabla Solo Performances. Proceedings of ISMIR.
12. Bhattacharjee A., Rao P. (2021), Four-Way Classification of Tabla Strokes with Models Adapted from Automatic Drum Transcription. Proceedings of NCC.
13. Bello J.P., Daudet L., Abdallah S., Duxbury C., Davies M., Sandler M.B. (2005), A Tutorial on Onset Detection in Music Signals. IEEE Transactions on Speech and Audio Processing, 13(5), 1035-1047.
14. Dixon S. (2006), Onset Detection Revisited. Proceedings of DAFx-06, Montreal, 133-137.
15. Senn O., Bullerjahn C., Kilchenmann L., von Georgi R. (2017), Rhythmic Density Affects Listeners Emotional Response to Microtiming. Frontiers in Psychology, 8.
16. Grabe E., Low E.L. (2002), Durational Variability in Speech and the Rhythm Class Hypothesis. Papers in Laboratory Phonology, 7, 515-546.
17. Patel A.D. (2008), Music, Language, and the Brain. Oxford University Press, Oxford.
18. Mehta A. et al. (2025), Music for All: Representational Bias and Cross-Cultural Adaptability of Music Generation Models. Findings of ACL: NAACL 2025, 4569-4585.
19. McFee B. et al. (2015), librosa: Audio and Music Signal Analysis in Python. Proceedings of the 14th Python in Science Conference, 18-25.
20. Grosche P., Muller M. (2011), Extracting Predominant Local Pulse Information from Music Recordings. IEEE Transactions on Audio, Speech, and Language Processing, 19(6), 1688-1701.
21. Ranade S.G. (1964), Frequency Spectra of Indian Music and Musical Instruments. Research Department, All India Radio, New Delhi.
22. Gowriprasad R., Aravind R. (2025), Unsupervised Stroke Clustering for Developing Common Stroke Set for Percussion in Indian Art Music. Journal of the Acoustical Society of America, 158(5), 3711.
23. Lartillot O., Toiviainen P., Eerola T. (2008), A Matlab Toolbox for Music Information Retrieval. Data Analysis, Machine Learning and Applications. Springer, 261-268.
24. Schubert E., Wolfe J., Tarnopolsky A. (2004), Spectral Centroid and Timbre in Complex, Multiple Instrumental Textures. Proceedings of ICMPC, 112-116.
25. Cohen J. (1988), Statistical Power Analysis for the Behavioral Sciences, 2nd ed. Lawrence Erlbaum Associates, Hillsdale NJ.
26. Neuman D.M. (1980), The Life of Music in North India. University of Chicago Press.