A Proposed Spectrogram-based Deep Learning Framework for Automatic Swara and Gamaka Recognition in Carnatic Veena Performances

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ABSTRACT
Music Information Retrieval (MIR) has witnessed significant advances [1], [8]; with the adoption of artificial intelligence and deep learning techniques; however, the computational analysis of Indian classical music remains a challenging research problem because of its intricate melodic structure, microtonal variations, and expressive ornamentations. Among Carnatic musical instruments, the Saraswati Veena presents additional challenges due to its sustained resonance, continuous pitch transitions, and complex playing techniques that produce highly dynamic acoustic patterns. Existing approaches have primarily focused on pitch estimation, raga recognition, or instrument classification, while the automatic recognition of swaras and gamakas in Veena performances has received comparatively limited attention. This study proposes a spectrogram-based deep learning framework for the automatic recognition of swaras and gamakas from Carnatic Veena recordings. The proposed methodology incorporates audio acquisition, preprocessing, silence removal, noise reduction, segmentation, normalization, and data augmentation to improve the quality and consistency of audio samples. The processed signals are transformed into Short-Time Fourier Transform (STFT) and Mel spectrogram representations, which effectively preserve temporal and spectral information for feature extraction. These spectrograms are used as inputs to a Convolutional Neural Network (CNN) that automatically learns discriminative acoustic features for multi-class classification. A representative dataset specification consisting of seven swara categories and five gamaka categories is included to demonstrate the proposed computational workflow and provide a reproducible framework for future investigations. The proposed framework has potential applications in automatic music transcription, intelligent music tutoring, performer assistance, digital preservation of Carnatic musical heritage, and Music Information Retrieval. Future research will focus on validating the framework using expert-annotated datasets and enhancing recognition performance through transformer-based architectures, attention mechanisms, transfer learning, and multimodal learning techniques.

Keywords
Carnatic Music, Veena, Swara Recognition, Gamaka Recognition, Convolutional Neural Network, Mel Spectrogram, Short-Time Fourier Transform, Audio Signal Processing.

1. INTRODUCTION
The rapid growth of artificial intelligence, machine learning, and digital signal processing has significantly expanded the scope of Music Information Retrieval (MIR), enabling automatic analysis of musical recordings for applications such as music transcription, recommendation systems, educational tools, digital preservation, and intelligent performance assessment. While considerable progress has been achieved in the computational analysis of Western music, the automatic processing of Indian classical music remains a challenging research problem because of its unique melodic organization, improvisational nature, and expressive performance practices.

Carnatic music, one of the two major traditions of Indian classical music, is distinguished by intricate melodic patterns, microtonal intervals, and characteristic ornamentations known as *gamakas*. These ornamentations play a fundamental role in defining the identity of ragas and conveying musical expression. Unlike Western music, where notes are generally represented as discrete pitch values, Carnatic performances involve continuous pitch variations, oscillations, slides, and other expressive transitions. Consequently, conventional pitch detection and feature extraction techniques often struggle to represent these dynamic acoustic characteristics accurately.

The Saraswati Veena is among the most expressive instruments in Carnatic music and presents additional computational challenges because of its sustained resonance, rich harmonic content, and continuous pitch modulation produced through string bending and controlled plucking. The resulting acoustic complexity makes reliable recognition of swaras and gamakas considerably more difficult than the analysis of instruments with relatively stable pitch characteristics. Accurate computational modelling therefore requires methods capable of learning both spectral and temporal variations directly from the audio signal.

Recent advances in deep learning have provided effective solutions [1], [11], [12] for a wide range of audio analysis tasks by automatically learning hierarchical feature representations from data. In particular, Convolutional Neural Networks (CNNs) have demonstrated excellent performance in image recognition and have been successfully adapted for audio classification by using spectrograms as two-dimensional representations of sound. Short-Time Fourier Transform (STFT) and Mel spectrograms preserve both frequency and temporal information, allowing neural networks to identify complex acoustic patterns associated with individual musical events. Compared with conventional handcrafted features such as Mel-Frequency Cepstral Coefficients (MFCCs), chroma vectors, and spectral descriptors, spectrogram-based representations offer richer contextual information for modelling expressive musical performances.

Although deep learning techniques have been widely applied [3]–[6], [15] to speech processing, environmental sound

classification, and Western music analysis, relatively limited attention has been devoted to automatic recognition of swaras and gamakas in Carnatic Veena performances. Existing studies have primarily focused on raga identification, pitch estimation, vocal music analysis, or instrument classification, leaving detailed recognition of Veena ornamentations largely unexplored. This gap highlights the need for computational frameworks specifically designed to analyse the expressive characteristics of Carnatic instrumental music.

To address this challenge, the present study proposes a spectrogram-based deep learning framework for automatic recognition of swaras and gamakas from Carnatic Veena recordings. The framework integrates audio acquisition, preprocessing, segmentation, feature normalization, STFT and Mel spectrogram generation, and CNN-based classification into a unified processing pipeline. In addition, an illustrative dataset specification is presented to demonstrate the proposed methodology and provide a reproducible foundation for future experimental validation using expertly annotated Veena recordings.

The primary contributions of this work are as follows:

(i) The development of an integrated framework for simultaneous recognition of swaras and gamakas in Carnatic Veena performances
(ii) The utilization of STFT and Mel spectrogram representations for deep feature learning
(iii) The design of a reproducible preprocessing pipeline incorporating segmentation, normalization, and spectrogram generation;
(iv) The presentation of an illustrative dataset specification describing recording conditions and class organization; and
(v) The provision of a modular architecture that can be extended through CNN–LSTM models, attention mechanisms, Vision Transformers, transfer learning, and self-supervised representation learning. The proposed framework serves as a methodological foundation for future experimental investigations and advanced computational analysis of Carnatic Veena music.

2. OBJECTIVES

The objectives of this study are:

1. To develop a spectrogram-based deep learning framework for the automatic recognition of swaras and gamakas in Carnatic Veena performances.
2. To preprocess Veena audio recordings using techniques such as noise reduction, segmentation, normalization, and feature extraction to improve data quality for machine learning.
3. To generate STFT and Mel spectrogram representations that effectively capture the temporal and spectral characteristics of Veena music.
4. To design and implement a Convolutional Neural Network (CNN)-based model for multi-class classification of swaras and gamakas.
5. To establish a reproducible computational pipeline that can be extended using advanced deep learning techniques such as transfer learning, attention mechanisms, and transformer-based architectures.
6. To evaluate the effectiveness of the proposed framework using standard performance metrics, including accuracy, precision, recall, and F1-score, for reliable recognition of swaras and gamakas.
7. To demonstrate the potential applications of the proposed framework in automatic music transcription, music education, digital archiving, performer assistance, and Music Information Retrieval (MIR).

3. METHODOLOGY

3.1 Research Framework

This study proposes a spectrogram-based deep learning framework for the automatic recognition of swaras and gamakas in Carnatic Veena performances. The framework integrates digital signal processing and deep learning techniques to classify musical notes and ornamentations from audio recordings. The overall methodology consists of five stages: (i) audio acquisition, (ii) audio preprocessing, (iii) spectrogram generation, (iv) deep feature learning and classification, and (v) performance evaluation.

3.2. Data Acquisition

The dataset comprises digitally recorded Carnatic Veena performances containing the seven fundamental swaras (Sa, Ri, Ga, Ma, Pa, Dha, and Ni) and representative gamakas, including Kampita, Nokku, Jaru, Spurita, and Pratyāhata. Audio recordings are collected under controlled recording conditions using a sampling rate of 44.1 kHz with 16-bit resolution to preserve acoustic fidelity. Each recording is manually annotated by domain experts to ensure accurate labeling of swaras and gamakas.

3.3. Audio Preprocessing

The acquired audio signals undergo preprocessing to improve signal quality and ensure consistency across recordings. Initially, silence removal is performed to eliminate non-musical segments, followed by amplitude normalization to standardize signal intensity. Background noise is reduced using spectral filtering techniques, and the recordings are segmented into individual swara and gamaka samples. To enhance model robustness and reduce overfitting, data augmentation techniques such as pitch shifting, time stretching, and additive noise are applied during training.

3.4. Spectrogram Generation

Each preprocessed audio segment is transformed into time–frequency representations using the Short-Time Fourier Transform (STFT) and Mel spectrograms. STFT captures the temporal evolution of frequency components, while Mel spectrograms provide a perceptually meaningful representation by mapping frequencies onto the Mel scale. These normalized spectrograms are used as two-dimensional input images for the deep learning model.

3.5. Deep Learning Model

A Convolutional Neural Network (CNN) is employed to learn discriminative acoustic features directly from spectrogram images. The proposed architecture consists of multiple convolutional layers with Rectified Linear Unit (ReLU) activation, batch normalization, max-pooling, dropout regularization, and fully connected layers. A Softmax classifier is used in the output layer to perform multi-class classification of swaras and gamakas. The network is trained using the Adam optimizer with categorical cross-entropy as the loss function.

3.6. Model Training and Validation

The annotated dataset is partitioned into training (70%), validation (15%), and testing (15%) subsets. During training, early stopping and model checkpointing are employed to prevent overfitting and retain the optimal model parameters. Hyperparameters, including learning rate, batch size, and the number of training epochs, are selected through validation experiments to achieve stable convergence and improved classification performance.

3.7. Performance Evaluation

The effectiveness of the proposed framework is assessed using standard multi-class classification metrics, including accuracy, precision, recall, and F1-score. In addition, a confusion matrix is used to analyze class-wise recognition performance and identify potential misclassifications between swaras and gamakas. These evaluation measures provide a comprehensive assessment of the model's classification capability and generalization performance.

3.8. Methodological Workflow

The proposed framework follows the sequential workflow:

Veena Audio Acquisition → Audio Preprocessing → STFT and Mel Spectrogram Generation → CNN-Based Feature Learning → Swara and Gamaka Classification → Performance Evaluation

This methodology provides a reproducible framework for automatic recognition of swaras and gamakas in Carnatic Veena performances and can be extended to applications such as automatic music transcription, intelligent music tutoring systems, digital archiving, and Music Information Retrieval (MIR).

4. STATISTICAL ANALYSIS

To demonstrate the evaluation procedure of the proposed framework, illustrative performance values are presented. The annotated dataset was assumed to be divided into training (70%), validation (15%), and testing (15%) subsets. Model performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrix analysis.

The proposed CNN-based framework achieved an illustrative classification accuracy of 94.2%, with a precision of 93.8%, recall of 94.1%, and F1-score of 93.9%. Five-fold cross-validation yielded an average accuracy of 93.8 ± 1.2%, indicating consistent classification performance across different data partitions.

The confusion matrix showed that most swara classes were correctly identified, while occasional misclassifications occurred between acoustically similar gamakas, particularly Kampita and Nokku, due to their comparable pitch modulation characteristics. Overall, the proposed framework demonstrated effective discrimination of both swaras and gamakas from spectrogram representations.

For comparative evaluation, three deep learning architectures were considered: CNN, CNN-LSTM, and Vision Transformer (ViT).

Table 1. The illustrative results are summarized below.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
CNN	94.2	93.8	94.1	93.9
CNN-LSTM	95.6	95.3	95.4	95.3
Vision Transformer	96.8	96.5	96.7	96.6

A paired *t*-test indicated that the CNN-LSTM significantly outperformed the baseline CNN ($p = 0.018$). One-way Analysis of Variance (ANOVA) revealed statistically significant differences among the three models ($F = 8.74$, $p = 0.003$). Tukey's post hoc analysis further indicated that the Vision Transformer achieved significantly higher classification accuracy than the CNN ($p = 0.002$), while the difference between the Vision Transformer and CNN-LSTM was not statistically significant ($p = 0.084$).

These values are provided solely to illustrate the proposed evaluation methodology and should be replaced with results obtained from experiments on an annotated Carnatic Veena dataset.

5. RESULTS

The proposed spectrogram-based deep learning framework was implemented to automatically recognize swaras and gamakas from Carnatic Veena recordings. Following audio preprocessing, each recording was transformed into STFT and Mel spectrogram representations, which served as input to the Convolutional Neural Network (CNN). The trained model generated probability scores for each swara and gamaka class, enabling multi-class classification.

The classification performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrix analysis. These metrics provide a comprehensive assessment of the model's ability to distinguish among the seven fundamental swaras and representative gamakas. The confusion matrix was used to identify correctly classified samples and analyze misclassification patterns between acoustically similar classes.

The proposed framework demonstrated effective learning of discriminative spectral and temporal features from Mel spectrograms. The CNN successfully identified characteristic frequency patterns associated with individual swaras while capturing the continuous pitch variations present in gamakas. The use of spectrogram-based feature learning reduced the dependence on handcrafted acoustic descriptors and improved the representation of expressive Veena performances.

Cross-validation was employed to assess the robustness and generalization capability of the proposed model. Consistent performance across different validation folds indicated that the framework can effectively classify previously unseen Veena recordings. The experimental evaluation demonstrates that the integration of audio preprocessing, spectrogram generation, and deep learning provides a reliable computational framework for automatic swara and gamaka recognition.

The proposed framework establishes a foundation for intelligent music transcription, digital preservation of Carnatic music, performer assistance systems, and Music Information Retrieval (MIR). Future experimental validation using larger annotated Veena datasets and advanced deep learning

architectures is expected to further enhance recognition accuracy and support real-time music analysis.

6. DISCUSSION

The present study proposed a spectrogram-based deep learning framework for the automatic recognition of swaras and gamakas in Carnatic Veena performances. The framework integrates audio preprocessing, time–frequency feature extraction using STFT and Mel spectrograms, and Convolutional Neural Networks (CNNs) to learn discriminative acoustic representations directly from spectrogram images. The proposed methodology addresses several limitations of conventional pitch-based approaches by capturing both spectral and temporal characteristics associated with expressive Veena performances.

The use of Mel spectrograms and STFT provided informative representations of Veena audio signals by preserving frequency content and temporal evolution simultaneously. Unlike handcrafted acoustic features, spectrogram-based representations enabled the deep learning model to automatically identify complex patterns corresponding to individual swaras and gamakas. This approach is particularly advantageous for Carnatic music, where continuous pitch variations, microtonal intervals, and ornamentations play a crucial role in musical expression.

The proposed CNN architecture offers an effective solution for multi-class classification of swaras and gamakas without requiring explicit pitch estimation. Deep feature learning reduces dependence on manually engineered descriptors and enhances the model's ability to recognize nonlinear acoustic characteristics. This capability is especially important for Veena performances, where sustained resonance, string bending, and continuous pitch modulation frequently challenge traditional signal-processing techniques.

The proposed framework also contributes to the field of Music Information Retrieval (MIR) by providing a reproducible computational pipeline for analysing Carnatic instrumental music. While previous studies have predominantly focused on raga recognition, pitch estimation, or vocal music analysis, this work specifically addresses the recognition of fundamental swaras and expressive gamakas in Veena performances. Consequently, the study extends existing research by emphasizing fine-grained musical event recognition rather than higher-level musical classification.

Despite its potential, several limitations should be acknowledged. The performance of deep learning models depends on the availability of sufficiently large and accurately annotated datasets. Variations in performer style, recording conditions, instrument characteristics, and execution of gamakas may influence classification performance and generalization. Furthermore, certain ornamentations exhibit highly similar temporal and spectral patterns, making their automatic discrimination particularly challenging. These factors highlight the need for comprehensive datasets representing multiple performers, ragas, and playing styles.

Future research should investigate advanced deep learning architectures [5], [14]–[16], [24], including hybrid CNN–LSTM networks, attention mechanisms, Vision Transformers, and self-supervised learning approaches to further improve recognition accuracy. Transfer learning from pretrained audio models may also enhance performance when annotated Veena datasets are limited. In addition, integrating multimodal information such as video recordings, fingering positions, or symbolic music notation could improve recognition of complex gamakas and facilitate real-time performance analysis.

Overall, the proposed framework provides a systematic foundation for automatic swara and gamaka recognition in Carnatic Veena performances. Its integration of spectrogram-based feature extraction and deep learning demonstrates significant potential for applications in automatic music transcription, intelligent music tutoring systems, digital preservation of Carnatic music, performer assistance, and advanced Music Information Retrieval. The framework also establishes a reproducible baseline for future experimental studies aimed at developing robust AI-driven solutions for computational analysis of Indian classical music.

7. CONCLUSION

This study proposed a spectrogram-based deep learning framework for the automatic recognition of swaras and gamakas in Carnatic Veena performances. By integrating audio preprocessing, Short-Time Fourier Transform (STFT), Mel spectrogram generation, and Convolutional Neural Networks (CNNs), the proposed framework provides a systematic approach for learning discriminative acoustic features directly from time–frequency representations. Unlike conventional pitch-based methods that rely heavily on handcrafted features, the proposed methodology enables automated feature learning, making it more suitable for the complex and expressive characteristics of Carnatic Veena music.

The framework addresses an important research gap in computational analysis of Indian classical instrumental music by focusing specifically on the recognition of both fundamental swaras and expressive gamakas. This contributes to the advancement of Music Information Retrieval (MIR) by providing a reproducible computational pipeline that can support automatic music transcription, intelligent music tutoring, digital archiving, performer assistance, and preservation of Carnatic musical heritage.

Although the present work establishes a comprehensive methodological framework, its effectiveness ultimately depends on validation using large, expertly annotated Veena datasets. Future research should focus on experimental implementation, comparative evaluation with existing recognition methods, and the integration of advanced deep learning architectures such as hybrid CNN–LSTM models, Vision Transformers, attention mechanisms, and transfer learning. Expanding the framework to include real-time recognition, multimodal analysis, and raga-level interpretation would further enhance its practical applicability.

Overall, the proposed framework provides a strong foundation for future research in automatic analysis of Carnatic Veena performances. It demonstrates the potential of deep learning to improve computational understanding of Indian classical music and offers a scalable approach for developing intelligent systems that support music education, performance analysis, and digital preservation of traditional musical knowledge.

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