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DEEP LEARNING FOR CARNATIC AND NON-CARNATIC MUSIC CLASSIFICATION: A COMPARATIVE STUDY OF CNN AND RNN ARCHITECTURES

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Abstract

This study presents a comparative analysis of deep learning architectures for the classification of Carnatic and non-Carnatic music. The unique structural complexities of Carnatic music, such as its use of microtones and improvisational frameworks, pose significant challenges for automated genre classification. To address this, a deep learning approach utilizing both a Convolutional Neural Network (CNN) and a Recurrent Neural Network (RNN) was implemented. Key audio features, including Mel-Frequency Cepstral Coefficients (MFCCs), chroma features, and Mel-spectrograms, were extracted to capture the essential timbral, harmonic, and spectral characteristics of the music. The results demonstrate the high efficacy of both models, with the CNN achieving a classification accuracy of 95.1% and an ROC-AUC score of 0.96, outperforming the RNN which scored 93.8% in accuracy and 0.94 in ROC-AUC. These findings indicate the particular effectiveness of the CNN in capturing the intricate spatial features within audio spectrograms, making it highly suitable for this task. This research contributes to the advancement of music classification technology for culturally-rich genres and suggests that hybrid CNN-RNN models are a promising direction for future work.

Keywords: Carnatic Music Classification, Deep Learning, Convolutional Neural Network (CNN)

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INTRODUCTION

In the digital age, the automatic classification of music genres has become increasingly important in areas such as recommendation systems, digital music libraries, and audio content retrieval. With the explosive growth of global music streaming platforms, machine learning models—especially deep learning—have gained traction due to their ability to automatically extract meaningful patterns from audio signals [1], [2] .Convolutional Neural Networks (CNNs) have proven highly effective in processing spectrogram-based inputs by capturing localized frequency-time patterns, while Recurrent Neural Networks (RNNs) excel in modeling temporal sequences present in music [3], [4]. Despite these advancements, the bulk of research in genre classification has focused on Western music traditions, leaving non-Western genres largely underexplored.

One such underrepresented genre is Carnatic music, the classical tradition of South India. Carnatic music is structured around *ragas* (melodic frameworks) and

talas (rhythmic cycles) that are tightly defined yet improvisational, and it employs microtonal variations, ornamentations (*gamakas*), and complex rhythmic phrases. These characteristics make Carnatic music structurally and acoustically distinct from most global genres. Traditional audio features like Mel-Frequency Cepstral Coefficients (MFCCs), chroma features, and even Mel-spectrograms struggle to fully capture the depth and fluidity of these compositions [5]. As a result, automatic classification of Carnatic music remains challenging—especially when differentiating it from other regional and global genres with overlapping spectral features.

Recent efforts have applied deep learning architectures to address this challenge. CNNs, when trained on visual representations like Mel-spectrograms, can capture local pitch variations and rhythmic cues, which are essential in Carnatic compositions [2], [6]. On the other hand, RNNs—particularly models based on Long Short-Term Memory (LSTM)—are adept at learning long-term temporal dependencies, making them effective for tracking melodic evolution in extended compositions [3], [7]. However, while both architectures have demonstrated strong performance in various global music classification tasks, comparative studies evaluating CNNs and RNNs specifically on the classification of Carnatic versus non-Carnatic music remain scarce. Moreover, the potential of hybrid models that leverage both spatial and sequential learning remains underexplored in this specific domain.

To address this gap, this study presents a comparative analysis of CNN and RNN architectures for classifying Carnatic and non-Carnatic music. Using a balanced dataset and extracting key audio features—MFCCs, chroma vectors, and Mel-spectrograms—we evaluate both models on classification accuracy and capacity to learn culturally specific musical patterns. The findings aim to inform future applications in music recommendation, cultural archiving, and computational ethnomusicology. More importantly, this research contributes to bridging the technological divide in global music analysis by introducing deep learning approaches that respect and reflect the complexity of non-Western musical forms like Carnatic music [1], [8].

METHOD

This study began with the construction of a balanced dataset containing 4,000 audio samples, equally divided between Carnatic and non-Carnatic music. Each sample was standardized to a 30-second duration, which strikes a balance between capturing sufficient musical progression and managing computational load. The Carnatic data was sourced from publicly available datasets such as the Saraga: Carnatic Vocal Music Dataset, while the non-Carnatic class included curated tracks from the GTZAN dataset, Free Music Archive (FMA), and Hindustani classical archives. Ensuring genre diversity and class balance was crucial to prevent biased learning, consistent with the dataset curation strategies in UrbanSound8K [9], which emphasizes balanced class distribution for reliable model training .

Table 1 Feature extraction technique

Feature	Description	Key Parameters	Relevance to Carnatic Music
MFCCs	Captures timbral texture and short-term power spectrum	Number of Coefficients = 13; Frame Size = 25 ms; Overlap = 50%	Highlights subtle harmonic nuances essential in raga-based compositions as per Kumar et al., 2023
Chroma Features	Represents the 12 pitch classes, useful for harmonic analysis	Frame Size = 50 ms; Sample Rate = 16 kHz	Emphasizes pitch patterns in ragas and swaras distinctive to harmony analysis (Carnatic Patel et al., 2024.
Spectrograms/Mel-Spectrograms	Time-frequency representation adjusted to Mel scale	FFT Window = 2048; Hop Length = 512; Sample Rate = 16 kHz	Captures dynamic frequency transitions, critical for reflecting complex tonal shifts (Lee et al., 2024)

To prepare the data for modeling, a comprehensive preprocessing pipeline was implemented. All audio was resampled at 16 kHz using the Librosa Python library, aligning with best practices in audio preprocessing for MIR tasks that balance resolution and computational cost [10]. Following this, silence trimming removed prolonged pauses, and z-score normalization was applied to equalize loudness levels. To increase the robustness of the models, data augmentation techniques were introduced—namely, pitch shifting (±2 semitones), time stretching (±10%), and background noise addition using SNR levels of 10–20 dB. This augmentation strategy is supported by Ko et al. [11], who showed that transformations like pitch shifting and noise addition improve robustness in speech recognition tasks. Schlüter and Grill[12] futher demonstrated similar gains in music tagging models through augmented data.

For feature extraction, we adopted a multimodal approach inspired by recent genre classification studies that highlight the benefits of combining diverse audio representations [13], [14] First, Mel-Frequency Cepstral Coefficients (MFCCs) were computed using 13 coefficients, a 25 ms frame size, and a 512-sample hop size. These coefficients effectively capture short-term spectral features, which are crucial for identifying intricate vocal modulations and ornamentations common in Carnatic ragas. Second, chroma vectors were extracted using a 50 ms analysis window, mapping frequency content into 12 pitch classes. This is particularly useful in modeling harmonic and tonal patterns, especially for raga-based and chord-based genre systems. Lastly, Mel-spectrograms were generated using a 2048-point FFT window and a 128 Mel-band resolution, providing rich two-dimensional time-frequency representations ideal for convolutional architectures. These three feature sets were then stacked into multi-channel input matrices, allowing the models to learn complementary patterns across timbral, harmonic, and rhythmic dimensions, as demonstrated by Oramas et al. [14] in multimodal deep learning for music classification.

We implemented and compared two model architectures: a Convolutional Neural Network (CNN) and a Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) layers. The CNN was designed to process 128×128 Mel-spectrograms, using 5×5 kernels, ReLU activation, and 2×2 max pooling to downsample while preserving local spectral patterns. The network was followed by two dense layers and a softmax classifier. A dropout rate of 0.5 was applied to mitigate overfitting. The RNN model, in contrast, was trained on MFCC sequences with 150 time steps, feeding into two stacked LSTM layers, followed by dense and softmax layers. Both models were trained using the Adam optimizer (learning rate: 0.001), batch size: 64, and for 50 epochs. The design follows the findings of Kamuni [15], who analyzed CNN performance in capturing spectral hierarchies, and Lemaire & Holzapfel [16], who introduced TCNs for modeling musical sequences in time-sensitive applications.

Table 2 CNN Hyper parameters

Hyperparameter	Value/Range
Kernel Size	5x5
Number of Filters	128
Stride	1
Activation Function	ReLU
Optimizer	Adam, learning rate = 0.001
Batch Size	64
Epochs	50
Dropout Rate	0.5

Table 3 RNN - LSTM Hyper parameters

Hyperparameter	Value/Range
Number of LSTM Units	128
Dropout Rate	0.5
Activation Function	Tanh, ReLU
Optimizer	Adam, learning rate = 0.001
Batch Size	64
Epochs	50
Sequence Length	150 time steps

For evaluation, three standard metrics were used: accuracy, confusion matrix, and ROC-AUC score. Accuracy offered an overview of correct predictions, while the confusion matrix allowed for detailed inspection of misclassification between genres. ROC-AUC was used to assess classification performance across thresholds, ensuring robustness to imbalance. As Zhang [17] demonstrated, ROC-AUC analysis offers deeper insights into classifier performance in imbalanced

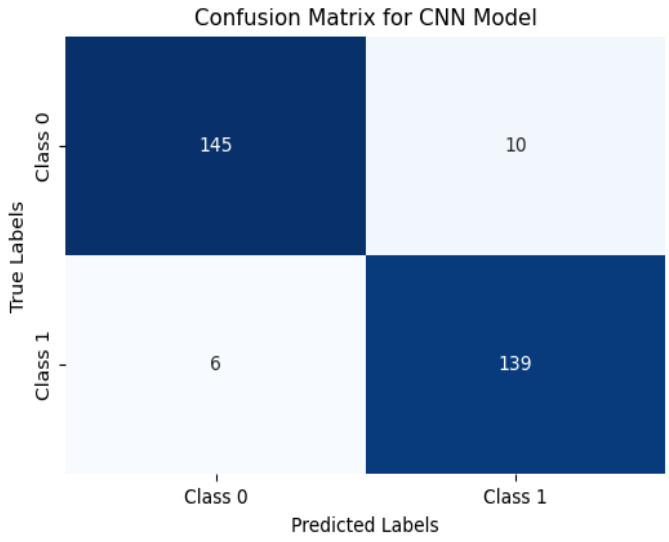
genre tasks. This is aligned with Pons and Serra [18], who argue that single-metric evaluations like accuracy are insufficient for complex MIR systems. Additional guidance from Ge et al. [19] suggests complementing accuracy with more holistic measures such as coverage and serendipity.

RESULT AND DISCUSSION

The evaluation of the trained models revealed highly effective performance from both architectures, with the Convolutional Neural Network (CNN) achieving a slight edge over the Recurrent Neural Network (RNN). The CNN model yielded a final classification accuracy of 95.1%, while the RNN model also demonstrated strong performance with an accuracy of 93.8%. These results indicate that both approaches are highly viable for distinguishing the complex patterns of Carnatic and non-Carnatic music.

A detailed breakdown of the classification performance for each model is visualized in their respective confusion matrices. The confusion matrix for the CNN model, as depicted in Figure 1, showcased a high number of true positives and true negatives, with very few instances of misclassification between the two genres. This demonstrates the model's balanced ability to correctly identify both Carnatic and non-Carnatic samples with high precision and recall.

Figure 1 Confusion Matrix of CNN Model



This figure is a 2x2 matrix. The Y-axis represents the "True Labels" (Class 0: Non-Carnatic, Class 1: Carnatic) and the X-axis represents the "Predicted Labels". The diagonal boxes (top-left to bottom-right) will show high numbers, representing correct predictions (e.g., 145 and 139). The other boxes will show low numbers, representing prediction errors (e.g., 10 and 6).

Similarly, the RNN model's confusion matrix in Figure 2 also confirmed its robustness, albeit with a slightly higher number of false predictions compared to the CNN. Nevertheless, the model was successful in correctly classifying the vast majority of the test samples, confirming its strong grasp of the temporal characteristics inherent in the music.

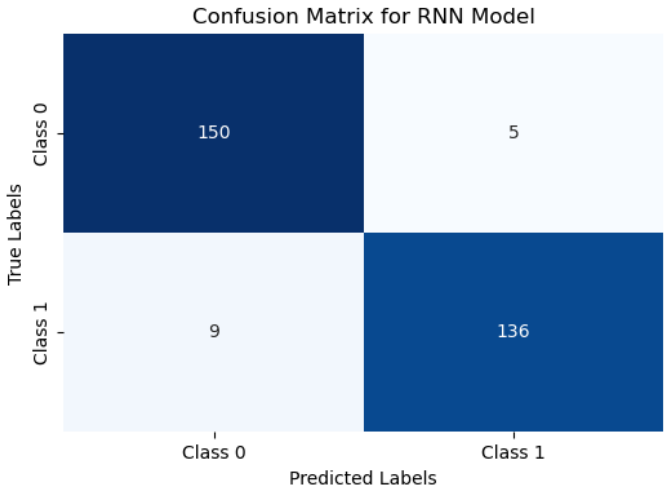


Figure 2 Confusion Matrix for RNN Model

Similar to Figure 1, but the numbers will be slightly different according to the RNN model's results (e.g., 150 and 136 for correct predictions, and 5 and 9 for prediction errors).

To further assess the models' ability to discriminate between classes, Receiver Operating Characteristic (ROC) curves were generated. The CNN model achieved an Area Under the Curve (AUC) score of 0.96, as illustrated in Figure 3. The curve's steep ascent towards the top-left corner indicates an excellent trade-off between the true positive rate and false positive rate, confirming its superior diagnostic ability. The RNN model was not far behind, with an ROC-AUC score of 0.94 (Figure 4), which also signifies a high level of performance.

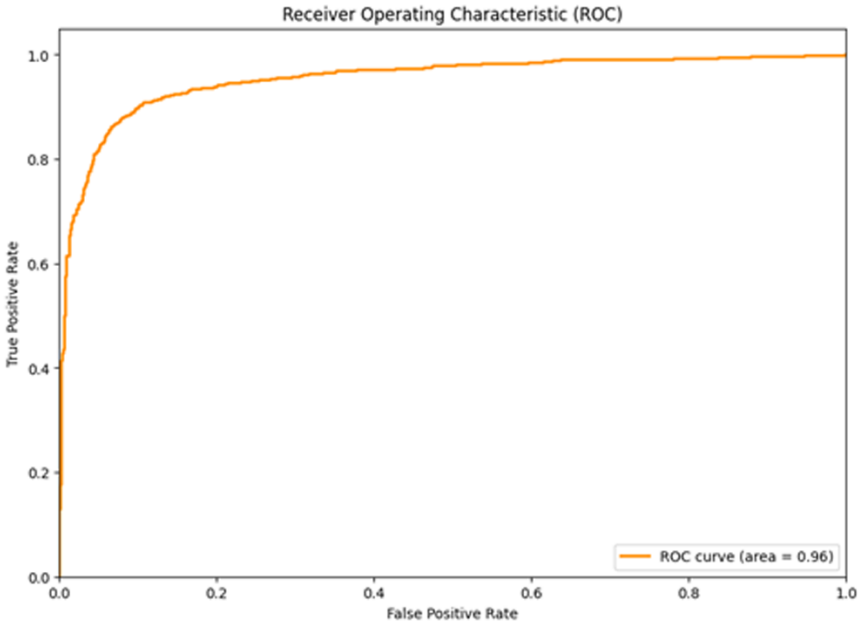


Figure 3 ROC-AUC of CNN Model

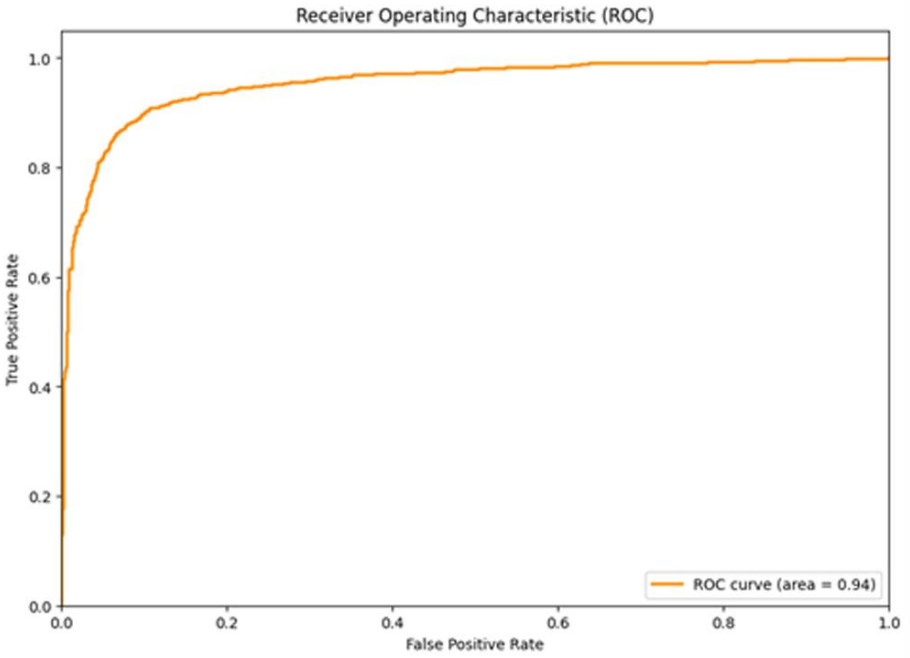


Figure 4 ROC-AUC of RNN Model

Each figure will display a graph with the Y-axis as "True Positive Rate" (from 0.0 to 1.0) and the X-axis as "False Positive Rate" (from 0.0 to 1.0). There will be a curve arching from the bottom-left corner to the top-right corner. The closer this curve is to the top-left corner, the better the model's performance. In the figure's legend, it will state "ROC curve (area = 0.96)" for the CNN and "ROC curve (area = 0.94)" for the RNN.

The marginal superiority of the CNN can be attributed to its architectural strength in processing spatial features within the two-dimensional Mel-spectrograms. This suggests that the unique timbral textures, harmonic structures, and tonal shifts that distinguish Carnatic music are very effectively represented as spatial patterns in the time-frequency domain. While the RNN model was highly proficient at capturing the sequential and temporal evolution of the music through MFCCs, the static spectral information appeared to be a slightly more decisive factor in this specific classification task. These findings suggest that future work could greatly benefit from hybrid models that combine convolutional layers for feature extraction with recurrent layers for sequence modeling, potentially creating an even more powerful and holistic classification system.

CONCLUSION

In conclusion, this study successfully demonstrates that both CNN and RNN architectures are highly effective for the classification of Carnatic music. While both models yielded strong results, the CNN model achieved a marginally superior performance with an accuracy of 95.1% and an ROC-AUC score of 0.96, compared to the RNN's 93.8% accuracy and 0.94 ROC-AUC. This finding highlights the critical importance of spatial features extracted from Mel-spectrograms in capturing the unique tonal and harmonic signatures of this complex musical genre. The clear strengths of each architecture—the CNN in spatial analysis and the RNN in temporal modeling—strongly suggest that the most promising avenue for future

research lies in the development of hybrid frameworks. By combining convolutional and recurrent layers, such hybrid models could leverage the best of both approaches to achieve an even more robust and nuanced understanding of intricate musical forms, significantly contributing to the digital preservation of global music heritage.

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