Enhanced Bengali audio categorization using audio segmentation and deep learning

Niaz Ashraf Khan, Md. Ferdous Bin Hafiz
Department of Computer Science and Engineering, University of Liberal Arts Bangladesh, Dhaka, Bangladesh

Article Info

Article history:

Received Feb 27, 2024
Revised Jun 6, 2024
Accepted Jul 24, 2024

Keywords:

Audio signal processing
Augmentation
MFCC
Neural network
Segmentation

ABSTRACT

This paper presents an enhanced approach for classifying Bengali songs into different genres by leveraging feature importance analysis and deep learning techniques. The research addresses the challenge of limited data points in the Bengali Song Dataset by employing strategies, including audio segmentation and feature importance analysis, to enhance model performance. Multiple machine learning and deep learning architectures are evaluated to identify the most effective models for Bengali song classification. Additionally, this research conducts feature importance analysis to identify significant audio features contributing to classification accuracy. The best-performing deep learning model achieves an impressive validation accuracy of 94.17%, showcasing the project efficacy of the proposed methodology. Our findings highlight the effectiveness of our proposed methodology, demonstrating significant improvements in classification accuracy and contributing to advancements in Bengali music classification research.

Corresponding Author:

Niaz Ashraf Khan
Department of Computer Science and Engineering, University of Liberal Arts Bangladesh
Dhaka, Bangladesh
Email: niaz.ashraf@ulab.edu.bd

1. INTRODUCTION

Recent advancements in audio processing, as demonstrated in [1], underscore the potential for more sophisticated methodologies in music genre classification, particularly with neural networks. Furthermore, highlights some of the advancements in this field, emphasizing the growing importance of leveraging neural networks for enhanced classification accuracy [2], [3]. In contrast, while considerable research has been conducted on English music [4], [5] little attention has been given to Bengali music. This disparity underscores the need for focused efforts in the domain of Bengali music classification. Building upon these innovations and addressing this gap, our research introduces a comprehensive approach that integrates feature analysis and deep learning techniques to enhance the interpretability and accuracy of Bengali song classification. The cultural legacy and creative expression of Bengali-speaking populations are reflected in the wide variety of genres that make up Bengali music, ranging from classic folk songs to modern compositions. Proper categorization of Bengali songs into distinct genres is crucial for several uses, such as music suggestion platforms, cultural conservation efforts, and showcasing Bengali music to an international viewership. Due to limited labeled data, standard classification algorithms struggle with capturing Bengali music's complex auditory qualities. Recent advancements in deep learning have sparked interest in neural network models for music genre categorization. However, designing an effective deep learning architecture remains challenging. Understanding how different auditory components contribute to genre categorization offers valuable insights into musical genres' fundamental qualities. Inspired by recent research in automatic classification of musical instruments [6], which utilizes acoustic features like mel-frequency cepstral coefficients (MFCC) and Sonogram, our study aims to apply similar methods to Bengali song classification. While [6] focuses on instrument classification using support vector machine (SVM) and K-nearest neighbors (KNN), we expand this approach to Bengali music, employing feature analysis and deep learning techniques to address specific classification challenges.

This research offers a novel method for automatically categorizing genres of Bengali songs through the use of feature analysis and deep learning models. The inclusion of feature significance analysis, which makes it possible to identify important audio elements that contribute to the classification of Bengali songs and improves the interpretability and comprehension of classification models, is one of the major achievements. In addition, the study uses audio segmentation and augmentation to improve model performance in Bengali music categorization and get over data constraints. The goal of this research is to improve automated Bengali music genre classification's interpretability and accuracy by achieving the objectives that follow:

- Enhanced data representation: improving the representation of data by splitting audio clips into smaller segments to increase the number of data points.
- Feature extraction: implementing methodologies such as audio segmentation and feature important analysis to overcome data limitations and improve model performance in Bengali song classification.
- Model evaluation and selection: evaluating multiple machine learning and deep learning architectures to identify the best-performing models for Bengali song classification.
- Feature importance analysis: conducting thorough feature importance analysis to identify significant audio features contributing to classification accuracy.

The rest of this paper is organized as follows: section 2 presents a comprehensive review of related works in the field of music genre classification, discussing prominent research papers and their contributions. Section 3 outlines the methodology employed in this study, including data preprocessing, feature extraction, and model evaluation techniques. Section 4 presents the experimental results and discusses the performance of various machine learning and deep learning models in classifying Bengali songs into different genres and analyzes the importance of features in the classification process and discusses the insights gained from feature importance analysis. Finally, section 5 concludes the paper by summarizing the key findings.

2. RELATED WORK

Recent advancements in music genre classification, exemplified by Islam *et al.* [7], emphasize the significance of preprocessing and model selection. Employing machine learning techniques, the study achieves promising accuracy of up to 90.22% with extreme gradient boosting (XGBoost), showcasing the field's progress. Chaudary *et al.* [8], a novel genre classification approach integrates dynamic music frame analysis and SVM. Leveraging MFCC and log energy, it attains an impressive 98% accuracy across six genres: classical, dance, lullaby, Bossa, piano, and blues. Baniya *et al.* [9] presents a comprehensive classification method incorporating timbral texture and rhythmic content features extracted from audio signals. Using ELM with bagging, it outperforms existing approaches on datasets like GTZAN and ISMIR2004. Additionally, Gessle and Åkesson [10] evaluates convolutional neural network (CNN) and long short-term memory (LSTM) models for genre classification using MFCCs, aiming to improve automated curation amid growing music data volumes. Results favor CNN, achieving 56.0% and 50.5% prediction accuracies on GTZAN and FMA datasets, respectively. Zhang *et al.* [11], researchers utilized CNNs along with music feature maps, achieving an accuracy rate of 91%. Liu *et al.* [12] also utilized deep CNN directly on music spectrograms, incorporating both time and frequency domain information. Deepaisarn *et al.* [13] addresses the challenge of categorizing music compositions by composer, leveraging MIDI and audio data of virtuosic piano pieces. By employing SentencePiece and Word2vec, the research innovatively represents musical pieces, aiming to capture correlated melodies as interpretable units via co-occurring notes.

Sawant *et al.* [14] introduces a method for separating speech and music signals in audio segments, leveraging distinct patterns in spectrograms and employing CNN on mel-spectrograms and MFCC-delta-RNN methods. Furthermore, recent studies, such as in paper [15], emphasize the increasing importance of music genre classification in contemporary music applications. This paper presents a study on music genre classification using a combination of digital signal processing and deep learning techniques. Recent studies, like the one referenced as [16], propose innovative approaches for audio music genre classification. The Deformer method, introduced in this paper, learns deep audio representations through a denoising process, eliminating the need for expensive pre-training methods like MoCo. Yu and Yang [17] addresses challenges in music feature extraction and classification amid expanding digital music collections. It suggests a new method for genre selection from user playlists using machine learning models like CBTG and FRAENN, achieving respectable classification results and extracting valuable song features. Additionally, Thuy *et al.* [18], data augmentation techniques like noise addition and echo generation are used to boost music genre classification. The study utilizes a DenseNet121 model to achieve high accuracy on the small free music archive dataset. Furthermore, Yang and Zhang [19] highlights the importance of music genre classification in modern music applications. It proposes a CNN-based method with mel-scale spectrograms and novel modifications to improve classification accuracy, as demonstrated on the GTZAN dataset, shedding light on deep learning's role in genre classification. The gaps identified in existing research include a lack of focus on Bengali music genre classification, limited exploration of deep learning techniques specifically tailored to Bengali music, and insufficient consideration of feature importance analysis. Our project addresses these gaps by focusing on Bengali music, employing tailored deep learning techniques, and conducting comprehensive feature importance analysis to enhance classification accuracy and interpretability.

3. METHOD

Our dataset comprises a diverse collection of Bangla songs, categorized into Metal (1040), Palligeeti (960), Rabindranath (900), Pop (840), Nazrul (800), and Hiphop (721). The distribution of our dataset across various genres is illustrated in Figure 1. The workflow of this research begins with the Bangla Song Dataset, consisting of audio clips, which undergoes segmentation to divide the data into manageable segments. Following segmentation, preprocessing techniques are applied to prepare the data for analysis. Augmentation methods may then be employed to augment the dataset for improved model performance. Subsequently, feature extraction techniques are utilized to extract relevant features from the data. The extracted features are then used as inputs for machine learning classifiers such as KNN, random forest (RF), and SVM, aimed at identifying patterns and making predictions. Additionally, deep learning models, including eight different architectures, are employed to further analyze the data and make predictions. The best performing models from both machine learning and deep learning approaches are selected for further analysis. Finally, a feature importance analysis is conducted to determine the significance of different features in the prediction process. This comprehensive workflow enables a systematic analysis of the Bangla Song Dataset. Figure 2 depicts the flowchart of our research, outlining the workflow employed in the analysis of the Bangla Song Dataset. The methodologies of this research are discussed details in subsections 3.1 to 3.3.

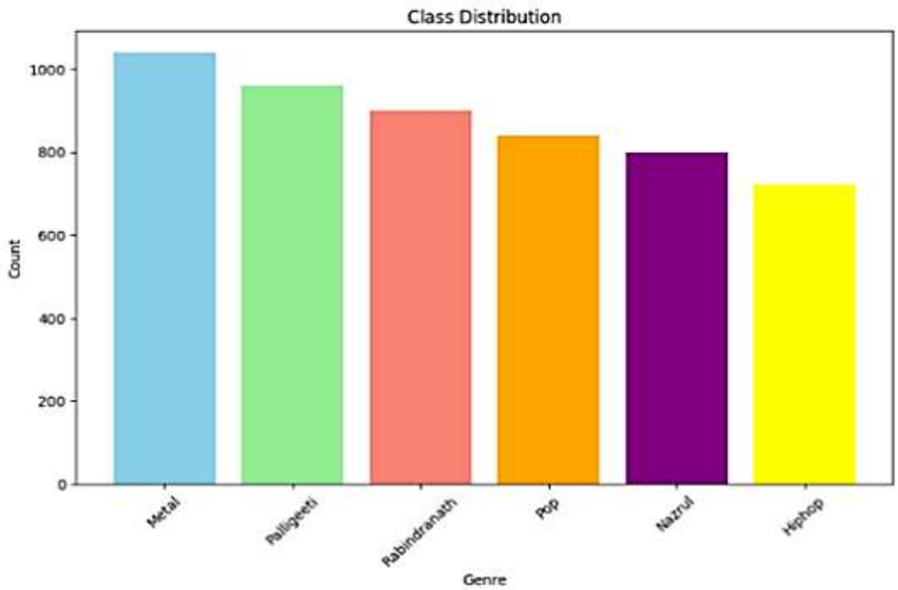


Figure 1. Distribution of the six genres in the dataset

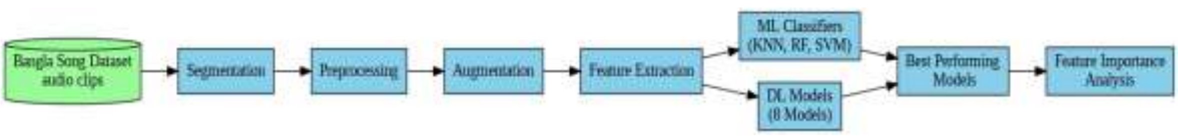


Figure 2. Workflow of the research

3.1. Segmentation and preprocessing

The following steps are done for preprocessing:

- The data was inspected for missing values and datapoints that were missing were removed.
- Features and labels were separated, with the features being scaled to ensure uniformity.
- The audio files are split into smaller segments to increase the number of data points.

3.2. Augmentation

Audio augmentations like pitch shifting and adding noise are done to increase the diversity of the training data, making the model more robust. Pitch shifting alters the pitch of the audio, simulating different tones or musical keys, while adding noise introduces variability akin to environmental conditions or recording imperfections. Figure 3 displays these effects: Figure 3(a) shows the original audio waveform, Figure 3(b) exhibits the waveform after pitch shifting, reflecting pitch alterations, and Figure 3(c) demonstrates the waveform post-noise addition, introducing environmental nuances.

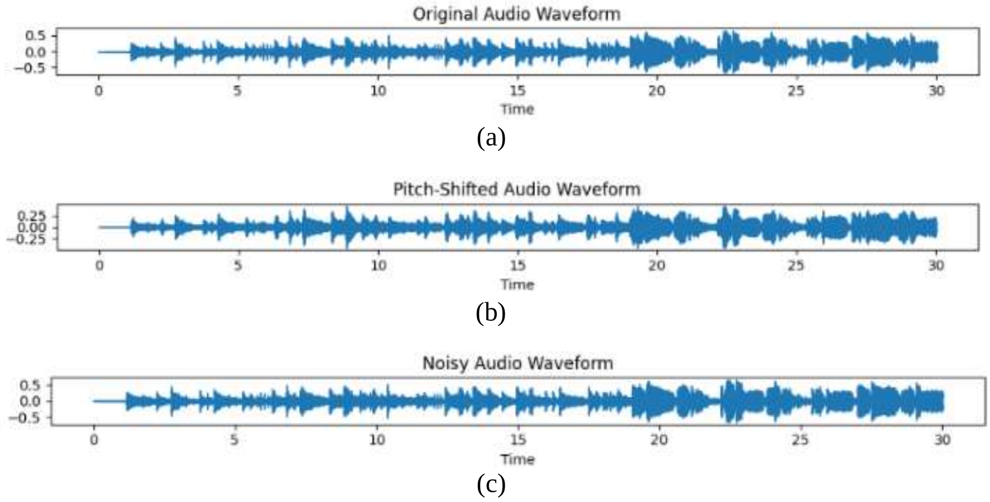


Figure 3. Waveplot of an audio song: (a) before augmentation, (b) after pitch shift, and (c) after adding noise

3.3. Feature selection

a) Chroma STFT mean: this feature captures the distribution of energy across musical notes in the chromatic scale, extracted from the short-time Fourier transform. Figure 4 illustrates the features of the audio signals. In Figure 4(a), we observe the distribution of energy across musical notes in the chromatic scale. By visualizing the distribution of energy across the chromatic scale, we can discern patterns and characteristics of the audio's tonal composition, aiding in genre classification and musical analysis.

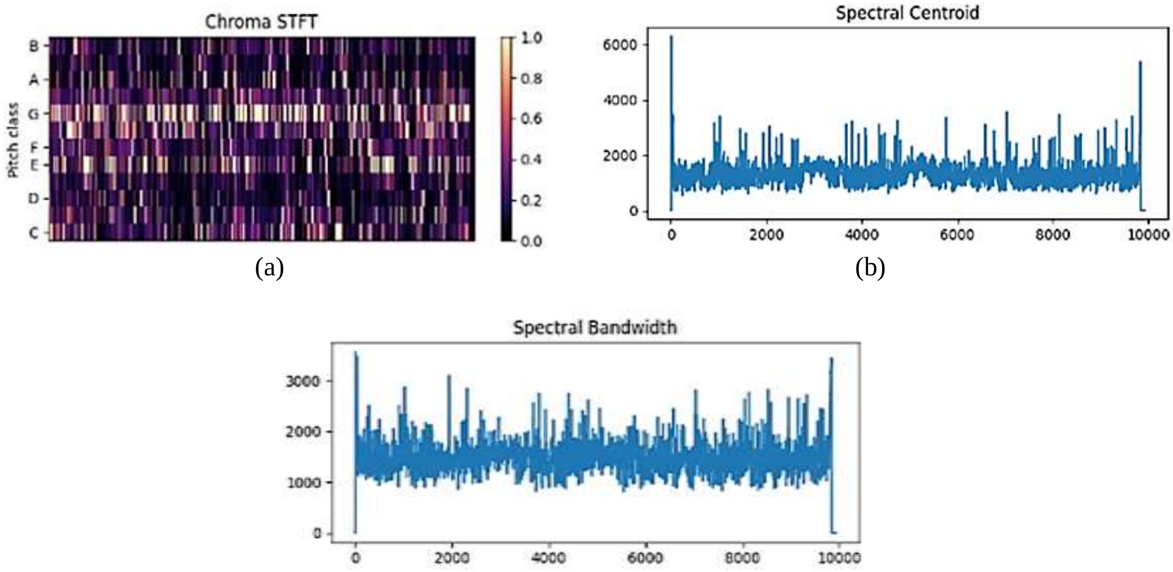
b) Spectral centroid mean: this represents the frequency point which is considered as the "center of mass" of the signal's spectrum, calculated as the weighted mean of the frequencies present in the signal. Figure 4(b) represents the frequency point considered the "center of mass" of the signal's spectrum. Calculated as the weighted mean of the frequencies present in the signal, the spectral centroid indicates where most of the energy in the audio signal lies. It indicates where most of the energy in the audio signal lies. This can be calculated by the following equation:

$$\text{Centroid}=\frac{\sum_{k=0}^{K-1} f(k)x(k)}{\sum_{k=0}^{K-1} n(k)} \tag{1}$$

Here, n(k) denotes the weighted frequency value or magnitude of bin number f(k) represents the center frequency of bin number k.

c) The spectral bandwidth mean: it measures the width of the frequency range containing a significant portion of the signal's energy. Additionally, in Figure 4(c), we depict the frequency energy spread, providing insights into the spread of frequencies containing a significant portion of the signal's energy. This feature offers valuable information about the tonal quality and distribution of energy within the audio signal.

d) Rolloff and Zero crossing rate mean: this feature offers insights into the overall shape of the spectrum and the dominance of low or high-frequency components. While zero crossing rate feature represents the rate at which the signal changes sign, often used to estimate the level of noise in the signal.
e) MFCC mean (1-20) and root mean square (RMS) mean: these coefficients represent the short-term power spectrum of a sound, derived from the fourier transform of the log power spectrum on a nonlinear mel scale of frequency. Meanwhile, RMS mean represents the square root of the average of the squares of the values in the signal, indicating the magnitude of the signal. It provides a measure of the overall loudness or amplitude of the audio signal.



(a) (b)

(c)

Figure 4. Various features of the audio signal: (a) dominant musical notes distribution, (b) center of mass frequency distribution, and (c) frequency energy spread

4. RESULTS AND DISCUSSION

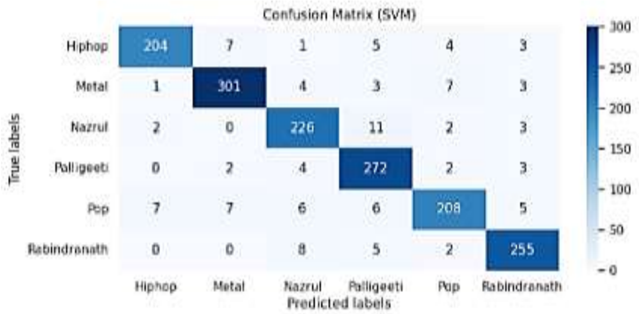
Several machine learning and deep learning algorithms were explored for classification, including RF, SVM KNN and CNNs. Table 1 shows the results of the machine learning classifiers along with their parameters. Figure 5 shows the confusion matrix of the ML models. SVM demonstrates the highest accuracy among the three models, as shown in Figure 5(a), followed by the KNN classifier, shown in Figure 5(b) and the RF, shown in Figure 5(c). SVM and KNN exhibit more consistent and balanced performance across different genres compared to the RF classifier.

Table 1. Performance of the machine learning classifiers

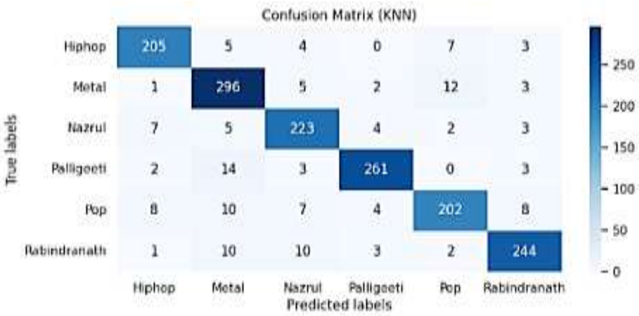
Model	Parameters	Accuracy
RF	n_estimators=100, random_state=42	84.48%
SVM (best parameters)	C=100, gamma=0.1	92.84%
KNN	n_neighbors=3	90.63%

Various deep learning models are employed to classify Bengali songs into genres. Model 1 employs three dense layers with 58, 258, and 258 neurons, respectively, achieving a validation accuracy of 81.25%. Model 2 follows a similar structure but with fewer neurons in the final layer, resulting in a validation accuracy of 80.05%. Model 3 incorporates a Flatten layer followed by three dense layers with 58, 258, and 128 neurons, achieving a validation accuracy of 80.93%. Models 4, 5, and 6 exhibit increasingly complex architectures with varying numbers of dense layers and neurons, culminating in validation accuracies of 93.98%, 94.17%, and 94.11%, respectively. Model 7 introduces a CNN architecture with convolutional and max-pooling layers, achieving a validation accuracy of 84.23%. Lastly, model 8 adopts an LSTM architecture, attaining a validation accuracy of 81.38%. These models collectively demonstrate the efficacy of deep learning techniques in accurately classifying Bengali songs into distinct genres, each offering unique architectural nuances to achieve high classification accuracies. Figure 6 shows the validation accuracy curve for the 8 neural network models. Model 5 achieved an accuracy of 93.35% with a validation accuracy of 94.17% as shown in Table 2. Model 5 outperforms the other artificial neural network (ANN) models due to its deeper architecture and larger number of units per layer. With dense layers of 1024, 512, 256, 128, 64 neurons, it has a more complex representation capability, allowing it to capture intricate patterns in the data. Our ANN model also demonstrates superior performance compared to several models from previous research, as evidenced by the results presented in Table 3. The accuracy of model 5 varies across different genres, with Palligeeti exhibiting the highest accuracy at 95.92%, closely followed by Hiphop at 95.56%. Meanwhile, Nazrul songs show a relatively lower accuracy of 87.45%. Despite some variability in accuracy levels, model 6 demonstrates promising results overall, showcasing strong performance in classifying Bengali music genres. The accuracy of model 5 across the various genre is depicted in Figure 7.

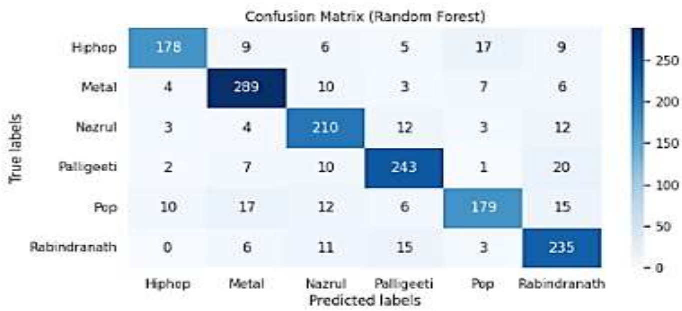
For feature analysis, we firstly compute the absolute magnitude of the input layer weights. This step ensures that both positive and negative weights contribute equally to the importance score, as we are interested in the overall impact of each feature regardless of the direction of the weight. We then calculate the feature importance scores by summing the absolute weights along each feature axis. This step gives us a measure of how much each input feature contributes to the model's predictions. Features with higher importance scores are considered more influential in making predictions. Regarding feature importance, the top 10 features play a crucial role in model performance as shown in Figure 8. In model 6, features like rms_mean, mfcc5_mean, and mfcc6_mean exhibit high importance scores, indicating their strong influence on classification accuracy. These features likely contain valuable information that distinguishes between different music genres.



(a)



(b)



(c)

Figure 5. Confusion matrix of: (a) SVM, (b) KNN, and (c) random forest classifier

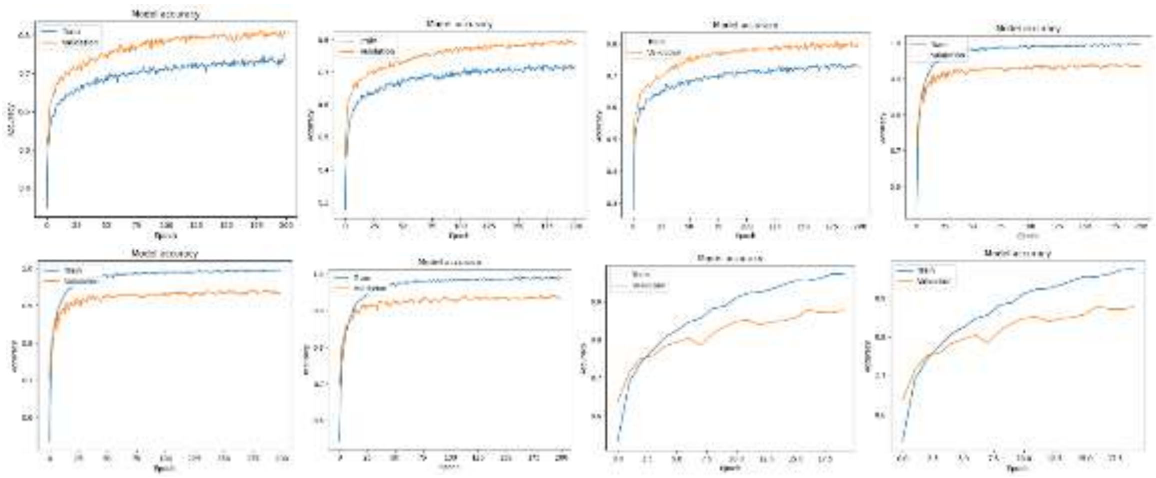


Figure 6. Training and validation accuracy curve for the eight ANN models: model 1, model 2, model 3, model 4, model 5, model 6, model 7, and model 8

Table 2. Performance of various neural network models

Model	Architecture (units per layer)	Model type	Validation accuracy
Model 1	3 Dense layers (58, 258, 258 neurons)	ANN	81.25%
Model 2	3 Dense layers (58, 258, 64 neurons)	ANN	80.05%
Model 3	Flatten, 3 Dense layers (58, 258, 128 neurons)	ANN	80.93%
Model 4	Dense layers (1024, 512, 256, 128, 64, 6)	ANN	93.98%
Model 5 (proposed model)	Dense layers (1024, 512, 256, 128, 64, 6)	ANN	94.17%
Model 6	Dense layers (512, 256, 128, 64, 6)	ANN	94.11%
Model 7	Conv1D (32), MaxPooling1D, Conv1D (64), MaxPooling1D, Flatten, Dense (128), Dense (6)	CNN	84.23%
Model 8	LSTM (64), Dense (128), Dense (6)	LSTM	81.38%

Table 3. Comparison with previous works

Paper	Model name	Accuracy
[20]	MLP	88.10%
[21]	RNN	64.00%
[22]	SFNN	84.83%
[23]	DBNN	84.30%
[24]	SVM	84.40%
[25]	DANN	90.00%
Our proposed model		94.17%

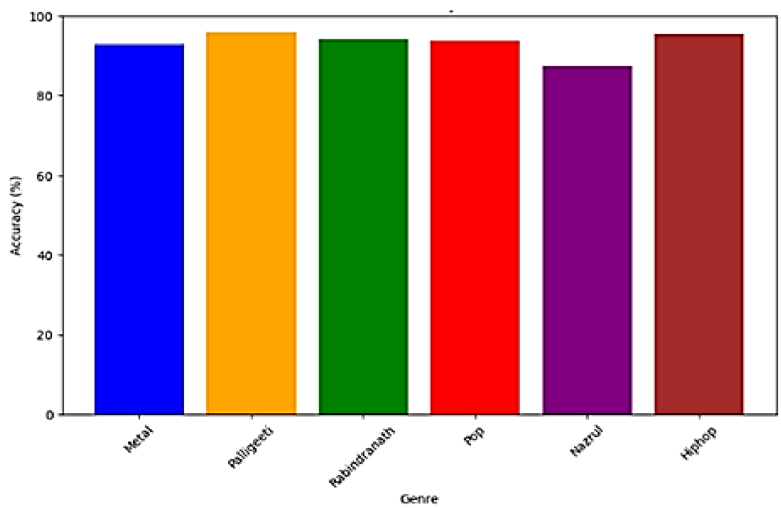


Figure 7. Genre wise accuracy of model 5

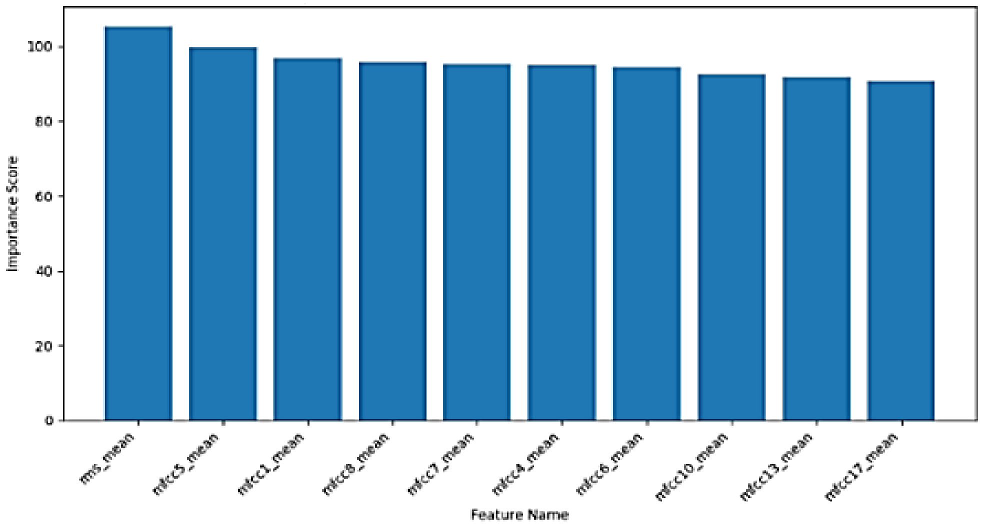


Figure 8. Top 10 important features for the best performing neural network architecture

5. CONCLUSION

In conclusion, this paper introduces a novel methodology for classifying Bengali songs into distinct genres, addressing the challenge of limited data points through innovative strategies like audio segmentation and feature importance analysis. Leveraging deep learning techniques, significant improvements in classification accuracy are achieved, showcasing the effectiveness of the proposed approach. Through thorough investigation of neural network architectures and feature importance analysis, the research enhances the interpretability and accuracy of genre classification models, contributing to the advancement of music analysis techniques in the context of Bengali music. The study underscores the importance of accurately categorizing Bengali music genres for various applications, such as music recommendation systems and cultural preservation efforts. Future research could explore leveraging spectrogram representations and advanced techniques like transfer learning and attention mechanisms for further refinement in genre classification models, thus continuing to push the boundaries of music analysis and classification. In summary, our study introduces an innovative method that combines deep learning and feature analysis to greatly improve the accuracy of classifying Bengali song genres, marking a notable advancement in music analysis for Bengali music.

REFERENCES

[1] A. Raju, Dr. S. R.S, D. Gurang, R. Kirthika, and S. Rubeena, “AI based music recommendation system using deep learning algorithms,” *IOP IOP Conference Series: Earth and Environmental Science*, vol. 785, p. 012013, Jun. 2021, doi: 10.1088/1755-1315/785/1/012013.

[2] M. Faizan, I. Intzes, I. Crețu, and H. Meng, “Implementation of deep learning models on an SoC-FPGA device for real-time music genre classification,” *Technologies (Basel)*, vol. 11, Jul. 2023, doi: 10.3390/technologies11040091.

[3] P. Ghosh, S. Mahapatra, S. Jana, and R. Jha, “A study on music genre classification using machine learning,” *International Journal of Engineering Business and Social Science*, vol. 1, pp. 308–320, Apr. 2023, doi: 10.58451/ijebss.v1i04.55.

[4] A. Elbir, H. B. Çam, M. E. Iyican, B. Öztürk, and N. Aydin, “Music genre classification and recommendation by using machine learning techniques,” in *2018 Innovations in Intelligent Systems and Applications Conference (ASYU)*, 2018, pp. 1–5, doi: 10.1109/ASYU.2018.8554016.

[5] A. Ghildiyal, K. Singh, and S. Sharma, “Music genre classification using machine learning,” in *2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA)*, 2020, pp. 1368–1372, doi: 10.1109/ICECA49313.2020.9297444.

[6] V. Rathikarani, P. Dhanalakshmi, and P. S., “Classification of musical instruments using SVM and KNN,” *International Journal of Innovative Technology and Exploring Engineering*, vol. 9, pp. 2278–3075, May 2020, doi: 10.35940/ijitee.G5836.059720.

[7] M. Islam *et al.*, “Machine learning-based music genre classification with pre- processed feature analysis,” *Journal of Information Technology and Electrical Engineering*, vol. 7, pp. 491–502, Dec. 2021, doi: 10.26555/jiteki.v7i3.22327.

[8] E. Chaudary, S. Aziz, M. U. Khan, and P. Gretschmann, “Music genre classification using support vector machine and empirical mode decomposition,” in *2021 Mohammad Ali Jinnah University International Conference on Computing (MAJICC)*, 2021, pp. 1–5, doi: 10.1109/MAJICC53071.2021.9526251.

[9] B. K. Baniya, D. Ghimire, and J. Lee, “Automatic music genre classification using timbral texture and rhythmic content features,” in *2015 17th International Conference on Advanced Communication Technology (ICACT)*, 2015, pp. 434–443, doi: 10.1109/ICACT.2015.7224907.

[10] G. Gessle and S. Åkesson, “A comparative analysis of CNN and LSTM for music genre classification,” 2019.

[11] W. Zhang, W. Lei, X. Xu, and X. Xing, “Improved music genre classification with convolutional neural networks,” in *Interspeech*, 2016, pp. 3304–3308.

[12] X. Liu, Q. Chen, X. Wu, Y. Liu, and Y. Liu, "CNN based music emotion classification," *arXiv preprint arXiv:1704.05665*, 2017.
[13] S. Deepaisarn, S. Chokphantavee, S. Chokphantavee, P. Prathipasen, S. Buaruk, and V. Sornlertlamvanich, "NLP-based music processing for composer classification," *Scientific Reports*, vol. 13, no. 1, p. 13228, 2023.
[14] O. Sawant, A. Bhowmick, and G. Bhagwat, "Separation of speech and music using temporal-spectral features and neural classifiers," *Evolutionary Intelligence*, pp. 1–15, 2023.
[15] A. Biswas, S. Dhabal, and P. Venkateswaran, "Exploring music genre classification: algorithm analysis and deployment architecture," *arXiv preprint arXiv:2309.04861*, 2023.
[16] J. Wang, S. Li, and Y. Sung, "Deformer: denoising transformer for improved audio music genre classification," *Applied Sciences*, vol. 13, no. 23, p. 12673, 2023.
[17] X. Yu and Y. Yang, "Music genre selection based on computer data analysis for user preference using fuzzy classification by deep learning model," *Journal of Intelligent and Fuzzy Systems*, no. Preprint, pp. 1–12.
[18] D. T. L. Thuy, T. Van Loan, C. B. Thanh, and N. H. Cuong, "Music genre classification using densenet and data augmentation.," *Computer Systems Science and Engineering*, vol. 47, no. 1, 2023.
[19] H. Yang and W.-Q. Zhang, "Music genre classification using duplicated convolutional layers in neural networks," in *Interspeech*, 2019, pp. 3382–3386.
[20] A. Ghildiyal and S. Sharma, "Music genre classification using data filtering algorithm: an artificial intelligence approach," in *2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA)*, IEEE, 2021, pp. 922–926.
[21] S. Zhang, H. Gu, and R. Li, "Music genre classification: near-realtime vs sequential approach," *PrePrint*, 2019.
[22] S. Das and A. K. Kolya, "A theoretic approach to music genre recognition from musical features using single-layer feedforward neural network," in *Emerging Technologies in Data Mining and Information Security: Proceedings of IEMIS 2018*, vol. 1, Springer, 2019, pp. 145–155.
[23] P. Hamel and D. Eck, "Learning features from music audio with deep belief networks," in *ISMIR*, Utrecht, The Netherlands, 2010, pp. 339–344.
[24] A. Zlatintsi and P. Maragos, "Comparison of different representations based on nonlinear features for music genre classification," in *2014 22nd European Signal Processing Conference (EUSIPCO)*, IEEE, 2014, pp. 1547–1551.
[25] U. Riaz, S. Aziz, M. U. Khan, S. A. A. Zaidi, M. Ukasha, and A. Rashid, "A novel embedded system design for the detection and classification of cardiac disorders," *Computational Intelligence*, vol. 37, no. 4, pp. 1844–1864, 2021.

BIOGRAPHIES OF AUTHORS

Niaz Ashraf Khan is a dedicated academic professional with over 5 years of experience in the field of Computer Science and Engineering. Currently serving as a Lecturer at the Department of Computer Science and Engineering at the University of Liberal Arts Bangladesh, Niaz holds a Master's degree in Computer Science and Engineering from North South University, Dhaka, Bangladesh, along with a Bachelor's degree from the same institution. his research interests lie in the intersection of sound signal processing, NLP, machine learning, and deep learning. He can be contacted at email: niaz.ashraf@ulab.edu.bd.

Md. Ferdous Bin Hafiz is working at University of Liberal Arts Bangladesh as a Lecturer in the Department of Computer Science and Engineering. He completed his B.Sc. in Computer Science and Information Technology from Islamic University of Technology (IUT), Bangladesh. He obtained Master of Information Technology degree from Charles Sturt University, Australia. He has worked as a full-time lecturer for almost four years (two years at Northern University Bangladesh, one year and eight months in East Delta University, Chattogram). His research interests lie in the area of data science, machine learning and cyber security. He can be contacted at email: ferdous.hafiz@ulab.edu.bd.