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Exploring the Machine Learning Techniques for Music Genre Classification

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Abstract: *Music information retrieval is the process of obtaining high-level information about music, such as artist, genre, and instrumentation. The field of music genre classification (MGC) is a significant and quickly developing MIR. MGC entails classifying music according to genres (such as hip-hop, disco, rock, classical, etc.) based on an examination of its lyrical content or aural qualities. With its quick expansion, MGC is a valuable tool for managing and organizing streaming services, advertising, and music recommendation systems. Usually, there are two stages to this task: Extraction of audio features and modeling with machine learning. The study compares and evaluates the viability, performance, and understandability of features used to define music in order to predict the genre of music using machine learning techniques like Support Vector Machine, K-Nearest Neighbor, Random Forest, and XGBoost. Music of the same genre frequently has comparable topics (such love or death), the same instrumentation (drum, guitar), conveys similar moods (happy, sad), and has a similar speed (ranging from slow to rapid).Because one must listen to each song for its whole if music is classified manually, the application is crucial and needs automation to decrease human error and time. Spotify and Sound Cloud use genre categorization to suggest songs to their subscribers.*

Keywords: Music Genre Classification, feature Extraction, Support vector Machine, K-Nearest Neighbor, Random Forest, XGBoost

I. INTRODUCTION

Music serves as a source of pleasure and entertainment, offering relaxation all while exerting significant effects on social and psychological aspects of our lives. Through the simultaneous and sequential blending of several musical parts, it is a potent medium that conveys message to the listeners. Training a model to automatically classify songs into preset genres based on auditory attributes is the process of classifying music genres. Two basic consistent processes comprise musical categorization: the first involves raw audio input and the second involves the creation of classification tags based on attributes from a known database. With the majority of music on streaming services these days merely having the title and author, most of these songs lack precise tags.Because of this, it might be difficult to find hidden tags in songs and to categorize them into different genres. You must extract pertinent characteristics from audio in order to train the machine learning model. Spectral bandwidth, zero crossing rate, spectral contrast tempo, chroma feature, Mel frequency, and spectral coefficient are a few of the properties. These features are taken out of the audio stream using the Librosa package. It is an audio and music analysis library for Python. Use the extracted audio characteristics as input and the genre labels as the intended output to train the chosen model on the training dataset.

II. LITERATURE SURVEY

[1]The task of automatically classifying traditional Nigerian music into genres has never been examined before, until this paper. To present the Nigerian song-containing ORIN dataset as a tool for research on music genre classification.The ORIN datasets were trained using 85–15 train-test splits on 4 different classifiers: k-Nearest Neighbor, Support Vector Machine, extreme Gradient Boosting (XGBoost), and Random Forest, for the purpose of genre classification. The size of the ORIN dataset might be restricted, which could affect how broadly applicable the results are. using several machine learning models to provide a thorough assessment. XGBoost emerged as the top-performing model, exhibiting an 81.94% accuracy and an 84.57% recall rate. More investigation is required to increase the dataset's diversity of Nigerian-English contemporary songs, which could enhance the model's generalizability.

[2]By obtaining a high classification accuracy and extracting features from a dataset of 1742 Bangla music compositions, this paper seeks to illustrate the efficacy of the BMNet-5 approach. The ineffectiveness of the suggested model in handling different deformations—especially when white noise was present—points to possible generalization flaws. Robustness is increased in the results by employing K-fold cross-validation to validate the consistency of the BMNet-5 model. The BMNet-5 model demonstrated its effectiveness in genre classification with a high accuracy rate of 90.32 percent when it came to classifying Bangla music genres. Unexplored is the idea to combine transfer learning with fine-tuning using a sizable dataset of Bengali music genres, which leaves space for future study and real-world implementation.

[3]This study describes a web application that gathers music from YouTube and categorizes it according to musical genres. It is difficult to validate genre predictions in the absence of an agreed-upon definition of music genres, particularly when contrasting them with classifications from other sources. Additionally, the application serves as a prototype for a future user-centered MGC tool that will allow users to rate how accurate the predictions are. The results of the deep learning models are comparable to those of the generic classifier study using the Audioset baseline, which achieves an average AUC score of 0.959 and a mean average precision (AP) of 0.314. Although the application presents the idea of user-generated feedback for genre classification, more research is necessary to determine the applicability and efficacy of this validation technique.

[4]The purpose of the project is to verify empirically whether or not automated music classification systems can benefit from using the trajectory of fifths as a knowledge source. Only two genre groups were included in the study experiments, which might not accurately. reflect the complexity of real-world music genre classification scenarios. The study's findings support more investigation into the trajectory of fifths' application in music classification, especially in more intricate genre classification contexts. Every machine learning algorithm has mean balanced accuracies that are higher than 0.9.Although the basic coefficients produced encouraging results, there may be a need to investigate more intricate and sophisticated aspects of the fifth-trajectory in order to improve the accuracy of music classification.

[5]The authors of this work describe a novel method that uses cross-modal contrastive learning to combine various music-related data types, enabling us to simultaneously learn an audio feature from heterogeneous data. The study notes that not all of the dataset's information types—such as title, playlist tags, authors, and other metadata—were used. This constraint might result in unrealized potential for enhancing the model. They can achieve better performance with contrastive learning than with models that are trained directly to predict the genre. playlist-level data, necessitating still another degree of abstraction.

[6]In the context of music genre classification, this study aims to compare the performance of the ATMGCM algorithm with well-known models such as Random Forest and Support Vector Machines (SVM). The ATMGCM algorithm is introduced in the paper, but it makes no mention of any potential drawbacks or difficulties that may arise during implementation. The ATMGCM algorithm is said to achieve higher accuracy, which is a major benefit for music genre classification, particularly in situations involving large databases or noisy data. The ATMGCM algorithm is introduced in the paper, but readers may find it difficult to comprehend its inner workings and limitations due to the lack of detailed information on its methodology.

[7]The goal of this project is to give users a fast and efficient way to find music of their choice without having to listen to a lot of different songs or make manual decisions. The lack of technical information regarding the CNN architecture in the paper makes it challenging to evaluate the model's shortcomings. The suggested CNN model appears to be useful in identifying music genres, as evidenced by the highest accuracy of 83.3% reported. This can improve the user experience. Although streaming media integration is mentioned in the paper, it does not offer a clear plan for how this integration will be accomplished or how it will improve the tool for classifying music genres.

[8]The study's goal is to use convolutional neural networks (CNNs) to build a machine learning system for musical genre classification. The accuracy of the current implementation is tested on a brief (2.56 s) segment of songs, which might not accurately reflect the variety of musical genres found in longer songs.The author shows a dedication to enhancing the model's performance by talking about upcoming work on feature engineering and modifications. The tested CNN-based model's 85% reported accuracy on the test data indicates that it can successfully classify different

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musical genres. Although the study acknowledges the problem of false positives, it makes no recommendations for concrete approaches or plans to deal with this issue.

[9]This paper presents new high-level features derived from song structures to enhance the accuracy of genre classification and analyse via CNN. Classification can be difficult since some musical works might not neatly fit into a single genre and there might be ambiguity in the genre labelling is demonstrated that the new high-level features greatly improve classification accuracy, which makes it an important advancement in the field. While increasing classification accuracy is the main goal of the work, user-facing applications and music recommendation systems may face practical difficulties that call for further investigation.

[10]The goal of the project is to create and apply a Convolutional Neural Network (CNN) that can predict sound waves and categorize different genres of music using MFCC spectrograms as input. The author mostly concentrates on employing MFCC spectrograms as the principal auditory characteristic for categorization. There is no discussion of the advantages and disadvantages of utilizing additional sound features. It emphasizes how CNNs are superior to manual feature selection in traditional machine learning because they can automatically extract features from images.

[11]The goal of the project is to create multiple models for the classification of musical genres using a variety of inputs, including audio mel-spectrogram data, and machine learning algorithms, including CNN, SVM, and Decision Tree. According to the study, some musical genres—like rock and country—were occasionally mistaken for other forms. This restriction might point to difficulties correctly categorizing particular genres. The accuracy of the suggested model is 91%. It does not address whether the GTZAN dataset can be applied to other music datasets or genres; instead, it focuses on this dataset.

[12]The goal of the project is to create a machine learning model that can categorize songs into different genres while being spoken in multiple languages. Although the model may show low confidence in its predictions, the study makes no mention of a confidence threshold or practical applications for this information. The ability of the model to categorize songs automatically simplifies the task of organizing a lot of music. 93.3% classification accuracy was attained by the deep learning model for every one of the twelve languages that were examined in the database. Although accuracy could be increased, the study makes no mention of possible solutions or next steps to deal with this problem.

[13]The goal of the project is to find out how Deep Learning techniques can be used to categorize different music genres, particularly those that are closely associated. Certain genres, like country and rock, have some overlap that could cause misclassifications if the specifics of this overlap are not further examined. It demonstrates how various Deep Learning architectures are effective for various genres, enabling customized model selection. It obtained a 79% accuracy rate. Additional experiments are necessary to increase accuracy, but they don't specify what needs to be experimented with or improved.

[14]Comparing, analysing, and assessing the viability, effectiveness, and comprehensibility of various aspects for the classification of musical genres is the main goal. Decision trees, Random Forests (RF), and K-Nearest Neighbors (KNN) algorithms are used in this. The features selected for genre classification may have an effect on the outcomes, and some pertinent features may be left out, which could reduce the analysis's overall scope. A quantitative understanding of musical genres can enhance user experience by optimizing the performance of music recommender systems. With the help of the KNN algorithm, 90% accuracy was attained. Including a wider range of music datasets in the analysis could aid in determining how reliable the results are across various music collections.

[15]This study's objective was to categorize explicit music using user annotation and music metadata. Utilizing a dataset comprising user annotations and music metadata for 200 songs, machine learning models—Support Vector Machine (SVM) and Random Forest (RF) in particular—are trained and evaluated. The size and dependability of the study's dataset are constrained, which could have an impact on how broadly applicable the findings are. In order to achieve explicit music classification, the research presents a novel method that combines user annotations with music metadata. putting into consideration a hybrid strategy for a more thorough examination of explicit music content, one that integrates audio features with textual metadata and annotations.

[16]The Information Gain Ranking algorithm is used by the writers to determine which characteristics are most important for precise genre classification. The possible drawbacks and restrictions of employing three-second duration features for genre classification as opposed to thirty-second duration features are not discussed in the paper. focuses on

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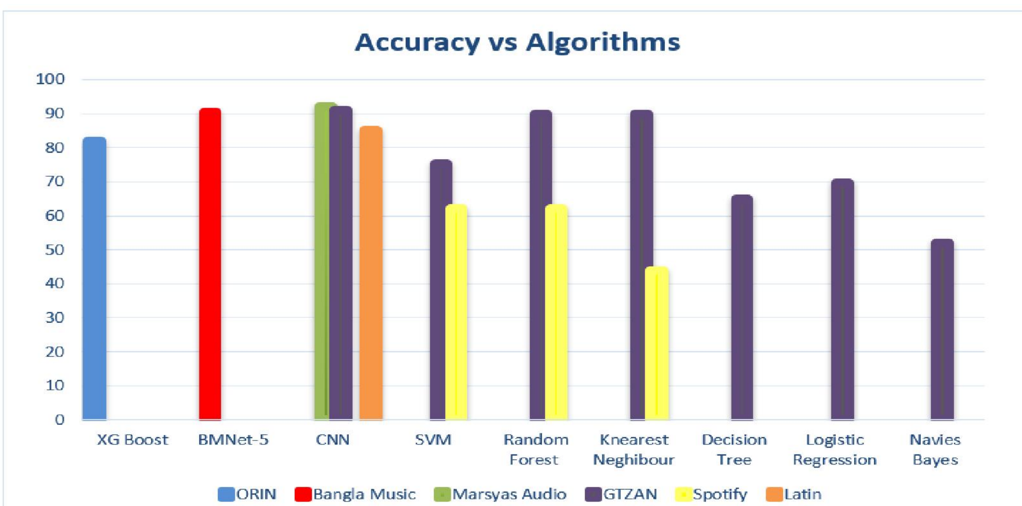
the k-Nearest Neighbors (kNN) algorithm as the top-performing model, achieving a 92.69% classification accuracy on input features with a three-second duration. concludes that for automatic music genre classification, traditional machine-learning models typically perform better than deep-learning techniques. It doesn't investigate how various input feature durations affect the models' ability to classify data.

[17]The original audio files are pre-processed by the authors using Librosa to create Mel spectrums, which are subsequently fed into the CNN model for training. The suggested CNN-based approach for music genre classification is not compared in the paper with other models or methods currently in use, which restricts our comprehension of its efficacy and relative performance. Professionals can no longer manually extract features from audio files' Mel spectrums by using CNNs to automatically extract features. The GTZAN dataset yielded an average accuracy of 84%, indicating the efficacy of the CNN-based method for music genre classification. The lack of a comparison between the proposed CNN-based approach and other current models or methods for music genre classification limits our understanding of the relative efficacy and performance of this approach.

[18]The GTZAN dataset is used to compare different Artificial Intelligence (AI) models for the classification of musical genres. The interpretability of the AI models, which may be crucial for comprehending the underlying causes of the classification results, is not discussed in the paper. The research findings may be used to analyze music in various contexts, aiding in the comprehension and classification of musical genres. With an accuracy of 90.22%, XGBoost was found to be the best-performing machine learning model, suggesting that it has the potential to accurately classify music genres. There was little discussion of how the research's findings might affect the music business or have real-world consequences for music streaming services.

[19]The study looks into ten different genres of music and emphasizes how important automatic genre classification is for music retrieval, organization, search, and recommendation. It is challenging to comprehend the rationale behind the recommendations since the paper offers no insights into how the genre classification and recommendation system can be interpreted. The system can accurately categorize song genres using word2vec, which improves comprehension of the musical content and allows for more accurate recommendations. The lack of user studies or feedback to support the users' satisfaction and experience with the music recommendation system is mentioned in the paper.

[20]The study solves the scalability issue by showing how Apache Spark can be used to shorten computation times for machine learning predictions without incurring any computational costs. The assessment of the training time of the random forest classifier is mentioned, but no precise information regarding hardware configurations or actions taken to address any problems is given. This research paper addresses the scalability issue by using Apache Spark to shorten the computation time for machine learning predictions without incurring any computational costs.



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III. METHODOLODY

[1]Data:

The ORIN dataset used in their research dataset consist of 478 Nigerian songs of different genre like fuji, juju, highlife, waka and apala.They decided to use the classifier based solely on how many music they could find in each genre. Every song has a duration of 30 seconds and is saved as an audio file in the.wav format. They were able to extract a great deal of information from the audio files by sampling each one at a rate of 22,050 hertz (Hz) and a 32-bit mono resolution. The ORIN dataset was specifically obtained in order to create a multi-class machine learning classification model for the aim of classifying the aforementioned musical genres.

Feature Extraction:

Feature extraction in the context of music audio processing was the process of obtaining numerical attributes included in a particular segment or frame of an audio file. This made it possible to process the information using a variety of additional techniques in addition to mathematical and statistical ones. Features pertaining to rhythmic content and timbral texture were retrieved for the investigation.

Timbral textural characteristics help distinguish between sounds that have a similar beat or melody.

1. Mel-Frequency Cepstral Coefficients -Timbral texture, pitch, and other spectral patterns are calculated to capture short-term spectral features that aid in differentiating sounds in audio processing and analysis.
2. Spectral Centroid-Utilized to gauge the spectral content's brightness and identify changes in emotion, particularly when a musician speaks more loudly
3. Spectral Flux -computed to characterize spectral shape; it aids in differentiating between various musical genres according to spectral energy distribution
4. Spectral Rolloff -to calculate the local spectral change's magnitude;
5. Zero Crossings -developed to measure the noise in signals
6. Spectral flatness -extracted to calculate a sound's noise-tonal level.
7. Spectral contrast -acquired to ascertain the distinction between a spectrum's peaks and valleys.
8. Spectral bandwidth -the range of wavelengths or frequency intervals that radiation from a monochromator can have between midpoints of emission line or minimally intrinsic width absorption band peaks and the continuous background, depending on the radiant power level limits.

The Rhythmic content features in a song's sound design are revealed by its rhythmic content features. They contain details about the beat, tempo, time signature, and regularity of the song's rhythm. The tempo, which is expressed in beats per minute (bmp), indicates the speed of the song.

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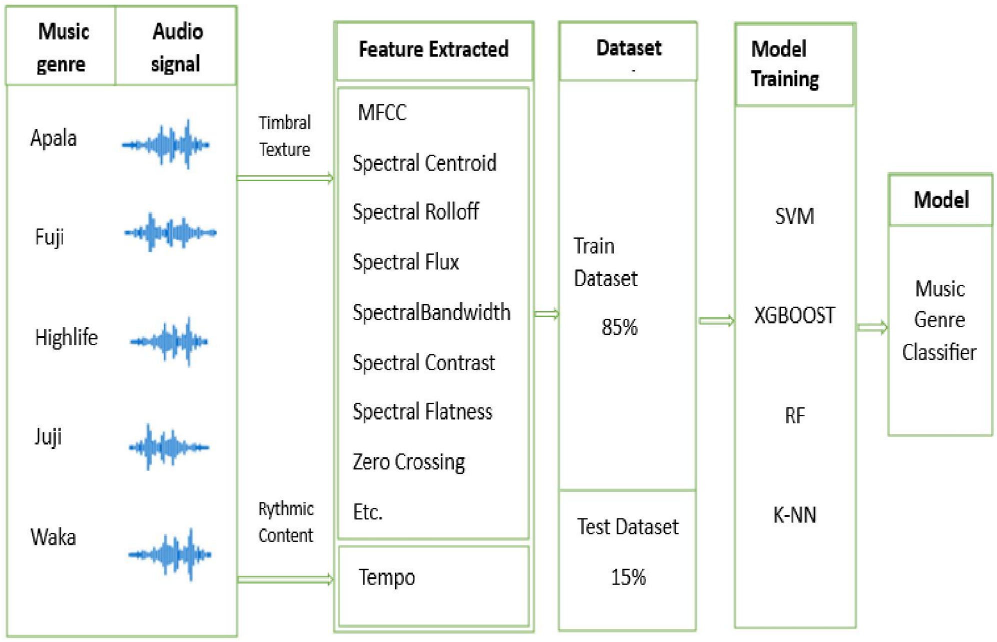

Fig: Architecture of Music Genre Classifier

CLASSIFICATION MODELS:

i)K-Nearest Neigbhour model (k-NN):The algorithm known as k-Nearest Neighbors uses the most frequent class among its k nearest training points to cast a vote and determine the class of an unclassified point. Songs that share similar timbral qualities, for example, are grouped together. The selection of k affects the classification outcomes; smaller positive integer values are advised to prevent subpar prediction and classification performance. In k-NN classification, this procedure is dependent on the Hamming distance function

ii) Support Vector Machine (SVM) :SVM was first created to address issues with binary classification. An SVM classifier typically creates a border between a set of training vectors that represent two distinct classes. In particular, if the classification problem is not linearly separable, SVM transforms the input vectors from a lower dimensional to a higher dimensional feature space and builds an optimal hyperplane in the higher dimensional feature space. The training cases close to the hyperplane serve as the support vectors. Because only these support vectors created the hyperplane, SVM is incredibly resilient to outliers.

iii) Random forest (RF): A collection of unpruned regression or classification trees make up the RF model. Random feature selection is used to create these trees from trained bootstrap samples of the training set. Majority voting is used to classify trees when a large number of trees have been generated. The random forest is created through the voting process on these trees. The number of trees in the forest and the characteristics that each tree in the forest grows are the two factors that need to be adjusted for effective classification.

iv) eXtreme Gradient Boosting classifier (XGBoosting):Regression and classification tasks can be completed by the highly scalable, effective, and portable optimized dispersed gradient boosting algorithm known as the XGBoost Classifier. The ensembles of decision trees that are used to train data with multiple features of xi in order to predict a label yi are the foundation of the XGBoost classifier. The XGBoost classifier was suggested for the purpose of classifying music genres because of its excellent prediction performance. Its application has been shown to provide cutting-edge data science performance, and it is an algorithm that wins competitions. Furthermore, it can choose the best variable and works with large data sets. The model was adjusted in the study using the following hyperparameters: max_-depth = 2, n_estimators = 1000, learning_rate = 0.05.

[2]The primary objective of this work is to use the proposed model BMNet-5 to extract features from audio signals in order to classify and predict data from the Bangla Music dataset. The raw music files that were gathered from the

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current dataset were first prepared in a few ways. Following the preparation of the data, features were extracted, and the feature vector was then sent to the training and validation stages. Next, the model's prediction accuracy against the test set is evaluated.

(A)Data: In their research, they conducted all tests on raw data from 1742 Bangla music files provided by Mamun. The data they worked with included audio files sourced from YouTube and other platforms. Approximately 7.3 GB (Gigabytes) of raw MP3 files were used. After obtaining all these MP3 files, they utilized specific segments of the files to enhance audio file loading times. These segments ranged from 20 seconds to 100 seconds in length. The extracted features were subsequently saved in a CSV file.

B) Split the dataset into training and testing sets: They divided their dataset in a 70:30 ratio for training and testing. They had 1220 data in training dataset and 522 data in test dataset after dividing by this ratio. using SubsetRandom Sampler and DataLoader library to shuffle and partition of dataset for getting more generic model by shuffling.

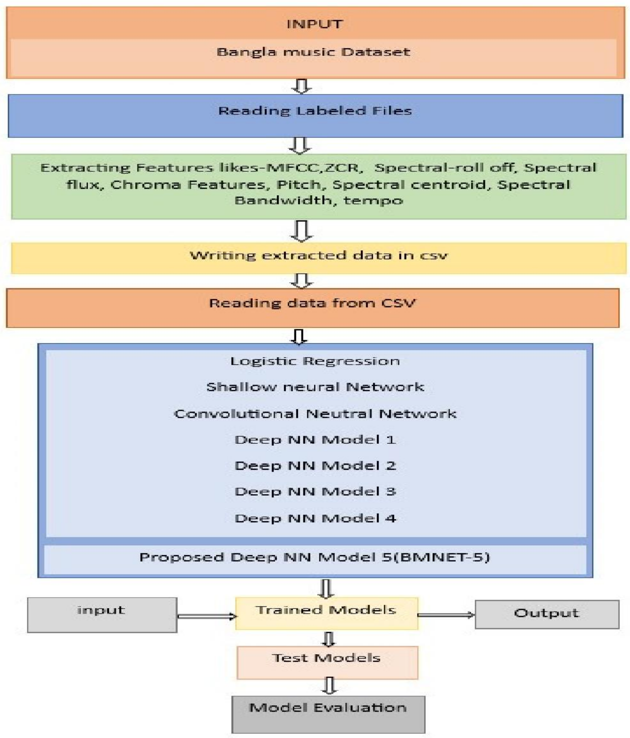

Fig: Architecture of Music Genre Classifier

D) Building and training models

LOGISTIC REGRESSION (LR) :A classification technique called logistic regression (LR) is predicated on the idea that an outcome is influenced by one or more independent factors. Although logistic regression is typically used as a binary classifier, one-vs-rest logistic regression (OVR) or multinomial logistic regression (MLR) can be utilized to adapt logistic regression to multi-class scenarios.

SHALLOW NEURAL NETWORK MODEL :Shallow neural nets have only one or two hidden layers.The input layer, hidden layer, and output layer of the neural network in the image below represent the three layers that make up a shallow neural network. ReLU activation functions were employed in the implementation of their model. There were 32 batches, 0.1 learning rate, and 1500 iterations in total. To calculate the loss, we used the Cross-entropy Loss Function and Stochastic Gradient Descent.

CONVOLUTIONAL NEURAL NETWORK (CNN) :The first use of the Convolutional Neural Network (CNN), a biological systems-inspired version of the Multilayer Perceptron (MLP), was in the area of number recognition. CNN's use of shared weights, sub-sampling, and local receptive fields gives the model some degree of shift, scale, and distortion invariance. The convolution of spectrograms provides a basis for categorizing music using these principles.

DEEP NEURAL NETWORK MODEL:Even the most complex and high-dimensional data can have its features automatically extracted and learned thanks to DNN's deep layer architecture. To categorize the genre of Bangla music, they used one, two, three, and four layers of DNN in their experiment. Fully-connected neural networks, like the DNN used in this study, have layers that are hidden from view in addition to an input layer and an output layer. The size of the input feature vectors and the number of input neurons are directly correlated, while the number of output neurons is directly correlated with the number of musical styles being studied

PROPOSED DEEP NN MODEL 5

They suggested using a modified deep neural network model with layer 5, known as BMNet-5, to categorize the genre of Bangla music. It has 512, 256, 128, 64, and 7 nodes with 29 features in the input layer, as shown. Six nodes with softmax activation make up the output layer since there are six classes to forecast. The Rectified Linear Unit, or RELU, was used to activate additional layers. After making a few simple adjustments, they discovered that using only 187 epochs and a batch size of 50 training data for each epoch produced better results than using 250–300 epochs at first.

IV. RESULTS

Paper	Dataset	Genre	Best Method	Accuracy
[1]	ORIN	5	XGBoost	82.0%
[2]	Bangla music	6	BMNet-5	90.32%

V. CONCLUSION

The model helps to categorize the music according to its genre. A fascinating and constantly developing field of study, machine learning approaches for music genre classification have major practical applications and implications for the music industry. The accuracy value of the XGBoost classifier for the ORIN datasets was 81.94% for classifying Nigerian songs, and 84.57% for recall; the BMNET-5 classifier had an accuracy value of 90.32% for classifying Bangla songs.Research into machine learning methods for classifying music genres has revealed a variety of approaches, such as deep learning models and feature-based techniques. Spotify and Sound Cloud use genre categorization to suggest songs to their users. The subjective and dynamic nature of genres means that classifying music remains a difficult task despite advancements. By employing sophisticated models and expanding the size of the dataset, genre classification can be made more effective. Furthermore, there is a strong need for additional research in the field of music genre classification, especially in light of the increased diversity of genre labels and the consideration of multiple languages.

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