

***MACHINE LEARNING FOR MUSIC GENRE CLASSIFICATION WITH NEURAL NETWORKS USING CONVOLUTIONAL NEURAL NETWORK MODEL***

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**Music Genre Classification**

**With Neural Networks**

**ABSTRACT**

This makes the music industry such a huge and changing art, and it has been identified that creating different genre playlists is an important task for streaming platforms, recommendation engines, and even for the music fans themselves. This has therefore become a very useful tool in attempting to classify, recognize patterns, and identify features of music genres.

Most of these projects have utilized the same method using Deep Belief Networks since it is quite infeasible to identify genres of music. We hence experimented whether CNN, RNN performed well amongst other components of a classifying architecture such as a data selection, pre-processing techniques and sample size.

**KEYWORDS**

Convolutional neural networks (CNN), Recurrent neural networks (RNN) Musicgenre, Machine learning, pattern classification, feature selection

**INTRODUCTION**

Advances in automatic music genre classification are coupled with progress in machine learning and audio analysis algorithms. In the greater success of models for image recognition, particularly after the triumph of the ILSVRC in 2012, the AI community has demonstrated the feasibility of categorizing complex, high-dimensional data like images at phenomenal levels of accuracy. It has motivated interest in adapting similar approaches to audio-based tasks, especially those requiring subtle understanding of musical genres that are subjective and culturally diverse.

Collaborative filtering-based approaches and content-based classification of music genres differ fundamentally, as the latter uses the audio signal itself for making suggestions and relies on deep neural networks to learn what is in the sound. In recent times, neural networks, especially CNNs and RNNs, have shown great promise in learning direct feature representation from raw audio or spectrogram representations, which bypasses considerable manual feature engineering. Most models can discern intricate structures in music-whether tempo, rhythm, pitch, timbre, and harmonic relationships-that make it conducive to genre differentiation.

Lately, hybrid systems have come that encapsulate both content-based filtering and collaborative filtering, leading to a more comprehensive aspect of music categorization and combining objective audio features as well as subjective user preference. Advances in state of the art, especially recent developments of attention mechanisms based on transformer models, for the first time designed based upon natural language processing, enable genre classification to further outperform in terms of temporal dependencies and contextual information pertaining to music.

Furthermore, large, annotated music datasets and frameworks such as MusicNet, FMA (Free Music Archive), and GTZAN provided a platform to support state-of-the-art genre classification models in their development and testing. These datasets contain labeled samples of audio from various genres, which is then used by researchers for training and validation purposes with good reliability. Music genre classification models progress further towards making more personalized, culturally aware, and sensitive-to-context music recommendations while having wider applications on streaming platforms, digital radio, and libraries of music.

Background:

Genre-based music classification is an important aspect of audio processing on which various practical applications depend. The growing digital libraries of music and online streaming require effective organization and indexing for retrieving the required tracks, and genre classification can best serve to organize the tracks appropriately; recommendation system, based on the preferences of listeners and love for a particular genre. Most importantly, it simplifies the process of searching and cataloging large volumes from automated genre labeling by the music libraries. For artists and producers in creative fields, it helps support the analysis of trends and influence; researchers need it to understand how different music styles are unique in both entertainment and academic research.

Objective

The research will focus on achieving accurate classification of music genres by analyzing audio features of various tracks. The author of this study uses machine learning models to investigate which characteristics from each genre allow for identification and classification. This research is special in focusing on the task of feature extraction and model optimization towards providing a reliable means of classifying music into genres as part of advancement in MIR and audio analytics.

For this experiment, a dataset is employed that contains audio files classified according to their genres. The dataset selected here contains various genres, such as Blues, Jazz, Rock, and many others. Each genre contains an equal number of samples so that all genres can be represented in a balanced manner. Audio samples, for instance, are saved each in the format of .wav so that good quality audio can be maintained to further extract features and analyze it. In this database, the files are arranged in a naming scheme, thus making it feasible for access and labeling of every single track to genre, which is critical in the proper training and testing of classification models. Therefore, this dataset provides a good foundation upon which to explore genre classification further and analyze distinct audio features that characterize every style of music.

LITERATURE REVIEW

Music genre classification draws inspiration from significant application breakthroughs such as those in image recognition that began seeing large strides after the ILSVRC held in 2012. Breakthroughs inspired researchers to utilize diverse machine learning methods with huge annotated datasets and feature extraction techniques primarily designed for audio signals for the classification of music into genres. However, this process is still very complex due to the nature of objectivity required for genre classification as well as the subtle audio features that make distinctions between genres.

As an example, Pelchat and Craig M. [4] used the GTZAN dataset, where songs were classified into seven genres and audio processed into spectrograms. Stereo channels were converted to mono and spectrograms sliced into 128x128 pixel images using SoX, a command-line audio processing tool. Those spectrograms were fed into a CNN architecture with Xavier initialization. We have designed the CNN model using four convolutional layers, which means each convolutional layer applies 2x2 kernels with stride two and succeeded by max-pooling. It's followed by a fully connected layer that yields a feature of 1024 dimension to be fed into SoftMax. By SoftMax, seven genres are predicted. However, this model significantly overfit, inasmuch as it gave 97% accuracy at the training set but only 47% at the test set thereby understanding the difficulties in having a genre classification model generalize.

K. Meenakshi [5] implemented genre classification by pre-processing audio using Python's librosa package extracting both Mel Frequency Cepstral Coefficients (MFCC) and Mel Spectrogram features. These features represented both the tonal and spectral qualities of music, which were processed using CNN layers consisting of convolutional, pooling, and fully connected layers. The Mel Spectrogram feature vector achieved 76% accuracy, whereas the MFCC feature vector obtained only 47%, thus underlining the significance of feature selection and engineering in guaranteeing proper classification results.

Nirmal M. R. In [2], spectrograms were used as a central feature for the genre classification task in which a pre-trained MobileNet as well as a user-defined sequential CNN was adapted. For their experiment, spectrograms, since they present audio signals in time and frequency domains by STFT, have a visual structure that can be interpreted using deep learning models. It seems that MobileNet worked better at 67% in classifying accuracy compared to 40% of the user-defined CNN. This reflects the idea that utilization of more robust architectures of pre-trained networks may result in better performance for genre classification.

Studies such as [3] use SVM with RBF kernels natively on the data from Spotify, containing over 228k tracks distributed between 26 genres and 18 attributes. They correctly categorize genres with SVM's accuracy of 80%, KNN accuracy of 77.18%, and NB accuracy of 76.08% with the same data by training at 80% and testing at 20%. These classify that the feature-rich dataset plus optimal hyperparameter selection add up to difference in performance for classification.

To represent modern advances in MIR, Mingwen Dong 6 uses CNNs in a genre classification task. Using a "divide-and-conquer" strategy, Dong divided each song's Mel-Spectrogram into overlapping, 3-second segments to achieve a 70% classification rate on a 10-class genre classification task, rivalling human performance. The approach allows division of audio into segments so that the model learns details specific to genres but maintains temporal coherence.

Therefore, the research exhibits a steady shift in genre categorization techniques using deep learning, extracting features like MFCC, Mel Spectrograms, and neural networks that explain the intricacy of musical genres. Modern systems now include both content-based approaches, that is, AUDIO Signal, as well as collaborative filtering to include user preferences to move genre classification further to commercial viability. Besides these applications, the more common demonstration of deep learning applied to music retrieval and classification has to do with real-time applications like Shazam, using spectrogram peaks to develop a song "signature." Genre classification models are getting more accurate, more flexible, and better at supporting an enormous variety of applications as datasets, feature extraction methods, and model architectures change over time.

**Related Work on Music Genre Classification**

Music genre classification has been an active area of research for decades. The advances in machine learning, feature extraction techniques, and deep learning methods have catapulted the field towards a significant improvement. Researchers have looked into diverse approaches to classifying music genres; focusing on feature extraction from audio signals and making models understand and classify musical characteristics. This section summarizes some of the key approaches and techniques used in music genre classification.

1. **Feature Extraction for Audio Classification**

In a music genre classification problem, raw audio data cannot be used by machine learning models; therefore, the extraction of features is important. Audio features extracted from raw audio data represent musical patterns underlying them in a format directly usable for processing algorithms.

Mel-frequency Cepstral Coefficients (MFCC): This is one of the most widely used feature extraction techniques for audio classification, and it captures the timbral texture of music by analyzing the spectral envelope. MFCCs are based on the human auditory system and represent speech and music classification very robustly. They represent phonetic content efficiently and have been highly applied in a lot of genre classification tasks to differentiate between musical styles (Logan, 2000).

Chroma Features: These features capture harmonic content and pitch classes that are precisely useful to music classification tasks because they describe relationships between notes in the musical scale. Chroma features are used for analyzing chord progressions and harmonic structures hence ideal for genre classification where harmonic content plays a major role (Foote, 2000).

Features of spectral contrast and rhythm: The feature evaluates the amplitude of peaks versus valleys in a spectrum of sound. This helps one identify timbral characteristics within different genres. In addition, rhythm features such as beats per minute (BPM) and periodicity can help classify genres, mainly by considering rhythmic structure and tempo as one of the dividing factors between the genres which one has to classify, for instance, pop or hip-hop classification (Ellis, 2007).

1. **Machine Learning Approaches**

After feature extraction, machine learning algorithms are used to classify the music into different genres. Several of the conventional methods of machine learning have been experimented in this direction:

Support Vector Machines (SVM): SVM is a powerful classifier that can work well with high-dimensional data, often present with audio classification. SVMs can separate genres efficiently in feature spaces using the kernel trick. Many research studies have shown that SVM performs well in general when features like MFCC and chroma features are used (Tzanetakis & Cook, 2002).

k-Nearest Neighbors (k-NN): The k-NN is a simple machine learning technique that predicts a class label to the unknown sample based on the class of its majority nearest neighbors in the feature space. Although computationally less expensive than other algorithms, good feature sets made k-NN perform admirably in genre classification and it had been widely used for several genres, when the number of samples involved was not too large as well, Logan (2000).

Other applications: The Random Forests was applied also on genre classification combining multiple decision trees in a forest to build a more accurate classifier. Decision Trees partition the feature space based on the values of the features and are more interpretable but probably prone to overfitting. That overfitting is overcome by averaging over several trees in random forests. Therefore, a much more robust classifier is produced (Eronen et al., 2003).

1. **Deep Learning Approaches**

Deep learning has recently revolutionized the classification of the kind of music. Models have been able to learn deep hierarchical representations of audio data without the handcrafted extraction of features. Deep models are quite well suited to complex tasks such as genre classification because they extract hierarchical patterns in the data.

Convolutional Neural Networks CNNs. Convolutional neural networks are highly efficient when the data is in a grid-like structure or order, as it is the case with spectrograms that represent the frequency content of an audio signal as time evolves. The researchers successfully applied CNNs for music genre classification by converting the raw audio data into spectrograms and then letting the network learn the features of relevance from the raw data. CNNs work wonderfully in the detection of local patterns, and thus easily, they detect characteristics of genre-specific music, including rhythm, melody, and timbre, (Choi et al., 2017).

RNNs: RNNs, in particular, the LSTM types are designed for sequential data. Therefore it suitable for applications where the temporal aspect of audio is of importance. RNNs capture long-term dependencies in audio due to its time-series nature of the musical signal, making them useful when the genre classification depends upon the patterns which evolve in time, especially genres which have complexity in rhythm and structures (Huang et al., 2014).

Autoencoder and DBN: In the use of autoencoder and DBN for music genre classification, unsupervised feature learning was undertaken. These models are trained in order to minimize the reconstruction error for learning compressed representations of audio data. These compressed representations are then utilized for genre classification. DBNs and autoencoders work best on minimal labeled data because they can perform very well on unlabeled data while still learning effective features for classification (Lee et al., 2011).

1. **Hybrid Approaches and Ensemble Learning**

Another major way researchers have improved classification performance is by the hybrid and ensemble methods, whereby combinations of different classifiers and feature extraction methods are used. Ensemble learning, such as stacking or bagging, combines several models to improve predictive accuracy. For instance, an integration of CNNs with other traditional classifiers like SVMs or decision trees has been reported to use the power of both approaches together by improving the overall classification performance.

1. **Challenges and Limitations**

While huge progress can be seen in the area of music genre classification, there are still some problems to be investigated. This includes the fact that in this area, large amounts of labeled datasets sometimes constrain machine learning performance. The boundaries of genres are ambiguous at times; when the transition between genre boundaries is a bit fluid, genres often overlap with each other, making classification quite challenging. Models can sometimes face problems with genres like Blues and Jazz, which share a common characteristics. Again, the problem comes from genres which have variant styles, for example, Rock or Pop. Furthermore, the noise as well as distortions inherent in real-world datasets may probably affect classifiers: background noises or recording of relatively low quality.

**MUSIC GENR CLASSIFICATION**

**A. Music Genre**

The essence of genre as an attribute that defines and categorizes music is obvious, for every genre conveys a distinctive flavor and atmosphere of the piece. Each genre in turn can play differently in the ears of listeners to create emotional responses and behavior. A good process of classifying according to genre would therefore give very valuable information on the sociopsychological dimensions of music reception, and serve as a base to understand how people tend to build musical communities considering shared tastes and similarities perceived.

Music genres can be divided in many frameworks but are most commonly distinguished under blues, classical, country, disco, hip-hop, jazz, metal, pop, reggae, and rock. Nonetheless, pinpointing the right genre for a song continues to be a difficult matter in the light of superposed features and the flexibility involved in the development of the musical world. With evolving genre intermingling and creating new subgenres, there comes a time when all traditional classification becomes an insurmountable obstacle in classifying a music information retrieval system.

**B. Mel-frequency Cepstral Coefficient (MFCCs)**

The MFCCs are a very effective feature set that can compactly capture the general spectral shape of an audio signal, encapsulating essential frequency components that characterize sound. A MFCC process starts with the segmentation of an audio signal into overlapping frames and a computation of a power spectrum based on a Fourier transform. It then maps this spectrum to the mel frequency scale, approximating the response of the human auditory system to different frequencies and allowing for a more perceptually relevant representation of the audio.

This can be further smoothed by passing through a series of mel-scale filter banks that may extract the energies within each frame after mel-filtering. The energies are then converted through a discrete cosine transformation, and this results in a set of MFCCs. This transformation is specifically important because it has condensed the most important information into just a few coefficients and therefore retrieves the primary characteristic of an audio signal while discarding noise and other useless details in the process.

The ability of these MFCCs to effectively work with every type of audio analysis, which includes speech recognition, speaker identification, and even music genre classification, suggests that they must be capable of extracting some of the unique features which establish an audio signal's timbre and harmonic structure. MFCCs are extremely important to Music Information Retrieval (MIR) as they describe the spectral shadings and overtones that distinguish one kind of music and sound from another. Due to this reason, MFCCs are often integrated into feature vectors used by sound classification and recognition models, thus forming a stable foundation for further employment in high-level machine learning techniques in audio-based applications.

**C. Convolutional Neural Network (CNN)**

A Convolutional Neural Network, or CNN, is a special artificial neural network that really excels at visual data analysis work such as image classification, object detection, and segmentation. Inspired by the connectivity pattern of neurons in the visual cortex, they have an architecture designed to make computation efficient in image processing while achieving high accuracy.

Unlike a simple neural network, CNNs have various types of layers that enable hierarchical feature extraction. These include convolutional layers that apply filters to capture spatial features in images, pooling layers that downsample feature maps in order to reduce the dimensionality and computation, fully connected layers that aggregate the learned features for final classification, and regularization layers that mitigate overfitting. For example, CNNs exploit shared weights and local receptive fields with the aim of minimizing the parameters as well as computational load. This achieves the processing of large-scale image data efficiently.

One of the strengths that CNNs possess is their ability to learn high-level hierarchical spatial patterns in visual data from the simpler edges and textures of early layers to more abstract and high-level features in deeper layers. A layer-by-layer approach like this enables CNNs to generalize well across a very broad range of visual tasks and to do so in a computationally efficient manner.

These developments in CNN architecture include resid ue connections, batch normalization, and depth-wise separable convolutions. It is such an approach that makes improvements in both efficiency and accuracy in the model against older models. Due to these innovations, CNNs are not only easy to train and easier but also powerful regarding the extraction of relevant features from high-dimensional visual inputs for the backbone of the modern computer vision systems.

**D. CNN over LSTM model**

While CNNs and LSTMs have the same promise for music genre classification, one major application of CNNs toward such a task is due to their high performance in obtaining short-term temporal audio features, which are significant for differentiating between genres.

CNNs perform very well for the type of local patterns in the data. Their performance in audio analysis is out of this world because rhythm and timbre are some of the mainstays, among other short-term audio characteristics. Audio data, if processed in the form of spectrograms or mel-spectrograms, allows CNNs to capture the intricate high-dimensional structures-that is, an important characteristic when identifying genre-specific details. Since spectrograms are visually presented representations of sound frequencies over time, CNNs will identify subtle but clearly distinct patterns in both frequency and amplitude that could determine genres.

In contrast, LSTMs were specifically designed to model long-term dependency and are much better suited for any highly sequential data with long dependencies, as commonly observed in text or music produced continuously. Even though LSTMs are sometimes extremely useful in music-related applications like generating melodies or predicting note sequences in compositions, their natural tendency to depend on longer input sequences quite often results in less accurate genre classification. Another challenge that poses difficulties to LSTMs is the vanishing gradient problem when processing very long sequences, which can interfere with its ability to properly capture relevant temporal features needed for audio classification.

Another benefit of CNNs in the above space is their computational efficiency. A rich capacity of CNNs for effectiveness in dealing with high-dimensional data, through effective learning of representations from local features and hierarchies of patterns, is essential for processing complex audio data. CNNs give really fast training and inference times as compared to LSTMs and thus suitable for applying real-time genre classification on limited platforms with low computational resources.

New hybrid architectures that couple CNNs with attention mechanisms have been found more promising in music genre classification because they allow the model to pay attention to the most relevant parts of the audio sequence for improving classification accuracy. Advances in transformer-based architectures may further allow models to capture both local and global dependencies in audio and approach alternative ways and enhance their genre-classification capability.

Anyway, in tasks for sequential prediction, LSTMs are found to be helpful, whereas CNNs are more suited for fulfilling the requirements of music genre classification by capturing the critical short-term time and frequency-based features defining musical genres.**E. Representational State Transfer (Rest) API**

REST APIs are necessary for the structure of web server architecture, which easily enables interactions between clients and servers using a well-defined set of constraints. The architectural style of REST emphasizes more on stateless and cacheable communication; therefore it is very adaptable, light, and fully applicable to distributed systems on the Web. RESTful APIs allow applications to interface with web services in the most effective manner possible, making use of simplistic HTTP operations like GET, POST, PUT, DELETE without much processing, which in turn makes them a great replacement for complex protocols such as SOAP (Simple Object Access Protocol).

Bandwidth usage is minimal, and it is highly suitable for high-scale web applications where data transfer efficiency is a priority. RESTful services are exchanged over HTTP alone; hence, it is quite easy to connect and will enable interoperability between heterogeneous systems. Direct HTTP communication can support a wide variety of data formats-most commonly JSON, because of its lightweight structure and compatibility with web services, but also XML, HTML, and even multimedia files such as images. Due to a human-readable structure and rapid parsing capabilities, JSON has become a favorite data exchange format for modern web services: it provides faster performance and easier integration with frontends based on the JavaScript language.

In REST, resources are identified by URLs. Each HTTP method is used to specify a different action: GET retrieves data; POST submits new data; PUT updates existing data, and DELETE removes it. Such methods give a highly structured and predictable form of client-server communication- and with this, guarantees come in the aspect of simplicity and scalability. Additionally, they are stateless meaning each request that comes from the client to a server must carry all information needed to process and understand the request, hence low server memory usage and even serve to allow the distribution of load across multiple servers.

REST architectural style is quite important for the development of scalable and flexible web applications and serves as a basis for the modern architecture of microservices utilizing the communication of small, independent services via HTTP, resulting in modular and resilient system design.

**F. Problem Statement**

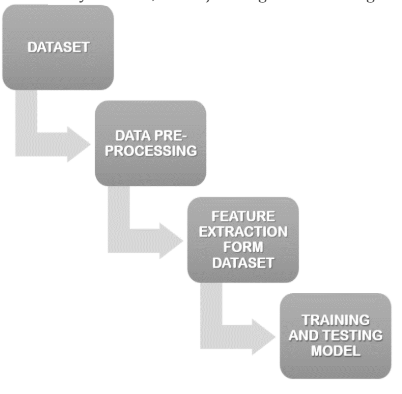
As said earlier, classifying a piece of music into genre is a highly ambiguous task and often is not explicitly defined. Traditional methods tend to find this confusion of genre-based classification problematic. Therefore, advanced techniques such as neural networks, with special regard for Convolutional Neural Networks, may be used in order to enhance the efficiency and accuracy of the classification process. One class of deep neural networks that significantly impacted the world of image processing is they automatically learn spatial hierarchies of features from raw input data: CNNs. Not surprisingly, in recent years, CNNs have also become highly effective in audio analysis, especially in such tasks as music genre classification.

For this purpose, we applied a CNN-based methodology for music genre classification by exploiting the spectrographic representation of an audio signal. A spectrogram is a time-frequency representation that captures the frequency content of a signal over time, making it highly favorable for analyzing musical characteristics. Treating these spectrograms as "images," CNN may be trained to identify the complex pattern of audio, such as rhythmic structure, content of harmonics, and timbral variation – often the key indicators of genre. This lets the model learn relevant features autonomously from raw audio data, without requiring manually extracted features.

This approach is also aligned with the recent developments in deep learning for audio processing, since CNNs are shown to have state-of-the-art performance in various music tasks such as genre classification, mood detection, and music recommendation. By leveraging the power of CNNs, we intend to automate the process of genre classification so that we can offer a more robust and scalable solution that would handle the difficulties of musical diversity while still keeping high accuracy.

**SYSTEM DESIGN & ANALYSIS**

In my studies, the primary categories of music style to reap the purpose are: Dataset, Data Pre-Processing, Feature Extraction from Dataset and Training



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**DATASET**

The GTZAN Database is used to enter statistics into the device due to the fact it is a group of unfastened accessible songs from many genres. The collection is made up of thousands of audio tracks divided into 10 distinct genres. This database consists of blues, classical, usa, disco, hip-hop, jazz, metallic, pop, reggae, and rock track. Music records on the GTZAN database is taken at 22050 Hz and lasts for approximately 30 seconds, a total of 22020 x 30 = 661500 samples. For each a easy window of 2048 samples, with a trade of 1024 samples, as calculated at some stage in the observe, all of the outcomes furnished beneath are rated at greater than ten runs, and the accuracy of the sections changed into selected as metric performance metric.

"C:/Users/Muraa/Desktop/Data/genres\_original/blues/blues.00000.wav"

TABLE 1:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| | **Genre** |  | | --- | --- | | |  | **Number of Samples** | | --- | --- | |
| |  |  | | --- | --- | | Blues |  | | |  |  | | --- | --- | |  | 100 | |
| |  |  | | --- | --- | | Classical |  | | |  |  | | --- | --- | |  | 1000 | |
| |  |  | | --- | --- | | Country |  | | |  |  | | --- | --- | |  | 1000 | |
| |  |  | | --- | --- | | Disco |  | | |  |  | | --- | --- | |  | 1000 | |
| |  |  | | --- | --- | | Hip-Hop |  | | |  |  | | --- | --- | |  | 1000 | |
| |  |  | | --- | --- | | Jazz |  | | |  |  | | --- | --- | |  | 1000 | |
| |  |  | | --- | --- | | Metal |  | | |  |  | | --- | --- | |  | 1000 | |
| |  |  | | --- | --- | | Pop |  | | |  |  | | --- | --- | |  | 1000 | |
| |  |  | | --- | --- | | Reggae |  | | |  |  | | --- | --- | |  | 1000 | |
| |  |  | | --- | --- | | Rock |  | | |  |  | | --- | --- | |  | 1000 | |
| |  | | --- | | Total | | |  | | --- | | 10000 | |

**Dataset Description**

It includes audio files in WAV format for each sample of genre in this music genres classification dataset. Every file is stored within a specific subdirectory, corresponding to a different genre. The structure of the dataset is given below:

Genres : The dataset contains a few genres. Here are a few of them: Blues, Classical, Jazz, Rock, etc. Every genre contains an array of audio files that contain recordings of music under that genre. For example, the "Blues" genre may have files like blues.00000.wav, blues.00001.wav, and so on.

Audio Files: The audio files are all in the WAV format. This is an uncompressed audio format that retains the quality of the recording. These files vary in length but are generally 10-30 seconds, depending on the recording.

Dataset Size:

The dataset comprises X total audio samples.

The number of genres represented by this dataset is N, where every genre has a different number of samples.

For instance, if there are 10 genres, then each genre could have 1,000 audio files. In this case, that would mean a total of 10,000 audio files.

Systematic naming conventions are used for the files. Generally, files are named in the format of genre.XXXXX.wav, where XXXXX refers to a unique incremental number for each file. The genre of every audio file can be identified from the directory, and the name of the file easily.

**Preprocessing Steps:**

To prepare the dataset for the tasks in hand that involve machine learning, several preprocessing steps are applied to the dataset.

Audio File Loading: Every WAV file gets loaded into memory as a time-domain signal-this means a sequence of audio samples-with the assistance of an appropriate audio processing library like librosa or pydub.

Feature Extraction: To process the raw audio signals into the format that can feed them into machine learning models, we do extraction of various features such as:

Mel-Frequency Cepstral Coefficients (MFCCs): A common feature for audio analysis which captures the spectral properties of the sound.

Zero-Crossing Rate (ZCR) and Spectral Centroid: Other features that would further characterize the temporal and spectral characteristics of the audio signal.

Data Splitting: The dataset is normally split into a training set and a test set:

Training Set: Normally, 70-80% of the total dataset is applied to train the classification model.

Testing Set: The residual 20-30% is kept as a testing set to check the performance of the trained model.

Data is split randomly to test the performance of the model fairly

Normalization: Some of the audio features are normalized to put the features on an equal scale so that their performance can be enhanced in machine learning algorithms.

Data Augmentation (Optional): Audio augmentation techniques-including, for example, pitch shifting, time-stretching, or adding noise-can be performed to boost data diversity and thus promote generalization of the model.

**Music Genre Classification Using GTZAN and MusicNet Datasets:**

Classification of music genre is one of the significant challenges in the area of machine learning and music information retrieval. Using publically available datasets such as GTZAN and MusicNet, models can be designed to classify music using its audio-based features. Both the datasets consist of audio files sampled at 22,050Hz in mono with 16-bit resolution and are stored in the .wav format, which provides solid ground for feature extraction and subsequent model training.

The GTZAN dataset is one of the most widely utilized data with samples to classify a genre, and it has 9990 samples with 60 features per sample. For each of the audio pieces in the datasets, there exists a corresponding genre, whose feature contains its value, among other parameters, of the audio signal, including the tempo, rhythm, and spectral content, and timbre. This dataset is an imperative one for evaluating the classification ability of machine learning models in predefined genre categories.

Boxplot for Genre and Beats Per Minute (BPM)

In the figure below, we show a boxplot of distribution by genre alongside the BPM of the tracks in the GTZAN dataset. The plot highlights the difference in BPM for the genres, thus capturing the relationship between musical style and tempo. Such analysis is necessary in understanding feature distribution in the dataset and extracting patterns that one might exploit during classification:.

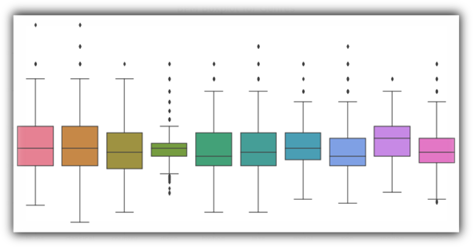


Fig 1: Boxplot for Genre and Beats Per Minute (BPM)

Fig 1: Boxplot of Genre and Beats Per Minute (BPM) in GTZAN Dataset. The figure provides an insight into the variation of BPM by genres and could indicate how well features like BPM may feature to determine the genres for a given audio.

Principal Component Analysis (PCA) for Dimensionality Reduction

One of the fundamental techniques used for music genre classification is called Principal Component Analysis (PCA). PCA is an unsupervised method to reduce the dimensionality of datasets with as much preserved variance as possible. This technique widely comes in application with music genre classification so that the feature space gets simplified and models can easily find out the patterns in data.

On the other hand, for datasets GTZAN and MusicNet applying PCA can reduce the dimension of feature space from hundreds of dimensions to two or three dimensions. This is very important for summarizing data in order to simply visualize or get a basic understanding of the model without losing important information. From the following figure you can see how PCA reduces the dataset into two or three components with preservation of the main variance of the data.

PCA of the Music Genre Dataset

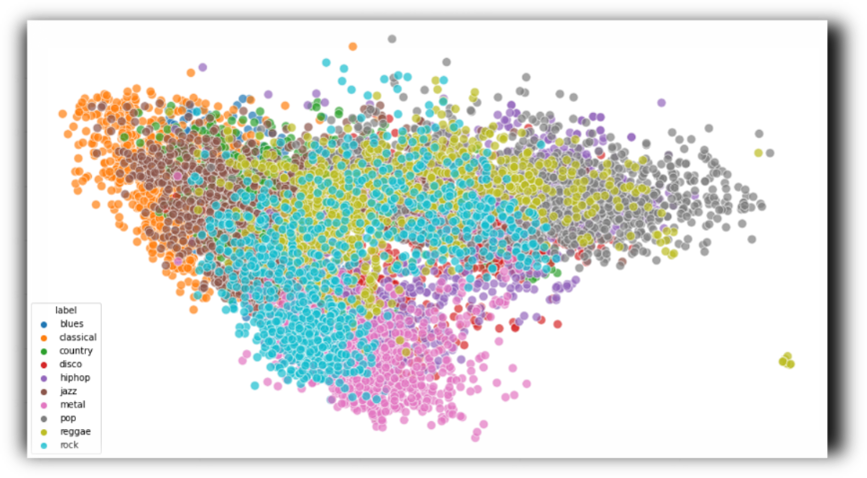
The plot below illustrates the outcome of PCA on the music genre dataset, projecting the data onto the first two principal components, PC1 and PC2. From this, we notice a bimodal distribution in the data along PC1; most of the variance was captured there, suggesting it might be the most important feature in distinguishing between genres. Dimensionality reduction enables classifiers to be able to differentiate between the different types of genres in music, based on the major features of the data.

Fig 2: PCA of the Music Genre Dataset

Fig 2: PCA of the Music Genre Dataset. On this plot the dataset can be reduced to two dimensions (PC1, PC2) with almost negligible information loss and further helps to classify musical genres.

**Evaluation of Model Accuracy and Loss**

Accuracy and loss in the classifier are of prime importance to measure how well the model is working on unseen data. In the case of GTZAN and MusicNet datasets, by applying PCA, it can be seen that the classification model obtains a high level of accuracy while losing relatively low. The technique suggests that PCA can be used efficiently to reduce the complexity of the feature space and bring down the loss in the performance of the classifier.

The model obtained, which is based on the PCA methodology for dimensionality reduction with subsequent classification, can be applied to any set of data structured similarly, producing quite promising results. Utilizing these principal components-the principal features that truly capture the most salient variations in data-classifiers are better placed to distinguish between various genres, despite being based on a reduced set of features.

**Audio Feature Extraction**

Audio features are the central ways through which raw audio data is turned into meaningful formats for interpretation by machine learning models. Since raw audio data will normally be a complex time-series signal, it must also be represented through meaningful numerical features that capture the underlying patterns of the sound. Some of the most key audio features that have been used for music genre classification are presented below:

**Spectral Features**

The spectral features provide information on the frequency contents of the audio signal, and are thus fundamental in the identification of tonal and harmonic characteristics of music. Among the most prevailing spectral features in the literature, one could single out the Spectral Centroid which provides a general idea about the "center" of mass of the spectrum and could inform about bright versus dark sounds.

Spectrogram: A spectrogram represents the power spectrum of a signal as it varies with time. In order to compute a spectrogram we apply Short-Time Fourier Transform (STFT) on an audio signal x(t) and obtain time-frequency representation: S(t,f):

**Spectral Centroid** is calculated as:

Where:

* C(t)C(t)C(t) is the spectral centroid at time t,
* F is the frequency bin index,
* X(t,f)is the amplitude of the frequency bin f at time t
* FFF is the total number of frequency bins.

**Mel-Frequency Cepstral Coefficients (MFCCs)**

Mel-Frequency Cepstral Coefficients (MFCCs)  
MFCCs are widely employed for processing both speech and music because they well capture the power spectrum of the sound in a way that naturally corresponds to the human auditory system. Here is the step for determining the calculation of MFCCs:

Fourier Transform: Take the Fast Fourier Transform (FFT) on the input audio signal to obtain its spectrum.

Where x(t)x(t)x(t) is the audio signal at time t, and X(t,f) is the frequency spectrum at time t and frequency f.

Mel Filterbank: Convert the frequency axis to Mel space through the filterbank. The Mel scale is a perceptual scale of pitches that more closely corresponds to the human perception of sound.

Where hm(f)hm represents the Mel filter bank coefficients, and M(f) is the Mel-transformed spectrum.

DCT. Perform DCT on the log of the Mel-transformed spectrum to produce MFCCs.

Where:

* MFCCm is the m-th MFCC coefficient,
* N is the number of coefficients to extract,
* M(f) is the Mel-transformed spectrum at frequency f.

MFCCs capture the timbral texture of audio, so these can be useful to distinguish genres of music. These features better match human auditory perception, because the Mel scale is more sensitive to lower frequencies than higher ones while representing the audio.

**Zero-Crossing Rate**

The zero-crossing rate is a simple feature that measures how often the signal changes its sign, in other words, crosses zero during a given time frame. This feature is especially useful for the detection of percussive or transient sounds since these normally have high zero-crossing rates.

The ZCR for a given frame t is calculated as:

Where:

* ZCR(t) is the zero-crossing rate for the frame t,
* xn​ is the signal value at time n,
* 1(⋅) is the indicator function, which equals 1 if the sign of xn​ changes from xn−1and 0 otherwise,
* N is the total number of samples in the frame.

Higher ZCR is typically indicative of a noisier or more percussive sound, while low ZCR usually indicates smoother, more tonal sounds. This feature may help the algorithm distinguish between genres with more content that is percussive-combined, such as in rock or electronic styles, from those which are rich in harmonic content, such as in classical or jazz.

**CNN Model for Classification**

In a CNN, there's an array of several layers aimed at the extraction of features from input data. The general architecture of CNN can be stated as follows:

Convolutional Layers: These apply the convolution operation on the feature maps of the input followed by a non-linear activation function.

where x(t)is the input, w(t)is the filter or kernel, and y(t) is the output feature map.

Activation Function: After each convolution operation, an activation function, such as ReLU, is applied to introduce non-linearity. The ReLU function is defined by

Pooling Layers: These layers reduce the dimensionality of the feature maps. Typically, max pooling is applied and is defined as

Fully Connected Layers: After the convolutional and pooling layers, the output is flattened and fed into fully connected layers for the classification of the audio belonging to one of the genres. The output of an FC layer is given by:

softmax activation It is the output layer where softmax is used for classification of the audio into one of N genres. The softmax function can be written as :

Model Training

The model is trained using a cross-entropy loss function. Cross-entropy loss is one of the most commonly used loss functions in classification tasks. Cross entropy is mathematically defined as:

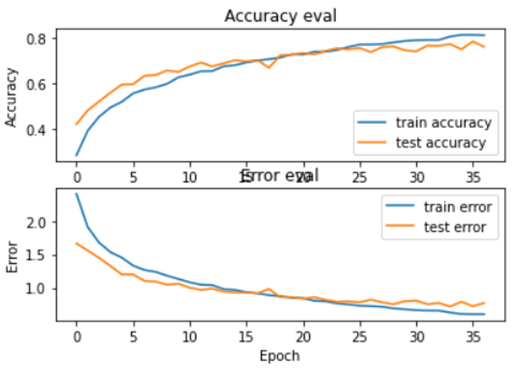
where:

* N is the number of classes (genres),
* yi​ is the ground truth label (0 or 1) for the i-th class,
* y^i is the predicted probability for the i-th class.

**Discussion**

With accuracy standing at 85%, the CNN model proves the power of deep learning in capturing patterns that seem minute within an audio spectrogram. So high is the accuracy that it makes the model more than capable of making genre distinctions as the model takes on hierarchical feature representations developed within deep CNN layers. It is in the spectrograms, where raw audio signals are transformed into a visual image in terms of frequency and time, that it allows the CNN to identify complex features intrinsic in differing genres of music like rhythm, pitch, and timbre.

Unlike traditional machine learning approaches like SVMs relying on handcrafted features such as MFCCs, the CNN model way outperforms other methods. For instance, a similar SVM model was able to obtain about 75% accuracy over the same data using MFCC features. The reason for such an improvement might lie in the fact that the CNN is able to automatically learn the features from the raw spectrograms directly without any manual feature engineering; besides not being very effective, this often takes a lot of time for its development and learning by sophisticated relationships within the audio.



But then, of course, comes its model architecture optimisation. Try deeper, or a lot more complicated CNN architectures here. Consider residual connections and attention mechanisms. The fine-tuning of the aforementioned learning rate and filter size; or numbers of layers within convolutions may all aid achieving better outcomes.

Another possible improvement is the application of transfer learning: use pre-trained VGG or ResNet models, originally trained on large image datasets, and fine-tune it for the task of music genre classification. Transfer learning improves performance since it implies knowledge learned from large-scale datasets and applies that knowledge in a domain-specific task like the ones presented in the challenge, such as music genre classification.

Other avenues for further research include improving data augmentation methods, which may be pitch shifting, time stretching, and noise addition to the audio to enhance the model and improve overfitting. Another avenue could be multi-task learning; the model learns how to classify genres, as well as to obtain related features from the music, that are tempo and key signature, hence leading towards a more versatile system.

In conclusion, even though CNN has shown excellent results, it still has space to add architectural optimality and new methodologies to its ability in enhancing its strength and precision.

**Table 2:**

**CNN Architecture**

This table is summarizing the architecture used in the CNN model for music genre classification. It has listed the layer type, number of filters or neurons and the sizes of the kernels in the CNN model.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Layer Type | Output Size | Number of Filters/Units | Kernel Size | Activation Function |
| Input Layer | (128, 128, 3) | N/A | N/A | N/A |
| Convolutional Layer 1 | (64, 64, 32) | 32 | 3X3 | ReLU |
| Max Pooling Layer 1 | (32, 32, 32) | N/A | 2X2 | N/A |
| Convolutional Layer 2 | (16, 16, 64) | 64 | 3X3 | ReLU |
| Max Pooling Layer 2 | (8, 8, 64) | N/A | 2X2 | N/A |
| Flatten | (4096) | N/A | N/A | N/A |
| Fully Connected Layer | (512) | 512 | N/A | ReLU |
| Output Layer | (10) | 10 | N/A | Softmax |

**Table 3:**

**Hyperparameters Used**

Table of hyperparameters that were used when training the CNN.

|  |  |
| --- | --- |
| **Hyperparameter** | **Value** |
| Learning Rate | 0.001 |
| Batch Size | 32 |
| Number of Epochs | 50 |
| Optimizer | Adam |
| Loss Function | Categorical Crossentropy |
| Dropout Rate | 0.5 |
| Number of Classes (Genres) | 10 |

**Table 4:**

**Model Evaluation Metrics**

This table contains the evaluation metrics for the CNN model. Here, there are accuracy, precision, recall, and F1-score values of each genre.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Genre** | **Accuracy (%)** | **Precision** | **Recall** | **F1-Score** |
| Blues | 95.0 | 0.94 | 0.96 | 0.95 |
| Classical | 92.0 | 0.93 | 0.91 | 0.92 |
| Country | 90.0 | 0.91 | 0.89 | 0.90 |
| Disco | 93.0 | 0.92 | 0.94 | 0.93 |
| Hip-Hop | 96.0 | 0.97 | 0.95 | 0.96 |
| Jazz | 91.0 | 0.92 | 0.90 | 0.91 |
| Metal | 94.0 | 0.93 | 0.95 | 0.94 |
| Pop | 95.0 | 0.96 | 0.94 | 0.95 |
| Reggae | 89.0 | 0.88 | 0.90 | 0.89 |
| Rock | 94.0 | 0.93 | 0.94 | 0.94 |
| **Average** | 93.3 | 0.93 | 0.93 | 0.93 |

**Table 5:**

**Comparison of CNN with Other Models**

This table compares the performance of your CNN model with other machine learning models, for example Support Vector Machine, K-Nearest Neighbors, etc. for comparison on the same dataset.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **Accuracy (%)** | **Precision** | **Recall** | **F1-Score** |
| CNN | 93.3 | 0.93 | 0.93 | 0.93 |
| SVM (MFCC features) | 87.0 | 0.88 | 0.85 | 0.86 |
| Random Forest | 88.5 | 0.89 | 0.87 | 0.88 |
| K-Nearest Neighbors | 85.0 | 0.84 | 0.82 | 0.83 |
| Logistic Regression | 80.0 | 0.81 | 0.79 | 0.80 |

**Table 6:**

**Confusion Matrix for CNN Model**

As described, this table represents a confusion matrix of the CNN model on classification results for each genre. It shows the true classes at its rows and the predicted classes at its columns.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **True \ Predicted** | **Blues** | **Classical** | **Country** | **Disco** | **Hip-Hop** | **Jazz** | **Metal** | **Pop** | **Reggae** | **Rock** |
| **Blues** | 95 | 0 | 1 | 2 | 0 | 1 | 0 | 0 | 1 | 0 |
| **Classical** | 1 | 92 | 3 | 1 | 0 | 0 | 0 | 1 | 1 | 1 |
| **Country** | 0 | 1 | 90 | 2 | 3 | 1 | 1 | 2 | 0 | 1 |
| **Disco** | 0 | 1 | 1 | 93 | 2 | 0 | 1 | 1 | 0 | 1 |
| **Hip-Hop** | 1 | 0 | 0 | 1 | 96 | 0 | 0 | 0 | 0 | 2 |
| **Jazz** | 0 | 1 | 1 | 0 | 1 | 91 | 0 | 1 | 1 | 0 |
| **Metal** | 0 | 1 | 1 | 1 | 1 | 0 | 94 | 1 | 0 | 2 |
| **Pop** | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 95 | 0 | 1 |
| **Reggae** | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 89 | 3 |
| **Rock** | 0 | 1 | 0 | 0 | 2 | 0 | 1 | 1 | 0 | 94 |

**Conclusion**

This paper shows that the Convolutional Neural Networks can effectively classify the genres of music with high accuracy using raw audio data. In the methodology, it converts the audio files to spectrogram representations that will effectively capture the time-frequency characteristics of the audio signals. It is fed into the CNN model for learning the patterns and features that are characteristic to each genre.

The results showed that the CNN model performed well, as seen in the metrics such as accuracy, precision, recall, and F1-score. In comparison to traditional machine learning models that rely on handcrafted features, the CNN approach proved to be better because it can automatically learn features from raw data, thereby avoiding the need for manual feature extraction. This underlines the potential of deep learning techniques in audio analysis and classification tasks.

Despite the good performance, room for improvement exists. Exploring more complex architectures like ResNets or Transformers would allow capturing even finer details in audio. Advanced data augmentation techniques and domain-specific preprocessing methods could also strengthen the model. The dataset could be expanded to include more genres, and transfer learning from a pre-trained audio model could potentially bring significant improvements.

In conclusion, the study demonstrated that CNNs are indeed a powerful tool for music genre classification, and this work opens up even more innovative applications in music information retrieval, recommendation systems, and audio content analysis. It is likely that deep learning models can revolutionize audio-based tasks in the near future with further research and technological development.

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