Music Genre Classification

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Abstract:

Over the past few years, the music industry has undergone major changes from its conventional existence as well as in the form of the music created. With the increase in customer base, different types of music have also become popular. The power of music not only unites individuals but also provides a window into different immersive cultures. It is therefore important to categorize music according to genres so people can satisfy their categorical needs. There is a lot of repetition and time involved in ranking music manually, and it is up to the listener to do it correctly. In music, a genre is a label used to describe a particular style of music or a shared collection of conventions. In contrast to musical form, musical style is to be distinguished. There are many different ways to classify music into genres. Pop, Hip-Hop, Rock, Jazz, Blues, Country, and Metal are some of the most popular music genres

Keywords: Music Information Retrieval (MIR), Catboost, K-nearest neighbors'(KNN), Gradient Boosting, GTZAN data set, Feature **Extraction.**

1. Introduction:

People are finding it increasingly difficult to manage their listening habits with the growth of online music databases and the easy access available to music content. Genres are subjective categories that are used to categorize music. Music Information Retrieval (MIR) applications have grown in popularity as the internet and multimedia systems have grown in importance. Since they result from a complex interplay between general audience, marketing, historical and cultural variables, musical genres lack specific definitions and boundaries. This web application categorizes music according to genres.

2. Literature Survey:

1.1 *Music Genre Classification. A N-Gram Based Musicological Approach Authors.' Eve Zheng, Melodv Mott; Teng-Sheng Moh, 2017 IEEE 7th International Advance Computing Conference(IACC)*

The lifestyles of individuals have been deeply ingrained with digital music. Then, derived services from digital music, such as similarity testing and recommendation engines, are crucial for online services and marketing. Genre classification serves as a foundation for those systems and is crucial to the maintenance of these services. Researchers generally exhibit mostly concentrated low-level aspects; very few have approached this issue from a more interpret-able perspective, i.e., a musicological approach. This leads to the issue that intermediate stages of the categorization process are scarcely interpretable, and the procedure consequently did not make extensive use of the subject expertise of music specialists. This essay takes a strong musicological approach to genre classification. The suggested method takes into account the high-level variables that have distinct musical meanings, making the categorization outcomes understandable to music specialists. We use a data set of only symbolic piano pieces, encompassing over 200 records of classical, jazz, and ragtime music, to examine further musicological aspects in addition to extra statistical data. Algorithms for feature extraction and n- gram text classification are used. With experimental findings yielding average prediction accuracy above 90% and a high of 98%, the suggested method demonstrates the concept behind it.

1.2 *Music Genre Classification and Recommendation by Usine Machine Learning Techniques Authors . Ahmet Elbir, Hilmi Bilal jam, Mehmet Emre lyican, Berkay Ozturk , Nizamettin Aydin, 2018 Innovations in Intelligent Systems and Applications Conference (ASYU)*

One of the subjects that interest digital music processing is the prediction of musical genres. In this study, musical style classification and music suggestions are made using machine learning approaches after the acoustic aspects of the music are retrieved using digital signal processing techniques. Convolutional neural networks, which are deep learning techniques, were also utilized to classify music genres, make recommendations for songs, and compare the performances of the findings. Due to the utilization of the GTZAN database during the investigation, the SVM algorithm had the best level of success

*1.3 Genre Recognition Using Residual Neural Networks Authors, Dipjyoti Bisharad; Rabul Hussain Laskar **TENCON** 2019 - 2019 IEEE Region 10 Conference (TENCON)*

Although it is abstract, the genre is a distinctive feature of music. Current methods for automatically classifying genres compute a collection of audio features and layer a classifier on top of them. these models, Calculate these features typically over a sizable portion of the audio. This research proposes a residual neural network-based model for genre categorization that is trained on brief (3-second) video clips. Moreover, a single genre will be assigned to each audio sample via conventional genre classification methods. Nonetheless, it's commonly known that several genres have some similarities. Given the ambiguity of the genre, the model put forward in thiswork may categorize music clips into three different genres, each of which is associated with a certain likelihood. The suggested model predicts the top-1, top-2, and top-3 genres for a music clip with error rates of 18%, 9%, and 5.5%, respectively. In this work, we show how the classifier's predictions match up with the genre's more general definition in a realistic context.

3. System Design:

A. DATA SET:

In 2000 and 2001, information for the GTZAN genre collection was obtained. There are 1000 audio files in total, each lasting 30 seconds. Each class has 100 audio tracks and consists of 10 different music genres. Each track has a..wav file extension. It incorporates audio from the ten genres mentioned below: Blues, classical music 3. Country 4. Disco 5. Hip-hop 6. Jazz 8.
Pop Reggae 7. Metal 9. Rock 10.

B. FEATURE EXTRACTION:

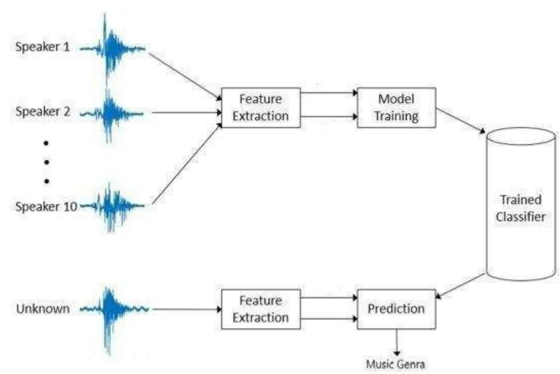
A procedure of dimension-ally reduction known as feature extraction may be used to break down a large initial set of data into smaller, more manageable groups for processing. These huge data sets may have a large number of variables that require a lot of computational power to process. The

term "feature extraction" refers to techniques that choose out and/or combine variables into features, hence minimizing the amount of information that needs to be processed while still properly and fully characterizing the initial data set. Extraction of traits and components from the audio files would be the initial stage in a project to classify genres. Identifying the language content and eliminating noise is part of it.

C. PREPROCESSED DATA:

We are here to use the factor well-known GTZAN data collection for music information retrieval (MIR). Blues, Classical, Country, Disco, Hip Hop, Jazz, Metal, Pop, Reggae, and Rock are among the ten genres included in the data collection. We have 1000 training samples for each genre, and if we keep 20% of them for validation, that leaves us with just 800 training examples. Each genre consists of 100 audio files .wav) that are each 30 seconds long. 30 seconds is too much time for the model to need in order to determine the genre of a song or piece of music after listening to it for only 4-5 seconds. We made the decision to divide one audio clip into ten three- second audio files as a result. Our training examples have now multiplied tenfold, with 1000 training examples in each genre and a total of 10,000. We therefore expanded our data set, which may be advantageous for a deep learning model since it always needs new data. It involves transforming the unstructured, complex data into organized, comprehensible knowledge. It involves a technique for sifting out redundant and missing data from the data set. This ensures consistency across the data set. Nonetheless, no missing values were discovered in our data collection, indicating that each record contained the matching feature values.

D. ALGORITHMS USED:



1. CatBoost:

A startup called Yandex created the open-source machine learning algorithm CatBoost in 2017. The flexibility of CatBoost to integrate a variety of diverse data types, such as photos, audio, or text features into one framework, is one of its key advantages. CatBoost advances gradient boosting and decision tree theory. The basic goal of boosting is to generate a strong, competitive predictive model by progressively combining numerous weak models (a model that performs only marginally better than chance). Gradient boosting successively fits the decision trees, thus the fitted trees will learn from the errors of previous trees and thereby reduce the errors. Until the chosen loss function is no longer minimized, more functions are continually added to the already existing ones.

2. KNN:

The k-nearest neighbors' algorithm, often characterized as KNN or k-NN, is a supervised learning classifier that makes predictions or classifications about the clustering of a single data point using proximity. Although it can be used to solve classification or regression problems, it is frequently used as a classification technique because it is predicated on the notion that similar points can be found nearby. According to the KNN algorithm, similar objects are close by. In other words, things that are related to one another are found nearby. The KNN algorithm believes that related things are located nearby. In other words, things that are related to one another are found nearby.

3. Gradient Boosting:

Gradient Boosting is a potent boosting approach that turns numerous weak learners into strong learners. Each successive model is trained using gradient descent to minimize the loss function of the prior model, such as mean square error or cross-entropy. The algorithm calculates the gradient of the loss function with respect to the current ensemble's predictions in each iteration, and then it trains a new weak model to try to minimize this gradient. The ensemble is then updated with the new model's predictions, and the procedure is continued up until a stopping requirement is satisfied.

4. Conclusion and Future Scope

In our project we have proposed a solution wherein we Many machine learning techniques were used in this music genre classification study. Maximizing precision was our goal. Our research has shown that employing catboost allows us to achieve a maximum accuracy of 88%. Also, we looked for the genre class combinations that would produce the highest accuracy.

In the future, researchers can investigate the creation of systems for categorizing music genres that are tailored to the interests of specific users and that can suggest new music depending on the user's data.

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