

IMPLEMENTING MUSIC GENRE CLASSIFICATION

Dr M.Suresh^{*1}, K.Kavya², G.Sowjanya³, B.Navya Sri⁴, N.Abdul Shareef⁵

^{*1}Professor, ^{2,3,4,5,6} B.Tech., Scholars

Department of Computer Science and Engineering,

Qis College of Engineering & Technology, Ongole, AndhraPradesh, India.

Abstract:

The main objective of the music genre classification is to categorize the music samples into different genres. It also aims to make the selection of songs quick and less cumbersome. The different types of music genres are Pop, Hip-Hop, Rock, Jazz, Blues, Country and Metal. So, to automate the process we can use different Machine learning algorithms like K- Nearest Neighbour, Random Forest, Naïve Bayes, Convolutional Neural Network, etc...

For this project, the dataset that we will be working with is Genre Classification dataset which consists of music tracks, each of 30 seconds long. We will divide the dataset into two parts as Training dataset and Testing dataset. We will consider the music track as a training dataset which can classify into different Genres. By using Random Forest algorithm, one can recognize the genre of an input music track with maximum accuracy.

Introduction

The digitalization of music has been widely embraced by a plethora of online music organizations in recent years. These organizations run different online [1,2] music channels and distribute entertainment services to their clients [3]. In addition, they group similar musical tracks, assign a tag, and deliver it to their clients. This grouping of similar musical tracks enhances clients' understanding and interest in musical libraries.

Clients can benefit from the analysis and categorization of musical tracks. As a result, the business demand and profitability margin can be achieved by many music organizations. Analysing a large volume of musical datasets for retrieving music information has become an emerging field of research areas recently [4]. A categorical label (genre) is assigned to each music piece to identify the kind of music. The user is responsible for assigning the genre tag to a particular song according to their judgement of music by acknowledging a set of music genres. This acknowledgement from users comes in a form of a huge music database for music organizations. Due to a large number of online music collections, the categorization of music genres is important for music organizations to search, retrieve, recognize, and recommend excerpts of music to their clients [5].

Music genre recognition (MGR) was first investigated by Cook and Tzanetakis (2002) [4]. The authors focused on the audio (music) pattern recognition job in the domain of music information retrieval (MIR). This is considered the first research on maintaining a large-size music dataset. Music genre recognition (or classification) contains several phases. The initial phase is to

extract a set of important features from raw music signals and implement feature selection methods on these raw audio signals. In addition, the analysis of several characteristics of the waveforms of music signals is an essential phase to understand audio signals [6,7]. The statistical measures of an audio segment that is composed of several frames calculate segment-level features. Song-level features, such as rhythmic information, tempo, and pitches, define music tracks in user-understandable formats. Various types of music (or audio) feature extraction procedures are adopted by researchers [6,7]. Some researchers use Mel frequency cepstral coefficients as the classification criteria, while other researchers prefer to use tempo and pitch features. Besides that, spectrograms computed from the audio signal are extracted in research for the classification of music genres [8,9]. Moreover, classifying the specific genre of music is the initial phase in recommendation and many music-based applications. In the recent years, machine learning models have been used to classify the kind of music for improving and recommending the music listening experience of the user [10,11]. Data science helps to define the steps to prepare the data before using it to train a machine learning classifier [12].

However, it is difficult to compute machine learning predictions with a large-scale music dataset, as the model training duration and computational cost increase extensively at a higher rate [14]. This has been a major drawback while developing an application with a massive amount of music datasets in recent years. It is a challenge of scalability for machine learning algorithms with large-scale datasets [15,16]. A distributed computing framework called Apache Spark was introduced to overcome this scalability problem. Apache Spark processes data in parallel using a directed acyclic graph (DAG) engine supporting cyclic data flow across multiple nodes, which makes machine learning computations faster for massive datasets [17].

Therefore, it is essential to improve the speed of data processing to run and update any application. Moreover, a comparison between an ensemble learning classifier such as random forest supported by Apache Spark and other machine learning classifiers in the domain of music genre classification can be considered as an additional gap with earlier research. The random forest which was developed by Breiman (2001) [18] is considered the best classifier following the supervised learning method. This research paper aims to analyse the statistical feature on a large number of music datasets and classify music into groups of similar music (music recommendation), using the ensemble learning classifier random forest supported by Apache Spark.

Literature Survey:

Music genre classification and music information retrieval have been actively investigated over the last decade. Different modern machine learning technologies have been adopted in this research field. Various reviews have been presented to analyse appropriate music features and classification algorithms that are explored in the domain of music genre recognition.

Wibowo and Wihayati (2022) [19] proposed a deep learning approach for the classification of music genres. The authors explored the GTZAN dataset with ten foreign music genres. The deep learning model obtained a classification accuracy above 90%. In the next stage, an additional dataset as popular as the dangdut music genre was added for the identification of the dangdut

music genre among Western music genres. It was observed that the performance of the deep learning model with the dangdut music genre decreased to around 76%. The result highlighted that dangdut music is different from other foreign music genres, but few music genres such as jazz and pop were identified. Puppla and Muvva (2021) [20] designed a convolutional neural network using a deep learning approach for the training and classification of music genres from the GTZAN dataset. The Mel frequency cepstral constant (MFCC) feature vector was extracted and utilized for the classification process. The dataset was divided into 60% for training and 40% for testing purposes.

Besides a convolutional neural network using a deep learning approach and a recurrent neural network, researchers also investigated the applications of different machine learning algorithms, such as K-nearest neighbor (KNN), support vector machine (SVM), and artificial neural network (ANN), in the domain of music genre classification. Kumar and Chaturvedi (2020) [23] elaborated an audio classification approach using an artificial neural network. The authors emphasized more audio feature extraction approaches, such as chroma- or centroid-based features, Mel frequency cepstral coefficients (MFCCs), and linear predictive coding coefficients (LPCCs), to understand the behaviour of the audio signal. An efficient neural network classifier was used for the classification of audio signals with a high accuracy rate. Alternatively, Kobayashi and Kubota (2018) [24] proposed a different approach to audio feature extraction and classification. The authors introduced unique data preprocessing steps to extract musical feature vectors. At the initial stage, the normalization was applied to input audio signals to decompose signals into many signals with different resolutions using the undecimated wavelet transform (UWT). The empirical mode decomposition (EMD) is an analysis method to decompose a signal in the time domain. Therefore, the appropriate region of the audio dataset was extracted by using the empirical mode decomposition (EMD) method, and the time and frequency domain features were selected for the linear support vector machine classifier. The suitable feature extraction with several methods was highlighted by the author in this article to decrease the cost of computation. After the data preprocessing stage, the machine learning algorithm support vector machine was used for its excellent performance in the classification of music genres. The blues, classical, metal, hip-hop, and pop.

Existing System:

In the existing system they used CNN which is a Deep Learning algorithm. These are organized in layers made up of interconnected neurons and process data in each layer and pass forward to next layers. The neurons cannot operate without other neurons - they are connected.

CNN is widely used for image and text classification. CNN will require much more data for processing because it requires filling missing values and converting categorical data into numerical. In the case of different ranges of features, there will be problems with model training.

Proposed System:

In the existing system they used CNN which is a Deep Learning algorithm. These are organized in layers made up of interconnected neurons and process data in each layer and pass forward to next layers. The neurons cannot operate without other neurons - they are connected.

CNN is widely used for image and text classification. CNN will require much more data for processing because it requires filling missing values and converting categorical data into numerical. In the case of different ranges of features, there will be problems with model training.

Modules:

Data-set Creation Using Extraction of Features: After Downloading the GTZAN dataset audio files for 10 genre, a python script is written to extract the required features. The features to be extracted are Spectral Centroid, Spectral Bandwidth and Spectral Roll off. These features helps us find the onset points in the audio signals.

Model Training and Normalization: The extracted data are then normalized using Min-Max Scaler into required range(-1,1). Here, the models learn the mean and standard deviations of the audio signals. The Machine Learning algorithms are used to train the data, here Random Forest Algorithm is used to train the data set.

Testing: The output from the model are compared with test genre present in the data-set. A confusion matrix is made to determine their accuracy and precision.

Genre Recognition: An unknown audio signal sample is taken as input and the required features are extracted in similar manner. The scaling is applied to this test data to remove the bias from our data. These features are taken as input for above mentioned suitable model and genre of the audio signal is classified.

Conclusion:

This research paper reveals the solution of reducing the computation duration of machine learning predictions without computational cost for a large-scale dataset using Apache Spark. This paper also presents the analysis of several music features and the development of a machine learning classifier to classify music genre. The GTZAN dataset is identified for the exploration of music features and classifying them into groups of similar music. Multiple machine learning classifiers supported by Apache Spark, including decision tree, random forest, naïve Bayes, and logistic regression, are implemented on the GTZAN dataset for the classification of music genres. The workflow of an ensemble learning algorithm is introduced in the domain of music genre classification. Time and frequency domain music features are

analysed to acknowledge the signals of music data. Moreover, the statistical features of music data are computed to understand the distribution of audio (music) data. The correlation coefficient is calculated to assess the relation between several music features and the target class. From the investigation, it is concluded that the random forest classifier is the best classifier for better performance in the music genre classification task due to its voting process of classification. The logistic regression and decision tree classifiers are suitable for short-term performances in any organization where music classes are less targeted.

primary contribution of the present work. Besides that, a piece of massive information on music features, correlation analysis, and statistical measures for the GTZAN dataset is provided in this work.

This research paper reveals the solution of reducing the computation duration of machine learning predictions without computational cost for a large-scale dataset using Apache Spark. This paper also presents the analysis of several music features and the development of a machine learning classifier to classify music genre. The GTZAN dataset is identified for the exploration of music features and classifying them into groups of similar music. Multiple machine learning classifiers supported by Apache Spark, including decision tree, random forest, naïve Bayes, and logistic regression, are implemented on the GTZAN dataset for the classification of music genres. The workflow of an ensemble learning algorithm is introduced in the domain of music genre classification. Time and frequency domain music features are analysed to acknowledge the signals of music data. Moreover, the statistical features of music data are computed to understand the distribution of audio (music) data. The correlation coefficient is calculated to assess the relation between several music features and the target class. From the investigation, it is concluded that the random forest classifier is the best classifier for better performance in the music genre classification task due to its voting process of classification. The logistic regression and decision tree classifiers are suitable for short-term performances in any organization where music classes are less targeted.

Reference:

1. Wu, J.; Hong, Q.; Cao, M.; Liu, Y.; Fujita, H. A group consensus-based travel destination evaluation method with online reviews. *Appl. Intell.* **2022**, *52*, 1306–1324. [CrossRef]
2. Zhao, C.; Chang, X.; Xie, T.; Fujita, H.; Wu, J. Unsupervised anomaly detection based method of risk evaluation for road traffic accident. *Appl. Intell.* **2022**, 1–16. [CrossRef]
3. Ganeva, M.G. Music Digitalization and Its Effects on the Finnish Music Industry Stakeholders. Ph.D. Thesis, Turku School of Economics, Turku, Finland, June 2012.
4. Tzanetakis, G.; Cook, P. Musical genre classification of audio signals. *IEEE Trans. Speech Audio Proc.* **2002**, *10*, 293–302. [CrossRef]
5. Chen, K.; Gao, S.; Zhu, Y.; Sun, Q. Music genres classification using text categorization method. In Proceedings of the 2006

IEEE Workshop on Multimedia Signal Processing, Victoria, BC, Canada, 3–6 October 2006; pp. 221–224.

6. Dai, J.; Liang, S.; Xue, W.; Ni, C.; Liu, W. Long short-term memory recurrent neural network based segment features for music genre classification. In Proceedings of the 2016 10th International Symposium on Chinese Spoken Language Processing (ISCSLP), Tianjin, China, 17–20 October 2016; pp. 1–5.
7. Sanden, C.; Zhang, J.Z. Enhancing multi-label music genre classification through ensemble techniques. In Proceedings of the 34th International ACM SIGIR Conference on Research and Development in Information Retrieval, Beijing, China, 24–28 July 2011; pp. 705–714.
8. Vishnupriya, S.; Meenakshi, K. Automatic music genre classification using convolution neural network. In Proceedings of the 2018 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 4–6 January 2018; pp. 1–4.
9. Ajoodha, R.; Klein, R.; Rosman, B. Single-labelled music genre classification using content-based features. In Proceedings of the 2015 Pattern Recognition Association of South Africa and Robotics and Mechatronics International Conference (PRASA-RobMech), Port Elizabeth, South Africa, 26–27 November 2015; pp. 66–71.
10. Bahuleyan, H. Music genre classification using machine learning techniques. *arXiv* **2018**, arXiv:1804.01149.