

Artificial Intelligence Induced Music Genre Prediction using KNN Architecture

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Abstract- The composition of sounds comprising common factors such as pitch, rhythm and dynamics constitute music. Music has been playing a crucial role in tweaking human emotions compared to other forms of media and entertainment, owing to dopamine regulation of the human brain. The abundance of music sources keeps increasing by the passing of days. Automatic musical genre classification, a modern computerised addition to music information retrieval systems, can reduce the need for human labour in this system. In addition, a web app has been created utilising HTML, CSS, JavaScript, JQuery, and Django to provide a user interface for uploading the supported audio file type and determining the genre of the music.

Index Terms -- Music Genre prediction, Data mining, Machine Learning, Neural Network, Deep Learning

I.INTRODUCTION

Genre categorization is already established in music (e.g., hip-hop, reggae, pop), and text is used with topic classification. However, genre is not a well-defined entity in the case of text (it is more defined in the arts and music), and debates over what exactly defines genre occur in the categorization community. The use of genre perception to characterise information may not be as evident in other types of content, but it penetrates the way we interpret and segment the information space around us.

Work in genre classification has been acknowledged as an important step toward reaching machine-controlled data production in linguistics. However, machine-controlled genre classification tools are still in the early phases of development, and an image tool for genre classification may require some preliminary research on the relationship between entirely separate feature types and various categories.

People are finding it increasingly difficult to control the songs they listen to as internet music databases and simple access to music content rise in popularity. Numerous musical genres, such as blues, classical, country, disco, hip-hop, jazz, metal, pop, reggae, and rock, are popular in

the present period. One method for categorizing and organizing songs is by genre, which is defined by musical features such as rhythmic structure, harmonic content, and instrumentation.

A huge dataset of music is required for genre categorization in songs.

It has real-world applications in a variety of domains, such as automated labelling of unfamiliar pieces of music. (Apps like Shazam, Spotify etc.).

Due to dopamine modulation in the human brain, music has played a critical role in modifying human moods when compared to other types of media and entertainment.

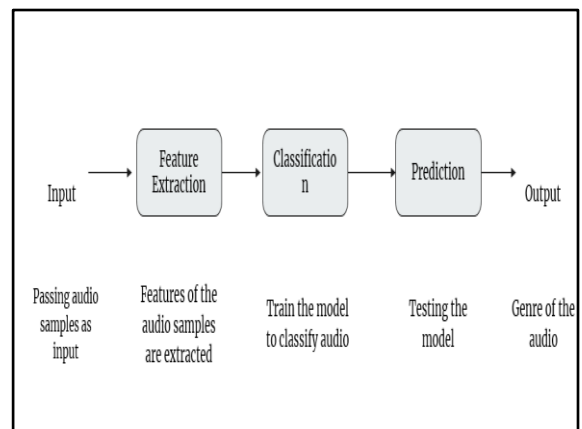


Figure 1 Processing of the Project

The basic purpose of this project is to apply Deep Learning techniques to predict the sentiment of a music track that may be recommended to users in order to improve their mood by leveraging the availability of large music data both online and offline.

A. Machine Learning

Because of the rapid advancement of computer technology, machine learning is currently a hot topic. Machine learning techniques are used to automate the analytical model. Learning is how machines learn and adopt.

Machine learning enables computers to learn and perform appropriately without the use of explicit programmes. This assists the computer in learning complicated models and predicting data. In addition to huge data, machine learning can calculate complicated mathematics. Iterative characteristics of machine learning enable independent adaption to fresh data. Machine learning allows you to properly examine large amounts of complicated data. Machine learning technology uses several ways to create distinct models depending on the type of information involved.

Figure 2 is the most common design of a neural network model.

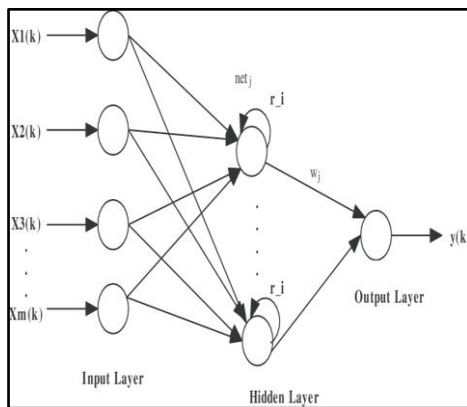


Figure 2 RNN LSTM

During training, the neural network is tested to detect overfitting and to assess the network's performance.

B. Deep Neural Network

Neural networks are made up of perceptions that are stacked in layers and linked together. This network is referred to as a deep neural network if it has more than two layers (inputs and outputs) (DNN). Each weight between the two levels is represented by the weight matrix W . We also require the bias vector b , which is simply the bias term's weight. Of course, the activation function f is also required (x). This is the sigmoid function $h = \frac{1}{1 + \exp(-x)}$ for all nodes in this scenario. The first layer's output for input x is $out = \frac{1}{1 + \exp(-Wx + b)}$ (1) The neural network should give classification and feature information using these fundamental equations with SGD and Softmax margins extraction model. There were about 3 dense layers and dropouts. Relu activation was used for high density layers. Softmax activation was used for the output level. Early stop was used when the training accuracy reached the convergence point. Fig.2 is the most common design of a neural network model.

C. Recurrent Neural Network

As shown in Figure 2 it is a multi-layer network with input, hidden, and output neurons. Neural Networks with Long Short Term Memory Neural networks are information processing systems that use linked neurons to ensure parallel processing. They have a layered structure, and the type of connection between these layers dictates the neural network's structure. A recurrent neural network is the best neural network for processing sequential data (RNN). The LSTM's hidden layer is structured similarly to the RNN, except the repeater has four linked layers rather than one. We employed two LSTM layers, two high density layers, and a dropout layer.

D. Deep Learning

In today's world, systems that make their own judgments based on intelligence are desperately needed. Breakthroughs are one of the most significant failures of artificial neural networks and are driving the birth of a new technique known as deep learning. Machine learning has given rise to a new strategy to achieving artificial intelligence's intrinsic goals. The world need a deep learning system capable of thinking like the neocortex. The system learns several sorts of patterns from training patterns used for real-world sensory prediction and categorization.

The most appropriate method is deep learning. Given the sheer number of data, the deep learning strategy beats all others. Deep learning has the advantage of allowing for autonomous feature extraction and feature learning. This method assists you in determining the structure of your data. Deep learning techniques are used to solve issues in both unsupervised and supervised learning.

Deep learning is the best method for training a big neural network. Given the sheer number of data, the deep learning strategy beats all others. Deep learning has the advantage of allowing for autonomous feature extraction and feature learning. This method assists you in determining the structure of your data. Deep learning models are capable of addressing inefficiencies in both supervised and unsupervised settings.

E. Support vector machine

Support Vector Machines are machine learning algorithms that can do both classification and regression tasks. The goal of SVM is to divide data sets into classes in order to find the largest marginal hyperplane (MMH). In order to decrease error, SVM will create the hyperplane iteratively. SVM's goal is to categorize data sets in order to find the optimal marginal hyperplane (MMH). The fundamental purpose of SVM is to partition data sets into classes in order to determine the maximum marginal hyperplane (MMH), which may be accomplished in two phases. – First, SVM will iteratively construct hyperplanes that best separate the classes. If a hyperplane can appropriately segregate the classes, then that hyperplane is valid and chosen as default.

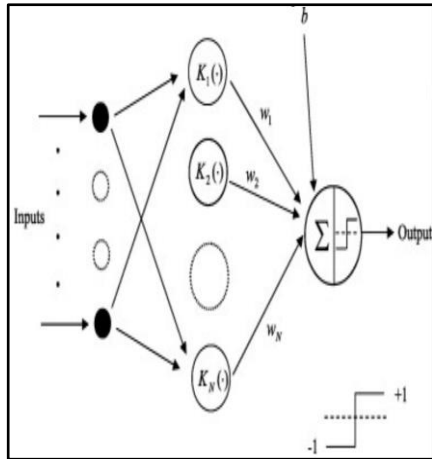


Figure 3 Architecture of SVM

F. Convolutional Neural Networks

We can observe that there are several distinguishing patterns in the spectrograms of various types of audio waves. As a result, spectrograms may be regarded as 'pictures' and fed into a CNN. In other words, they classify raw data by detecting patterns that may indicate, for example, that an input image should be labelled "folk" or "experimental"

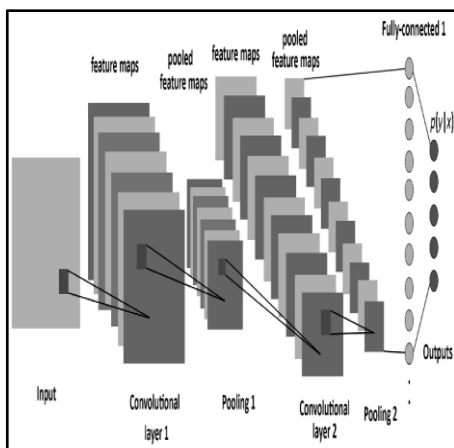


Figure 4 CNN Framework

The network categorises information it has never seen before using the learnt set of parameters (or weights, often known as a model). A trained feedforward network will not recognise the first image it sees when presented with any random selection of photos. It must alter its classification of the second. The next time you see a spectrogram of a folk song, the net will not recognise a spectrogram of an experimental music. Seeing a folk song spectrogram will not recognise a spectrogram of an experimental tune the following time. The next time you see a spectrogram of a folk song, the net will not recognise a spectrogram of an experimental music. That is, a feedforward network has no idea of chronological order and evaluates simply the most recent example to which it has been exposed.

Each block in a CNN consists of the following operations:

- **Convolution:** A convolutional filter or kernel is applied to the input picture to generate a feature map, which basically

filters out information from the image. A 3x3 matrix, for example, can be multiplied with the input picture by striding over the full resolution of the input image, yielding a total that gives a features value.

- **Pooling :** The pooling layer serves to down sample and consolidate the information acquired after convolution. Because over fitting is a risk, the pooling layer aids in feature generalization.

G. K-Nearest Neighbour

K-Nearest Neighbor is a supervised machine learning technique for regression and classification issues. The number of nearest neighbours to another unknown variable that must be predicted or categorized is represented by the symbol 'K.' Its purpose is to find all of the closest neighbours to a new unknown data point in order to establish which class it belongs to. It's a method based on distance. KNN calculates the distance between all focuses near the obscure data and selects the ones with the smallest distances. As a result, it is also known as a distance-based calculation. To appropriately organize the results, we must first establish the value of K (Number of Nearest Neighbours), as shown in Figure 5.

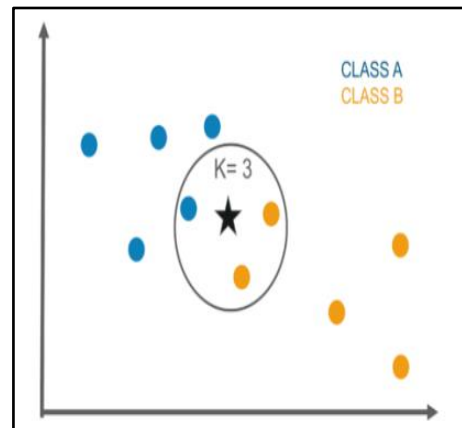


Figure 5 K-NN Algorithm

For executing any algorithm, we need dataset. So, during the initial step of KNN, we should stack the training similarly as test data.

II. LITERATURE SURVEY

Many scholars have expressed an interest in music genre classification. This section will go through some of the previous studies done in this topic.

[1] Vishnupriya S and K Meenakshi have proposed a Neural Network Model to perform the classification.

[2] Tzanetakis and Cook pioneered their work on music Neighbours methods to perform classification.

[3] Changsheng Xu et al. demonstrated the usage of support vector machines (SVM) for this task.

[4] Stanford University's Matthew Creme, Charles Burlin, and Raphael Lenain employed four distinct approaches to conduct the categorization. They employed

machine learning algorithms to classify genres using Support Vector Machines, Neural Networks, Decision Trees, and K-Nearest Neighbours. They developed the GTZAN dataset, which is still used as a standard for genre categorization today.

[5] Tao uses constrained Boltzmann machines to generate additional data from the starting dataset, GTZAN, and achieves better results than a generic multilayer neural network. Following completion of the above mentioned literature review, a Convolutional Neural Network is employed to conduct classification, the specifics of which are discussed in the following sections.

III. OVERVIEW

The GTZAN dataset contains 1000 music files in .au format divided into ten genres, with 100 tracks in each category.

To make the audio file understandable by the machine learning model used for training, 130 features were extracted.

The GTZAN music database is used to train and assess a model's performance. This dataset is available on the MARSYAS software framework's official website. The SVM and LSTM neural networks are trained independently in the proposed model. The accuracy of the predictions made in the test set is used to evaluate the model's performance.

The experiments are carried out on a subset of GTZAN. We used 1000 GTZAN songs in our trial. These are split into four sections. One training direction for N class classifiers, one testing direction, and four permutation test folds (i.e. 6040, 7030, 8020, and 9010). The number of successfully identified instances divided by the total number of connected instances is used to assess accuracy.

IV. DATA SOURCE

The UCI Repository's publicly accessible GTZAN dataset is used. They are each made up of 1000 records.

Data Pre-Processing was done in the following manner:

1. A database of the whole collection was constructed and saved in a .csv file
2. The LibROSA library is used for vector extraction. LibROSA is a Python module for music and audio analysis that offers the foundation for creating music information retrieval systems.
3. The feature vector of each audio file is computed. The extracted feature vector is referred to as the MFCC (Mel-Frequency Cepstral Coefficients). The MFCC procedures are depicted in Figure 7. The MFCCs encode the timbral properties of the music signal by capturing the approximate shape of the log-power spectrum on the Mel frequency scale. This graph shows how many times the signal passes the zero level for each audio track.

S.No	Class	Clips
1	Blues	100
2	Classical	100
3	Country	100
4	Disco	100
5	HipHop	100
6	Jazz	100
7	Metal	100
8	Pop	100
9	Reggae	100
10	Rock	100
	Total	1000

Table 1. Dataset collection

V. RELATED WORK

Some of the research works done on predicting the genre by employing data mining techniques and other Artificial Neural Network are deliberated in the following section:

Neural Network Music Genre Classification [2019]

In his work the number of song genre classes and the spectrum discs have been increased. In this work, the number of layers in the neural network has been increased, the activation functions have been altered and different window functions have been used during the conversion of the audio file to a spectrum.

A Hybrid Model for Music Genre Classification Using LSTM and SVM [2018]

This white paper introduces two classifiers, a hybrid model of SVM and LSTM, and combines their separate findings to increase performance. As a consequence, the combination of LSTM and SVM enhanced accuracy significantly. Finally avoid skewed assessments, three distinct models were tested and employed in the same GTZAN training dataset. The SVM LSTM hybrid model (the model suggested in this work) categorises 10 different genres with 89 percent accuracy. The suggested approach used two classifiers and merged them to accurately categorise all ten genres.

Musical genre classification of audio signals [2002]

Tzanetakis' work for categorization purposes, for classification, many conventional Statistical Pattern Recognition (SPR) classifiers have been applied. SPR's main principle is to calculate the probability density function (pdf) of each class's feature vector. A labelled training set is used in supervised learning to estimate the PDF for each class. Each PDF is assumed to have a multivariate Gaussian distribution with a simple Gaussian classifier (GS), and its parameters are determined using a training set. The Gaussian Mixture Model (GMM) classifier assumes that each class pdf is made up of a number of multidimensional Gaussian distributions.

Long short-term memory recurrent neural network based segment features for music genre classification [2016]

This research presents an LSTM RNN-based segment function for music genre classification. Long-term contextual feature sequences that better depict music data are excelled at by LSTM RNNs. LSTM RNN sequence training, on the other hand, gathers both misclassified and properly classified frames. Then, by integrating the LSTM-RNN with the scattering function, we suggest a fusion segment function that alleviates this difficulty. Significant improvements to the suggested function show that the proposed model is successful.

Middle-Level Learning Feature Interaction Method with Deep Learning for Multi-Feature Music [2021]

The influence of learning function interactions between different branches and layers on the final classification in a multifunctional model is discussed in this work. Because the Mel frequency spectrogram is still an image, the model employs the CRNN structure for visual feature extraction. The model employs a straightforward and effective DNN framework for audio feature extraction for audio feature combinations. As a result, the model is made up of a VFE module, an AFE module, and a classifier.

Classification of music genres using machine learning [2020]

The suggested study uses the GTZAN dataset to develop different models for this music categorization job. The suggested model takes many inputs for various models, including the audio Mel spectrogram, and transfers it to the CNN and various sound file attributes recorded in the ANN, SVM, MLP, and decision tree csv archives. Bottom. The very finest. This corresponds to precise performance. Traditional blues was easy to distinguish, but certain genres, such as country or rock, were highly unique, while others were mistaken with other forms.

Music Classification based on Genre [2020]

Music is analysed using audio signal processing technology in this work, and the qualities that distinguish music by genre are retrieved. The function of the Mel Frequency Cepstrum Coefficient (MFCC), which is extremely close to the function of the human ear, dominates

audio signal processing. Music is time series data, and the LSTM network can analyse it to discover patterns across time that are specific to each type of data. The latest advancements in mixed genre music can be used to inform future work. You may also separate music into various genres, and each short audio file can be identified as belonging to a specific genre.

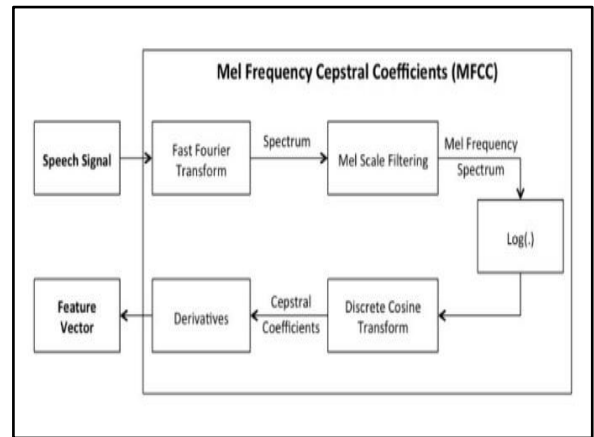
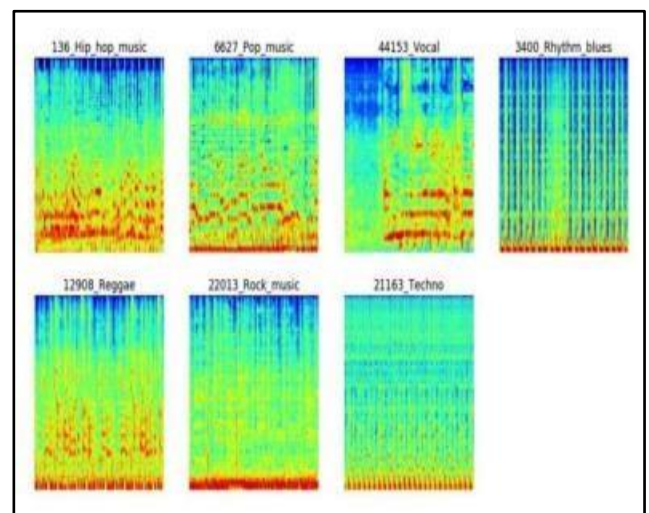


Figure 7 Steps in MFCC

VI. FEATURE EXTRACTION AND DATA PROCESSING

We utilized Librosa, a prominent Python audio analysis tool, for data processing and feature extraction. The Librosa package contains all of the essential tools and strategies for extracting data from any audio sample. We must extract important features from among many that are required to address our challenge. Feature extraction is the technique of extracting characteristics from audio recordings. Some of the characteristics are discussed more below.



Zero-Crossing Rate: It is the pace at which the graph transitions from negative to positive or vice versa. The characteristic is commonly utilised in speech recognition and is currently being used to categorize audio samples.

Spectral Centroid: It computes the weighted mean of the frequencies in the sound and determines its 'centre of mass.'

Consider a song in the metal genre that has more frequencies at the conclusion contrasted to a song in the blues genre that has the same frequencies throughout the length.

Mel Frequency Cepstral Coefficients (MFCC's): Are the characteristics that define the overall form of the spectral envelope. The collection has between 10 and 20 features. Used to simulate the qualities of the human voice. On our dataset, 20 MFCCs are generated across 97 frames, and feature scaling is also performed.

Chroma Feature: This is one of the most popular and effective ways to depict the audio or music element. Based on the time domain and frequency, we may extract numerous distinct attributes specified in the dataset. The best characteristics are picked from among these extracted features, and these completed features are added to a CSV file that our algorithms utilize to perform Music Genre Classification.

There are three major feature selection techniques namely:-

- Filter methods
- Wrapper methods
- Embedded methods

We tried the several models on our extracted data from the CSV files after we finished all of the processing and feature selection, the first being k closest neighbour.

VII.DISCUSSIONS

Before we begin modelling, we must extract features from the audio samples. We retrieved around 130 features for each sample in our model using MFCC. The extracted features are saved in csv format.

10 excerpts from each of ten musical genres are used in the experiment. Each snippet was 30 seconds in duration. This yields a dataset of (10 x 10 x 30seconds = 3000seconds).

Our initial model is developed with the KNN model displayed in Figure 10. KNN is used to categorise the extracts into genres. Deep neural networks are used to develop models after KNN classification.

The SVM model displayed in Figure 11 is used as our next model. As our dataset, we send the music characteristics collected from MFCC here.

The dataset is separated into two sets: training and testing; this allows the model to be trained and tested using the same dataset. We'll utilize a sequential model to solve classification issues.

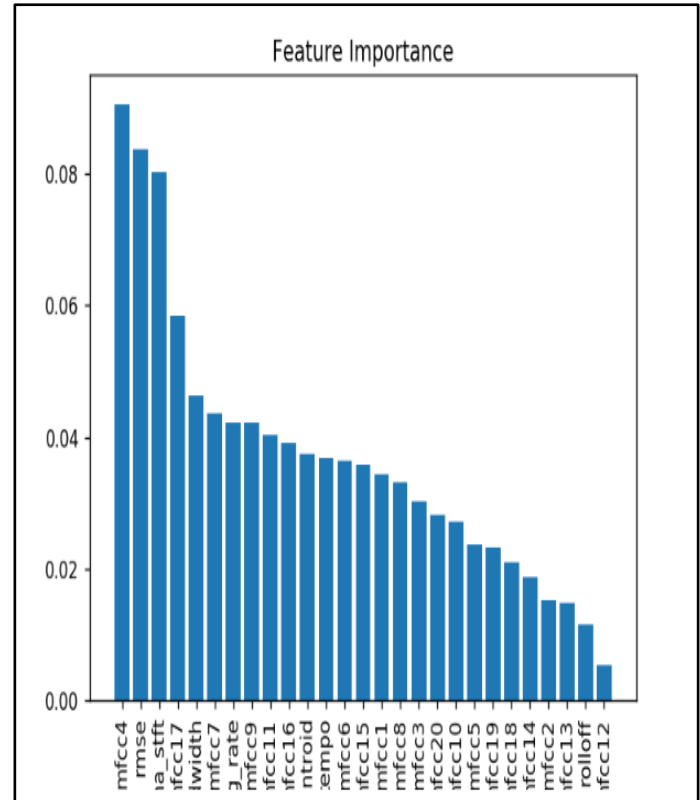


Figure 9 Feature Importance

There are two LSTM layers, two Dense Layers, and one Output Layer in this model. We train this model using various training and testing ratios and then compare the efficiency of each model.



Figure 10 K-NN Input and Output

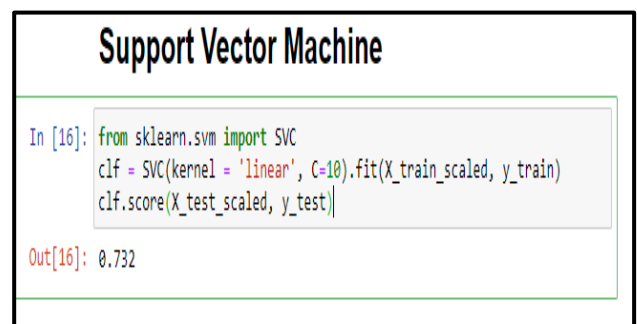


Figure 11 SVM Input and Output

The KNN model and an SVM-based model are compared. As can be seen, the SVM-based model outperforms the KNN-based model. Furthermore, we can see that test accuracy has improved more than validation accuracy. It is also demonstrated that sequence training with SVM outperforms independent frame training with KNN.

VIII.RESULTS

The experiments are carried out on a subset of GTZAN. We used 1000 GTZAN songs in our trial. These are split into four sections. Cross validation is used to compare the correctness of all music genres in the outcome. One training direction for N class classifiers, one testing direction, and four permutation test folds (i.e. 6040, 7030, 8020, and 9010). Accuracy is calculated by dividing the number of correctly categorised cases by the total number of linked occurrences. We are using MFCC for feature extraction. Totally we have 1000 audio samples for 10 genres. Before starting with model building we have to extract features from the audio samples. In our model using MFCC we extracted around 130 features for each sample. The feature extraction results are stored in .csv.

For Following feature extraction, SVM is employed for classification. Deep neural networks are utilized to create models.

LSTM is being used to extract features from MFCC. The dataset has also been divided. We use sequential models with two LSTM layers, two dense layers, and an output layer. Different training and testing ratios were employed with LSTM.

IX.CONCLUSION

To achieve this goal in this piece of music categorization, the suggested study effort used the GTZAN dataset and developed numerous models. Some genres were extremely distinct, while others, such as country and rock, were frequently mistaken with other forms, however traditional and blues were clearly recognizable. The network can run on arbitrarily long sequences, and it can also be trained on data sets comprising sequences of varying lengths.

Trainin g set(%)	Testing Set(%)	Training Accuracy(%)	Testing Accuracy(%)
90	10	71	76
80	20	72	61
70	30	73	60
60	40	74	56

Table 2. SVM Accuracy

The suggested model learns the data distribution of time series with long-term temporal relationships, as seen in actual data. Along with the audio Mel spectrogram, the suggested model utilised different inputs for various models.

Training set(%)	Testing Set(%)	Training Accuracy(%)		Testing Accuracy(%)	
		SVM	LSTM	SVM	LSTM
90	10	71	97	76	81
80	20	72	96	61	83
70	30	73	90	60	75
60	40	74	88	56	73

Table 3. LSTM Accuracy

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