MUSIC GENRE CLASSIFICATION USING MACHINE LEARNING

PROJECT REPORT

Submitted by

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ABSTRACT

The music industry has undergone major changes from its conventional existence and also in the form of music created in last few years. The ever-growing customer base has also increased the market for different music styles. Music not only bring the individuals together, but also provides insight for various cultures. Therefore, it is essential to classify the music according to the genres to satisfy the needs of the people categorically. The manual ranking of music is a repetitive, lengthy task and the duty lies with the listener. The proposed research work has compared few classification models and established a new model for CNN, which is better than previously proposed models. This research work has trained and compared the proposed models on GTZAN dataset, where most of the models were audio file trains, while a few of the models were trained on the spectrogram.Sound is represented in the form of an audio signal having parameters like frequency, decibel, bandwidth etc. These audio signals come in various different formats which make it possible and easy for the computer to read and analyse them. Some formats are: mp3 format, WMA (Windows Media Audio) format and wav (Waveform Audio File) format. Companies use music classification, either to place recommendations to their customers, or simply as a product.To determine music genres, we can use machine learning algorithms which in turn proven to be very handy in Music Analysis too. Classification of genre can be very valuable to explain some interesting problems such as creating song references and it can also be used for survey purposes. The concept of automatic music genre classification has become very popular in recent years as a result of the rapid growth of the digital entertainment industry.

CHAPTER 1

INTRODUCTION

1.1 Music Genre

Sound is represented in the form of an audio signal having parameters like frequency, decibel, bandwidth etc. These audio signals come in various different formats which make it possible and easy for the computer to read and analyse them. Some formats are: mp3 format, WMA (Windows Media Audio) format and wav (Waveform Audio File) format. Since music has become more easily accessible (Spotify, iTunes, YouTube, etc.), more people have begun listening to a broader and wider range of music styles. In addition, social identity also plays a large role in music preference. Personality is a key contributor for music selection. Those who consider themselves to be "rebels" will tend to choose heavier music styles like heavy metal or hard rock, while those who consider themselves to be more "relaxed" or "laid back" will tend to choose lighter music styles like jazz or classical music. Companies use music classification, either to place recommendations to their customers, or simply as a product.

The music industry has undergone major changes from its conventional existence and also in the form of music created in last few years. The ever-growing customer base has also increased the market for different music styles. Music not only bring the individuals together, but also provides insight for various cultures. Therefore, it is essential to classify the music according to the genres to satisfy the needs of the people categorically. The manual ranking of music is a repetitive, lengthy task and the duty lies with the listener. The proposed research work has compared few classification models and established a new model for CNN, which is better than previously proposed models. This research work has trained and compared the proposed models on GTZAN dataset, where most of the models were audio file trains, while a few of the models were trained on the spectrogram.

To determine music genres, we can use machine learning algorithms which in turn proven to be very handy in Music Analysis too. Classification of genre can be very valuable to explain some interesting problems such as creating song references and it can also be used for survey purposes. Classification algorithm is a Supervised Learning technique that is used to identify the category of new observations on the basis of training data. In Classification, a program learns from the given dataset or observations and then classifies new observation into a number of classes or groups. Such as, Yes or No, 0 or 1, etc. Classes can be called as targets/labels or categories.

The concept of automatic music genre classification has become very popular in recent years as a result of the rapid growth of the digital entertainment industry. Developing a machine learning model that classifies music into genres shows that there exists a solution which automatically classifies music into its genres based on various different features, instead of manually entering the genre. Another objective is to reach a good accuracy so that the model classifies new music into its genre correctly. This model should be better than at least a few pre-existing models.

1.2 Problem Statement

Until now genre classification for digitally available music has been performed manually. Thus, techniques for automatic genre classification would be a valuable addition to the development of audio information retrieval systems for music.

1.3 Contribution

Developing a machine learning model that classifies music into genres shows that there exists a solution which automatically classifies music into its genres based on various different features, instead of manually entering the genre.

- Another objective is to reach a good accuracy so that the model classifies new music into its genre correctly.

- This model should be better than at least a few pre-existing models.

CHAPTER 2

LITERATURE SURVEY

V Vanitha and et al,2021 [10] In music genre classification, the application of convolutional neural networks and convolutional recurrent neural networks are discussed. In addition the well-known architecture transfer learning techniques are used. Genre classification will be valuable when there are some interesting facts or problems, finding the most specific song which has been listened to many times. Different approaches like fine-tuning, initializations and optimizers are implemented for the betterment of results. Multiframe approach is used to analyze the song in detail. A pretrained model on a large dataset and fine-tune its weights to adapt it to perform a new task. In order to derive the output, frame acquisition and confusion matrix are used. The evaluation and performance of both handmade dataset and GTZAN dataset are used in a lot of works that compares the execution of this approach from one state. The most challenging task is to categorise the audio files as per their genre in the field of music information retrieval. The real world application in this field is automatic tagging of unspecified frames of music(apps like Saavn, Wynk, Spotify etc.,) Most companies use this field to satisfy the customer's. Finding the type of music genre is the first process for these applications.

Anirudh Ghildiyal and et al,2020 [1] The music industry has undergone major changes from its conventional existence and also in the form of music created in last few years. The ever-growing customer base has also increased the market for different music styles. Music not only bring the individuals together, but also provides insight for various cultures. Therefore, it is essential to classify the music according to the genres to satisfy the needs of the people categorically. The manual ranking of music is a repetitive, lengthy task and the duty lies with the listener. The proposed research work has compared few classification models and established a new model for CNN, which is better than previously proposed models. This research work has trained and compared the proposed models on GTZAN dataset, where most of the models were audio file trains, while a few of the models were trained on the spectrogram.

Che-Nan Kuo and et al,2020 [4] Information has become a necessity in online social media life, from important things to ordinary things like gossip. The abundance of information that is on the Internet, makes someone enter the virtual world to find the information needed. The information needs are related to the selection of information keyword criteria to be appropriate and appropriate to the information seekers. This information can be in the form of Indonesian text news, but Indonesian text news on the internet is very abundant. So that, when the information seeker wants the news, it is done manually, which is like reading the title that has similarities, and the content of the news, then the information can be stored if it is in accordance with the information seeker's desire. But this method will use a lot of time to get the right information. This study classifies news from the official website of Okezone. The categories discussed are only Finance, Lifestyle, News and Sport. The document used for training data is 8 data which is then changed in the form of txt. The classification method used is the naïve bayes classifier.

Nirmal M R,Shajee Mohan BS,2020 [7] Music genre recognition (MGR) is an area of research in the broad scope of music information retrieval (MIR) and audio signal processing. Music genres are categorical labels created by humans to determine the style of music. The paper proposes a method to classify music using spectrograms. A spectrogram is the Short Time Fourier Transform (STFT) of an audio signal. They are images showing time and frequency components of an audio signal. In this work, the music signals are first converted to their corresponding spectrograms. These spectrograms are then given as input to the classifier. The classifier used in this work is a Convolutional Neural Network (CNN). Two CNN models are discussed in this paper: A user-defined CNN model and a pre-trained convnet. Pre-trained convnet makes use of the concepts of fine tuning and transfer learning. The performance of the classifier is evaluated using performance measures such as confusion matrix and classification accuracy. Three music genres such as blues, classical and rock from the GTZAN dataset are selected for experimentation. The classification accuracy is found to be good.

Bisharad and et al,2019 [3] In recent years, the complexity of music production has gradually decreased, resulting in many people creating music and uploading their created music to streaming media. The huge music streaming media has caused people to spend much time searching for specific music. Therefore, the technique of quick classification of music genres is very important in today's society. As machine learning and deep learning technologies maturing, the Convolutional Neural Networks (CNN) are applied to many fields, and various CNN-based variants have emerged one after another. The traditional music genre classification requires relevant professional knowledge to manually extract features from time series data. Deep learning has been proven to be effective and efficient in time series data. In order to save the user's time when searching for different styles of music, we applied CNN's advantages and characteristics in audio to implement a music genre classification model. In the pre-processing, Librosa is used to convert the original audio files into their corresponding Mel spectrums. The converted Mel spectrum is then fed into the proposed CNN model for training. The majority voting is applied to the decisions made by the 10 classifiers, and the average accuracy obtained on the GTZAN dataset is 84%.

Sarfaraz Masood ,2014 [9] The objective here is to eliminate the manual work of classifying genres of song in each song. With this startup work songs can be classified in real-time and proposed parallel architecture can be implemented on the multi-processing system as well. In this paper a set of features are obtained like beats/tempo, energy, loudness, speechiness, valence, danceability, acousticness, discrete wavelet transform etc., using Echonest libraries and are fed into the Parallel Multi-Layer Perceptron Network to obtain the genres of the song. The proposed scheme has an accuracy of 85% when used to classify two genres of songs that are Sufi and Classical.

Ardiansyah Dores and et al,2018 [2] Genre is an abstract, yet a characteristic feature of music. Existing works for automatic genre classification compute a set of features from the audio and design a classifier on top of it. Such models, in general, compute these features over a relatively long duration of the audio. In this paper, a residual neural network based model is proposed for genre classification which is trained on short clips of just 3 seconds duration. Also, traditional genre classification algorithms will assign a single genre to an audio clip. However, it is well established that different genres have overlapping characteristics. Considering this ambiguous nature of the genre, the model proposed in this work can assign three genre labels to a music clip, with each genre associated with some probability. The proposed model has an error rate of 18%, 9%, and 5.5% while predicting into top-1, top-2 and top-3 genres for a music clip respectively. We demonstrate in this work that the predictions made by the classifier align with the broader understood meaning of genre in a realistic setting.

Rajib Sarkar and et al, 2018[8] Automatic music genre classification is an active and most popular area of research in the Music Information Retrieval (MIR) domain. Such classification enables organised storage and retrieval of music information from a large collection. In this work, we have utilized spectral features that represents important musical properties like timbre, tonality and pitch which play important role in discriminating the genres. For classification, support vector machine and random forest are considered. Experiment is carried out on three different benchmark dataset. Result shows that presented features perform satisfactorily for both the classifiers. Comparison with reported systems reflect the superiority of the proposed system. Selection of the feature set is well justified as improved performance is achieved across the classifier and dataset.

Glaucia M. Bressan and et al,2017 [6] The interest in the music classification has increased due to its wide applicability and discoveries obtained from researches. However, efficient methods for systemic organization of digital libraries are required, since users need to classify the available music files. When an automatic classification is desired, the extraction of input attributes and an efficient system, able to process them, are needed. In this context, the use of decision trees as a tool to predict musical genres classes allows the monitoring of the ramification, since nodes and branches of the tree can be accessed in this process. Decision tree is a technique very useful in data mining to extract information of a data set, normally using a TDIDT (Top-Down Induction Decision Tree) algorithm. Therefore, the goal of this paper is to propose an automatic classification method for Latin musical genres, by applying decision tree approach. The real database used is named Latin Music Database . Two algorithms are executed: CART (Classification and Regression Tree) and C4.5 , which have constructive criteria distinguished. The obtained results are compared and discussed in order to evaluate the classification performance.

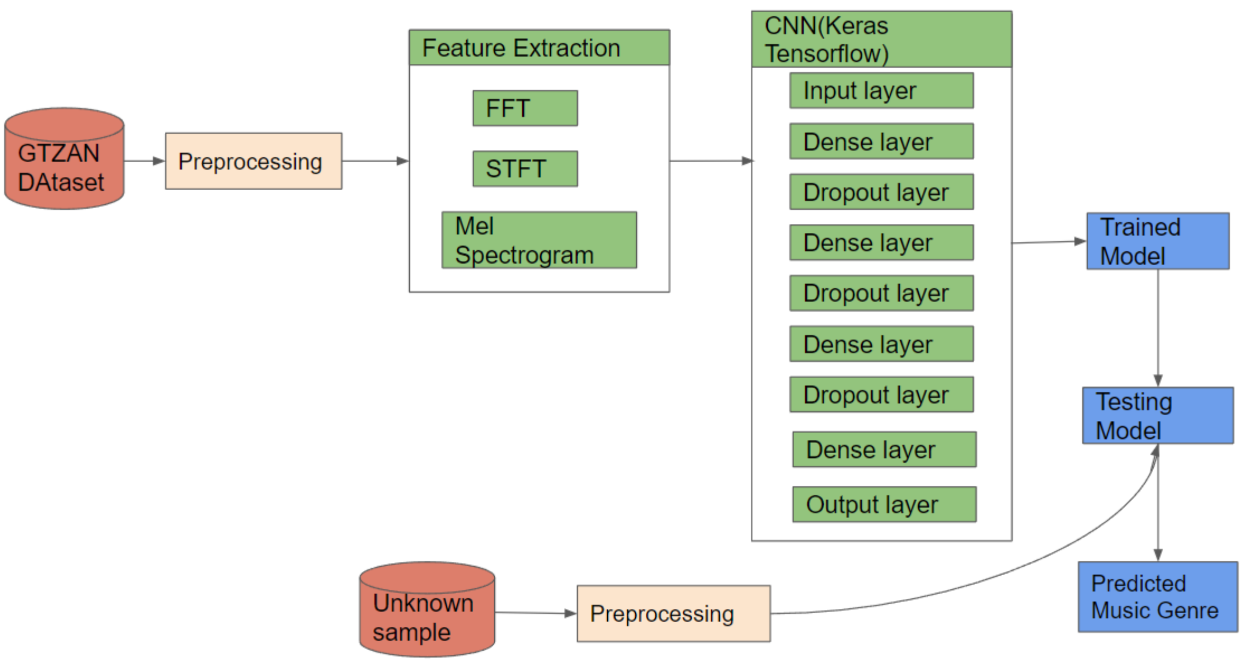
George Tzanetakis and Perry Cook,2002 [5] Musical genres are categorical labels created by humans to characterize pieces of music. A musical genre is characterized by the common characteristics shared by its members. These characteristics typically are related to the instrumentation, rhythmic structure, and harmonic content of the music. Genre hierarchies are commonly used to structure the large collections of music available on the Web. Currently, musical genre annotation is performed manually. Automatic musical genre classification can assist or replace the human user in this process and would be a valuable addition to music information retrieval systems. In addition, automatic musical genre classification provides a framework for developing and evaluating features for any type of content-based analysis of musical signals. In this paper, the automatic classification of audio signals into a hierarchy of musical genres is explored. More specifically, three feature sets for representing timbral texture, rhythmic content and pitch content are proposed. The performance and relative importance of the proposed features is investigated by training statistical pattern recognition classifiers using real-world audio collections. Both whole file and real-time frame-based classification schemes are described. Using the proposed feature sets, classification of 61% for ten musical genres is achieved. This result is comparable to results reported for human musical genre classification.

CHAPTER 3

PROPOSED SYSTEM

3.1 System Architecture

In this Proposed System, PCA is used for extracting important variables (in form of components) from a large set of variables available in a data set. For feature extraction,the librosa library is used to extract the mfcc features.In CNN,dense layer is used to classify image and dropout is used to prevent the overfitting in the model.After training all CNN models,testing occurs to predict the genre of the given music.



3.2 Proposed Methodology

The proposed methodology of Music genre classification is composed of following methods.

3.2.1 Data Pre-processing

Input

The raw training dataset that is collected.

Output

Dimensionality reduction occurs in the dataset.

Process Flow

Using Principle Component Analysis, extracting important variables (in form of components) from a large set of variables available in a data set. It extracts low dimensional set of features from a high dimensional data set with a motive to capture as much information as possible. With fewer variables, visualization also becomes much more meaningful. It is always performed on a symmetric correlation or covariance matrix. This means the matrix should be numeric and have standardized data . So, 64% variance was explained by Principal component 1 and 35% was explained by Principal component 2. This shows that we have extracted most of the insights from the dataset in two principal components. Hence, we did not suffer any major loss of information after the dimensionality reduction.

3.2.2 Feature Extraction

Input

Dimensionally reduced dataset is obtained.

Output

The MFCC features for all the audio samples.

Process Flow

For extracting mfcc features the audio must be clean without any noise. Thus, the sound file which is denoised has and removed is fed to this module. Here, the library librosa is used for extracting mfcc features. It slices the audio frames and derives mfcc values for the sliced frames.These features are then integrated to produce the mfcc feature array of a given frame.

3.2.3 Training Module

For the CNN model, we had used the Adam optimizer for training the model. Keras is an open-source software library that provides a Python interface for artificial neural networks. Keras acts as an interface for the TensorFlow library. The epoch that was chosen for the training model is 700.All of the hidden dense layers are using the RELU activation function and the output layer uses the softmax function. Dropout is used to prevent overfitting.We chose the Adam optimizer because it gave us the best results after evaluating other optimizers.The model accuracy can be increased by further increasing the epochs but after a certain period, we may achieve a threshold, so the value should be determined accordingly.Here,we are using 4 models for training purpose.In first model,4 dense layer is used and training for 70 epochs,got an validation accuracy of 88.93%.In second model,5 dense and 4 dropout layers are used and training for 100 epochs,got an validation accuracy of 92%.In third model, 5 dense and 4 dropout layers are used and training for 700 epochs using Stochastic gradient descent optimizer,got an validation accuracy of 91.39%.In fourth model, 6 dense and 5 dropout layers are used and training for 500 epochs using Root Mean Squared Propagation optimizer,got an output of 92.44%.

3.2.4 Testing Module

In machine learning, model testing is referred to as the process where the performance of a fully trained model is evaluated on a testing set. The testing set consisting of a set of testing samples should be separated from the both training and validation sets, but it should follow the same probability distribution as the training set. Each testing sample has a known value of the target. Based on the comparison of the model's predicted value.

3.2.5 Prediction Module

Predictive modeling is a statistical technique using machine learning and data mining to predict and forecast likely future outcomes with the aid of historical and existing data.The accuracy we achieved for the test set is 92.44 percent which is very decent.

CHAPTER 4

RESULT AND EVALUATION

4.1 Evaluation Measure

The three parameters are used to estimate the performance of the model, sensitivity, specificity, and accuracy. Here sensitivity tells us how well our models classify a particular class, and specificity tells us how well our model is classified for non-current class. Accuracy tells us about the overall ratio of correctly detected events. All these parameters are defined as follows:

I. Sensitivity =TP/(TP+FP)
II. Specificity =TN/(TN+FP)
III. Accuracy =(TP+TN)/ Total Events

- Here sensitivity and specificity are calculated for each class and accuracy for the overall results. For calculating sensitivity and specificity for a particular class say X,
- TP for X is all the X instances that are classified as X
- TN for X is all the non-X instances that are not classified as x
- FP for X is all the non-X instances that are classified as X positive rate.

4.1.1 PCA

Principal component analysis (PCA) is the process of computing the principal components and using them to perform a change of basis on the data, sometimes using only the first few principal components and ignoring the rest.

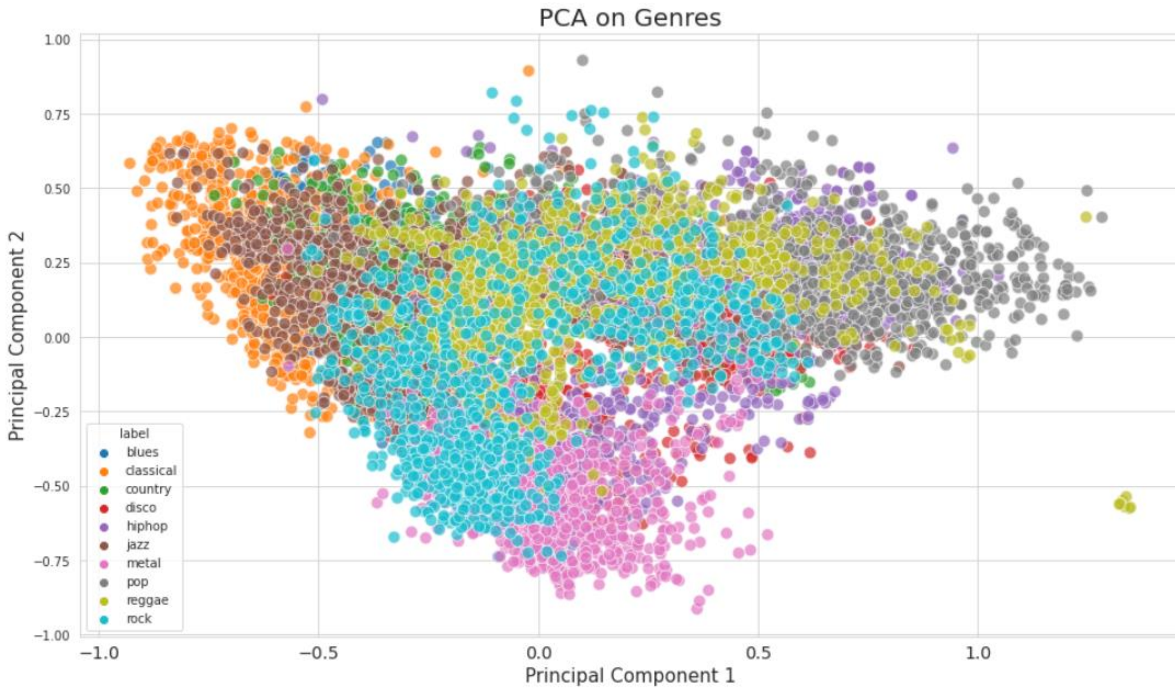


Fig 4.1.1

Fig 4.1.1 shows the alignment of predictor values and target value.

4.1.2 Beats Per Minute

A composer's most accurate way to indicate the desired tempo is to give the beats per minute (BPM). This means that a particular note value (for example, a quarter note) is specified as the beat, and the marking indicates that a certain number of these beats must be played per minute.

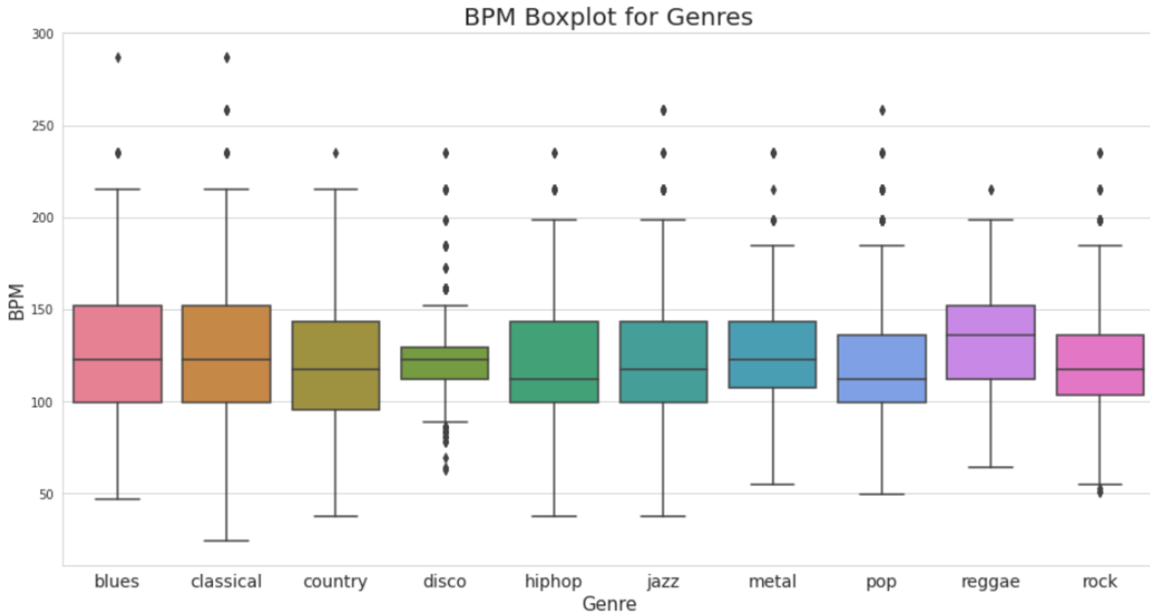


Fig 4.1.2

4.1.3 CNN Model

CNN is a type of neural network model which allows us to extract higher representations for the image content. CNN takes the image's raw pixel data, trains the model for better classification.

```
Epoch 490/500
55/55 [==============================] - 2s 32ms/step - loss: 0.1953 - accuracy: 0.9894 - val_loss: 1.6012 - val_accuracy: 0.9323
Epoch 491/500
55/55 [==============================] - 2s 32ms/step - loss: 0.1311 - accuracy: 0.9886 - val_loss: 1.6116 - val_accuracy: 0.9338
Epoch 492/500
55/55 [==============================] - 2s 31ms/step - loss: 0.0990 - accuracy: 0.9884 - val_loss: 1.7468 - val_accuracy: 0.9282
Epoch 493/500
55/55 [==============================] - 2s 32ms/step - loss: 0.1369 - accuracy: 0.9874 - val_loss: 1.8102 - val_accuracy: 0.9282
Epoch 494/500
55/55 [==============================] - 2s 31ms/step - loss: 0.0641 - accuracy: 0.9906 - val_loss: 1.8617 - val_accuracy: 0.9262
Epoch 495/500
55/55 [==============================] - 2s 31ms/step - loss: 0.1414 - accuracy: 0.9880 - val_loss: 1.9274 - val_accuracy: 0.9262
Epoch 496/500
55/55 [==============================] - 2s 31ms/step - loss: 0.1037 - accuracy: 0.9894 - val_loss: 1.9349 - val_accuracy: 0.9287
Epoch 497/500
55/55 [==============================] - 2s 32ms/step - loss: 0.1543 - accuracy: 0.9853 - val_loss: 1.8146 - val_accuracy: 0.9232
Epoch 498/500
55/55 [==============================] - 2s 32ms/step - loss: 0.1537 - accuracy: 0.9897 - val_loss: 1.8315 - val_accuracy: 0.9272
Epoch 499/500
55/55 [==============================] - 2s 32ms/step - loss: 0.1257 - accuracy: 0.9908 - val_loss: 1.6279 - val_accuracy: 0.9363
Epoch 500/500
55/55 [==============================] - 2s 31ms/step - loss: 0.1357 - accuracy: 0.9890 - val_loss: 1.6165 - val_accuracy: 0.9282
```

Fig 4.1.3

Fig 4.1.4 Testing Accuracy of Trained Model

```
8/8 [==============================] - 0s 6ms/step - loss: 1.7462 - accuracy: 0.9293
The test Loss is : 1.7461915016174316

The Best test Accuracy is : 92.934250831604
```

Fig 4.1.4

Fig 4.1.5 Testing Accuracy of new model

```
5/5 [==============================] - 0s 5ms/step - loss: 1.0238 - accuracy: 0.8897

The Best test Accuracy is : 88.97058963775635
```

Fig 4.1.5

4.2 Result Analysis

From the results we could see that the proposed model could successfully identify the correct genre of the music. It is to be noted that all the training and testing are carried out entirely on the device ensuring privacy and security.

Fig 4.2.1 Training Accuracy

Max. Validation Accuracy 0.9368048310279846

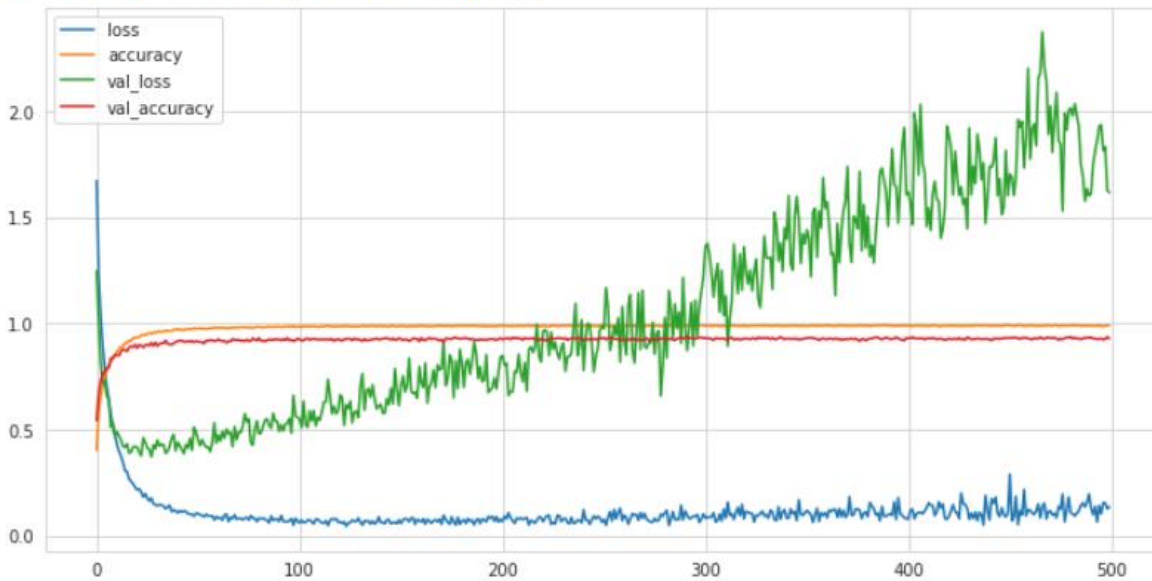


Fig 4.2.1

Fig 4.2.2 Testing Accuracy

Max. Validation Accuracy 0.9186046719551086

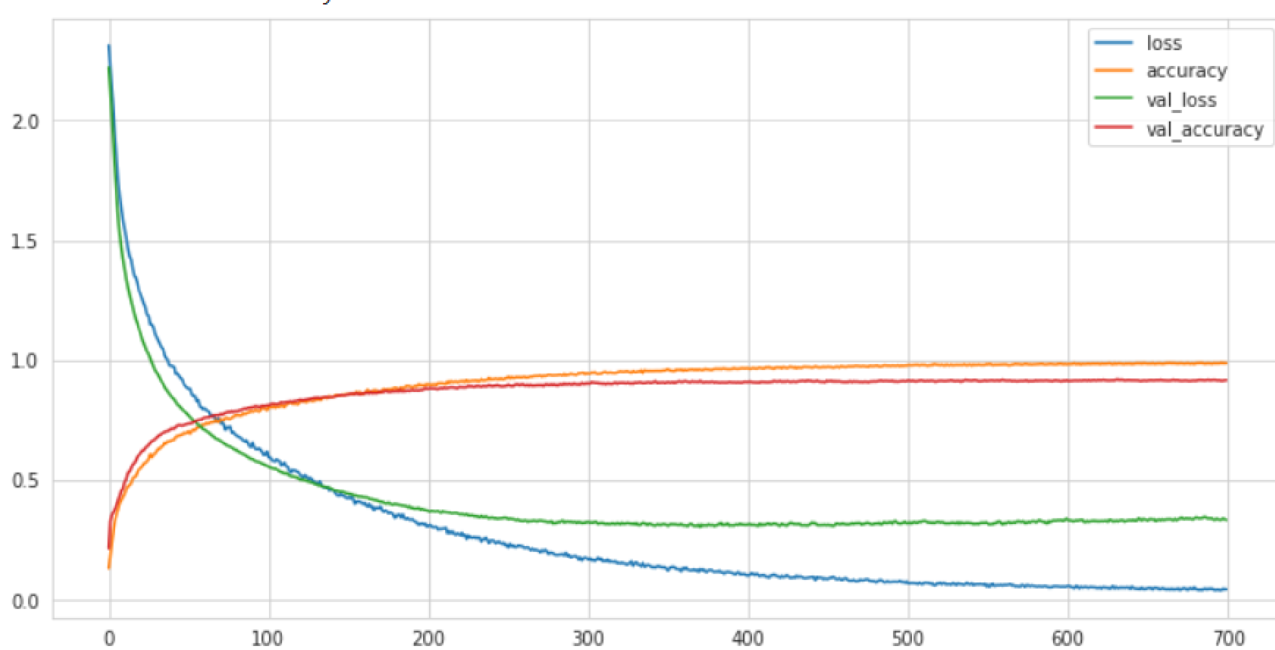


Fig 4.2.2

CHAPTER 5

CONCLUSION

The proposed research work has utilized the GTZAN dataset and produced multiple models to complete this task in this piece of music classification. The proposed model has used multiple inputs for various models along with the audio me l-spectrogram and transferred this to our CNN archives 92%, equivalent to the human understanding of genre with highest accurate achievement. Since, some styles were quite distinctive and some rather distinctive such as the country and the rock genre were confused with other styles, although traditional and blues were easily identified.

APPENDICS

PCA

```
data = df.iloc[0:, 1:]
X = data.loc[:, data.columns != 'label']
y=data['label']
# normalize
cols = X.columns
min_max_scaler = skp.MinMaxScaler()
np_scaled = min_max_scaler.fit_transform(X)
X = pd.DataFrame(np_scaled, columns = cols)
# Top 2 pca components
from sklearn.decomposition import PCA
pca = PCA(n_components=2)
principalComponents = pca.fit_transform(X)
principalDf = pd.DataFrame(data = principalComponents, columns = ['pc1', 'pc2'])
# concatenate with target label
finalDf = pd.concat([principalDf, y], axis = 1)
plt.figure(figsize = (16, 9))
sns.scatterplot(x = "pc1", y = "pc2", data = finalDf, hue = "label", alpha = 0.7, s = 100);
plt.title('PCA on Genres', fontsize = 20)
plt.xticks(fontsize = 14)
plt.yticks(fontsize = 10);
plt.xlabel("Principal Component 1", fontsize = 15)
plt.ylabel("Principal Component 2", fontsize = 15)
plt.savefig("PCA_Scattert.png")
```

FEATURE EXTRACTION

```
# Default FFT window size
n_fft = 2048 # window size
hop_length = 512 # window hop length for STFT
stft = librosa.stft(audio_data, n_fft=n_fft, hop_length=hop_length)
stft_db = librosa.amplitude_to_db(stft, ref=np.max)
```

```
plt.figure(figsize=(12,4))
lplt.specshow(stft, sr=sr, x_axis='time', y_axis='hz')
plt.colorbar()
plt.title("Spectrogram with amplitude")
plt.show()
plt.figure(figsize=(12,4))
lplt.specshow(stft_db, sr=sr, x_axis='time', y_axis='log', cmap='cool')
plt.colorbar()
plt.title("Spectrogram with decibel log")
plt.show()

# plot zoomed audio wave
start = 1000
end = 1200
plt.figure(figsize=(16,4))
plt.plot(audio_data[start:end])
plt.show()
```

BEATS PER MINUTE

```
x = df[["label", "tempo"]]
fig, ax = plt.subplots(figsize=(16, 8));
sns.boxplot(x = "label", y = "tempo", data = x, palette = 'husl');
plt.title('BPM Boxplot for Genres', fontsize = 20)
plt.xticks(fontsize = 14)
plt.yticks(fontsize = 10);
plt.xlabel("Genre", fontsize = 15)
plt.ylabel("BPM", fontsize = 15)
plt.savefig("BPM_Boxplot.png")
```

.TRAINING AND TESTING SPLIT

```
# remove irrelevant columns
df_shuffle.drop(['filename', 'length'], axis=1, inplace=True)
df_y = df_shuffle.pop('label')
```

```
df_X = df_shuffle
# split into train dev and test
X_train, df_test_valid_X, y_train, df_test_valid_y = skms.train_test_split(df_X, df_y, train_size=0.7, r
andom_state=seed, stratify=df_y)
X_dev, X_test, y_dev, y_test = skms.train_test_split(df_test_valid_X, df_test_valid_y, train_size=0.66,
 random_state=seed, stratify=df_test_valid_y)
```

TRAINING MODEL

```
model_4 = k.models.Sequential([
    k.layers.Dense(1024, activation='relu', input_shape=(X_train.shape[1],)),
    k.layers.Dropout(0.3),
    k.layers.Dense(512, activation='relu'),
    k.layers.Dropout(0.3),
    k.layers.Dense(256, activation='relu'),
    k.layers.Dropout(0.3),
    k.layers.Dense(128, activation='relu'),
    k.layers.Dropout(0.3),
    k.layers.Dense(64, activation='relu'),
    k.layers.Dropout(0.3),
    k.layers.Dense(10, activation='softmax'),
])
print(model_4.summary())
model_4_history = trainModel(model=model_4, epochs=500, optimizer='rmsprop')

plotHistory(model_4_history)


test_loss, test_acc  = model_4.evaluate(X_test, y_test, batch_size=128)
print("The test Loss is :",test_loss)
print("\nThe Best test Accuracy is :",test_acc*100)
```

```
dict2={0: 'blues', 1: 'classical', 2: 'country', 3: 'disco', 4: 'hiphop', 5: 'jazz', 6: 'metal', 7: 'pop', 8: 'reggae',
9: 'rock'}
predicted_values=pd.DataFrame(y_test)
predicted_values=predicted_values.replace({"label":dict2})
predicted_values.reset_index(drop=True, inplace=True)
predicted_values=list(predicted_values.label)
i=0
for item in predicted_values:
   print("The prediction of song no. {} in our dataset is {}".format(i,item))
   i=i+1
```

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