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Music Genre Classifier using Machine Learning Algorithms

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Abstract: Audio data extraction and analysis is important and less explored compared to other forms of data. Here we use an Audio dataset (GTZan) to extract musical information and categorize the musical genre based on the parameters of audio. We compared the study on seven Machine learning algorithms and tested on unvisited user data to see the model performance seeing the algorithms' accuracy ranging from 45% to 87%.

I. INTRODUCTION

The growth of musical data, user personalization and the exploration of its usages has grown in the past few years. The applications like Spotify, Gaana, I-Music utilize this data from users' music history and provide recommendations based on analysis done on such musical data.

Categorization of music into different fields of music is a very integral step of this process. The research here shows an approach to collect musical data from the user's input audio, different musical features like Mel-spectrum features, harmony, chroma etc were collected and machine learning algorithms are applied to those.

We use machine learning algorithms like KNN, Ensemble algorithms, Logistic Regression for the data and try to classify it into 10 musical genre labels.

The paper discusses various steps of the whole procedure from data augmentation, hyperparameter tuning, data extraction and analysis.

II. DESIGN

A. Literature Survey

Tzanetakis and Cook (2002) [1] were one of the first contributors in this field of musical data analysis. The GTZAN dataset was created by them and is to date considered as a standard for genre classification. Scaringella and Zoia(2005) gave a comprehensive survey of both features and classification techniques used in genre classification. Most of the work deals with supervised learning approaches. *Riedmiller(2012)[2]* et al use unsupervised learning to create a dictionary of features gives a detailed account of the evaluation of previous work on genre classification. Along with reference to these papers, the *official Librosa Documentations [3]* were referred for the implementation.

B. Diagram

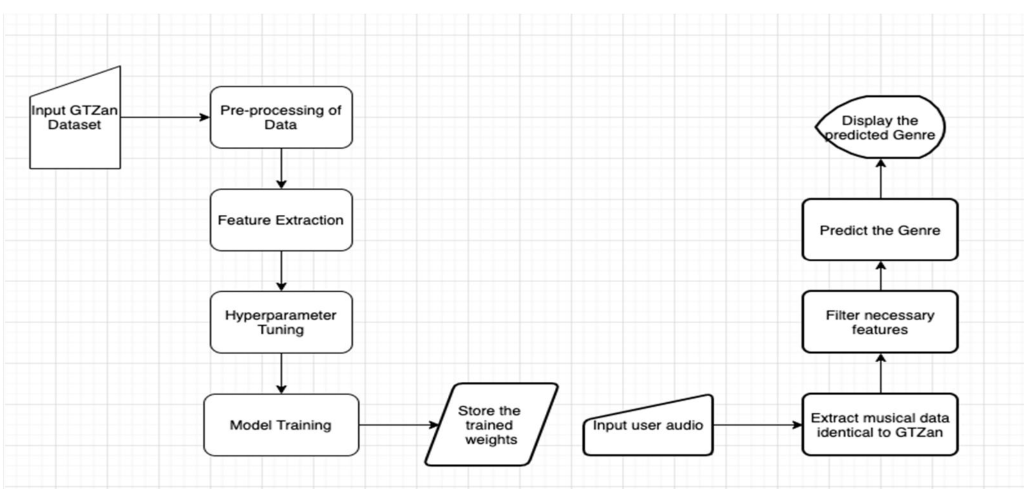

Figure: 2.2

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III. DATASET

The main musical datasets researched were: Million Song Dataset, GTZan Dataset and Midi Files. *Tzanetakis and Cook (2002) [1]* were the contributors to the GTZan dataset consisting of 10000 30 second songs with 10 different genre labels including Pop, Rock, Jazz, Reggae, etc. The dataset we used consisted of each music and its different musical features. The features included. Mel-frequency cepstral coefficients (MFCCs), spectral contrast, spectral roll-off and chroma features were some of the features. These features were displayed in a tabular form of 55 features for 30-second songs. The dataset also consisted of the same audio dataset for the songs split in 3 seconds each. The 3 seconds set of data increases the dataset by 10 times and much better accuracy. The musical audio sounds are given in the format of ".wav" which are converted in NumPy arrays later for computation purposes.

IV. METHODOLOGY

A. Data-Preprocessing

The audio data is converted into an array format. This array is made sure that it gets void of all the blank spaces in the audio which is limited to a duration of 30 seconds to have a fixed state of data. This 30 seconds audio data is now converted into 10 smaller arrays of 3 seconds data each to have a much wider dataset for our program in order to give a much better performance. The input parameters data was created in the form of a pandas data frame for easier processing.

B. Features

There are a total of 55 parameters given in the GTZan dataset. The parameters are various musical features t help to characterize different genres. These parameters include:

1) *Mel-frequency Cepstral Coefficients (MFCC):* Introduced in the early 1990s by Davis and Mermelstein, MFCCs have been very useful features for tasks such as speech recognition *(Davis and Mermelstein, 1990)* [5]. First, the Short-Time Fourier-Transform (STFT) of the signal is taken with n fft=2048 and hop size=512 and a Hann window. Next, we compute the power spectrum and then apply the triangular MEL filter bank, which mimics the human perception of sound. This is followed by taking the discrete cosine transform of the logarithm of all filterbank energies, thereby obtaining the MFCCs. The parameter n Mels, which corresponds to the number of filter banks, was set to 20 in this study.
2) *Chroma Features:* This is a vector that corresponds to the total energy of the signal in each of the 12 pitch classes. (C, C#, D, D#, E, F, F#, G, G#, A, A#, B) *(Ellis, 2007) [6]*. The Chroma vectors are then aggregated and their mean and standard deviation is taken.
3) *RMSE Features*

The signal's energy is calculated as:

$$\sum_{n=1}^{k} |x(n)|^2$$

The Root Mean Square value can be calculated as:

$$\sqrt{\frac{1}{N}\sum_{n=1}^{N} |x(n)|^2}$$

RMSE is calculated frame by frame. We then take the average and standard deviation across all frames

4) *Spectral Centroid:* For each frame, this corresponds to the frequency around which most of the energy is centred *(Tjoa,2017) [7]*. It is a magnitude weighted frequency calculated as:

$$f_c = \frac{\sum_{k=0}^{n} \mathrm{S(k)f(k)}}{\sum_{k=0}^{n} \mathrm{f(k)}}$$

where S(k) refers to the spectral magnitude of the frequency of bin k and f(k) refers to a frequency corresponding to bin k

5) *Spectral Bandwidth:* The p-th order spectral bandwidth corresponds to the p-th order moment about the spectral centroid (Tjoa, 2017) [7] and is calculated as

[k(S(k)f(k) - fc)p]1/p

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$$\left[\sum_k (S(k)f(k) - f_c)^p\right]^{\frac{1}{p}}$$

For example, p= 2 is analogous to a weighted standard deviation

6) *Spectral Roll off:* This feature corresponds to the value of frequency below which 85% (this threshold can be defined by the user) of the total energy in the spectrum lies (Tjoa, 2017) [8]. For each of the spectral features described above, the mean and standard deviation of the values taken across frames is considered as the representative final feature that is fed to the model. The features described in this section would be used to train machine learning algorithms. The features that contribute the most to achieving a good classification performance will be identified and reported.
7) *Zero-Crossing:* Ratel A zero-crossing point refers to one where the signal changes sign from positive to negative *(Gouyon et al.,2000)* [8]. The 3-second audio data when converted to NumPy array is divided into smaller frames and the zero-crossing quantity is each frame is determined. The frame length is set to be 2048 points with a hop size of 512 points. Note that these frame parameters have been used consistently across all features discussed in this section. Finally, the average and standard deviation of the Zero-Crossing Rate across all frames are chosen as representative features.
8) *Tempo:* In general terms, tempo refers to how fast or slow a piece of music is; it is expressed in terms of Beats Per Minute (BPM). Different kinds of music genres would have different levels of tempos. Since the tempo of the audio piece can vary with time, we aggregate it by computing the mean across several frames. The functionality in Librosa first computes a tempogram following *(Grosche et al.,2010)* [10] and then estimates a single value for tempo.

C. Classifiers

We tried executing various Classification models. The list included KNN, Logistic Regression and 5 Ensemble algorithms.

1) *Logistic Regression:* A supervised learning algorithm used for classification purposes. There are 3 main classifications in Logistic Regression: Binomial, Multinomial and Ordinal. We used a multinomial classifier in order to differentiate between the 10 genres categories.
2) *XGBoost Algorithm:* An ensemble learning algorithm. It stands for eXtreme Gradient Boosting which is known for its speed and performance. The Gradient Boosting is implemented on Decision Trees.
3) *AdaBoost Algorithm:* An ensemble learning algorithm. AdaBoost, which stands for Adaptive Boosting, is a statistical classification meta-algorithm formulated by *Yoav Freund and Robert Schapire. [4]*
4) *Gradient Boosting Method:* An ensemble learning algorithm. It combines results from multiple decision trees and generates a final decision. All weak learners are decision trees in gradient boosting.
5) *CatBoost Algorithm:* CatBoost stands for Categorical Boosting. The library works well on different Categories of data. Boosting since the algorithm is based on Gradient Boosting Algorithm.
6) *Random Forest Algorithm:* A supervised ensemble learning algorithm used for both Regression and Classification (Here classification). It makes use of multiple decision trees and then generates the result using voting.
7) *KNN:* A simple supervised ensemble learning algorithm that categorizes the data based on their similarities. It is used mainly for classification.

D. Hyperparameter Tuning

Hyperparameter tuning refers to the optimizing of learning algorithms by setting particular parameters which leads the models to learn in a certain way. The learning method is controlled by initialized variables. XGBoost and Random Forest are two algorithms where run hyperparameters and the results were extensively good.

E. Features Selection

There are in total 55 features extracted from model analysis. Out of the 55 features, we select the 30 most important features necessary for our analysis. We use the eli5 library along with logistic regression to select our top 30 features from permutation importance.

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Feature Importances using Permutation Importance

Weight	Feature
0.1722 ± 0.0118	spectral_centroid_mean
0.1473 ± 0.0085	spectral_bandwidth_mean
0.1452 ± 0.0094	mfcc1_mean
0.1366 ± 0.0086	rolloff_mean
0.1268 ± 0.0072	zero_crossing_rate_mean
0.1026 ± 0.0036	perceptr_var
0.0961 ± 0.0048	mfcc3_mean
0.0865 ± 0.0046	rms_mean
0.0859 ± 0.0025	chroma_stft_mean
0.0786 ± 0.0068	mfcc2_mean
0.0728 ± 0.0059	mfcc4_mean
0.0565 ± 0.0075	mfcc9_mean
0.0485 ± 0.0048	spectral_centroid_var
0.0388 ± 0.0050	mfcc6_mean
0.0378 ± 0.0053	rms_var
0.0299 ± 0.0042	mfcc17_mean
0.0298 ± 0.0033	spectral_bandwidth_var
0.0290 ± 0.0049	mfcc11_mean
0.0286 ± 0.0025	zero_crossing_rate_var
0.0267 ± 0.0070	mfcc7_mean
… 35 more …	

V. EVALUATION

A. Metrics

We used 4 main metrics for model analysis: F1 Score, Accuracy, Precision and Recall. Each model also gave a different set of analysis based on how they performed for a particular genre. The final accuracy noted was a mean of all.

Parameter→ Algorithm↓	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.675	0.671	0.675	0.672
Random Forest	0.828	0.829	0.828	0.827
AdaBoost	0.456	0.433	0.455	0.421
GBM	0.762	0.764	0.762	0.762
XGBoost	0.879	0.879	0.879	0.878
CatBoost	0.863	0.864	0.863	0.863
KNN	0.867	0.870	0.867	0.867

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B. Confusion Matrices and Model Analysis

A confusion matrix is a tabular representation of model analysis of a classification model of a set of data for which true values are given.

1) Logistic Regression

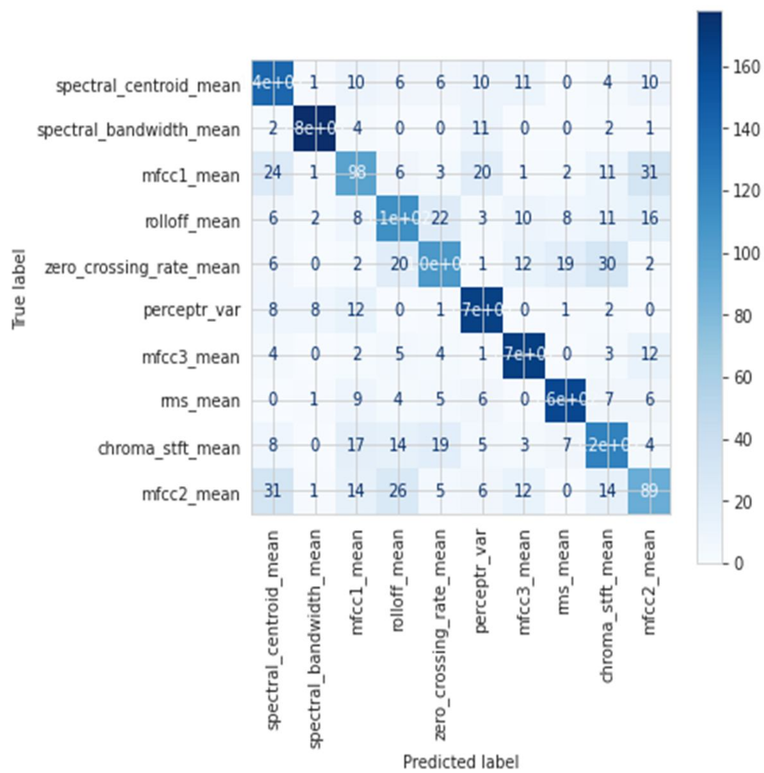

Figure: 5.2.1

	precision	recall	f1-score	support
blues	0.794	0.818	0.806	198
classical	0.950	0.965	0.957	198
country	0.750	0.746	0.748	197
disco	0.827	0.798	0.812	198
hiphop	0.871	0.787	0.827	197
jazz	0.784	0.899	0.838	198
metal	0.870	0.914	0.892	198
pop	0.872	0.859	0.865	198
reggae	0.782	0.813	0.797	198
rock	0.826	0.717	0.768	198
accuracy			0.832	1978
macro avg	0.833	0.832	0.831	1978
weighted avg	0.833	0.832	0.831	1978

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2) XGBoost Algorithm

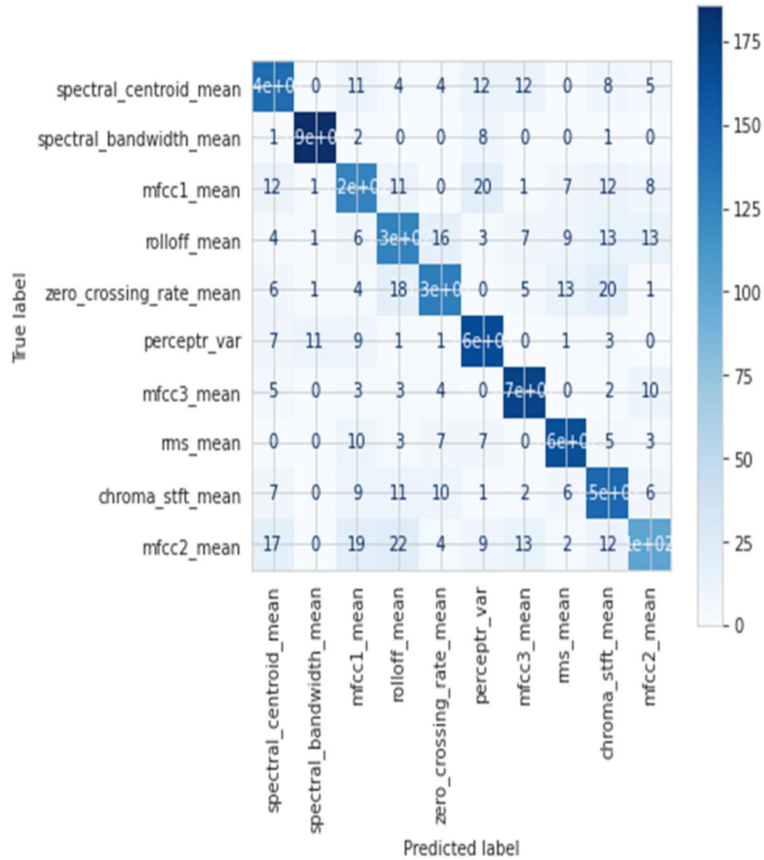

Figure: 5.2.2

	precision	recall	f1-score	support
0	0.876	0.859	0.867	198
1	0.945	0.955	0.950	198
2	0.816	0.858	0.837	197
3	0.868	0.833	0.851	198
4	0.898	0.853	0.875	197
5	0.838	0.914	0.874	198
6	0.917	0.944	0.930	198
7	0.916	0.884	0.900	198
8	0.869	0.904	0.886	198
9	0.847	0.783	0.814	198
accuracy			0.879	1978
macro avg	0.879	0.879	0.878	1978
weighted avg	0.879	0.879	0.878	1978

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3) AdaBoost Algorithm

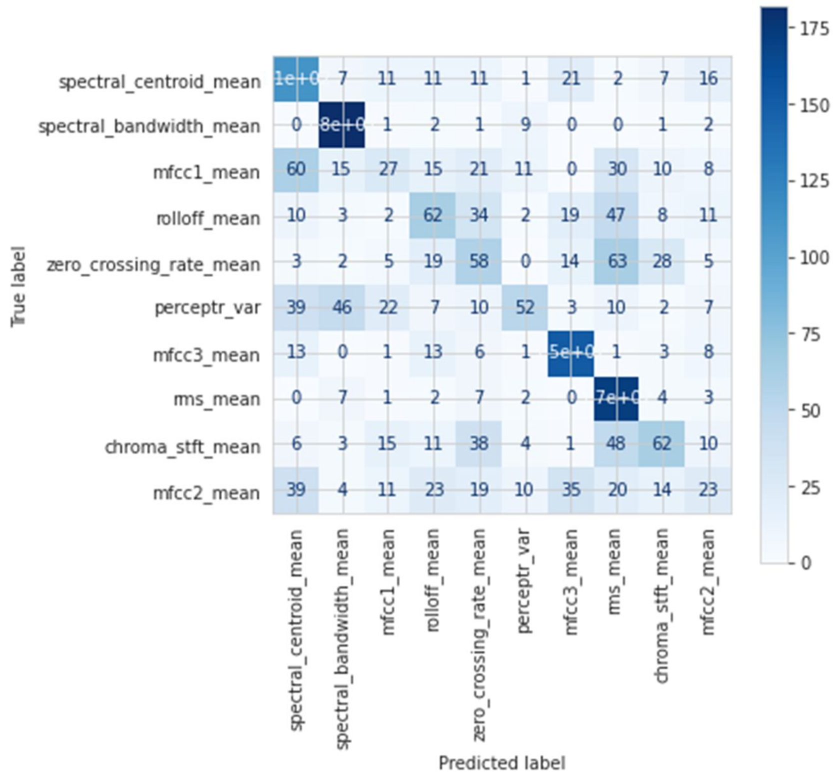

Figure: 5.2.3

	precision	recall	f1-score	support
blues	0.395	0.561	0.463	198
classical	0.677	0.919	0.779	198
country	0.281	0.137	0.184	197
disco	0.376	0.313	0.342	198
hiphop	0.283	0.294	0.289	197
jazz	0.565	0.263	0.359	198
metal	0.620	0.768	0.686	198
pop	0.438	0.869	0.582	198
reggae	0.446	0.313	0.368	198
rock	0.247	0.116	0.158	198
accuracy			0.456	1978
macro avg	0.433	0.455	0.421	1978
weighted avg	0.433	0.456	0.421	1978

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4) Gradient Boosting Method

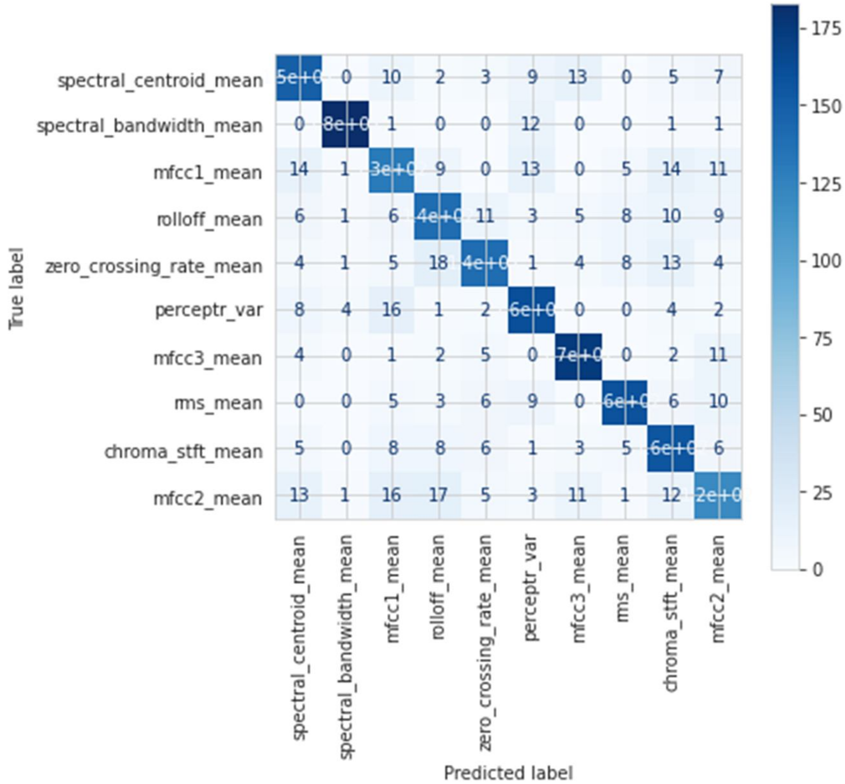

Figure: 5.2.4

	precision	recall	f1-score	support
blues	0.734	0.753	0.743	198
classical	0.958	0.924	0.941	198
country	0.657	0.660	0.658	197
disco	0.698	0.702	0.700	198
hiphop	0.785	0.706	0.743	197
jazz	0.759	0.813	0.785	198
metal	0.828	0.874	0.850	198
pop	0.855	0.803	0.828	198
reggae	0.700	0.788	0.741	198
rock	0.661	0.601	0.630	198
accuracy			0.762	1978
macro avg	0.764	0.762	0.762	1978
weighted avg	0.764	0.762	0.762	1978

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5) CatBoost Algorithm

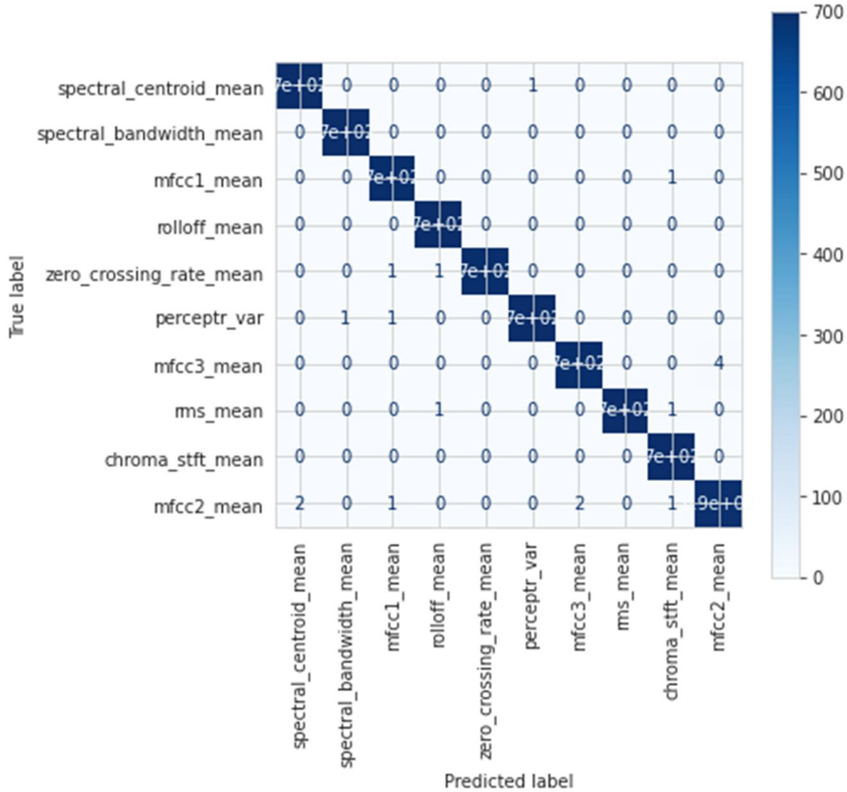

Figure: 5.2.5

	precision	recall	f1-score	support
blues	0.882	0.833	0.857	198
classical	0.964	0.949	0.957	198
country	0.787	0.787	0.787	197
disco	0.837	0.828	0.832	198
hiphop	0.889	0.853	0.870	197
jazz	0.824	0.919	0.869	198
metal	0.902	0.934	0.918	198
pop	0.921	0.879	0.899	198
reggae	0.838	0.889	0.863	198
rock	0.799	0.763	0.780	198
accuracy			0.863	1978
macro avg	0.864	0.863	0.863	1978
weighted avg	0.864	0.863	0.863	1978

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6) Random Forest Algorithm

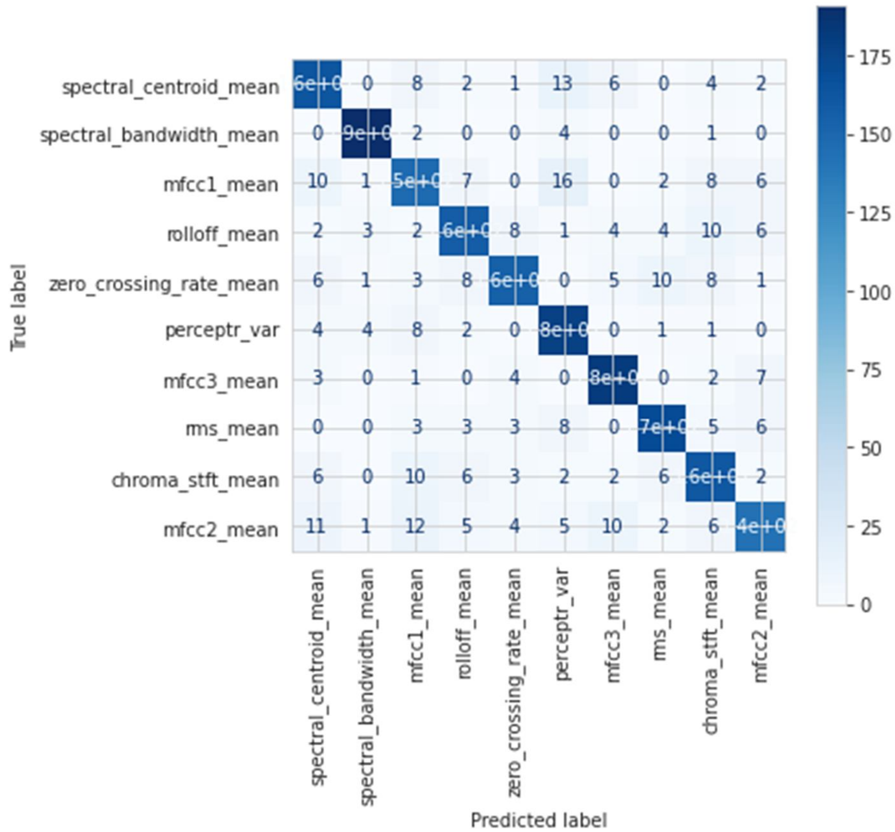

Figure: 5.2.6

	precision	recall	f1-score	support
blues	0.832	0.803	0.817	198
classical	0.940	0.955	0.947	198
country	0.737	0.766	0.751	197
disco	0.832	0.778	0.804	198
hiphop	0.864	0.807	0.835	197
jazz	0.799	0.904	0.848	198
metal	0.844	0.904	0.873	198
pop	0.859	0.864	0.861	198
reggae	0.770	0.813	0.791	198
rock	0.810	0.687	0.743	198
accuracy			0.828	1978
macro avg	0.829	0.828	0.827	1978
weighted avg	0.829	0.828	0.827	1978

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7) KNN

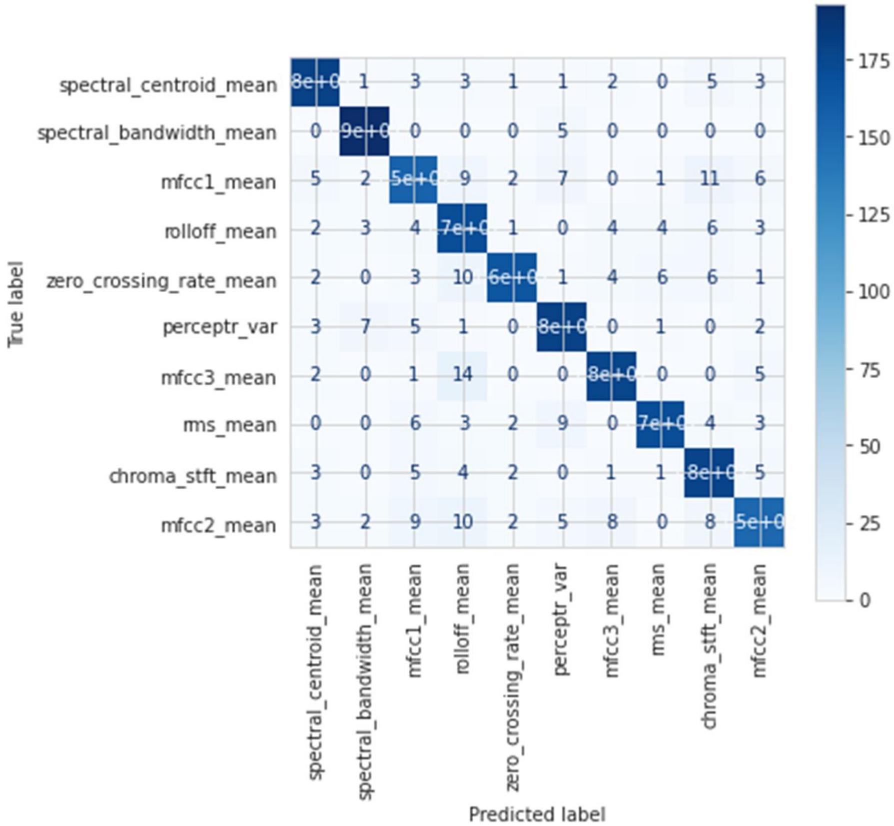

Figure: 5.2.7

	precision	recall	f1-score	support
blues	0.899	0.904	0.902	198
classical	0.928	0.975	0.951	198
country	0.811	0.782	0.796	197
disco	0.760	0.864	0.809	198
hiphop	0.943	0.832	0.884	197
jazz	0.865	0.904	0.884	198
metal	0.903	0.889	0.896	198
pop	0.929	0.864	0.895	198
reggae	0.816	0.894	0.853	198
rock	0.844	0.763	0.801	198
accuracy			0.867	1978
macro avg	0.870	0.867	0.867	1978
weighted avg	0.870	0.867	0.867	1978

===

C. Output

The program checks the accuracy of different machine learning models. The trained models are then tested on the input musical data. The user inputs .wav music files which on white space removal converts the audio into a NumPy array format. The data is split into 10 three seconds data files that run on the trained models. The most recurred output is then selected as the prediction.

VI. RESULT

The classifier on inputting audio takes in the first 30 seconds and extracts the audio features and tries to detect the genre. The accuracy of detection depends on the model applied, each model given varied efficiency, from 45.6% (average) on AdaBoost and 87.9% (average) on XGBoost. The model also saw variation in accuracies for independent genres. The maximum average accuracy of a genre prediction is classical music and the minimum being country in most cases.

VII. CONCLUSION

The classifiers that produce the best accuracies are KNN and XGBoost. The 3 seconds split audio data set is much more efficient at giving the final results. Hyperparameter tuning worked very effectively in the case of XGBoost and Random Forest. Classical music gave the best prediction accuracy while the worst genre varied model to model (maximum being Classical. We concluded that the input audio files with noise removal and preprocessing gave much better results. There are other methods that could be followed as an approach to classify genre.

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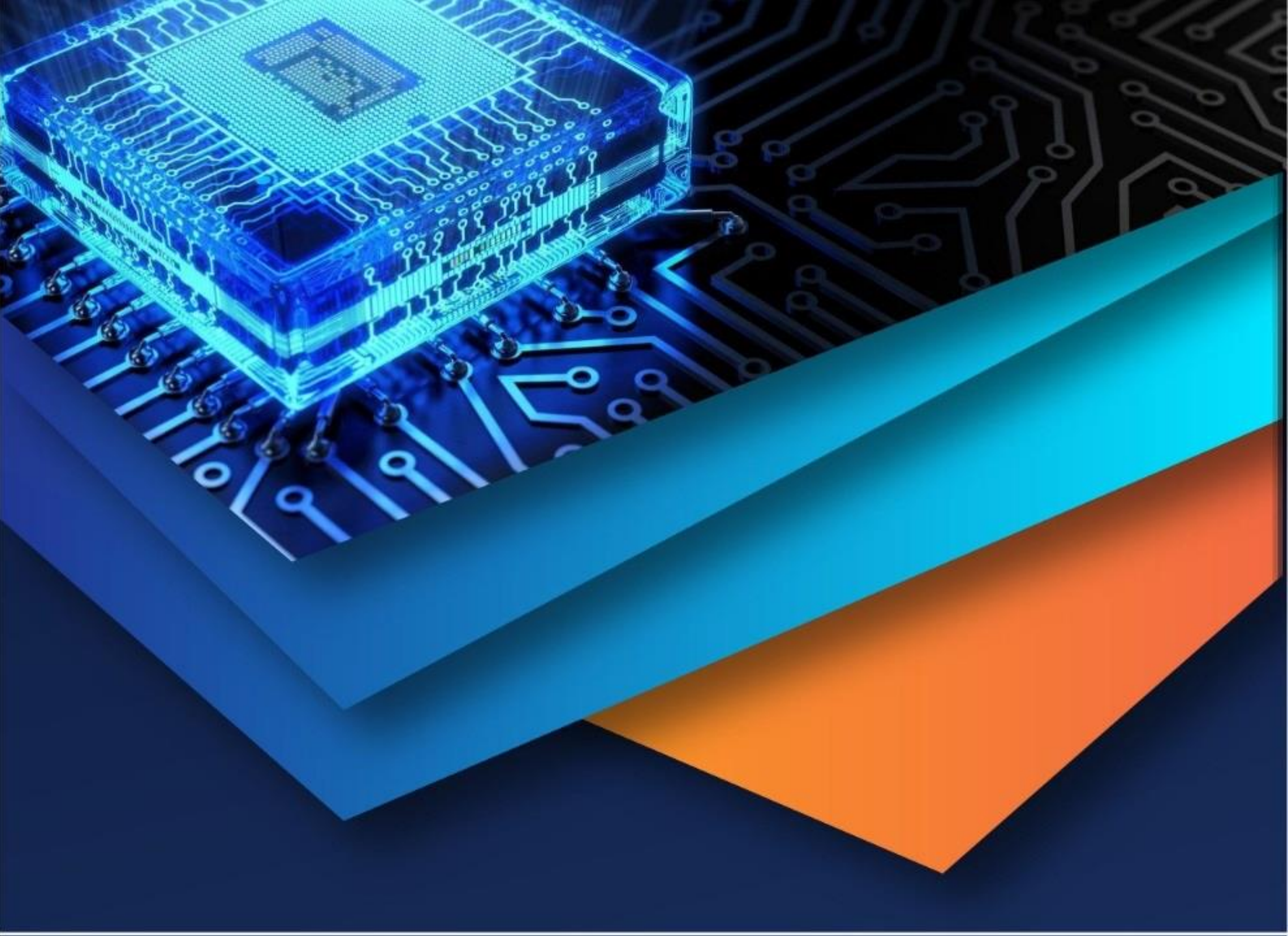

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