Music Genre Classification

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Abstract - **Music Genre Classification is a task within the field of Music Information Retrieval. Over time, different techniques have been developed to perform this task, starting from classical algorithms followed by the use of deep learning techniques in the last few years. In the present project, we discuss how prepare the data when dealing with audio files, we evaluate the different features that can be extracted. Then, we analyze different classical algorithm, such as SVM or XGBoosting and some Deep Learning techniques, such as CNN or RCNN. We will use the GTZAN dataset, the most popular database in this area, for all the models in order to be able to compare them with each other**.

Keywords: **Music Genre Classification, Machine Learning, GTZAN**

1 Problem Description

With the exponential growth of online music streaming services, it has become a challenging task both for users and the service providers to maintain music library manually. Accurate and automated music classification to different genres using machine learning algorithms can not only solve this problem for music streaming companies like Spotify and iTunes and improve user experience as well.

Musical Information Retrieval (MIR) is the science of retrieving information from music. The information can be used for different research topics like genre classification, recommender systems, instrumental recognition or sentiment analysis. In this project we will focus on music genre classification, a field where it can be found rich and varied literature. Different approach has been proposed to solved this task, going from classic algorithms to deep learning models.

Nearly 40,000 tracks get added to Spotify along everyday. A robust classifier is essential to characterize the music and tag unlabelled music. At the same time, lack of standardization and ambiguous boundaries between music genres make this a very challenging task. Moreover, human perception change depending on their experiences and opinion and this idea stands out especially when talking about art, particularly in music. This leads to an absence of a global data-set that can be used to obtain reproducible results. Each data-set has its unique structure, presenting different number of genres and descriptors.

Through our project, we will dive and explore the shallow learning and deep learning approaches to perform classification. We will understand, implement and leverage the work already done for feature extraction and lay majority of the focus towards the actual classification problem. Starting from diverse shallow learning algorithms like SVC, Random Forest or XGBoost. Then, we'll go on to explore the deep learning techniques like CNN and RNN for music classification. The implementation and design of these models will be driven by the type of data available, classification goal and our understanding of the problem. Towards the end of our project we'll do a comparative analysis and see which algorithm performs the best job.

2 Background

The study on this field started in 2002 with Tzanetakis and Cook [1], where the authors extracted 30 features from the audio files to predict 10 different music genres. They also build the GTZAN dataset [2], which has become the most well known dataset. However, this dataset present inconsistencies and is relatively small, with only 1000 songs. Other available and public datasets such as FMA dataset [3] counts with 0.1 million songs, which enables more complex models, that requires a greater amount of data, to be trained. We can also find MillionSong Dataset (MSD) [4] or AudioSet [5]. Historically, this challenge started getting addressed by employing classical methods. The most commonly used classical methods included decision trees, an appealing approach as this is a classification task and trees have proved to show good results [1], probabilistic classifiers, such as Naïve Bayes Classifier [1] and Support Vector Machine (SVM) [1]. These models relied basically on three categories of features; rhythm, pitch and temporal structure. However, recently using audio spectrogram has become popular for music genre classification. Spectogram encodes time and frequency information of the music track in its entirety [2]. While it is true that the classical algorithms have shown good results, over the course of time, deep learning techniques have demonstrated outstanding results, close to human level of accuracy. Within this field, there exist literature using Fully Connected Neural Networks which potential relies when the audio file is introduced as input with some extra information so the problem becomes richer and more suitable for this type of deep models. Convolutional Neural Networks [2] using spectrogram results as an input have achieved great results. Since the beat, rhythm, frequencies and tone of the music changes with time, Recurrent Neural Networks, have been recently used to model temporal information and sequences. The most popular architecture that has been used in this field is Long-short term memory (LSTM) [6].

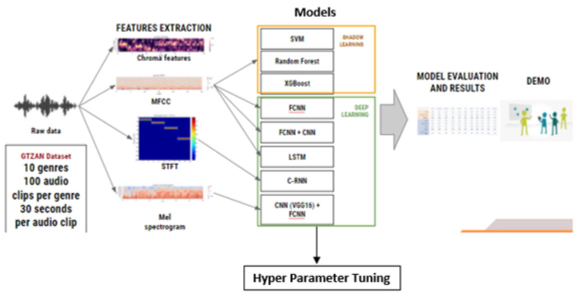


Figure 1. Proposed solution.

3 GTZAN Dataset: Description and feature extraction

After researching different databases we have chosen to use GTZAN. GTZAN is the most popular dataset and most-used public dataset for this type of task. The main reason for using this dataset is to find a common ground to make our algorithms comparable to the research that has already been done.

GTZAN has total 10 different genres, each containing 100 audio clips that are 30 seconds long. Therefore, the dataset consists of 1000 total audio-clips. It comprises of following 10 different genres.

1. Blues
2. Classical
3. Country
4. Disco
5. Hiphop
6. Jazz
7. Metal
8. Pop
9. Reggae
10. Rock

Each instance is a 30 second audio file in .wav format. The instances are audio files, therefore, they should be preprocessed before feeding them into any algorithm we want to train. There are different approaches to audio processing. In the following section, we will show how to carry out each of them and the results obtained. In addition, we will compare each of the genres after processing them.

4 Data/Audio Pre-processing

An audio signal is an analog signal. In order to make it compatible with the Machine Learning algorithm, we need to convert it into a digital signal first. This should be followed by fetching meaningful insights from the digital signal and feeding them to the model. For that, we will have to look for different characteristics and study if they are distinguishable enough so that they can be used as attributes/features to train our algorithms.

But before doing so, the first important question which comes to our minds is that, how to convert audio signal to a digital signal. This can be achieved by rapidly sampling the data from analog audio signal. For this, we've to decide the sample rate first.

Sample Rate:

Sample rate defines the number of discrete data instances used per second to represent the analog sound in digital form. The sample rate we used for our models was **22050**.

Window Size:

The digital audio signal is transformed from a time domain to frequency domain using a Fourier transform. In order to perform a Fast Fourier transform, a window size and the number of samples has to be defined on which transform will be performed. While pre-processing the audio signal, we set the window size to 0.1 and number of sample size to **2048**. Optimal Window size is the one in which it's expected that properties of the signal chunk do not vary too fast.

Overlap and Hop Size:

Overlap defines how much two successive windows overlap with each other. Higher the overlap, more consistent is the information from one window to another and information isn't lost while taking the Fourier transforms. We set overlap to **50%.** Hop size define the number of samples we shift to the right each time we take the Fourier transform of the next window.

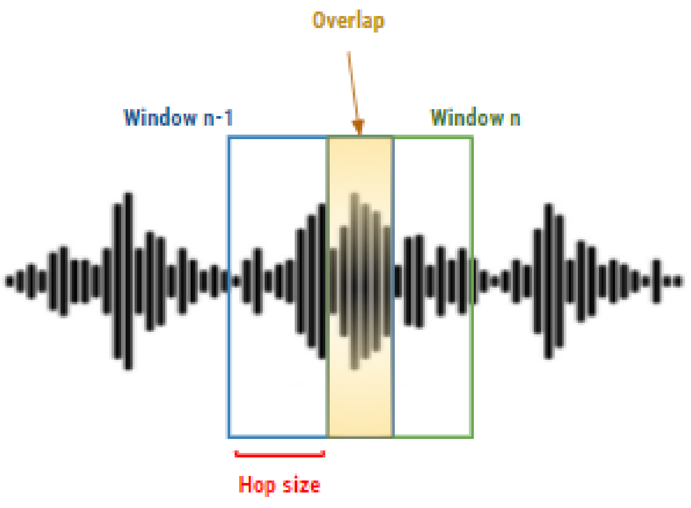


Figure 2. Overlap and hop size representation .

Data Augmentation/Audio Clip Segmentation:

The music signal is extremely high dimensional in time domain. This makes training deep learning models as well as shallow learning models very tedious and time consuming. The workaround of this problem was to divide each and every audio clip into small segments. What we did was that we divided each and every audio signal into 10 segments, each segment being of 3 seconds. Intuitively it made sense since each segment of the song should belong to same genre. Moreover, this helped us to achieve two main motives,

1. Reduced the dimension of audio sample in time domain by ten folds
2. Increased the training samples by ten folds since all the segments were used for predictions independently.

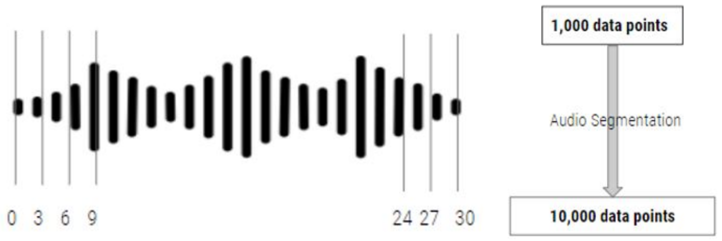


Figure 3. Audio Clip Segmentation .

5 Feature Engineering

The next logical steps was to fetch meaningful features from the segmented and transformed audio signal.

As mentioned before, audio signals can be transformed to time domain, frequency domain (with Fourier) and time-frequency domain (a combination of the two above, which allows less information to be lost). First we will overview the time domain features of an audio file. We can represent an audio by plotting the amplitude vs time. We will plot the amplitude feature for different genres and analyze if there are differences.

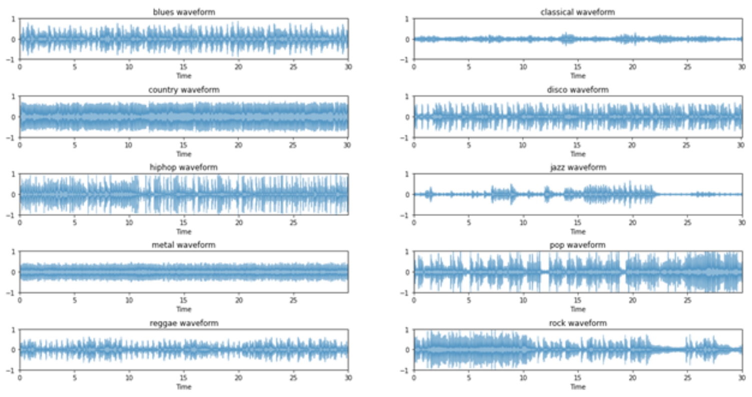


Figure 4. Amplitude feature for different genres.

As it can be seen, although for some genres the curves are sufficiently differentiable, for some others this task becomes more challenging. For example, disco, pop and hip hop share a common structure, high peaks, which correspond to drums. This feature can help when considering the instruments and/or voices separately, since the waveform of each one of them is different, but when analyzing a song where different instruments and voices are mixed this feature is no longer beneficial.

Also, this type of audio feature extraction is that it is sensitive to outliers. So we look to other types of features that can be more representative.

We explored following features from the transformed audio signal,

- Mel-spectrograms (MFC)
- Chroma features
- STFT features
- Mel-frequency cepstrum (MFCC'S)

5.1 Chroma features

Chroma features represent the twelve semitones (or Chroma) versus time. The twelve semitones, also known as pitch classes, are C, C#, D, D#, E, F, F#, G, G#, A, A#, B. In simple words, it contains information about the pitch of the audio signal vs time and divides the pitch into twelve categories When we plot this feature we will observe 12 different boxes stacked on top of each other for each period of time, these boxes represent the pitches. The contribution of each semitone class is represented by the color intensity.

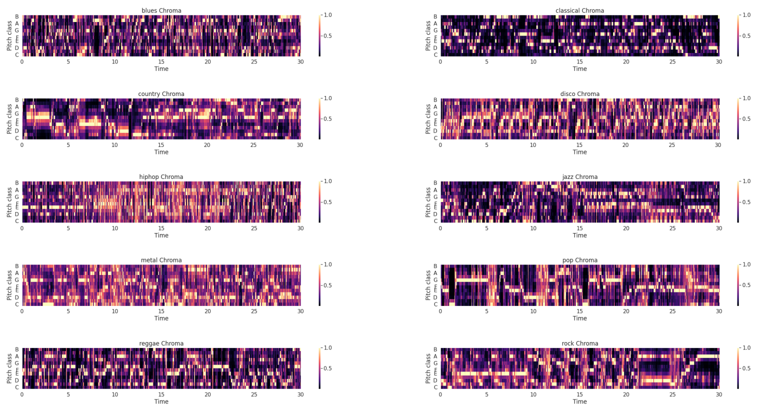


Figure 5. Chroma for one sample per genre .

Chroma features have turned out to be a powerful mid-level feature representation in content-based audio retrieval such as cover song identification. However, pop and commercial music share pitches, therefore, leading to ambiguity.

5.2 Short-time Fourier transform (STFT)

Fourier transforms converts the audio signals from time domain to frequency domain. It allows us to decompose the signal into individual frequencies it's made of and the corresponding amplitude of those frequency levels. Short-time Fourier transform (STFT) is a sequence of Fourier transforms of a time windowed signal. It allows us to represent the spectrum of the audio signals as they vary over time. STFT empowers us to discover sensitive information related to frequency in a localized time domain and it gives very useful insights when we are dealing with non-periodic signals. It converts the signal such that we know the amplitude of the given frequency at a given time.

5.3 Mel Spectrograms and Mel frequency cepstral coefficients (MFCC) Features

The representation of an audio signal frequencies vs time is called spectrogram. Mel's spectrogram is simply a spectrogram of an audio signal on Mel's scale. The Mel's transformation is a non-linear transformation and it scales the frequencies on a scale which approximates the human perception of audio extremely well in comparison to the untransformed frequency bands. Mel's spectrograms comprises of 32-64 frequency bands. MFFC features are derived from the Cepstral representation of an audio clip. Cepstral representation is derived by taking the log of Mel's frequency followed by a Discrete Cosine Transform. It is useful for investigating periodic trends in frequency spectrum. MFCC compresses the bands of Mel's Frequency to 12-13 coefficients which perform extremely well in music classification.

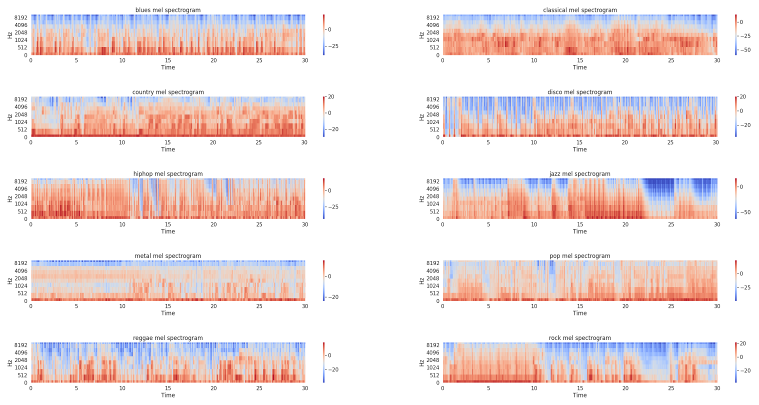


Figure 6. Mel spectrograms for one sample per genre .

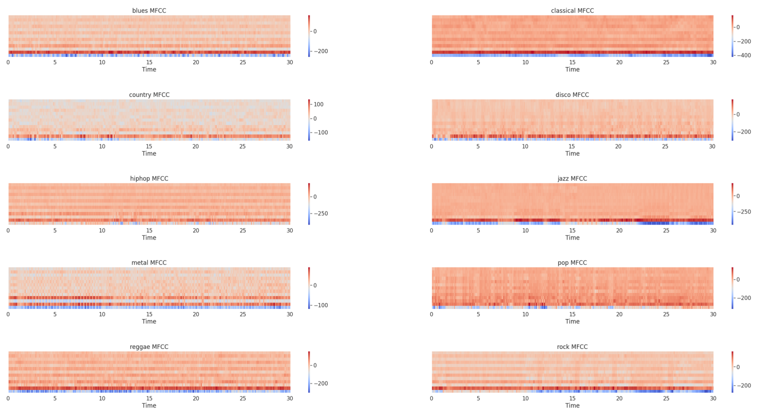


Figure 7. MFCC for one sample per genre .

MFCC features are very robust to the presence of additive noise and enables the algorithm to get rid of those features and frequency bands which adversely affect the classification of signal. In simple words, MFCC is a transformation of STFT on a Mel's scale. Below is a flow chart which describes the journey of an audio signal to MFCC features.

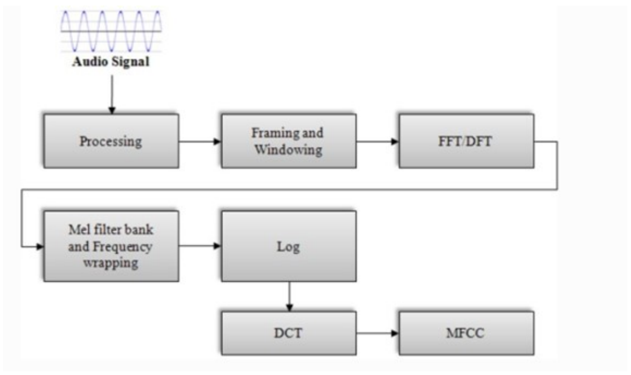


Figure 8. Process from audio signal to MFCC .

5.4 Fetching STFT, MFCC and Mel's spectrogram from Audio signals

Feature extraction forms the foundation of machine learning problem. The first challenge was to fetch the right features from the data. After extensive research, we decided to go with STFT, MFCC and Mel's spectrograms to be used in model building. The intuition was that STFT and MFCC features can prove useful for shallow learning and some deep learning models and spectrograms can be experimented with CNN and its variants. We used Librosa python package to extract STFT, MFCC and Mel's spectrograms from the segmented audio clips. The features were saved in different numpy arrays and the reshaped depending on whether they were being input in classical models or deep learning models.

6 Model building

6.1 Training, validation and test split and label transformation

After feature extraction, the next important step was to transform the labels using one hot encoding and reconstruct them to utilize them in the context of multi-class classification problems. As far as the division between training, validation and testing goes, this was the logical breakdown we came up with

Training – 70%
Validation – 20%
Testing – 10%

Figure 9. Data split: train, validation and test.

We decided to approach this problem from through classical models and deep learning models both. The intent was to see that how popular shallow learning models fare in comparison various deep learning models.

6.2 Hyperparameter Tuning

There are two different approaches of hyperparameter tuning. • Random • Bayesian

We tried Random approach of hyperparameter tuning for shallow learning algorithms but didn't see any significant improvement in results. We didn't try hyperparameter tuning with deep learning networks since the training time of models was roughly 7-10 hours.

6.3 Shallow learning approach

The input data had following characteristics

- **Input features** – MFCC feature
- **Audio Segments per clip** – 5
- **Number of samples in one FFT** – 2048
- **Sampling rate** – 22050
- **Hop length** - 512

MFCC features were chosen because they looked most promising and are the closest approximation to human auditory perception. For shallow learning, we chose to go with these three classifiers.

6.3.1 Support Vector Classifier (SVM)

The support vector classifiers are discriminative classifiers which aim to create the best decision boundary that can segregate the n-dimensional space into different classes depending upon the input set of attributes. The decision boundary is referred to as hyperplane. SVM uses extreme points also called as support vectors to construct the hyperplane.

SVMs are traditionally designed for binary classifications but multi-class classification can be obtained by using one versus rest classification approach which splits the dataset into multiple binary classification problems. Binary classifications are made using SVM and the predictions are made using the model which is most confident. In this approach we train C binary classifiers, where the data from class c is treated as positive and the data from other classes is treated as negative.

When the data is linear then the hyperplane is also a linear one, but for non-linear data we can apply the kernel trick to find the optimal decision boundary. Kernel basically transforms the non-linear data into a high dimensional space to find a hyperplane and then maps the data back to original dimension. Since the audio data is a very high dimensional one, it wouldn't have been wise to go with a linear boundary. Rather, what we did was that we used a popular kernel RBF (Radial Basis Function). If a and b are two feature vectors in some input space then RBF maps these features into a new space by following transformation

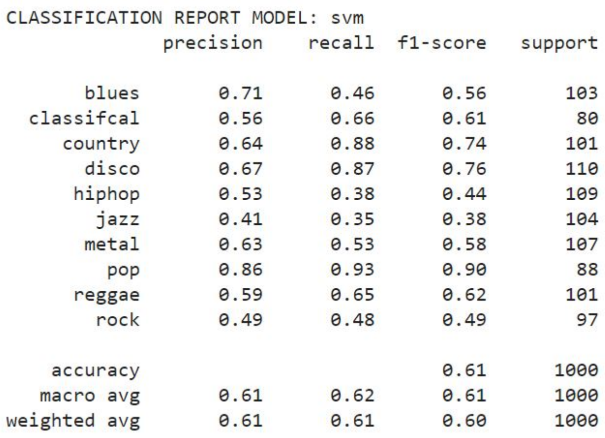
$$K(a,b) = exp(\frac{||a-b||^2}{2\sigma^2})$$

Where $||a-b||^2$ is the squared Euclidean distance between two feature vectors and σ is a free parameter.

Hyperparameters:
Kernel: RBF
Degree: 3
Gamma: scale
Class weight: None

Decision function shape: ovr
Tol: 1e-3

Results The results for the SVM model are displayed in Figure 13

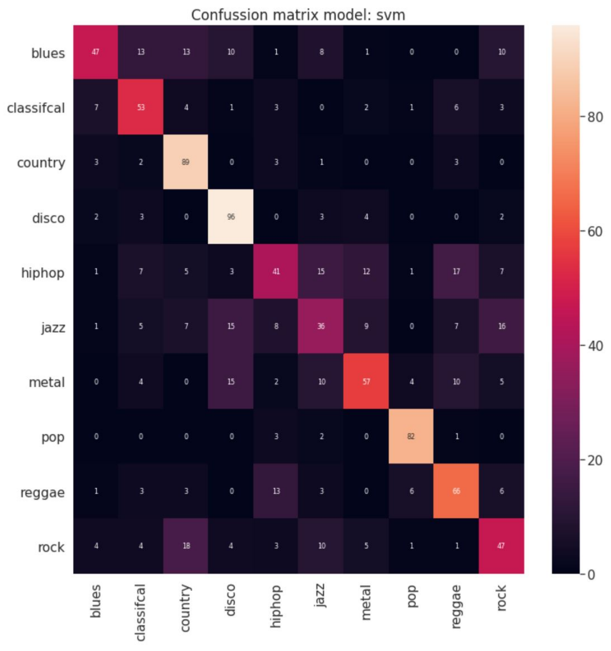


```
CLASSIFICATION REPORT MODEL: svm
              precision    recall  f1-score   support

       blues       0.71      0.46      0.56       103
   classifcal       0.56      0.66      0.61        80
     country       0.64      0.88      0.74       101
       disco       0.67      0.87      0.76       110
      hiphop       0.53      0.38      0.44       109
        jazz       0.41      0.35      0.38       104
       metal       0.63      0.53      0.58       107
         pop       0.86      0.93      0.90        88
      reggae       0.59      0.65      0.62       101
        rock       0.49      0.48      0.49        97

    accuracy                           0.61      1000
   macro avg       0.61      0.62      0.61      1000
weighted avg       0.61      0.61      0.60      1000
```

Figure 10. SVM results report.



	blues	classifcal	country	disco	hiphop	jazz	metal	pop	reggae	rock
blues	47	13	13	10	1	8	1	0	0	10
classifcal	7	53	4	1	3	0	2	1	6	3
country	3	2	89	0	3	1	0	0	3	0
disco	2	3	0	96	0	3	4	0	0	2
hiphop	1	7	5	3	41	15	12	1	17	7
jazz	1	5	7	15	8	36	9	0	7	16
metal	0	4	0	15	2	10	57	4	10	5
pop	0	0	0	0	3	2	0	82	1	0
reggae	1	3	3	0	13	3	0	6	66	6
rock	4	4	18	4	3	10	5	1	1	47

Figure 11. SVM Confussion Matrix.

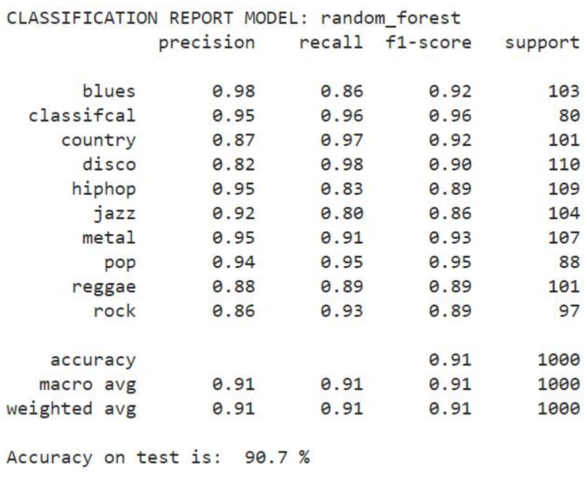
6.3.2 Random Forest Classifier

Random forest is a non-parametric ensemble learning method for classification and it operates by constructing a number of decision trees while training. It outputs the class which is the mode of the classes of all decision trees. Simple decision trees are weak learners as they tend to overfit i.e. low bias and high variance. Random forest overcome this challenge by creating a large number of trees on subset of input data and making models more generalizable.

Since they are one of the most popular classifiers for a variety of classification tasks, they were our second choice for music genre classification. Default hyperparameters were used to train these models.

Hyperparameters:
N estimators: 100
Criterion: gini
Max depth: none
Min samples split: 2
Max features: auto
Min impurity decrease: 0.0
Bootstrap: True
Class weight: none
Ccp alpha: none

Results The results for the Random Forest Classifier model are displayed in Figure 12



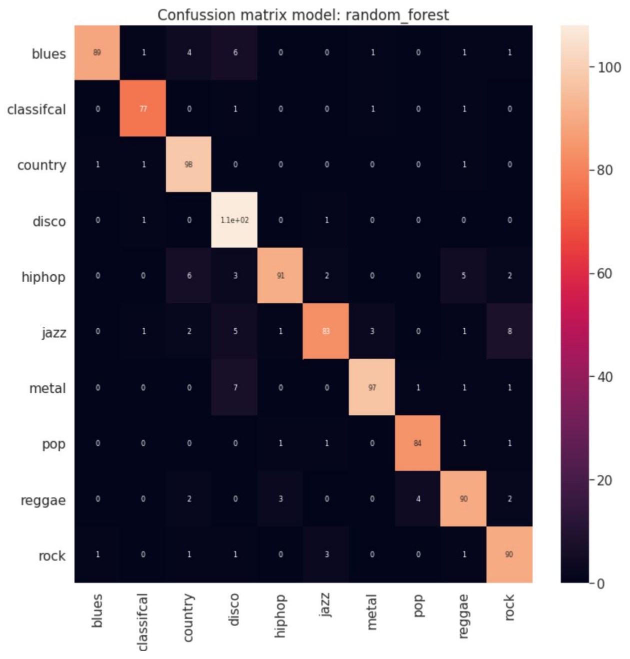
```
CLASSIFICATION REPORT MODEL: random_forest
              precision    recall  f1-score   support

       blues       0.98      0.86      0.92       103
   classifcal      0.95      0.96      0.96        80
     country       0.87      0.97      0.92       101
       disco       0.82      0.98      0.90       110
      hiphop       0.95      0.83      0.89       109
        jazz       0.92      0.80      0.86       104
       metal       0.95      0.91      0.93       107
         pop       0.94      0.95      0.95        88
      reggae       0.88      0.89      0.89       101
        rock       0.86      0.93      0.89        97

    accuracy                           0.91      1000
   macro avg       0.91      0.91      0.91      1000
weighted avg       0.91      0.91      0.91      1000

Accuracy on test is:  90.7 %
```

Figure 12. Random Forest results report.



	blues	classifcal	country	disco	hiphop	jazz	metal	pop	reggae	rock
blues	89	1	4	6	0	0	1	0	1	1
classifcal	0	77	0	1	0	0	1	0	1	0
country	1	1	98	0	0	0	0	0	1	0
disco	0	1	0	1.1e+02	0	1	0	0	0	0
hiphop	0	0	6	3	91	2	0	0	5	2
jazz	0	1	2	5	1	83	3	0	1	8
metal	0	0	0	7	0	0	97	1	1	1
pop	0	0	0	0	1	1	0	84	1	1
reggae	0	0	2	0	3	0	0	4	90	2
rock	1	0	1	1	0	3	0	0	1	90

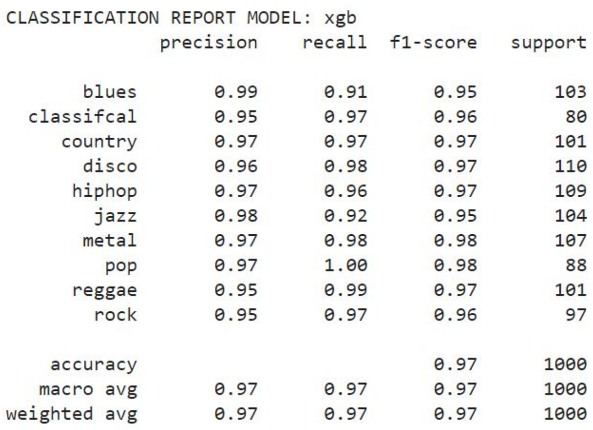
Figure 13. Random Forest Confussion Matrix.

6.3.3 Extreme Gradient Boosting (XGBoost)

With huge popularity amongst all the classification algorithms XGBoost was a natural choice. When we studied the literature, we found this technique to be extremely promising. Boosting is an ensemble learning technique which fits multiple models to the data. XGBoost works on the phenomenon of Gradient Boosting. It starts by fitting an initial model to the data. The second model is built with the focus to on accurately predicting the cases where first model performs poorly. The process is repeated many times and the combination of multiple models is expected to perform better than a standalone model. Each successive model attempts to correct the shortcomings of combined boosted ensemble of previous models. In technical terms, it builds a series of decision trees with a pre-defined depth. The trees are not built independently rather they are built in such a way that each tree assigns more weightage to the misclassified samples of the previous tree and thereby lays more focus to predict those samples correctly. Each tree tries to predict the residuals of the previous tree in case of regression or log odds in case of classification and is scaled by a learning rate eta. Each tree takes a small step in the direction of minimizing the cost function. Moreover, XGBoost also has in-built pruning of the trees which is configurable and it can help to avoid overfitting. XGBoost cost function is also regularized which again helps us to account for model complexity and prevent overfitting. The training is additive as it depends on the additive output of multiple models. The output of all the trees are added and scaled by the learning rate to make the final prediction.

Hyperparameters:
Eta: 0.3
Gamma: 0
Max depth: 6
Min child weight: 1
Sampling method: Uniform
Lambda: 1

Results The results for the XGBoost model are displayed in Figure 14



```
CLASSIFICATION REPORT MODEL: xgb
              precision    recall  f1-score   support

       blues       0.99      0.91      0.95       103
  classifcal       0.95      0.97      0.96        80
     country       0.97      0.97      0.97       101
       disco       0.96      0.98      0.97       110
      hiphop       0.97      0.96      0.97       109
        jazz       0.98      0.92      0.95       104
       metal       0.97      0.98      0.98       107
         pop       0.97      1.00      0.98        88
      reggae       0.95      0.99      0.97       101
        rock       0.95      0.97      0.96        97

    accuracy                           0.97      1000
   macro avg       0.97      0.97      0.97      1000
weighted avg       0.97      0.97      0.97      1000
```

Figure 14. XGB results report.

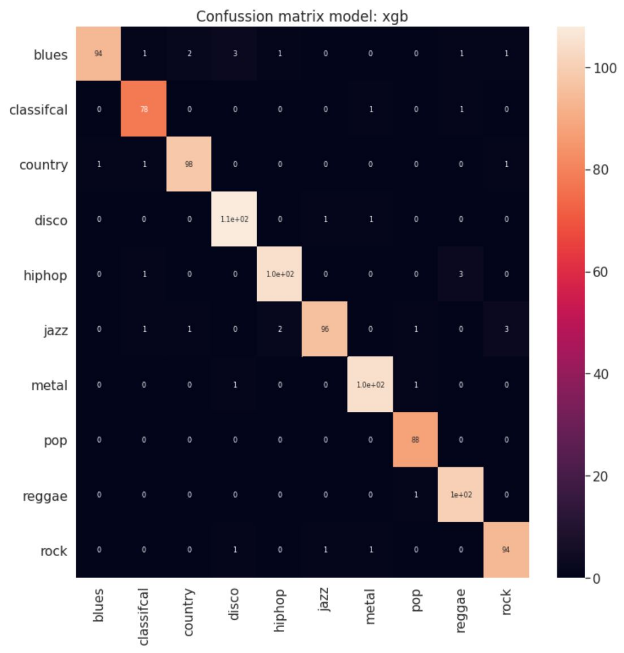


Figure 15. XGB Confussion Matrix.

6.4 Deep Learning approach

Deep learning networks have proved extremely useful non-linear classification problems recently. Since the deep learning works extremely well with big and high dimensional datasets, with this motivation, we tried different deep learning networks to classify GTZAN dataset.

The plan was to start with a fully connected neural network as a baseline model and modify the network by incorporating CNN, LSTM and different CNN architectures.

The input data had the same characteristics with a little change in the choice of features for few architectures,

- Audio Segments per clip – 5
- Number of samples in one FFT – 2048
- Sampling rate – 22050
- Hop length - 512

The network architecture along with the input will be discussed when we discuss each model separately.

6.4.1 Fully Connected Neural Networks (FCNN)

The Fully Connected Neural network was used with MFCC input features. The architecture of the network can be seen in Figure 17

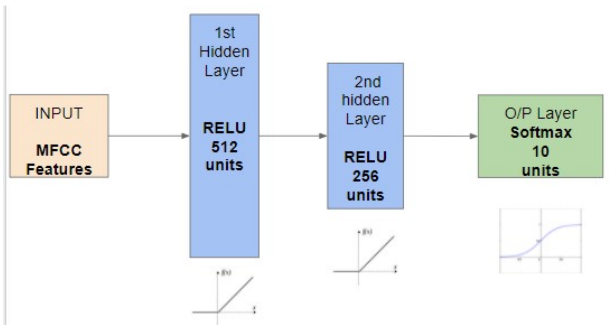
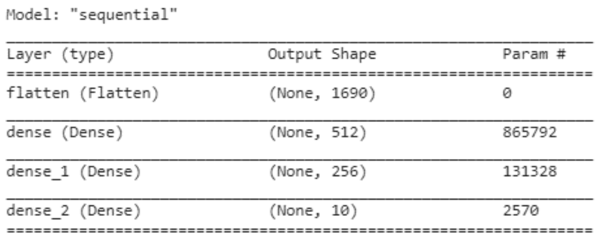


Figure 16. FCNN Architecture.

Hyperparameters:
Hidden Layer Activation: RELU
Output Layer Activation: Softmax
Loss function: Sparse Categorical Crossentropy
Epoch: 100
Batch size: 32
Optimizer: Adam
Learning Rate: 0.0001



```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten (Flatten)            (None, 1690)              0
_________________________________________________________________
dense (Dense)                (None, 512)               865792
_________________________________________________________________
dense_1 (Dense)              (None, 256)               131328
_________________________________________________________________
dense_2 (Dense)              (None, 10)                2570
=================================================================
```

Figure 17. FCNN Architecture.

Results The results for the FCNN model are displayed in Figure 18. As expected, the results of the model were not impressive.

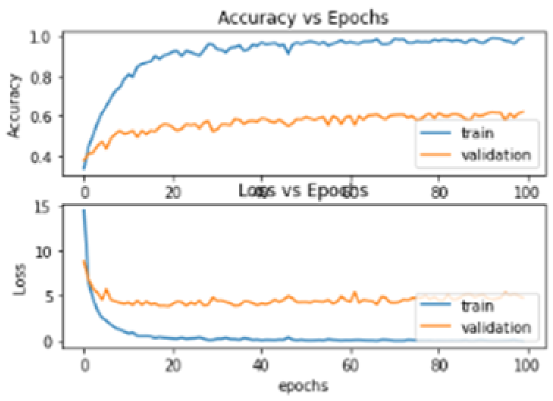


Figure 18. FCNN Results.

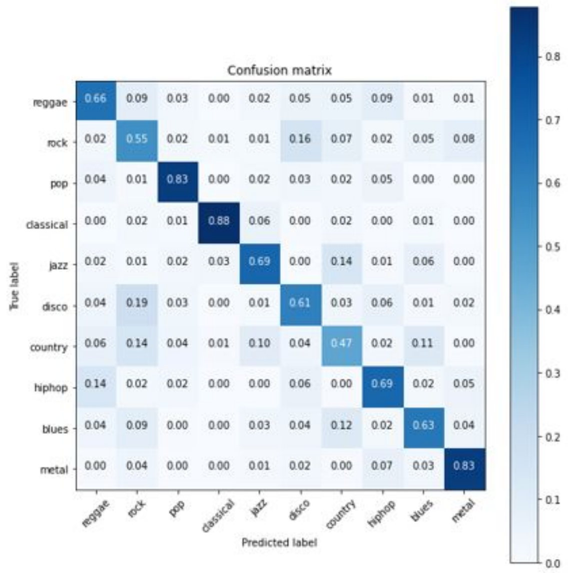


Figure 19. FCNN Confussion Matrix.

6.4.2 CNN + FCNN

The next step was to try a very simple CNN architecture for feature extraction before inputting the data in FCNN. The type of input used with CNN was still MFCC features. The network had following architecture

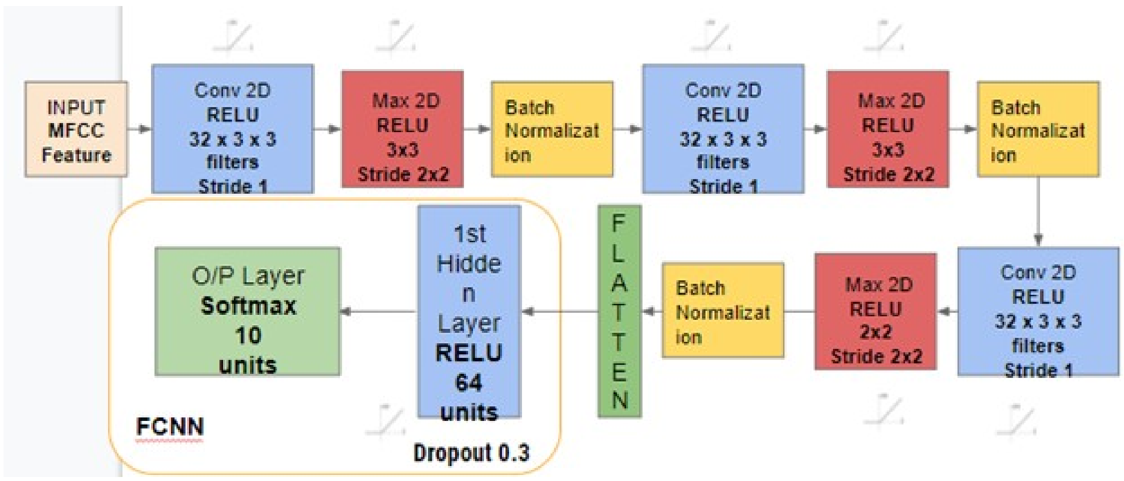
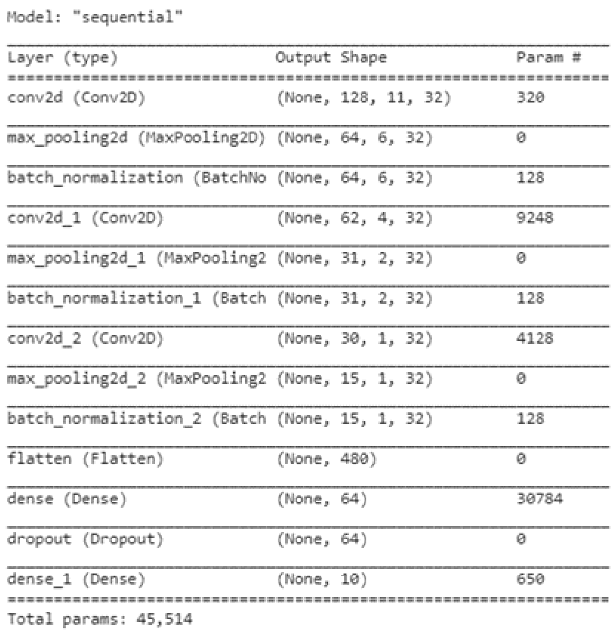

INPUT MFCC Feature
Conv 2D RELU 32 x 3 x 3 filters Stride 1
Max 2D RELU 3x3 Stride 2x2
Batch Normalizat ion
Conv 2D RELU 32 x 3 x 3 filters Stride 1
Max 2D RELU 3x3 Stride 2x2
Batch Normalizat ion
Conv 2D RELU 32 x 3 x 3 filters Stride 1
Max 2D RELU 2x2 Stride 2x2
Batch Normalizat ion
FLATTEN
1st Hidden Layer RELU 64 units
Dropout 0.3
O/P Layer Softmax 10 units
FCNN

Figure 20. FCNN + CNN Architecture.

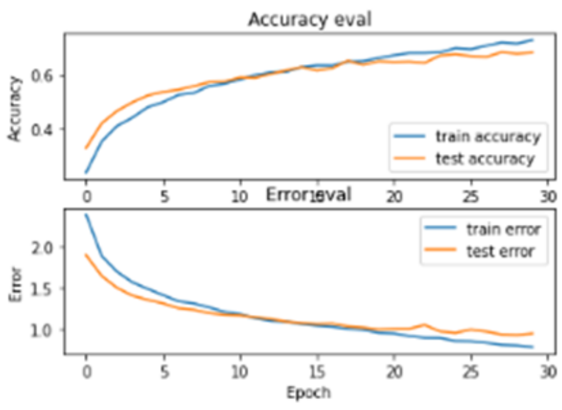


```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d (Conv2D)              (None, 128, 11, 32)       320       
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 64, 6, 32)         0         
_________________________________________________________________
batch_normalization (BatchNo (None, 64, 6, 32)         128       
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 62, 4, 32)         9248      
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 31, 2, 32)         0         
_________________________________________________________________
batch_normalization_1 (Batch (None, 31, 2, 32)         128       
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 30, 1, 32)         4128      
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 15, 1, 32)         0         
_________________________________________________________________
batch_normalization_2 (Batch (None, 15, 1, 32)         128       
_________________________________________________________________
flatten (Flatten)            (None, 480)               0         
_________________________________________________________________
dense (Dense)                (None, 64)                30784     
_________________________________________________________________
dropout (Dropout)            (None, 64)                0         
_________________________________________________________________
dense_1 (Dense)              (None, 10)                650       
=================================================================
Total params: 45,514
```

Figure 21. FCNN + CNN Model.

Hyperparameters:
Hidden Layer Activation: RELU
Output Layer Activation: Softmax
Loss function: Sparse Categorical Crossentropy
Epoch: 30
Batch size: 32
Optimizer: Adam
Learning Rate: 0.0001

Results The results for the FCNN combined with CNN model are displayed in Figure 22. The results had a noticeable improvement compared to simple FCNN model and accuracy improved from 63 % to 67 % on test set.



```
79/79 - 1s - loss: 0.9213 - accuracy: 0.6707
```

Figure 22. FCNN + CNN Results.

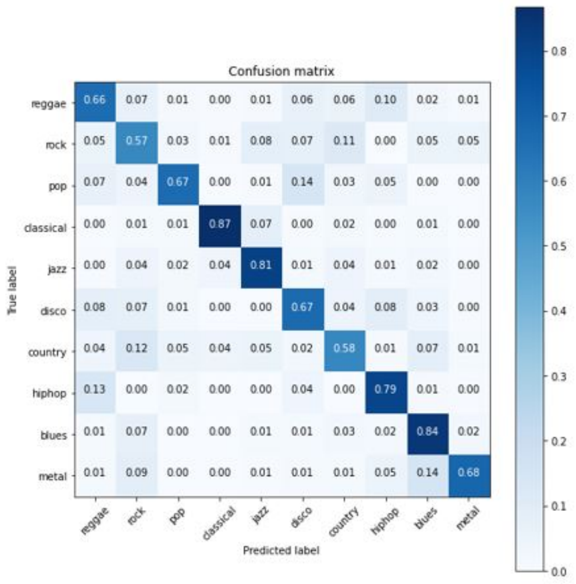


Figure 23. FCNN + CNN Architecture.

6.4.3 Long Short Term Memory (LSTM)

LSTM is very good with recognizing sequences. As the song is nothing but a sequence of different harmonies and tones, the next logical step was to try with LSTM. LSTM keeps a track of time based sequences in a song. The model was again trained with MFCC features as input. The architecture can be seen in Figure 25.

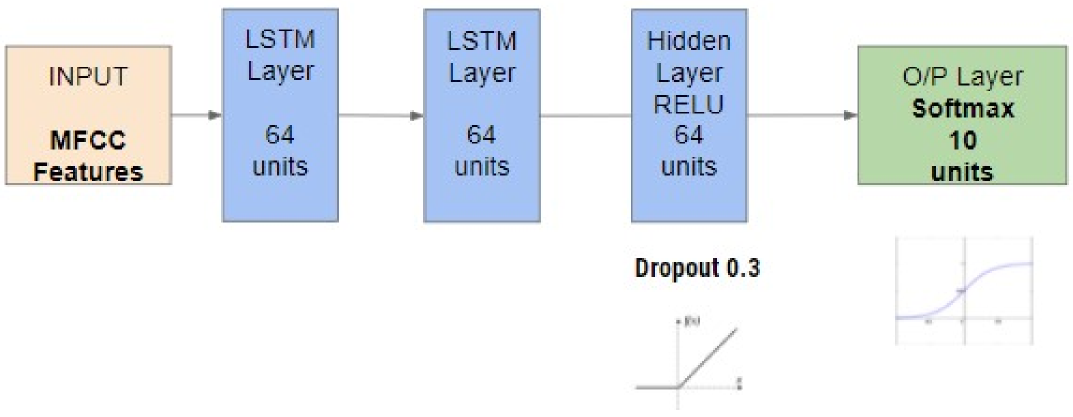
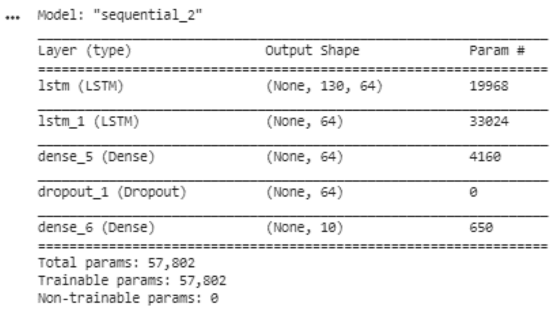


Figure 24. LSTM Model.

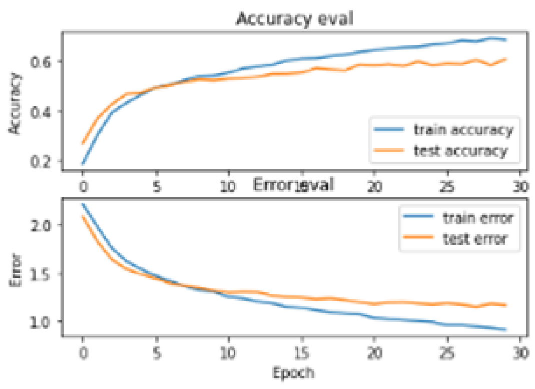


```
... Model: "sequential_2"
    _________________________________________________________________
    Layer (type)                 Output Shape              Param #
    =================================================================
    lstm (LSTM)                  (None, 130, 64)           19968
    _________________________________________________________________
    lstm_1 (LSTM)                (None, 64)                33024
    _________________________________________________________________
    dense_5 (Dense)              (None, 64)                4160
    _________________________________________________________________
    dropout_1 (Dropout)          (None, 64)                0
    _________________________________________________________________
    dense_6 (Dense)              (None, 10)                650
    =================================================================
    Total params: 57,802
    Trainable params: 57,802
    Non-trainable params: 0
```

Figure 25. LSTM Architecture.

Hyperparameters:
Hidden Layer Activation: RELU
Output Layer Activation: Softmax
Loss function: Sparse Categorical Crossentropy
Epoch: 30
Batch size: 32
Optimizer: Adam
Learning Rate: 0.0001

Results The results for the LSTM are displayed in Figure 26. LSTM alone performed very poor with the classification task



```
79/79 - 2s - loss: 1.1905 - accuracy: 0.5958

Test accuracy: 0.5958383083343506
```

Figure 26. LSTM Results.

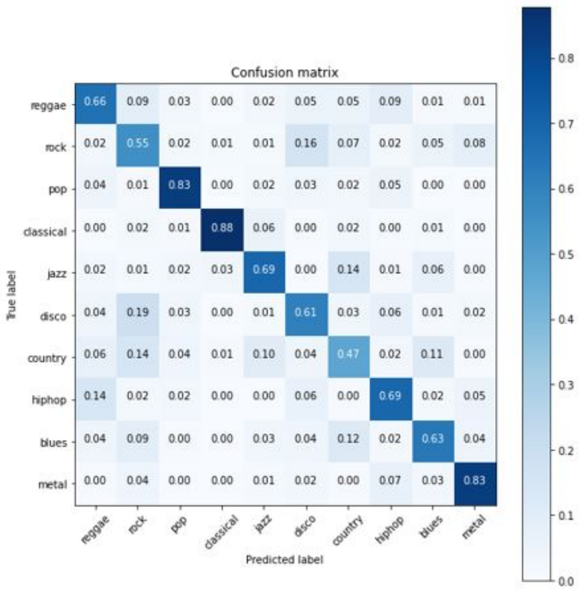


Figure 27. LSTM Confussion Matrix.

6.4.4 C-RNN

Recently it has become increasingly popular to combine CNN with RNN, to process audio signal with the inclusion of sequential information to the model. In convolutional recurrent networks, CNN is used to extract useful features while the RNN part is used to take care of the temporal effect and features of the signal. The input used for C-RNN of our model was a little different compared to other models and we decided to experiment with STFT features. The rest of the input configurations were the same. In Figure 29 we can observe a snapshot of network architecture

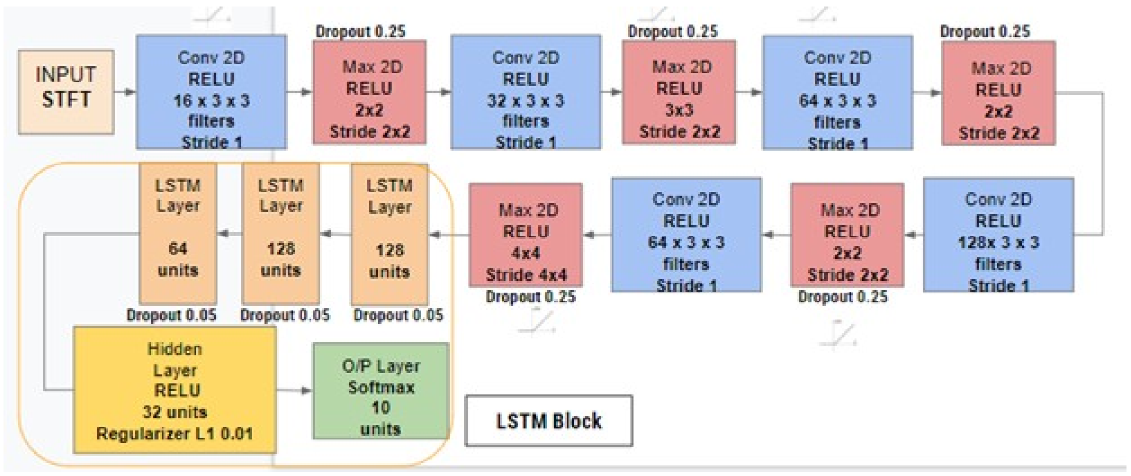
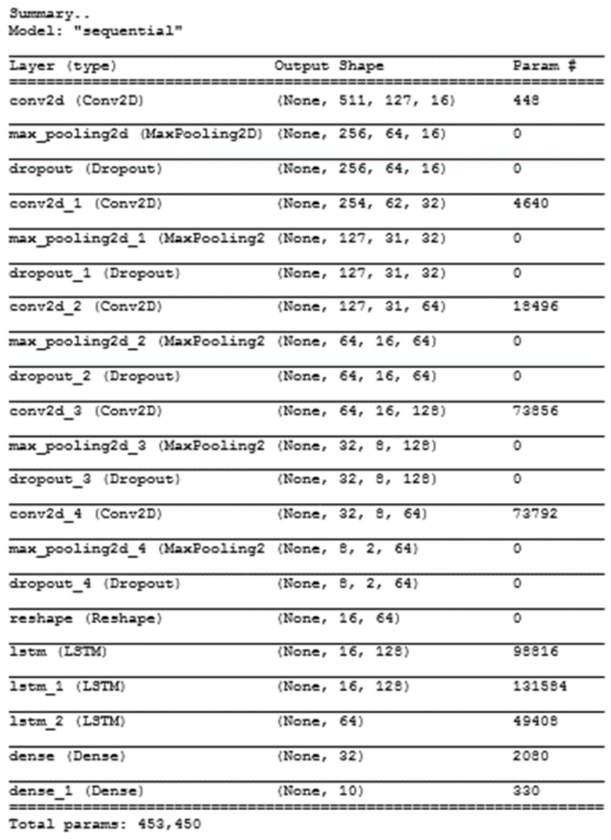

INPUT STFT
Conv 2D RELU 16 x 3 x 3 filters Stride 1
Dropout 0.25
Max 2D RELU 2x2 Stride 2x2
Conv 2D RELU 32 x 3 x 3 filters Stride 1
Dropout 0.25
Max 2D RELU 3x3 Stride 2x2
Conv 2D RELU 64 x 3 x 3 filters Stride 1
Dropout 0.25
Max 2D RELU 2x2 Stride 2x2
Conv 2D RELU 128x 3 x 3 filters Stride 1
Max 2D RELU 2x2 Stride 2x2
Dropout 0.25
Conv 2D RELU 64 x 3 x 3 filters Stride 1
Max 2D RELU 4x4 Stride 4x4
Dropout 0.25
LSTM Layer 128 units
Dropout 0.05
LSTM Layer 128 units
Dropout 0.05
LSTM Layer 64 units
Dropout 0.05
Hidden Layer RELU 32 units Regularizer L1 0.01
O/P Layer Softmax 10 units
LSTM Block

Figure 28. CRNN Architecture.



```
Summary..
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 511, 127, 16)      448
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 256, 64, 16)       0
_________________________________________________________________
dropout (Dropout)            (None, 256, 64, 16)       0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 254, 62, 32)       4640
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 127, 31, 32)       0
_________________________________________________________________
dropout_1 (Dropout)          (None, 127, 31, 32)       0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 127, 31, 64)       18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 64, 16, 64)        0
_________________________________________________________________
dropout_2 (Dropout)          (None, 64, 16, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 64, 16, 128)       73856
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 32, 8, 128)        0
_________________________________________________________________
dropout_3 (Dropout)          (None, 32, 8, 128)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 32, 8, 64)         73792
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 8, 2, 64)          0
_________________________________________________________________
dropout_4 (Dropout)          (None, 8, 2, 64)          0
_________________________________________________________________
reshape (Reshape)            (None, 16, 64)            0
_________________________________________________________________
lstm (LSTM)                  (None, 16, 128)           98816
_________________________________________________________________
lstm_1 (LSTM)                (None, 16, 128)           131584
_________________________________________________________________
lstm_2 (LSTM)                (None, 64)                49408
_________________________________________________________________
dense (Dense)                (None, 32)                2080
_________________________________________________________________
dense_1 (Dense)              (None, 10)                330
=================================================================
Total params: 453,450
```

Figure 29. CRNN Model.

Hyperparameters:
Hidden Layer Activation: RELU
Output Layer Activation: Softmax
Loss function: Sparse Categorical Crossentropy
Epoch: 70
Batch size: 128
Optimizer: Adam

Results The results for the CRNN are displayed in Figure 30. The results of CNN LSTM were the most promising amongst all different neural networks that we have tried up to this point.

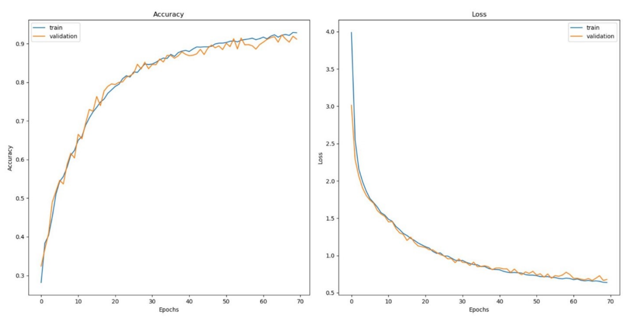
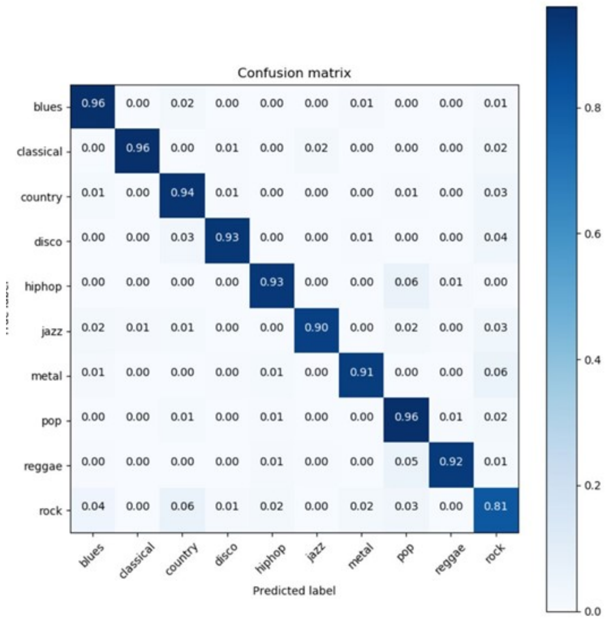


Figure 30. CRNN Results.



	blues	classical	country	disco	hiphop	jazz	metal	pop	reggae	rock
blues	0.96	0.00	0.02	0.00	0.00	0.00	0.01	0.00	0.00	0.01
classical	0.00	0.96	0.00	0.01	0.00	0.02	0.00	0.00	0.00	0.02
country	0.01	0.00	0.94	0.01	0.00	0.00	0.00	0.01	0.00	0.03
disco	0.00	0.00	0.03	0.93	0.00	0.00	0.01	0.00	0.00	0.04
hiphop	0.00	0.00	0.00	0.00	0.93	0.00	0.00	0.06	0.01	0.00
jazz	0.02	0.01	0.01	0.00	0.00	0.90	0.00	0.02	0.00	0.03
metal	0.01	0.00	0.00	0.00	0.01	0.00	0.91	0.00	0.00	0.06
pop	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.96	0.01	0.02
reggae	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.05	0.92	0.01
rock	0.04	0.00	0.06	0.01	0.02	0.00	0.02	0.03	0.00	0.81

Figure 31. CRNN Confussion Matrix.

6.4.5 CNN VGG 16 with FCNN

The CNN VGG 16 architecture was implemented along with a simple FCNN model for this step. CNN VGG 16 is an extremely popular architecture and works extremely well with images. The input used for this step was mel's spectrogram. The output of VGG16 was fed to a one layer neural network having 32 hidden units with Relu activation. The output layer of FCNN had softmax activation.

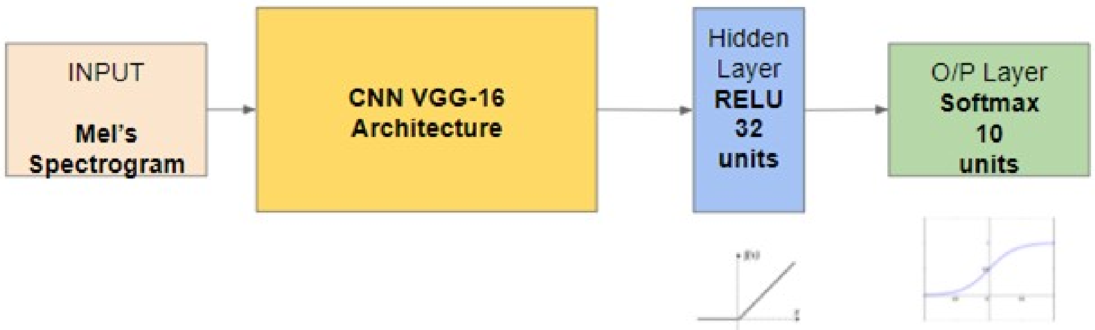


Figure 32. CNN VGG 16 with FCNN Architectures.

Hyperparameters:
Hidden Layer Activation: RELU
Output Layer Activation: Softmax
Loss function: Sparse Categorical Crossentropy
Epoch: 20
Batch size: 100
Optimizer: Adam
Learning Rate: 0.0001

Results The results for the CNN VGG 16 wih FCNN are displayed in Figure 33.

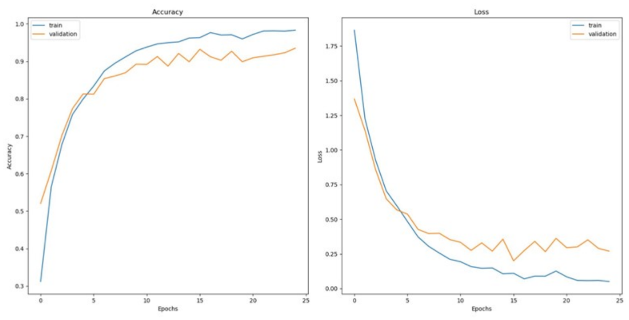


Figure 33. CNN VGG 16 with FCNN Results.

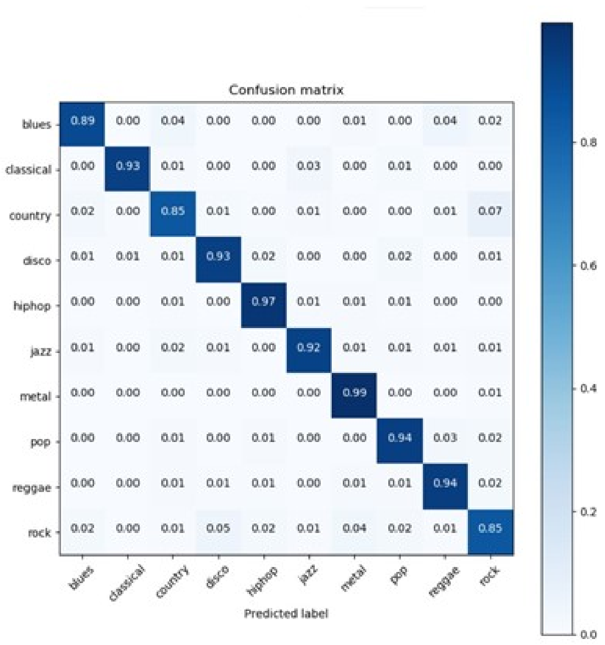


Figure 34. CNN VGG 16 with FCNN Confussion matrix.

7 Final Results

Overall, XGBoost classifier stood out amongst the rest with 97% test set accuracy. C-RNN performed the best amongst different deep learning models with 93 % accuracy.

Table 1: Final Results

Results			
Algorithm	Input Features	Accuracy	F1-score
SVM	MFCC	60 %	60 %
Random Forest	MFCC	91%	91%
XGBoost	**MFCC**	**97 %**	**97 %**
FCNN	MFCC	62 %	61 %
FCNN + CNN	MFCC	71 %	70 %
LSTM	MFCC	62 %	61 %
C-RNN	**STFT**	**93 %**	**93 %**
CNN (VGG16) + FCNN	Mel Spectrogram	92 %	92 %

The developed project present the comparison between different architectures, both shallow models and deep models, when trained with the same dataset, GTZAN dataset. Overall, the XGBoost classifier with MFCC features shows a best performance with 96.6% accuracy in the test set, while the next best model, among the deep learning model, was CRNN with Mel spectrogram features, with a 92.2By classifying genres each 10 seconds fragments, instead of 30 seconds, we can comprehend of how the model perceives each fragment of the song. Moreover, we are able to conclude how not all the segments in a song are representative of its own genre. Among the different features, we find the MFFC features represent good characteristic to perform this task. However, the data preprocessing is closely linked to the architecture chosen. Moreover, we conclude how shallow models can exceed deep models, which tells us that not always more complex or deep models are always the best option and that other many factor have to be taken into account when selecting the final model.

8 Future Work

One interesting line to continue this work is to use more complex genres and evaluate how the models behave in this cases. The genres we have worked with are quite well separated, even for human point of view, however when working with different genres such as indie, punk, techno, trance, ska, soul, house and so on, this can be a new challenging task as the difference becomes less noticeable. However, it is the next logical step as the music is evolving through the creation of new genres. Another interesting line to continue this work will be to create a comparative with different segment fragmentation and so, being able to define which are the sections in the song that are the most representative in the song. One step further, will be to classify the entire songs, but not just as one genre but as multi labeled genres, and catalogue them with multi tags and study how different genres can be merged in the same song.

References

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[5] J. R. Castillo and M. J. Flores. Web-based music genre classification for timeline song visualization and analysis. *IEEE Access*, 9:18801–18816, 2021. doi:10.1109/ACCESS.2021.3053864.

[6] Chi Zhang, Yue Zhang, and Chen Chen. Songnet: Real-time music classification. *Standford*, 2018.