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Play Music to Tune up your Mood

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Abstract: Music is a powerful language to express our feelings and in many cases is used as a therapy to deal with tough moments in our lives. Emotions and moods can be easily reflected in music, when we are doing sports, we tend to listen to energetic music, similarly when we are anxious or tired a nice, relaxed song can help us to calm down. That's why I have tried to figure out how classification models could help to determinate which is the mood of a specific track. So, this will help people and students who are more towards stress and suicidal thoughts and can help to reduce andcalm them using a Multi-Class Neural Network for Classification and a cool Dataset provided from Spotify.

Index Terms- *Machine learning, dataset, Exploratory data analysis*

I. INTRODUCTION

Music therapy is the use of music to address the physical, emotional, cognitive, and social needs of a group or individual. It involves various activities, such as

- Listening to melodies,
- Playing an instrument,
- Singing songs
- Writing songs, and
- Guided imagery.

Music therapy is appropriate for people of all ages, whether they are virtuosos or tone-deaf, struggling with illnesses or healthy. Music therapy touches all aspects of the mind, body, brain, and behavior. Music can provide a distraction for the mind, it can slow the rhythms of the body, and it can alter our mood, which in turn can influence behavior. [1]

Trained and certified music therapists work in a variety of healthcare and educational settings. They often work with people suffering from emotional health issues such as grief, anxiety, and depression. They also help people address rehabilitative needs after a stroke, a traumatic head injury, or with chronic conditions like Parkinson's or Alzheimer's disease. [2]

II. LITERATURE REVIEW

But due to busy life and a lot of stress due to WFH people are seeing the effect it is causing on the brain and leading to Depression and Emotion imbalance. Depression is a highly prevalent psychiatric disorder due to the negative consequences on the patient's mental health and quality of life, depression is associated with physical health problems, difficulties in workplace productivity, interpersonal problems, high mortality rates and large societal economic costs. The Global Burden of Disease report estimates the point prevalence of unipolar depressive episodes to be 1.9% for men and 3.2% for women, and the one-year prevalence has been estimated to be 5.8% for men and 9.5% for women. It is estimated that by the year 2020 if current trends for demographic and epidemiological transition continue, the burden of depression will increase to 5.7%. that the vast number in young generations.[3]

Mood

Music is commonly used to regulate emotions, but the effects may be both beneficial and harmful. People listening actively use music to enhance positive emotions and reduce negative emotions, or simply to regulate levels of arousal.

A mood is an affective state. In contrast to emotions or feelings. Moods are like to very delicate for human to control it they may be provoked or instantiated by a particular stimulus, or an event happening around

you, moods are typically described as having either a positive or negative.

People usually talk about being in a good mood or a bad mood. There are many varied factors that influence mood, and these can lead to positive or negative effects on mood. [4]

A qualitative study found that depressed individuals listened to music to express their mood more often than non-depressed individuals Thus, there is reason to assume that the emotion-regulation skills of depressed individuals could also be impaired in music-listening situations.

Figure 1: Sound Waves

So, these projects help you understand how a state of mind will help with music and how can it improve the state of mind know that emotion which are Sad, Happy, Energetic, and clam music by the mood of the person. [5]

III. METHODOLOGY

In this section we are going to discuss the flow chart of the method used to the emotion of the song that played while listening and to check what will be the state of mind when you listen to music.

I have taken Spotify as the main source of extraction of datasets because it consists of various playlist in which different mood song also can be found to see how that will improve that state of mind so started using API tool and gathered the information on all different songs. Each of the song will have a different frequency and wavelength, this how we can listen to the songs like that, and Spotify has given these details in their page

1. Acoustic: A confidence measure from 0.0 to 1.0 of whether the track is acoustic. 1.0 represents high confidence the track is acoustic.

2. Danceability: Danceability describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity. A value of 0.0 is least danceable and 1.0 is most danceable.

3. Energy: Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. For example, death metal has high energy, while a Bach prelude scores low on the scale. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy.

4. Instrument Alness: Predicts whether a track contains no vocals. “Ooh” and “aah” sounds are treated as instrumental in this context. Rap or spoken word tracks are clearly “vocal”. The closer the instrument Alness value is to 1.0, the greater likelihood the track contains no vocal content. Values above 0.5 are intended to represent instrumental tracks, but confidence is higher as the value approaches 1.0.

5. Liveness: Detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live. A value above 0.8 provides a strong likelihood that the track is live.

6. Loudness: the overall loudness of a track in decibels (dB). Loudness values are averaged across the entire track and are useful for comparing the relative loudness of tracks. Loudness is the quality of a sound that is the primary psychological correlate of physical strength (amplitude). Values typically range between -60 and 0 DB.

7. Speechiness: Speechiness detects the presence of spoken words in a track. The more exclusively speech-like the recording (e.g., talk show, audiobook, poetry), the closer to 1.0 the attribute value. Values above 0.66 describe tracks that are made entirely of spoken words. Values between

0.33 and 0.66 describe tracks that may contain both music and speech, either in sections or layered, including such cases as rap music. Values below 0.33 represent music and other non-speech-like tracks.

8. Valence: A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g., happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g., sad, depressed, angry).

9. Tempo: The overall estimated tempo of a track in beats per minute (BPM). In musical terminology, the tempo is the speed or pace of a given piece and derives directly from the average beat duration.

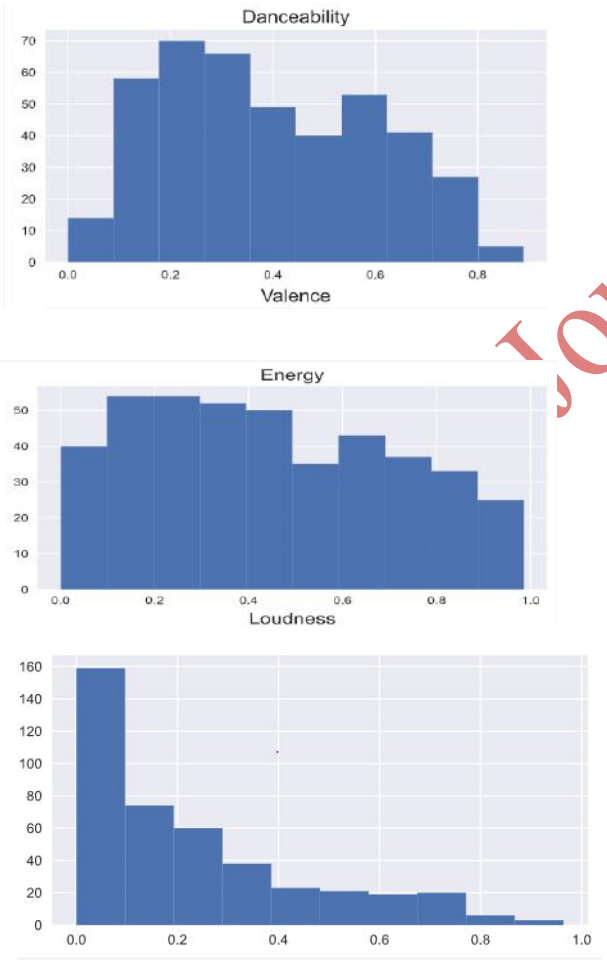
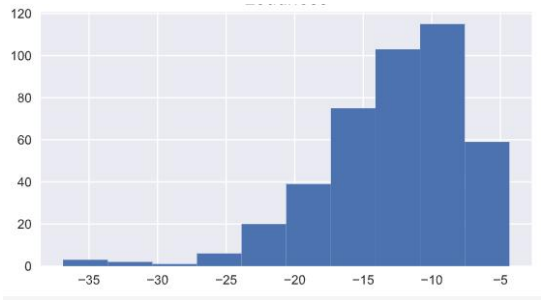


Figure 2:Distribution of waves among the songs

Spotify is the developer tool that can be accessed using your Spotify Id, using Spotify id and we will be



able to extra different albums to analyze the mood of the listener.

I am using different libraries of python to extract the data and to do Exploratory data analysis on the data. The data that I extracted are classified into 4 different datasets to label the tracks, these categories are "Energetic"," Calm", "Happy" and "Sad".

The main data have eight hundred rows and 18 columns, but for information reduction purposes I decided to use the features of Length, Danceability, Acoustic Ness, Energy,InstrumentAlness, Liveness, Valence, Loudness, Speechiness and Tempo because they have more influence to classify the tracks. I grouped the data frame by labels calculating the mean of the tracks' features. I obtained the following result:

mood	popularity	length	danceability	acousticness	energy	instrumentalness	liveness	valence	loudness	speechiness	tempo	key	time_signature
Calm	40.47	193201.170	0.408640	0.882410	0.155783	0.890175	0.117788	0.150011	-20.934005	0.040607	108.892180	5.47	3.760
Energetic	42.42	213207.345	0.538110	0.030970	0.870085	0.124303	0.234581	0.403070	-4.962845	0.076633	130.375665	5.28	3.960
Happy	47.48	222282.345	0.619370	0.109826	0.780096	0.128872	0.220174	0.503411	-6.564875	0.063018	124.692345	5.03	3.970
Sad	37.78	247506.235	0.495431	0.577908	0.399422	0.201679	0.140375	0.286996	-10.542255	0.041858	115.985005	5.56	3.835

Figure 3: Dataset classification

Doing this simple analysis, I quickly noticed that the most popular songs are Happy, Sad songs tend to have a long length, energetic songs are most fast in tempo, and Calm songs tends to be acoustic.

Building the Model:
Pre-Processing the Data:
To normalize the features, I used MinMaxScaler to scale the values between a range of [0,1] and preserving the shape of the original distribution. I also encoded the 4 labels because Neural Networks uses numerical values to train and test. Finally, I split the data by 80% for training and 20% for testing.

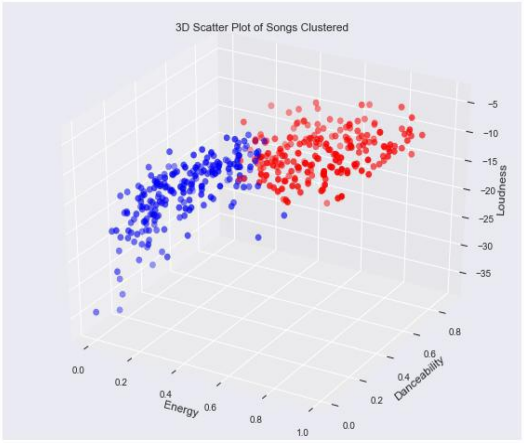


Figure 4:Clustering of song on the bases of decibels

Creating the model:
To build the model I used the library Keras, this library is designed to enable fast experimentation with Deep Neural Networks, focused on being user-friendly. My main goal is to classify tracks in the 4 categories of moods (Calm, Energetic, Happy and Sad) so my model consists of a Multi-Class Neural Network with an input of 10 Features, 1 Layer with 8 nodes, and 4 outputs with the output Layer. I also need to use a Classifier as an Estimator, in this case, the Classifier is Kera Classifier, which takes as an argument a function that I created previously with the Neural Network model defined. The activation Function corresponds to a Rectified Linear Unit (Relu), the Loss function is a

Evaluating the model:
Using K-Fold Cross Validation I evaluated the estimator using the train data. The number of splits is K=10 shuffling all the values.

```
640/640 [==============================] - 0s 30us/sample - loss: 0.5575 - acc: 0.7437
Epoch 290/300
640/640 [==============================] - 0s 45us/sample - loss: 0.5572 - acc: 0.7437
Epoch 291/300
640/640 [==============================] - 0s 39us/sample - loss: 0.5568 - acc: 0.7469
Epoch 292/300
640/640 [==============================] - 0s 47us/sample - loss: 0.5563 - acc: 0.7453
Epoch 293/300
640/640 [==============================] - 0s 44us/sample - loss: 0.5559 - acc: 0.7453
Epoch 294/300
640/640 [==============================] - 0s 45us/sample - loss: 0.5556 - acc: 0.7453
Epoch 295/300
640/640 [==============================] - 0s 34us/sample - loss: 0.5551 - acc: 0.7422
Epoch 296/300
640/640 [==============================] - 0s 33us/sample - loss: 0.5546 - acc: 0.7422
Epoch 297/300
640/640 [==============================] - 0s 30us/sample - loss: 0.5542 - acc: 0.7437
Epoch 298/300
640/640 [==============================] - 0s 31us/sample - loss: 0.5537 - acc: 0.7437
Epoch 299/300
640/640 [==============================] - 0s 36us/sample - loss: 0.5532 - acc: 0.7406
Epoch 300/300
640/640 [==============================] - 0s 33us/sample - loss: 0.5529 - acc: 0.7406
```

Figure 5: Kerns prediction

```
predict_mood('0VjIjW4GlUZAMYd2vXMi3b')
```

```
Blinding Lights by The Weeknd is a ENERGETIC song
```

Figure 6: Result

Accuracy of the Multi-Class Neural Network:
Finally, to evaluate the accuracy of the model I plotted a Confusion Matrix using Seaborn Library and Matplotlib. I also calculated the accuracy score provided by Sklearn Library.

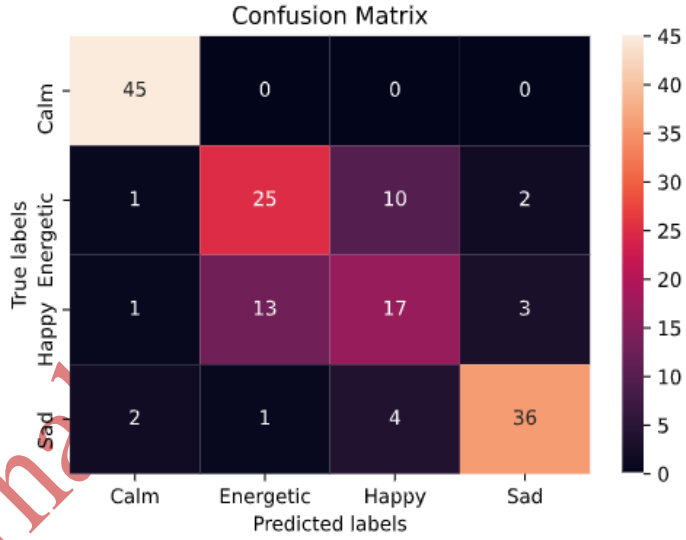


Figure 7: Correlation between emotions

With a Final Accuracy score of 76% and looking at the Confusion Matrix, I noticed my model is good at classifying Calm and Sad songsbut is having some issues dealing with Energetic and Happy songs. I could modify some parameters like the batch size, epochs, or maybe aggregate or delete some track features to train my model and thus help to improve the accuracy of the model.

CONCLUSION

The project tells us that the purpose of having mood swings and depression can be let go with music and this will help people to analyze on the songs that make their mind happier and alleviate their emotions so they can gradually improve their general mood.

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