

# Predicting a Person's Mood based on Music

“FAANG”



UNIVERSITY OF NEW HAVEN

TAGLIATELA COLLEGE OF ENGINEERING, WEST HAVEN, CT

SUBMITTED TO:

ASSISTANT PROFESSOR.

Dr. SHIVANJALI KHARE

## Table of Contents

TITLE.....	
EMAILS AND AFFILIATION OF THE AUTHORS.....	
ABSTRACT .....	
INTRODUCTION .....	
RELATED WORKS .....	
PROPOSED METHODS.....	
EXPERIMENTAL RESULTS .....	
DISCUSSION ON RESULTS .....	
CONCLUSION .....	
FUTURE WORK.....	
APPENDIX FOR LINK TO THE GITHUB REPOSITORY.....	

REFERENCES.....

PROOFREADING.....

**TITLE:**

# **Predicting a Person's Mood based on Music**

## **EMAILS AND AFFILIATION OF THE AUTHORS:**

- 1) Swetha Mamidiga ([Smami3@unh.newhaven.edu](mailto:Smami3@unh.newhaven.edu))

Department of Computer Science, Tagliatela College of Engineering, University of New Haven,  
West Haven, Connecticut.

- 2) Sruthi Sunderrajan (ssund3[@unh.newhaven.edu](mailto:@unh.newhaven.edu))

Department of Computer Science, Tagliatela College of Engineering, University of New Haven,  
West Haven, Connecticut.

- 3) Ajay Kumar Vattam ([avatt1@unh.newhaven.edu](mailto:avatt1@unh.newhaven.edu))

Department of Computer Science, Tagliatela College of Engineering, University of New Haven,  
West Haven, Connecticut.

## ABSTRACT:

Music holds a significant place in the hearts and lives of ordinary people, and it is of a subjective and universal character. The Music Identifier System is worried. with offering a personal and meaningful experience Items, such as songs, music, and playlists, are recommended based on the consumers' mood, emotions, interests, and preferences listeners. Quick technological advancements have resulted in rapid

As the internet has grown in popularity, it has become increasingly usual to utilize it. music or song streaming services to listen to and enjoy music or songs more conveniently in a convenient manner An attempt has been made in this work to do a comparative analysis, conduct systematic research, and conduct an empirical study

a detailed examination of the many techniques or tactics that have been offered and have been used by a variety of scholars in the endeavor of creating a music system that works Identification or a suggestion The paper's main focus is on the music identification system, its components, and various aspects, with an emphasis on the methodologies, metrics, general framework, and state-of-the-art tactics offered during the previous two decades or more. The previous study was found to be insufficient in terms of systematic research on user behavior, requirements, and preferences, as well as a low degree of feature extraction and restrictions in the field of evaluating the performance of music identification systems. Although the research shows that systems based on effective social information, emotional features, content, context, and expertise have been extensively used and have improved the quality of music identification and recommendation to a great extent, it is still insufficient. In the future, more in-depth studies or research work will be needed to broaden the scope of the personalized contextual awareness-based music identifier system and generate a continuous and automatic top playlist of music and songs with added tracks that match the user's profile, mood, emotional traits, and behavior in a mobile environment.

**KEYWORDS:** Logistic regression, Random Forest and Decision Tree



## **INTRODUCTION:**

Music is one of the most popular forms of entertainment in the digital age. Music is defined as a work of human creation that uses melody, harmony, and rhythm to communicate thoughts and feelings via sound. Pop, rock, jazz, blues, folk, and other genres can all be classified as music. Listening to music has never been easier in the digital era, thanks to smartphone capabilities that allow you to listen to music both offline and online. Because there is so much digital music available nowadays compared to the previous age, sorting through it all takes a long time and generates information fatigue. As a result, developing a music recommender system that can automatically scan music collections and propose songs that are appropriate for users is quite beneficial.

Spotify and Pandora, for example, provide tools that allow users to be recommended music. These characteristics can assist in obtaining a list of relevant music from popular music libraries based on previously heard music. As a result, the recommender system is critical to the success of the streaming music industry. Music recommendations are made by comparing one piece of music to another or by assigning a preference to one user over another. The goal of a music recommender system is to design a system that can constantly locate appealing new music while also understanding the users' musical tastes. This necessitates that the music-tailored recommender system accurately reflects the individual's tastes. It will need to be tweaked to generate customized suggestions for varied audiences' needs. As a result, the personalized music recommender system is more complex than the standard recommender system. To extract the music features, it is vital to take into account all user demands and integrate music feature detection and audio processing technologies. The purpose of this study is to develop a personalized recommender system that has both practical and research value.

## **RESEARCH QUESTION:**

- Using data mining techniques and Spotify to predict a person's mood.  
Would it be possible of predicting a person's mood to play the same type of song if a person chooses one type of song? The data behind their music listening history would reveal any insight into their emotional states.?

## RELATED WORKS:

Using the Spotify music analysis dataset, a lot of work has been done to predict persons' moods playing music. Varied data mining approaches have been used to achieve various levels of accuracy, as discussed below.

Hu, X., Choi, K., & Downie, J. S and colleagues investigate a variety of machine learning algorithms that can be used to classify cardiac disease. A study was conducted to compare the accuracy of Decision Tree, KNN, and K-Means algorithms that can be utilized for classification[1]. This study found that the Decision Tree had the highest accuracy and that it may be made more efficient by combining several methodologies and fine-tuning parameters.

Guo Y., Liu Y, and colleagues [2] created a system that combined data mining techniques with the MapReduce algorithm. According to this article, the accuracy gained using a conventional fuzzy artificial neural network for the 45 instances of the testing set was higher than the accuracy obtained using a conventional fuzzy artificial neural network. Because of the employment of dynamic schema and linear scaling, the accuracy of the method was increased.

Ioffe S., Szegedy C developed a machine learning model that compares five alternative techniques [3]. When compared to Matlab and Weka, the Rapid Miner tool produced greater accuracy. The accuracy of the classification algorithms Decision Tree, Logistic Regression, Random Forest, Naive Bayes, and SVM was compared in this study. The most accurate algorithm was the decision tree algorithm.

Siriket K., Sa-Ing V., Khonthapagdee S. introduced a system that employs NB (Nave Bayesian) approaches for dataset categorization and the AES (Advanced Encryption Standard) algorithm for safe data transport for disease prediction.

Ioffe S., Szegedy C. conducted a study that looked at various classification algorithms for predicting cardiac disease. Naive Bayes, KNN (K- Nearest Neighbour), Decision tree, and Neural network were utilized as classification techniques, and the accuracy of the classifiers was evaluated for a variety of attributes [5].

Erion Cano M.M used various Algorithms for the prediction of heart disease. Net Achieve optimum performance than K Star, Multilayer perception, and J48 techniques using k fold cross-validation. The accuracy performances achieved by those algorithms are still not satisfactory. Therefore, the accuracy's performance is improved more to give better decisions to diagnose disease

Lidy T., Schindler A conducted a study on predicting later CHD in a middle-aged white population sample. Prediction models have typically been based on the logistic function, although the Weibull

distribution has also been used. The predictive capability of the continuous model described here is similar to the accelerated failure model used in an earlier Framingham CHD prediction equation.

## **PROPOSED METHODS:**

The proposed research investigates the three classification algorithms and performs performance analysis on Persons' moods. The goal of this study is to accurately predict whether or not they predict a person's mood. The input values from the person's music reports are entered by the music apps.

The data is entered into a model that forecasts the likelihood of developing a prediction on the music of their mood.

## **DATA SET:**

The Music Dataset was used, which is made up of four separate databases, although only the UCI Spotify dataset was used. Although there are 76 attributes in this database, all published experiments only use a subset of 14 of these. As a result, we conducted our research using the already processed UCI Spotify dataset available on the Kaggle website. Below contains a detailed description of the qualities used in the proposed study.

## **METHODS AND ALGORITHMS USED:**

### **LOGISTIC REGRESSION:**

The statistical analysis approach of logistic regression is used to forecast a data value based on prior observations of a data set. It assesses new cases on their likelihood of falling into a certain outcome group based on historical data about previous outcomes involving the same input criteria.

The classification algorithm logistic regression is mostly used for binary classification problems. Instead of fitting a straight line or hyperplane, the logistic regression algorithm squeezes the output of a linear equation between 0 and 1 using the logistic function. Because there are 13 independent variables, logistic regression is a viable choice for categorization.

### **Random Forest:**

The Random Forest algorithm is based on the Supervised Learning technique and is one of the most basic Machine Learning algorithms.

The Random forest method assumes that the new case/data and existing cases are similar and places the new case in the category that is most similar to the existing categories.



The Random forest method stores all available data and classifies a new data point based on its similarity to the existing data. This means that new data can be quickly sorted into a well-defined category using the Random forest method.

The Random forest approach can be used for both regression and classification, but it is more commonly utilized for classification tasks.

## **DECISION TREE:**

The Decision Tree algorithm is represented as a flowchart, with the inner node representing the dataset properties and the outer branches representing the result. Decision Trees were chosen because they are quick, dependable, and simple to read, and they require very little data preparation. The prediction of class labels comes from the root of the tree in a Decision Tree. The root attribute's value is compared to the records attribute's value. As a result of the comparison,

$$P(A|B) = (P(B|A)P(A)) / P(B) \quad (1)$$

## **DATA EXPLORATION:**

The first exploration technique which we have used in our project is univariate analysis. The attributes which we have considered for this analysis are a count of record and target. We have used histograms for this analysis.

1. Acousticness: number A confidence measure from 0.0 to 1.0 of whether the track is acoustic. 1.0 represents high confidence the track is acoustic.  $0 \leq 1$
2. Danceability: number 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 the least danceable and 1.0 is the most danceable.
3. Duration\_ms: integer The duration of the track in milliseconds.
4. Energy: number 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.
5. Instrumentalness: number 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 instrumentals 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.

6. Liveness: number 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.

7. Loudness: number 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.

8. Mode: integer Mode indicates the modality (major or minor) of a track, the type of scale from which its melodic content is derived. Major is represented by 1 and minor is 0.

9. Speeches: number 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 probably 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 most likely represent music and other non-speech-like tracks.

10. Tempo: number 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.

11. time\_signature: integer An estimated time signature. The time signature (meter) is a notational convention to specify how many beats are in each bar (or measure). The time signature ranges from 3 to 7 indicating time signatures of "3/4", to "7/4".  $\geq 3 \leq 7$

12. Valence: number A measures 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).  $\geq 0 \leq 1$

The figures for the above explorations are present in the ipynb file attached to this pdf Link: <https://github.com/Ajay-kumarv/music-makes-an-impact>

## EXPERIMENTAL RESULTS:

### DATA PREPROCESSING:

The data from the data set is impure so the cleansing of the data is done. The removal of the null values from the data set. Because the number of null values is so small, we can either ignore them or impute them. The mean has been imputed in place of the null values; however, these rows can alternatively be deleted entirely.

## Training and testing:

Data split into 70% train and 30% test data, which was further passed to the Logistic Regression, Random Forest, and Decision Tree model to fit, predict and score the model.

```
from sklearn.metrics import roc_curve
fpr_keras, tpr_keras, thresholds_keras = roc_curve(y_test, y_pred)

from sklearn.metrics import auc
auc_keras = auc(fpr_keras, tpr_keras)

plt.figure(figsize=(8,6))
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr_keras, tpr_keras, label='Logistic (area = {:.3f})'.format(auc_keras))
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
plt.title('ROC curve')
plt.legend(loc='best')
plt.show()
```

## DATA MODELING:

Used three machine learning models to find the patterns or relationship between the features and the output with the help of the model. fit() function.

### 1.Created Logistic Regression Model using Scikit-learn.

```
from sklearn.linear_model import LogisticRegression
LRmodel = LogisticRegression(C=1e20)
```

```
#fit the model
X = LRmodel.fit(X_train, y_train)
```

```
#predict how well model fits the known data.
y_pred = LRmodel.predict(X_test)
```

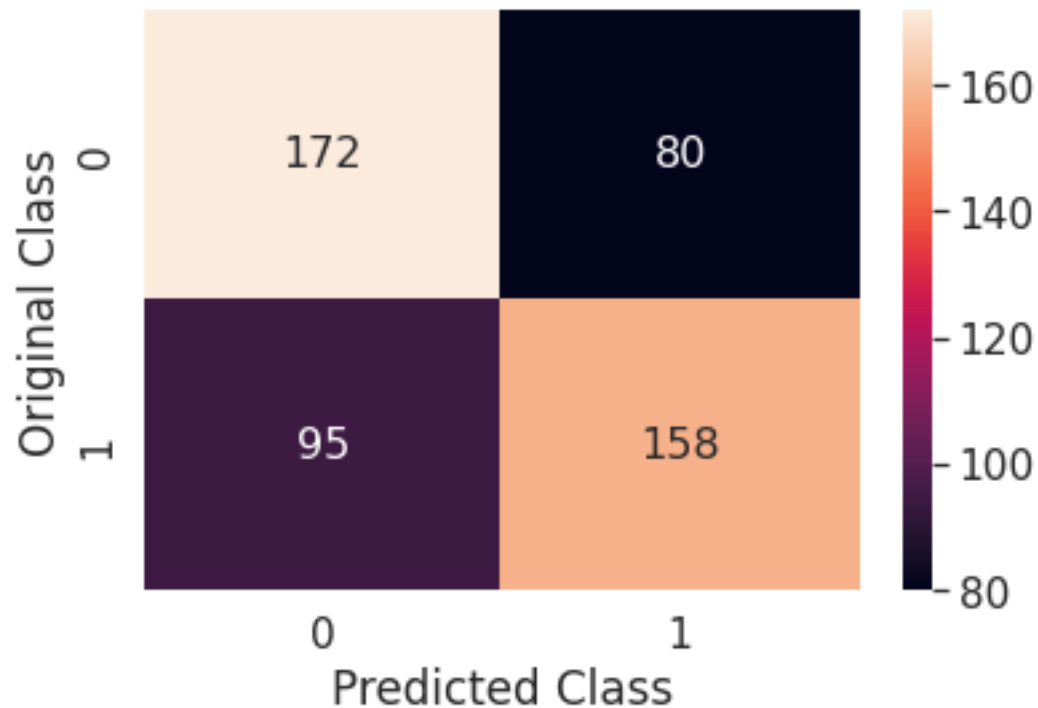
### Model Evaluation:

Accuracy is calculated using actual test values from the data set and predicted values  
Using the code below, we calculated accuracy.

```
test_all_lg = round(LRmodel.score(X_test, y_test),3)

print('Testing Score':round(LRmodel.score(X_test, y_test),3),'\n')
```

A **confusion matrix** was used to have a better understanding of how well the classification model worked.



### Accuracy

'Testing Score': 0.736

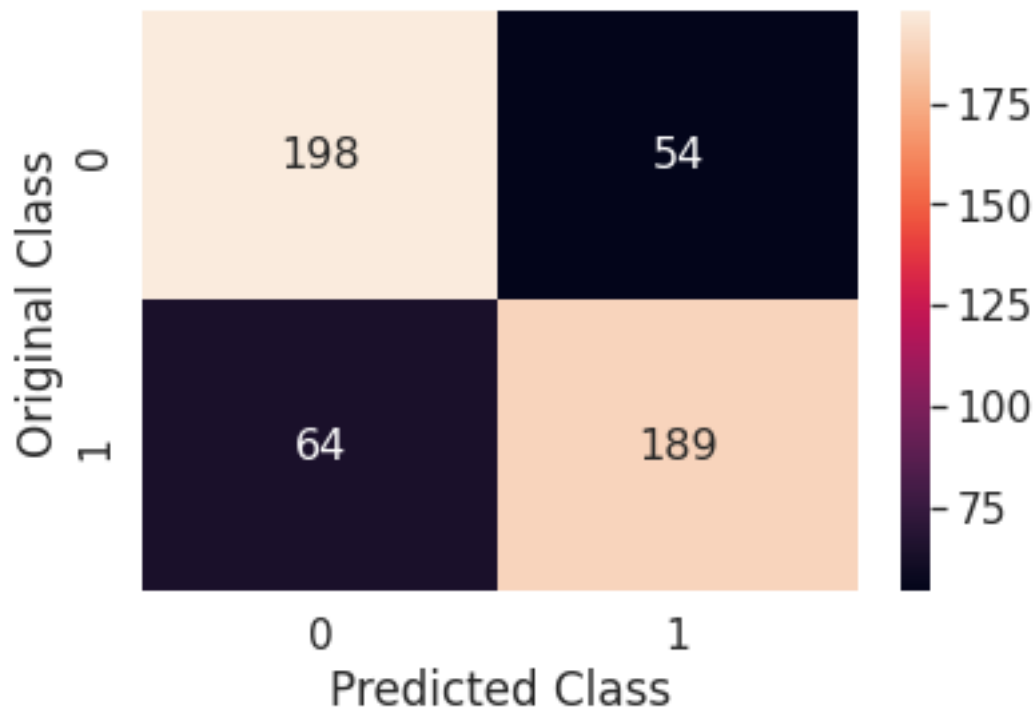
## 2.Created a Random forest Model using Scikit-learn.

```
Rclassifier = RNeighborsClassifier( n_jobs=-1)
Rclassifier.fit(X_train, y_train)
Rclassifier_pred = kRclassifier.predict(X_test)
```

### Model Evaluation for **Random forest Model**:

```
Rclassifier_score_train = round(Rclassifier.score(X_train,
y_train),3) Rclassifier_score_test = round(Rclassifier.score(X_test,
y_test),3) print('Training Score: ',Rclassifier_score_train)
print('Testing Score: ',Rclassifier_score_test)
```

Confusion Matrix :



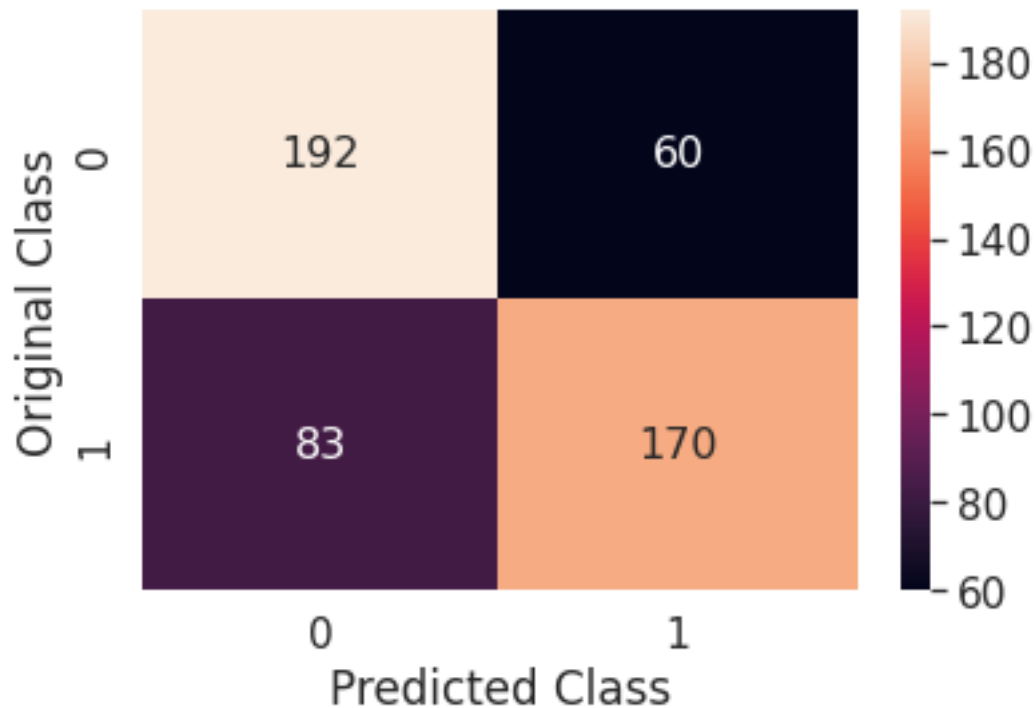
### 3.Created Decision Tree using Scikit learn:

```
from sklearn.tree import DecisionTreeClassifier dtree =  
DecisionTreeClassifier() dtree.fit(X_train,y_train)
```

#### Model Evaluation for Decision Tree:

```
predict = dtree.predict(X_test)  
#scores dt_score_train = round(dtree.score(X_train,  
y_train),3) dt_score_test = round(dtree.score(X_test, y_test),3)  
print('Training Score: ',dt_score_train) print('Testing Score:  
' ,dt_score_test)
```

Confusion Matrix :



## DISCUSSION ON RESULTS:

The accuracy achieved from the models are:

- 1) Testing accuracy for Logistic Regression: 0.674
- 2) Testing accuracy for Random forest: 0.671
- 3) Testing accuracy for Decision Tree:: 0.785

## Hyperparameters Tuning:

We have improved the accuracy of the model by using the tuning of the Hyperparameters method. This process is known as Data Optimization

- For logistic regression  
`'penalty' : ['l1', 'l2', 'elasticnet', 'none'], 'C' : np.logspace(-4, 4, 20),`

```
'solver' : ['lbfgs','newton-cg','liblinear','sag','saga'], 'max_iter' : [100, 1000,2500, 5000]}
```

- For Random forest :

```
param_grid = [{'n_estimators': [10, 25], 'max_features': [5, 10], 'max_depth':  
[10, 50, None], 'bootstrap': [True, False]]}
```

- For Decision tree:

```
'max_depth': [2, 3, 5, 10, 20], 'min_samples_leaf': [5, 10, 20, 50, 100], 'criterion':  
['gini','entropy']
```

- We have used grid search algorithm for the above three classifiers and at last with the help of best fit estimator algorithm we got the best parameters.

The accuracy achieved after the hyperparameter tuning is:

- 1) Testing accuracy after optimization for Logistic Regression: 0.673
- 2) Testing accuracy after optimization for Random forest: 0.671
- 3) Testing accuracy after optimization for Decision Tree: 0.781

## CONCLUSION:

- We have used various hyperparameters for each data mining technique to improve our accuracy for KNN, Logistic regression, and decision tree. As a result, we obtained the below accuracies for the techniques:
  1. Random forest: 67.1
  2. Logistic regression: 67.3
  3. Decision Tree: 78.1

Decision Tree with higher accuracy of 78.1 is the best performer on our dataset, followed by Logistic regression with 67.3.

- Using a Decision Tree we can predict the data with high accuracy.

## LIMITATIONS:

- The sample size that reflects a specific geographic area is extremely small and limited.
- Only one type of data set is used for our project. So there may be changes in the outcome if there is a change in the data provided to it.

- A total of 1500 songs were included in the American music dataset from 2000. There were 70 albums with 138 artists and 20 same label companies are repeated.

## **FUTURE WORK:**

- We can collect more data, not area-specific but global data. We can link our project too big data and continue the research.
- In addition we can create a mobile application or web application.
- Not only 3 classifiers, but we can also use classifiers like KNN, support vector machine, and artificial neural network for this study.
- In further IoT(internet of things) can also utilize this study.

## **Appendix for the link to the GitHub repository:**

<https://github.com/Ajay-kumarv/music-makes-an-impact>

## **REFERENCES:**

1. Hu, X., Choi, K., & Downie, J. S. (2016). A framework for evaluating multimodal music mood classification. *Journal of the Association for Information Science and Technology*, (February), n/a-n/a. <https://doi.org/10.1002/asi.23649>
2. Dong H.W., Hsiao W.Y., Yang L.C., Yang Y.H. *MuseGAN: Multi-Track Sequential Generative Adversarial Networks for Symbolic Music Generation and Accompaniment*. AAAI; Menlo Park, CA, USA: 2018
3. Lidy T., Schindler A. Parallel Convolutional Neural Networks for Music Genre and Mood Classification. 2016.  
  
<http://www.ifs.tuwien.ac.at/~schindler/pubs/MIREX2016.pdf>
4. Erion Cano M.M. MoodyLyrics: A Sentiment Annotated Lyrics Dataset; Proceedings of the 2017 International Conference on Intelligent Systems, Metaheuristics & Swarm Intelligence; Hong Kong, China. 25–27 March 2017
5. Guo Y., Liu Y., Oerlemans A., Lao S., Wu S., Lew M.S. Deep learning for visual understanding: A review. *Neurocomputing*. 2016;**187**:27–48.  
doi: 10.1016/j.neucom.2015.09.116.



6. Ioffe S., Szegedy C. Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift; Proceedings of the International Conference on Machine Learning; Lille, France. 6–11 July 2015.
7. Siriket K., Sa-Ing V., Khonthapagdee S. Mood classification from Song Lyric using Machine Learning; Proceedings of the 2021 9th International Electrical Engineering Congress (iEECON); Pattaya, Thailand. 10–12 March 2021; pp. 476–478.
8. Data set for the heart attack: <https://www.kaggle.com/code/aeryan/spotify-music-analysis>