International Journal For Recent Developments in Science & Technology
2581-4575
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A Machine Learning Approach-based Music Mood Classification for Emotionally Intelligent Playlists

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ABSTRACT

Music is a fundamental aspect of human life and has the power to evoke various emotions and moods. Understanding and categorizing music based on its emotional content, also known as music mood classification, has become a prominent area of research in recent years. Analyzing the emotional aspect of music is crucial in applications such as personalized music recommendations, mood-based playlist generation, and emotion-aware music therapy. The traditional approach to music mood classification involved employing music experts to listen to each track and manually assign mood labels, such as happy, sad, calm, energetic, etc. This process was highly subjective and prone to inconsistencies due to individual biases. The annotated data would then be used to build handcrafted rule-based systems or simple statistical models to classify music into different mood categories. While these approaches provided some insights, they were limited in scalability, generalization, and accuracy. In addition, manual annotation is time-consuming, expensive, and lacks objectivity. Moreover, human listeners may not always agree on the emotional interpretation of a particular piece of music, leading to discrepancies in the labeled data. To overcome these challenges and enable large-scale mood analysis of music collections, there is a demand for automated and data-driven approaches. Machine learning techniques offer a promising solution to this problem by leveraging computational models to learn patterns and relationships from data, thus enabling the automatic classification of music based on its emotional content. Therefore, this project develops an emotion recognition-based music recommendation system, which performs the mood analysis first, and then recommend the music according to the detected mood of the users. The experiments on real data confirm that the proposed mood classification system can be integrated to any music recommendation engine.

Keywords: Emotion recognition, Music mood classification, Machine learning, Intelligent playlists.

1. INTRODUCTION

The pursuit of understanding and categorizing the emotional content of music, referred to as music mood classification, has emerged as a central focus in contemporary research, reflecting the profound impact of music on human emotions. The intricate interplay between music and mood is a fundamental aspect of the human experience, with the potential to elicit a myriad of emotions. This research endeavors to delve into the realms of machine learning to revolutionize the conventional methods of music mood classification, which historically relied on the subjective assessments of music experts. Traditionally, experts would meticulously listen to each musical track, manually ascribing mood labels such as happy, sad, calm, or energetic. However, this approach was fraught with subjectivity and inconsistencies, owing to individual biases and varying interpretations of emotional nuances. The conventional method, although providing valuable insights, faced limitations in terms of scalability, generalization, and accuracy. The reliance on manual annotation not only proved to be time-consuming and expensive but also lacked the objectivity required for a standardized classification system. Furthermore, the inherent variability in human perception meant that different listeners might interpret the emotional content of a particular musical piece divergently, leading to discrepancies in the labeled data. Recognizing these challenges, there emerged a compelling need for automated, data-driven approaches that could overcome the limitations of traditional methods.

Machine learning, as a powerful computational tool, presents a promising solution to the challenges posed by manual annotation and subjective interpretation. By harnessing the capabilities of machine learning algorithms, this project endeavors to develop an emotion recognition-based music recommendation system. The novel approach involves conducting mood analysis as a precursor to recommending music, thereby enhancing the personalization of music suggestions based on the detected mood of the users. The core principle revolves around leveraging computational models to learn intricate patterns and relationships inherent in the data, facilitating the automatic classification of music based on its emotional content.

2. LITERATURE SURVEY

The concept that peoples who listen to different types of music will change emotions and physical states has been widely accepted. Several studies have shown the relationship between psychology and physiology [5,6]. According to Bason et al. [7], the heart rate changes mainly for the following reasons. First, the heart rate is changed by the external auditory stimulation that leads to the neuron coupling into the cardiac centers of the brain, further arousing the sinus entrainment of rhythms. Another cause of changing the heart rate is the autonomic nervous system (ANS) that controls and sustains homeostasis in our body, such as blood pressure, body temperature, and sleep qualities. It mainly consists of the parasympathetic nervous system (PNS) and sympathetic nervous system (SNS). Additionally, it is typically distinguished by opposing characteristics. For instance, in an emergency state, the SNS increases the heart rate, but on the other hand, the PMS typically retards the heart rate in the static state. Some studies indicate that quality of life can be improved by different types of music, such as raising sleep quality, relieving pressure, supporting exercise, and enhancing brain liveliness [8,9,10]. In summary, we could further infer that there supposedly is a connection music stimuli and heart rate.

According to the above-mentioned factors, listening to different music genres changes one's emotions and heart rate, which is a kind of music therapy method. There are some benefits of music therapy, such as socialization, cognition, emotion, and neuron motor function [11]. Continuing music therapy research has led to many new and fascinating applications in sports and autistic and handicapped fields. According to Van Dyck E et al. [12], music rhythm can affect running cadence. In other words, the slower rhythm of music brings out a decrease in running cadence; on the other hand, the faster rhythm of music gives rise to an increase in running cadence. Moreover, another significant research of promoting exercise efficiency is proven by Karow et al. [13]. They provided extensive discussions of the importance of primary selected music. For instance, primary music could make humans more powerful and more stimulated during exercise. Moreover, it could effectively decrease the Rating of Perceived Exertion (RPE), which evaluates the degree of effort that a person feels by themselves. Consequently, music could draw attention away from uncomfortable feelings [14].

Nowadays, most playlists are supplied by famous sports brands, which causes unfamiliarity to the users. In addition, the playback mode is typically played by sequence or at random. However, we consider that the previous playback mode is not reasonable during exercise and that the playback sequence should be adjusted depending on the different physical situations of each person. As a result, we propose an algorithm to solve the playback mode during exercise. In order to apply it to individuals, we also consider the biological data and fuzzy algorithm [15]. The fuzzy algorithm is based on the different

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exercise levels to suggest the canter speed through the biological data of users. We intend to introduce a complete music system consisting of pace match music rhythm.

There are many ways to implement emotion classification models. First, simple machine learning models include random forest trees, KNN, and K-means. Although these traditional methods can solve the problem quickly with a small amount of data, they only obtain low accuracy of classification results [16]. Second, RNN [17] has a time series algorithm to solve the emotion classification task. However, the disadvantage of its architecture is prone to generating gradient disappearance and gradient explosion. However, the LSTM and GRU improve time series models to avoid the gradient disappearance and gradient explosion, which need additional parameters to control different gates [17].

3. PROPOSED METHODOLOGY

In the domain of music mood classification, the progression from raw data to model predictions involves a structured research procedure comprising key steps such as dataset acquisition, data preprocessing, data splitting, existing XGBoost model training, proposed Random Forest with Adaboost model training, performance evaluation, and the final prediction from test data. Figure 1 shows the proposed system model. The journey commences with the acquisition of a comprehensive and diverse dataset. The dataset forms the bedrock of the research, encapsulating a broad spectrum of musical genres, styles, and emotional nuances. Collecting a representative dataset is crucial to ensure the model's ability to generalize across various music types and capture the intricate emotional patterns inherent in diverse musical compositions. This initial step sets the stage for robust and inclusive music mood classification.

Subsequent to dataset acquisition, the data preprocessing phase unfolds. This step involves the systematic cleansing and transformation of raw musical data to make it amenable for machine learning model training. In the context of music mood classification, data preprocessing may encompass tasks such as feature extraction from audio signals, considering elements like tempo, pitch, and spectral characteristics. Additionally, textual data, if available, could be processed to extract relevant information about song lyrics, contributing further to the holistic understanding of the emotional content of music. This preprocessing step ensures that the data fed into the models is structured, informative, and conducive to extracting meaningful patterns related to music mood. Following data preprocessing, the next critical stage is data splitting. This involves partitioning the dataset into distinct subsets for training and testing purposes. The purpose of this division is to enable the evaluation of the model's performance on unseen data, a crucial measure of its generalization capabilities. The training set, constituting the majority of the data, serves as the foundation for the model to learn and internalize the patterns and relationships between features and mood labels. The test set, on the other hand, remains untouched during model training and is reserved for assessing how well the model extrapolates its learning to new, unseen instances.

With the data split into training and testing sets, the research progresses to the training of an existing XGBoost model. XGBoost, known for its efficiency and predictive power, undergoes a rigorous training process using the training set. The model learns the complex relationships between the extracted features and the corresponding mood labels, aiming to create a robust and accurate mapping. However, as discussed earlier, XGBoost comes with certain limitations, such as potential overfitting, sensitivity to imbalanced datasets, and challenges in interpretability. Acknowledging these drawbacks, the research seeks to explore an alternative model for comparison and potential improvement.

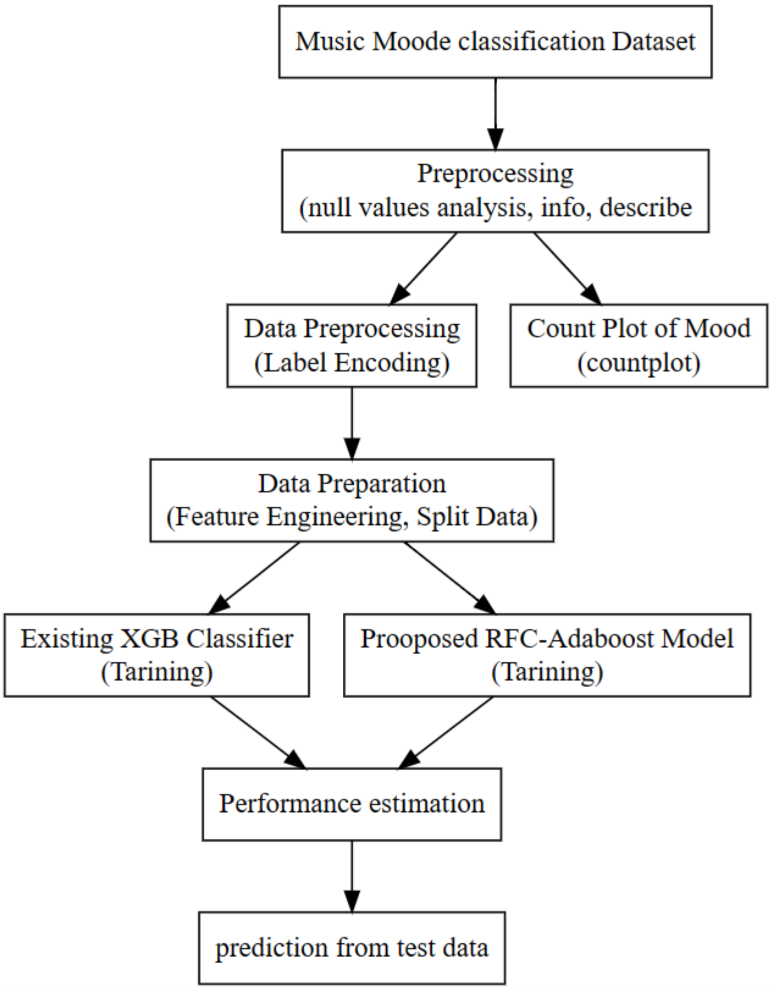

Figure 1. Proposed system model.

Data Preprocessing

Data pre-processing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine learning model. When creating a machine learning project, it is not always a case that we come across the clean and formatted data. And while doing any operation with data, it is mandatory to clean it and put in a formatted way. So, for this, we use data pre-processing task. Getting the dataset

- Importing libraries
- Importing datasets
- Finding Missing Data
- Encoding Categorical Data
- Splitting dataset into training and test set

Dataset Splitting

In machine learning data pre-processing, we divide our dataset into a training set and test set. This is one of the crucial steps of data pre-processing as by doing this, we can enhance the performance of our machine learning model. Suppose if we have given training to our machine learning model by a dataset and we test it by a completely different dataset. Then, it will create difficulties for our model to

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understand the correlations between the models. If we train our model very well and its training accuracy is also very high, but we provide a new dataset to it, then it will decrease the performance. So we always try to make a machine learning model which performs well with the training set and also with the test dataset. Here, we can define these datasets as:

Training Set: A subset of dataset to train the machine learning model, and we already know the output.

Test set: A subset of dataset to test the machine learning model, and by using the test set, model predicts the output.

Random Forest Algorithm

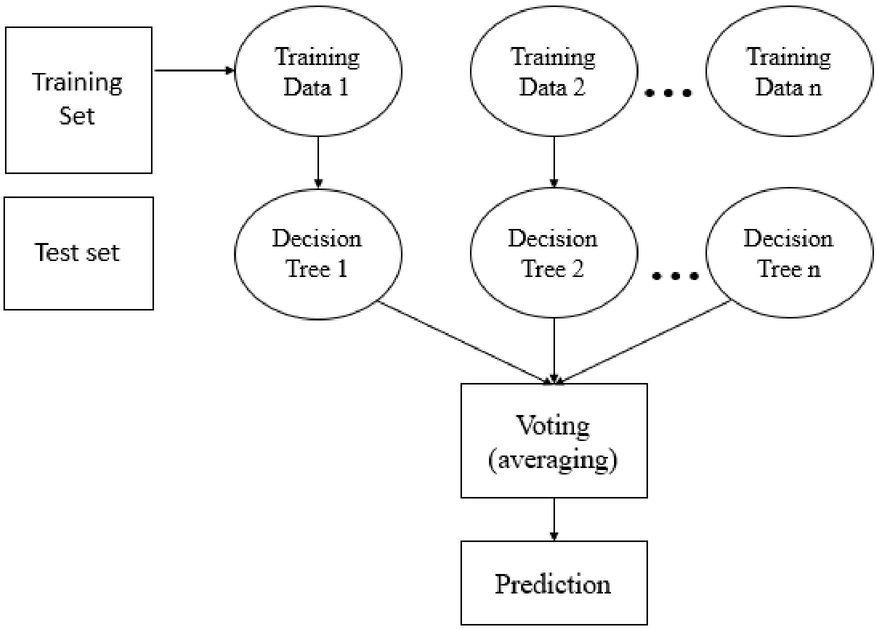

Fig. 2: Random Forest algorithm.

Random Forest algorithm

Step 1: In Random Forest n number of random records are taken from the data set having k number of records.

Step 2: Individual decision trees are constructed for each sample.

Step 3: Each decision tree will generate an output.

Step 4: Final output is considered based on Majority Voting or Averaging for Classification and regression respectively.

Assumptions for Random Forest

Since the random forest combines multiple trees to predict the class of the dataset, it is possible that some decision trees may predict the correct output, while others may not. But together, all the trees predict the correct output. Therefore, below are two assumptions for a better Random Forest classifier:

- There should be some actual values in the feature variable of the dataset so that the classifier can predict accurate results rather than a guessed result.
- The predictions from each tree must have very low correlations.

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Advantages of proposed system

- It can be used in classification and regression problems.
- It solves the problem of overfitting as output is based on majority voting or averaging.
- It performs well even if the data contains null/missing values.
- Each decision tree created is independent of the other thus it shows the property of parallelization.
- It is highly stable as the average answers given by a large number of trees are taken.
- It maintains diversity as all the attributes are not considered while making each decision tree though it is not true in all cases.
- It is immune to the curse of dimensionality. Since each tree does not consider all the attributes, feature space is reduced.

4. RESULTS DESCRIPTION

	name	album	artist	id	release_date	popularity	length	danceability	acousticness	energy	instrumentalness	l
0	1999	1999	Prince	2H7PHVdQ3mXqEHXcvcITB0	1982-10-27	68	379266	0.866	0.13700	0.7300	0.000000	
1	23	23	Blonde Redhead	4HIwL9ii9CcXpTOTzMq0MP	2007-04-16	43	318800	0.381	0.01890	0.8320	0.196000	
2	9 Crimes	9	Damien Rice	5GZEeowhvSieFDiR8fQ2im	2006-11-06	60	217946	0.346	0.91300	0.1390	0.000077	
3	99 Luftballons	99 Luftballons	Nena	6HA97v4wEGQ5TUCIRM0XLc	1984-08-21	2	233000	0.466	0.08900	0.4380	0.000006	
4	A Boy Brushed Red Living In Black And White	They're Only Chasing Safety	Underoath	47IWLfIKOKhFnz1FUEUIkE	2004-01-01	60	268000	0.419	0.00171	0.9320	0.000000	
...	...	...	...	...	...	...	...	...	...	...	...	
681	windcatcher	windcatcher	Leo Nocta	59VApBbrS2IADQk4ml5mdo	2020-06-19	36	123066	0.402	0.96100	0.2360	0.919000	
682	yellow is the color of her eyes	yellow is the color of her eyes	Soccer Mommy	4D3nttJPU6L0M2epr7sId6	2019-11-19	5	435080	0.452	0.75700	0.5150	0.120000	
683	you broke me first	you broke me first	Tate McRae	45bE4HXI0AwGZXfZtMp8JR	2020-04-17	87	169265	0.642	0.78600	0.3740	0.000000	
684	you were good to me	brent	Jeremy Zucker	4CxFN5zON70B3VOPBYbd6P	2019-05-03	76	219146	0.561	0.91300	0.0848	0.000026	
685	æfre	æfre	praam	2irbT1BSYaIEF44PlyKaoM	2020-07-17	41	186331	0.377	0.99400	0.0156	0.881000	

Figure 3. Sample Dataset.

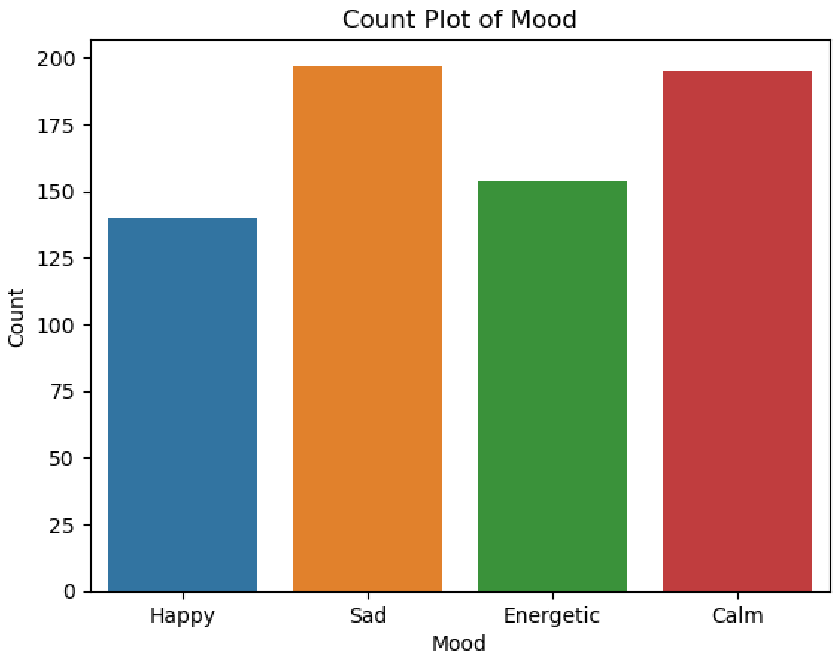

Figure 4. Count plot of target variable.

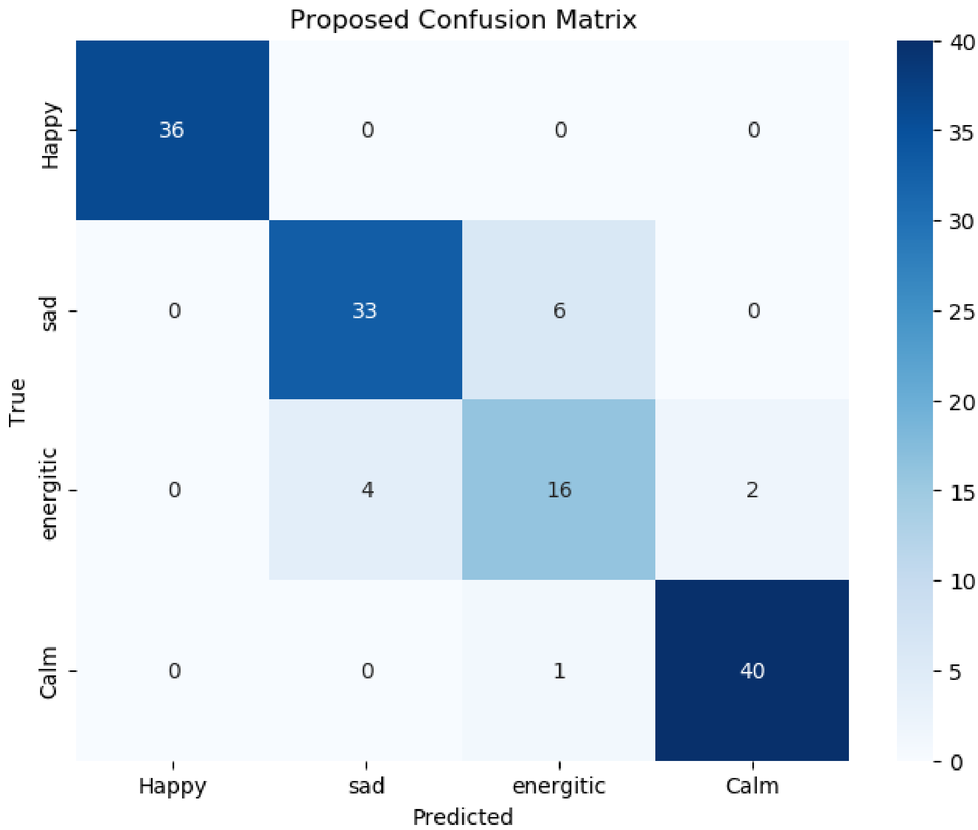

Figure 5. Proposed confusion matrix.

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	name	album	artist	release_date	popularity	length	danceability	acousticness	energy	instrumentalness	liveness	valence	loudness	speechiness
482	482	535	517	20130101	0	166560	0.684	0.905000	0.0646	0.000019	0.0789	0.334	-18.052	0.0522
23	23	500	447	20031110	39	219573	0.429	0.000019	0.9820	0.018500	0.3120	0.583	-2.962	0.0617
189	189	185	515	20191122	47	240000	0.500	0.671000	0.1850	0.000000	0.0827	0.159	-13.209	0.0302
47	47	57	175	20170201	0	290736	0.399	0.848000	0.4430	0.000406	0.0899	0.265	-9.168	0.0272
363	363	205	477	19790101	74	295400	0.586	0.058900	0.7000	0.001250	0.0318	0.897	-9.558	0.0363
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
365	365	323	457	20180518	25	250373	0.665	0.336000	0.5600	0.085700	0.3270	0.414	-7.301	0.0667
362	362	16	278	19990222	72	169026	0.494	0.001290	0.9460	0.000000	0.3980	0.741	-2.757	0.0637
378	378	304	525	20160603	66	237973	0.581	0.893000	0.4000	0.576000	0.1610	0.433	-8.739	0.0291
262	262	104	258	20191025	57	203946	0.432	0.807000	0.3400	0.000000	0.0864	0.449	-7.977	0.0824
666	666	641	11	20200710	49	239500	0.634	0.819000	0.1930	0.000000	0.1130	0.159	-9.503	0.0277

138 rows × 17 columns

```
predictions = adaboost_model.predict(X_test)
predictions
```

```
array([3, 1, 3, 3, 2, 1, 3, 1, 3, 1, 0, 0, 1, 1, 3, 1, 3, 0, 3, 1, 2, 0,
       1, 0, 1, 1, 1, 0, 3, 3, 1, 3, 2, 3, 0, 2, 1, 0, 1, 2, 2, 0, 1, 3,
       3, 0, 1, 1, 1, 0, 3, 1, 3, 0, 3, 0, 1, 3, 0, 1, 2, 3, 1, 0, 3, 2,
       1, 0, 1, 3, 1, 1, 2, 2, 2, 3, 0, 1, 0, 0, 0, 0, 3, 2, 2, 3, 0, 2,
       1, 0, 3, 3, 2, 1, 1, 1, 0, 3, 0, 3, 1, 3, 0, 0, 3, 1, 0, 0, 2, 1,
       0, 0, 2, 1, 0, 3, 2, 1, 3, 2, 3, 0, 2, 2, 3, 3, 0, 3, 1, 2, 0, 0,
       3, 3, 1, 3, 3, 3])
```

Figure 6. Prediction from test data.

5.CONCLUSION AND FUTURE SCOPE

In conclusion, the exploration of machine learning approaches for music mood classification represents a significant stride toward unraveling the intricate relationship between music and human emotions. The journey from traditional, manual methods relying on human experts to automated, data-driven approaches, particularly leveraging algorithms like XGBoost and Random Forest with Adaboost, showcases the evolving landscape of this field. The dataset, with its wealth of music-related attributes, serves as a valuable resource in this pursuit, enabling a nuanced analysis of songs and their emotional impact.

The dataset's attributes, ranging from fundamental details like song name and artist to more complex musical characteristics such as danceability, valence, and instrumentalness, contribute to a holistic understanding of each musical composition. The inclusion of a mood attribute emerges as a pivotal element, providing a categorical lens through which songs can be classified based on their emotional or thematic essence. This categorization lays the foundation for developing models that can predict and classify music moods, offering applications in personalized music recommendations, mood-based playlist generation, and even extending into the realm of emotion-aware music therapy.

The training and comparison of machine learning models, specifically XGBoost and Random Forest with Adaboost, illuminate the strengths and limitations inherent in these algorithms for music mood classification. XGBoost, known for its efficiency and predictive power, excels in learning intricate patterns from data. However, challenges such as potential overfitting, sensitivity to imbalanced datasets, and limited interpretability underscore the need for alternative models. The introduction of Random Forest with Adaboost, leveraging ensemble learning techniques, presents a promising avenue for addressing these challenges. The combination of these algorithms offers a more stable and potentially less biased approach, enhancing the robustness of music mood classification systems.

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