Music and Mental Health: Is there a Correlation?

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Introduction

Mental health impacts everyone, though its effects vary among individuals. This study seeks to understand the influence of music on mental health—whether it is beneficial or detrimental. Utilizing a dataset from Kaggle, compiled by Catherine Rasgaitis, which includes survey responses from 736 individuals regarding their musical preferences and self-reported mental health status, we aim to uncover these relationships (Rasgaitis, 2022).

The primary objective is to determine if this dataset can be used to develop a model capable of predicting the likelihood of depression, anxiety, OCD, or insomnia based on musical tastes and other factors. The key question is whether music improved the overall mental health of the individual.

This analysis will explore the effects of variables such as age, streaming service, favorite genre, and listening duration on mental health. The results could contribute to preventing mental health issues and suicide by identifying individuals at higher risk based on their demographics and musical preferences.

The proposed model will use an individual's response to predict their likelihood of improving mental illness by listening to music. Streaming services could use this model to deliver targeted advertisements, including timely suicide prevention messages. Even a single ad that saves a life would be invaluable.

Graphical Analysis

I began with a graphical analysis of the respondents' ages, which revealed that the respondents ranged in age from 10 to 88. The data also revealed that the vast majority of survey participants were under the age of 30 (see figure 1).

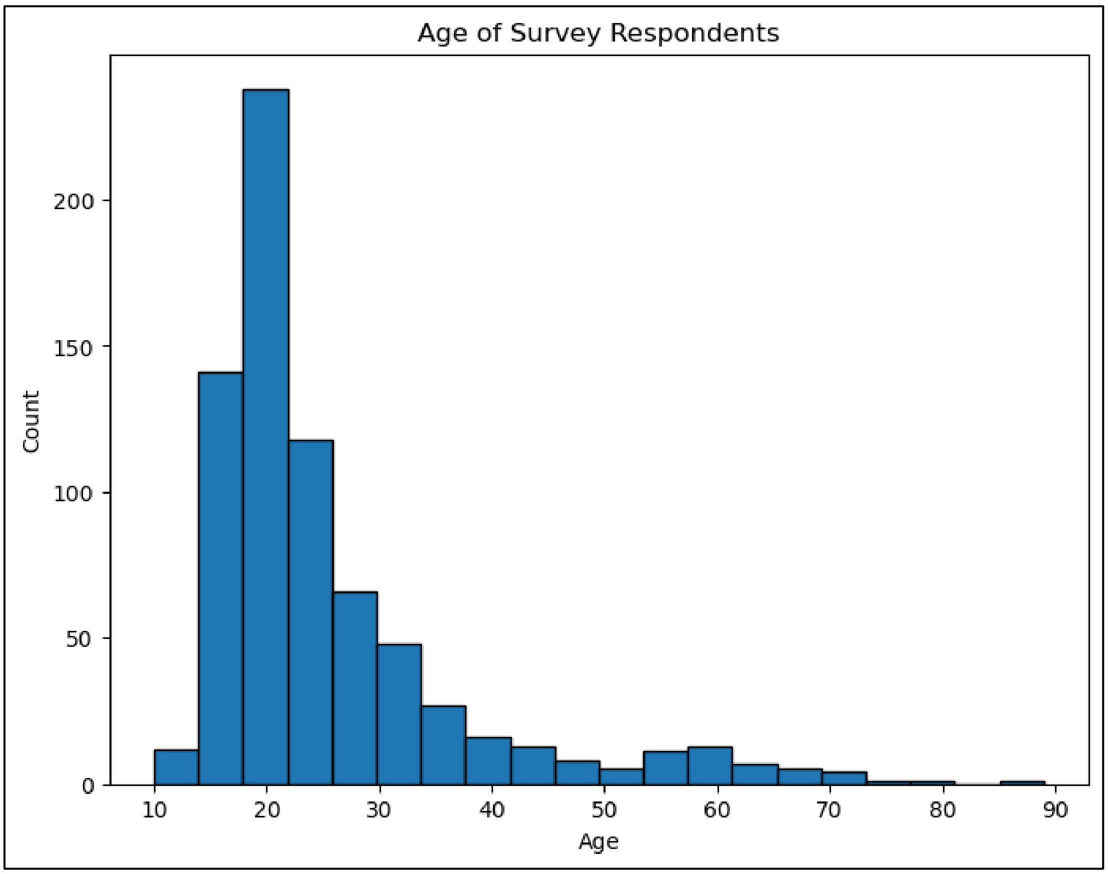

Figure 1: Age distribution of survey respondents. This graph was generated using Python with the Matplotlib library.

Survey results for streaming services indicated that Spotify was the most frequently used service. YouTube Music, Apple Music, and Pandora had fewer respondents, and options such as "I do not use a streaming service" and "other" were also reported (see figure 2).

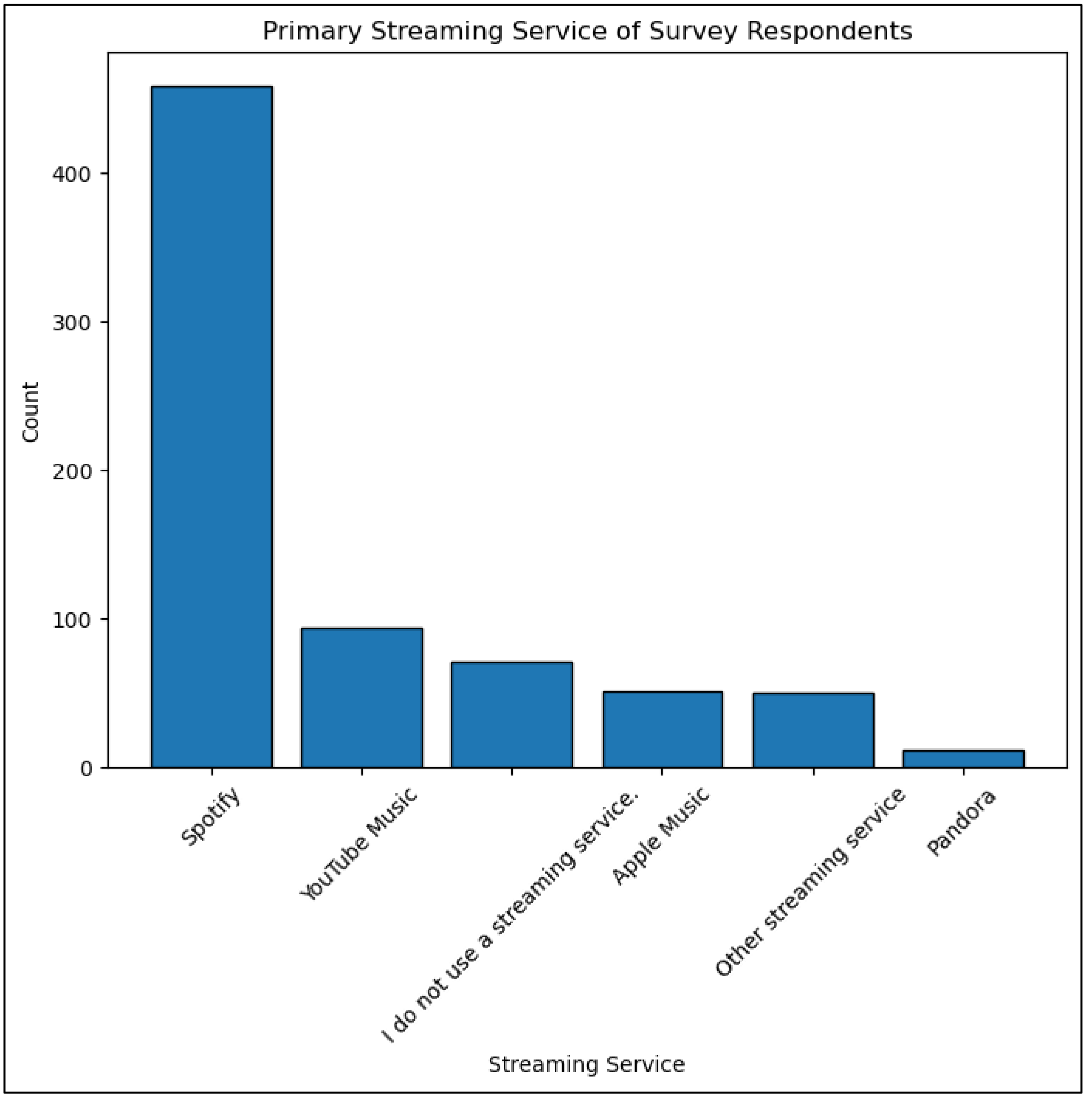

Figure 2 : Primary streaming service of survey respondents. This graph was generated using Python with the Matplotlib library.

How does music affect our mood? Survey respondents reported that 74.5% felt that music improved their mood, 23.2% reported no effect, and 2.3% reported that it worsened their mood (see Figure 3).

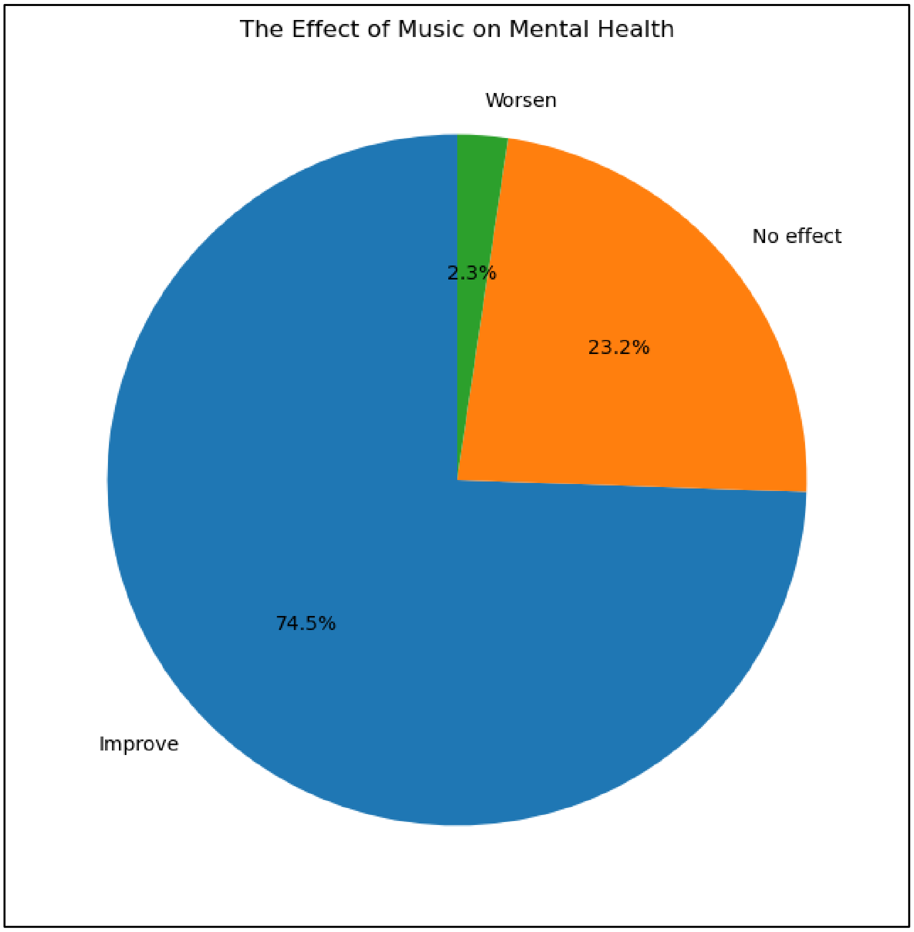

Figure 3: The effect of music on mental health. This graph was generated using Python with the Matplotlib library.

Finally, I conducted a graphical analysis of favorite music genres and the reported levels of anxiety, depression, OCD, and insomnia. The analysis revealed that individuals who reported higher levels of anxiety often preferred folk music (see figure 4). Those who favored lo-fi music reported higher levels of depression (see figure 5), OCD (see figure 6), and insomnia (see figure 7).

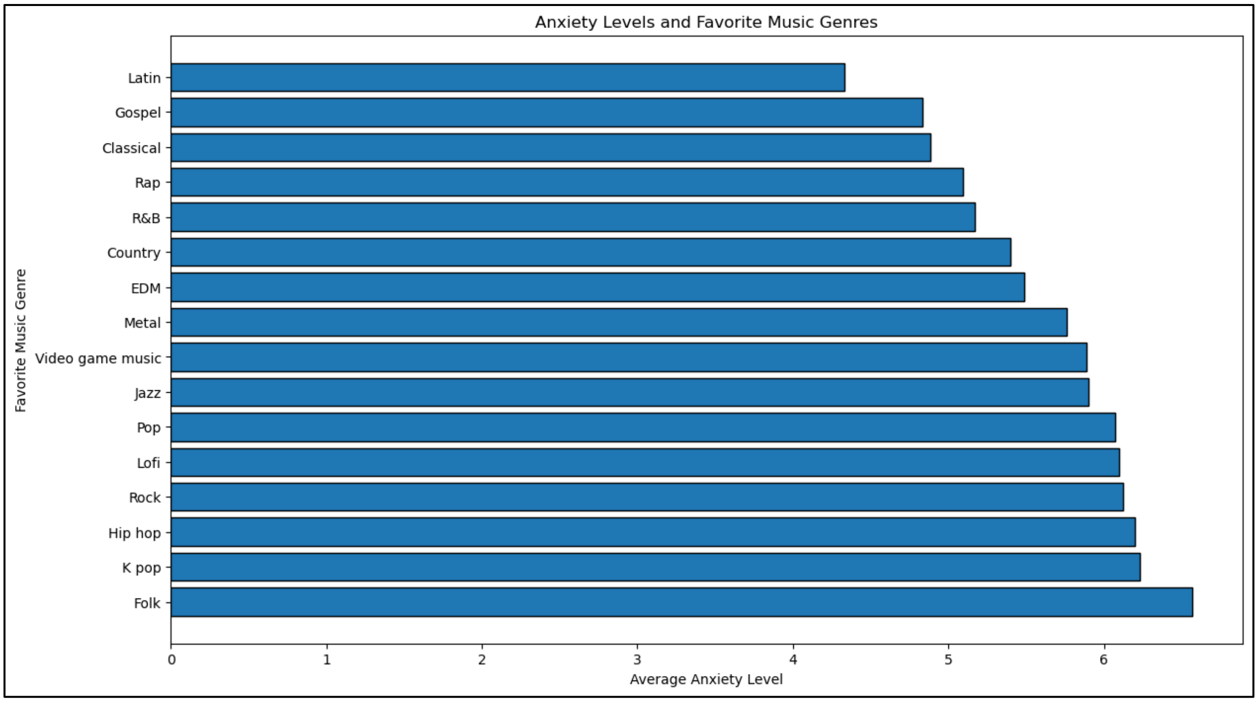

Figure 4: Anxiety levels and favorite music genres. This graph was generated using Python with the Matplotlib library.

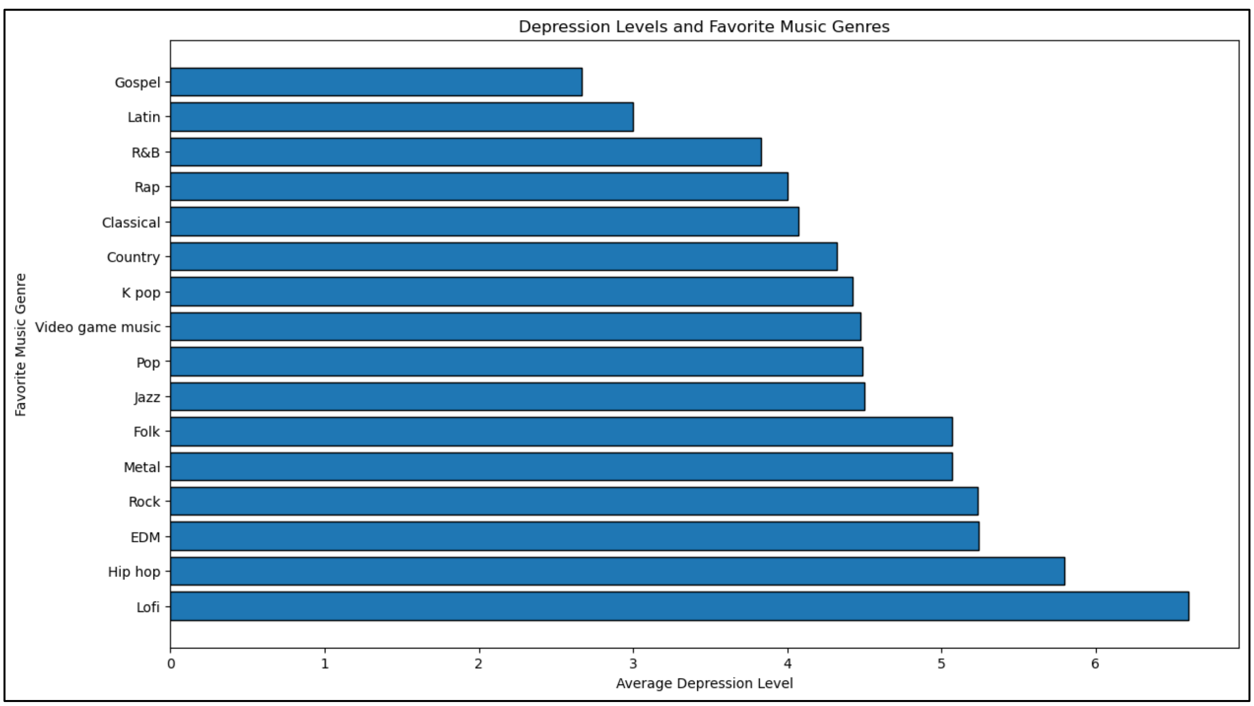

Figure 5: Depression levels and favorite music genres. This graph was generated using Python with the Matplotlib library.

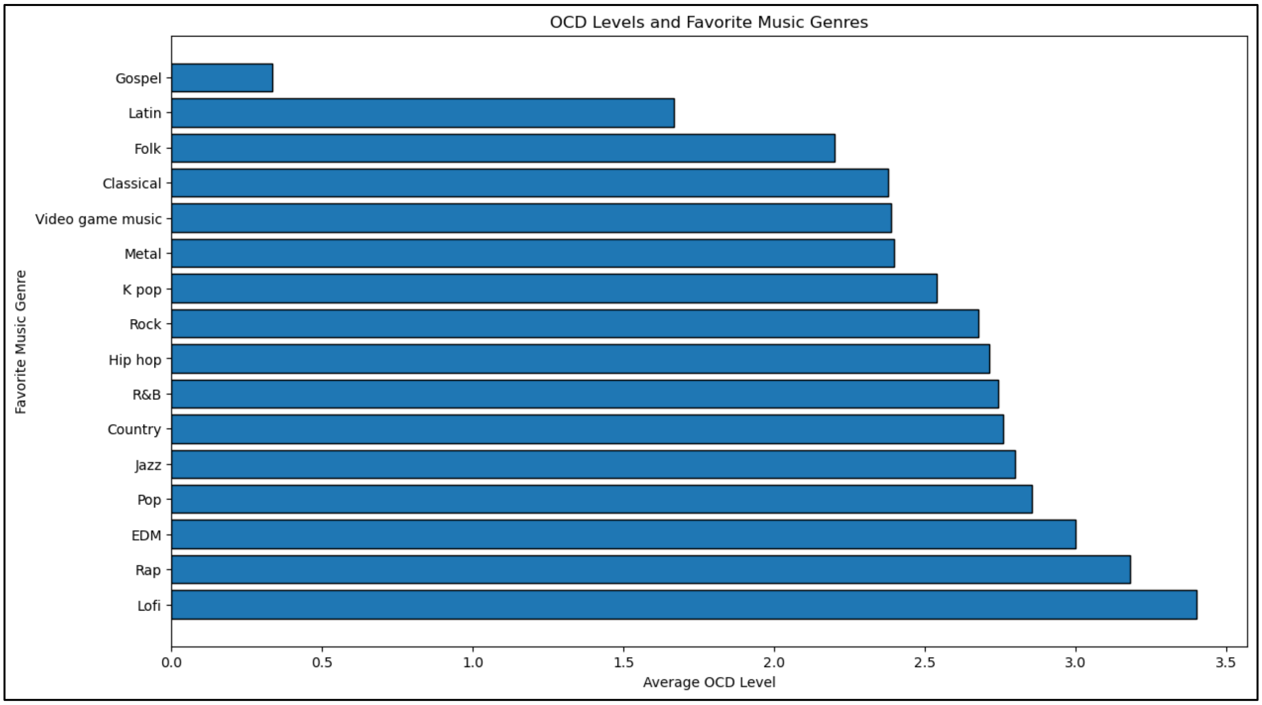

Figure 6: OCD levels and favorite music genres. This graph was generated using Python with the Matplotlib library.

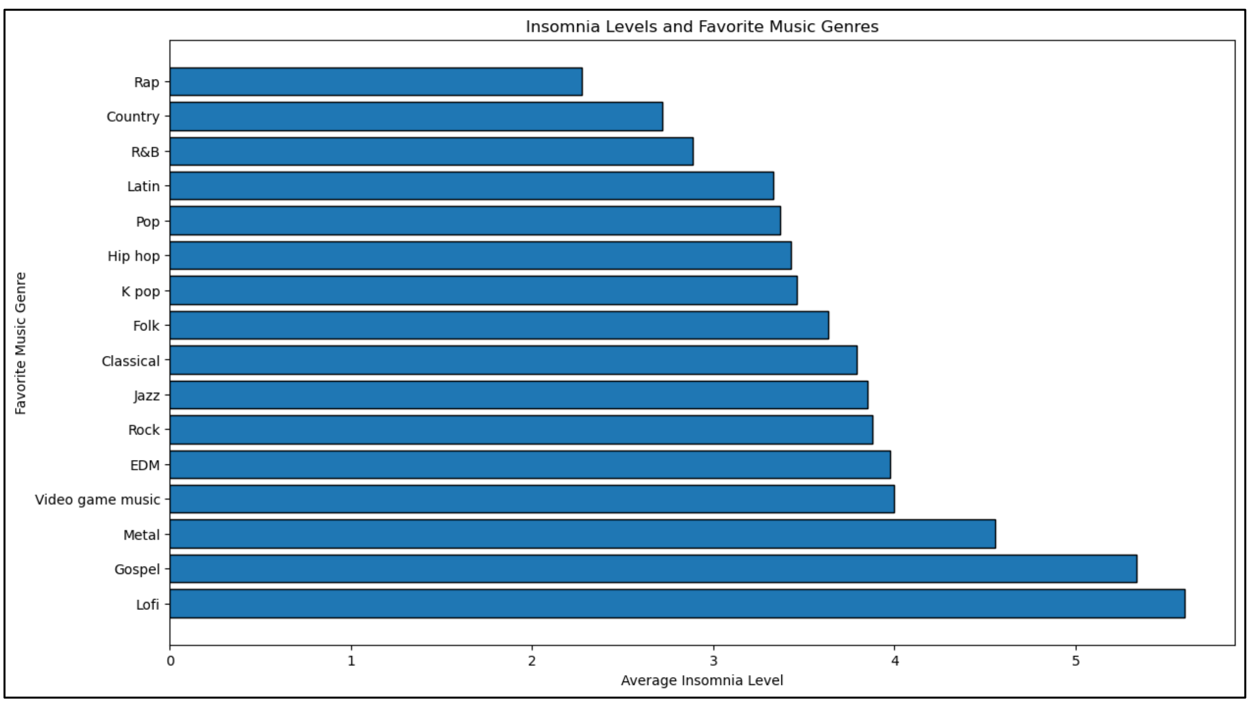

Figure 7: Insomnia levels and favorite music genres. This graph was generated using Python with the Matplotlib library.

Music therapy is commonly employed in mental health treatment and rehabilitation settings. Specifically, gospel music has been found to effectively reduce symptoms of anxiety, depression, and OCD, though it appears to exacerbate insomnia. Conversely, listening to lo-fi music is associated with negative effects across all measured mental health conditions.

EDA

I performed some exploratory data analysis (EDA) to prepare the data for optimal analysis. Initially, I renamed several column names for clarity. The original data had columns labeled "Frequency [Classical]", "Frequency [EDM]", etc. I simplified these to just "Classical" and "EDM".

Next, I identified and removed columns unnecessary for our model. The "Timestamp" and "Permissions" columns were deemed

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There are some columns that are unnecessary for our model. I deleted the "Timestamp" and "Permissions" columns as they are not needed. Additionally, I removed the "Instrumentalist", "Composer", "Exploratory", and "Foreign Languages" columns, as they are irrelevant to my intended model and not well-defined enough to provide meaningful data.

For columns with many blank cells, such as "Beats Per Minute", I replaced missing values with the column's average. The same approach was applied to the "Age" and "Hours Per Day Listened" columns.

Finally, I used the **`.get_dummies`** method to convert categorical columns into dummy variables, facilitating better analysis.

Model Building

I tested three models on the cleaned data, using whether the respondent reported that music improved their mood as the basis for the model. I started with the Naïve Bayes Classifier. Here are the performance metrics:

- **Accuracy**: 76.35%
- **Precision**: 76.35%
- **Recall**: 100.0%
- **F1-score**: 86.59%

The accuracy of 76.35% indicates a reasonable level of correctness in the model's predictions. The precision of 76.35% means that when the model predicts a positive outcome, it is correct 76.35% of the time. The recall of 100% suggests that the model identified all actual positives without missing any, but this might also indicate potential overfitting. The F1-score of 86.59%, which is the harmonic mean of precision and recall, reflects an overall good model performance.

While the high recall indicates that the model is effective at capturing all actual positives, the precision suggests room for improvement to reduce the number of false positives. Enhancing precision would help balance the trade-off between precision and recall, leading to a more robust model.

I then applied a KNN classifier, initially achieving an accuracy score of 75%. However, after integrating hyperparameters into the pipeline, I observed significant enhancements in the metrics. Here are the performance metrics for the KNN Classifier:

- **Accuracy**: 81.08%
- **Precision**: 81.48%
- **Recall**: 97.35%
- **F1-score**: 88.71%
- **Best N value parameter found**: 12

With the inclusion of additional parameters, our model's accuracy increased to 81%, surpassing the performance of the previous Naive Bayes model. Precision improved marginally to 81.48%. Notably, the recall surged to 97.34%, indicating the model's ability to effectively capture actual positives. The F1-score, a harmonized measure of precision and recall, climbed to 88.71%.

I then employed a decision tree classifier, which yielded the following metrics:

- **Accuracy**: 98.65%
- **Precision**: 100.0%
- **Recall**: 98.23%
- **F1-score**: 99.11%

The accuracy of 98.64% is remarkably high, indicating exceptional correctness in the model's predictions. However, the precision of 100% suggests potential overfitting, as the model predicts positive outcomes with perfect accuracy. This aspect warrants further investigation to ensure the model's generalization to unseen data.

The recall of 98.23% implies that the model successfully captured most actual positives with few false negatives, demonstrating its efficacy in identifying positive instances. The F1-score of 99.10%, an aggregate measure of precision and recall, reflects the overall excellence of the model.

In summary, while the decision tree classifier exhibits outstanding performance, the possibility of overfitting requires careful consideration. Further evaluation and refinement may be necessary to ensure the model's robustness and generalizability.

Conclusion

My findings suggest that music plays a significant role in influencing mood and mental health outcomes. Specifically, we observed that certain genres, such as gospel music, demonstrated positive effects on reducing symptoms of anxiety, depression, and OCD. Conversely, excessive consumption of lo-fi music appeared to correlate with higher levels of depression and insomnia.

Moreover, our predictive models, including Naïve Bayes, KNN, and decision tree classifiers, showcased varying levels of accuracy and precision in predicting mental health conditions based on musical preferences and demographic factors. While each model exhibited strengths and limitations, the decision tree classifier emerged as particularly promising, boasting an accuracy rate of 98.65%.

However, it is crucial to acknowledge the limitations of this study, including potential biases in the dataset and the need for further validation and refinement of the predictive models. Future research endeavors could explore longitudinal studies and delve deeper into specific music genres and demographic groups to gain a more nuanced understanding of the complex interplay between music and mental health.

Resources

- RASGAITIS, C. (2022, August 30). *Music & Mental Health Survey Results*. Kaggle. Retrieved May 31, 2024, from https://www.kaggle.com/datasets/catherinerasgaitis/mxmh-survey-results