Musical Mindscapes: A Machine Learning Exploration of Music's Impact on Mental Health

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Music, a timeless and universal language, has been an integral part of human culture for centuries, fostering emotional connections that transcend boundaries. Beyond its artistic and entertainment value, recent research suggests that music plays a pivotal role in influencing mental health. This intersection of music and mental well-being has become a focal point across various disciplines, including psychology, neuroscience, and, intriguingly, machine learning.

Significance of the Problem: In the context of today's prevalent mental health challenges, our project seeks to explore the profound impact of music on mental well-being. Leveraging the capabilities of machine learning, we aim to analyze extensive datasets comprising musical compositions, individual preferences, and psychological responses. The driving question behind our exploration is whether music can emerge as a therapeutic tool to address contemporary mental health concerns.

Motivation: As music enthusiasts, our motivation arises from a fundamental inquiry: Can music play a role in addressing mental health challenges? We acknowledge the sensitivity of this topic but believe that using the universal language of music can make it more relatable and potentially more impactful. Building upon past work that underscores the influence of music on mood, we aim to delve into the intricate relationship between music, mood, and mental well-being.

Inspiration: Inspired by the transformative impact of music on mood, we recognize that the mood we experience offers valuable insights into our mental well-being. Numerous articles have highlighted the potential of music to heal wounds that may not be physically treatable. Our project draws inspiration from these findings, with a focus on exploring the transformative potential of music therapy as a catalyst for positive change in people's lives.

Abstract: In this project, we employ machine learning algorithms to analyze diverse datasets encompassing musical compositions, individual preferences, and psychological responses. The goal is to understand the nuanced relationship between music and mental health. By examining the impact of music on mood and its potential as a therapeutic intervention, we aim to contribute to the growing body of knowledge at the intersection of music and mental well-being.

Inputs and Outputs: Inputs to our project include extensive datasets of musical compositions, individual preferences, and psychological responses. Outputs comprise insights into the relationship between music, mood, and mental health, with the ultimate goal of identifying potential therapeutic applications of music.

Through this exploration, we aspire to shed light on the intricate dynamics between music and mental health, offering new perspectives and potential interventions for the benefit of individuals facing mental health challenges.

Related Work

Sources: **https://www.psychiatry.org/news-room/apa-blogs/power-of-music-in-mental-well-being**

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8566759/

1. **APA Blog: "The Power of Music in Mental Well-Being"**
    - **Findings:** Emphasizes music's therapeutic potential in enhancing mental well-being, serving as a coping mechanism for conditions like anxiety and depression.
2. **NCBI Article: "The Impact of Music on Mental Health"**
    - **Findings:** Explores music's psychological and physiological effects, advocating for its role in stress reduction, mood regulation, and cognitive function.

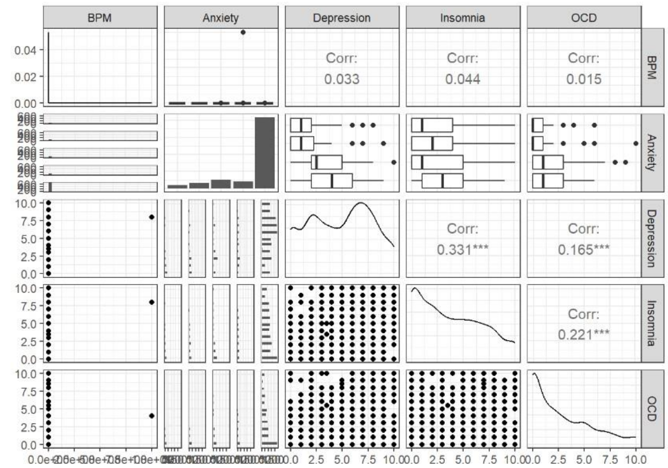
Comparison and Contribution: While acknowledging music's positive impact, our project innovates by employing machine learning. Unlike traditional studies, we leverage algorithms to analyze extensive datasets, providing a deeper understanding of the complex relationship between music and mental wellbeing. For instance, through our analysis, we discovered how different music genres can significantly impact sleep patterns and, by extension, mental health. Such insights are the result of our model's ability to process and learn from large volumes of data, considering numerous variables and their interrelations simultaneously. This approach offers a data-driven enhancement to traditional methodologies, contributing to a more nuanced comprehension of music's therapeutic potential in mental health.

Data Description The data set that we are using to solve this problem is “music – mental health”. It is a survey dataset that highlights observational aspects of the data capturing diverse aspects of individuals' music preferences, habits, and mental health. Before modelling we did some data cleaning to handle the missing values. We then began summarizing the data to understand the data composition which helped us answer our question. We made our response variable binary, so that we have enough values to understand what the results stand for. We also combined the ‘worsen’ and ‘no effect’ values in the music effects column to enhance the modelling process. We had 1124 samples and 32 variables for our project. We did the data partitioning by 70-30.

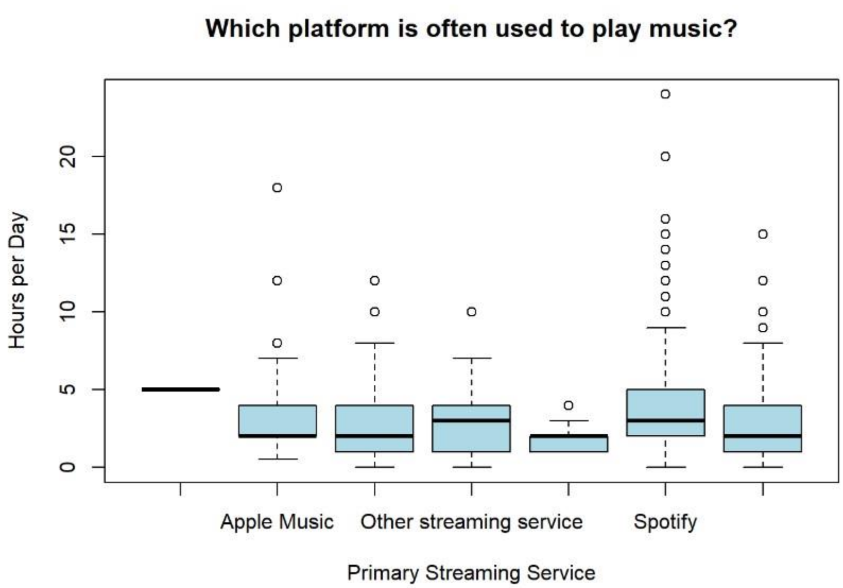
The brief overview of some of the columns:

1. **Age**: The age of the individual.
2. **Primary streaming service**: The main platform used for streaming music.
3. **Hours per day**: The number of hours spent streaming music per day.
4. **While working**: Whether the individual listens to music while working (Yes/No).
5. **Instrumentalist, Composer**: Whether the individual is an instrumentalist or composer (Yes/No).
6. **Fav genre**: Favorite music genre.
7. **Exploratory**: Whether the individual explores new genres (Yes/No).
8. **Foreign languages**: Ability to understand foreign languages in music (Yes/No).

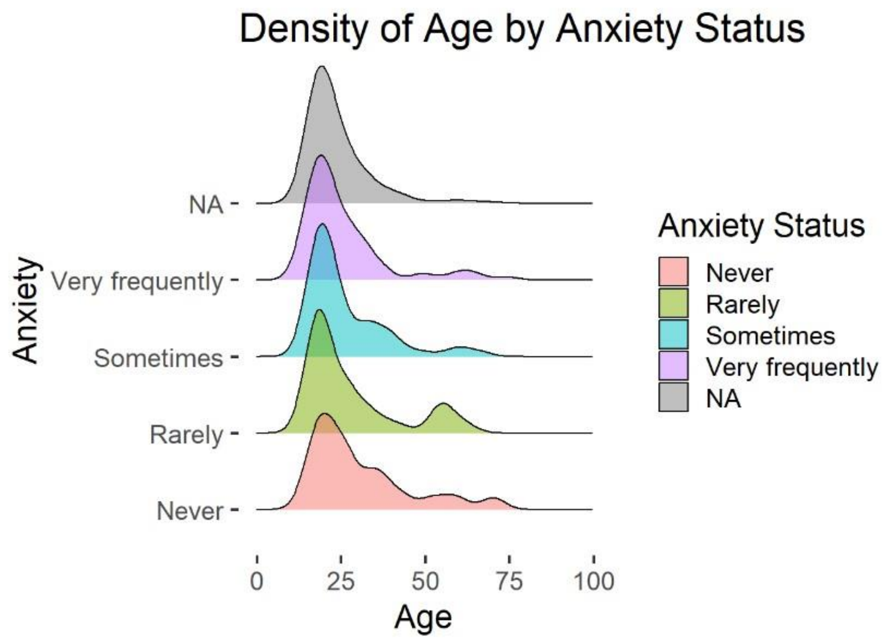
9. **BPM**: Beats per minute of preferred music.
10. **Frequency [Genre]**: Frequency of listening to specific genres.
11. **Anxiety, Depression, Insomnia, OCD**: Self-reported mental health indicators.
12. **Music effects**: Perceived effects of music on mood or well-being.
13. **Permissions**: Agreement or understanding of data usage.



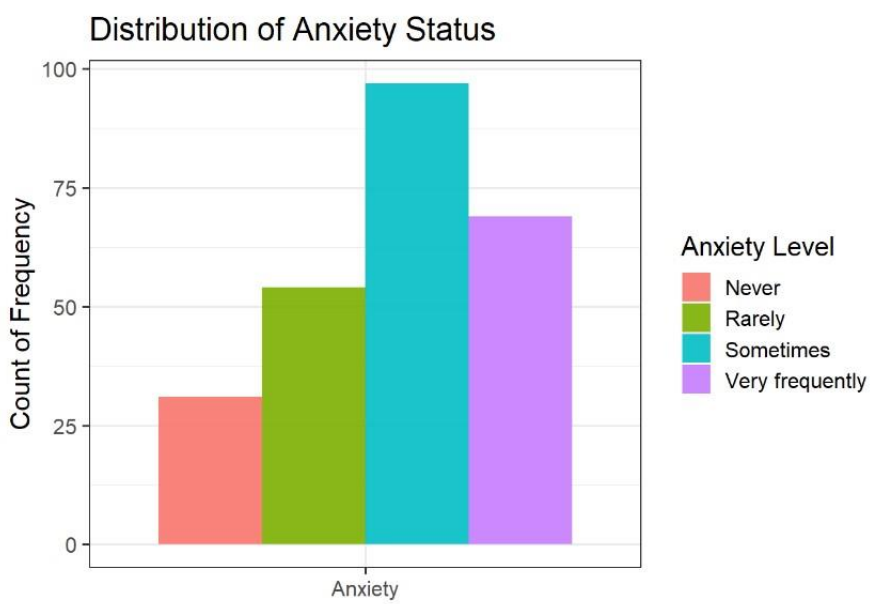
Interpretation: The analysis uncovers a statistically significant positive correlation of 0.044 between Insomnia levels and BPM, indicating that higher beats per minute are connected with increased Insomnia. Likewise, for Depression and OCD, correlations of 0.033 and 0.015 are noted, respectively, suggesting relationships between elevated beats per minute and heightened levels of these mental health conditions.



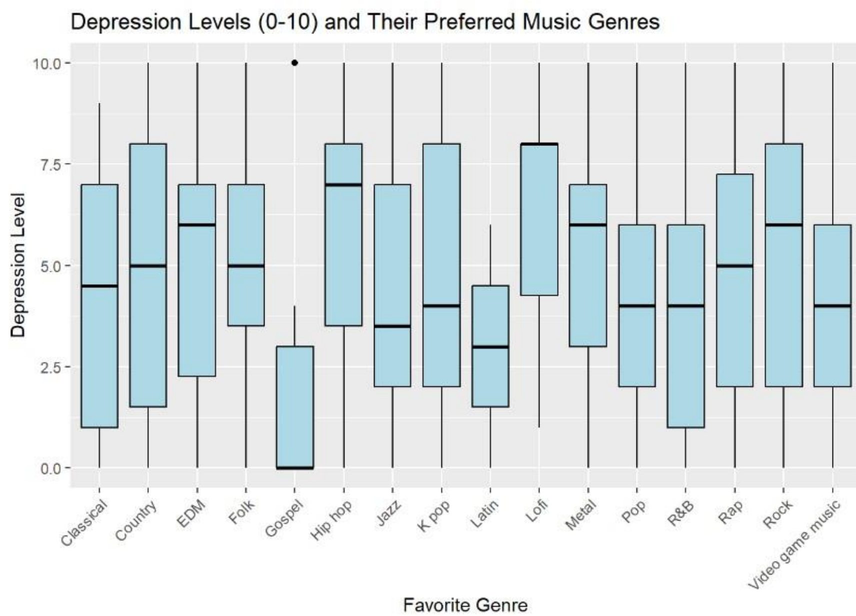
Interpretation: Among various platforms, Spotify has the highest number of listeners. This indicates that, on average, a majority of people use Spotify for listening to music.



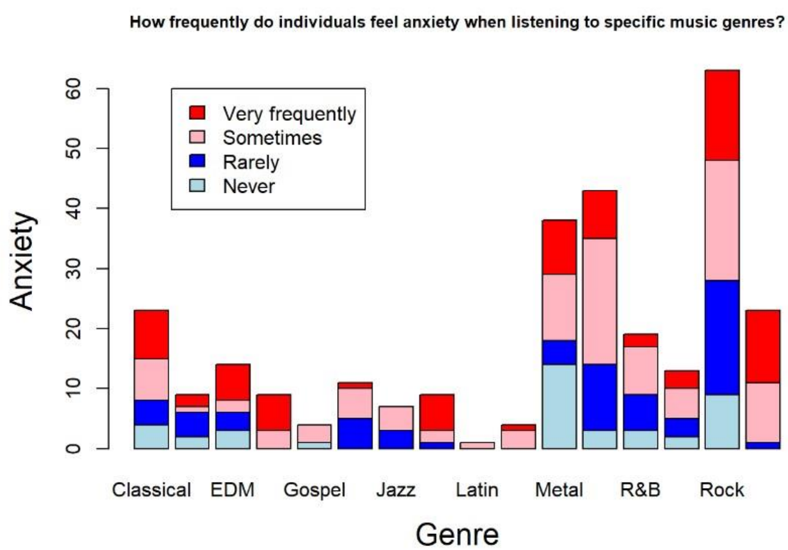
Interpretation: Examining the correlation between individuals' ages and the levels of anxiety they experience.The graph illustrates an increase in anxiety levels among individuals aged 17 to 23, followed by a gradual decrease after the age of 23.



Interpretation: Based on the depicted graph, it can be inferred that the majority of individuals experience anxiety either occasionally or frequently.



Interpretation: The box plot indicates a preference for Lofi and Hip hop music to alleviate depression, while, on average, rock music stands out as the second most commonly chosen genre among individuals seeking relief from depressive feelings.



Interpretation: On average, the majority of individuals experience anxiety when listening to Rock and Pop music.

Methods

For the analysis of the relationship between music consumption and mental health, we employed three machine learning models: random forest, bagging, and XGBoost. These methods are well-suited for complex datasets with multiple predictors and can handle both numerical and categorical variables effectively.

Random Forest: It is an ensemble learning method that builds multiple decision trees and merges them to improve accuracy and control overfitting. We opted for Random Forest in our analysis due to our dataset's mixed numerical and categorical variables. This choice facilitated effective modeling for our survey data, capturing complex interactions among variables by constructing and combining multiple decision trees. Noteworthy is its resilience to outliers, a crucial consideration given the nature of survey data where outliers can significantly impact model performance. Overall, the strategic use of Random Forest in our analysis facilitated a comprehensive exploration of intricate relationships within the dataset, yielding valuable insights for our survey-based study.

Bagging, or Bootstrap Aggregating, involves creating multiple models with different subsets of the training data and then combining their predictions. This approach helped us to reduce variance and enhance the overall model's robustness. In our study, where individual preferences and behaviors related to music may vary widely, bagging can be advantageous in capturing the overall patterns within the data and improving generalization to unseen cases. In the context of music consumption, people have diverse tastes, and bagging helps capture the overall patterns and trends in the relationship between music and mental health across different subsets of the population.

XGBoost, or Extreme Gradient Boosting, is a powerful and efficient machine learning algorithm that falls under the category of ensemble learning. It is particularly well-suited for a wide range of datasets, including those with a mix of numerical and categorical features, making it a potentially good fit for our dataset on music consumption and mental health. It excels in handling missing data, managing imbalanced datasets, and has a built-in regularization term, reducing the risk of overfitting. Given the variety of variables in our dataset and the potential for noise in self-reported mental health indicators, XGBoost's ability to handle such challenges makes it a suitable choice.

However, it's essential to acknowledge the limitations of these methods. While ensemble methods like Random Forest and bagging can enhance predictive performance, they might not offer as much interpretability as simpler models. The complexity of XGBoost may make it prone to overfitting if not tuned properly, and careful consideration should be given to hyperparameter tuning. Additionally, the success of these models depends on the quality and representativeness of our dataset, and biases within the data may impact the generalizability of the findings. In conclusion, the ensemble methods we chose are well-suited for exploring the complex relationships between music consumption and mental health, but we had to do careful model evaluation, interpretation, and consideration to avoid potential biases and to draw meaningful conclusions.

Results

In our study, we decided to use the Random Forest method as our main analytical tool. This choice was driven by the fact that our dataset had a mix of numerical and categorical variables. Random Forest is good at building and combining multiple decision trees, which helped us model the complex relationships within our survey data. One cool thing about Random Forest is that it's not easily thrown off by outliers, which is important in survey data where outliers can mess up the accuracy of the model. Overall, using Random Forest allowed us to thoroughly explore the intricate connections in our dataset and gain valuable insights for our survey-based study.

To make our model even more robust, we also included Bagging, or Bootstrap Aggregating. This technique involves creating different models with subsets of the training data and then putting their predictions together. It helped us reduce variability and make our model better at predicting things it hasn't seen before. Since people's preferences and behaviors related to music can vary a lot, especially in our study, Bagging turned out to be really helpful in capturing general patterns and trends in the relationship between music and mental health across different groups of people.

We also brought in XGBoost, which stands for Extreme Gradient Boosting. It's a powerful tool in machine learning that's good for datasets like ours with a mix of numerical and categorical features. XGBoost is handy because it can handle missing data, deal with imbalanced datasets, and has a built-in feature to prevent overfitting. Considering the diverse variables in our dataset and the potential for inaccuracies in self-reported mental health indicators, using XGBoost made a lot of sense. It helped us tackle these challenges and draw meaningful conclusions about the connection between music consumption and mental health in our study.

Some of the hyperparameters chosen are:

- **eta**: Learning rate, set to 0.1.
- **max.depth**: Maximum depth of a tree, set to 7.
- **nrounds**: Number of boosting rounds, set to 100.
- **early_stopping_rounds**: The number of rounds without improvement in the evaluation metric to stop training, set to 20.
- **eval_metric**: Evaluation metric to use, set to "auc" and "error".

We made sure that the model would not overfit but using the early_stopping_rounds hyperparameter. If the evaluation metric (AUC in this case) doesn't improve for 20 rounds, training is stopped to prevent overfitting. All the methods that we used gave us confusion matrices and also a few graphs to interpret and proceed further with the best suitable method. Our methods performed fine on training, test and validation sets. We did not have very high accuracy of prediction but it was mediocre.

We used the ROC plots to judge our methods. We defined the AUC values of each method before selecting one. The AUC value of RF was 0.792, the AUC of bagging was 0.795 and the AUC of xgboost was 0.819. Therefor, it was obvious that we chose xgboost method as our best bet.

RF Confusion Matrix:

```
Confusion Matrix and Statistics
##
##
## rf_pred_class Improve Worsen
##      Improve      38      9
##      Worsen        6     16
```

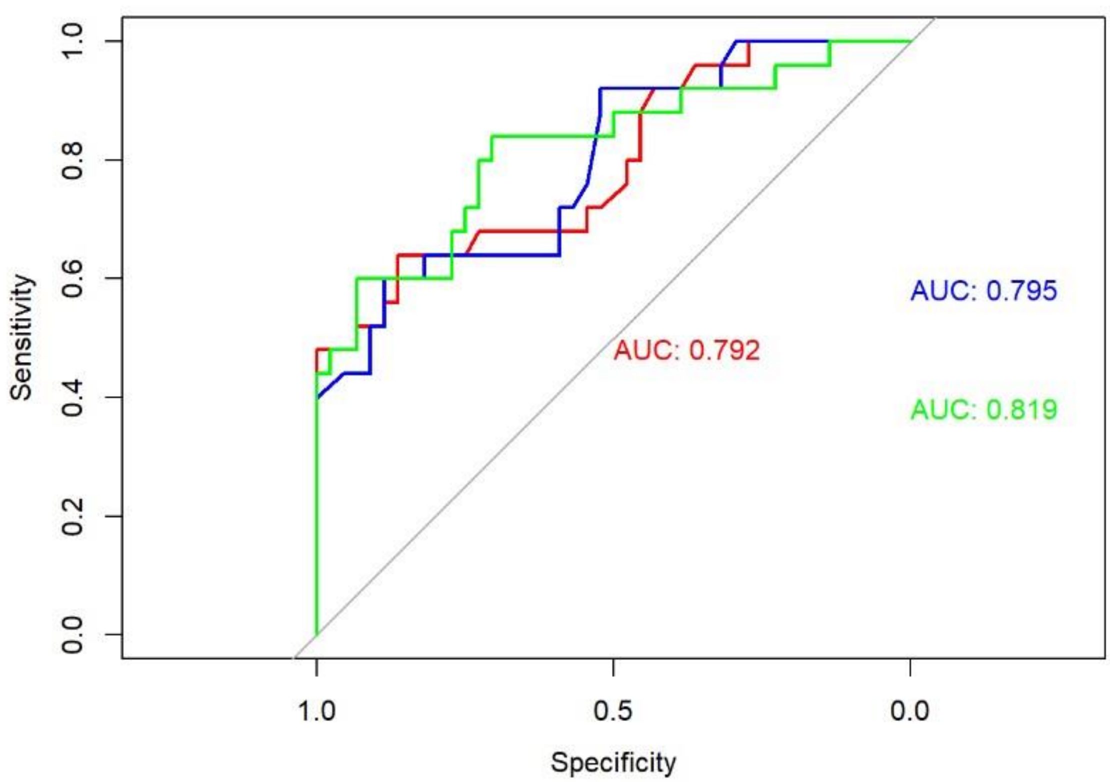
Bagging Confusion Matrix

```
Confusion Matrix and Statistics
##
##
## bag_preds Improve Worsen
##   Improve      36      9
##   Worsen        8     16
```

XGBoost Confusion Matrix

```
## Confusion Matrix and Statistics
##
##
## boost_pred_class  1  2
##                1 36 10
##                2  8 15
```

The major challenge that we faced while doing this project is that we had a lot of categorical variables, so we had to carefully choose the variables we would like to use to solve our question. One of the most challenging part of doing this project was the missing values. They were removed for XGBoost model but not when creating the training and test data sets for random forest. That was when we had to figure a lot of things out before modifying the code to do it in advance.



Discussion

The sensitivity, also known as recall or true positive rate, is 0.64. It represents the ability of the model to correctly identify "Worsen" instances among all actual "Worsen" instances. The specificity is 0.8636, indicating the ability of the model to correctly identify "Improve" instances among all actual "Improve" instances.

The accuracy on the test data is 0.7536, indicating the proportion of correctly classified instances. The bagging model performs reasonably well, with accuracy metrics indicating its ability to generalize to new data. The confusion matrix provides a detailed breakdown of predicted and actual classes, helping to assess the model's strengths and weaknesses. The OOB error estimate gives an indication of the expected performance on unseen data.

The XGBoost method gave a 95% confidence interval for the accuracy, ranging from 61.94% to 83.75%, suggests that if the model were applied to new data, its accuracy would likely fall within this range 95% of the time. The No Information Rate of 63.77% indicates the accuracy that would be achieved by always predicting the most frequent class, suggesting that the model is performing better than a naive approach. The p-value of 0.04928 shows that the model's accuracy is statistically significantly better than the No Information Rate.

1. **Insomnia's Predominant Role in Model Predictions:**
    - The fact that insomnia is identified as the most influential feature in the XGBoost model plays a significant role in the relationship between music and mental health. This insight suggests that insomnia may be a key mediator or indicator in how music genres affect mental well-being. It could prompt further investigation into specific aspects of insomnia, like its duration, severity, and the types of sleep disturbances associated with different music genres.
2. **Nuanced Understanding of Music Genres and Insomnia:**
    - The heatmap analysis offers a nuanced view of how various music genres correlate with different levels of insomnia. It might reveal, for instance, that certain genres are consistently associated with higher or lower levels of insomnia. This could lead to hypotheses about the characteristics of these genres (such as tempo, rhythm, or lyrics) that might influence sleep patterns.
3. **Potential for Tailored Music Therapy:**
    - The insights gained could be pivotal in developing tailored music therapy interventions. Understanding which music genres positively or negatively correlate with insomnia can guide music therapists in creating personalized playlists or music-based interventions that cater to individual mental health and sleep needs.
4. **Cross-Disciplinary Applications:**
    - These findings have potential applications across multiple disciplines. In psychology, they can contribute to understanding the psychological effects of music. In sleep studies, they can aid in exploring non-pharmacological treatments for insomnia. In musicology, they offer a window into the emotional and physiological impacts of music.
5. **Predictive Modeling in Mental Health Research:**

- The effectiveness of the XGBoost model in predicting the relationship between music genres and insomnia highlights the utility of machine learning in mental health research. It showcases how predictive modeling can uncover complex patterns in behavioral data that might not be apparent through traditional analytical methods.

6. **Cultural and Demographic Considerations:**

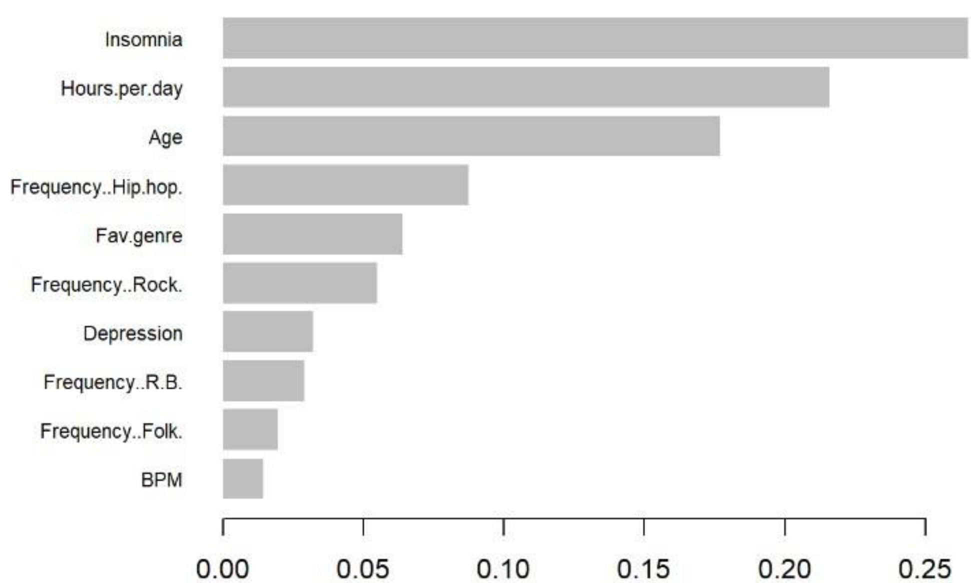
    - The relationship between music genres and insomnia might vary across different cultural and demographic groups. This aspect could be explored further to understand how cultural background and demographic factors (like age, gender, and ethnicity) influence music preferences and their impact on sleep and mental health.

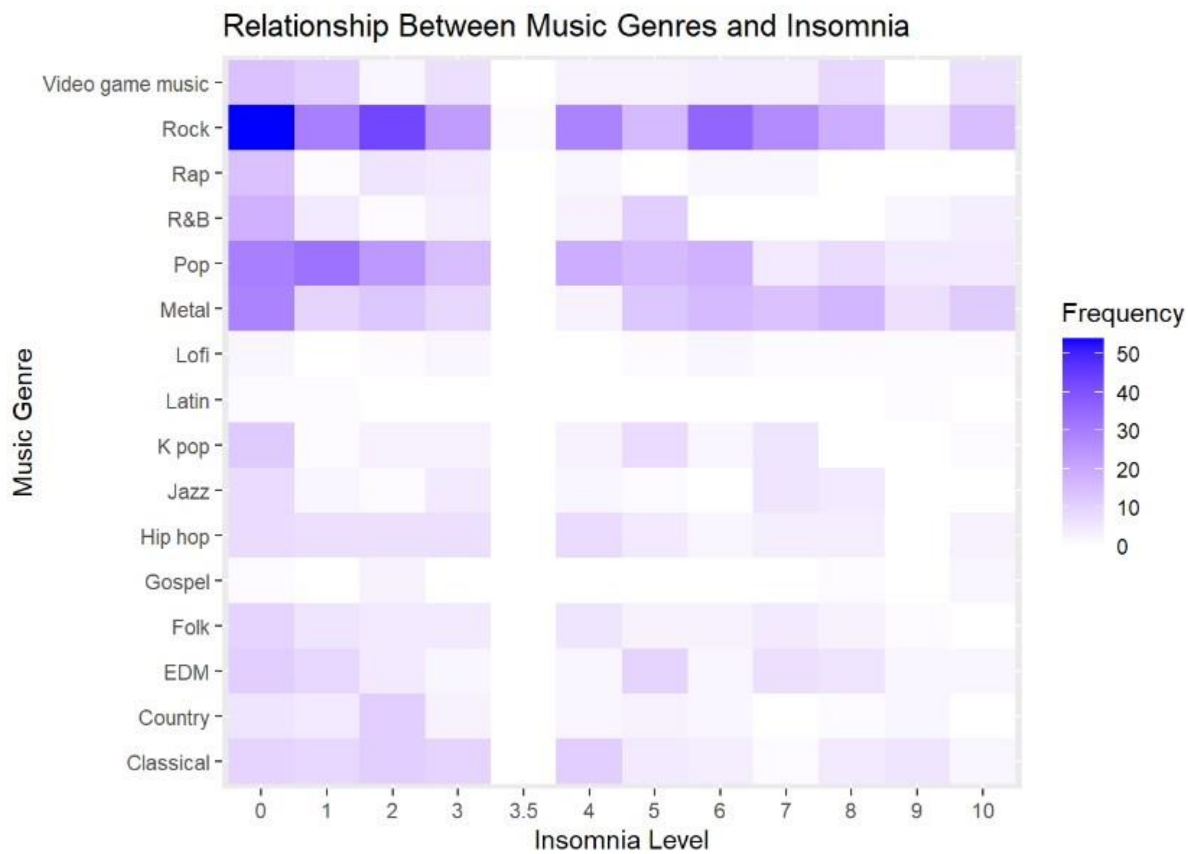
7. **Longitudinal Studies for Dynamic Understanding:**

    - Conducting longitudinal studies could provide insights into how the relationship between music preferences and insomnia evolves over time. This could be particularly relevant for understanding how life changes or interventions might alter one's music preferences and subsequent sleep quality.

8. **Public Health Implications:**

    - The findings could have implications for public health strategies aimed at improving mental health and sleep hygiene. Educational campaigns or app-based interventions that suggest music genres based on personal sleep patterns could be developed as part of holistic health approaches.





Conclusion

This report delved into the intricate relationship between music genres and insomnia, utilizing machine learning techniques, particularly an XGBoost model, and statistical analysis. The findings highlighted insomnia as the most impactful feature, suggesting a strong link between sleep patterns and music preferences. A heatmap effectively illustrated how different music genres correlate with varying levels of insomnia, offering insights for psychology, music therapy, and sleep studies. The XGBoost model outperformed Random Forest and Bagging models in accuracy, demonstrating the potential of machine learning in behavioral research.

Looking ahead, the project could expand into longitudinal studies to observe changes over time, crosscultural analyses to understand diverse impacts, and detailed investigations into specific musical elements like tempo and lyrics. Collaborations with experts in related fields and development of practical applications, such as music-based interventions and educational campaigns, are promising next steps. These efforts could offer a deeper understanding of music's influence on mental health and sleep, with potential applications in therapeutic and public health domains.

Contribution

We both shared everything we did in this project. This includes the code, analyzing the errors, modelling, finding insights and interpreting the visualizations. We also worked on our presentation together by gathering information that we thought was useful to make recommendations for the problem that we worked on, along with the limitations that we found while doing this project.

Bibliography

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