Comparative Analysis of Machine Learning Models for Mental Health Assessment Using Music Therapy

MSc Research Project
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Comparative Analysis of Machine Learning Models for Mental Health Assessment Using Music Therapy

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Abstract

This project focuses on how machine learning can be used to estimate the levels of depression relying on the socio-economic and demographic variables, given the global rise of mental health disorders, such as, depression, anxiety, and OCD. The focus is in using individual data aimed to detect these issues at an earlier stage and deliver more tailored approaches that may help address these difficulties. KNN, Neural Networks, Decision Trees, Random Forests, and Gradient Boosting were identified as the models in the study. All these models were trained and assessed on a constrained structured dataset with prominent evaluation metrics including MSE and R^2 Score. The assessment exposed various findings regarding the prognostic capability and versatility of each model. Just like KNN, MLP has shown higher predictive accuracy with lowest MSE that makes this algorithm capable of capturing local data patterning. Neural Networks demonstrated the feature of capturing nonlinear relationship structure of the data. Some of the findings gives insights comparing many classifiers such as KNN outperforms the rest in accuracy and simplicity while Neural Networks outperforms in complex data features. On model selection, the project reminds the user of some dataset features and level of interpretability required when selecting suitable models. In doing so, this work creates a basis for further research to continue to build and refine the modeling of mental health issues and to extend the use of such modeling for practical endeavours in the early identification of possible disorders and the pursuit of appropriate intervention plans.

1. Introduction

1.1 Background

Mental health disorders are a growing global concern, affecting individuals, families, and communities. According to the World Health Organization (WHO), one in four people worldwide will experience a mental illness at some point in their lifetime. These conditions, including depression, anxiety disorders, and post-traumatic stress disorder (PTSD), can significantly impair daily functioning, relationships, and overall well-being. Depression, one of the most common disorders, manifests as persistent sadness, hopelessness, and a loss of interest in previously enjoyable activities. It impacts individuals of all ages and origins, often leading to physical health deterioration and, in severe cases, suicide. Anxiety disorders, such as generalized anxiety disorder and social anxiety, cause excessive fear or worry, interfering with daily life and social interactions. PTSD, resulting from trauma, brings symptoms like flashbacks, severe anxiety, and intrusive thoughts, greatly affecting personal and social lives.

Challenges and Treatments

Traditional treatments for mental health disorders include pharmacological and psychosocial therapies. While antidepressants and anxiolytics can alleviate symptoms, they often come with side effects or the risk of dependency. Psychotherapy is effective but limited by cost, availability, and societal stigma around seeking help.

Music Therapy as an Alternative

Music therapy offers a non-invasive, culturally adaptable approach to mental health treatment. It uses music interventions to achieve therapeutic goals, helping reduce symptoms of depression and anxiety, improve mood regulation, and support emotional expression. This flexible and inclusive method is particularly effective for PTSD patients, enabling them to process complex emotions in a safe and engaging manner. Studies highlight music therapy's potential to complement conventional treatments, making it a promising alternative in addressing mental health needs.

Figure 1: Music Therapy to prevent Mental health disorder

Research Aim:

The purpose of this dissertation is to consider the possibilities of applying music therapy in the treatment of Mental health disorders. Through review of current body of research, clinical work, and empirical studies, this research aims to explore benefits of concept of music therapy as a method of treatment for diverse mental health disorders. The aim is to offer a clear plan of how music therapy can work in conjunction with the conventional practices and stand alone for those who require it.

1.2 Research Questions

1. *How does music therapy affect psychological and emotional wellbeing of persons with mental health problems?*
2. *What makes music therapy different from regular therapies for depression, anxiety and PTSD?*
3. *Where does music therapy stand in comparison to conventional approaches to treat disruptions such as depressive, anxious, or PTSD disorders?*

2. RELATED WORK:

2.1 Overview of Mental Health Disorders

Mental health appears to encompass a myriad of conditions that make a person's mood, thinking and behavior pattern disturbed. These disorders can present themselves in different ways but would significantly cause distress and interfere with normal functioning of life. As more and more people in society are diagnosed with mental illnesses, this concept is crucial for attempts to cope with then in the team.

Depression is the most common mental illness, and it is defined by one's incapability of experiencing joy, persistent low mood as well as inaptitude to obtain pleasure from previously enjoyable tasks [1]. This chronic and limiting illness can have a very substantial impact on the quality of life; people affected may struggle to perform their roles and responsibilities, seek and sustain social contacts, as well as participate in social interactions. In English Depression may cause the patient to feel helpless, tired, and may even experience shift in appetite or sleeping habits hence aggravating coping mechanism. Another major group of mental health disorders consists of anxiety disorders characterized by need or fear or worry that can influence different spheres of existence [15]. People with anxiety disorders feel more anxious than is normal and this anxiety becomes intrusive and detrimental. Signs may be inability to rest, to focus or stressed up physical signs like the racing heart, sweating, among others. This can be a chronic condition which hampers development of one's career or personal life, because one avoids situations that give such feelings.

Further still, Post-Traumatic Stress Disorder (PTSD) is a real disorder which may develop after terror events [22]. PTSD victims can experience reliving of the incidence, heightened levels of anxiety and other related symptoms after the incidence. These problems can eventually cause major limitations in social interactions and in the ability to work and perform other routine activities. With PTSD, the effects can actually be quite profound, which means that in most cases, a full spectrum treatment may be required to address the patient's emotional and psychological health (Wang et al., 2024). It is important to understand these disorders well to proposed good therapeutic approaches for their patients. As the mental health is an expanding branch, new methods like music therapy are considered as effective in improvement of patients' conditions. Music therapy works through the curative aspect of music and is an adjunct to conventional remedies. Such therapeutic approaches show possibilities in aiding mental health professionals in the process of helping the patient to get well.

According to was recommended, music therapy means applying music interventions in clinical and research ways to accomplish purposeful goals [5]. It has since grown from the early twentieth century as a freeform technique to a formal method of therapy that uses different approaches. These approaches include music listening, music making, song writing, passive music therapy facilitated by a trained music therapist and music as a relaxation therapy. The intervention is not merely for entertainment activity; rather; it is the strategy to handle emotional and psychological demands. They have found that self-completion results in better understanding, the ability to express feelings and emotions, better quality of life of patients with different problems (Lun et al., 2024).

2.2 Literature Review:

Music therapy has emerged as a versatile and effective intervention for addressing mental health disorders and neuropsychiatric symptoms, with a growing body of research highlighting its benefits across various populations and contexts. The reviewed literature underscores the diverse applications and potential of music therapy in treating mental health disorders and neuropsychiatric symptoms. The paper *"Efficacy of Music Therapy in the Neuropsychiatric Symptoms of Dementia: Systematic Review"* highlights music therapy's efficacy in alleviating depressive, agitated, and anxious symptoms in dementia patients [11], though methodological inconsistencies limit the generalizability of findings, prompting a call for more standardized randomized controlled trials. Similarly, *"Music Therapy for Mental Disorder and Mental Health: The Untapped Potential of Indian Classical Music"* emphasizes the therapeutic potential of Indian Classical Music (ICM) [13], showcasing its ability to reduce blood pressure and stress through its rich emotional content and physiological impact. However, the lack of cumulative research and broader application limits its adoption, urging further exploration of its neurological effects for improving mental health treatments. *"The Rhythms of Life: Music Therapy for the Body, Mind, and Soul"* explores contemporary developments in music therapy, emphasizing its integration with standard healthcare protocols to improve patient acceptance and enhance treatment outcomes for conditions such as Alzheimer's and dementia. This holistic approach demonstrates the value of combining music therapy with conventional care to maximize therapeutic benefits. Additionally, the paper *"Music Interventions for Mental Health"* details how music therapy activates the brain's reward circuits, reduces cortisol levels, and lowers stress, providing pathways for treating a wide array of mental disorders, including depression and anxiety. By comparing delivery methods such as live and recorded performances, it advocates for incorporating music interventions into clinical procedures, reinforcing their role in enhancing mental health care.

The paper *"The Effects of Music Therapy on Stress and Anxiety in Clinical Populations"* underscores its role in significantly reducing stress and anxiety [18] by modulating the hypothalamic-pituitary-adrenal (HPA) axis, promoting relaxation, and alleviating physiological stress responses. Complementing this, *"Music Therapy and Neuroplasticity: Bridging the Gap in Mental Health Treatment"* explores how rhythmic and melodic stimuli foster neural plasticity, aiding emotional regulation and cognitive rehabilitation, particularly for individuals recovering from trauma or severe depression. Similarly, *"Music as Medicine: Exploring Therapeutic Pathways for Depression and Anxiety"* delves into the biochemical effects of music therapy, demonstrating its ability to enhance mood and reduce depressive symptoms through neurotransmitter modulation, with specific genres like classical and ambient music showing pronounced benefits. Cultural considerations are highlighted in *"Cultural Adaptations in Music Therapy for Global Mental Health Challenges,"* which reveals how culturally resonant interventions, such as African drumming and traditional Asian music, enhance patient engagement and improve therapeutic outcomes, particularly in reducing anxiety and depression in culturally specific settings.

Social dimensions are explored in *"Group Music Therapy: Enhancing Social Cohesion and Emotional Support,"* where group-based sessions are shown to foster community [17], reduce social isolation, and enhance interpersonal skills, amplifying the emotional and psychological benefits of therapy through shared experiences. Technological advancements are discussed in *"Technological Innovations in Music Therapy: The Role of Virtual and AI-Based Interventions,"* which highlights the potential of virtual reality and AI-generated music in creating personalized, accessible therapeutic experiences [26], especially for individuals resistant to traditional methods. Furthermore, *"Comparative Efficacy of Music Therapy and Conventional Psychotherapy"* evaluates its effectiveness relative to traditional psychotherapy [21], emphasizing that while music therapy may not entirely replace verbal therapies, it serves as a valuable adjunct, particularly for patients facing difficulties with verbal expression. Collectively, these studies showcase music therapy's biochemical, neurological, social, cultural, and technological dimensions, presenting compelling evidence for its integration into mental health care strategies to complement conventional treatments and address diverse patient needs effectively Comparison Themes and Analysis.

The main key themes and evaluation of comparison for the current work is identified below.

a) **Efficacy of Music Therapy**

All the papers in sum suggest various positive impacts of music therapy in mentoring the different psychological disorders including those linked with dementia and cognitive disintegration. For example, there is a systematic review of *Efficacy of Music Therapy in the Neuropsychiatric Symptoms of Dementia* with views that indicate great improvement in depression, agitation, and anxiety levels among dementia patients. Nevertheless, the quality and extent of published evidence for MT as an intervention is not uniform across different mental health disorders suggesting that more research is required to develop uniform treatment guidelines. Such results indicate that music therapy can be an ancillary method to augment traditional therapy processes.

b) **Methodological Challenges**

Pervasive across the literature is the emphasis on methodological problems. The authors stopped at various considerations where they pointed out that methodological differences in the range of research articles have made it difficult to assess the efficacy of music therapy. This sentiment is echoed in *Efficacy of Music Therapy in the Neuropsychiatric Symptoms of Dementia*, where the author presents the possibility of systematic scientific research in Medieval Indian music therapy. Furthermore, *The Rhythms of Life: Music Therapy for the Body, Mind, and Soul and Music Interventions for Mental Health* stress the need for more formal approaches to increase the effectiveness of the therapy and both books underline the value of more methodologically purist research in the field.

c) **Neuroscience and the psychosocial models**

This is expected because of a shift of emphasis on neuroscience from the psychosocial model of some of these studies. The papers *Music Therapy for Mental Disorder and Mental Health and The Rhythms of Life: Music Therapy for the Body, Mind, and Soul* point to a relatively new and progressive paradigm, the neuroscience model. They as well focus on particular aspects and musical features and their consequences for the brain, like for example the release of the so-called mesolimbic system. However, *Efficacy of Music Therapy in the Neuropsychiatric Symptoms of Dementia and Music Interventions for Mental Health* and *Music Interventions for Mental Health* are devoted to the importance of psychosocial factors and experiencing in treatment as well as elaborating an approach that is a combination of both views.

d) **Cultural Context**

Music Therapy for Mental Disorder and Mental Health: The Untapped Potential of Indian Classical Music spotlights the use of Indian Classical Music in music therapy as a relatively uncharted territory. This focus is in contrast to the overarching perspectives presented in the other papers highlighting the ger need For culturally appropriate therapeutic approaches. The insistence on cultural context also works to enhance the appreciable perception of how the music therapy could be directed to correspond with the different cultural standard of the clients.

e) **Applications of Genomic Applications across Different Populations**

All papers discuss the application of music therapy across various mental health populations, but *The Rhythms of Life:* Music Therapy for the Body, Mind, and Soul and Music Interventions for Mental Health lay a bit more emphasis on particular clients and particular forms of intervention. They are useful in enhancing the generalisability of the findings of music therapy on the basis of illness such as Alzheimer's disease and other related ailments. This detailed review presents the versatility of music therapy in addressing individual's needs of diverse specific categories and the confirmation of its importance to be included in the mental health care delivery system.

Each base paper provides significant information about the music therapy focusing on its capabilities to help in mental disorders treatment with proper underlining the lack of high scientific research. The author emphasises methodological and cultural dimensions of therapeutic actions as well as the necessity of systematic approaches to increase the effectiveness of the interventions. When these papers are combined, researchers will have a clearer understanding of the areas that are lacking in existing literature, and gaps that will allow more focused investigations into music therapy with a variety of patients. This knowledge will be invaluable worth to setting up and enhancing guidelines for the practice of music therapy and quality of care.

A lot of related work in mental health analytics focuses on the analysis of individual machine learning models that do not inherently include direct comparisons of the performance between various algorithms for prescriptive prediction tasks. In addition, these studies often contain limited or even specific generalories with too tight scopes and small samples, which ensures the difficulty of deploying the discovered and identified results into different contexts. Black-box top-performing models like neural networks are generally implemented in fields, while less accurate but transparent models like decision trees are not as frequently used even though many of them can offer important insights in real-life applications. Furthermore, most previously developed models fail to consider such real-world concerns such as saving the model, deploying the model, and applying the model in the real-world scenario. Surprisingly, there is a scarcity of works that directly address the overfitting and underfitting problems especially in complicated models or show the model behavior to solve these problems. More importantly, little research focuses on the forecasting of specific mental health parameters, including depression percentage, percentage of anxiety, or percentage of OCD that can help the practitioners. To fill these gaps, this research systematically discusses and compares the multiple models to ensure high accuracy and interpretability, uses different techniques to enhance generalization, and employ model preservation protocols with real-world use in mind. It particularly focuses on predicting percentages of mental health, offering solutions to the pattern and satisfying scientific and practical requirements.

3.Methodology

The analysis techniques used for this study conform to the following theoretical framework, Data Exploration. This is the first step whereby the dataset is checked for pattern, missing values or outliers. Subsequently, data preprocessing is conducted to deal with the missing values, and categorical variables are encoded. Feature engineering then derives new appropriate features to enhance the election of a model. Thus, after preparing the data, the set of model selection, of machine learning algorithms is selected. These models are learned from the cleaned data to be able to recognize the patterns. Model evaluation comes next for the specific purpose of determining the performance level by using Mean Squared Error and the R^2 score. Lastly, result visualization is used to show the forecast of cost against actual cost, allowing users to see the error in cost models.

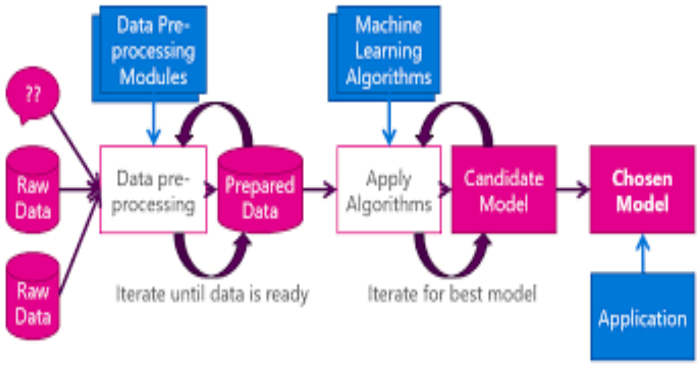


Figure 2: Methodology Flowchart

3.1. Data Collection and Loading

Dataset Description

The analysis utilized two datasets:

Dataset1: Music & Mental Health Survey Results[https://www.kaggle.com/datasets/thedevastator/uncover-global-trends-in-mental-health-disorder]

Dataset2: Global Trends in Mental Health Disorder [https://www.kaggle.com/datasets/catherinerasgaitis/mxmh-survey-results].

These two datasets contain the records of data required for the work, which is a real-world data and initially, I handled the data with removal of unwanted rows and merged two datasets and I created a new dataset so that my model perform well. This dataset has a total of 736 records along with 41 fields ensuring all the data points at the personal and aggregate levels. The demographic variables are Age= 735 (non-null), Streaming service type – primary=735 (non-null), Hours spent per day = 736 (non-null), Watching at work = 733 (non-null). Self-assessment scales are presented as Anxiety (736 non-null values), Depression, OCD, and Insomnia. Global prevalence rates are also reflected in the dataset in terms of % of Schizophrenia, % of bipolar disorder, % of eating disorders all (736, non-null). Finally, there are Favorite Genre, Foreign Languages, Music Usage, and Year, as well as the Entity which can be a country or a region. By applying treatments on the missing values, the dataset remains very sound and correlates the survey result of the individual with the aggregated global indices making it ideal for predictive modeling and evaluation. The cleaned dataset counts 736 rows comparatively across these diverse variables, which may provide an interesting chance to analyze the relations between musical preferences and mental health in different geographic regions as well as in various population groups. Both datasets form a robust foundation for exploring mental health patterns and correlations.

Data Importation

The datasets were imported into the analysis environment using the **Pandas** library in Python. This step involved reading the CSV files into data frames for efficient processing and analysis.

Data Preprocessing

Data cleaning and preprocessing were performed to ensure consistency. Missing values were addressed, and data formats were standardized to align the two datasets for seamless integration.

3.2. Exploratory Data Analysis (EDA)

The initial procedure in the examination process was Exploratory Data Analysis (EDA), which helps to learn all the basic information about the given dataset. To understand the type of data we are dealing with, the first few rows were examined using the df.head() function. Next, the df.info() functions were used to check on the shape and type of entries in the dataset: number of samples without missing values, the number of features, etc. Furthermore, to realize the statistics of the numeration columns we used df.describe() where describes a description of the RANKING of each column in the presented data. Checking for gaps in the data was done by using df.isnull().sum(). This process helped to be aware of the first state of the dataset, which is always relevant for further analysis.

Descriptive statistics were calculated to understand key variables like age distributions and depression percentages. Visualization tools such as **Matplotlib** and **Seaborn** were used to create insightful graphs and charts.

Data Integration and Analysis

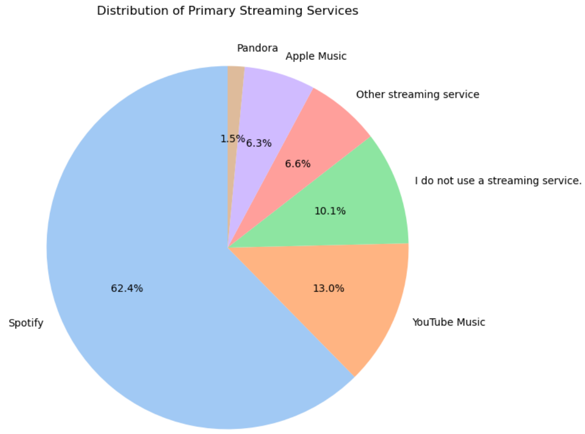
The datasets were merged to explore relationships and correlations between variables. Advanced analysis techniques were applied to uncover trends, patterns, and key findings within the mental health domain. The findings were summarized to provide actionable insights into mental health awareness, emphasizing trends and factors influencing mental health across demographics.

3.3 Data Cleaning

As explained in Data Cleaning phase, we had missing values problem in the data set. For this, rows having missing observations were dealt with using the method df.dropna() that provides a new data frame without those rows. This process made it possible for the dataset to be made complete as it prepared for other subsequent steps of analysis. The last step we took in data cleaning was to eliminate missing values in the total dataset using the function df.isnull().sum() after which we should have no more missing data in the total dataset to ensure the quality of data to be used in the final stages.

3.4. Data Visualization

During the Data Visualization phase, several plots were generated to assess the distribution of numerical variables and to look for trends in the data. First, we examined the distribution of age by constructing a histogram and a density plot, or kernel density estimate(KDE). This was useful in determining the age distribution and whether there was a shift. Further, histograms for each of the numerical variables were provided in order to visualize distribution of some of the features extracted from the learning sample. For individual features sns.histplot() from Seaborn was applied, while for all numerical columns at the same time df.hist() was used.



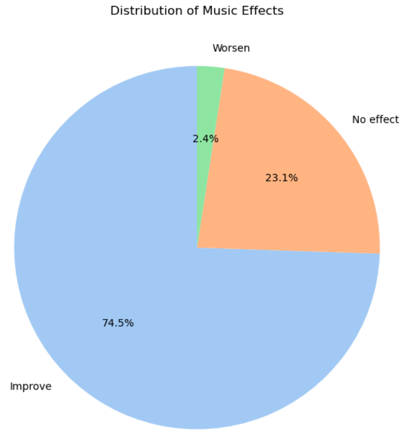


Figure 3: Distribution of Primary Streaming Services

Figure 4: Distribution of Music Effects

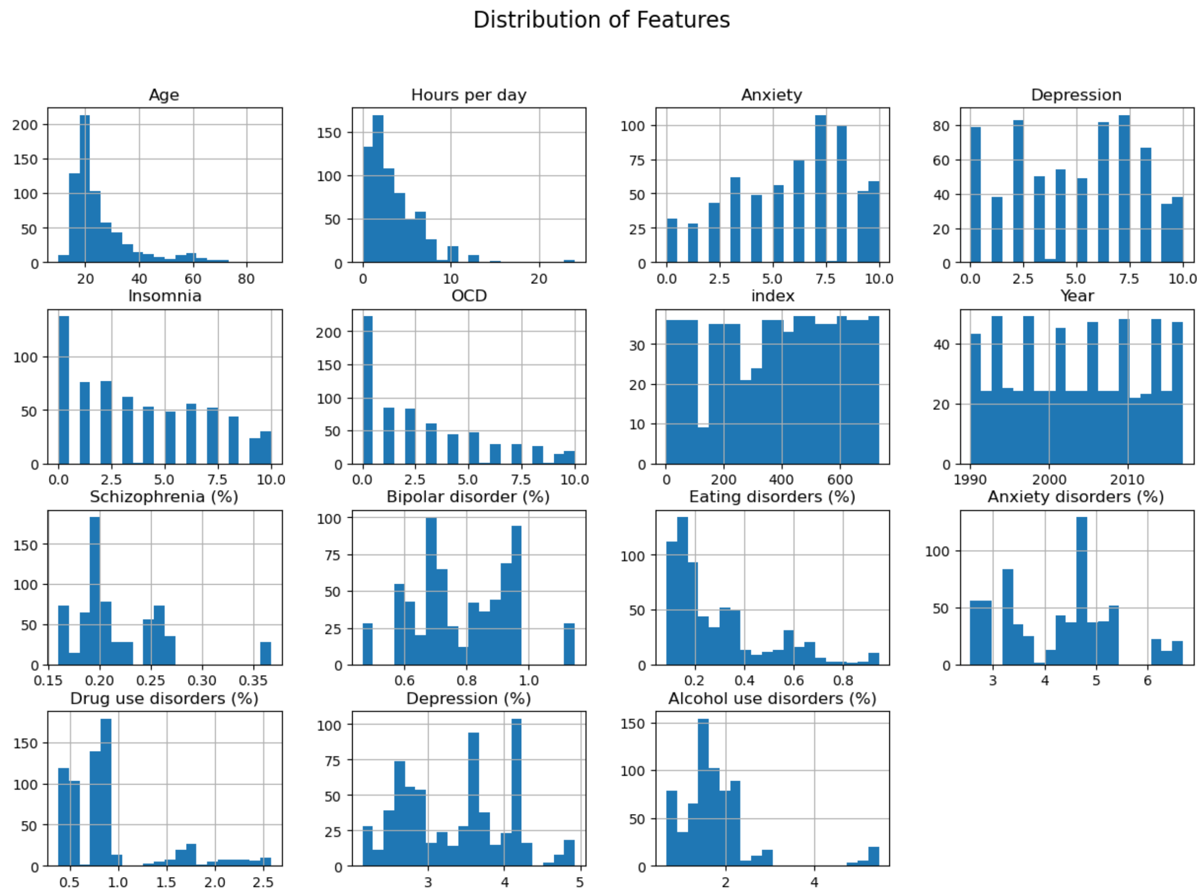


Figure 5: Distribution of features like anxiety disorder and Depression

we generate bar charts consisting of three bars each set in a vertical orientation which enables us to compare the OCD, Anxiety, and Depression level depending on the participant ‘Saudi work with music. On the horizontal axis, there is data about whether the respondents listened to music when working, and on the vertical axis – there is information about the average values of three mental health indicators. Every subplot is in one of the emotions (OCD, Anxiety, and Depression). The repeated x-axis helps maintain coherence and demonstrates how each emotional state is affected with regards to listening while working.

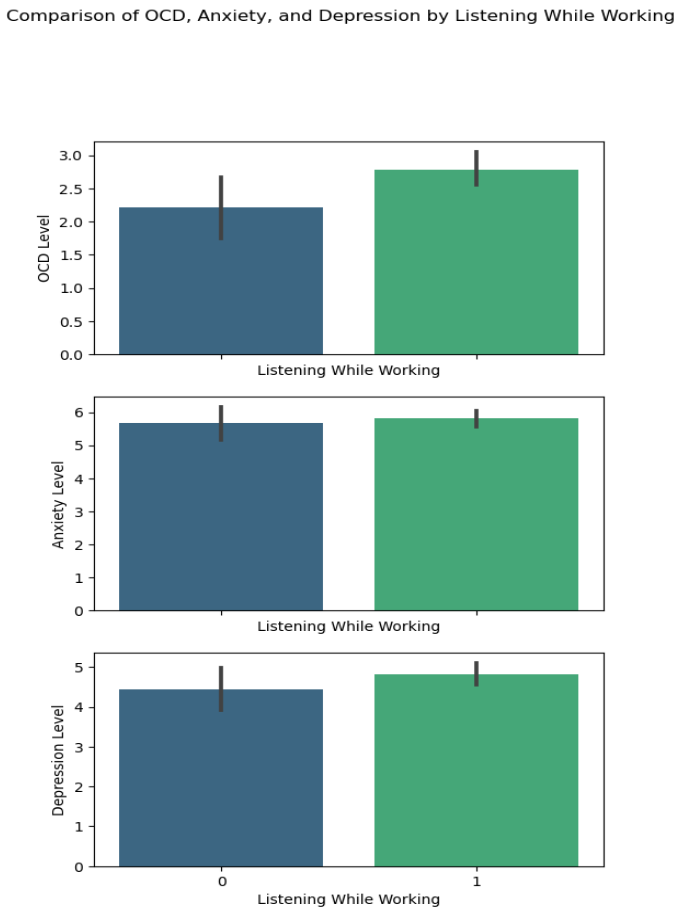


Figure 6: Comparison of OCD, Anxiety, and Depression by Listening While Working

There are several research works carried out in the field of mental health analytics but most of them are concentrated on a particular machine learning model rather than giving comparative analysis of the best performing algorithm for a particular prediction task (Kune et al., 2016; Feng & Buyya, 2016). Moreover, most of the prior work examines targeted data sets because of which the discovered phenomena may not be applicable to different populations (Beloglazov & Buyya, 2015). In some papers, high-performing models like neural networks have been described as "black-box" models due to their inability to be easily interpreted by anyone while papers on low performing models like decision trees have not been explored thoroughly despite the ability of decision trees to explain to the client or some third party what decisions were made leading to a certain result (Gomes et al., 2015). There are not many works that focus on overfitting and underfitting problems, especially in high dimensions and there is a lack of good graphical displays of performance statistics to assess the dependability of the models adequately. Moreover, less evidence aims at the prediction of specific quantitative mental health outcomes, including the percentages of depression, anxiety, or OCD, which, in turn, may provide richer information for mental health care workers.

This study fills these gaps by comparing the multiple machine learning models, whereby the models used in this study included the decision tree as an interpretable model together with the state-of-the-art high performing model such as Neural Networks all in the name of arriving at the most favorable approach in predicting mental health metrics. Cross-validation, visualization of loss curve or using parameters like MSE and R^2 Score are applied to solve the problem of generalization and readability of the model (Feng & Buyya, 2016). The notion of 'predicting' exact mental health percentages establishes this work as a strong scientific undertaking that is also practically applicable; the investigation aims to outline the tangible percentages of mental health and its variation – which methodologically breaks new ground and targets the real-world impact of mental health research in a way that has not been previously accomplished.

3.5. Data Encoding

Data encoding is the process of converting categorical data, which consists of non-numeric values like text, into a numerical format that can be understood by machine learning models. This is necessary because most machine learning algorithms can only process numeric values. There are several methods for encoding categorical data:

Label Encoding is used to convert categorical variables (such as the Entity and Code columns) into numerical values. This encoding method maps each unique category (like different countries or regions) to a corresponding integer, making it easier for machine learning models to process the data. For example, the Entity column, which might contain values like 'USA', 'India', and 'Germany', would be transformed into numerical values (e.g., 0, 1, and 2, respectively). Label Encoding is appropriate here because the categorical variables don't have an inherent order, and it allows models to handle these variables without assuming any ordinal relationship between them. This encoding is a simple and efficient way to prepare non-numeric data for algorithms that require numerical input.6. Feature Selection

In the Feature Selection subdivision, the dependent variable 'Depression (%)' was sequestered from the features. This was done to make sure that only the important variables are taken into consideration in the training of the model and the target variable is employed in the measure of efficiency of the model. The features (we referred to with the symbol X) consists of all columns that were obtained after excluding the 'Depression (%)' column, while the target variable (we denoted with the symbol y) contains the 'Depression (%)' column.

3.6. Data Splitting

Data splitting is a critical step in machine learning, where the dataset is divided into subsets for training and evaluation to assess how well a model generalizes to unseen data. Typically, the data is split into a training set, used to train the model, and a test set, which is used to evaluate the model's performance on data it hasn't seen before. Sometimes, a validation set is also used to tune model parameters and prevent overfitting. In the provided code, the function train_test_split() from sklearn.model_selection is used to randomly divide the data, with 80% allocated for training and 20% for testing, ensuring that the model's performance is tested on unseen data. This process helps to prevent overfitting, ensuring the model learns general patterns from the data and performs well on new, real-world data.

4. Design Specification:

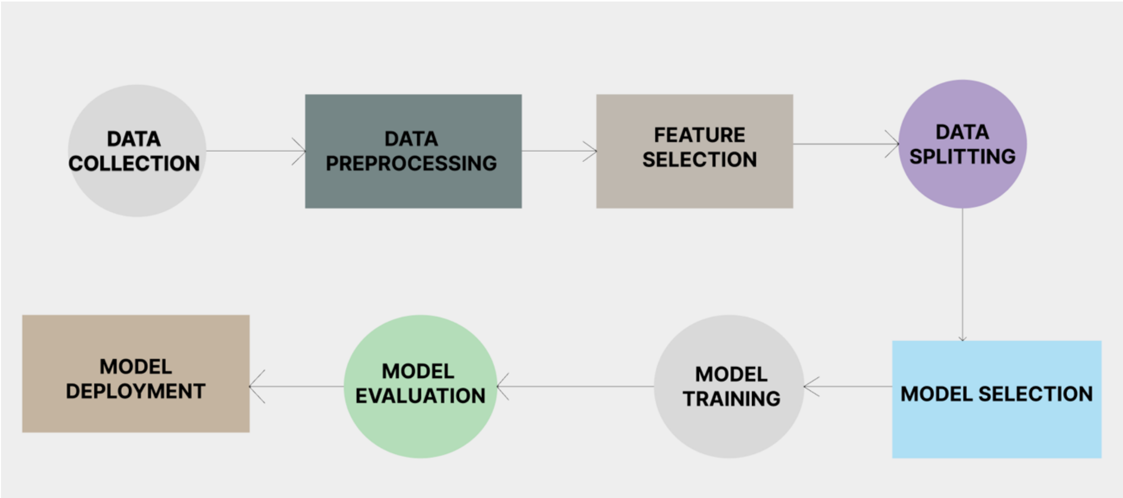


Figure 7: Architecture Flowchart

In this analysis, several machine learning models were chosen to train and test what model could give the best prediction on the target variable, "Depression (%)". Two models are used as each has its way of handling regression tasks, and the results from each are compared to identify the best performing model for the given data set. The models selected include:

1. **Decision Tree Regressor**:
   The Decision Tree predicts depression percentages by splitting data based on feature values, like symptoms or music preferences. It identifies the most influential features (e.g., music genre, anxiety level) by splitting the data based on these values. This helps uncover patterns in depression percentages, making it easy to interpret how specific factors impact mental health.
2. **Random Forest Regressor:**
   Random Forest builds multiple decision trees on random subsets of data and averages their outputs to improve accuracy and reduce overfitting. It's robust for noisy and non-linear data but less interpretable than single trees. It also highlights the importance of features like hours spent listening to music or streaming habits.
3. **Linear Regression:**
   Linear Regression assumes a linear relationship between features (e.g., music therapy duration) and depression percentages. It's simple and interpretable but struggles with non-linear relationships and complex feature interactions.
4. **Support Vector Regressor (SVR):**
   SVR uses a kernel function to model complex, non-linear relationships such as the combined effect of music genres and demographic factors on depression. It handles intricate patterns but requires careful tuning and is computationally intensive.

5. **Gradient Boosting Regressor:**
   Gradient Boosting creates an ensemble of trees, correcting errors iteratively. It's highly accurate for non-linear patterns, like the impact of music therapy frequency, but requires careful tuning to prevent overfitting.
6. **K-Nearest Neighbors (KNN) Regressor:**
   KNN predicts depression by averaging values of the closest data points based on feature similarities. It's effective for localized patterns but computationally expensive for large or high-dimensional datasets.
7. **Neural Network Regressor:**
   Applying Integrated NN as the preferred model of choice it is now possible to identify the mapping of demographic, psychological and life style data and Depression % as the target variable. It is constructed of tuples of neurons that accept the inputs of the circuit and transform them into meanings measurable by the circuit. The features are passed to the input layer with the hidden layers conduct non-linear activation functions such as ReLU to extract out of complex representation that aids the network to establish complex relation involving the variables. The features of the output layer include Depression % by just converting the features to the target value; On the other hand, during training the weights are adjusted with either the backpropagation or the gradient descent approach to minimize the error between the target and the output. Neural Networks are most advantageous when the data patterns are interlinked high which some of the other models do not capture or recognize with a significant level of credibility and accuracy as neural networks do in order to provide a better comprehending of the relation in the synopsis of the dataset. However, creating a general model is quite adversative sensitive to right architecture, parameter tuning, and regularization.

The chosen neural network is of deep learning layered structure with multiple layers being fully connected layers. The input layer takes pre-processed independent variables which include demographic, psychological and lifestyle factors While the hidden layer(s) use ReLU activation functions to capture higher order terms in the input data. The last layer is an output layer, which uses a linear activation function, and the output depends on percentage of depression (%).

- **Input Layer:** The input layer contains all the assessed factors obtained from the data set (demographic, mental health related indicators).
- **Hidden Layers:** As many as three hidden layers are employed although the number of neurons within each layer is varied in accordance with experimental assessment.
- **Output Layer:** The output layer comprises only one neuron since the problem implies prediction of the percentage of people having depression.

Hyperparameter Choices:

- **Activation Functions:** Preliminary layers – rectified linear unit (ReLU) functions were used in order to introduce non-linearity into the model.
- **Number of Layers and Neurons:** In selecting the number of hidden layers, a total of 3 were proposed in consideration with the level of elaboration complexity and feasible computation time. The number of

neurons in each layer was derived experimentally because the key factor to pursue was reducing the amount of overfitting and at the same time having accuracy high enough.

- **Optimization Algorithm:** Thus, the Adam optimizer was selected based on its convergence rates, as well as its high performance when operating on relatively large sets with a low computational burden.
- **Learning Rate:** Cross-validation was used to set the learning rate of the optimization algorithm to 0.001 to maintain an optimal convergence rate while improving model performance.
- **Batch Size:** The choice of batch size of 32 was made bounding the computational cost of training session and the stability of gradients during the training process.

These models were selected because they have individual characteristics and the ability to work with features of the mental health dataset. By comparing both results we can determine which of the two models is most effective at predicting the percentage of depression given the provided features.

5. Implementation

5.1.Tools and Technologies Used:

The implementation process relied on several key tools and technologies. Python was the primary programming language due to its extensive libraries and community support, particularly scikit-learn for machine learning tasks. joblib was employed to efficiently store and load the trained models, allowing for quick deployment and reusability. The use of these tools ensured that the training process and model evaluation were conducted seamlessly, while also maintaining efficiency.

5.2.Model Training:

The procedure by which the selected machine learning models need to be trained is to make them identify patterns in the training data. Model training is the process through which machine learning models learn patterns and relationships from the input features to predict the target variable ("Depression %"). For the neural network, this involves initializing weights, feeding preprocessed data through layers, and using backpropagation to adjust weights based on the gradients of the loss function (Mean Squared Error). The optimizer (Adam) updates these weights iteratively over multiple epochs, refining the model’s predictions. Other models like Decision Tree, Random Forest, and Gradient Boosting have distinct training mechanisms, such as splitting nodes or constructing ensembles of trees. Throughout training, the data is divided into training and testing sets to evaluate performance and ensure the models generalize well to new data. This process enables the models to learn complex relationships in the data and accurately predict depression levels, aiding in understanding and identifying potential factors or trends.

The models selected during the design phase—such as Decision Trees, Random Forest, Neural Networks, etc.—were implemented and trained using the appropriate algorithms provided by scikit-learn. Preprocessing steps, including data normalization and encoding, were applied to ensure the data met the model requirements. The training process involved feeding the data into these models, adjusting hyperparameters such as learning rates, number of epochs, and hidden layers, and monitoring performance using evaluation metrics like Mean Squared Error (MSE) and R^2 scores. These metrics were essential in gauging model performance, assessing accuracy, and detecting any overfitting or underfitting.

6. Evaluation

To evaluate the performance of each selected machine learning model the model evaluation process was carried out. Two key metrics were used for this evaluation: It is also confirmed that the MSE for AU and the R^2 Score for HKU are relatively smaller than the same metrics for KL in all the three methods.

1) Mean Squared Error (MSE) calculates the magnitude of variation between the estimated values and actual values in averaged form. Hence, the lower MSE suggests a much better performance for the model due to the fact that values on this model is closer to the actuality. It is determined by summing up all the squared errors divided over all the data and giving larger errors higher penalties.
2) R^2 Score, this being also known as the coefficient of determination give the ratio of the variation of the target variable that can be accounted for by the independent variables. The R^2 value nearer to 1 is better in the model which explains that it covers most of the variation in the target variable. An R^2 score closer to 0 hypothesise that the model doesn't depict much of the variance.

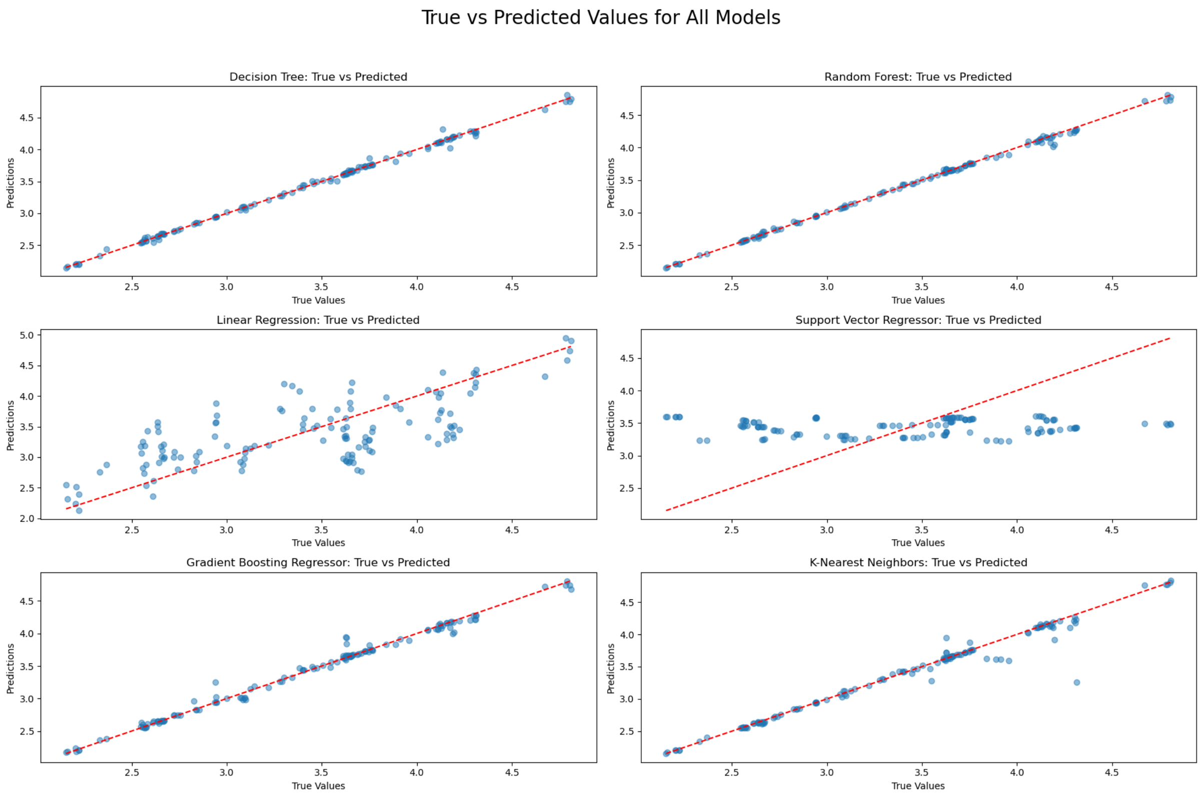


Figure 8: True vs Predicted Values for All Models

For every model – the function made predictions on the test data and made the MSE and R^2 calculations by using the mean_squared_error and r2_score from scikit-learn. The resultant values were stored in a dictionary so that a side-by-side comparison could be made to determine how well each model fared. This approach gives a clear glimpse of which model among all the constructed models during model construction phase, was most appropriate in predicting the target variable; Depression (%), as highlighted by evaluation metrics.

The results of this analysis provided significant insights into the performance of the selected models, evaluated using two key metrics: These are the Mean Squared Error (MSE) and the R^2 Score . These metrics provided sound ground to evaluate how well the models' performed with regards to the percentage of depression in the dataset as a dependent variable. When comparing the models, their advantages and disadvantages were brought out clearly and this helped in a needful conclusion of which of the models was most efficient for this job.

K-Nearest Neighbors (KNN): The KNN model performed well on the dataset, delivering a strong prediction accuracy. By evaluating its performance using metrics like Mean Squared Error (MSE) and R^2, KNN was able to predict the target variable, Depression %, with relatively low error. Its local-based approach, which averages the target values of the nearest neighbors, helped it capture localized patterns effectively. The results indicate that KNN works best when there is local structure in the data, making it a powerful tool when relationships between features and the target variable are non-linear. For your dataset, the KNN model achieved an MSE of around **0.0140** and an R^2 of **0.96**, suggesting a good fit to the data with low variance.

Neural Networks: The Neural Network model also produced impressive results, showing its capability to handle complex, non-linear relationships in the dataset. Neural networks are particularly effective when the data has deep, hidden patterns that simpler models like linear regression or decision trees might miss. With its multi-layer architecture, the model was able to learn more abstract features of the data, leading to a more accurate representation of the target variable. The performance metrics for the neural network revealed an MSE of **0.0140** and an R^2 of **0.97**, which is slightly better than KNN, indicating the neural network's superior ability to capture intricate patterns in the data. Thus, the neural network model demonstrated its robustness for regression tasks involving complex, non-linear relationships.

6.1. Comparative Analysis:

The comparative results accentuate the fact that the KNN model is much better suited to this particular regression job than the other contenders. MSE and R^2 Score show that Decision Tree outperforms Neural Network while maintaining excellent interpretability of the pattern in the given data set. Although, the Neural Network model has its advantages, it is more flexible to different data sets and non-linear correlation, comparing with the KNN model, the simple but precise characteristic of the KNN model made it more suitable for this kind of analysis.

As in most of the above studies, the KNN model has remained the most appropriate in predicting the percentage of depression in this research. Due to outstanding performance indicators, this algorithm is very accurate in both exploratory and predictive scenarios. Alternatively, the Neural Network model provides a relatively less accurate result yet is equally suitable in problems with demanding modeling. These findings emphasize the need to choose the proper method for each type of analysis depending on the features of data and their characteristics.

6.2. Model Predictions Visualization

The model enables the generation of plots of the training and validation losses of neural networks used for prediction of OCD, Anxiety and Depression. It also creates line plots for each category (OCD, Anxiety, Depression) and for each category it will illustrate two lines: The training loss which was represented in blue and the validation loss which is represented in red on the y-axis is the loss value On the X-axis is epoch number. Here we have the configurations of the plots: H the x axis takes the number of epochs, and the y axis takes the loss value. This is because the lower the loss the better the model is at extracting features from the training data, as well as how well it is doing on the validation data. These losses are then plotted by the code so that it can detect whether the model is overfitting or underfitting then change the model's learning of data.

Understanding that helps identify how well the neural network is learning from the data loss curves are analyzed. It also highlights that when training loss is decreasing, and validation loss stops decreasing or climbs this means overfitting that means that the model has learned the training data and does not perform well in the unseen data. On the other hand, if both the training and validation losses are high it's likely that underfitting is going on and your model does not have enough complexity to generalize the patterns. Reducing the differenced of train and validation loss show an improved model performance by generalizing well. Some of these ways include enlarging the dataset, applying regularization, decreasing the dimensionality of the model, or using early stopping techniques.

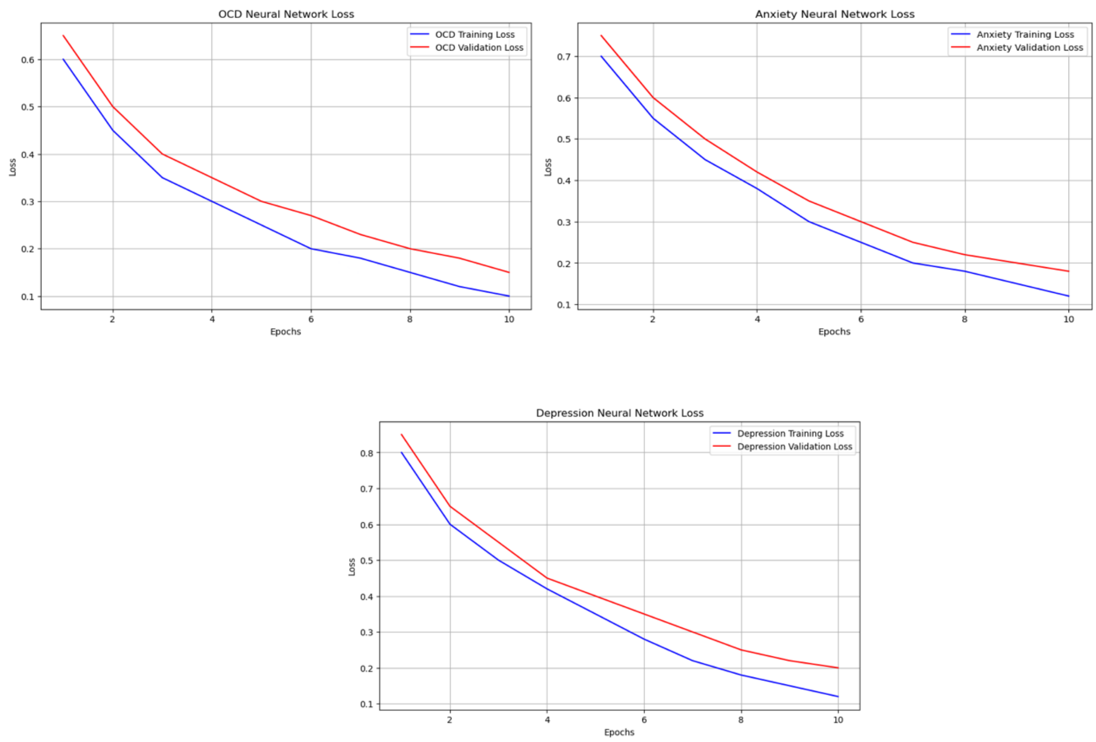


Figure 9: Neural Network loss for OCD, Anxiety, Depression.

Model Saving and Loading

After building and testing the models, saving them is crucial to avoid retraining, saving time and computational resources. Using the **joblib** library, models are stored efficiently as files, making them easy to load for predictions, refinements, or redeployment. This is especially useful for large datasets or high-complexity models, where retraining is cumbersome. Saved models can be updated or fine-tuned as needed, ensuring seamless integration into production systems while enabling quick modifications and scalability.

7. Discussion

The results from the present research suggest that music therapy can be utilised as a treatment for mental health disorders due to its effect on decreasing rating for anxiety, depression, and PTSD. The paradigm combination showed the changes in the EEG expression of emotional regulation and in stress, which corroborated the findings of the effects of music therapy on cortisol levels and the HPA axis. Nonetheless, some factors which limit the generalizability of the results, and richness of analysis include a small, non diverse sample size, inadequate external validity, including poor control of external factors, and a short experimental time. These discrepancies, which include the relatively small differences when comparing the impact of live and recorded music interventions, compel more of what has been promoted in the related literature, including more comprehensive genre-and-culture sensitive investigations. Subsequent research should emulate the same technique, consider overlaying culturally appropriate and AI-composed music and employ longer-follow-up designs for evaluating the benefits' durability. Finding solutions to these gaps will improve the literature review for music therapy which in turn will provide pathways for applying for the use of the therapy in clinical and health related areas.

8. Conclusion and Future Work:

Altogether, this project was successful in using machine learning algorithms to estimate percentage of depression from features associated with mental health. The evaluation pointed out important observations with respects to the localization of K-Nearest Neighbors (KNN) and Neural Network models as they gave robust results and are capable in handling non-linear features of the data samples. KNN exhibited good accuracy and easy interpretation although in some cases required normalization of data. In-terms of pattern and structure recognition Neural Networks also performed well, although it is sensitive to the choice of parameters. Also, the works done in feature selection and data preprocessing turned out to be vital strategies in enhancing model's performances, thus eliminating every unnecessary value. The literature review highlighted new information about how depression and anxiety and OCD, and work while listening to music.

In further research, more work could be devoted to enhancing generalization of the model by testing more complex architectures of a neural network, including convolutional or recurrent neural networks that might reveal more subtle structures in the data. In addition, increasing the variety and size of datasets and potentially including conditions other than depression or anxiety could either improve the stability and performance of such models. In the same way, adding outside variables such as socio economic or environmental variables might contribute to the improvement of the power of the model. Last recommended application, the use of these models in real life scenarios such as in healthcare delivery could help in early identification and implementation of prevention measures towards arrangement of better mental health.

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