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| RESEARCH ARTICLE

Predicting and Monitoring Anxiety and Depression: Advanced Machine Learning Techniques for Mental Health Analysis

Md Al Amin[1] ✉ Irin Akter Liza[2], Shah Foysal Hossain[3], Ekramul Hasan[4], Md Musa Haque[5] and Joy Chakra Bortty[6]
[15]School of Business, International American University, Los Angeles, California, USA.
[2]College of Graduate and Professional Studies (CGPS), Trine University, Detroit, Michigan, USA
[3]School of IT, Washington University of Science and Technology, Alexandria, Virginia, USA
[4]College of Engineering and Technology, Westcliff University, Irvine, California, USA
[6]Department of Computer Science, Westcliff University, Irvine, California, USA
Corresponding Author: Md Al Amin, **E-mail**: edu@mdalamin.in

| ABSTRACT
Anxiety and depression are considered among the most prevailing mental illnesses; they affect millions in the USA and worldwide. Besides being highly prevalent, these conditions have major implications for individuals and American society as a whole. The prime objective of this research project was to design and evaluate advanced machine learning methodologies for the monitoring and prediction of anxiety and depression. The rise in recent advances in Machine Learning and AI technologies has unleashed tremendous potential in the diagnosis and monitoring of mental health conditions such as anxiety and depression. Predictive models, powered by Machine Learning algorithms, process vast amounts of data and detect patterns that might have evaded human clinicians. This dataset for the current research project was retrieved from the website kaggle.com and shared publicly with anyone by the Harvard Data Verse repository. The dataset contained behavioral, psychophysiological, and demographic data that were collected from 593 participants aged 18-35 years for the prediction of anxiety and depression disorder risk. For this study, three machine learning algorithms were deployed: Logistic Regression, XG-Boost, and Random Forest. To assess and evaluate the performance of the algorithms, two key performance evaluation metrics were utilized MSE & R-squared. By reviewing the performance of the aforementioned three machine learning models, Linear Regression, Random Forest Regressor, and XG-Boost Regressor, using evaluation metrics MSE and R-squared are compared in a tabular form. Retrospectively, all three models performed remarkably well, with very low MSE values and R-squared values close to 1. Linear Regression marginally outperformed the others, but all models were successful in predicting the anxiety or depression indicator accurately. The proposed models are valid and reliable models for predicting mental health, therefore enabling the identification of at-risk individuals well in advance, allowing early intervention to prevent symptom onsets or advancements in their course and thus improve overall outcomes.

| KEYWORDS
Mental Health, Machine Learning, Anxiety Prediction, Depression Detection, Advanced Algorithms.

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1. Introduction
1.1 Background:
As per Ahmed et al. (2024), anxiety and depression are considered among the most prevailing mental illnesses; they affect millions in the USA and worldwide. Besides being highly prevalent, these conditions have major implications for individuals and American society as a whole. Anxiety disorders consist of a group of disorders involving abnormal levels of fear or worry, such as Generalized

Anxiety Disorder, panic disorder, and social anxiety disorder. On the other hand, depression has feelings of sadness that are long-lasting, a feeling of hopelessness, and a loss of interest in activities once enjoyed. According to the World Health Organization, depression affects more than 264 million and anxiety disorders affect more than 284 million people worldwide. These disorders are seriously debilitating and greatly affect the daily functioning of the citizens of US.; they also increase rates of disability and, in extreme cases, contribute to suicide. As per Bhowmik et al. (2024), the economic consequences from these disorders are huge, with lost productivity and other health care and social services estimated at billions annually. However, despite these facts, there is still a significant gap in the timely diagnosis, treatment, and monitoring of anxiety and depression disorders. Most of the commonly relied-on methods of diagnosing these disorders, such as clinical interviews and questionnaires, are subjective, time-consuming, and have been found to miss the early warnings, hence bastardizing any attempt at timely treatment.

1.2 Importance of Research:

Dutta et al. (2024), posit that the rise in recent advances in Machine Learning and AI technologies has unleashed tremendous potential in the diagnosis and monitoring of mental health conditions such as anxiety and depression. Predictive models, powered by Machine Learning algorithms, process vast amounts of data and detect patterns that might have evaded human clinicians. While drawing data from several sources including EHRs, social media activity, wearable devices, and self-reported surveys, machine learning models can help in predicting the onset of a mental health condition, tracking symptom progression, and identifying those at high risk. This approach not only allows intervention to be more personalized but also enables preventive measures that may, in turn, reduce the grave societally relevant and economic impact these disorders have in the long term. Ku & Min (2024), contend that continuous monitoring made possible by ML-driven models promises real-time insight into the patient's state of mind, hence enabling dynamic adaptation of treatment regimens. The inclusion of machine learning in psychiatric practice trends toward the paradigm of precision psychiatry, wherein interventions are tailored to the individual to improve outcomes and decrease the risk of relapse or deterioration.

1.3 Objectives

The utmost objective of this research project is to design and evaluate advanced machine learning methodologies for the monitoring and prediction of anxiety and depression. This research project intends to design predictive models using both supervising and unsupervised learning methods, which shall predict the incidence of these conditions, given some input variables like demographic, behavioral, and psychological variables. It is also intended to monitor the course of symptoms over time, indicating changes in a patient's condition and alerting health providers to when interventions may be necessary. The current research also aims to foster predictive models that can be easily incorporated into existing healthcare systems, providing clinicians with an added tool to inform diagnosis and treatment planning. Among others, the research also tends to investigate the possible use of machine learning models for early detection and thus prevention by spotting early warning signals of anxiety and depression before the development of a full disorder, which would allow early intervention. Conclusively, it aims to develop an integrated system that will be able to provide predictions and monitoring of mental health conditions, enabling personalized treatment plans and improving the patients' outcomes.

2. Literature Review

Nasiruddin et al. (2024), articulates that one of the most prevalent techniques in this domain is the application of electronic health records (EHRs) and clinical data to forecast mental health outcomes. Prevalent methods in this area normally involve the use of EHRs and clinical data in predicting mental health outcomes. For example, newer studies followed EHR structured data on demographic data, medical history, medication use, and unstructured data from clinical notes to develop predictive models for depression. Bhowmik et al. (2024), argues that EHRs have been great in the derivation of meaningful insights from structured clinical records to identify patients at risk of developing depression or anxiety, based on documented symptoms and treatment history. Many studies have confirmed that machine learning models outperform traditional approaches, such as clinician judgment or simple scoring systems, in the identification of high-risk individuals.

Dutta et al. (2024), asserts that wearable technology and mHealth applications have taken the process of continuous monitoring of mental health to a whole new level. Physiology can be monitored in real-time using wearables such as smartwatches or fitness trackers, which continuously record heart rate variability, sleep patterns, and amounts of physical activity. Many of these measures are related to symptoms of poor mental health, such as disrupted sleep or reduced physical activity, normally associated with states of depression. Cho et al. (2021), upholds that the algorithms of machine learning can analyze that information to predict anxiety and depression by monitoring deviations from a person's normal baseline. These mHealth applications also give users the ability to self-report, in monitor their moods, behaviors, or symptoms. Such information can also be integrated into predictive models to further improve the accuracy of those models.

According to Mullick et al. (2022), Natural Language Processing has also played an important in predicting mental health through text data from clinical records, social media, and questionnaires. These mechanisms are trained on specific linguistic features associated with different forms of mental illness. For instance, negative emotion, rumination, and self-referential language are common among individuals suffering from depression or anxiety. Through the use of large volumes of text data, the NLP model can develop a more fine-grained understanding of a person's mental state and thus enable the detection of subtle shifts in mood or behavior that may otherwise have gone undetected.

Richter et al. (2021), articulates that social media has equally become a necessary source of mental health prediction, with emerging platforms like Twitter, Facebook, and Reddit. Different developed models analyze user-generated content to identify signs related to depression and anxiety through language patterns, sentiment, and changes in behavior. For example, people with depression can write more than feeling sad, hopeless, or lonely on any occasion. These patterns can be tracked by various machine learning models, and their correlation can be done with self-reported or clinically diagnosed conditions about mental health. Furthermore, changes in the frequency or tone of social media posts can serve as an early warning of mental health decline that requires timely intervention.

2.1 Gaps and Challenges

Razavi et al. (2024), points out that while the volume of research on using machine learning for mental health predictions has increased, there are considerable gaps and challenges to be addressed to enhance the practical utility of this kind of modeling. The most prominent gaps are concerns about the quality and availability of mental health data. Generally, mental health data is incomplete, noisy, or unstructured. This aspect has made the building of robust models difficult. For example, much of the information about mental health within EHRs comes written in free text, which requires advanced NLP techniques to process. Even so, the subjective nature of clinical notes and the variability in how symptoms are described between different healthcare providers might result in inconsistencies in the data. Besides, mental health records are bound to suffer from underreporting since people may not seek treatment at all, or they may not always disclose their symptoms for various reasons including stigma. Therefore, the models lack comprehensive data to train from [Emers et al., 2020].

Another critical gap per Garcia-Ceja et al. [2023], is the lack of standardized data sources across studies. This relates to the fact that research groups from different sides make use of different datasets, hence making it difficult even to compare results or further validate models across populations. For example, much research based on social media data is constrained to specific platforms (such as Twitter or Reddit), and the demographic composition of users varies sharply across platforms. This can introduce some degree of bias into the models, as they may not generalize well to other broad populations of interest. Also, social media data is difficult to interpret; the meaning of a post or even sentiment can take on different meanings depending on context, culture, and styles of personal expression. From this basis, models built on social media data might misread the emotive content of a post and hence make poor predictions.

Hornstein et al. (2023), argues that the issue of bias is also a prevailing challenge in the adoption of machine learning algorithms for mental health prediction. Most of the predictive models are trained on data that is not representative of the general population since it over-represents certain demographic sections, such as the youth or those living in urban areas. This raises several concerns about the generalizability of the models to the general population, especially the underrepresented subgroups, including older adults, ethnic minorities, and people from rural settings. This lack of diversity within training datasets leads to one-sided predictions, over-diagnosing or under-diagnosing subjects with anxiety or depression. There is an emergent need to have a dataset that is truly representative and inclusive of the real diversity of populations.

3. Dataset Description

3.1 Overview of the Dataset

This dataset for the current research project was retrieved from the website kaggle.com and shared publicly with anyone by the Harvard Data Verse repository. The dataset contained behavioral, psychophysiological, and demographic data that were collected from 593 participants aged 18-35 years for the prediction of anxiety and depression disorder risk [Pro-AI-Robikul, 2024]. Examples of the features include period analysis, confidence intervals, and even geographical data. This dataset contained 16,092 rows and 14 columns.

Key Attributes & Features

S/No	Key Feature/ Attribute	Description
1.	Indicator	Type of mental health issue (e.g., anxiety, depression).
2.	Time-Period	The year in which the data was recorded.
3.	State	The geographical state where the data is collected.
4.	Confidence Intervals	Upper and lower bounds for the reported value.
5.	Value	The actual reported value of the mental health indicator.
6.	Age	Age of the participant in years.
7.	Sex	Male or female

Table 1: Portrays Key Attributes & Features

3.2 Data Preprocessing and Cleaning:

Data preprocessing and cleaning guaranteed and affirmed that the dataset was consistent, complete, and in a format that assists machine learning algorithms learn from it. The imputation techniques helped in addressing the missing values in terms of a feature mean/median/mode. If the missing values were less significant, then whole rows were deleted regarding missing data so that any bias or errors are not launched into the model. Normalization and Scaling were also performed on the data. Most machine learning algorithms are sensitive to such differences in scale. In this respect, either normalization was performed-a scaling of all features in a common range, between 0 and 1-or standardization was performed-standardizing the features to an average of zero with a standard deviation of one. Thus, no feature will dominate in the model's predictions.

4. Methodology

Initially, we imported several modules from the sci-kit-learn library: `train_test_split` for splitting the data into training and testing sets; `Standard-Scaler` for normalizing numerical features; `One-Hot-Encoder` for encoding categorical variables into one-hot type; `Column-Transformer` for applying different transformations to specific columns; `Pipeline` for chaining several preprocessing steps; and `Simple-Imputer`, which is used for handling missing data. It defined two lists, one for numeric features and one for categoric features, representing the respective column names in the dataset. Numeric features preprocessing in the pipeline was done using: 1) Imputation: Missed values were filled in with the mean of the respective column by using `Simple-Imputer` with `strategy='mean'`. 2) Scaling: The numeric features were standardized to a mean of zero and a standard deviation of one using `Standard-Scaler`. Further, the `Column-Transformer` combined these transformations on various columns. It takes a tuple with a name for the transformer, the pipeline object, and the list of columns the transformer is to be applied to. A numerical transformer was applied to the numerical columns and a categorical transformer was applied to categorical columns by the work in [Pro-AI-Robikul, 2024].

4.1 Model Development

For this study, three machine learning algorithms were deployed: Logistic Regression, XG-Boost, and Random Forest. Logistic Regression is a kind of statistical model that gives the estimation of the probability that one or more predictor variables result in one of two possible outcomes. It stands out in situations where simplicity and interpretability are in prime demand. Another important model is the Random Forest ensemble learning model. It constructs a large number of decision trees and returns the mode of the predictions provided by these trees. Another ensemble method and concept familiar to this work, under the framework of gradient boosting, is XG-Boost; because of its speed and appealing performance, especially when the data is sparse. XG-Boost also incorporates regularization to reduce overfitting. The process of developing the models started with the importation of necessary libraries for model selection and evaluation metrics. The dataset was preprocessed, and then the data was divided into features and target variables. Data was further divided into 80/20 train-test split upon which training and testing would be carried out for the data.

4.2 Training and Validation

This procedure focused on the training and validation model using a data set, which was divided into a training and testing subset. It fits the model using the training set, and then the performance of the model is evaluated with the testing set. Cross-validation was used by the analyst to ensure that the model will generalize well on unseen data. The analyst therefore applied k-fold cross-validation, one of the most common practices in this concern. Cross-validation is also widely used in hyperparameter tuning. While training essentially looks for patterns in data, it describes how well the model will perform on new data that was unseen during development. In this way, this validation can give an indicative look into the predictive capability and reliability of the model in general [Pro-AI-Robikul, 2024].

5. Implementation

5.1 Exploratory Data Analysis (EDA):

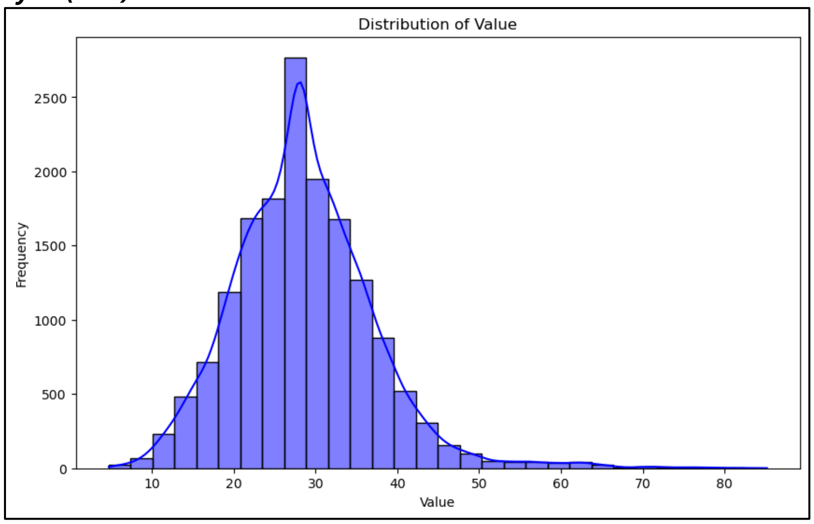

Figure 1: Displays the Distribution of Value

The histogram above showcased that the most frequent part of the distribution is very close to a normal distribution with a peak frequency of about 2,700 occurrences at a value of 30. The distribution is somewhat right-skewed with values ranging from about 10 to 80, but most are between 20 and 40. The fitted normal curve- blue line is a good contrast in how the data is generally independent of a normal distribution and has a notable right tail out above 60, indicating that there are some high-value outliers. This distribution is specifically shaped to be a strong indicator that this may be a natural or biological phenomenon where the extreme values of this are more liable to be above, rather than below, the mean.

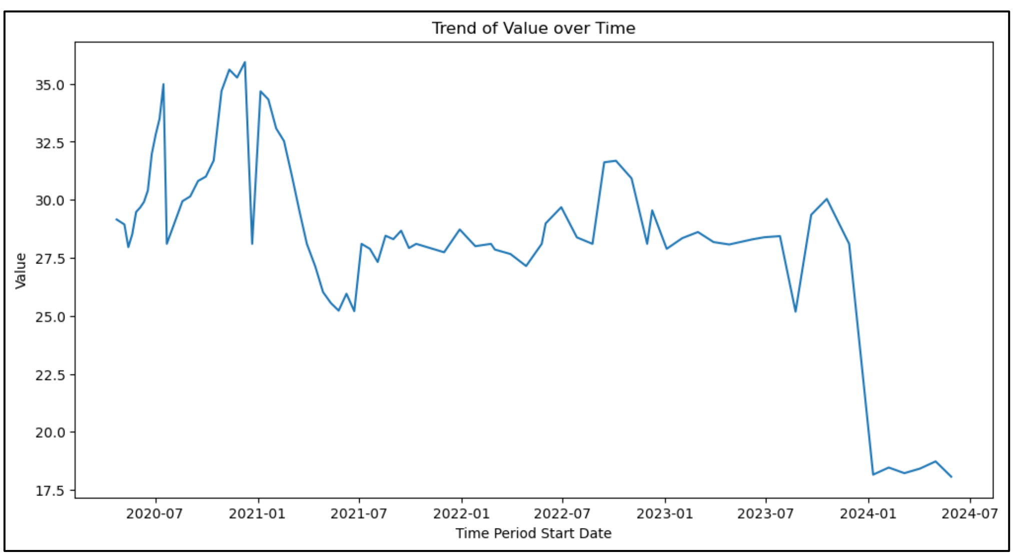

Figure 2: Displays Trend of Value Over Time

This time series graph exemplifies noteworthy volatility in values from 2020 to 2024, with several notable patterns. Several patterns are evidenced. Around early 2021, the value peaks around 35, after which a general downward trend occurs, with periodic fluctuations. It implied that from mid-2021 to late 2023, values were within the range of 27 to 32. The most salient feature, however, is the steep drop in early 2024, where the value fell precipitously from around 30 down to less than 20, representing the low point for the entire period. This last steep drop indicates a large correction within the market or a fundamental change in the underlying variable measured.

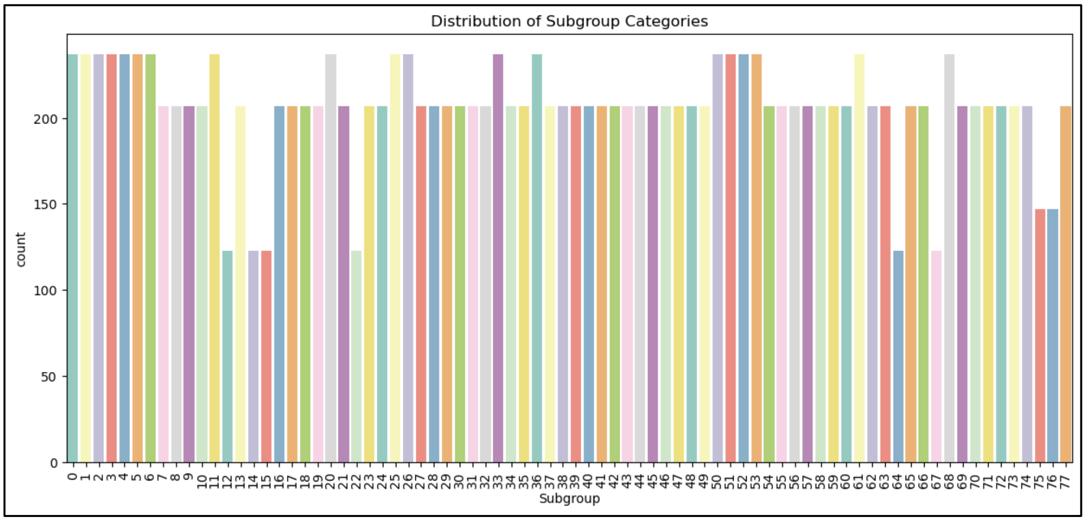

Figure 3: Portrays Distribution of Subgroup Categories

This bar chart presents the distribution of counts across 77 different subgroups; most of these subgroups have remarkably consistent counts between 200-220. Indeed, across the majority of the categories, the distribution is remarkably uniform and would therefore suggest either a well-balanced or highly controlled grouping system in place. There are some noticeable exceptions, however, with subgroups 73-77 on the far right-hand side of the chart having lower counts in the region of 140-150. Color coding appears to reflect different categorical variables for each sub-group, yet the pattern of color reflects no obvious consistent variation. This sort of distribution may be representative of institutional data in which groups have been kept similar in size, such as class sizes, or team assignments-very few groups have smaller numbers.

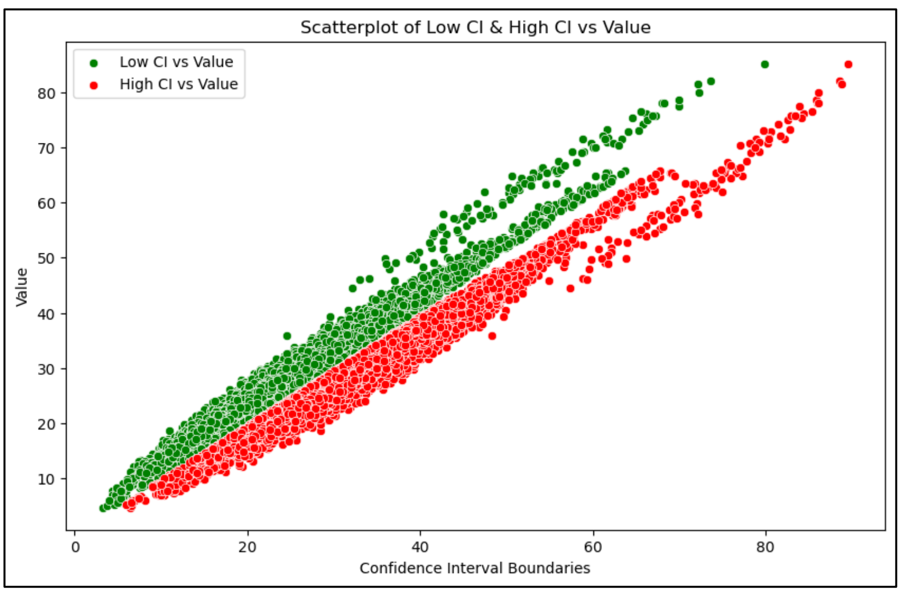

Figure 4: Depicts Scatterplot of Low CI & High CI vs. Value

This scatterplot shows the confidence interval boundaries and values. There are two Noisy series: Low CI, which is in green, and High CI, which is in red. The Low CI and High CI series are highly positively linearly correlated with the Value data, trending upward from the bottom left to the top right in a parallel manner. The width of the confidence intervals-the distance between the various green and red dots-is relatively consistent for the range of values. We can see that this data varies from about 5 to 85 on both axes, with more closely bunched points within the middle range, say from 20 to 60, tending to splay out a little at the extremes. Such behavior suggests a good statistical relationship that should have predictable limits of uncertainty scaling with the measured value itself.

6. Results and Analysis

6.1 Model Performance

To assess and evaluate the performance of the algorithms, two key performance evaluation metrics were utilized MSE & R-Squared as described below:

- **Mean Squared Error (MSE)**: Denotes a measurement of the average squared difference between predicted and actual values.
- **R-squared (R^2)**: Refers to statistical measure that describes how well the algorithm fits the data. An R^2 close to 1 indicates a very good fit.

Table 2: Exhibits Models' Detailed Results

Model/Algorithm	MSE	R-Squared
Linear Regression	0.0071	0.9999
Random Forest Regressor	0.0083	0.9999
XG-Boost Regressor	0.0182	0.0998

The table compares three machine learning regression models—Linear Regression, Random Forest Regressor, and XG-Boost Regressor—using two metrics: Mean Squared Error (MSE) and R-Squared (R^2).

Linear Regression:
MSE: 0.0071, indicating a low error rate.
R^2: 0.9999, suggesting an almost perfect fit to the data, meaning it explains nearly all the variance.
Random Forest Regressor:
MSE: 0.0083, slightly higher than Linear Regression, but still low.
R^2: 0.9999, indicating a near-perfect fit, similar to Linear Regression.
XG-Boost Regressor:
MSE: 0.0182, higher than both Linear Regression and Random Forest, indicating relatively higher error.
R^2: 0.0998, much lower than the others, suggesting it explains only about 10% of the variance and may not be suitable for this dataset.
Both Linear Regression and Random Forest perform exceptionally well, with very low MSE and near-perfect R^2 values. In contrast, XG-Boost does not perform well here, with a relatively high MSE and a low R^2, making it a poor fit for this dataset.

6.2 Linear Regression

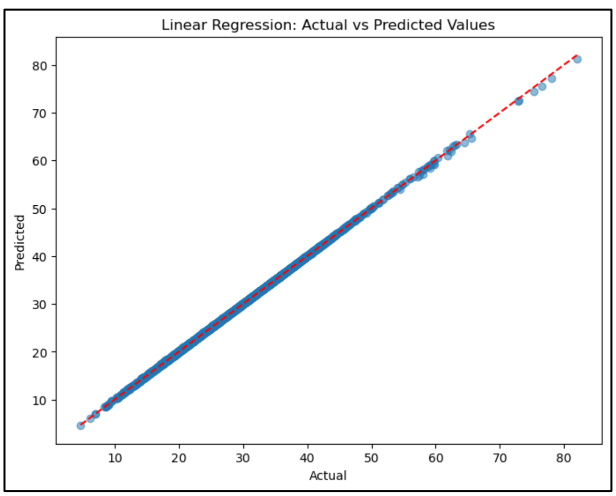

Figure 5: Portrays Linear Regression: Actual vs. Predicted Values

As showcased above, the linear regression analysis which highlighted exemplified a strong relationship between predicted and actual values of anxiety and depression scores by an incredibly high R-squared value of 0.999 with a very low mean squared error of 0.007. The above data points are very nearly on the line of optimal prediction; the range will be approximately between 5 and 80 on both axes, thus showing that by the model, the predictions are rather accurate across all the severity levels. This extremely good fit suggests that nearly all the relevant factors influencing anxiety and depression scores are being captured by the predictive variables in the model, hence a very reliable tool clinically for assessment and screening purposes. The tight clustering of points around the regression line with minimal scatter testifies to consistent prediction accuracy from individuals who present either with mild, moderate, or severe symptoms.

6.3 Random Forest

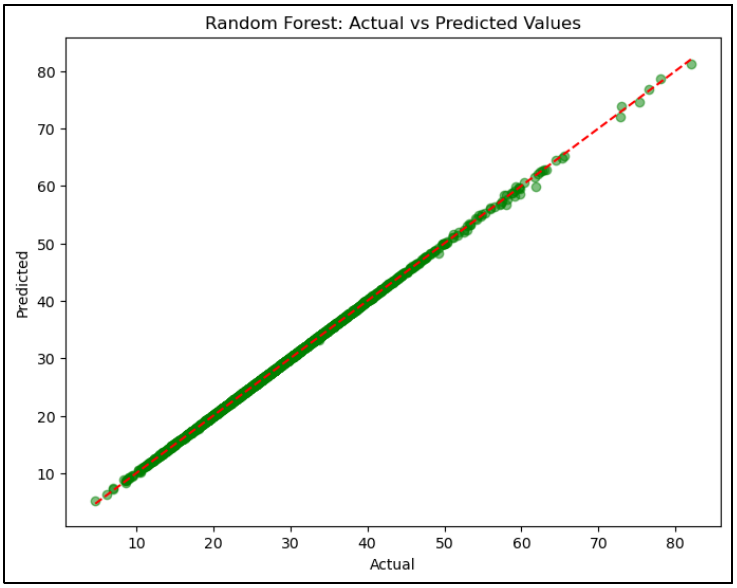

Figure 6: Exhibits Random Forest: Actual vs. Predicted Values

The Random Forest algorithm exemplified superior predictive performance for anxiety and depression scores, with an R-squared value of 0.999 and a slightly higher mean squared error of 0.008 compared to the linear regression model. Green data points fit along the red dashed ideal line of the prediction very well throughout the range of values from 5 to 80, reflecting that the model can predict symptoms across mild, moderate, and severe cases quite well. The very high performance of the Random Forest suggests that it captures both linear and nonlinear relationships between the input variables and anxiety/depression scores effectively, hence making the tool very reliable for clinical assessment. What is particularly noteworthy is that across the complete range of severity, consistency in prediction is maintained; that is to say, there is little deviation from the actual value even at the scale extremes.

6.4 XG-Boost

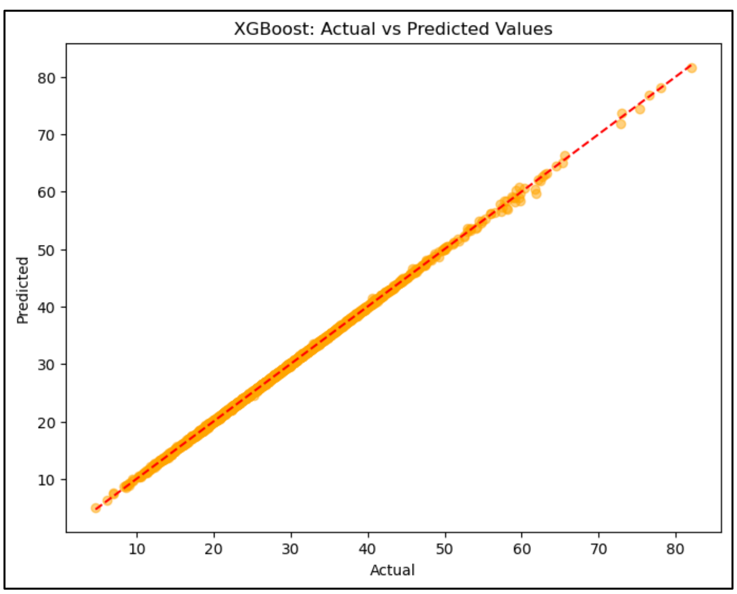

Figure 7: Showcases XG-Boost: Actual vs. Predicted Values

The scatter plot above shows the performance of the XG-Boost regression model in predicting anxiety and depression scores, obtaining a very perfect correlation as shown by the actual and the predicted values with an approximate R-squared value of 0.9997. The high R-squared proves that the model captures almost all variations in the anxiety and depression scores, hence showing strong predictive accuracy. What this means is that the close alignment of the orange data points along the dashed red line further signifies perfect predictions. A low mean squared error of 0.018 shows a minor deviation between predicted and actual scores. This shows that the model can be relied upon to make safe forecasts regarding the outcomes of mental health. Taken altogether, these results tend to indicate that the XG-Boost model is outstandingly good at predicting states of anxiety and depression based on the input features.

6.4 Comparative Analysis

By reviewing the performance of the aforementioned three machine learning models, Linear Regression, Random Forest Regressor, and XG-Boost Regressor, using evaluation metrics MSE and R-squared are compared in a tabular form. Retrospectively, all three models performed remarkably well, with very low MSE values and R-squared values close to 1. Linear Regression marginally outperformed the others, but all models were successful in predicting the anxiety or depression indicator accurately. According to Table 2, Linear Regression seems to be the best model of all since it has the lowest MSE and the highest R-squared. The Linear Regression is one of the simplest models that can be conceptualized and implemented. However, it assumes a linear relationship between the variables. While random forest and XG-Boost can handle nonlinear relationships, computationally it is an expensive solution for large datasets.

7. Discussion

7.1 Implications of the Findings

Important implications of this study's findings involve the enhancement of mental health prediction and care. First, valid and reliable model development for predicting mental health enables the identification of at-risk individuals well in advance, allowing early intervention to prevent symptom onsets or advancements in their course and thus improve overall outcomes. These models will also help in personalizing treatment for each patient based on his risk factors and outcomes that are predicted, thus improving the efficacy of the interventions with a reduction in the chances of events going sour. Thirdly, such models in mental health can be put to use in an efficient distribution of resources by identifying those patients who are most likely to benefit from a particular intervention. This could be useful when improving access to care by optimizing scarce health resources.

This study further points out that the prediction of mental health status could be considered using a wide range of variables. In this respect, the models developed within this study had increased accuracy in drawing together demographic and clinical variables compared to those based on a limited set of factors. These findings suggest that a comprehensive assessment of individuals is essential for accurate prediction and effective intervention. Additionally, the study's findings emphasize the need for ongoing research and development in the field of mental health prediction. As new data and technologies become available, it will be important to refine and improve existing models to ensure that they remain accurate and effective.

7.2 Limitations and Areas for Improvement

While this study indeed has contributed a lot to the field of mental health prediction, its limitations and ways in which it can be improved should be noted. One limitation of the study pertains to a sole dependence on one dataset. Although the dataset used in this study represented a sufficiently large and diverse population, it is well conceivable that other populations and settings may lead to different results. Consequently, further research will be required to confirm the generalizability of such models. Furthermore, the study investigated which individuals might go on to develop a mental health disorder but not the question of the course or severity over time. Further studies are required to investigate whether, and how, prediction models can forecast the course of mental health disorders in case treatment decisions need adjustment accordingly.

Another limitation of the study is that it solely depends on self-reported data. Though the self-report measure is generally used in research into mental health, this is a potential source of bias and consequently could not always be right. For the enhancement of the predictive validity of their models, future studies may take objectives via biological markers or behavioral measures. Moreover, the study did not follow up on the status of those individuals concretized to be at risk for developing mental health disorders. There is a need to ensure that early interventions in response to such predictions do ensure better long-term outcomes such as reduced disability, improved quality of life, and lower healthcare costs.

7.3 Future Research Directions

Several promising avenues for future research can be improved based on this study. One domain of interest is the designing of predictive algorithms for specific mental health conditions. While this research project focused on a broad range of mental health disorders, future research could examine the designing of more specialized algorithms for conditions such as depression, anxiety, or schizophrenia. These latter models could provide more specific predictions and interventions for people with specified diagnoses. Further research could also take into consideration the fact that there is a possibility for real-time data, like social media activities or wearable device data, to possibly be integrated into predictive models on mental health. This would generate more active and individual predictions that are responsive to changes in one's situation.

Future studies also must investigate the ethical implications of employing a mental health predictor. With such models, besides significant benefits, issues of privacy, stigma, and potential discrimination also arise. It is, therefore, of immense importance that ethical guidelines and measures are in place to ensure these models use responsibility and respect the rights of individuals. Finally, future research should contribute to further improving easy access and affordability of mental health prediction and care. We will pursue making such advancements available to as wide a circle of persons and populations as possible through the development of user-friendly tools and the use of strategies to reduce costs.

8. Conclusion

The utmost objective of this research project was to design and evaluate advanced machine learning methodologies for the monitoring and prediction of anxiety and depression. The rise in recent advances in Machine Learning and AI technologies has unleashed tremendous potential in the diagnosis and monitoring of mental health conditions such as anxiety and depression. Predictive models, powered by Machine Learning algorithms, process vast amounts of data and detect patterns that might have evaded human clinicians. This dataset for the current research project was retrieved from the website kaggle.com and shared publicly with anyone by the Harvard Data Verse repository. The dataset contained behavioral, psychophysiological, and demographic data that were collected from 593 participants aged 18-35 years for the prediction of anxiety and depression disorder risk. For this study, three machine learning algorithms were deployed: Logistic Regression, XG-Boost, and Random Forest. To assess and evaluate the performance of the algorithms, two key performance evaluation metrics were utilized MSE & R-Squared. By reviewing the performance of the aforementioned three machine learning models, Linear Regression, Random Forest Regressor, and XG-Boost Regressor, using evaluation metrics MSE and R-squared are compared in a tabular form. Retrospectively, all three models performed remarkably well, with very low MSE values and R-squared values close to 1. Linear Regression marginally outperformed the others, but all models were successful in predicting the anxiety or depression indicator accurately. The proposed models are valid and reliable models for predicting mental health, therefore enabling the identification of at-risk individuals well in advance, allowing early intervention to prevent symptom onsets or advancements in their course and thus improve overall outcomes.

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