Lifestyle Metrics for Predicting Mental Health

With increasing concerns over the rise in mental health issues among adolescents, it is important to explore and utilize the power machine learning and feature detection strategies may play in early detection of traits which may lead to a decrease in mental well-being. This paper aims to identify key features indicative of mental health issues, with a focus on identifying lifestyle trends prevalent among university students. Utilizing surveys on student mental health, various machine learning techniques were applied to pinpoint significant predictors in the classification of troubles in mental health. This study covers data preprocessing, model training, evaluation, and feature importance analysis.

1. Introduction

Mental health is a critical issue among university students, impacting academic performance, social interactions, and overall well-being. According to the CDC, the number of adolescents experiencing mental health issues has been increasing since 2011 (Center for Disease Control and Prevention, 2023). This project aims to develop predictive models that explore the relationship between mental health issues and various lifestyle and work-related factors. The objective is to identify patterns that may assist in developing strategies to mitigate negative impacts on mental health due to work stress, lifestyle choices, and other related factors, as well as identifying features that may play a role in general mental health diagnoses. Accurate predictive models may provide insights into earlier diagnosis, enhance our understanding of the impact of lifestyle and work on mental health, and aid in the earlier identification of mental health issues. This understanding can potentially lead to better mental health resources, tailored lifestyle recommendations, and improved safeguards for mental health, potentially leading to targeted approaches aiming to reduce the number of adults experiencing mental illness. The National Alliance on Mental Illness reported that one in five U.S. adults experienced mental illness in 2021 (National Institute of Mental Health, 2023). Early identification of mental health issues in adolescents can enable timely intervention and support. This study builds on existing research by leveraging student survey responses and employs various machine learning techniques, including SVM, Random Forest, and Linear Regression, to predict the presence of mental health issues and observe which lifestyle factors influence a person's mental health status. The data used in this study comes from student survey responses across various universities, prompting responses on student lifestyle and mental health (University Student Mental Health, 2022). Mental health status is predicted via binary classification, 0 indicating no significant mental health issues and 1 indicating its presence. It is important to note that mental health is a complex issue which may not adhere to a binary classification problem. To mitigate generalization, survey responses indicating poor mental health were categorized by their relevance to symptoms associated with common mental health diagnosis, namely ADHD, anxiety, and depression. These were compared against a general metric containing all responses indicating significant struggle with mental health. The models shared key features across the different metrics, indicating correlation between mental health and certain lifestyle choices such as sleep and exercise. Although the identification of key factors is not enough to diagnose mental disorders, these traits could aid in earlier detection of mental disorders and help establish preventative measures.

2. Previous Studies

In the paper titled "A Review of Machine Learning and Deep Learning Approaches on Mental Health Diagnosis", Ngumimi Karen Iyortsuun and colleagues analyze various machine learning and deep learning techniques applied to mental health diagnostics (Iyortsuun et al.). This paper critically evaluates how different algorithms can interpret complex datasets to identify patterns indicative of mental health disorders. The authors focus on three main types of algorithms: Support Vector Machines (SVMs), Neural Networks, and Decision Trees, each with distinct advantages for handling mental health data. Most of the studies reviewed in the paper compare existing methods using data collected from previous research. Data sources include Twitter posts obtained via the GetOldTweetsAPI, medical checkup data from the National Health Insurance Sharing Service cohort, questionnaires, and search-based databases such as Google Scholar, PubMed, Scopus, and Web of Science. These datasets typically encompass clinical assessments, patient self-reports, and physiological data. Preprocessing steps discussed in the paper include normalization, handling missing values, and data augmentation, particularly for deep learning models requiring large datasets. The paper reviews SVMs, highlighting their effectiveness in high-dimensional classification problems and robustness against overfitting, especially when the number of dimensions exceeds the number of samples, making them suitable for certain mental health datasets. The review also covers various neural network architectures, including feedforward, convolutional, and recurrent neural networks, emphasizing their capability to model non-linear and complex data patterns. Furthermore, the paper examines decision trees, noting their efficiency in handling both categorical and continuous data and providing clear criteria for node splitting – particularly beneficial for clinicians to understand the model's decision-making process. The paper serves as a valuable resource for analyzing how machine learning can predict mental health conditions, offering strategies applicable to predictive models. Commonly used metrics such as accuracy, precision, recall, and F1 score are discussed, with an emphasis on balancing sensitivity and specificity, which is crucial in clinical settings where both false positives and false negatives have significant implications. The study revealed that both Machine Learning and Deep

Learning methodologies offer significant potential for improving mental health diagnosis. SVM and RF models remain robust choices for training models, while deep learning architectures, such as Convolutional Neural Networks, show exceptional promise at accurately predicting mental health status. The integration of ML and DL techniques further enhance predictive accuracy, offering a comprehensive approach to mental health diagnostics. These findings highlight the importance of continued research and development in this field to refine these technologies and improve mental health outcomes.

To analyze the role lifestyle has on mental health, the paper titled "The Association Between Adolescent Well-being and Digital Technology Use" by Amy Orben et. al, investigates the relationship between digital technology use and adolescents' well-being (Orben and Przybylski). The study aimed to identify potential differential impacts based on various factors such as the duration and type of usage, and individual characteristics of adolescent users. The authors review large-scale data analysis from multiple datasets, including self-reported measures of digital technology use and psychological well-being among adolescents. The data and methods are publicly available on the Open Science Framework (OSF), ensuring reproducibility and accessibility. The datasets were sourced from the UK Millennium Cohort Study, the Monitoring the Future survey on adolescent mental health, and the Youth Risk Behaviour Surveillance System representative survey on U.S. adolescents. These datasets provided information on adolescents' psychological well-being and digital technology use, including social media, gaming, and general internet usage, and well-being was assessed using standardized psychological scales. For data preprocessing, the researchers adjusted for missing variables and multiple confounding factors by treating certain features as continuous and others as categorical, or by removing outliers. The researchers used specification curve analysis (SCA) to test the strength and consistency of the association between technology use and well-being. The findings concluded that the association between digital technology use and adolescent well-being was negative but practically minor, suggesting that digital technology use was unlikely to have substantial adverse effects on adolescent well-being in most cases, contradicting the mainstream outlook on technology. By employing a robust methodology and publicly available datasets, the study provides a comprehensive analysis that challenges the widespread belief that digital technology is largely harmful to adolescents. The use of specification curve analysis (SCA) allowed for a detailed examination of various factors influencing this relationship, revealing that individual differences play a significant role. These findings are crucial for developing balanced perspectives on digital technology use, encouraging further research to explore how specific contexts and individual traits mediate this relationship. Overall, this study underscores the importance of considering individual variability when assessing the effects of digital technology on mental health, advocating for more personalized approaches in future research and interventions.

In another paper referencing the use of machine learning for predicting mental health, Roger Garriga *et. al*, explore the use of machine learning to predict mental health crises (Garriga, R., Mas, J., Abraha, S. *et al*). Utilizing predictive algorithms, the authors showed how vast amounts of data, such as patient demographics, clinical notes, medication history, and past medical diagnoses, can be analyzed to detect patterns and features indicative of impending mental health crises. These models can identify symptom patterns, medication adherence issues, clinical note sentiments, historical data, and social determinants that contribute to mental health conditions. The application of ML in this context has significant implications for medical diagnosis and patient care, as predictive models can facilitate early intervention, allowing healthcare providers to prevent crises and reduce hospitalizations. Personalized care becomes more feasible as treatment plans are tailored to the unique features identified by the ML models. Additionally, healthcare systems can allocate resources more effectively and reduce overall costs by targeting high-risk individuals. This approach not only improves patient outcomes but also enhances the understanding of mental health conditions, paving the way for more refined and accurate predictive capabilities in the future.

3. Personal Work

3.1. Data

Analysis and evaluation of mental health predictors were evaluated using the Borealis dataset collected by Paterson and Reeves through surveys targeting university students, containing 147 variables and 1192 student responses. This survey aimed to gather comprehensive information on various aspects of student life, such as student demographics, academic performance, and self-reported and their mental health status. Students were recruited primarily via social media platforms, leveraging the widespread use of these channels among university populations. The dataset offers a detailed snapshot of the mental health landscape among university students, enabling an in-depth analysis to identify key features associated with mental health issues.

In addition to the Borealis survey, the same performance metrics were run on behavioural datasets containing information regarding technology and social media use. Two such datasets were obtained from Kaggle ("Social Media and Mental Health" , "Mental Health in Tech Survey") and one was from OpenICPR (Braghieri, Luca, et al.)

3.2. Software and Libraries

In building the predictive models, I utilized Python and its various training libraries. Key libraries included Pandas and NumPy for data manipulation and numerical operations, respectively. Scikit-learn provided a wide range of machine learning algorithms for classification and tools for model evaluation. Matplotlib and Seaborn were used for data visualization, enabling clear graphical representations of the data and results.

3.3. Data Preprocessing

The data cleaning process involved several critical steps to ensure the dataset's quality and relevance for analysis. Due to the variable nature of surveys, the responses needed to be thoroughly assessed to ensure proper results. Columns containing technical information, irrelevant features, or missing values were completely omitted from the dataset. This reduction in dimensionality helped streamline the dataset, focusing only on the most relevant features. Additionally, data handling required manual classification for the subcategories of ADHD, Anxiety, and Depression. For this categorization, responses indicating difficulty concentrating or restlessness were classified as ‘ADHD’, responses indicating poor or unstable mood were set under ‘Depression’, and symptoms relating to anxiety or nervousness were placed under ‘Anxiety’. It is important to note that mental health is very complex, and many of these responses could have overlapping symptoms, so this categorization was solely for the purpose of having a more targeted understanding of how lifestyle can impact specific mental responses. For general mental health as a predicted variable, all symptoms of irregular mental health were considered. This careful cleaning and categorization enabled a more targeted and effective analysis, laying a strong foundation for the subsequent machine learning modeling.

3.4. Encoding and Scaling

To prepare the data for machine learning models, categorical variables were converted into numerical formats using techniques like label encoding. This conversion allowed the algorithms to process and analyze the data effectively. Standardizing the features was another essential preprocessing step. By scaling the data, we ensured that all features contributed equally to the model training process, thus improving the overall performance and reliability of the models.

3.5. Classification and Predicted Value

For the final analysis, I classified the predictive variable to indicate the presence or absence of mental health issues among university students, where 1 indicated the presence of mental health issues, and 0 indicated no mental health issues. This binary classification was derived from the survey responses, where students self-reported their mental health status. This binary approach allowed for a clear and straightforward distinction between students with and without mental health issues, facilitating the application of machine learning algorithms to predict these outcomes based on other features in the dataset.

3.6. Training

In the analysis, various classification models were employed to predict the presence of mental health issues among university students. The models were evaluated using metrics such as accuracy, F1 score, and ROC-AUC to ensure a comprehensive assessment of performance.

Classification Model	Rationale
K-Nearest Neighbours (KNN)	This algorithm provides a good baseline for comparison since it usually works well for smaller datasets. It classifies output based on the majority class among the k-nearest neighbors of a point.
Support Vector Machines (SVM) (Comparing the two models against each other allows for observation for linearity)	Linear SVM: Linear SVM is effective for linearly separable data and provides a clear margin of separation between classes. RBF SVM: RBF SVM uses a radial basis function kernel to handle non-linear relationships in the data, making it more flexible for complex patterns.

Gaussian Process Classifier	This probabilistic model is based on Gaussian processes, capable of providing uncertainty estimates along with the predictions which can be useful for understanding model confidence.
Decision Tree	Decision trees work well for capturing non-linear relationships and interactions between features.
Random Forest	Random forests improve predictive accuracy and control overfitting by averaging multiple trees' predictions. They were also used to provide feature importance estimates.
Neural Network (MLPClassifier):	Neural networks can model complex relationships and interactions between features. The MLPClassifier is a feedforward neural network that can capture non-linear patterns in the data.
AdaBoost	AdaBoost combines multiple weak classifiers to form a strong classifier, improving accuracy by focusing on misclassified instances in each iteration.
Naive Bayes	This probabilistic classifier is based on Bayes' theorem and assumes independence between features. It is simple, fast, and works well for high-dimensional datasets.
Logistic Regression	Logistic regression is a widely used linear model for binary classification. It provides interpretable coefficients and probabilistic predictions.

Table 1. Classification models alongside rationale for their usage ("Classifier Comparison").

4. Results and Analysis:

Note: Additional, in-depth analysis of model performance can be found in the supplementary material.

4.1. Predicting General Mental Health:

The results from the various classification models provide a comprehensive view of their performance in predicting the presence of any feature indicative of a mental health issue among student responses. Each model's performance is evaluated based on accuracy, F1 score, and overall score.

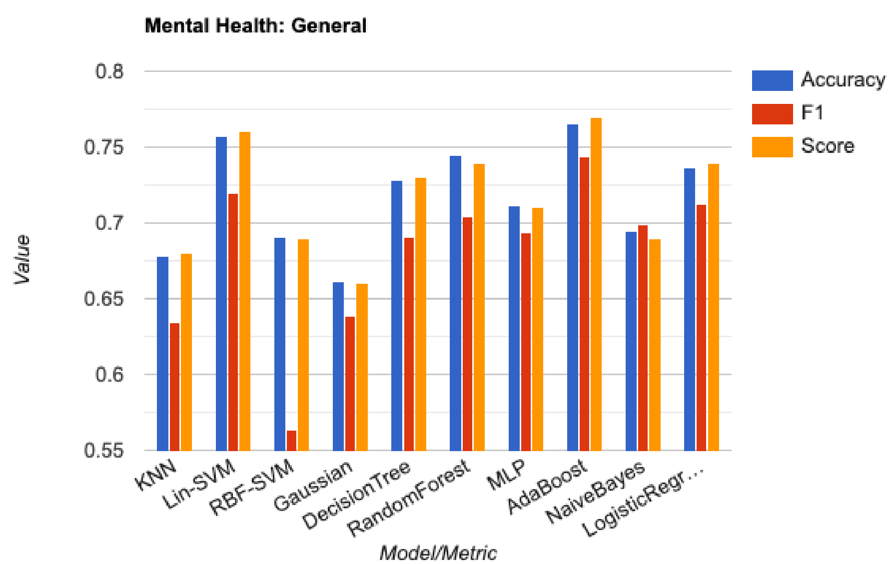


Fig.1. Classification model performance for detecting presence of mental health issues.

Best Performing Model: AdaBoost

The AdaBoost model emerged as the best performing model with an overall score of 77%. Its ability to handle misclassified instances effectively and the ensemble approach contributed to its superior performance. This model's feature importance analysis also provided valuable insights, making it a strong candidate for predicting mental health issues among university students.

4.2. Predicting Mental Health – ADHD:

In this analysis, the target mental illness was ADHD. Presence of ADHD symptoms was identified as difficulty concentrating among university students. Same as in the prior analysis, each model's performance was evaluated based on accuracy, F1 score, and overall score.

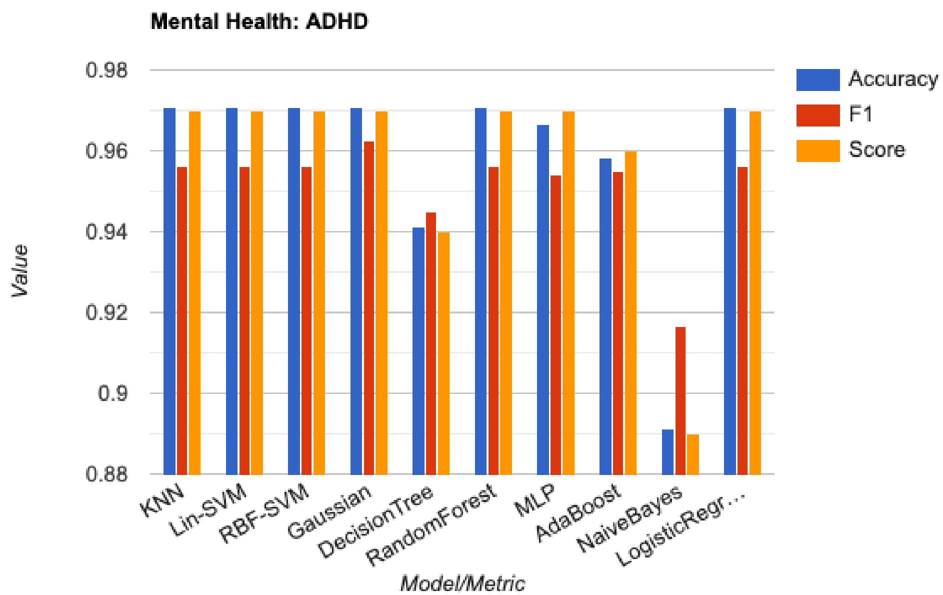


Fig.2. Classification model performance for detecting presence of ADHD symptoms.

Best Model: The Gaussian Process model emerged as the best performing model with a slight edge in the F1 score, achieving an overall score of 97%. Its probabilistic approach allowed it to handle the classification task with high precision and recall, making it a strong candidate for predicting ADHD among university students.

4.3. Predicting Mental Health – Anxiety:

In this analysis, the target mental illness was anxiety. Symptoms of anxiety among university students were identified as nervousness and physical symptoms of stress.

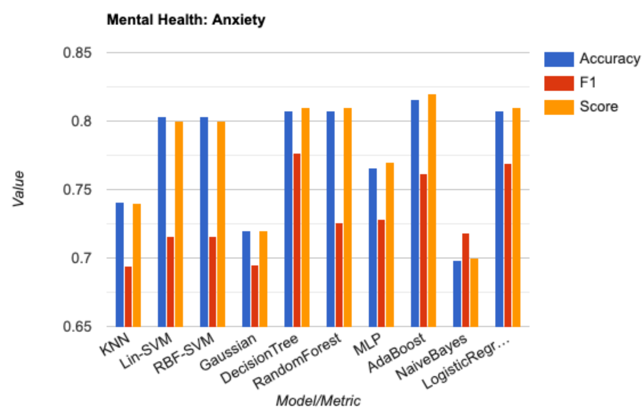


Fig.3. Classification model performance for detecting presence of Anxiety symptoms.

Best Performing Model: AdaBoost. The AdaBoost model emerged as the best performing model for detecting anxiety among students. The rationale follows previous models.

4.4. Predicting Mental Health – Depression:

In this analysis, the targets for signs of mental illness were features of depression. The same classification models as before were employed to predict the presence of depression among university students. As before, each model's performance was evaluated based on accuracy, F1 score, and overall score.

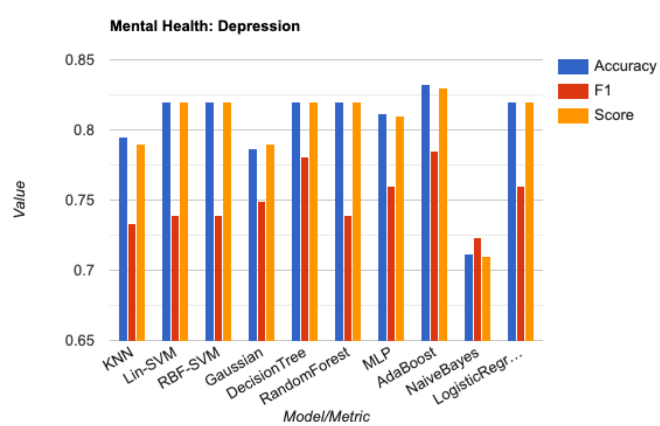


Fig.4. Classification model performance for detecting presence of Depression symptoms.

Best Performing Model: AdaBoost. Same rationale as in prior analysis

4.5. Conclusion for Model Performance

The analysis highlighted the AdaBoost classifier as the most effective model for predicting general mental health issues, anxiety, and depression. Linear models like Linear SVM and Logistic Regression also performed exceptionally well, indicating some linear separability in the data. Overall, the models had high accuracy on classifying the presence of the mental illness on the test sets. Future work could focus on further refining these models and exploring additional features or more complex models to enhance predictive accuracy further.

4.6. Top Features Identified

The rankings for feature importance were identified using the Random Forest training model. Though Random Forest was not the most robust model, its metrics were comparable in performance and it includes convenient methods for feature identification and ranking.

Rank	**ADHD**	**Anxiety**	**Depression**	**General**
1	Disability	Disability	Disability	CATS_6
2	Age	Mild exercise	Age	Hours_sleep
3	Mild exercise	SSS_6	Hours_sleep	Mild exercise
4	Hobbies_Time_6	Ethnicity	Hobbies_Time_6	SSS_11
5	Hobbies_Imp_2	Age	Year_credits	Age
6	CATS_5	Hours_sleep	Moderate exercise	Moderate exercise
7	Mindfulness_freq	Moderate exercise	Mild exercise	CATS_4
8	CATS_2	Hobbies_Time_4	Living	SSS_8
9	CATS_8	CATS_7	CATS_7	Hobbies_Imp_4
10	CATS_6	Program	CATS_4	CATS_2

Table 2. Top 10 features identified for prediction of specified mental illness. Full description of features can be found in the code document.

The top features identified by Random Forest provide valuable insights into the factors that contribute to symptoms of ADHD, Anxiety, Depression, and general mental health struggles among university students. Variables related to lifestyle (exercise, hobbies), sleep patterns, and specific survey responses for Charlotte's Attitude Towards Sleep (CATS) and Seeking Social Support (SSS) were significant predictors among all chosen features. Understanding how these factors interact with each other and general well-being can help in designing interventions and support systems for students struggling with their mental health.

4.7. Additional Analysis (Tried)

To obtain a more selective and robust ranking of key identifiers for mental health, I tried implementing a Multilayer perceptron with a customized Mean Squared Error which implemented feature rank as a weight function in the loss. Training over many epochs, this would (theoretically) assign features of greater importance a high rank based on their performance over time. Though a baseline for this was created, the results did not show a great improvement over the performance of scikitlearn's classification models which were much more simple in implementation.

In addition to feature rankings as a target of interest, I wanted to observe the role of technology and social media in the general well-being of adolescents. Unfortunately, every other dataset I analyzed gave poor performance metrics and did not lead to any significant results. This may have been due to the smaller sample size or biased questionnaires. Features indicating social media usage appeared in the top ten identifiers for Anxiety and general mental health (Hobbies_Imp_4 and Hobbies_Time_4), so some correlation would likely be observed given more data.

5. Summary of Achieved Results

The high performance of models across different mental health issues indicates that surveys capturing a wide range of lifestyle, demographic, and psychological factors can provide valuable insights for early identification and intervention.

Based on the key features identified, lifestyle features such as exercise and sleep consistently emerged as significant predictors across all three mental health issues. This underscores the importance of promoting healthy lifestyle habits to support mental well-being among students. The hobbies identified

are related to technology use (such as video games and social media) and the importance of studying, and should be explored further to identify their effects on health.. Demographic factors such as age, disability status, and living situation were also important in predicting mental health outcomes, indicating that these demographic factors should be considered when developing mental health support programs.
Comprehensive Assessments:

6. Future Work

To build on this study, future work could be conducted to observe interactions between key features identified by the classification models. More robust models, such as deep learning models, could be applied to iteratively train until convergence to ensure that features identified hold substantial merit in their correlation to poor mental health symptoms. More time for the project would allow me to fully explore the analysis I had started comparing my results with different datasets and building more intricate models and iteratively adjusting hyperparameters based on prior performance. Acquiring more diverse datasets could also enhance model generalizability and provide results applicable to a larger demographic of people.

7. Conclusion

This study demonstrates the potential of machine learning models to predict mental health issues among university students with high accuracy. By identifying key features associated with ADHD, anxiety, and depression, the analysis provides actionable insights for developing targeted interventions and support systems. Future work should focus on refining these models, exploring additional features, and applying these findings to real-world mental health programs. The correlation between social support and mental health stood out, emphasizing the role of peer interactions in mental well-being. Additionally, the variability in model performance across different metrics highlighted the importance of a holistic evaluation approach.

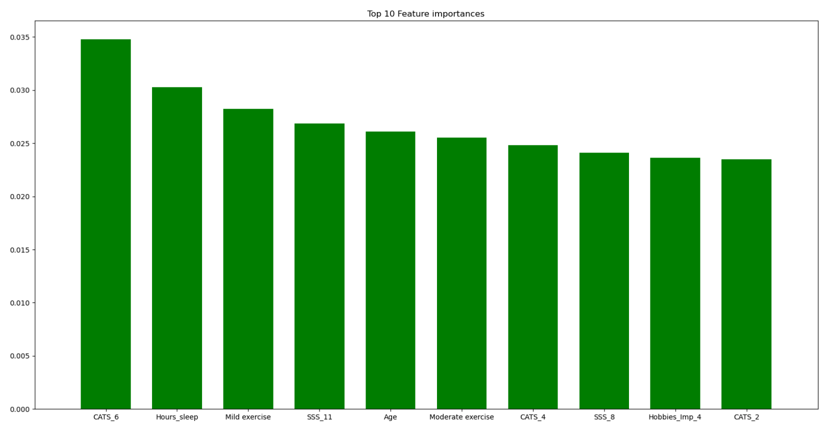
Throughout the project, I faced surprising challenges in handling categorical data, understanding how features interact with one-another, and unpredictability in using the same methods across different datasets. Throughout this work, many different methods and techniques for data handling had to be tested, leading to a better understanding of why preprocessing is important for model performance. Research into previously conducted research also led me to have a better understanding of the material as I was exposed to different approaches for handling the same issues. I also found that dataset limitations pose a great issue in research and it is critical to find substantial volumes of data for the specific question you are trying to answer.

Supplemental Analysis:

1. Model Performance for General Mental Health

- The KNN model achieved a decent accuracy of 67.78% and an F1 score of 63.39%. While the accuracy is relatively high, the F1 score suggests some difficulty in balancing precision and recall, possibly due to the high-dimensional nature of the data and the simplicity of the KNN algorithm.
- The Linear SVM model showed a substantial improvement with an accuracy of 75.73% and an F1 score of 72.03%. This indicates that the data may be approximately linearly separable, and the linear SVM was effective in finding a separating hyperplane.
- The RBF SVM performed reasonably well, with an accuracy of 69.04% but a lower F1 score of 56.39%. This discrepancy suggests that while the RBF kernel captured some non-linear patterns, it may have struggled with precision and recall balance.
- The Gaussian Process classifier achieved an accuracy of 66.11% and an F1 score of 63.86%. While better than some models, its performance was not as strong as the Linear SVM or the Random Forest. The probabilistic nature of this model might not have provided a significant advantage for this specific classification task.
- The Decision Tree classifier had a strong performance with an accuracy of 72.80% and an F1 score of 69.10%. Decision Trees can capture non-linear relationships effectively, but they are prone to overfitting, which might have affected the results.
- The Random Forest classifier was one of the top performers, with an accuracy of 74.48% and an F1 score of 70.43%. The ensemble approach of combining multiple decision trees helped reduce overfitting and improve predictive performance, making it a robust model for this task.
- The Neural Network (MLP Classifier) achieved an accuracy of 71.13% and an F1 score of 69.41%. Neural networks can model complex relationships, but their performance depends heavily on the architecture and tuning. In this case, the neural network performed well but did not surpass the ensemble methods.
- AdaBoost showed the best performance with an accuracy of 76.57% and an F1 score of 74.37%. By focusing on misclassified instances in each iteration, AdaBoost effectively improved the model's performance, making it the best performing model in this analysis.

- The Naive Bayes classifier performed well, with an accuracy of 69.46% and an F1 score of 69.90%. Despite its simplicity and the assumption of feature independence, Naive Bayes provided competitive results, highlighting its robustness for high-dimensional data.
- Logistic Regression achieved an accuracy of 73.64% and an F1 score of 71.28%. As a linear model, its performance was comparable to other linear models like the Linear SVM, demonstrating its effectiveness for binary classification tasks.

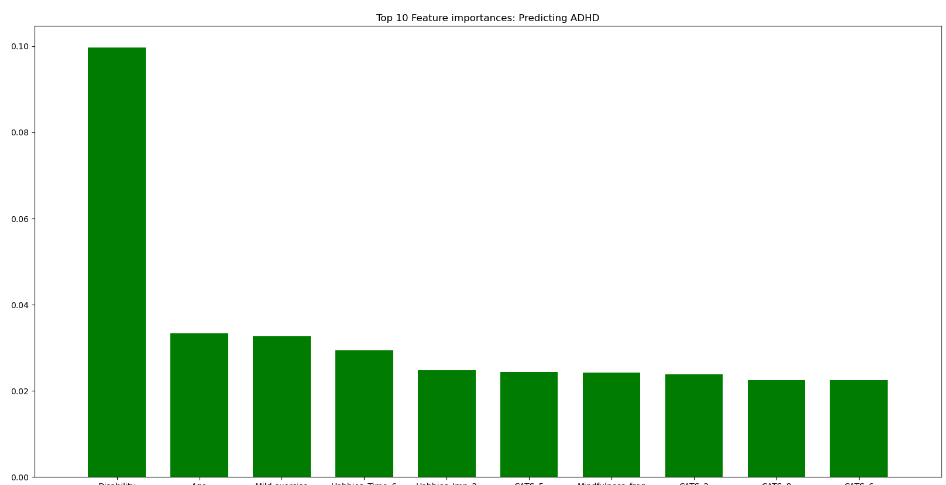


Supplementary Fig. 1: Top 10 features for predicting general mental illness.

2. Model Performance for ADHD

- The KNN model achieved an outstanding accuracy of 97.07% and an F1 score of 95.63%. This high performance suggests that the nearest neighbors approach was very effective in distinguishing between students with and without ADHD. The model's success could be attributed to the distinct clustering of the data points, making it easier for KNN to find the nearest neighbors accurately.
- The Linear SVM model also achieved an accuracy of 97.07% and an F1 score of 95.63%. This indicates that the data is linearly separable to a large extent, allowing the linear SVM to find a clear hyperplane that separates students with ADHD from those without.
- Similar to the Linear SVM, the RBF SVM achieved a high accuracy of 97.07% and an F1 score of 95.63%. The RBF kernel was able to handle any non-linear relationships effectively, although in this case, it did not provide a significant improvement over the linear kernel.

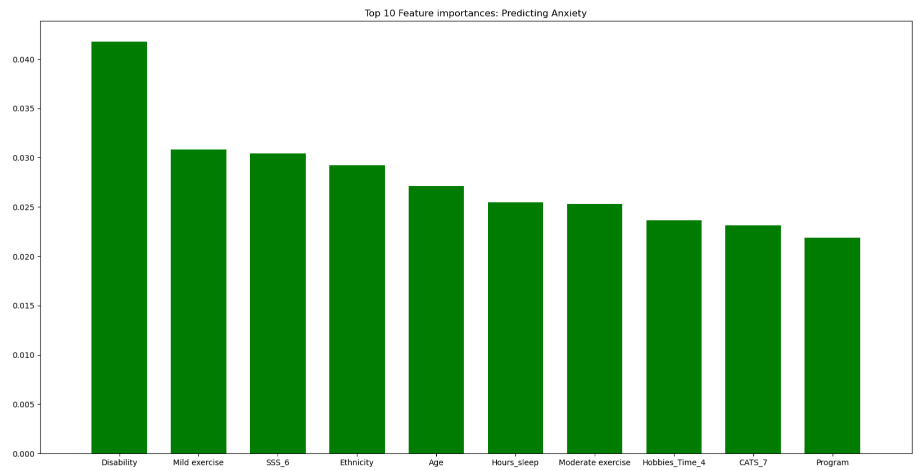
- The Decision Tree classifier achieved an accuracy of 94.14% and an F1 score of 94.50%. While slightly lower than other models, it still performed well. Decision Trees are prone to overfitting, which might explain the slight dip in accuracy compared to ensemble methods.
- The Random Forest classifier matched the top-performing models with an accuracy of 97.07% and an F1 score of 95.63%. The ensemble approach of combining multiple decision trees helped improve predictive performance and robustness against overfitting.
- The Neural Network achieved an accuracy of 96.65% and an F1 score of 95.42%. Neural networks can model complex relationships, and this performance indicates that it captured the nuances of the data effectively, though it did not outperform the simpler models significantly.
- AdaBoost showed strong performance with an accuracy of 95.82% and an F1 score of 95.48%. By focusing on misclassified instances in each iteration, AdaBoost effectively improved the model's performance, though it was slightly behind the top models in this analysis.
- The Naive Bayes classifier performed well, with an accuracy of 89.12% and an F1 score of 91.67%. Despite its simplicity and the assumption of feature independence, Naive Bayes provided competitive results, though it lagged behind the more sophisticated models.
- Logistic Regression achieved an accuracy of 97.07% and an F1 score of 95.63%. As a linear model, its performance was comparable to the Linear SVM, demonstrating its effectiveness for binary classification tasks in this context.



Supplementary Fig. 2: Top 10 features for predicting symptoms of ADHD.

3. Model Performance for Anxiety

- The KNN model achieved an accuracy of 74.06% and an F1 score of 69.44%. This performance indicates that KNN was reasonably effective in predicting anxiety but struggled with balancing precision and recall, likely due to the high-dimensional nature of the data and the algorithm's simplicity.
- The Linear SVM model showed significant improvement with an accuracy of 80.33% and an F1 score of 71.57%. This suggests that the data may be approximately linearly separable, allowing the linear SVM to effectively classify students with and without anxiety.
- Similar to the Linear SVM, the RBF SVM also achieved an accuracy of 80.33% and an F1 score of 71.57%. The RBF kernel was able to handle non-linear relationships effectively, though in this case, it did not provide a significant improvement over the linear kernel.
- The Gaussian Process classifier achieved an accuracy of 71.97% and an F1 score of 69.47%. While better than some models, its performance was not as strong as the SVMs or the ensemble methods. The probabilistic nature of this model might not have provided a significant advantage for this specific classification task.
- The Decision Tree classifier had a strong performance with an accuracy of 80.75% and an F1 score of 77.68%. Decision Trees can capture non-linear relationships effectively, and this model's performance indicates that it was able to identify significant patterns related to anxiety.
- The Random Forest classifier matched the Decision Tree in terms of accuracy (80.75%) but had a lower F1 score (72.56%). The ensemble approach of combining multiple decision trees helped reduce overfitting and improve predictive performance.
- The Neural Network achieved an accuracy of 76.57% and an F1 score of 72.83%. Neural networks can model complex relationships, and this performance indicates that it captured the nuances of the data effectively, though it did not outperform the simpler models significantly.
- AdaBoost showed the best performance with an accuracy of 81.59% and an F1 score of 76.17%. By focusing on misclassified instances in each iteration, AdaBoost effectively improved the model's performance, making it the best performing model in this analysis.
- The Naive Bayes classifier performed reasonably well, with an accuracy of 69.87% and an F1 score of 71.82%. Despite its simplicity and the assumption of feature independence, Naive Bayes provided competitive results, though it lagged behind the more sophisticated models.
- Logistic Regression achieved an accuracy of 80.75% and an F1 score of 76.94%. As a linear model, its performance was comparable to the Linear SVM, demonstrating its effectiveness for binary classification tasks in this context.

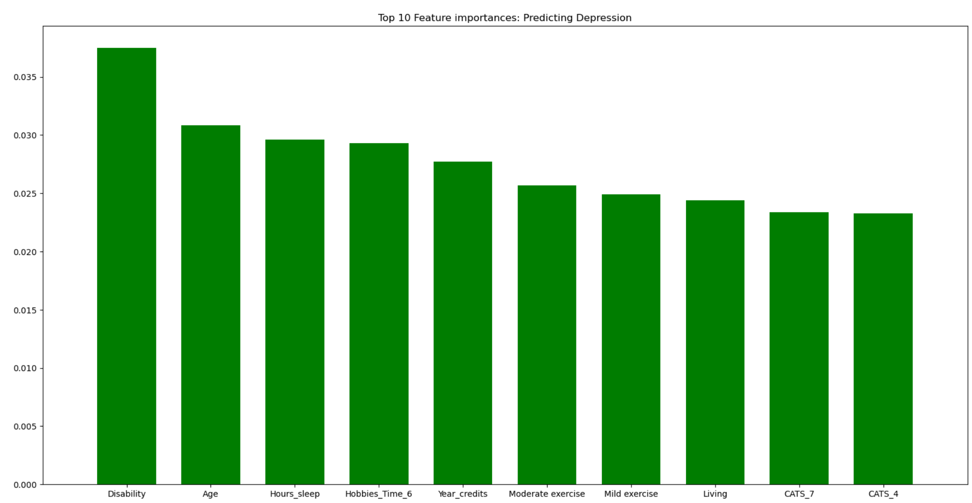


Supplementary Fig. 3: Top 10 features for predicting symptoms of Anxiety.

4. Model Performance for Depression

- The KNN model achieved an accuracy of 79.50% and an F1 score of 73.30%. While this performance is relatively high, the KNN model struggled somewhat with balancing precision and recall, likely due to the high-dimensional nature of the data and the algorithm's simplicity.
- The Linear SVM model showed improvement with an accuracy of 82.01% and an F1 score of 73.90%. This suggests that the data may be approximately linearly separable, allowing the linear SVM to effectively classify students with and without depression.
- Similar to the Linear SVM, the RBF SVM also achieved an accuracy of 82.01% and an F1 score of 73.90%. The RBF kernel handled non-linear relationships effectively, but it did not provide a significant improvement over the linear kernel in this case.
- The Gaussian Process classifier achieved an accuracy of 78.66% and an F1 score of 74.93%. While better than some models, its performance was not as strong as the SVMs or the ensemble methods. The probabilistic nature of this model might not have provided a significant advantage for this specific classification task.
- The Decision Tree classifier had a strong performance with an accuracy of 82.01% and an F1 score of 78.05%. Decision Trees can capture non-linear relationships effectively, and this model's performance indicates that it was able to identify significant patterns related to depression.
- The Random Forest classifier matched the performance of the Decision Tree in terms of accuracy (82.01%) but had a lower F1 score (73.90%). The ensemble approach of combining multiple decision trees helped reduce overfitting and improve predictive performance.

- The Neural Network achieved an accuracy of 81.17% and an F1 score of 76.04%. Neural networks can model complex relationships, and this performance indicates that it captured the nuances of the data effectively, though it did not outperform the simpler models significantly.
- AdaBoost showed the best performance with an accuracy of 83.26% and an F1 score of 78.46%. By focusing on misclassified instances in each iteration, AdaBoost effectively improved the model's performance, making it the best performing model in this analysis.
- The Naive Bayes classifier performed reasonably well, with an accuracy of 71.13% and an F1 score of 72.35%. Despite its simplicity and the assumption of feature independence, Naive Bayes provided competitive results, though it lagged behind the more sophisticated models.
- Logistic Regression achieved an accuracy of 82.01% and an F1 score of 75.99%. As a linear model, its performance was comparable to the Linear SVM, demonstrating its effectiveness for binary classification tasks in this context.



Supplementary Fig. 4: Top 10 features for predicting symptoms of Depression.

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