Predicting Mental Health with Machine Learning Algorithms

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***Abstract*—Mental health disorders are a significant global concern, impacting individuals, communities, and healthcare systems. Early detection and precise prediction of mental health conditions play a vital role in facilitating timely interventions and personalized treatment plans. This research explores the utilization of machine learning methodologies for anticipatory analysis in the field of mental health. This paper aims to assist people in realizing that they might be suffering from depression. To apply the machine learning algorithms, data was collected from varied ages, professions, and genders. This study explores supervised learning techniques, leveraging historical data encompassing demographics, clinical history, and behavioral attributes to predict mental health conditions. Various algorithms—Gradient Boosting, Random Forest, and Stacking—are employed to classify individuals at risk, achieving accuracies exceeding 90 percent.**

***Index Terms*—Mental Health Prediction, Machine Learning Algorithms, Artificial Neural Network**

I. Introduction

In the evolving landscape of modern society, the enduring struggle with mental health challenges persists, marking a notable increase in prevalence compared to historical contexts. In the Indian context, mental health remains a pressing concern. Government statistics indicate that a substantial portion of the Indian population, specifically 56 million individuals, contends with various forms of mental illnesses. The substantial prevalence of mental health issues can be attributed to systemic challenges within the healthcare infrastructure, including inadequate resources and insufficient governmental support. A 2015 report from the World Health Organization (WHO) revealed that 4.5 percent of the Indian populace experienced depressive disorders, a factor potentially contributing to elevated suicide rates. This research delves into the intricate landscape of mental health in India, seeking to address the underlying factors and propose viable solutions. [1].

This project seeks to explore the use of machine learning algorithms in predicting mental health outcomes using a variety of datasets containing clinical and behavioral data. This study intends to analyze the usefulness and potential constraints of using machine learning for predictive analysis in mental health by using the capabilities of computational models.

Supervised learning is the most often utilized approach in machine learning in many studies and trials, particularly for predicting mental disease in the medical industry. In this instance, the machine learns from previously classified data.

This involves using prior data where people are labeled with certain mental health issues based on things like their age, Gender, family history, and other crucial details. [2]

II. LITERATURE SURVEY

The article's authors Satvik Gurjar and his Co-authors [3] discuss the prevalence of mental health issues in India and the lack of awareness and support for these problems. The authors aim to use machine learning algorithms to predict mental health conditions such as depression, anxiety, PTSD, and insomnia. They collected data from diverse demographics and applied various machine-learning algorithms for prediction. The study achieved good accuracy in predicting mental health conditions and suggests future enhancements, such as adding more diseases to the model and combining multiple methods

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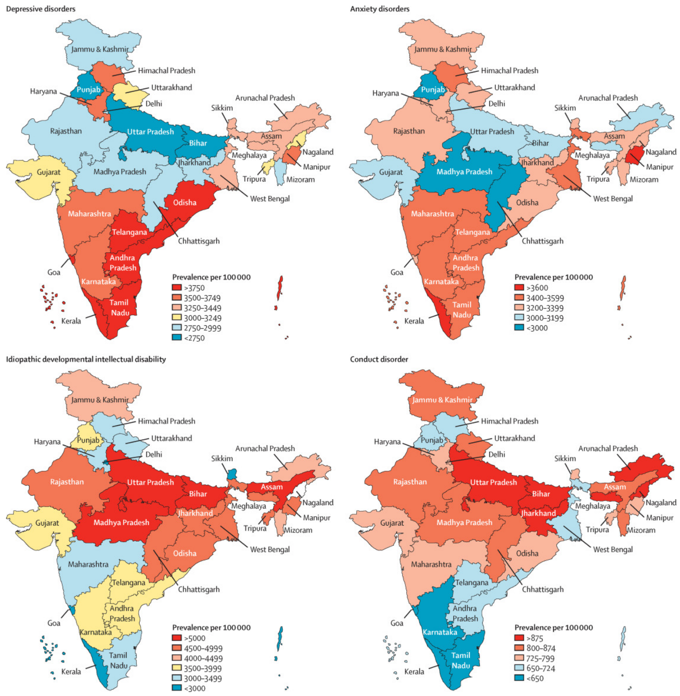

Fig. 1. Average frequency of major mental diseases in Indian states

with questionnaires to strengthen the prediction process. the logistic regression algorithm achieved the highest accuracy of 97.27 percent for depression.

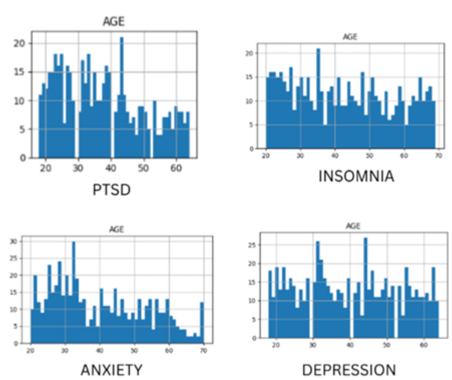

Fig. 2. Dataset-Overview

The authors of the second paper [4] discuss how different machine learning algorithms can be used to forecast mental health disorders based on personal characteristics like income, spending, family structure, and investments. Eight machine learning methods were used in the study, including Decision Tree, Random Forest, Support Vector Machine (SVM), Naïve Bayes, Logistic Regression, XGBoost, Gradient Boosting Classifier, and Artificial Neural Network. The dataset used in the study had 76 features. The evaluation of the algorithms was based on parameters such as sensitivity, specificity, precision, negative predicted value, F1 score, false negative rate, false positive rate, false discovery rate, false omission rate, and accuracy. The study found that the Support Vector Machine (SVM) algorithm achieved the highest accuracy of 87.38 percent.

The third paper [5] delves into integrating deep learning (DL) algorithms within mental health outcome research. It emphasizes the critical link between mental and physical health, underscoring the necessity of early detection for mental health issues. The study surveys various artificial intelligence methods, focusing primarily on DL techniques like deep feed-forward neural networks (DFNN), recurrent neural networks (RNN), convolutional neural networks (CNN), and autoencoders. Autoencoders, a special type of DFNN, are highlighted for their ability to learn new data representations. The research categorizes the application of DL methods into four groups based on the data type analyzed: clinical data, genetic and genomics data, vocal and visual expression data, and social media data. It extensively discusses how DL algorithms are used in analyzing neuroimages (like fMRI and sMRI) for identifying mental health disorders. Moreover, it explores the utilization of DL in analyzing visual expression data, genetic and genomics data, and social media data.

In this fourth research paper, The author Sofianita Mutalib and co-authors [6] aim to identify factors contributing to mental health problems among higher education students and develop prediction models using machine learning algorithms.The research centers on categorizing students into various groups based on mental health issues such as stress, depression, and anxiety. The investigators gathered data from an institution of higher education located in Kuala Terengganu. They applied various machine learning algorithms, including Decision Tree, Neural Network, Support Vector Machine, Naïve Bayes, and Logistic Regression. The study found that factors such as lack of social support, financial difficulties, and the learning environment contribute to mental health problems among students. The Decision Tree model was found to be the most accurate for stress prediction, while the Support Vector Machine was the most accurate for depression prediction. Linear Regression and Neural Networks provided fair results for anxiety prediction.

The author of the Fifth paper explores the intersection of artificial intelligence and mental health, with a focus on machine learning algorithms for predicting public mental health. Drawing insights from the Second International Conference on Artificial Intelligence and Smart Energy , the survey emphasizes the importance of mental health in overall well-being.

The fifth research paper [7] introduces deep learning algorithms, including deep feedforward neural networks and recurrent neural networks, into mental health research. It classifies applications into clinical, genetic, vocal, visual, and social media data types. The survey addresses challenges in mental health and presents a framework for data-driven interventions.

Highlighting technological advancements, such as high-speed internet and smartphones, the survey delves into K-Nearest Neighbor, Random Forest, Logistic Regression, and

Decision Tree algorithms for mental health prediction. Key findings include the link between lifestyle factors and mental health, as well as stress and social interaction correlations in social networks.

III. DATASET DESCRIPTION

The dataset [8] used in this study serves as a fundamental basis for predictive analysis in mental health. Comprising 27 attributes and 1257 entries, it encompasses diverse information crucial for understanding and predicting mental health conditions. The many factors that go into mental health assessments are reflected in the attributes, which include things like age group, gender, medical history, benefits, care alternatives, privacy, leave, and interference with the job.

The dataset has been prepared to ensure data quality and consistency to the scope of mental health prediction. Preprocessing steps involved handling missing values, and normalizing data formats to enhance the robustness and reliability of the predictive models. We partitioned the dataset into training (80 percent) and testing (20 percent) subsets, adhering to established methodologies in constructing machine learning models.This allocation allows enough model training while keeping an independent set for rigorous evaluation and validation, which is necessary for defining Generalizability and real-world application.

IV. PROPOSED METHODOLOGY

This project addresses the issue of Mental Health detection by using the Ensemble learning method. which specifies achieving precise detection using examples. The primary objectives involve improving the model's ability to detect effectively ensuring accurate identification of depressive disorders through the utilization of the Ensemble learning method and using feature extraction. The aim is to develop a resilient and adaptable mental health detection model that excels in accurately recognizing depressive disorder with training data

V. MACHINE LEARNING ALGORITHMS

To ensure the best working of machine learning algorithms it is necessary to work with key parameters. Each task requires a different model based on the type of data. Hence, it is crucial to adjust the parameters of the model to improve its utility and accuracy. In our work, we have tried to tune all the models with adequate parameter values for the best value for our models.

After selecting the right parameters, we use our gathered dataset to apply machine learning techniques. The gathered dataset is frequently split into training and testing subsets. In order to avoid overfitting, this is done. An ideal dataset split would be 80:20, meaning that 80 percent of the information is used to train the model and the remaining 20 percent is used to verify that the model is correct. To find the best machine learning algorithm that could provide us the most accuracy, we investigated the following algorithms.

1) Logistic Regression (LR): Logistic regression is a supervised learning technique used for binary classification and linear classification by modeling the relationship between features and the probability of an outcome, using the logistic function.

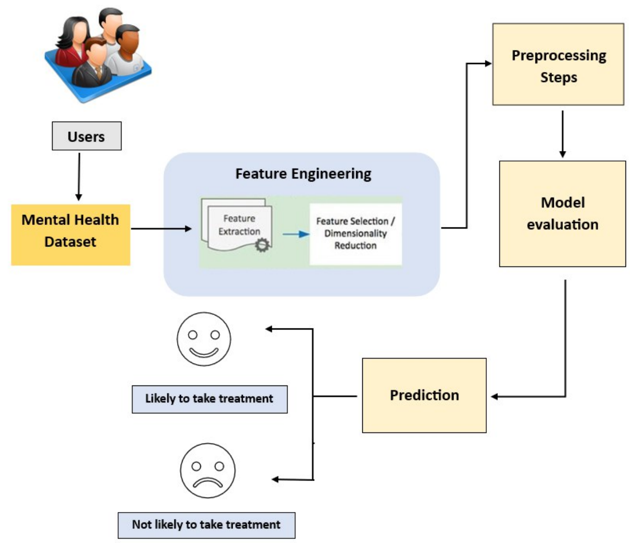

Fig. 3. Architecture

The coefficients are estimated using methods like maximum likelihood estimation, and the decision boundary is determined by the threshold value for classification.

The logistic regression model is defined by the sigmoid function:

$$P(Y=1|X) = \frac{1}{1+e^{-(\beta_0+\beta_1X_1+\beta_2X_2+\ldots+\beta_pX_p)}}$$

where:

$$\begin{aligned} P(Y=1|X) &: \text{Probability of the positive outcome} \\ X &: \text{Predictor variables/features} \\ \beta_0, \beta_1, \ldots, \beta_p &: \text{Coefficients/weights} \\ e &: \text{Base of the natural logarithm} \end{aligned}$$

2) Random forest classifier (RF): It belongs to the realm of supervised algorithms in machine learning. The process involves creating numerous decision trees during the training phase and yields the mode (for classification) or mean prediction (for regression) of the individual trees as output.

3) Support Vector Machine (SVM):A widely used approach for both regression and classification is the support vector machine (SVM). This algorithm aims to establish the most effective line or decision boundary for classifying n-dimensional space, enabling swift categorization of new data points in the future. The optimal decision boundary is termed a hyperplane. To construct this hyperplane, SVM identifies the extreme points, a method known as the Support Vector Machine, as these exceptional instances are denoted as support vectors.

Linear SVM:

1. **Decision Function:**

$$f(x) = \text{sign}\left(\mathbf{w}\cdot\mathbf{x}+b\right)$$

2. **Linear SVM Objective Function:**

$$\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2 \quad \text{subject to} \quad y_i(\mathbf{w}\cdot\mathbf{x}_i + b) \geq 1 \quad \forall i$$

4) Gradient Boosting classifier: For regression and classification issues, gradient boosting is a supervised machine learning method. It combines several weak learning models to produce a robust predicting mode.

The general equation for Gradient Boosting can be represented as:

$$F(x) = F_0(x) + \lambda \sum_{m=1}^{M} \gamma_m h_m(x)$$

where:

$$\begin{aligned} F(x) &: \text{Final model/prediction} \\ F_0(x) &: \text{Initial model/prediction} \\ \lambda &: \text{Learning rate (shrinkage parameter)} \\ M &: \text{Number of boosting iterations} \\ \gamma_m &: \text{Weight of the weak learner} \\ h_m(x) &: \text{Weak learner (e.g., decision tree)} \end{aligned}$$

5) K-nearest neighbor (KNN): Also recognized as a lazy or nonparametric algorithm, this approach relies on feature similarity. Predictions are determined through the calculation of the closest data points. Due to the storage of training data, when applied to extensive datasets, it may pose computational challenges in terms of expense.

K-Nearest Neighbors (KNN) Algorithm:

1. **Distance Calculation:** Calculate the distance between the new data point (X_{new}) and each point in the training dataset (X_{train}) using a distance metric (commonly Euclidean distance).

$$\text{distance}(X_{\text{new}}, X_{\text{train}}) = \sqrt{\sum_{i=1}^{n}(X_{\text{new},i} - X_{\text{train},i})^2}$$

2. **Neighbor Selection:** Select the "k" training instances with the smallest distances to the new data point.

3. **Majority Vote (for Classification):** For classification, assign the class label that is most common among the "k" neighbors.

$$\text{Prediction} = \text{argmax}\left(\sum_{i=1}^{k} I(y_i = c)\right)$$

where y_i is the class label of the i-th neighbor, c is a class label, and I is the indicator function.

4. **Average (for Regression):** For regression, predict the average of the target values of the "k" neighbors.

$$\text{Prediction} = \frac{1}{k}\sum_{i=1}^{k} y_i$$

6) Artificial Neural Networks (ANNs): These are brain-inspired models comprising connected neurons organized in layers. They learn patterns, adjust internal weights, and make predictions by processing data through forward and backward passes. ANNs excel in capturing complex patterns from data, enabling applications in image recognition, language processing, and more, as referred in [9].

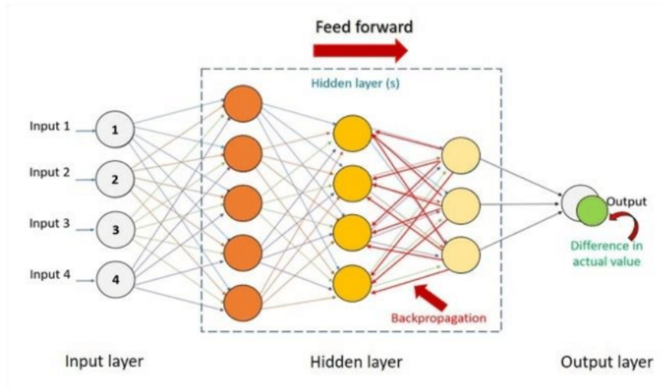

Fig. 4. ANN Architecture

The forward propagation equation for a single neuron in an Artificial Neural Network (ANN) is given by

Formula:

$$y = f\left(\sum_{i=1}^{n} w_i \cdot x_i + b\right)$$

where:

$$\begin{aligned} y &: \text{Output of the neuron} \\ f &: \text{Activation function} \\ w_i &: \text{Weight associated with input } x_i \\ x_i &: \text{Input to the neuron} \\ b &: \text{Bias term} \\ n &: \text{Number of inputs to the neuron} \end{aligned}$$

7) Decision Tree Classifier (DTC): The algorithm learns from labeled examples, creating a tree-like structure of questions and decisions. By selecting the best questions to split the data, accurately predicts outcomes for new data based on its features. This method finds use in various fields to make predictions or classifications based on given data.

8) Bagging: It is an ensemble learning method that involves training multiple models independently on random subsets of the data. Its technique is to improve the performance and accuracy of machine learning algorithms.

9) Boosting: The goal of the ensemble modeling technique known as "boosting" is to build a strong classifier from a group of weak classifiers. The process involves building a model by the serial operation of weak models.

10) stacking: Stacking is an ensemble learning technique that generates a more accurate prediction by aggregating the predictions of multiple models. It functions by first using the data to train many models, and then another model learns from these distinct forecasts to generate the final prediction.

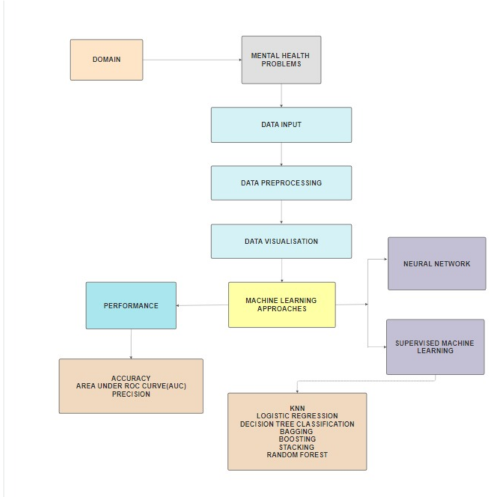

Fig. 5. Methological-Framework

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The system goes through multiple steps before the final value can be predicted. These steps are data collection, pre-processing, data visualization, training, and algorithm testing. Once the expected accuracy is obtained, we can integrate the system with an application for real-world use.

VI. IMPLEMENTATION

For this study's implementation, a standardized dataset was utilized, obtained from the GitHub repository. The dataset from this repository served as a fundamental resource for our experimentation and analysis in predicting mental health conditions using machine learning algorithms. It contains a comprehensive collection of attributes encompassing Age, Gender, Country, state self-employed, family history, treatment work-interfere, and other relevant information essential for mental health prediction tasks.[7]

The use of this standardized dataset allowed us to perform consistent evaluations, comparisons, and implementations of various machine-learning algorithms within the scope of mental health prediction. It also ensured compatibility with established criteria and simplified reproducibility in our experimentation process. Our predictive model seeks to evaluate the possibility of a patient seeking treatment for mental health concerns based on the stated features, which include age, gender, family history, benefits, care alternatives, anonymity, leave, and work interference.

It is important to fill out the missing values in the dataset to increase the quality of the dataset. The pre-processing involves the elimination of the comment, time-stamp, and state columns during the preprocessing phase, followed by the combining of different gender categories into three primary groups: male, female, and others.

A. Evaluation Metrics

In this section, we employ standardized metrics, including F1 score, recall, and precision, Accuracy, ROC-AUC, MCC, Confusion Matrix as our primary evaluation Metrics.

1) F1 Score Calculation: The following formula is used to determine the F1 score, which is a harmonic mean of recall and precision:

$$F1\ score = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

2) Accuracy Calculation: The ratio of accurately anticipated instances to the total number of instances is the measure of accuracy.

$$Accuracy = \frac{\text{True Positive + True Negative}}{\text{Total Predictions}}$$

3) Recall Calculation: Recall, also known as sensitivity or true positive rate, is calculated as:

$$Recall = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

4) Precision Calculation: Precision, the positive predictive value, is calculated as:

$$Precision = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

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VII. RESULTS

To achieve high accuracy with the model the data needs to be properly cleaned and pre-processed until it is well fitted. We used Python libraries like NumPy, pandas, and matplotlib. To get the best result for our work we had to pass each of our datasets through multiple ML algorithms like logistic regression, SVM, random forest, k-neighbors, and deep learning algorithms, etc. we ran the algorithms as mentioned above and achieved an accuracy of 97.08 Percent, 96 percent, 95 percent, 90, etc. respectively.

The bar plot visualizes the probability (represented on the y-axis) of individuals receiving mental health treatment across different age ranges (on the x-axis), further categorized by gender (shown in different colors).

Algorithms with Highest Accuracy	Accuracy (%)
K-Neighbors Classifier	97.08 %
Gradient Boosting Classifier	96.25 %
Stacking	96.25 %
Random Forest	96.6 %
ANN	96.15 %
Bagging	96 %
Decision Tree Classifier	95 %
Boosting	90.83 %
SVM	90.41 %
Logistic Regression	85.4 %

TABLE I
ALGORITHM ACCURACY COMPARISON

In the context of this study, a correlation analysis was conducted to explore the relationships among key variables associated with mental health outcomes. The findings reveal

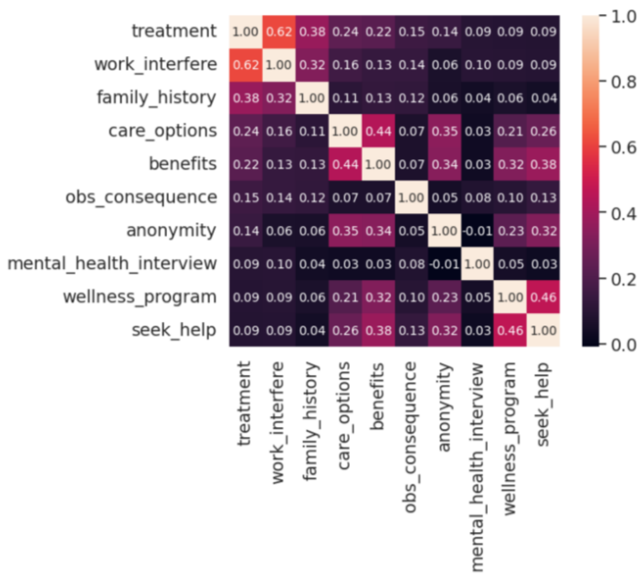

Fig. 6. Co-relation Matrix

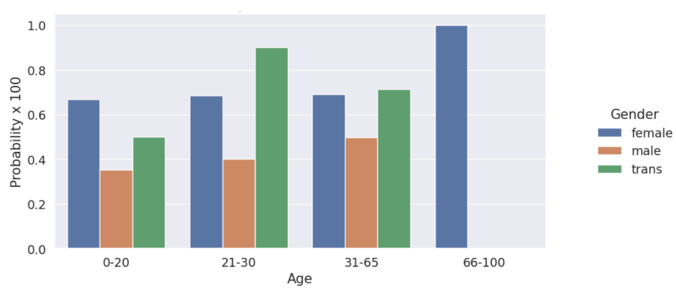

Fig. 7. Probability of Mental Health Condition

that the variable *”treatment”* demonstrates the strongest positive correlations with *”mental_health_interview,” ”seek_help,” ”care_options,”* and *”benefits.”* This suggests that individuals who are more likely to undergo a mental health interview, seek help, have access to care options, and receive benefits are also more inclined to have received mental health treatment.

Additionally, the variable *”work_interfere”* exhibits the strongest positive correlations with *”treatment,” ”care_options,”* and *”mental_health_consequence.”* This implies that individuals who have undergone treatment, have access to care options, and have experienced mental health consequences are more likely to report that their work is influenced by their mental health.

Concerning the *”family_history”* variable, a weak positive correlation with the *”treatment”* variable was observed, indicating a modest but positive relationship between having a family history of mental illness and receiving treatment.

In terms of age, the *”age”* variable demonstrates a weak negative correlation with the *”treatment”* variable, suggesting a minor but negative relationship between age and the likelihood of receiving mental health treatment.

Lastly, the variable *”mental_health_interview”* shows the strongest positive correlations with *”treatment,” ”seek_help,” ”care_options,”* and *”mental_health_consequence.”* This implies that individuals who have undergone a mental health interview are more likely to have received treatment, sought help, have access to care options, and have experienced mental health consequences. Overall, these findings contribute valuable insights into the intricate interplay of factors influencing mental health outcomes in this study. It’s important to note that the features discussed here are the ones utilized to train our model, and *”treatment”* is the column that our model predicts.

VIII. Conclusion and Future work

In this research, the utilization of machine learning methods for predicting mental health exhibited encouraging outcomes and noteworthy consequences for early identification and intervention. Using diverse algorithms such as Gradient Boosting, Random Forest, and Stacking, we explored the predictive potential in identifying individuals at risk of mental health conditions.

The analysis revealed that certain algorithms, notably the K-Neighbors Classifier and Gradient Boosting Classifier, exhibited remarkably high accuracy rates, surpassing 95 Percent accuracy in predicting mental health conditions based on diverse attributes.

This further can be improved by creating image classification where we can see the image classified from the diseases.

However, it’s crucial to acknowledge the complexities and challenges inherent in mental health prediction. Factors like data quality and feature selection can raise critical challenges in implementing these predictive models.

For papers published in translation journals, please give the English citation first, followed by the original foreign-language citation [6].

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