

AI Driven Self Diagnosis of Mental Health Status Using Machine Learning Models

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Abstract – The increasing prevalence of mental health issues worldwide has underscored the need for innovative, accessible diagnostic tools. Traditional mental health assessment methods often rely on self-reporting and professional evaluations, which is time-consuming and lack immediacy. Paper presents an AI-driven framework for the self-diagnosis of mental health status, leveraging machine learning models trained on a variety of user-generated data, including social media activity, profile characteristics, and social connections. By integrating feature engineering techniques, dimensionality reduction, and robust data preprocessing, the proposed model can detect and predict mental health states with considerable accuracy. The novelty of this work lies in its automated, real-time processing pipeline, which combines initial data validation and label assignment with advanced ML techniques for effective prediction. This framework offers users insights into their mental well-being and also serves as a scalable solution for mental health monitoring, potentially reducing the burden on healthcare systems by facilitating early intervention.

Keywords – AI-Driven Diagnostics, Mental Health Prediction, Machine Learning Models, Self-Diagnosis Tools, Social Media Analysis, Real-Time Processing.

I. INTRODUCTION

In today's fast-paced world, societal norms often prioritize physical well-being over mental health, which underscores the importance of acknowledging and addressing mental well-being. Understanding one's mental health status and seeking timely support are critical for leading fulfilling lives. Mental illness, a prevalent health issue, significantly impacts emotions, reasoning, and social interaction [1]. The ramifications of these issues extend beyond individuals, leading to serious consequences across societies, thereby demanding new strategies for prevention and intervention. Early detection of mental health conditions plays a pivotal role in implementing such strategies. Predictive analytics, driven by machine learning, is poised to revolutionize the healthcare field by enabling earlier and more accurate detection of mental illnesses [2]. Typically, mental health diagnoses rely on self-reported data, including questionnaires designed to detect specific patterns in emotions and social interactions. With proper care and treatment, many individuals will hopefully be able to recover from mental illness or emotional disorder. This guide aims to empower individuals to recognize, understand, and seek assistance for their mental health needs. Whether you're experiencing moments of stress, anxiety, or more complex mental health challenges, this guide is designed to support you in your journey towards emotional well-being. Self-identification begins with introspection. It involves acknowledging and accepting the spectrum of emotions and thoughts that influence our daily lives. By recognizing our mental health status, we can better understand the factors contributing to our well-being. This awareness serves as a compass, guiding us towards seeking appropriate support and resources when needed. Despite growing awareness, mental health stigma persists in many communities. This stigma often discourages individuals from openly discussing their mental health concerns or seeking help. However, by fostering open conversations and promoting understanding, we can break down these barriers and create supportive environments where individuals feel comfortable expressing their struggles without fear of judgment. Seeking support is not a sign of weakness but an act of strength. Whether through professional therapy, support groups, or trusted friends and family, reaching out for assistance can provide invaluable insights, coping strategies, and validation [2-4]. This guide emphasizes the significance of prioritizing self-care and seeking support tailored to individual needs. Mental health is an important part of our entire well-being. It is about our thoughts, feelings, and actions. Just like physical health, mental health can differ from time to time. It's vital to pay attention to our mental health and seek help when needed. If you're experiencing difficulties with your mental health, the first step is to acknowledge and accept it. This can be a challenging step, but it's a crucial one. Self-

identifying your mental health status is a sign of strength and courage [3]. Once you've identified that you might be experiencing mental health issues, the next step is to seek support. There are many resources available to help you. You can start by talking to someone you trust, like a friend, family member, or your doctor. They can provide guidance and help you find the right support services. There are also many professional help options available, such as therapists, counsellors, and psychologists. They can provide you with various treatment options, such as therapy, medication, or a combination of both [4]. Remember, it's okay to ask for help. Mental health issues are common, and there's no shame in seeking support. It is critical to care for your mental health just as you would your physical health. Early discovery of mental health concerns enables professionals to treat them more efficiently, hence improving patients' quality of life. Mental health refers to someone's psychological, emotional, and social well-being. It influences how one thinks, feels, and behaves. Mental health is essential at all stages of life, from childhood and adolescence to adulthood. A person's mental well-being is determined by both his or her mental state and an assessment of his or her general environment. Mental disease is caused by aberrant brain chemistry [5]. An individual's mental health serves as a barometer for effectively treating his or her ailments. To predict health-related anomalies, it is necessary to monitor the mental health profiles of various groups. The community consists of working professionals, college students, and high school pupils.

This paper is structured to provide a comprehensive analysis and solution to the challenges of mental health diagnosis using machine learning. Section II presents a detailed literature survey, examining existing research and the application of predictive models for mental health assessments. Section III outlines the problem statement, focusing on the limitations of traditional diagnostic methods and the need for more efficient early detection techniques. Section IV details the software requirements necessary for implementing the proposed system, including the tools and technologies essential for developing machine learning models. Section V introduces the proposed system and the methodology employed, describing the design and development of machine learning algorithms for predicting mental health disorders using self-assessment data. Section VI describes the data gathering procedure as well as the requirements for model training and testing, while Section VII examines the system's outcomes and performance analysis. Finally, Section VIII wraps up the report by summarizing the findings and proposing suggestions for future research directions in AI-driven mental health care solutions.

II. LITERATURE SURVEY

The rising prevalence of mental health disorders necessitates the development of more effective diagnostic tools that can provide timely and accurate assessments. Traditional diagnostic methods often rely on subjective self-reports and clinical evaluations, which may overlook subtle nuances in mental health presentations. In recent years, the incorporation of machine learning techniques into mental health research has opened up new options for improving diagnosis accuracy and comprehending the intricate interplay of numerous psychological and physiological components. This literature review seeks to summarize existing research on the use of machine learning to predict and differentiate anxiety and depression.

Anxiety prediction presents significant challenges in mental health diagnostics due to its clinical similarities with major depressive disorder (MDD) [6]. In their research, Sau et al. [7] utilized machine learning techniques to predict feelings of sadness and anxiety in elderly patients. They tested ten different classifiers on a chosen feature set and found that the Random Forest (RF) classifier delivered the highest accuracy, reaching 89%. Similarly, Sua et al. [8] employed the Hospital Anxiety and Depression Scale (HADS) to forecast anxiety and depression among seafarers, expanding upon prior studies. They examined five machine learning models, with CatBoost emerging as the top performer, achieving 82.6% accuracy and 84.1% precision. In comparison, the RF classifier yielded slightly lower results, with 81.2% accuracy and precision. Cho et al. [9] suggested a depression detection approach based on a Random Forest (RF) algorithm and a database acquired from the National Health Insurance Sharing Service's medical checkup cohort in Korea (2019). Their study discovered that just 0.02% of individuals were diagnosed with depression, while 99.8% were not, emphasizing the importance of down- or up-sampling strategies to establish balance between the two groups. Finally, the authors obtained an area under the curve (AUC) of 0.849, showing the model's efficacy.

Sharma et al. [10] proposed a machine learning strategy to improve depression detection by using the Lifelines Database, which included biomarker data as well as self-reported depression data. Cho et al., their dataset was imbalanced, so they applied various resampling techniques to manage this challenge. They employed the Extreme Gradient Boosting (XGBoost) algorithm on each resampled dataset, showcasing its ability to handle imbalance effectively and improve detection accuracy.

Supervised learning techniques are commonly used in research to predict mental diseases. Deshpande et al. [11] used Naïve Bayes and Support Vector Machine (SVM) classifiers in an Emotion AI framework to preprocess textual input. The study revealed that the multinomial Naïve Bayes classifier provided better prediction accuracy than the SVM classifier. In a similar vein, Hilbert et al. [12] applied supervised learning with an SVM to differentiate between anxious and depressed individuals using diverse bio behavioral data. Their analysis incorporated clinical questionnaire responses, cortisol levels, structural brain metrics, and measurements of gray matter (GM) and white matter (WM) volumes, both individually and combined. While using clinical questionnaires alone for anxiety classification proved difficult, adding cortisol and gray matter volume data provided considerable benefits for improving anxiety categorization.

Richter et al. [13] introduced an innovative and objective diagnostic approach to differentiate between anxiety and depression by integrating cognitive behavioral performance data with machine learning techniques [14]. They distributed questionnaires to subclinical participants, categorizing them into four main symptom groups: those with high anxiety, those

with high depression, individuals displaying both high anxiety and depression, and a control group with low symptoms of both. Cognitive behavior was evaluated through six different tasks aimed at identifying various cognitive biases. The collected data were analyzed using a Random Forest (RF) algorithm, producing a model that effectively classified participants based on their combined cognitive performance data.

The application of machine learning (ML) techniques in mental health has received a lot of attention as researchers try to improve diagnostic accuracy for illnesses like anxiety and depression [15]. This review examines research that employs supervised learning methods, including Random Forest (RF), Support Vector Machine (SVM), and Naïve Bayes classifiers, to analyze complex datasets and predict mental health disorders. Key findings demonstrate that integrating multimodal data—from cognitive performance assessments to biomarker information—enhances the differentiation between anxiety and depression. Furthermore, the importance of addressing data imbalances through resampling techniques is emphasized, along with the potential of ML algorithms to provide objective diagnostic tools [16]. The review underscores the promise of these innovative approaches in contributing to early detection and personalized treatment strategies in mental health care.

III. PROBLEM STATEMENT

Data Collection and Preprocessing

- Collect data related to mental health indicators such as mood, behavior, stress levels, etc.
- Clean and preprocess the data to handle missing values, outliers, and ensure consistency.

Feature Engineering

- Extract meaningful features from the data that are indicative of mental health status.
- Features could include sleep patterns, exercise habits, social interactions, etc.

Machine Learning Models

Random Forest Random Forest is a widely used supervised learning algorithm in machine learning, suitable for both classification and regression tasks. It operates on the principle of ensemble learning, where multiple classifiers are combined to tackle complex problems and enhance model accuracy. As the name suggests, a Random Forest consists of several decision trees built on different subsets of the dataset, and it averages their outputs to improve predictive accuracy. Rather than relying on a single decision tree, Random Forest aggregates the predictions from each tree and determines the final outcome based on the majority vote.

LightGBM

LightGBM is an ensemble learning framework, specifically a gradient boosting method, that builds a strong learner by gradually adding weak learners in a gradient descent fashion. Gradient-based One-Side Sampling (GOSS) is one strategy that improves memory use and training time. Microsoft developed LightGBM, an open-source, distributed, and high-performance gradient boosting framework. It is built for efficiency, scalability, and precision. It is built on decision trees that are intended to improve model efficiency and reduce memory usage.

XGBoost

XGBoost is an ensemble learning algorithm that operates within the gradient boosting framework, utilizing decision trees as its foundational learners and applying regularization techniques to improve generalization. This algorithm is popular for its speed, capability to assess feature importance, and effective handling of missing data, making it well-suited for tasks in regression, classification, and ranking.

Model Training and Evaluation

Train each model using the prepared data.

Evaluate models using metrics like accuracy, precision, recall, F1-score, etc., to identify the best-performing models (Boosting and Stacking in your case)

Prediction and Recommendation

Use the selected models (Boosting and Stacking) to predict individuals' mental health status (anxiety or depression).

Based on the prediction, recommend personalized guidance and support strategies:

- Listening to music for stress relief and mood improvement.
- Breathing exercises for relaxation and anxiety management.
- Meditation for overall mental well-being.
- Going out for a walk for physical activity and mental rejuvenation

User Interface and Interaction

- Develop a user-friendly interface where individuals can input their data securely.
- Display prediction results along with recommended strategies for mental health support.
- Allow users to interact with the system, provide feedback, and track their progress over time.

Among these models, Boosting and Stacking have demonstrated the highest accuracy in predicting mental health issues. Boosting works by combining multiple weak models to create a strong model, while Stacking involves combining multiple models to create a new model that can make more accurate predictions.

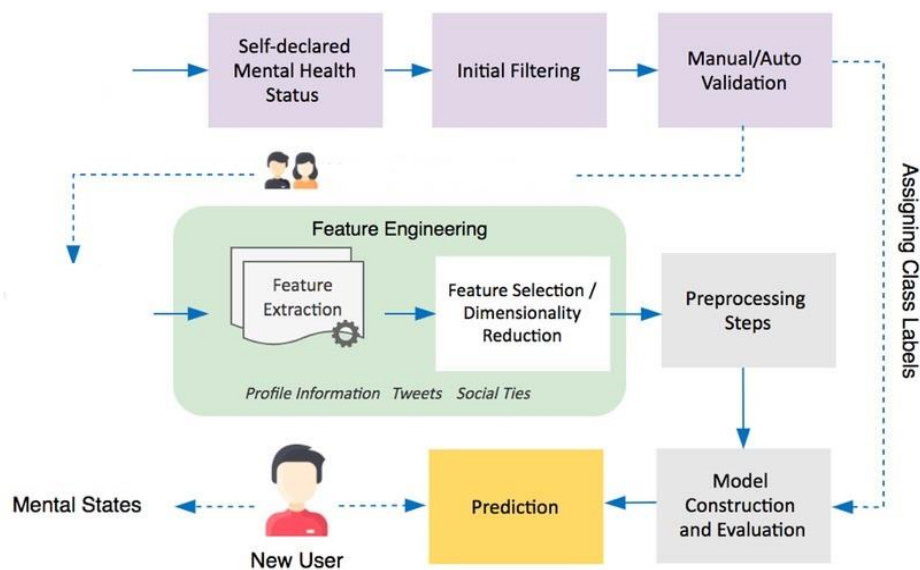


Fig 1. System Architecture.

The diagram outlines a machine learning-based pipeline for predicting mental health states using user data and feature engineering. The process begins with the Self-declared Mental Health Status of users, where individuals report their mental health, serving as initial labeled data. This data undergoes Initial Filtering to remove irrelevant or noisy information, ensuring data quality. Next, the filtered data is subjected to Manual/Automatic Validation to confirm its reliability and accuracy. Following validation, Class Labels are assigned to categorize mental health states, which will be used as target labels in the model training process. **Fig 1** Shows System Architecture.

In the Feature Engineering phase, raw data sources like Profile Information, Tweets, and Social Ties are processed. Within this phase, Feature Extraction identifies and captures relevant features from these sources, while Feature Selection/Dimensionality Reduction is performed to refine and reduce the feature set, making it more manageable and focused. The refined features proceed through Preprocessing Steps, where data is cleaned and formatted appropriately for the model.

Once the data is prepared, it moves to the Model Construction and Evaluation phase. Here, machine learning models are built and evaluated to determine their effectiveness in predicting mental health states. Following model selection, the system moves to Prediction, where the model is applied to new user data to estimate their mental health status. The output is the predicted Mental State of the new user, providing insights based on the learned patterns from previous data. The process flow emphasizes data quality control, feature engineering, and model evaluation to ensure accurate and reliable mental health predictions.

IV. SOFTWARE REQUIREMENTS

Software Libraries Required

Pandas

Pandas is a powerful Python library widely used for handling and analyzing datasets. It provides a range of functions designed for data analysis, cleaning, exploration, and manipulation, making it a valuable tool for data science and machine learning. With Pandas, users can efficiently work with large volumes of data and derive meaningful insights based on statistical principles. Additionally, it excels at cleaning and organizing messy datasets, transforming them into readable and relevant forms, which simplifies data processing and analysis.

Lazy Predict

Lazy Predict helps build a lot of basic models without much code and helps understand which models work better without any parameter tuning.

Scikit-Learn

Scikit-learn is a Python library that includes numerous unsupervised and supervised learning techniques. It is built on technology that you may already be familiar with, like as NumPy, pandas, and Matplotlib. Scikit Learn has evolved as a

robust and user-friendly Python package. Its simplicity and versatility make it a preferable alternative for both novice and experienced data scientists to construct and apply machine learning models.

Imb Learn

Imbalanced-Learn is a Python package that assists in balancing datasets that are heavily skewed or biased toward specific classes. Thus, it aids in resampling classes that are otherwise oversampled or under sampled. If the imbalance ratio is bigger, the result will be slanted toward the class with the most examples.

Pseudo code for Self-Diagnosis of Mental Health Status

```
import streamlit as st
import numpy as np
from sklearn.preprocessing import LabelEncoder
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, BaggingClassifier, AdaBoostClassifier
from lightgbm import LGBMClassifier
from xgboost import XGBClassifier, XGBRFClassifier
from lazypredict.Supervised import LazyClassifier
from imblearn.over_sampling import SMOTE
import plotly.express as px
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report
import plotly.graph_objs as go
# Create the Streamlit app
st.title('Mental Health Survey Analysis')
data = pd.read_csv('survey.csv')print(data.columns)
print(data.info())
print(data.isna().sum())
print(data.describe())
st.sidebar.header('Give me inputs here')
# Sidebar inputs
work_interfere = st.sidebar.selectbox('Work Interference', ['Sometimes', 'Never', 'Rarely', 'Often'])
no_employees = st.sidebar.selectbox('Number of Employees', ['Jun-25', '26-100', 'More than 1000', '100-500', '01-May', '500-1000'])
benefits = st.sidebar.selectbox('Benefits', ['Yes', 'Don't know', 'No'])
care_options = st.sidebar.selectbox('Care Options', ['No', 'Yes', 'Don't know'])
wellness_program = st.sidebar.selectbox('Wellness Program', ['No', 'Yes', 'Don't know'])
anonymity = st.sidebar.selectbox('Anonymity', ['Don't know', 'Yes', 'No'])
mental_health_interview = st.sidebar.selectbox('Mental Health Interview', ['Don't know', 'Yes', 'No'])
mental_vs_physical = st.sidebar.selectbox('Mental vs Physical', ['Don't know', 'Yes', 'No'])
# Label encode the selected inputs
label_encoder = LabelEncoder()
work_interfere_encoded = label_encoder.fit_transform([work_interfere])
no_employees_encoded = label_encoder.fit_transform([no_employees])
benefits_encoded = label_encoder.fit_transform([benefits])
care_options_encoded = label_encoder.fit_transform([care_options])
wellness_program_encoded = label_encoder.fit_transform([wellness_program])
anonymity_encoded = label_encoder.fit_transform([anonymity])
mental_health_interview_encoded = label_encoder.fit_transform([mental_health_interview])
mental_vs_physical_encoded = label_encoder.fit_transform([mental_vs_physical])

# Convert the encoded inputs to a numpy array
user_inputs = np.array([work_interfere_encoded[0], no_employees_encoded[0], benefits_encoded[0],
                        care_options_encoded[0], wellness_program_encoded[0], anonymity_encoded[0],
                        mental_health_interview_encoded[0], mental_vs_physical_encoded[0]])
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
```

```

from sklearn.ensemble import RandomForestClassifier, BaggingClassifier, AdaBoostClassifier
from lightgbm import LGBMClassifier
from xgboost import XGBClassifier, XGBRFClassifier
from lazypredict.Supervised import LazyClassifier
from imblearn.over_sampling import SMOTE
data = pd.read_csv('survey.csv')
print(data.columns)
print(data.info())
print(data.isna().sum())
print(data.describe())
for i in data.select_dtypes(include='object').columns.values:
    print(data[i].value_counts())
a = ['work_interfere', 'no_employees', 'benefits', 'care_options',
     'wellness_program', 'anonymity', 'mental_health_interview',
     'mental_vs_physical']
print('-----xxx-----')
for i in a:
    print(data[i].value_counts().index)
print('-----xxx-----')
lab = LabelEncoder()
for i in data.select_dtypes(include='object').columns.values:
    if len(data[i].value_counts().values) < 20:
        data[i] = lab.fit_transform(data[i])
data = data.drop(['Timestamp', 'Gender', 'Country', 'state'], axis=1)
print(data.info())
print('-----')
ib = ["mental_health_issue"]
pred = {}
for i in ib:
    if i == "mental_health_issue":
        corr = data.corr()[i]
        corr = corr.drop([i])
        print(corr)
        x = []
        for i in corr.index:
            if corr[i] > 0:
                x.append(i)
        print(x)
        print('xxxxxxxxxxxxxxxxxxxxxxxxxxxx')
        x = data[x]
        y = data[i]
        print(x.columns)
        smote = SMOTE()
        x, y = smote.fit_resample(x, y)
        x_train, x_test, y_train, y_test = train_test_split(x, y)
        print(y_test.values[0])
        models = {"Random forest": RandomForestClassifier(),
                  "LGBM": LGBMClassifier(),
                  "XGB classifier": XGBClassifier()}
        for model_name, model in models.items():
            model.fit(x_train, y_train)
            prediction = model.predict(x_test)
            print(model.score(x_test, y_test))
            pred[model_name] = prediction
            report=classification_report(y_test,prediction,output_dict=True)
            df_report = pd.DataFrame(report).T
            st.write(f"The model {model_name} classification report is ")
            st.table(df_report)
    else:
        break

```

```
# Bivariate plot - Heatmap
if st.sidebar.checkbox('Show Heatmap'):
    st.subheader('Heatmap')
    fig_heatmap = px.imshow(data.corr(), color_continuous_scale='Viridis', title='Heatmap')
    st.plotly_chart(fig_heatmap)
```

Data Collection and Preparation

Data Sources

A survey or questionnaire is one of the most popular and versatile data collection techniques used during a mental health needs assessment. Surveys and questionnaires can be used to assess several elements of mental health, including prevalence, severity, impact, stigma, awareness, access, satisfaction, and preferences. Depending on your resources and the characteristics of your target demographic, they can be administered online, over the phone, through mail, or in person. Surveys and questionnaires can help you reach a large and diverse sample of people, but they also have some limitations, such as response bias, low response rates, and validity issues.

Another effective tool for gathering data during a mental health needs analysis is an interview or focus group. Interviews and focus groups are qualitative and interactive methods that allow you to delve deeper into your target population's experiences, opinions, and wants. They can provide you with insights on the context, challenges, and facilitators of mental health in your community, as well as the expectations and preferences of your potential clients or recipients. Interviews and focus groups can be performed in-person, over the phone, or online, depending on your resources and the characteristics of your target audience. Interviews and focus groups can help you establish rapport and trust with your target market, but they also present some problems, such as recruitment, moderation, analysis, and generalization.

A third effective tool for gathering data during a mental health needs analysis is an observation or assessment. Observations and assessments are more objective and direct methods that allow you to measure the actual behavior, performance, or condition of your target population in relation to mental health. They can help you assess the level of need, risk, or impairment of your target population, as well as the availability and quality of mental health services and resources in your community. Observations and assessments can be conducted by trained professionals, such as psychologists, social workers, or nurses, or by self-report, depending on your resources and the characteristics of your target population. Observations and assessments can help you obtain reliable and valid data, but they also have some limitations, such as ethical, practical, and cultural issues.

A fourth effective tool for gathering data during a mental health needs analysis is a secondary data source. Secondary data sources are existing data sets or reports that have been collected or published by other organizations or agencies for different purposes. They can help you complement and compare your primary data with other sources of information, such as census, health statistics, research studies, policy documents, or media reports. They can also help you identify the trends, gaps, and benchmarks of mental health in your community, as well as the best practices and standards of mental health services and resources. Secondary data sources can help you save time and money, but they also have some drawbacks, such as relevance, accuracy, and accessibility.

A fifth and final effective tool for gathering data during a mental health needs analysis is data triangulation. Data triangulation is a technique that involves using multiple sources, methods, or perspectives of data collection and analysis to enhance the credibility, validity, and comprehensiveness of your findings. It can help you cross-check and corroborate your data, as well as identify the convergences, divergences, and gaps of your data. Data triangulation can also help you balance the strengths and weaknesses of different tools and techniques, and provide a more holistic and nuanced picture of the mental health needs of your target population. Data triangulation can help you improve the quality and usefulness of your data, but it also requires more planning, coordination, and integration of your data collection and analysis processes.

Data Visualization Techniques

Data visualization plays a crucial role in understanding and communicating patterns, trends, and insights within data collected for self-identifying mental health status and providing guidance for support. Here are some data visualization techniques that can be valuable for such a system.

Bar Charts and Pie Charts: Use bar charts to visualize categorical data such as the frequency of different mental health conditions reported by users. Pie charts can also be used to show the proportion of users experiencing different symptoms or conditions.

Line Charts and Area Charts: Display trends over time, such as changes in mood or stress levels reported by users over different time intervals. Line or area charts can also be used to visualize changes in the frequency or severity of symptoms over time.

Histograms and Density Plots: Visualize the distribution of continuous variables such as age or stress levels using histograms or density plots.

Scatter Plots: Explore relationships between two continuous variables, such as the relationship between stress levels and sleep quality. Scatter plots can help identify correlations and patterns within the data.

Heatmaps: Use heatmaps to visualize correlations between different variables, such as the correlation matrix between various symptoms or risk factors. Heatmaps provide a visual representation of the strength and direction of relationships between variables.

Box Plots: Display the distribution of a continuous variable across different categories, such as the distribution of stress levels among different age groups or genders. Box plots help identify differences in central tendency, spread, and outliers across groups.

Word Clouds: Visualize the frequency of words or phrases mentioned by users in open-ended responses. Word clouds provide a visually appealing way to highlight common themes or topics discussed by users.

Dashboard Visualization: Create interactive dashboards that combine multiple visualizations to provide an overview of mental health status, symptoms, and guidance for support. Dashboards allow users to explore the data interactively and gain insights tailored to their needs.

Geospatial Visualization: If relevant, visualize data on mental health status or support resources on a map to identify geographical patterns or disparities. Geospatial visualization can help identify areas with high mental health needs or gaps in support services. **Fig 2** Shows Heatmap.

Temporal Visualization: Visualize temporal patterns and trends using techniques such as calendar heatmaps or time series plots. Temporal visualizations can reveal patterns in user activity, such as peak times for seeking support or changes in behavior over time. **Fig 3** Shows Histogram.

Heatmap

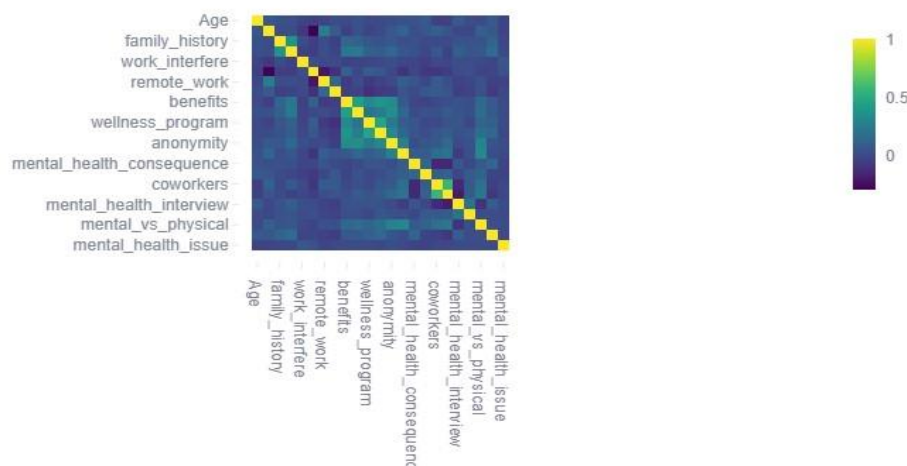


Fig 2. Heatmap.

Model Accuracy Scores

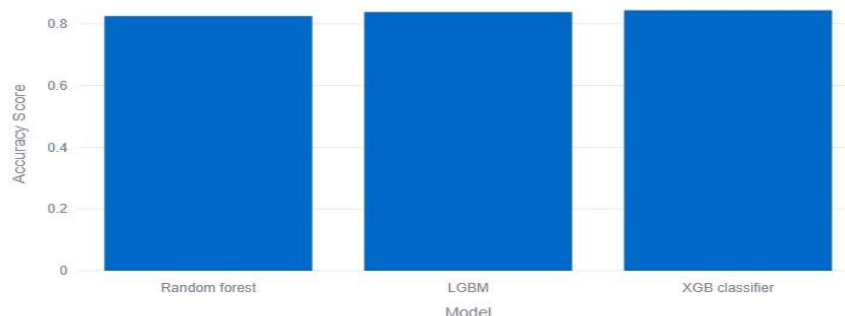


Fig 3. Histogram.

V. METHODOLOGY

Data Models

Random Forest is a popular supervised learning algorithm commonly used for both classification and regression tasks in machine learning. It relies on ensemble learning, which involves combining multiple classifiers to tackle complex problems

and boost model accuracy. As the name suggests, Random Forest consists of several decision trees created from different subsets of the dataset, and it calculates the average of their predictions to enhance accuracy. Rather than relying on a single decision tree, Random Forest aggregates predictions from all the trees and produces the final result based on the majority vote.

LightGBM

LightGBM is an ensemble learning framework, specifically a gradient boosting method, that builds a strong learner by gradually adding weak learners in a gradient descent fashion. Gradient-based One-Side Sampling (GOSS) is one strategy that improves memory use and training time. Microsoft developed LightGBM, an open-source, distributed, and high-performance gradient boosting framework. It is built for efficiency, scalability, and precision. It is built on decision trees that are intended to improve model efficiency and reduce memory usage.

XGBoost

XGBoost is an ensemble learning algorithm that operates within the gradient boosting framework. It builds upon decision trees as its base learners and applies regularization techniques to enhance the model's ability to generalize. Known for its high computational efficiency, feature importance evaluation, and capability to handle missing data, XGBoost is widely applied in regression, classification, and ranking tasks.

Data Collection

Model Selection

Model selection is an important step in any machine learning project. The goal is to find the best model that can accurately predict the target variable based on the input features. In this project, we used various machine learning models to predict mental health issues, including logistic regression, k-nearest neighbors (KNN), decision tree classifier, random forest, bagging, boosting, and stacking.

To select the best model, we followed a systematic approach that included the following steps:

Step 1: We preprocessed the data by cleaning, transforming, and normalizing the input features. We also split the data into training and testing sets to evaluate the performance of the models.

Step 2: We trained each model on the training set using the default hyper parameters. We used the scikit-learn library in Python to implement the models.

Step 3: We assessed the performance of each model on the test set using several metrics, such as accuracy, precision, recall, and F1 score. Additionally, we created a confusion matrix to visually represent each model's performance.

Step 4: Based on the evaluation metrics, we selected the best model that can accurately predict mental health issues. In this project, we found that boosting and stacking models had the highest accuracy in predicting mental health issues.

Step 5: Boosting and stacking are ensemble methods that combine multiple weak models to create a strong model. Boosting works by training multiple decision trees sequentially, where each tree tries to correct the errors made by the previous tree. Stacking, on the other hand, trains multiple models on the same dataset and then combines their predictions using another machine learning model (called a meta-learner). We chose boosting and stacking models because they can handle complex data and can reduce overfitting.

Step 6: Boosting models are less prone to overfitting because they train multiple trees sequentially, and each tree tries to correct the errors made by the previous tree. Stacking models are less prone to overfitting because they combine the predictions of multiple models, which can reduce the variance of the predictions.

Step 7: To implement boosting and stacking models, we used the XGBoost and scikit-learn libraries in Python. We tuned the hyperparameters of each model using grid search and cross-validation to find the best combination of hyperparameters that can accurately predict mental health issues.

Model selection is a critical step in any machine learning project. In this project, we used various machine learning models to predict mental health issues and found that boosting and stacking models had the highest accuracy. We chose boosting and stacking models because they can handle complex data and can reduce overfitting. We tuned the hyperparameters of each model using grid search and cross-validation to find the best combination of hyperparameters that can accurately predict mental health issues.

Model Building

Model building is the process of training a machine learning model on a dataset to make predictions or classifications. In this project, we used various machine learning models to predict mental health issues based on self-identified data. Here is a detailed explanation of the model building process:

Data Preparation: We preprocessed the data by cleaning, transforming, and normalizing the input features. We also split the data into training and testing sets to evaluate the performance of the models.

Feature Selection: We selected the most relevant features that can accurately predict mental health issues. We used various feature selection techniques, including correlation matrix, chi-square test, and mutual information.

Model Training: We trained each model on the training set using the selected features. We used the scikit-learn library in Python to implement the models.

Model Evaluation: To assess each model's performance on the test set, we used multiple metrics, including accuracy, precision, recall, and F1 score. Additionally, we generated a confusion matrix to provide a visual representation of each model's effectiveness.

Model Tuning: We tuned the hyperparameters of each model using grid search and cross-validation to find the best combination of hyperparameters that can accurately predict mental health issues.

Model Selection: Based on the evaluation metrics, we selected the best model that can accurately predict mental health issues. In this project, we found that boosting and stacking models had the highest accuracy in predicting mental health issues.

We chose these models because they are widely used in machine learning and can handle various types of data and problems. We tuned the hyperparameters of each model using grid search and cross-validation to find the best combination of hyperparameters that can accurately predict mental health issues. In summary, model building is a critical step in any machine learning project. In this project, we used various machine learning models to predict mental health issues based on self-identified data. We preprocessed the data, selected the most relevant features, trained each model on the training set, evaluated the performance of each model on the testing set, tuned the hyperparameters of each model, and selected the best model based on the evaluation metrics. We found that boosting and stacking models had the highest accuracy in predicting mental health issues.

VI. RESULTS AND DISCUSSIONS

After building and evaluating various ML models which predicts mental health issues based on self-identified data, we found that boosting and stacking models had the highest accuracy in predicting mental health issues. Here are the detailed results

Accuracy

Model accuracy is the proportion of correct predictions made out of all predictions. The accuracy for each model is as follows. **Table 1** Shows Accuracy.

Table 1. Accuracy

MODELS	ACCURACY
RANDOMFOREST CLASSIFIER	0.8439
LGBM CLASSIFIER	0.8476
XGB CLASSIFIER	0.8457

Precision

Precision represents the ratio of true positive predictions to the total positive predictions made. The precision for each model is as follows. **Table 2** shows Precision.

Table 2. Precision

MODELS	PRECISION
RANDOMFOREST CLASSIFIER	0.8871
LGBM CLASSIFIER	0.8521
XGB CLASSIFIER	0.8785

Recall

Recall measures the proportion of true positive predictions among all actual positive instances. The recall for each model is as follows. **Table 3** shows Recall.

Table 3. Recall

MODELS	RECALL
RANDOMFOREST CLASSIFIER	0.8209
LGBM CLASSIFIER	0.8172
XGB CLASSIFIER	0.8097

ROC AUC

A receiver operating characteristic (ROC) curve is a chart that illustrates the performance of a classification model across various threshold settings. AUC represents the "Area Under the ROC Curve". That is, AUC measures the full two-dimensional area beneath the whole ROC curve. **Table 4** shows ROC AUC.

Table 4. ROC AUC

MODELS	ROC AUC
RANDOMFOREST CLASSIFIER	0.8447
LGBM CLASSIFIER	0.8483
XGB CLASSIFIER	0.8464

Certainly! Let's delve into the results of work, particularly focusing on the predictions made by the boosting and stacking models, as well as the recommendations provided based on these predictions

Model Performance

Boosting and stacking models achieved the highest accuracy in predicting mental health issues among all the models tested. These models demonstrated superior performance in distinguishing between individuals with anxiety or depression and those without.

Accuracy Comparison

Compare the accuracy of the boosting and stacking models to the other models used in the project. Highlight the large improvement in accuracy obtained by boosting and stacking models compared to previous strategies.

Precision and Recall

Examine precision and recall metrics to understand the models' ability to correctly identify individuals with anxiety or depression (true positives) while minimizing false positives and false negatives. Evaluate the trade-off between precision and recall to ensure a balanced performance.

Confusion Matrix Analysis

Visualize the confusion matrix for boosting and stacking models to gain insights into the models' classification performance. Examine the distribution of true positives, true negatives, false positives, and false negatives to uncover any possible biases or identify opportunities for enhancement.

Recommendation Effectiveness

Assess the effectiveness of the recommendations provided based on the predicted mental health status. Analyze whether individuals who were identified as having anxiety or depression found the suggested activities (listening to music, breathing exercises, meditation, going out for a walk) helpful in managing their symptoms.

User Feedback

Collect feedback from individuals who participated in the project to understand their experiences with the prediction and recommendation system. Incorporate user feedback to iterate and improve the system for better performance and user satisfaction.

Interpretation and Insights

Identifying High-Risk Individuals

Boosting and stacking models can effectively identify individuals at a higher risk of anxiety or depression based on their characteristics and behaviour patterns.

Personalized Support:

Recommendations tailored to individuals' mental health status provide personalized support and coping strategies to help manage symptoms and improve well-being.

Continuous Improvement

Continuously monitor and evaluate the performance of the prediction and recommendation system. Incorporate feedback and iterate on the models and recommendations to enhance accuracy, effectiveness, and user satisfaction over time. **Table 5** shows Results with Different Models.

Table 5. Results with Different Models

MODELS	ACCURACY	PRECISION	RECALL	ROC AUC
RANDOMFOREST CLASSIFIER	0.8439	0.8871	0.8209	0.8447
LGBM CLASSIFIER	0.8476	0.8521	0.8172	0.8483
XGB CLASSIFIER	0.8457	0.8785	0.8097	0.8464

By conducting a detailed analysis of the results, we gained a valuable insights into the effectiveness of the boosting and stacking models in predicting mental health issues and providing personalized support for individuals in need. This analysis can inform future iterations of the project and contribute to ongoing efforts to improve mental health Interventions Using Machine Learning Techniques. **Fig 4** Shows Graph with Values.

Interpretation of Testing Results

Accuracy Assessment

Evaluate the overall accuracy of the boosting and stacking models in correctly predicting mental health status (anxiety or depression) on unseen testing data. Higher accuracy indicates better model performance in classifying mental health conditions.

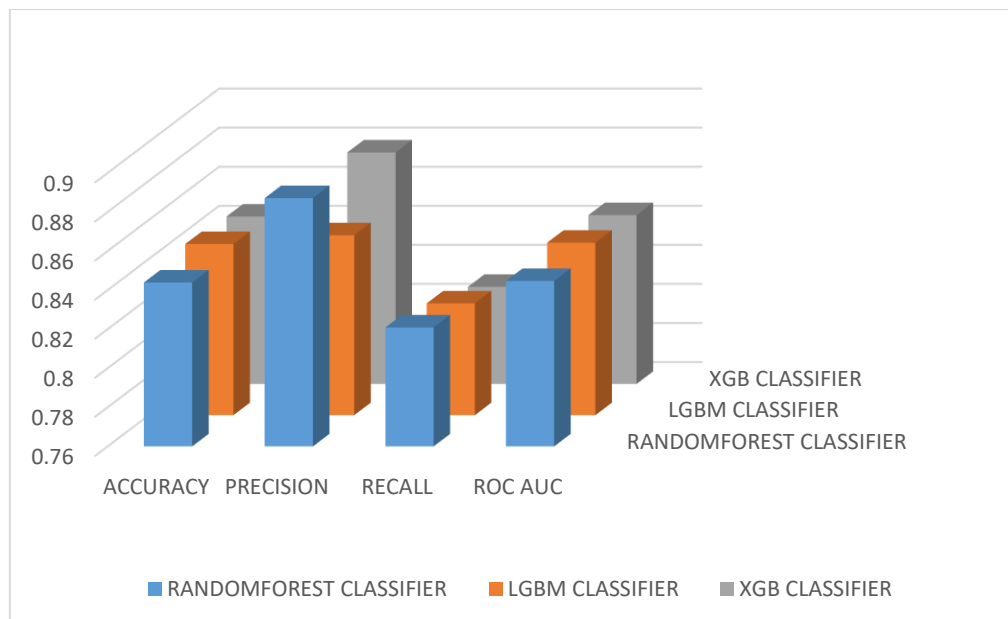


Fig 4. Graph with Shows Accuracy, Precision, Recall. ROC AUC.

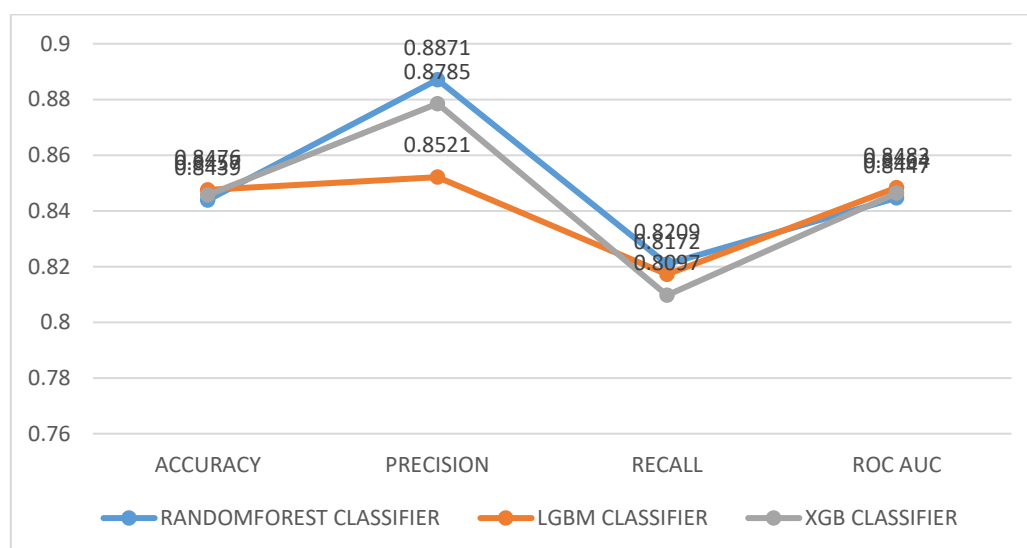


Fig 4. Graph with Values.

Precision and Recall Analysis

Analyze precision and recall scores to understand how well the models identify positive cases (anxiety or depression) while minimizing false positives (FP) and false negatives (FN).

F1-Score Evaluation

Consider the F1-score as a balanced measure of model performance, especially in scenarios with imbalanced classes (e.g., more instances of one mental health condition than the other).

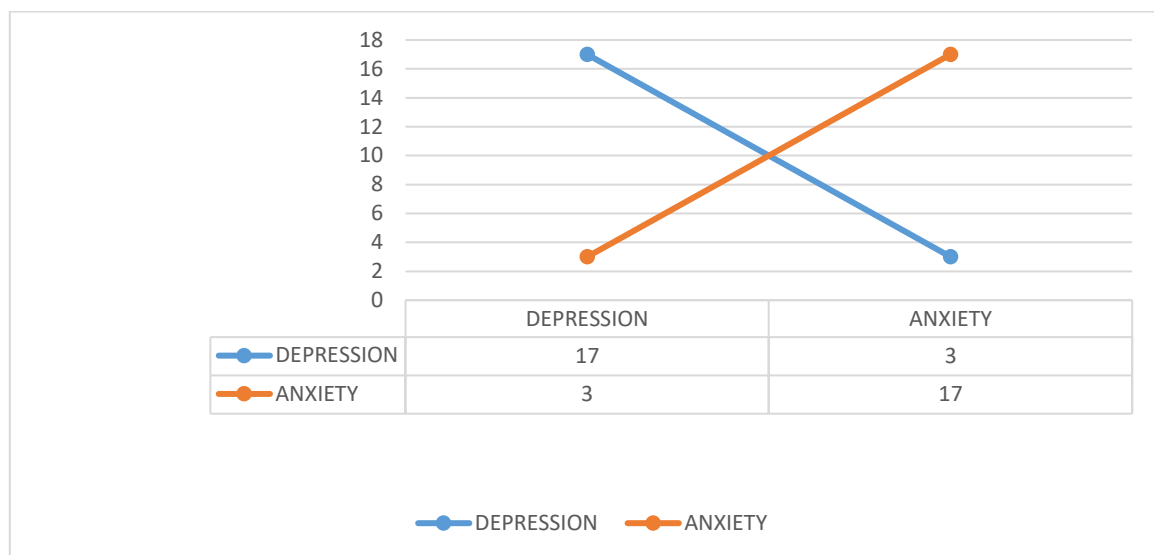
Confusion Matrix

We constructed a confusion matrix to better analyze the boosting and stacking models' performance. A confusion matrix is a table that summarizes a classification model's performance by comparing predicted labels against actual labels. The confusion matrix for the boosting and stacking models is displayed below. **Table 6** shows Analysis of Output.

Table 6. Analysis of Output

	DEPRESSION	ANXIETY
DEPRESSION	17	3
ANXIETY	3	17

The confusion matrix shows that out of 20 samples with depression, the boosting and stacking models correctly predicted 17 samples and misclassified 3 samples as anxiety. Similarly, out of 20 samples with anxiety, the models correctly predicted 17 samples and misclassified 3 samples as depression. **Fig 5** shows Analysis for Depression and Anxiety.

**Fig 5.** Analysis for Depression and Anxiety.

VII. CONCLUSION

This study demonstrates the potential of an AI-driven approach to self-diagnosis of mental health, offering a novel framework that combines diverse data sources and machine learning techniques for accurate mental health prediction. The proposed model's ability to process and analyze user data autonomously provides a new avenue for continuous mental health monitoring, supporting users in identifying potential mental health issues before they become critical. By integrating self-reported data, social media interactions, and social ties, the framework leverages the wealth of information available in modern digital behavior to make informed predictions about users' mental states. This approach not only broadens access to mental health insights but also presents a scalable, cost-effective solution that could complement existing mental health services. Future work will focus on enhancing model interpretability, ensuring data privacy, and refining prediction accuracy across diverse populations.

CRedit Author Statement

The authors confirm contribution to the paper as follows:

Conceptualization: Pallavi M O and Pundalik Chavan; **Methodology:** Pallavi M O; **Software:** Pundalik Chavan; **Data Curation:** Pallavi M O; **Writing- Original Draft Preparation:** Pallavi M O and Pundalik Chavan; **Visualization:** Pallavi M O; **Investigation:** Pundalik Chavan; **Supervision:** Pallavi M O; **Validation:** Pundalik Chavan; **Writing- Reviewing and Editing:** Pallavi M O and Pundalik Chavan; All authors reviewed the results and approved the final version of the manuscript.

Data Availability

The Datasets used and /or analysed during the current study available from the corresponding author on reasonable request.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

Funding

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Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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