APP TO SCREEN THE POSSIBLE MENTAL HEALTH ISSUES IN ADOLESCENTS AND PERSON WITH DISABILITIES(PEDS)

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ABSTRACT

The app aims to address growing concerns about the mental wellbeing of these vulnerable populations by offering them early intervention and support.The app uses advanced technologies, including machine learning algorithms, to analyze various factors such as behavioral patterns, mood indicators and social interactions. By collecting and analyzing data from user input, the app can detect potential signs of mental health issues such as depression, anxiety and mood disorders.The screening process is user-friendly and can be conveniently accessed via smartphones or tablets. Users, including teens and their caregivers, can complete a series of customized assessments, questionnaires, and interactive activities specific to their age group and demographics. The app also includes gamification elements to engage users and enhance their experience.After the screening process is complete, the app generates personalized reports that highlight any potential mental health concerns. These messages can be shared with healthcare professionals, allowing for early intervention and treatment. In addition, the app provides access to a comprehensive database of mental health resources, including helplines, support groups and counseling services.Finally, the "Screening App for Mental Health Concerns in Adolescents and Individuals with Disabilities (PED)" provides a desperately needed tool for identifying and addressing mental health concerns in these at-risk populations. The app seeks to promote the well-being and quality of life of teenagers and people with disabilities by utilizing technology and offering accessible support.

Keyword - Healthcare, Underprivileged, Inequality, Infrastructure, Insufficient health.

1. INTRODUCTION

Today, there are literally tens of thousands of applications available for those who are depressed. Some are designed around the idea of communicating with doctors via calls or SMS.

A serious issue that frequently goes unrecognized and addressed is the prevalence of mental health problems among teenagers. The situation is made worse by the absence of readily available screening methods that are effective in detecting mental health issues in this group, which leads to postponed treatments and detrimental long-term effects. Due to a variety of issues, including communication challenges, physical restrictions, and cognitive impairments, the current methods of screening for mental health issues in adolescence, such as conventional questionnaires and face-to-face assessments, may not be suitable for people with disabilities. Therefore, it is necessary to create an app-based screening tool that can efficiently detect and evaluate mental health concerns among teenagers with impairments.

1.1. Problem Summary and Introduction

There are 150 million people in India that need mental health care. Per 100,000 persons, there are 0.75 psychiatrists in India. In India, people are still reluctant to seek expert assistance directly. Particularly during the present pandemic, tension, worry, and dread have spread throughout the world. Most sad persons frequently experience loneliness and attempt to conceal their feelings from others. It can cause the sufferer to take dramatic measures if not treated properly. On the plus side, it is easily curable if treated at the outset. Additionally, the majority of Indians avoid visiting their doctors in person.Therefore, making plans to consult a therapist may also be a wiser choice. Of course, direct intervention is required in critical or terminal instances.

1.2. Aim and Main Objective of the Project

The app is designed to assist users in tracking their mood swings, increasing their level of self-awareness, and fostering optimistic attitudes and constructive behavior.

The rising need for accessible and early mental health screening among youth and persons with disabilities might be considerably met by it. The app can promote prompt intervention, enhance treatment outcomes, and ultimately contribute to the general wellbeing of these groups by spotting potential mental health difficulties at an early stage.The application uses an intuitive layout and fun features to encourage frequent use and foster introspection. It includes individual questionnaires made to account for the unique requirements and developmental phases of adolescents. Based on the user's responses, the app uses assessment scales and algorithms that have been confirmed by science to produce thorough results. The app's results are not meant to be a final diagnosis; rather, they are meant to be a first screening and instructional tool. In addition to offering a network of nearby mental health options, such as clinics, hotlines, and therapists that specialize in teenage mental health, the app urges users to seek professional assistance.This promotes self-care and mental health literacy by enabling users to create personal objectives, monitor their progress, and access pertinent educational materials. The software places a high priority on user privacy and uses stringent data security procedures to guarantee confidentiality and anonymity.

1.3. Advantages in Mental Health App

1.3.1. Accessibility:

Anyone with a smartphone or a computer can simply access it. This broad accessibility increases the likelihood that people may seek help or support, especially those who might not have easy access to traditional mental health therapies due to financial or geographic restrictions.

1.3.2. Anonymity and Privacy:

On a mental health app, users can opt to remain anonymous, which makes it simpler for people to chat about their issues without being concerned about criticism. Since this software frequently has robust privacy and security measures in place to protect user data, more people are likely to utilize it.

1.3.3. Early Detection:

Software for mental health screening can help in the early identification of potential mental health issues. Early symptom recognition enables people to obtain the appropriate support and treatment, delaying the onset of more serious illnesses.

1.3.4. Self-Awareness:

By analyzing their emotional state, behaviors, and cognitive patterns, the app can help users better understand their mental health. The improved coping mechanisms and healthier habits that can result from this heightened self-awareness.

1.3.5. Cost-Effectiveness:

This app for mental health screening is frequently less expensive than conventional in-person counseling or therapy sessions. A bigger audience can now access services that are free or fairly priced and offer mental health care thanks to the help of this app.

1.3.6. Timely Support:

Since mental health screening applications are accessible round-the-clock, people may get help whenever they need it, including after regular business hours or in an emergency.

2. SCOPE

A person is considered to have a mental disorder if they struggle with emotional, physical, or behavioral problems that pain them or get in the way of their everyday lives. Like any other illness, it can affect anyone at any age or occupation. Like many ailments, there is a cure for mental illness. If the right care and recommendations are followed promptly, thivbs illness can be treated. In Bangladesh, 13% of children and adolescents and 18.5% of adults suffer from a mental disease. However, 92% of them disregard all medical advice and services. Because in our culture, having a mental disease equates to being insane. However, skilled psychologists can be contacted while sitting at home thanks to such app technologies. However, the majority of the current systems use wearable technology to assess mental health or app technologies that do not offer a direct line to medical professionals.This paper describes the development of an app that allows anyone to get professional psychological services from the comfort of their own home.

For the entire system, there are different login procedures for patients and doctors. The patients can see which doctors are available after logging in, and the doctors can see the patients' appointments with them.The patient must pay up ahead but can choose the doctor of their choice and arrange a video consultation or speak with them. The patient will get a prescription through text message on their phone following the appointment. The Jitsi API was used to manage video consultations across the system, which was built entirely in Java. The system was tested after it was developed in a trial phase, and it worked as expected. If individuals adopt this strategy, they won't have to go to the hospital and wait in line to see a doctor; instead, they may receive cutting-edge, premium treatment while unwinding at home.

3. LITERATURE REVIEW

The title of the project is: “App to screen the possible mental health issues in adolescence and persons with disabilities”. We frequently engage in negative interactions with friends, coworkers, family, and a variety of other people. Unintentionally, we could say something that we later come to regret. Some victims of harm experience depression and other severe mental health problems as a result!

S.Saini at el(2022) studied that Particularly in these historic COVID-19 pandemic times, mental health is a very significant topic. Mobile phones that are widely available can help people manage their mental health and enhance psychiatric care. Apps for mobile mental health (MMH) are a viable alternative that can help with a variety of psychological problems and close the critical accessibility gap between patients and providers. However, it also brings up serious issues with leaks of private data. Lack of user understanding and the absence of an open privacy policy may seriously jeopardize the usefulness of such solutions.They carried out a thorough analysis of five different topics: 1) Privacy policies (both manually and using Polisis, an automated framework to evaluate privacy policies); 2) App permissions; 3) Static Analysis for inherent security issues; 4) Dynamic Analysis for threat surface and vulnerabilities detection; and 5) Traffic Analysis.According to their research, applications' exploitable flaws, hazardous permissions, and incorrect data handling might put users' security and privacy at risk. 145 vulnerabilities were discovered in 20 of the top MMH apps, allowing malicious software and attackers to get access to private information. 45% of MMH programmes make use of a unique identification called Hardware Id. It provides for user tracking and mental health evaluation. According to traffic research, unsecured data transfer might cause the release of sensitive information on mental health. Stronger control and regulation are required for MMH apps to be utilized more broadly and to meet the expanding need for mental health treatment without interfering with the already vulnerable population[2].

O. Oyebode at el(2020)Their actions are Mobile health (mHealth) apps have become more common as smartphones have become more widely used. In order to assess these apps, it is crucial to spot any flaws or obstacles that prevent them from providing their intended functions effectively. In this study, they used machine learning (ML) to perform sentiment analysis on 88125 user reviews to evaluate 104 mental health applications available on Google Play and the App Store. They then thematically analyzed the reviews to determine the apps' usefulness.They utilized supervised ML techniques, which are frequently employed for resolving classification issues, to develop five classifiers and compare their performance. In order to predict the sentiment polarity of reviews, the top performing classifier—with an F1-score of 89.42%—was then applied. Then, they used a thematic analysis of both positive and negative reviews to find themes that represented different aspects that had a favorable or negative impact on the effectiveness of mental health apps. 29 positive motifs and 21 negative themes were found in their research. The problematic themes can be divided into the following groups: usability problems, content problems, moral problems, customer service problems, and billing problems. Aesthetically pleasant user interface, app reliability, customizability, high-quality material, content variety/diversity, personalized content, privacy and security, and inexpensive membership costs are a few of the positive themes. Finally, they provide design advice on how to address the highlighted drawbacks to increase the efficiency of mental health apps[3].

I S. Santoso at el(2021)The gamification function has been employed in the majority of available mobile mental health (mMHealth) applications. However, there are practical challenges with mMHealth gaming, especially in developing nations. However, it's important to be careful when selecting game aspects because the wrong ones could have a negative effect on those with mental problems. The majority of mMHealth's adoption of gamification poses a difficulty because many young people with anxiety and depressive illnesses, as well as social dysfunction, do not want to use mMHealth to manage their mental health. Based on functionality and suitability for people with mental illnesses, this study suggests employing gamification to encourage patient participation in using the mMHealth programme. With an average score of 82.5, the System Usability Scale has been utilized as a system-wide test to assess the usability of the apps in comparison to the suggested solution. Overall, the SUS score for the mMHealth solution shows how the patient's subjective assessment of the suggested solution's suitability for patients—especially patients with mental illness—finds it to be effective, efficient, and enjoyable[4].

M. Nouman et al(2023). highlighted the high frequency of mental health problems in the modern period and the advantages of early depression detection and treatment. Two ML techniques are utilized in sentiment analysis for text categorisation: convolutional neural networks (CNN) and random forest classifiers (RFC). CNN has been found to be an effective and successful approach, especially for image and text data. When textual data is being prepared for sentiment analysis with tools like the Natural Language Toolkit (NLTK), standard cleaning techniques include lemmatization, stemming, and stop word removal. The translation of phrases into numerical feature representations, or vectorization, is a crucial step in text categorisation for further analysis. NLP applications frequently make use of recurrent neural networks (RNNs), which can identify the connections between words in a sequence. Traditional RNNs, however, have performance restrictions. These issues were addressed in popular RNN variations including long short-term memory (LSTM) and GRU networks by employing gates to regulate information flow and prevent gradient vanishing as well as memory cells to store information at random intervals. The LSTM model that the authors utilized has a 91.2% accuracy rate. By using LSTMs to fully extract the text's meaning, the authors were able to overcome the usual NLP challenges. As a result, text classification tasks can be carried out more successfully[6].

K. S. Thach at el(2018) published and examined the introduction of CBT-based mental health applications holds out hope for their potential to aid people in coping with prevalent mental diseases. Despite the large number of users, there is a very low level of app adherence. The causes of this situation, meantime, are not thoroughly investigated. It is unclear which aspects encourage people to use and stick with a service. This study aims to fill this void in the literature. The study focuses on applications whose primary design is based on a CBT strategy. According to the review research, users value the apps' ability to help them track their mood, reflect on themselves, and monitor their own behavior.Additionally, the capability to send emails, prompts, or notifications to remind users to complete associated activities is a useful approach to keep users interested and focused. Additionally, it is highly valued to be able to offer various interactions for patients and medical professionals. The majority of design-related input carefully considers usability traits and research-based features. Contrarily, the most frequent cause for consumers to stop using interventions is technological problems. The absence of customer services, transparent security protocols, and a clear privacy policy are further issues that cause concerns. Similar to how many people grumble when an app's design is complex and it has a lot of advertisements.Therefore, these aspects should be carefully taken into account throughout the design stage of the apps' creation in order to improve user experience and user adherence[7].

D. Stephen at el(2022) has studied that the COVID-19 response includes mental health disorders, according to the World Health Organisation (WHO). However, in lower-income communities, mental health illnesses received less attention and treatment. Despite the fact that smartphones are infrequently used in the medical field, a number of handheld devices that can record multimodal data, including wearable technology and smartphone integrated sensors, have been created. This essay will examine and comprehend the most helpful feature of psychological apps using a smartphone. The study's goal will be accomplished by evaluating the app's viability for preventing mental disorders and its usability for the broader market with users of all ages using a scoring learning approach[8].

M. Sánchez-Peña at el(2019) researched speaking about mental health in the media and in academia has just recently become more popular. Environmental triggers, such as scholastic stress, interpersonal conflict, financial stress, and professional concerns, are frequently responsible for mental health disorders. In the event of a mental health crisis at school, students with mental illnesses may decide to drop out of college. Engineering, however, is a difficult field that calls for extensive education. Consequently, engineers may face overexertion during their scholastic and professional careers. Engineering professionals and students who are dealing with a recognised mental condition may find this burden to be considerably greater. Furthermore, the stigma associated with mental illness has become increasingly severe, which may discourage this group from getting support and continuing their engineering careers. However, little is known about how individuals with a mental condition navigate the engineering curriculum and culture[5].

The first step to adopting change in engineering education that would provide sufficient assistance for these individuals to achieve their goals is acknowledging and understanding the difficulties experienced by engineering students and professionals living with a mental illness. This ongoing project summarizes the findings from the preliminary phase of a wider exploratory study that aims to explain the experiences of engineering students and professionals who are living with a mental illness and to ascertain the effects of engineering culture on those experiences. The findings will guide future investigations into student persistence and engineering programmes that support students who are dealing with mental illness. In the end, our study will assist in eradicating stigma in engineering education and fostering the achievement of those who are dealing with mental health issues.

4. METHODOLOGY

The quality of life for patients is improved and treatment outcomes are improved by early detection of mental health issues. It's crucial to have a healthy social, emotional, and psychological life. It affects one's feelings, thoughts, and actions. Mental health is highly valued at every stage of life, from infancy and adolescence to maturity.We tested the detection accuracy of five machine learning techniques for mental health issues using a range of accuracy criteria. The five machine learning algorithms are Stacking, Random Forest, K-NN Classifier, Decision Tree Classifier, and Logistic Regression. The stacking strategy, which is based on a forecast accuracy of 81.75%, was likewise determined to be the most accurate after we compared these approaches and put them to use.

Data Collection, Data Cleaning, Data Encoding, Finding Covariance Matrix, Scaling and Fitting, Tuning, Evaluation Models, Finding Accuracy, Predicting Data and Results are all parts of Knowledge Discovery from Data as depicted in Figure 3.1. We start by taking into account the dataset with 1259 items and 27 columns.The following phase is data cleaning, which comprises locating any incorrect, incomplete, superfluous, or missing data and updating, changing, or eliminating it as required. We found that the missing data is contained in three columns. In Data Frames and Numpy arrays, a cell with no value is indicated by the special value Not a Number, or NaN. The next phase is data encoding. When the categorical characteristic is marked as ordinal, we employ this method of categorical data encoding.

In this case, maintaining order is essential. Therefore, the encoding ought to represent the sequence. Each label will be changed into an integer value during label encoding.

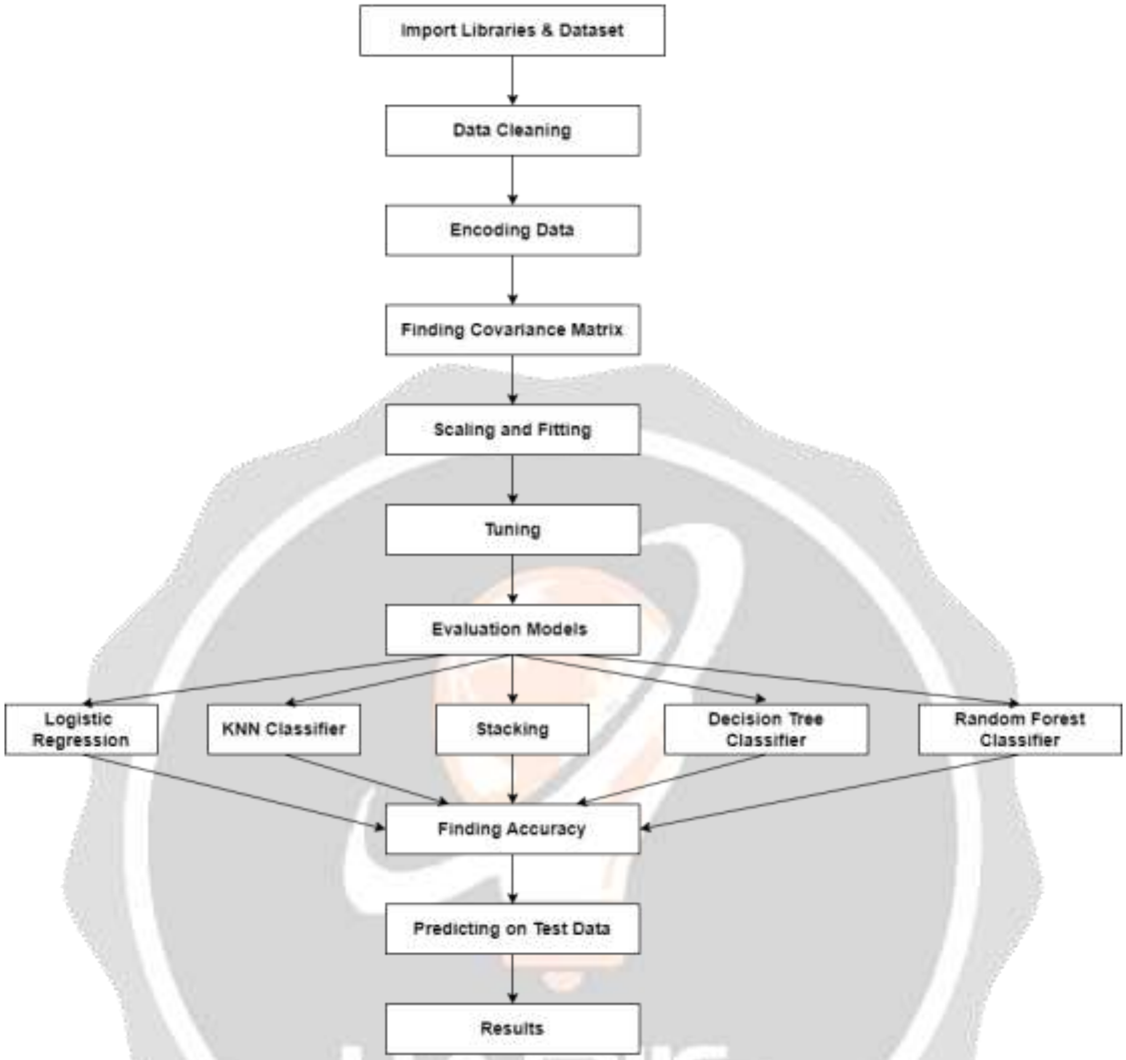


Figure 3.1. Workflow

After that, we'll look for the covariance matrix. It is one of the fundamental matrices used in machine learning and data science. On the connection of feature movement, it gives specifics. The variance-covariance matrix main diagonal will include the variances of the variables, while the remaining matrix positions will have the covariances between each pair of variables. The mean vector holds the means of each variable. We scale the independent properties of the data by putting them within a predefined range.

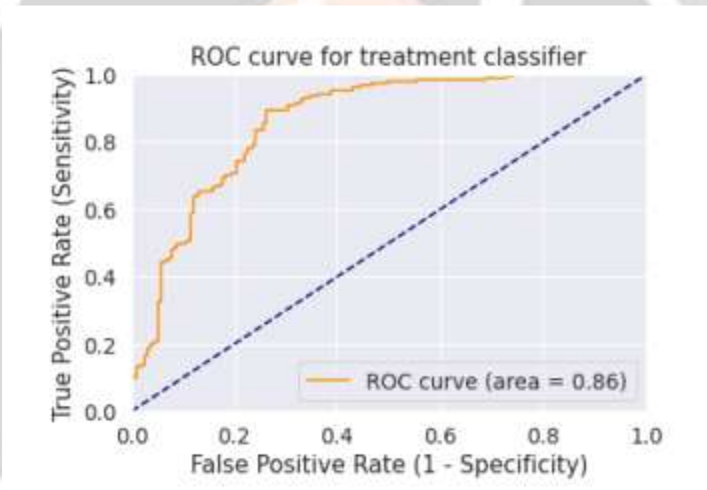
It handles significantly varying values, units, or magnitudes during data pre-processing. The training data set and the testing data set were created from the dataset. The significance of a feature is the following. Feature selection is important in machine learning since it is the core method of guiding variable usage to what is most useful and effective for a certain machine learning system. The next stage is tuning. Tuning is the process of improving a model's performance while guarding against overfitting or excessive variance. This is achieved in machine learning by selecting the appropriate hyperparameters. In a machine learning model, the "dial" or "knobs" are analogous to the hyperparameters.

Stacking, logistic regression, K-nearest neighbour classifier, decision tree classifier, and random forest classifier are some of the machine learning techniques that are used to evaluate the models after that.

4.1. MACHINE LEARNING TECHNIQUES:

4.1.1. Logistic Regression:

Logistic regression is a well-known machine learning technique that belongs to the supervised learning approach. We may use this technique to forecast a certain dependent variable by employing a collection of unbiased variables. Logistic regression is used to forecast the output of a certain structured variable. As a result, the result must be a discrete or categorical value. It may be 0 or 1, Yes or No, true or false, and so on, but rather than offering



precise values between 0 and 1, it provides probabilistic values that fall inside that range.

Figure 3.2. ROC of Logistic Regression

4.1.2. K nearest neighbor classifier :

The K-Nearest Neighbour is a fundamental machine learning technique that makes use of the Supervised Learning approach. In the K-NN technique, new case/data and existing case comparisons will be made. The KNN method is non-parametric and makes no assumptions either the distribution or the highlighted data. It also works with a variety of classes.

4.1.3. Decision tree classifier:

The decision tree is the most often used supervised machine learning technique in data mining. To establish the sequence of events, actions, or consequences, or to depict statistical probability, people use decision trees as a diagram.

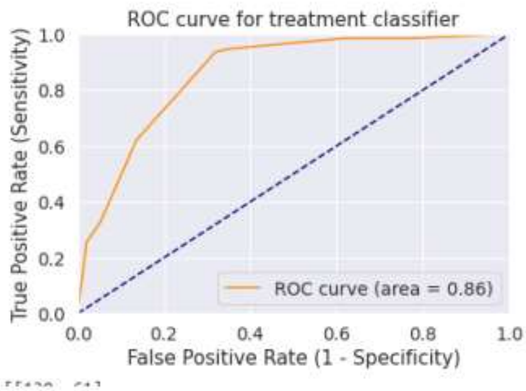


Figure 3.3. Decision tree Classifier

4.1.4. Random forest classifier:

Both classification and regression problems are addressed using a method called random forest, which is based on the supervised machine learning methodology. However, it is frequently used to categorise objects. Because it combines numerous decision trees into one "forest" and feeds them random attributes from the input dataset, it is known as a random forest.

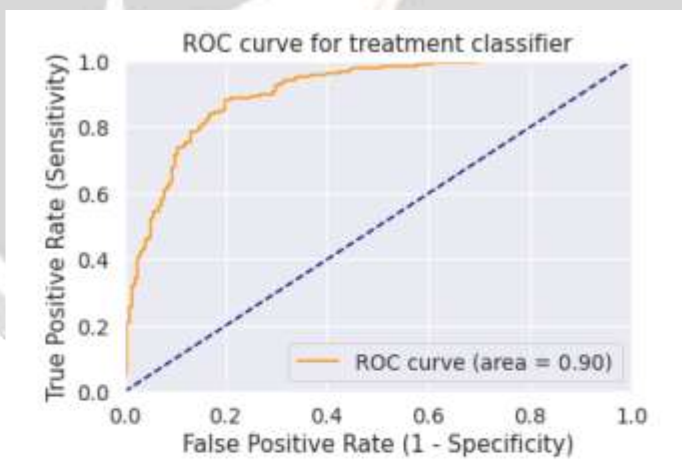


Figure 3.4. Random Forest Classifier

4.1.5. Stacking:

Stacking Generalisation, sometimes referred to as "Stacking," is a machine learning ensemble method. Similar to bagging and boosting, it involves integrating predictions from many machine learning models on the same dataset. The idea is that different models may be used to address a learning problem, but each model can only learn a specific area of the problem, not the full problem space. In order to construct intermediate predictions for each learned model, you may design a variety of learners and use them. Next, you incorporate a fresh model that builds on the aim of the intermediate projections.

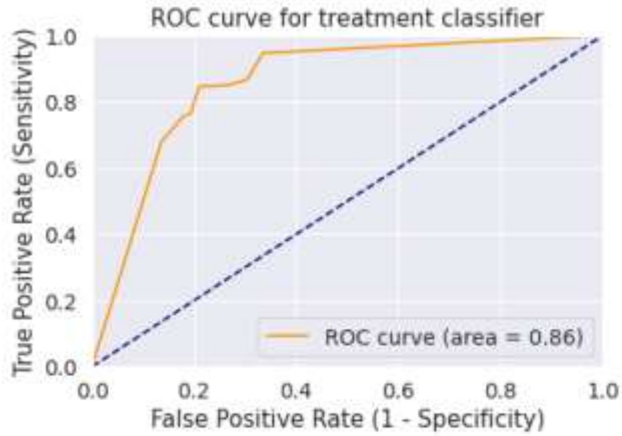


Figure 3.5. Stacking

This study found five machine learning methods: random forest, decision tree and stacking, logistic regression, and k closest neighbor classifier. And we evaluated how well they were able to spot mental health problems. We first ran the classifiers with all 27 characteristics that were extracted from the text documents, and then we ran them with 8 additional attributes that were chosen using the feature selection approach.

The proportion of test set occurrences that are properly identified using the classifier is the accuracy of a specific test set for that classifier. The ability of a classifier to accurately categorize the test data set will determine how accurate the classifier is. Utilizing the area under the receiver operating curve, we calculated that. A perfect test will represent a 1 in the ROC area, whereas a useless test will represent a 0.5. Five classifiers' graphs on ROC Area values are shown in Figure 2-5. Because all of the classifiers utilized have ROC areas between 0.8 and 0.9, we found that these classifiers were superior to other classifiers in their ability to predict the state of mental health.

Since there are several machine learning approaches accessible, it is crucial to compare them all and then choose the one that best fits the target domain. Today, there are several specialized programmes in the medical profession that can forecast disease quite precisely in advance, allowing for effective and quick therapy. In the proposed work, five different machine learning approaches that were employed to categorize a dataset of diverse mental health issues were compared. The results make it quite evident that all five machine learning methods provide more accurate outcomes. The accuracy of all the classifiers are above 79%. The data set used in the research is very minimal and in the future, a large data set can be used and the research can be applied on the same for more accuracy.

4.2. MATERIALS AND TECHNOLOGIES USED

Machine learning and deep learning algorithms have provided human solutions such as understanding emotions, expressions behind texts and speech and predicting what should be done next given the current scenario from text, images or speech inputs. Methods using ML with libraries available in python, machine learning algorithms implemented with python will be used. Visual studio for web-app development with firebase will be used.

4.2.1. Python

Python is a well-known programming language. It was primarily created for making code meaningfulness simple for the ones who don't come from a programming language foundation, and python is linguistically simple. For the framework, python innovation will be utilized to plan application-based calculations (i.e., for the order into classes). Following APIs from python will be utilized in our undertaking with the end goal of model preparation purposes.

a. Scikit Learn :

Straightforward and proficient devices for data mining and data analysis. Available to everyone, and reusable in different settings.

b. Pandas :

Pandas is an open source, BSD-licensed library providing high-performance, easy-to-use data structures and data analysis tools for the Python programming language.

c. Scipy:

Scipy is an open-source Python library which is used to solve scientific and mathematical problems. It is based on the NumPy expansion and permits the client to control and imagine information with many undeniable level orders.

d. Seaborn:

Seaborn is a library for making statistical graphics in Python. It builds on top of matplotlib and integrates closely with pandas data structures.Seaborn helps us explore and understand our data. Its plotting capabilities work on dataframes and clusters containing entire datasets and inside play out the important semantic planning and measurable conglomeration to create instructive plots. Its dataset-oriented, declarative API lets us focus on what the different elements of your plots mean, rather than on the details of how to draw them.

e. Flask:

Flask is a micro web framework written in python. It is a micro web framework because it does not need particular tools or libraries to operate. We have used it for our web integration because it's weight and easily extensible.

4.2.2. Jupyter Notebook:

Jupyter Notebook is a robust tool utilized in machine learning to investigate and assess data, including the detection of mental health disorders. This tool offers an interactive interface and the ability to merge code, text, and visualizations, creating a flexible and efficient environment for research in this domain

One notable advantage of Jupyter Notebook is its compatibility with various programming languages like Python and R, which are commonly employed in machine learning. This versatility allows researchers to take advantage of a wide range of specialized libraries and frameworks designed specifically for the analysis of mental health.

Moreover, Jupyter Notebook's integration with data visualization libraries like Matplotlib and Seaborn facilitates the exploration and interpretation of results. Researchers can generate informative graphs and plots that visually represent patterns and trends in the data. This visual representation aids in comprehending the intricate relationships between various factors and mental health disorders.

4.2.3. Visual Studio Code:

Visual Studio Code is a versatile and powerful code editor that has gained widespread popularity due to its lightweight nature, rich feature set, and extensive customization options. Here, visual studio code is used for web applications, and frontend/backend development. It supports popular web languages like HTML, CSS, JavaScript, and frameworks like React, Angular, and Vue.js.

5. PROPOSED WORK

5.1.COLLECTION OF DATASET AND CLASSIFYING USING RANDOM FOREST CLASSIFICATION ALGORITHM

Predicting Adolescents Mental Health using random forest classification Algorithm which will predict the probability of Mental illness based on inputs provided by the user.

```
RangeIndex: 1259 entries, 0 to 1258
Data columns (total 27 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Timestamp                  1259 non-null   object
 1   Age                        1259 non-null   int64
 2   Gender                     1259 non-null   object
 3   Country                    1259 non-null   object
 4   state                      744 non-null    object
 5   self_employed              1241 non-null   object
 6   family_history             1259 non-null   object
 7   treatment                  1259 non-null   object
 8   work_interfere             995 non-null    object
 9   no_employees               1259 non-null   object
 10  remote_work                1259 non-null   object
 11  tech_company               1259 non-null   object
 12  benefits                   1259 non-null   object
 13  care_options               1259 non-null   object
 14  wellness_program           1259 non-null   object
 15  seek_help                  1259 non-null   object
 16  anonymity                  1259 non-null   object
 17  leave                      1259 non-null   object
 18  mental_health_consequence  1259 non-null   object
 19  phys_health_consequence    1259 non-null   object
 20  coworkers                  1259 non-null   object
 21  supervisor                 1259 non-null   object
 22  mental_health_interview    1259 non-null   object
 23  phys_health_interview      1259 non-null   object
 24  mental_vs_physical         1259 non-null   object
 25  obs_consequence            1259 non-null   object
 26  comments                   164 non-null    object
dtypes: int64(1), object(26)
```

Figure 5.1 Dataset Attributes

First, we executed the classifier which included all the 27 attributes and 1259 rows

DATA CLEANING:

The following phase is data cleaning, which is the process of finding incomplete, erroneous, unneeded, or missing data and then modifying, replacing, or eliminating it based on the specific necessity. We found that three columns have the missing data. Not a Number, or NaN, is a special value in Data Frames and Numpy arrays that represents a cell with no value.

Cleaning NaN

```
[ ] # Assign default values for each data type
    defaultInt = 0
    defaultString = 'NaN'
    defaultFloat = 0.0
    intFeatures = ['Age']
    stringFeatures = ['Gender', 'Country', 'self_employed', 'family_history', 'treatment', 'work_interfere',
                      'no_employees', 'remote_work', 'tech_company', 'anonymity', 'leave', 'mental_health_consequence',
                      'phys_health_consequence', 'coworkers', 'supervisor', 'mental_health_interview', 'phys_health_interview',
                      'mental_vs_physical', 'obs_consequence', 'benefits', 'care_options', 'wellness_program',
                      'seek_help']
    floatFeatures = []
    for feature in train_df:
        if feature in intFeatures:
            train_df[feature] = train_df[feature].fillna(defaultInt)
        elif feature in stringFeatures:
            train_df[feature] = train_df[feature].fillna(defaultString)
        elif feature in floatFeatures:
            train_df[feature] = train_df[feature].fillna(defaultFloat)
        else:
            print('Error: Feature %s not recognized.' % feature)
    train_df.head()
```

Next, we split the dataset into a training and testing data set. The next step is feature importance. Feature selection is critical in machine learning since it is a fundamental strategy for directing variable usage to what is most efficient and effective for a certain machine learning system.

Spilitting Dataset

```
# define X and y
feature_cols = ['Age', 'Gender', 'family_history', 'benefits', 'care_options', 'anonymity', 'leave', 'work_interfere']
X = train_df[feature_cols]
y = train_df.treatment

# split X and y into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=0)

# Create dictionaries for final graph
# Use: methodDict['Stacking'] = accuracy_score
methodDict = {}
rmseDict = ()
```

Figure 5.3 Splitting Dataset

Random Forests

```
def randomForest():
    # Calculating the best parameters
    forest = RandomForestClassifier(n_estimators = 20)

    featuresSize = feature_cols.__len__()
    param_dist = {"max_depth": [3, None],
              "max_features": randint(1, featuresSize),
              "min_samples_split": randint(2, 9),
              "min_samples_leaf": randint(1, 9),
              "criterion": ["gini", "entropy"]}
    tuningRandomizedSearchCV(forest, param_dist)

    # Building and fitting my_forest
    forest = RandomForestClassifier(max_depth = None, min_samples_leaf=8, min_samples_split=2, n_estimators = 20, random_state = 1)
    my_forest = forest.fit(X_train, y_train)

    # make class predictions for the testing set
    y_pred_class = my_forest.predict(X_test)

    accuracy_score = evalClassModel(my_forest, y_test, y_pred_class, True)

    #Data for final graph
    methodDict['Random Forest'] = accuracy_score * 100
```

Figure 5.3 Random Forest Classifier Model

Accuracy of a given dataset is 81.22.

```
randomForest()

Rand. Best Score:  0.8305206349206349
Rand. Best Params:  {'criterion': 'entropy', 'max_depth': 3, 'max_features': 6, 'min_samples_leaf': 7, 'min_samples_split': 8}
[0.831, 0.832, 0.831, 0.831, 0.831, 0.83, 0.831, 0.831, 0.831, 0.834, 0.833, 0.831, 0.831, 0.831, 0.831, 0.831, 0.831, 0.831, 0.827, 0.831]
Accuracy: 0.8121693121693122
Null accuracy:
 0    191
1    187
Name: treatment, dtype: int64
Percentage of ones: 0.4947089947089947
Percentage of zeros: 0.5052910052910053
True: [0 0 0 0 0 0 0 0 1 1 0 1 1 0 1 1 0 1 0 0 0 1 1 0 0]
Pred: [1 0 0 0 1 1 0 1 1 1 0 1 1 0 1 1 1 1 0 0 0 0 1 0 0]
```

Figure 5.4 Accuracy of Random Forest Model

5.2.Detecting Mental Health Illness Module

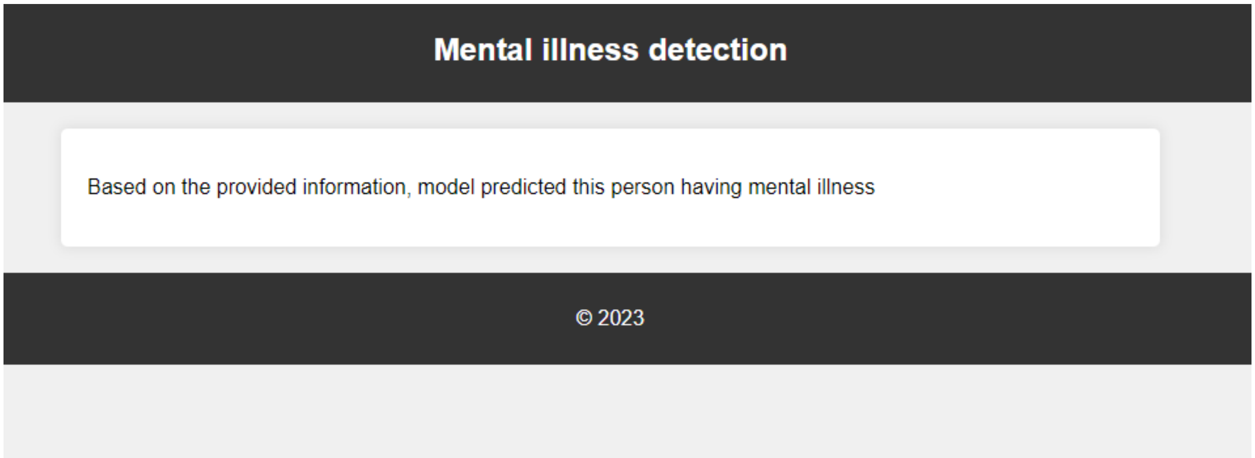
Typically, users are asked a number of questions aimed at evaluating their mental health. These enquiries can be about a variety of things, such as behavior, worry, and mood.

Users are invited to respond by selecting yes or no as an input and, if necessary, typing the information.

```
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 334 entries, 0 to 333
Data columns (total 31 columns):
 #   Column                                                Non-Null Count  Dtype
---  ------                                                --------------  -----
 0   I am currently employed at least part-time            334 non-null    int64
 1   I identify as having a mental illness                 334 non-null    int64
 2   Education                                             334 non-null    object
 3   I have my own computer separate from a smart phone    334 non-null    int64
 4   I have been hospitalized before for my mental illness 334 non-null    int64
 5   How many days were you hospitalized for your mental illness  297 non-null    float64
 6   I am legally disabled                                 334 non-null    int64
 7   I have my regular access to the internet              334 non-null    int64
 8   I live with my parents                                334 non-null    int64
 9   I have a gap in my resume                             334 non-null    int64
 10  Total length of any gaps in my resume in months.      334 non-null    int64
 11  Annual income (including any social welfare programs) in USD  334 non-null    int64
 12  I am unemployed                                       334 non-null    int64
 13  I read outside of work and school                     334 non-null    int64
 14  Annual income from social welfare programs            334 non-null    int64
 15  I receive food stamps                                 334 non-null    int64
 16  I am on section 8 housing                             334 non-null    int64
 17  How many times were you hospitalized for your mental illness  334 non-null    int64
 18  Lack of concentration                                 333 non-null    float64
 19  Anxiety                                               334 non-null    int64
 20  Depression                                            334 non-null    int64
 21  Obsessive thinking                                    333 non-null    float64
 22  Mood swings                                           333 non-null    float64
 23  Panic attacks                                         333 non-null    float64
 24  Compulsive behavior                                   333 non-null    float64
 25  Tiredness                                             333 non-null    float64
 26  Age                                                   334 non-null    object
 27  Gender                                                334 non-null    object
 28  Household Income                                      334 non-null    object
 29  Region                                                332 non-null    object
 30  Device Type                                           334 non-null    object
dtypes: float64(7), int64(18), object(6)
memory usage: 81.0+ KB
```

Based on the input entered or selected(yes or no) by the user , the selected input is processed as binary values i.e. 0 or 1 and added to the dataset file. Now the dataset file is run through the machine learning algorithm we have used to classify the person's mental health illness and we get our output displayed on the screen as the person having mental illness or not.



5.3.User Interface Module

The splash screen is the perfect place to display your brand's logo, tagline, or a visually appealing graphic that represents your identity. A splash screen is the initial screen that users see when they open your application or website. It serves as a brief, eye-catching introduction to our platform and can set the tone for the user's experience.

The login page is where users enter their credentials to access our platform. It's a critical component for security and personalization. Designing the login page with a clean and user-friendly interface. It includes fields for username/email and password. After successful login, we provide a welcoming message and redirect to the home page. Making users feel valued and oriented within your platform.

The home page is where users land after logging in. It's the central hub for accessing the main features and content of our website. Customizing the home page to display content and features that are relevant to our website.

Figure 5.5 Splash Screen

Figure 5.6 Homepage

6. ADVANTAGES

The results of the application implementation and testing phase have been highly promising.The application was developed with a user-friendly interface and intuitive features to ensure ease of use for both adolescents and individuals with disabilities. The tool incorporates various validated psychological assessment scales and questionnaires tailored to capture the unique mental health challenges faced by these populations. The outcomes encompassed various dimensions of psychological well-being, including depression, anxiety, stress, self-esteem, and overall life satisfaction.

In our study it is revealed that there is significant reduction in symptoms of depression and anxiety among app users. The interactive features of the app, such as cognitive-behavioral therapy exercises, live session, and gamification were found to be effective in improving mood and promoting emotional regulation.

In addition, the convenience and accessibility of our mental health app were highlighted as significant advantages, allowing users to access support at their convenience and in the privacy of their own homes.

Furthermore, it emphasized the positive impact of social support features within our mental health app. Live sessions slots and gamification functionalities were reported to enhance users' sense of belonging and reduce feelings of isolation. The user's ability to connect with doctors through video or chat was found to be valuable in a sense of support and understanding.

Early identification of mental health illness can help reduce mental illnesses and people feel comfortable seeking help early on, it can foster a more supportive and understanding society.The utilization of Random Forest Classification algorithm handles complex, high-dimensional data and produces accurate predictions.

Random Forest mitigates overfitting, a common issue in machine learning, by combining multiple decision trees. This ensures that the model's predictions generalize well to unseen data, increasing the reliability of mental health assessments. Furnishing patients with precise data about their wellbeing status can engage them to arrive at informed conclusions about their treatment and way of life. Prior location can prompt possibly lower treatment costs and decreased hospitalization costs by forestalling illness movement to further developed stages.

7. CONCLUSION

In conclusion, the development and implementation of the mental health screening app hold significant promise in addressing the pressing issue of mental health. This initiative has effectively used technology to offer easily accessible, practical, and stigma-free help for those dealing with mental health issues. The app may be able to empower users to better understand their mental well-being and seek appropriate support when necessary by providing a user-friendly design, personalized evaluations, stress-relieving activities, and useful resources.

We have shown via this research that it is possible to close the gap between people and mental health support services. The app's capacity to test for a variety of mental health conditions and offer useful insights may help with early identification and intervention, eventually improving user outcomes. User information is also kept private and safe by the incorporation of data protection measures and adherence to ethical standards.

Recognising that no app can fully replace expert medical advice and diagnosis is crucial. Despite the fact that the app is a useful tool, it should be utilized in addition to conventional healthcare services. Maintaining the app's efficacy and relevance over time will need frequent upgrades and improvements based on user input and developments in mental health research.

The app's capabilities will be improved as we go along, and its reach will be widened through cooperation with researchers, organizations, and mental health experts. We can continue to make significant progress in promoting mental health and tackling mental health concerns on a larger scale by encouraging a holistic approach that integrates technology, medical knowledge, and community support. The good effects of this initiative might last much beyond its initial deployment, and they represent a huge step towards a more accepting and encouraging environment for mental health.

6. REFERENCES

[1] A. Ahmed, P. Dixit and M. M. Khan, "Development of an Online Mental Well-being Mobile Application for Covid-19 Pandemic,"2022 6th International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2022, pp.1553-1558,doi: 10.1109/ICCMC53470.2022.9754112.

[2] S. Saini, D. Panjwani and N. Saxena, "Mobile Mental Health Apps: Alternative Intervention or Intrusion?," 2022 19th Annual International Conference on Privacy, Security & Trust (PST), Fredericton, NB, Canada, 2022, pp. 1-11, doi: 10.1109/PST55820.2022.9851975.

[3] O. Oyebode, F. Alqahtani and R. Orji, "Using Machine Learning and Thematic Analysis Methods to Evaluate Mental Health Apps Based on User Reviews," in IEEE Access, vol. 8, pp. 111141-111158, 2020, doi: 10.1109/ACCESS.2020.3002176.

[4] I. S. Santoso, A. Ferdinansyah, D. I. Sensuse, R. R. Suryono, Kautsarina and A. N. Hidayanto, "Effectiveness of Gamification in mHealth Apps Designed for Mental Illness," 2021 2nd International Conference on ICT for Rural Development (IC-ICTRuDev), Jogjakarta, Indonesia, 2021, pp. 1-6, doi: 10.1109/IC-ICTRuDev50538.2021.9655706.

[5] M. Sánchez-Peña, X. R. Xu, N. Ramirez and N. Sambamurthy, "Engineering students and professionals living with a mental illness: an exploration of their experiences and challenges," 2019 IEEE Frontiers in Education Conference (FIE), Covington, KY, USA, 2019, pp. 1-5, doi: 10.1109/FIE43999.2019.9028416.

[6] M. Nouman, H. Sara, S. Y. Khoo, M. P. Mahmud and A. Z. Kouzani, "Mental Health Prediction through Text Chat Conversations," 2023 International Joint Conference on Neural Networks (IJCNN), Gold Coast, Australia, 2023, pp. 1-6, doi: 10.1109/IJCNN54540.2023.10191849.

[7] K. S. Thach, "User’s perception on mental health applications: a qualitative analysis of user reviews," 2018 5th NAFOSTED Conference on Information and Computer Science (NICS), Ho Chi Minh City, Vietnam, 2018, pp. 47-52, doi: 10.1109/NICS.2018.8606901.

[8] D. Stephen, A. A. Attallah and M. Anugerah Ayu, "Improving Early Detection and Prevention of Depression Using an Interactive Mobile App," 2022 IEEE 8th International Conference on Computing, Engineering and Design (ICCED), Sukabumi, Indonesia, 2022, pp. 1-6, doi: 10.1109/ICCED56140.2022.10010529.

[9] G. Parimala, R. Kayalvizhi and S. Nithiya, "Mental Health: Detection & Diagnosis," 2022 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 2022, pp. 1-6, doi: 10.1109/ICCCI54379.2022.9740834.

[10] V. M. Deshmukh, B. Rajalakshmi, S. Dash, P. Kulkarni and S. K. Gupta, "Analysis and Characterization of Mental Health Conditions based on User Content on Social Media," 2022 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI), Chennai, India, 2022, pp. 1-5, doi: 10.1109/ACCAI53970.2022.9752596.

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