Diagnosis and Classification of Mental Disorders using Machine Learning Techniques

MSc Research Project
Data Analytics

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Diagnosis and Classification of Mental Disorders using Machine Learning Techniques

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Abstract

Today's lifestyle and work cultures have increased people's levels of pressure and stress, which has led to different mental disorders like stress, schizophrenia, depression, anxiety, bipolar disorder, post-traumatic stress disorder (PTSD), and many more. The majority of symptoms are quite common, which leads people to ignore them, as it is challenging to diagnose mental disorders. The objective of this research is to identify and classify the level of anxiety, stress, and depression among individuals. It will be classified based on the input provided to several questions related to their current emotion and the number of events they are experiencing. The DAAS 42 dataset from Kaggle is considered for this research. Deep learning models like the feed-forward neural network (FNN) and ensemble models of voting classifiers are used in this study, along with traditional models like Extreme Gradient Boosting (XG boots), Adaptive Boosting (Ada boost), Decision Tree, K-Nearest Neighbors (KNN), and Gaussian Naive Bayes. Overall, the deep learning model and voting classifier performed well, followed by XGBoost. The voting classifier trained with 20 features had the highest accuracy for anxiety at 91.6% and FNN with an accuracy of 93.8% had the highest accuracy for stress data. For depression, both the FNN and the voting classifier had the highest accuracy of 93%.

1 Introduction

Technology advancement and globalization have made today's modern world more competitive, creating pressure on people to fulfill their desires and causing tension among them, eventually leading to various mental disorders. Today, most people have mental illness and the numbers are just drastically growing day by day. Early treatment is essential as the illness might worsen and lead to several serious issues. Severe mental illness can lead to different illnesses such as Stress, Schizophrenia, anxiety, bipolar disorder, depression, post-traumatic stress disorder (PTSD), and many more. Depression, Anxiety, and stress are the most common mental illness in most individuals. On average, 50% of adults will have mental health issues at a certain stage in their lives, yet only 20% of them will seek psychiatric help, with the rest being ignorant or unaware of their issues (Umar and Qamar; 2019). Among the individuals in the US suffering from Major Depressive Disorder(MDD), 74.6% of them are characterized by anxiety or distress, generally of moderate or severe levels. The average lifespan of those who suffer from mental diseases is getting shorter, and in the Years Lived with Disability (YLDs) 32.4% are of mental illness (Hasin et al.; 2018). A severe level of depression can lead to suicide. According to WHO, around 800,000 individuals commit suicide every year (Silva et al.; 2019). Today, mental illness is a widespread problem that affects many people, but not everyone gets treated. The illness will have a serious negative impact on each individual's stability and quality of life. The diagnosis of the sickness is based on various symptoms because there aren't many biological tests that can identify the condition.

The healthcare industry has started using cutting-edge technology like machine learning models to identify or predict numerous diseases using historical data or sometimes based on available images. Similarly, psychological disorders can also be identified using machine learning models. It is generally challenging to identify a psychological illness as the symptoms are subtle or common. Predicting mental illness through a machine learning model can benefit the individual as well as the psychiatrist. Individuals can learn right away if they have a mental illness and the severity of their condition. Also, it will provide the psychiatrist with insight into how to proceed with the diagnosis. It will highly benefit the clinical sector, as the psychologist will have a clear understanding of the issue and can then proceed with the necessary counseling. This can be implemented in the clinical industry as a mobile or web application for the initial identification of psychological illness levels as a preliminary test. The models will help in predicting the severity level of the illness. This will give a high-level insight into the illness to both psychiatrists and individuals. The psychiatrist can proceed with further counseling and medications based on the results provided. It will help the individuals identify their illnesses which will lead people to be less likely to ignore any mental health problems.

The objective of this research is to classify and predict the level of depression, anxiety, and stress among individuals using traditional machine learning models like Decision Tree, K-Nearest Neighbor (KNN), Gaussian Naive Bayes, boosting models like Extreme Gradient Boosting (XGBoost), Ada boost, ensemble voting classifier, and the deep learning model Feed Forward Neural Network (FNN) is implemented. Traditional machine-learning models have been used in the majority of research that has been conducted to identify mental diseases. From the detailed study of research work in this field, the ensemble model voting classifier and the deep learning model FNN are considered novel approaches that have been implemented in this research.

This research will address the following research question:

How accurately can traditional machine learning models (DT, KNN, Gaussian Naive Bayes, XGBoost, and AdaBoost), an ensemble model voting classifier, and a deep learning model Feed Forward Neural Network identify and classify the severity level of depression, stress, and anxiety disorders among individuals?

The study is limited only to the "Depression, Anxiety, and Stress Scale" (DAAS) 42 dataset taken from Kaggle[1] which is based on a set of questions asked to participants for the three common psychological states which include stress, anxiety, and depression. Machine learning and deep learning models will help in identifying and classifying the severity level of the illness by considering features like education, race, age, TIPI (Extraverted-Enthusiastic, CriticalQuarrelsome, Dependable-Self-Disciplined, etc) in addition to the 42 questionnaires and its score.

This section is followed by Section 2, which covers the related works in this research field. The methodology used for the research is given in Section 3, and the design specifications are in Section 4. Section 5 discusses the implementation of the models, followed by results and evaluation in Section 6. The conclusion is provided in Section 7.

[1]https://www.kaggle.com/datasets/lucasgreenwell/depression-anxiety-stress-scales-responses?select=data.csv

2 Related Work

These days, mental illness is very prevalent among individuals and is increasing day by day. Lots of research is being done in this field of classification and prediction of mental disorders using machine learning and deep learning methodologies for different types of data. This section will provide detail on the research that has been conducted in this field and will discuss the methodologies that have been implemented, the kinds of data collected, and the results obtained from the research.

2.1 Diagnosis of Mental Disorder using Traditional Machine Learning Techniques

The DAAS21 and DASS42 datasets were selected by the author (Kumar et al.; 2020) for the identification of different levels of anxiety, depression, and stress. A variety of classification methods were then employed, including tree-based models, naive Bayes, hybrid models, and neural network models. The hybrid K-Starr model with random forest improved performance and accuracy. However, it took a long time of 30 to 45 minutes and had less accuracy of 89.65% when compared to the RBFN neural network model. Since the neural network model has a higher learning capacity than other models, it performed better. Through the use of kernels to divide the classes into higher dimensions, the RBFN outperformed the other neural network models. The random forest provided 100% accuracy for anxiety data. This is due to imbalanced data and a lower number of instances. Balancing the data and adding more instances can provide better values.

From the Depression, Anxiety, and Stress Scale dataset(DAAS 21) the author (Priya et al.; 2020) predicted the stress, depression, and anxiety using the traditional machine learning algorithms K nearest neighbor (KNN), random forest, support vector machine (SVM), Naive Bayes, Decision Tree (DT). The data considered for this study were collected from 348 individuals. As the data was imbalanced, the author evaluated it based on the F1 score along with the accuracy. Despite the fact that the Naive Bayes has a high accuracy of 74% for stress, the F1 score of 75% was better for the random forest, with a decent accuracy of 72%, while the Naive Bayes had only 55% F1 score. Hence, a random forest was considered a better model for stress. For depression, Naive Bayes had better accuracy and fl scores of 73% and 83%, respectively, and was considered a better model. The f1 score for anxiety was lower for all the models, in the range of 40%, while the accuracy was high for the naive Bayes, at 73%. Boosting models and deep learning models could have been used by the author to compare the prediction with traditional models. The data considered for this research is very limited and could have been even more extensive.

Mental illness can be due to various factors like social anxiety, stress, drug addiction, the workplace, etc. The author, (Laijawala et al.; 2020) conducted this research using Open Sourcing Mental Illness (OSMI). Because the dataset was gathered from working professionals, the available data is limited to adults aged 18 and up. The machine learning models Naive Bayes, decision trees, and random forests were considered for this research. The decision tree provided a high accuracy of 82%, followed by the random forest and naive Bayes with 79% and 78% of accuracy, respectively. The model predicts only if the person has a mental illness or not. Instead, it could have been an identification of a particular illness, which would have been more specific. For prediction comparison, more boosting and hybrid models could have been used.

Working professionals are increasingly suffering from mental health issues. It is essential to identify them and provide the necessary care. The author (Katarya and Maan; 2020) used the Open Sourcing Mental Illness (OSMI) dataset from the survey conducted in 2019 that contained both tech and nontech employees for this research. The dataset contains over 70 attributes with both personal and professional information. The machine learning models considered for this research are KNN, SVM, logistic regression, Naive Bayes, Random Forest, and Decision Tree. Both the decision tree and logistic regression provided a high accuracy of 84%, but the decision tree provided better precision and recall values of 83% and 92%, respectively. The decision tree was the best-predicted model, followed by naive Bayes. Other models than traditional machine learning algorithms could have been considered, like hybrid, ensemble, and deep learning.

The OSMI dataset was used by (Elmunsyah et al.; 2019) for depression identification among the employees. A traditional machine learning model, the K-Nearest Neighbor Algorithm, was implemented for this dataset. The features were selected based on the chi-square. The model's accuracy, precision, and recall were 87.27%, 84.21%, and 66.7%, respectively. The author states that KNN has performed well compared to the model accuracy of Naive Bayes and SVM provided by earlier research work. The accuracy has improved by 2.27%. The data split of 85% and 15% was implemented in this research, and the author states that it has performed well and is stable. More models could have been implemented, and accuracy could have been improved by changing the K value.

Using the Open Sourcing Mental Illness (OSMI) Mental Health dataset, the author (BH et al.; 2022) conducted research on the causes of mental illness among tech and non-tech employees. An analysis is carried out to determine if variables like location, number of employees, and many more can contribute to health problems. Various machine learning methods were put into practice, including KNN, XGboost, Light GBM, AdaBoost, Decision Tree, and Random Forest. The KNN outperformed others with an accuracy 85.49%. The XGBoost model had a better classification report overall, with precision, recall, F1 score, and accuracy values of 86%, 84%, 85%, and 85%, respectively. According to the report, non-tech workers experience higher mental health problems than tech workers since their employment is more disruptive. On the other hand, the remote work environment and limited leave policies cause stress among tech workers. In addition, geography also makes a difference, as working in a city tends to have more issues. The researcher suggests that in the future, hybrid models and deep learning models will be applied to better prediction.

2.2 Diagnosis of Mental Disorder using Deep Learning and Ensemble Model

It is essential to identify depression in its initial stages in order to prevent the increasing number of suicides these days. Teenagers are the main victims. The first step in prevention is to identify the mental illness. The author (Jain et al.; 2021) conducted research of to predict depression among people based on their lifestyles, which include marital status, income, age, property, child, alcohol and cigarette consumption, and many other similar qualities, with a total of 76 of the sort. The models considered for the research are support vector machines, logistic regression, XGBoost, random forests, decision trees, gradient boosting classifiers, Nave Bayes, and artificial neural networks (ANN). The survey was conducted among 1429 individuals. The support vector model predicted well, with an accuracy of 87.39. The decision tree had a lower accuracy of 78.32 percent when compared to other models. Hyperparameter tuning could have been done to check if the accuracy was improving.

The disorder-specific data from YODA was considered by the author (Xiong et al.; 2021) to predict different types of anxiety disorder. It includes social anxiety disorder, separation anxiety disorder, and generalized anxiety disorder. A novel ensemble model based on Bayesian Neural Network (FE-BNN) was applied. It performs well, and one could see from the evaluation metrics that the model FE-BNN has predicted well, with an AUC value of 0.8683, 0.9091, and 0.8769 for separation anxiety disorder, social anxiety disorder, and generalized anxiety disorder, respectively. By interpreting and explaining the outcomes, the model's performance can be even more improved.

Another study was conducted by (Reddy et al.; 2018) to predict stress among working employees. The Open Sourcing Mental Illness (OSMI) dataset was used for this research. Ensemble models and traditional machine learning models were considered for this research. The model includes logistic regression, a decision tree, K-nearest neighbors, random forest, bagging, boosting, and stacking. The ensemble boosting model provided a higher accuracy of 75%. Even though the other models, logistic, KNN, and random forest, had the same accuracy of 73%, the random forest had a lower false positive rate of 32% and a precision value of 80%. Different types of machine learning models, like tree bases, boosting, and ensemble, were well implemented in this research.

The researcher (Yadav et al.; 2020) used routine survey data for the analysis of depression among individuals. The algorithms K-Nearest Neighbors, Random Forest Classifier, Bagging, Decision Tree, Multinomial Logistic Regression, Boosting, and Stacking were implemented. The boosting algorithm performed well, with an accuracy of 81.75%, followed by the Random Forest model and KNN model with 81.22% and 80.42%. As the accuracy of boosting and random forest are very close, the author could have used other evaluation techniques like precision and the f1 score to determine a more accurate model. In the future, the researcher intends to integrate the model with the government and non-governmental organization (NGOs) databases, which will be highly beneficial to focus on mental health among individuals in society.

2.3 Summary of the research work

A detailed study of the research work related to the prediction and classification of mental illness was conducted. It could be seen that the majority of the research has been implemented using traditional machine learning models like KNN, SVM, decision trees, and naive Bayes. Few researchers have tried ensemble models like boosting, stacking, and bagging and deep learning has rarely been used. The traditional models and ensemble models have provided decent accuracy. For model prediction, we will implement another ensemble model voting classifier and a deep learning model called Feed Forward Neural Network (FNN), which will be compared and analyzed with the traditional machine learning models. These models will be the novel approach in this research.

3 Methodology

The Knowledge Discovery in Databases (KDD) methodology is used in this research to predict the different levels of stress, anxiety, and depression symptoms. It helps in interpreting and extracting important information from the data to effectively apply it to the targeted application. The KDD methodology is divided into various steps, which include

Author	Model	Accuracy
(Elmunsyah et al.; 2019)	KNN	87.27%
(Jegan et al.; 2022)	SVM	91%
(Laijawala et al.; 2020)	Decision Tree	82%
(BH et al.; 2022)	XGBoost	82.55%
(Reddy et al.; 2018)	Ensemble Boosting Model	75.13%
(Yadav et al.; 2020)	Ensemble Boosting Model	81.75%
(Jain et al.; 2021)	SVM	87.39%

Table 1: Summary of Literature Review

data selection, data preprocessing, exploratory data analysis, data transformation, data modeling, evaluation, and result interpretation.

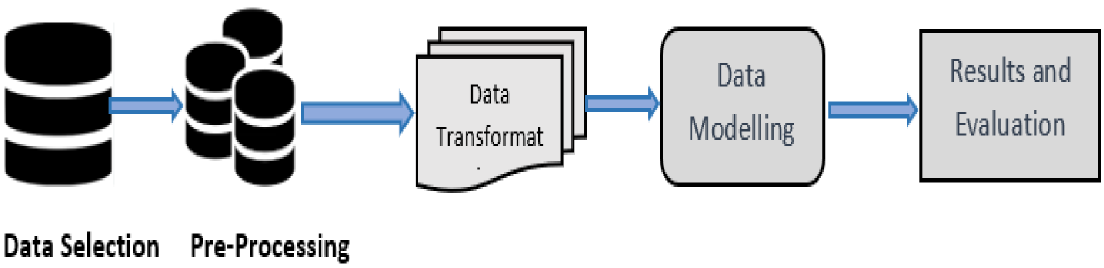

Figure 1: KDD Methodology

3.1 Data Acquisition

For this research, the DASS 42 dataset is considered from Kaggle [2]. It is survey data collected and conducted by the Psychology Foundation of Australia from individuals to check their personalized results related to depression, stress, and anxiety. In the end, a survey form was provided to get their concern regarding publishing the data, and the data of people who had no objection was only considered and posted publicly for research purposes.

The dataset consists of 39775k records of responses provided by people for the 42 questions. The questions will be related to their mental states, like their thoughts on the future, their interests, their current state of mind, any physical symptoms or uneasiness, and many more, which will help to determine the existence of any mental disorders like depression, stress, and anxiety. The responses to the 42 questions are available as a separate column and the time recorded and positioned are in separate columns for each question. Each question will have options as given below in Figure 2[3] from which the individual had to pick accordingly.

[2]https://www.kaggle.com/datasets/lucasgreenwell/depression-anxiety-stress-scales-responses?select=data.csv

[3]https://www.kaggle.com/datasets/lucasgreenwell/depression-anxiety-stress-scales-responses?select=codebook.txt

1 = Did not apply to me at all

2 = Applied to me to some degree, or some of the time

3 = Applied to me to a considerable degree, or a good part of the time

4 = Applied to me very much, or most of the time

Figure 2: Responses

In addition to the 42 questions, the interlopes, test elapse, and survey elapse details like the time spent on the introduction, and time spent on the DASS questions were included from the survey side. A few demographic details and The Ten Item Personality Inventory (TIPI) were also included. With all these questions the dataset will have a total of 172 attributes.

3.2 Data Preprocessing

In the preprocessing step, the first thing checked was if the columns had any null or missing values. The column "major" had null values, which were updated as "no degree." Then the data in the major column was analyzed, and the graph plotted showed that more than 12k records were "no degree." As the count for "no degree" is high, the column (major) will not have any impact on the data modeling and hence the column is dropped. The interlopes, tests, and survey elapse columns were similarly eliminated because they would not impact the modeling prediction. The age column data was divided into several age groups, like those under 12, teens, adults, elder adults, and older people. One hot and label encoding was applied for all the categorical data. The data is then divided into depression, stress, and anxiety datasets based on the understanding shown in Figure 3 provided in the site[4].

Each disorder dataset comprises 14 questions. The total score was calculated by summing the responses received for each question, and from the score, the level of severity was determined. Any score greater than 28 was considered extremely severe, scores between 21 and 27 were considered severe, and scores between 14 and 20 were considered moderate. The scores between 10 and 13 are mild, and less than 9 are normal as given in the data details [5]

3.3 Exploratory Data Analysis

Exploratory data analysis was conducted to understand the behavior of the data and how the severity level are distributed.

Figures 4 and 5 show the number of people suffering from different illnesses. More than 10k people have extremely severe depression and stress, while around 5k people have extremely severe anxiety. In comparison to anxiety, the majority of people suffer from depression or stress. There are approximately 12,000 people who are normal and do not have an anxiety disorder. The number of people with depression and stress is higher

[4] http://www2.psy.unsw.edu.au/dass/over.htm

[5] https://www.kaggle.com/datasets/luteensreadultsl/depression-anxiety-stress-scales-responses?select=codebook.txt

Characteristics of high scorers on each DASS scale

Depression scale

- self-disparaging
- dispirited, gloomy, blue
- convinced that life has no meaning or value
- pessimistic about the future
- unable to experience enjoyment or satisfaction
- unable to become interested or involved
- slow, lacking in initiative

Anxiety scale

- apprehensive, panicky
- trembly, shaky
- aware of dryness of the mouth, breathing difficulties, pounding of the heart, sweatiness of the palms
- worried about performance and possible loss of control

Stress scale

- over-aroused, tense
- unable to relax
- touchy, easily upset
- irritable
- easily startled
- nervy, jumpy, fidgety
- intolerant of interruption or delay

Figure 3: Splitting into Depression, Stress, and Anxiety

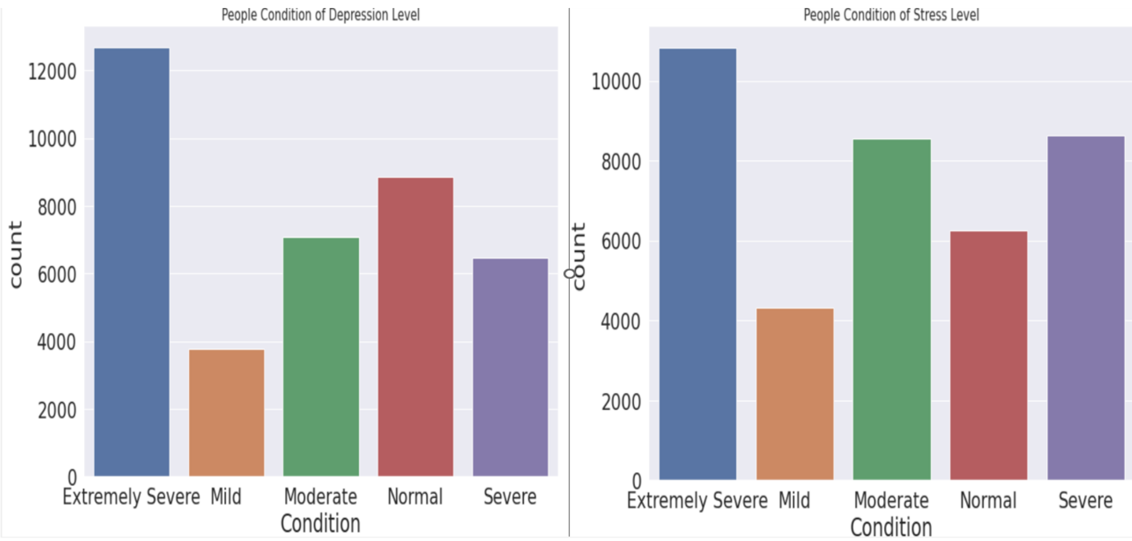

Figure 4: Different level of Severity for Depression and Stress

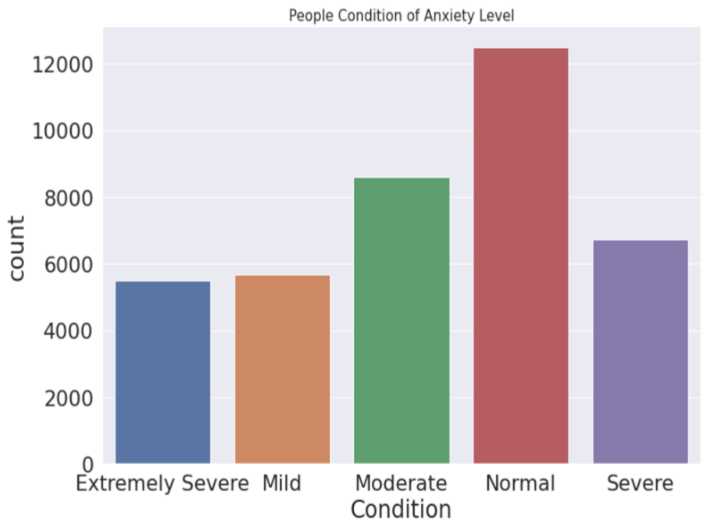

Figure 5: Different level of Severity for Anxiety

than the number of people with anxiety. The majority of individuals with anxiety have moderate conditions.

Figures 6 and 7 depict the different levels of severe conditions among males, females, and other genders. It could be seen that, in general, the number of females suffering from mental illness is high compared to males and other genders. More than 8K females have extremely severe depression or stress issues. Extremely severe cases of anxiety are less common in about 4K people, while mild anxiety affects about 8K females. Males with anxiety have a higher rate than males with depression or stress. Males suffering from depression or stress number less than 3k people. Around 4K males have moderate anxiety, with extremely severe cases affecting less than 1K individuals.

Figure 8 shows that depression is high among adults, followed by teens. Around 7K adults have extremely severe depression, while 5K teens suffer from extremely severe depression. Hardly 500 elder adults suffer from depression. The adults are the most affected by stress as well, with 6K people suffering, followed by teens, with 4K suffering from extremely severe conditions. A smaller number of older people and Elder adults have stress. Figure 9 shows that anxiety is more common among adults and elder teens. Around 8K elderly people suffer from mild anxiety. The number of older people and teens elder people from anxiety is less than 1k. Adults and teens are the two age groups that get affected by stress, depression, and anxiety when compared with old and elder people.

3.4 Feature Selection

Feature selection is a technique used for reducing the total number of features for model implementation. It helps in determining the most influential or significant feature that should be considered for implementation. Reducing the features by removing the not-impacted ones can increase the model's accuracy and performance. In this research chi-square, the feature selection method is implemented, which is generally used for categorical data.

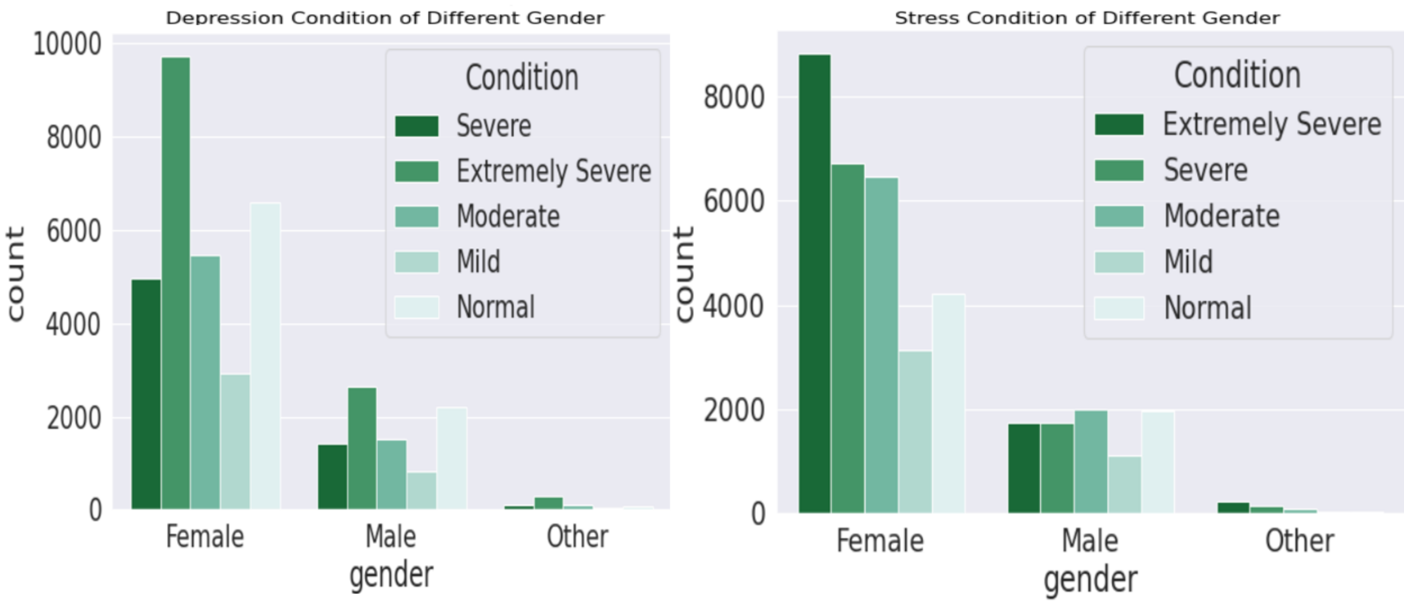

Figure 6: Condition based on gender for Depression and Stress

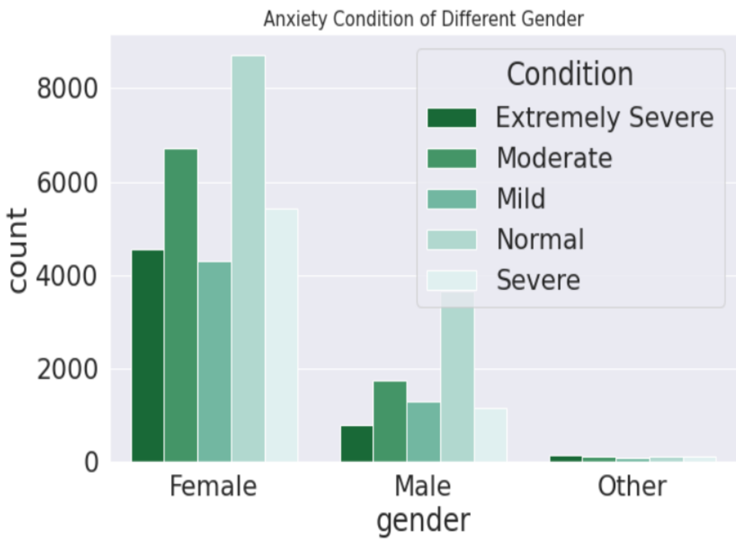

Figure 7: Condition based on gender for Anxiety

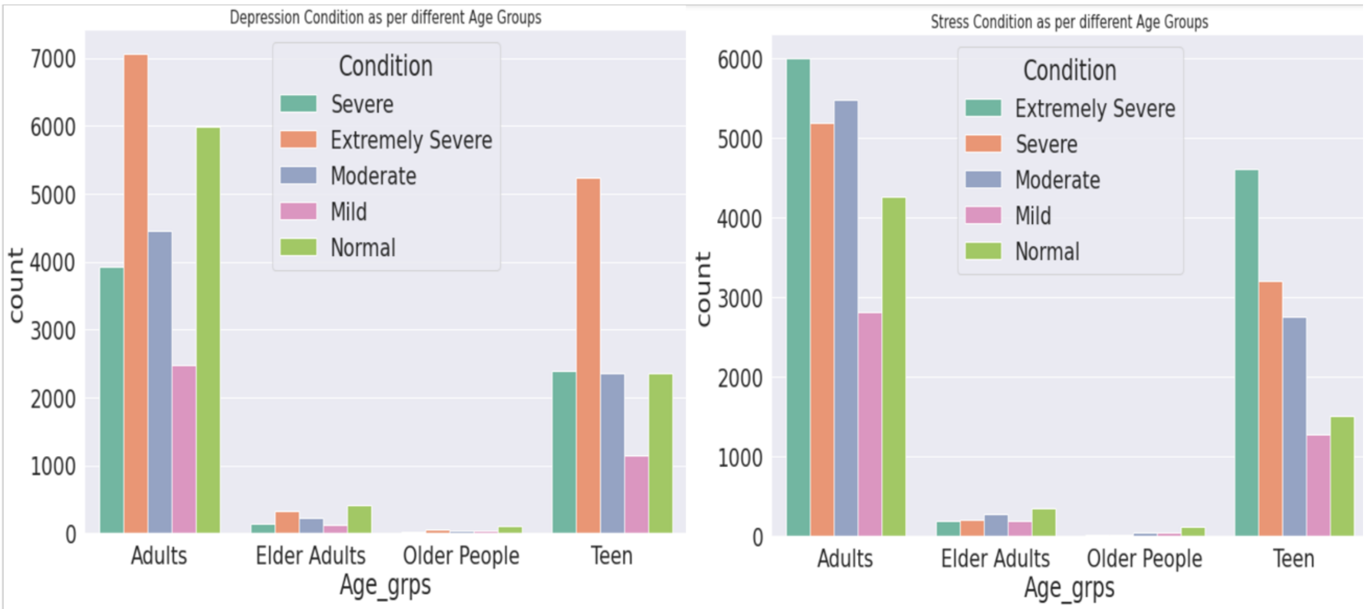

Figure 8: Depression and Stress Conditions based on age group

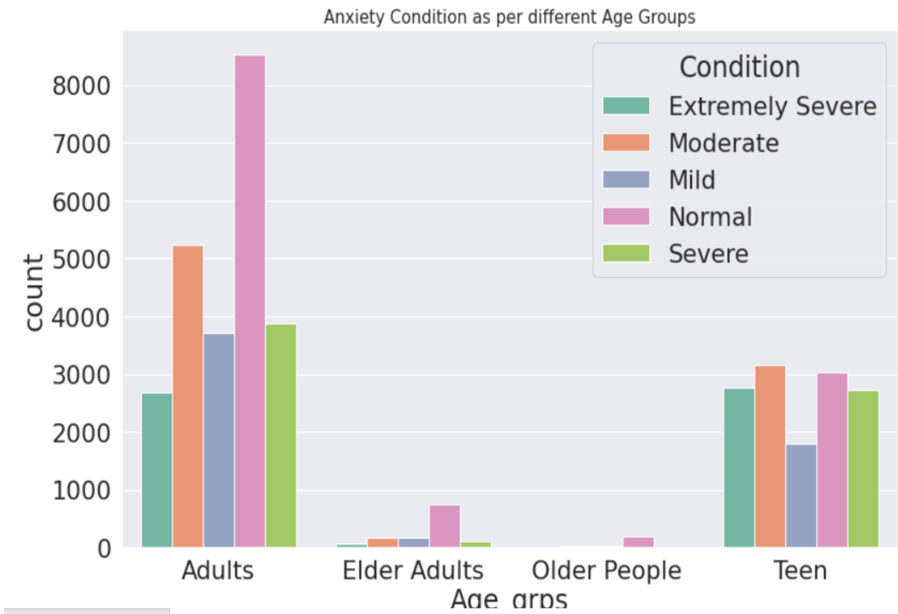

Figure 9: Anxiety condition based on age group

3.5 Data Modelling approaches

3.5.1 Decision Tree

The decision tree is one of the machine learning models preferred for classification problems. It is, as the name implies, a tree-like structured classifier that begins at the root node and branches out. It is typically based on straightforward yes-or-no questions and branches out into sub-trees based on that. The nodes are the dataset features, the branches are the decision rule, and the final outcome is represented by the leaf node. The decision nodes make the decision based on the data set's features. The decision nodes make the decision based on the data set's features. It keeps things simple, and its logic is simple to understand. The algorithm begins at the root node of the tree and compares the root value with the given dataset, then branches out accordingly. Similarly, the next node again compares with the other sub-nodes and proceeds until the leaf node is reached. It is highly helpful for solving decision problems and considering all the possible outcomes.

3.5.2 K- Nearest Neighbour

K nearest neighbor is a supervised learning model. As the name implies, it identifies the nearest class to predict the data. It is based on the idea that data points that are close to one another are treated as belonging to the same class. The value of K will have a significant impact on how well this algorithm predicts. Based on K, it will search for that many neighboring data points and vote for the most prevalent class.

3.5.3 Gaussian Naive Bayes

Gaussian Naive Bayes is a Naive Bayes algorithm. It is based on a discovery by Thomas Bayes. It is a probabilistic model that determines the mean and standard deviation of the train data in order to approximate the normal distribution. The model's features are independent of one another, therefore, changing one feature won't affect the other features. This methodology is both easy to use and effective.

3.5.4 Boosting model

By training weak models into strong prediction models, the boosting model improves prediction performance and accuracy. It uses ensemble techniques.

- Ada Boosting - In Ada Boost, the data point's weight is automatically adjusted after every decision tree. The weight is given based on the correctly and incorrectly classified items. More weight is given to the incorrectly classified item. It is an iterative process, and it continues to iterate till the residual error, or the difference between the actual and predicted value, falls below the threshold.

- Extreme Gradient Boosting Model - XGBoost is an improved version of gradient boosting in which learning and training occur simultaneously. It can handle a large dataset. Parallelization, optimization, and distributed computing are its key features.

3.5.5 Voting Classifier

It is one of the classification models that will be trained using an ensemble of models or a number of models, and it will produce a predicted result based on the majority vote of the chosen class. It may provide more accurate findings than the base models and can be employed when the single models produce biased results. There are two model voting classes: soft voting and hard voting. Hard voting will base its predictions on the class that received the majority of votes, but soft voting will base its predictions on the average probabilities of the classes.

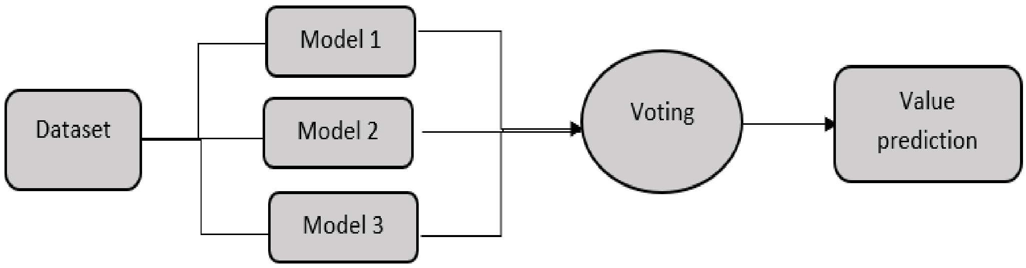

Figure 10: Voting Classifier

3.5.6 Feed Forward Neural Network

The feed-forward neural network is one of the artificial neural networks where the nodes will not form any loops. It is also called a "multi-layer neural network" as the information is sent forward but not received back. The data is received by the input node, which passes it to the hidden layer before exiting via the output node. While training, it adjusts the weights so that it can compare the output with the desired values.

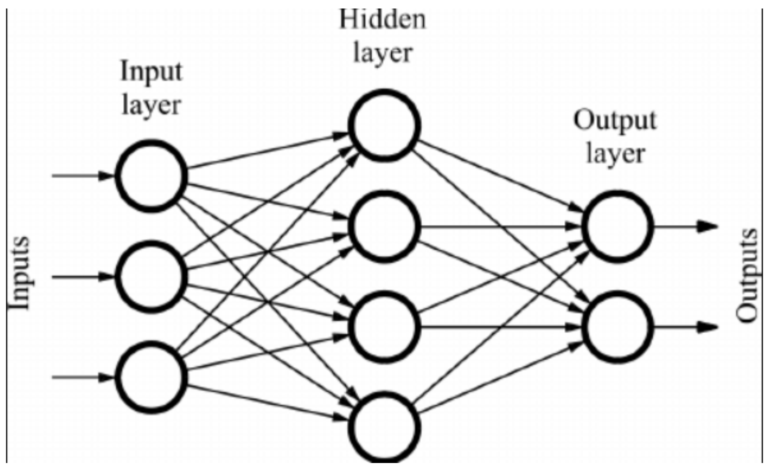

Figure 11: Feed Forward Neural Network

4 Design Specification

The data is first collected from the available sources. The CSV file containing the dataset is then imported, and the data is preprocessed, which involves cleaning the data and checking for null or missing values. It is then followed by exploratory data analysis, which uses visualization to gain a full understanding of the data. Through feature selection, the best features are taken into account. Then data modeling is carried out. In this research, the ensemble model voting classifier and deep learning model FNN are implemented along with the base models. Finally, the predicted value is evaluated and compared with the traditional model's performance.

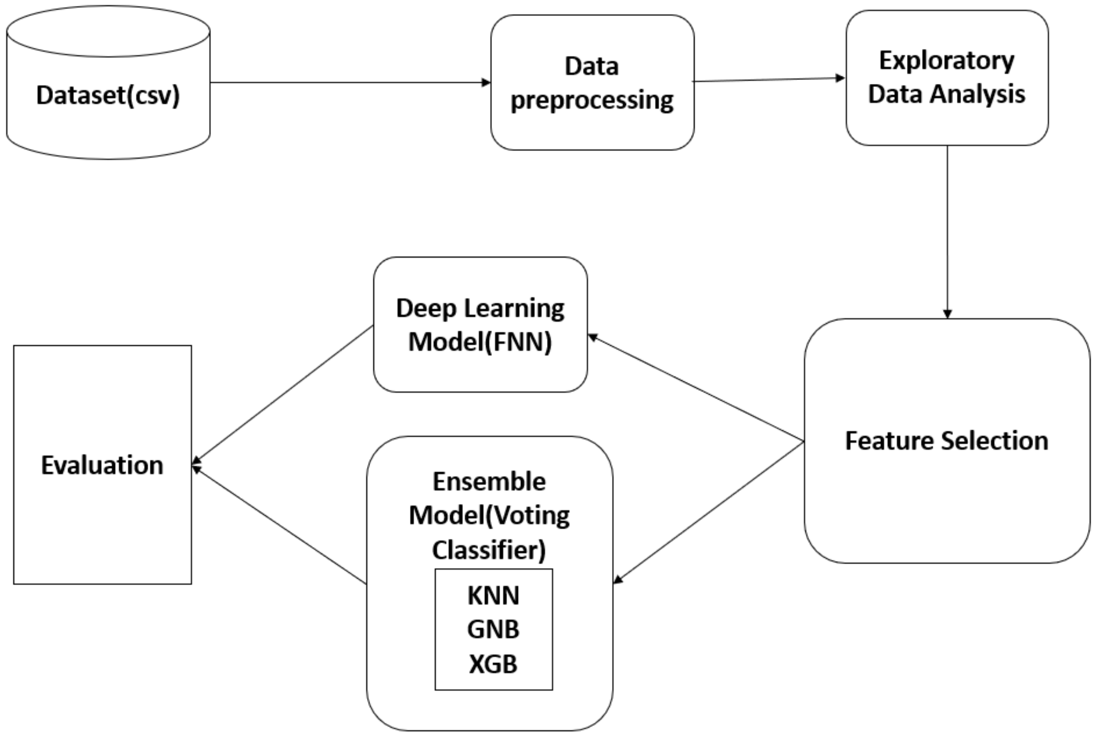

Figure 12: Design Flow

5 Implementation

A CSV file representing the DAAS 42 data set was downloaded from Kaggle. The data was then loaded onto Google Drive for further use. In Google Colab, the data is imported from the drive for preprocessing and implementation. First, the data is cleaned by looking for null or missing values. Then the categorical variables are one hot encoded to numerical values. The dataset is split into depression, stress, and anxiety, and the score was calculated for every individual response by summing the values obtained for each question. Based on the score, the level of severity is split and added in a new column called condition. The condition column will be the target column for prediction.

The complete project is coded in Python in Google colab. Python has many built-in packages and tools for implementing machine learning models. Python packages such as pandas, NumPy, sklearn, and skit were used for data analysis, graph plotting, other preprocessing techniques, model implementation, and evaluation.

Following pre-processing and data exploration, features were chosen, and the data was then prepared for implementation. The data set was split for training and testing in the ratio of 80% and 20% respectively. The scalar transformation was done to standardize the scaling features. The "condition" column, having a different level of severity, was considered the target column. Three different sets of training and testing data were split and prepared for depression, anxiety, and stress respectively. Then the models were fit.

5.1 Traditional Models

Traditional models such as KNN, Decision Tree, Gaussian Naive Bayes, and boosting models XGBoost and AdaBoost were considered, and the models were fit with 80% and 20% of training and testing, and results were evaluated. Similarly, the best 20 features were selected for each dataset (depression, anxiety, and stress) using chi-square feature selection. Then the model was fitted with the 20 best features, with the training and test data in the ratio of 80% and 20%. The results obtained are evaluated and compared with the results obtained before feature selection.

5.2 Ensemble Model (Voting Classifier)

An ensemble voting classifier model was implemented. It is implemented by providing three different traditional machine-learning models as input. One of the well-performing models, XGBoost, along with Gaussian Naive Bayes and KNN was considered for voting classifier model fit. The model was fit for the three different data sets of depression, stress, and anxiety with train and test split of 80% and 20%. One model with all the features and another model with only the 20 selected best features were implemented. The results were evaluated, analyzed, and the performances were compared.

5.3 Deep Learning Model (FFN)

The deep learning model with the best 20 features was built. The train+validation and test splits are 80% and 20% for this model as well. The data test was split into train, test, and validation data. In the training data set, the number of classes is computed. Then the model parameters were assigned. The batch sizes of 64 and 1 are passed for the train loader and test leader, respectively. A 3-layer feed-forward neural network was built with drop-out and batch norms. The model is initialized. CrossEntropyLoss can be used instead of manually applying soft layers. For validation, softmax is used. To store the accuracy and loss, two different dictionaries were created. Then the model is trained and validated. The same implementation is followed for all types of datasets related to depression, stress, and anxiety. The model was evaluated based on train and validation accuracy and train and validation loss values.

Model performance was evaluated based on precision, recall, accuracy, and f1 score values. The confusion metrics of true positive, true negative, false positive, and false negative were also used for validating the results of the implemented models.

6 Evaluation

This section discusses in detail the evaluation of all the models applied. The main objective of the research is to determine the model's performance and see the prediction level for each. The evaluation metrics are calculated based on the confusion matrices. The accuracy, precision, and recall value were calculated for each model and compared with the performance of the rest of the model.

The true negative (TN) and true positive (TP) are the correct predictions, while the false negative (FN) and false positive (FP) are the incorrect predictions.

$$Accuracy = \frac{TN + TP}{TN + FP + TP + FN}$$

6.1 Decision Tree

From the table, it shows that the decision tree implemented with all the features has provided an accuracy of 79.5% for depression, 72%, and 74.3% for stress respectively. It shows that around 70 to 80 samples have correctly predicted the classes for depression, anxiety, and stress. Precision, recall, and F1 scores were similar to accuracy, with a 0.1% difference for all three datasets. The decision tree with feature selection provided a better accuracy of 81.1% for depression, 74.5% for anxiety, and 76.6% for stress when compared to the previous model without feature selection. The decision tree didn't perform as well as it performed in the previous research (**?**). This might be due to the difference in the dataset and class being predicted.

6.2 K Nearest Neighbor(KNN)

The KNN with all the features provided an accuracy of 84.5%, 79.9%, 81.3% and for depression, anxiety, and stress, respectively. This has performed better than the decision tree. The KNN model with feature selection provided an improved accuracy of 90.3%, 86.5%, and 89% for depression, anxiety, and stress, with almost a 6% to 8% increase in accuracy when compared with the accuracy predicted by the model with all the features. Similar to the DT model, the precision, recall, and F1 score values were 0.1 or 0.2% more or less than the accuracy value. For KNN, the model trained with feature selection provided better accuracy for all depression, stress, and anxiety datasets.

6.3 Gausian Naive Bayes(GNB)

The Gaussian Naive Bayes provided an accuracy of 87.5%, 83.8%, and 85.7% for depression, anxiety, and stress, respectively, for the model without any feature selection. The precision and F1 score values were 1% higher than accuracy while the recall had values similar to accuracy. The model implemented with feature selection had a slightly higher value for depression, anxiety, and stress with an accuracy of 88.7% and 85.7%, and 87.1%. The precision and F1 score had values greater than the accuracy, with a 1% to 2% increase. The recall was similar to that of accuracy. KNN performed better than Gaussian Naive Bayes after the feature selection.

6.4 XG Boost

The XGBoost model without feature selection provided an accuracy of 91.7%, 87.9%, and 89.6% for depression, anxiety, and stress, respectively. The accuracy of the model trained with feature selection had similar values to the model trained without feature selection, with hardly a difference of 0.1% to 0.2%. The feature selection did not have any impact on the XGBoost model. The accuracy for the model with feature selection is 91.8%, 87.8%, 89.9% Similar to other models, the precision, recall, and f1 score were similar to accuracy, with a slight increase or decrease.

6.5 ADA Boost

The ADA Boost provided an accuracy of 75.3%, 69.1%, and 72.9% for depression, anxiety, and stress, respectively. In comparison to the other models implemented, this model had the lowest accuracy. The recall and F1 scores were similar to accuracy, with a slight increase of 1%. The precision value was high with the value of 83.4%, 79.2%, and 80.7%. Similar to XGBoost the model implemented with selected features did not have an impact on the prediction accuracy. It was similar to the one without feature selection.

Models	Accuracy			F1 Score			Precision			Recall		
	Depression	Anxiety	Stress	Depression	Anxiety	Stress	Depression	Anxiety	Stress	Depression	Anxiety	Stress
DT	79.5	72	74.3	79.5	72.1	74.4	79.7	72.2	74.5	79.5	72	74.3
KNN	84.5	79.9	81.3	84.0	79.5	81.3	84.1	79.5	81.5	84.5	79	81.3
GNB	87.5	83.8	85.7	88.0	84.4	86.1	89.6	85.8	87.1	87.5	83.8	85.7
XG Boost	91.7	87.9	89.6	91.3	87.5	89.1	91.8	88	89.6	91.7	87.9	89.6
ADA Boost	75.3	69.1	72.90	76.1	69.4	72.3	83.4	79.2	80.7	75.3	69.1	72.9
Voting Classifier	92.2	88.8	90.0	92.2	88.9	90.0	92.4	89.1	90.2	92.2	88.8	90.0

Figure 13: Final Result for the model without feature selection

6.6 Ensemble Model

The voting classifier without feature selection provided an accuracy of 92.2%, 88.8%, and 90% for depression, anxiety, and stress, respectively. While the model with feature selection provided an increase in accuracy of 93.3%, 91.6%, and 92.3% for the three different datasets, respectively, The accuracy predicted by the voting classifier is the best compared to the other models implemented. The precision, recall, and f1 scores were similar to the predicted accuracy.

6.7 Deep Learning Model

The implemented feed-forward neural network is 3 layered. The model was implemented with the selected 20 features. It has provided a validation and training accuracy of 93.1%, 90.34% for depression. The accuracy provided is similar to that of the voting classifier. The validation loss was very less with 0.19. Similarly, the validation accuracy for the Stress dataset was higher, at 93.8 percent, and 85.9 percent for the training accuracy. The validation loss is very minimal for the stress data model as well, at 0.21. The FNN model for anxiety had validation and training accuracy of 87.2% and 88.5%, respectively, with significantly higher validation loss than the stress and depression model, which had 0.3.

The feed-forward neural network model and voting classifier model performed well for all three depression, anxiety, and stress datasets. The Adaboost model had the lowest

Models	Accuracy			F1 Score			Precision			Recall		
	Depression	Anxiety	Stress	Depression	Anxiety	Stress	Depression	Anxiety	Stress	Depression	Anxiety	Stress
DT	81.1	74.5	76.5	81.1	74.5	76.4	81.1	74.6	76.4	81.1	74.5	76.5
KNN	90.3	86.5	89	90.2	86.2	88.9	90.2	86.2	88.9	90.3	86.5	89
GNB	88.7	85.7	87.1	89.1	86.2	87.4	90.5	87.6	88.4	88.7	85.7	87.1
XG Boost	91.8	87.8	89.9	91.3	87.3	89.4	91.9	87.9	89.9	91.8	87.8	89.9
ADA Boost	75.3	69.1	72.9	76.1	69.4	72.3	83.4	79.2	80.7	75.3	69.1	72.9
Voting Classifier	93.3	91.6	92.3	93.4	91.7	92.4	93.6	91.8	92.5	93.3	91.6	92.3

Figure 14: Final Result for the model with feature selection

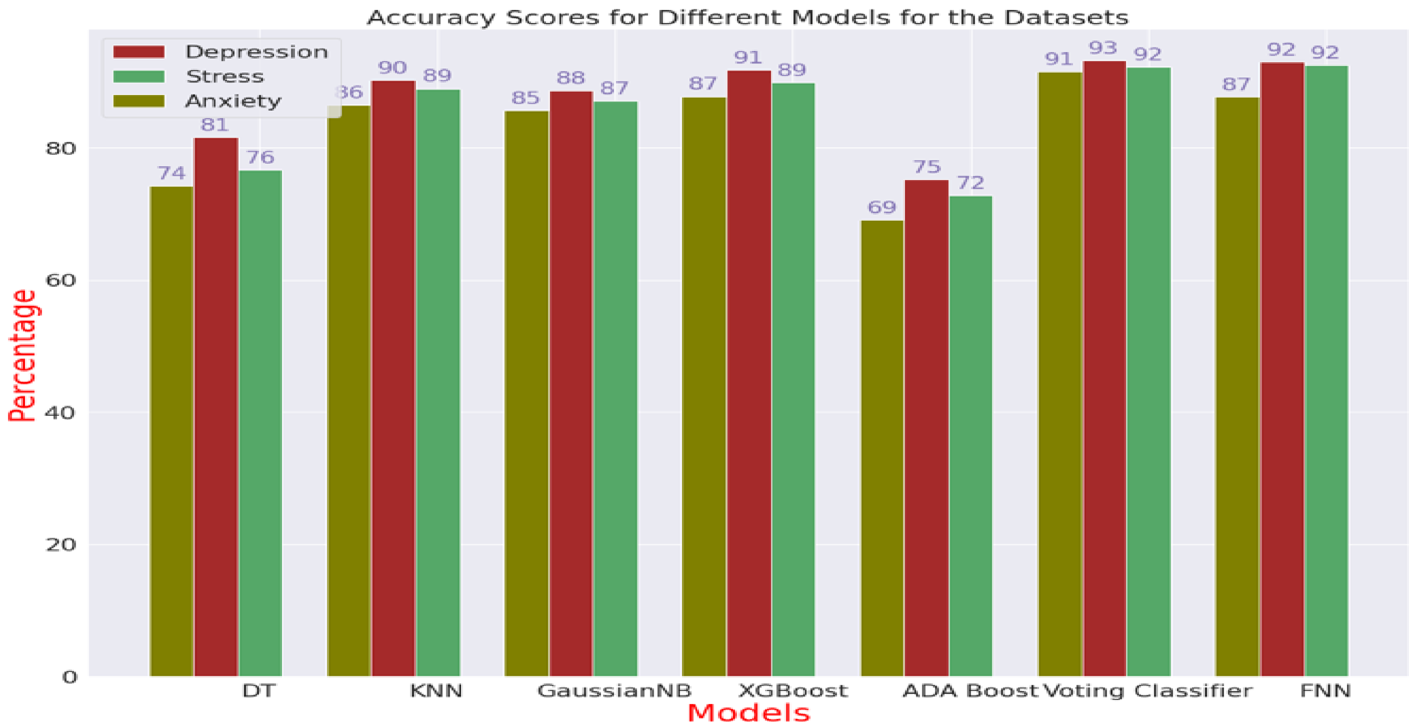

Figure 15: Model comparison

accuracy value compared to the other models for the depression, stress, and anxiety datasets.

Type	Val Accuracy	Val Loss	Train Accuracy	Train Loss
Depression	93.1	0.19	90.34	0.24%
Anxiety	87.2	0.3	88.5	0.28%
Stress	93.88	0.21	85.97	0.34%

Table 2: FNN Results

6.8 Discussion

The research aimed to classify the severity level of mental illness for stress, depression, and anxiety among individuals. The KDD methodology was followed, and the processes were divided into various steps. The initial step of identifying and understanding the data was quite challenging, as the DASS 42 had multiple attributes, and understanding the attributes was quite challenging. It was necessary to understand the dataset to proceed with the corresponding steps. The pre-processing and data-cleansing steps were challenging too, as they involved a number of attributes with both numerical and categorical data. And the data had to be split into their different illnesses based on the details provided.

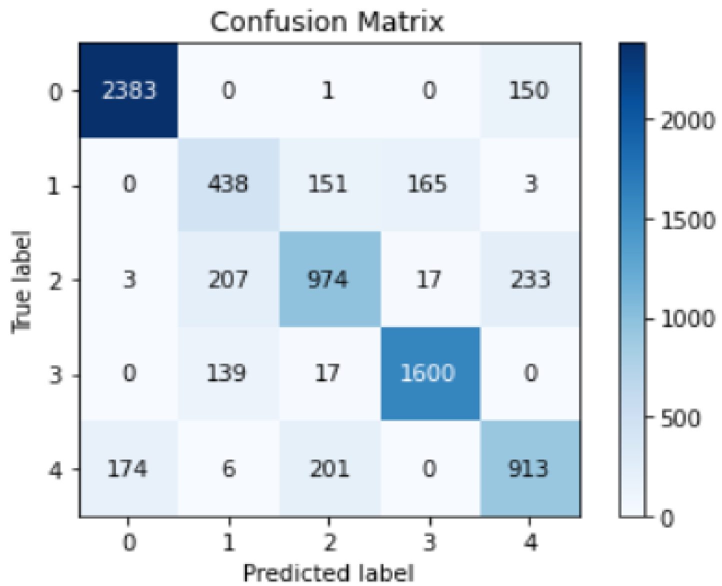

Figure 16: Depression Confusion Matrix

Overall, all the models that were implemented provided quite a fair result as the number of samples correctly classified is more. For instance, it care be inferred from the confusion matrix in the Figure 16 that most of the samples in class 0 (extremely severe) have been classified in the correct class except for one sample that was incorrectly classified in class 4 (severe). Class 4 (severe) has classified 1223 samples correctly, with 97 samples classified incorrectly in class 0 (extremely severe) and 56 samples in class 2 (mild). Class 2(mild) had the highest number of incorrect classifications with 114 samples incorrectly predicted in class 1(moderate) and 70 samples in class 4(severe). It has correctly classified 1330 samples. Even though there are samples that are classified incorrectly, a high number of samples have been classified correctly. The few falsely predicted samples will not have a high impact on the individuals as it is a preliminary analysis that helps the individual identify if the mental illness exists and, if so, its severity level. It gives an individual an insight into the illness they have, and it is not the final result. With these results, individuals can consult or arrange for a counseling session with the psychiatrist for further analysis and medications.

The Ada Boost provided the least accuracy of 75.3%, 69.1%, and 72.9%. The model with the lowest accuracy has correctly predicted 75–80% of the samples. FNN, voting classifier and XG boost performed well compared to the rest. The FNN and voting classifier models provided the highest accuracy of 93.1% and 93.3% for depression, respectively. Both models accurately predicted depression. The precision, recall, and F1 score of the voting classifier were highly similar to their accuracy. Similarly, the FNN model had a very minimal validation loss of 0.19. Hence, for depression, both models predicted well. For anxiety, the voting classifier predicted well compared to the deep learning model, with an accuracy of are.3%. It was followed by FNN and XG boost, which had similar accuracy 87.8% and 87.2% respectively. When compared to these models, the voting classifier's accuracy was higher by 3%, with a prediction, recall, and F1 score of 93%. The FNN also had the highest accuracy for stress, with an accuracy of 93.8 percent for the voting classifier, which had good accuracy but was 1% less accurate than the FNN.

The depression, stress, and anxiety dataset were classified and predicted with high accuracy, with FNN and voting classifier providing the best accuracy, followed by XG Boost, which had a slightly lower accuracy value of 2% to 3%. The FNN has taken a considerably high execution time compared to the voting classifier, in general, the neural network takes more time due to the number of parameters considered for training. It tends to perform well with a high amount of data. For a dataset of around 35k records, the execution time for the models is less than 90 sec, which is fast. Overall, the models with feature selection performed well compared to the models implemented with all the features. Among the three different datasets for depression, stress, and anxiety, the depression dataset set had higher accuracy compared to the rest.

7 Conclusion and Future Work

As discussed, the identification of different mental disorders is one of the major research projects being conducted nowadays. This is due to the steep increase in mental illness among individuals. Taking care of mental health is as important as taking care of physical health. But it is mostly ignored by most people, as they are either unaware of it or ignorant of mental health. Easy identification of the disorder will help raise awareness among individuals, and serious mental issues can be avoided with the initial diagnosis. From the exploratory analysis, it is seen that depression and stress are more common among individuals compared to anxiety. Mental illness is highly severe for females compared to males, and it is higher for adults and teens compared to young and elderly people.

The models used to classify and predict the various levels of stress, depression, and anxiety in individuals performed well, with 93% accuracy for the depression dataset using FNN and voting classifier models.

This research is limited to only the Depression, Anxiety, and Stress Scale (DAAS 42) dataset for the three illnesses. Along with these three conditions, other psychological diseases can be added in the future. The features other than the 42 questionnaires are limited only to personal related attributes like TIPI, race, age, education, marriage, and more. Other features like employment-related can be added in addition to the existing features which can influence the model performance and can give more insight into illness. In this research, the deep learning model feed-forward neural network (FNN) is only implemented. Other deep learning models can also be implemented and validated.

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