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IMPLEMENTING MACHINE LEARNING ALGORITHMS FOR PREDICTING DEPRESSION

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Abstract: Psychological health problems such as anxiety, depression, and stress have become prevalent among people in today's fast-paced society. This research paper utilizes machine learning algorithms to forecast depression. To employ these algorithms, data was obtained from individuals with varying backgrounds, including students, employed and unemployed individuals, and homemakers, from different cultures and communities via the PHQ-9. The machine learning algorithms can predict depression across four levels of severity with high accuracy, making them especially effective in predicting mental health issues.

***Index Terms* - Support Vector Machine (SVM),Decision Tree, Machine Learning, Predicting Depression**

I. INTRODUCTION

Depression iscomplicatedphenomenon characterized by having many different aspects or features responsible for multiple factors rather than single factor. Furthermore, along with psychiatric and physical conditions patients such as continuous or frequent fluctuation in mood or emotional instability, a presence or an absence of psychotic features ranging in scale from mild to severe symptoms of depression.There canbe simultaneouspresence of two or more diseases or medical conditions in a patient. Notably, continuous sense of sadness, loss of interest or pleasure in activities are some of the core symptoms of depression. On the other hand, mood disorder that alters individual affective, cognitive and behavioral functioning is called major depressive disorder, also called as clinical disorder.

In a society characterized by technological, innovation and increasing human interconnection and globalization, there has been a significant increase in the number of individuals experiencing depression. This may result in difficulties performing daily activities and feelings of hopelessness. The Diagnostic and Statistical Manual of Mental health, Fourth Edition (DSM-IV) describes it as Major Depressive Disorder. DSM-IV characterizes depression has having one or more major episodes of depression without having any noteworthy history related to manic, mixed or hypomanic incidents [2]. It is estimated that as high as 20% of the general population has experienced depression in their lifetime with females being 2.5 times more likely to experience depression than males [34]. It is observed by researchers that depression can relate to likely course of medical condition following myocardial infarction. Myocardial infraction condition increases the risk of developing coronary artery disease.Depression affects a person's thoughts and feelings about both themselves and those around them and are sometimes also referred to as a psychiatric disorder. Depression is a psychological element faced by everyone at some point in their lives. This could be in the form of a personal tragedy or an incident with a close friend or family member. Depressionmainly comprises of fairly common human emotions such as sadness, worry, anxiety, etc. Given the vast prevalence of depression among the general population, and the growing rate of medically diagnosed patients increasing each year, there is a need for the development of a highly accurate model for diagnosing depression. This study focuses on the research and development of a model with an improved ability to identify people struggling with depression so as to ensure that they receive the necessary treatment and assistance.

II. Symptoms of Depression

It is possible for a person to have multiple episodes of depression even if it occurs once in their lifetime. A person having multiple episodes of depression can show very clear or obvious feelings or qualityby the way the subjectacts or appears throughout the day.Symptoms associated with episodes of depression include as hopelessness, feelings of sadness, emptiness, frustration, irrational behavior, loss of interest in day-to-day activities, irritation, issues with sleep and low energy levels leading to difficulty performing normal activities and fatigue.Moreover, all kinds of weight fluctuations, weight loss or weight gain, loss of appetite or binge eating may also be observed. Conditions are also often characterized by anxious episodes, constant sense of unease, worry, slow speech and physical activity. Feelings of guilt, worthlessness, difficulty with memory, focus and concentration, lack of decision making and self-blaming behavior can be seen frequently in people with depression. Extreme cases may include suicidal thoughts and behaviors. Additionally, inexplainable symptoms such as body aches, back pain and headaches can also be experienced alongside episodes of depression [31]. People experiencing depression often exhibit anger and irritability over minor issues. Sleep disturbances such as Insomnia are a recurring theme with individuals experiencing depression. Research studies have shown the risk factors associated with insomnia are considerably higher even in people with no other symptoms of depression. People experiencing depression may find it difficult to suppress their recurring negative thoughts on a daily basis [32].

III. Screening Tools For Detecting Depression

3.1 Geriatric Depression Scale (GDS)

The Geriatric Depression Scale (GDS) is used to assess depression in medically unfit individuals of the age 65 years and older. It consists of 30 questions. GDS takes response in a dichotomy format (yes or no) to evaluate the emotional condition of an older adult. The high sensitivity (92%) and specificity (89%) of GDS make it a reliable and valid assessment tool for identifying depression in older adults [15]. GDS severity level is be shown in Table 1.

Table 1 GDS Severity

Severity	Depression
Normal	0-4
Mild	5-8
Moderate	9-11
Severe	12-15

3.2 Patient Health Questionnaire (PHQ)

The Patient Health Questionnaire (PHQ) have several purpose or functions that helps in evaluating, assessing and diagnosis of severity of depression. It consists of twocomponents, the PHQ-2, and the PHQ-9, which are both independent of each other. The PHQ-2 is consisting of two items and estimates the rates of depression in an individual over the previous two weeks. While, the PHQ-9 has a broad scope and consist of nine items that evaluates depression severity level in an individual [15]. The PHQ severity level is shown in Table 2.

Table 2. PHQ Severity Level

Severity	Depression
Mild	0-5
Moderate	6-10
Moderate severe	11-15
Severe	16-20

3.3 Depression Anxiety Stress Scale 21 (DASS-21)

The DASS-21 provide details about the medical or psychological conditions by evaluating distress, anxiety, and depressive symptoms in patients. Sadness manifests stress, while anxiety and depression that appears simultaneously manifests mental health disorder. DASS-21 consist of 21 questions that evaluates depression, anxiety and stress level in an individual. Its primary purpose is to aid researchers and clinicians in monitoring a patient's emotional state over time and in determining the most appropriate course of treatment based on the severity of negative affect. [15]. The DASS-21 severity level is shown in Table 3.

Table 3. DASS-21 Severity Level

Severity	Depression	Anxiety	Stress
Normal	0-9	0-7	0-14
Mild	10-13	8-9	15-18
Moderate	14-20	10-14	19-25
Severe	21-27	15-19	26-33
Extremely Severe	28+	20+	34+

3.4 Patient Health Questionnaire (PHQ-8)

The Patient Health Questionnaire has an eight-item depression scale (PHQ-8) is an approved tool for diagnosis and measuring severity for depressive disorders inclinical studies. The PHQ-8 uses the same classes as the PHQ-9 questionnaire with a difference in the number of questions asked to the user. The PHQ-8 consists of 8 questions omitting the 9th question of PHQ-9, which relates to suicidal thoughts[36]. The severity level in PHQ-8 is described in table 4.

Table 4. PHQ-8 Severity Level

Total Severity Score (PHQ-8)	Depression
0-4	Minimal Depression
5-9	Mild Depression
10-14	Moderate Depression
15-19	Moderately Severe Depression
20-24	Severe Depression

3.5Patient Health Questionnaire (PHQ-9)

The PHQ-9 is a widely used screening tool, comprising nine questions applicable to depressive symptoms such as hopelessness and loss of interest in activities [15].

Data for the study is gathered using the PHQ-9, which consists of9 questions. The following are the text- or number-based solutions that might be:

0 Not at all
1 Several days
2 More than half the days
3 Nearly every day

The questions asked are described in table 6.

Table 5. PHQ-9 Severity Level

Total Severity Score (PHQ-9)	Depression
0-4	None - Minimal Depression
5-9	Mild Depression
10-14	Moderate Depression
15-19	Moderately Severe Depression
20-27	Severe Depression

Table 6.PHQ-9 Questionnaire for Depression

1	Little interest or pleasure in doing things
2	Feeling down, depressed or hopeless
3	Trouble falling asleep, staying asleep, or sleeping too much
4	Feeling tired or having little energy
5	Poor appetite or overeating
6	Feeling bad about yourself - or that you're a failure or have let yourself or your family down
7	Trouble concentrating on things, such as reading the newspaper or watching television
8	Moving or speaking so slowly that other people could have noticed. Or, the opposite - being so fidgety or restless that you have been moving around a lot more than usual
9	Thoughts that you would be better off dead or of hurting yourself in some way

IV. AI Use Cases For Treating Depression

AI has played an immense role in providing significant importance to healthcare and economy as depressive symptoms in an individual arises economic burden that leads to 200 million of downtime in work or up to $44 billion in annual costs to employers according to the Centers for Disease Control and Prevention (CDC). Smartphones have enabled many new AI applications in the mental health field. However, as shown by digital phenotyping, there has been an increased emphasis on smartphones being used as a source of data collection than simply being a device for displaying diagnosis. Digital phenotyping is gaining popularity among the researchers within and beyond the mental health space and may well be used as the basis of upcoming innovations in the AI and IoT sectors. The four major areas of AI applications for treating depression are:

4.1 Virtual Counseling

Companies have developed software that can identify a persons depressed mood and bolster support using machine learning and natural language processing. A San Francisco based startup by the name of Woebot[37] is one such example. The company has created a chatbot that helps users analyze their mood patterns to reduce depression. Woebot was used by 85% of participants almost daily as analyzed in a two-week study. PHQ-9 health questionnaire for depression, which determines depression using a scale from 0(no depression) to more than 20(severe depression),was used to assess success rateof the system.

Wysa[38], a competitor of Woebot, distinguishes users' emotions and suggests users to maintain mental or emotional balance by using machine learning algorithms. The application responds to text messages and take part in interventions such as cognitive-behavioral techniques (CBT), meditation, and breathing exercises by utilizing natural language processing

4.2 Patient Monitoring

Patient Monitoring technique uses machine learning to predict and prevent the onset of mental health crises. Ginger.io[39], is an application that provides users with human mental health professionals. Patient's data is analyzed using machine learning. It also describes what patient wants to achieve during episode of care, within the context of their clinical situation. The patients are also assisted by a "care team" comprising of licensed therapists, emotional support coaches and board-certified psychiatrists.

4.3 Precision Therapy:

Companies observe the progress and correlate cognitive function, clinical symptoms, and brain activity using machine learning analytics. A California-based startup called Mindstrong Health uses smartphone data combined with machine learning for the detection and treatment of various behavioral disorders with emphasis on "digital phenotyping". Digital Phenotyping is term coined by Harvard researchers in 2016 which simply refers tothe quantified analysis of an individual's smartphone and other personal devices usage data which can be used for the treatment and identification of behavioral disorders.

4.4 Natural language Processing

Natural Language Processing (NLP) methods uses speech analysis technique to evaluate, observe and detect depression in older individuals. NLP methods helps in controlling mental disorders and facilitates early diagnosis by providing evidence for improvements in capturing mental illness and multi-factorial complex associations expressed in various forms of textual data, including social media posts, interviews, and clinical notes.[41]

V. Machine Learning Algorithm For Predicting Depression

Mental Health has sustained significant recognition with the progress of machine learning algorithms in fields like healthcare. Machine learning techniques are used by researchers to point out patterns in data. These patterns enable to expand their findings and develop innovative theoretical frameworks in a hypothesis-free manner.[42]The variables from large datasets that are not normally distributed can be explained proficiently using machine learning algorithms.

5.1 Convolutional Neural Networks (CNN)

Convolutional Neural Networks have been proven to be highly competent in detecting depression with applications ranging from extracting predictive features from motor and speech data [43][44], as well as biological data models such as EEG signal reports [45]. Some of the limitations of CNN are, it requires the need for large training datasets[46] and difficulty in interpretation[47]. Additionally, CNNs can be liable to overfitting and adverse attacks. In contempt of all these limitations, researchers are addressing these issues. CNN is still continuing to be influential and adaptable to tools used in various application.

5.2 Bag-of-words

The Bag-of-Words (BoW) method is a fairly simple yet powerful approach for detecting depression from user data. It analyzes the existence of specific words in a document. It represents a text document as a collection of words, disregarding grammar, and word order. The application of the BoW approach can be seen in studies such as the research by Zhang, et al. [48], where BoW is used in conjunction with the logistic regression to identify symptoms of depression from social media data.

5.3 Term Frequency-Inverse Document Frequency

Another frequently used method for depression detection is Term Frequency-Inverse Document Frequency (TF-IDF). The importance of words in a document is calculated by combining term frequency (TF) and inverse document frequency (IDF). TF measures how often a word appears in a document, while IDF evaluates the uniqueness of a word across the entire dataset. TF-IDF captures significant words by assigning weights to words. Coppersmith, et al. [49] demonstrates an example of depression prediction using TF-IDF alongside SVM from depression related tweets on social media.

5.4 Naïve Bayes

A probabilistic model, Naïve Bayes uses machine learning algorithm to predict depression. It considers that a feature of class in independent of feature of another class.The study by Choudhury, et al. [50] returned promising results in identifying symptoms of depression from textual data usingNaïve Bayes method on Twitter posts by actual users. Naïve Bayes is based on the popular Bayes' theorem. It relies on the underlying assumption that each feature is independent of another and therefore simplifies the computational space.

5.5 K- Nearest Neighbor (K-NN)

K-NN is aclassification algorithm that takes multivariate valuesto prediction depression. K-NN classifies the new data points according to the majority class of its K nearest neighboring data points. K-NN determines the similarity between data points by calculating the distances between the instances. Applications of K-NN can been seen in various studies such as the research by Hakguder et al. [52], which explored the efficacy of K-NN in identifying symptoms of depression from actual social media posts.

5.6 Random Forest

Random Forestcombines multiple decision trees to make predictions. It is an ensemble learning method.It trains the data and features on a set of decision trees to get predictions. Application of Random Forest combined with feature selection techniques can be seen in studies[53] to identify patterns relating to depression in textual data.

5.7 Support Vector Machine (SVM)

SVM is a dominant machine learning algorithm used in various domains, including depression prediction. SVM maps the data points across high-dimensional spaces and separates the different classes by an optimal hyperplane. SVM has been used extensively in studies for depression prediction, such as Cao et al. [54], in which SVM is used in combination with recursive feature elimination technique to identify symptoms of depression from Twitter data.

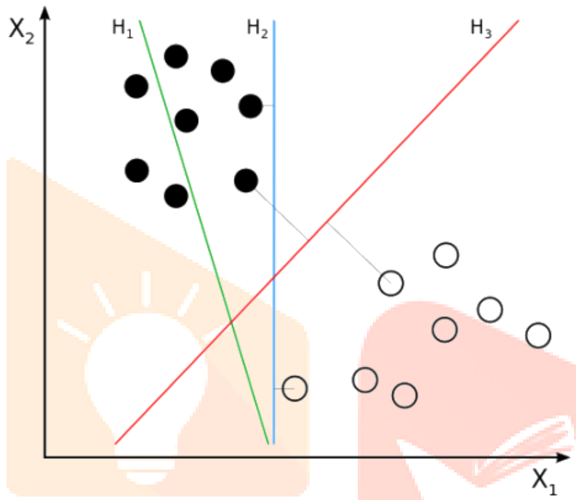

Figure 1. Visualization of a Support Vector Machine: if the white and black dots represent the classes, H1 does not separate the classes, H2 minimally separates the classes, and H3 maximally separates the classes. [60]

Consider a training dataset of n points of the form (X1, Y1), ……, (Xn, Yn), where Yi is 1 or -1, indicating the class to which the point Xi belongs. Each Xi is a p-dimensional real vector. The objective is to define the highest margin hyperplane between the points Xi for which Yi = 1 and separating them from the points for which Yi = -1. Thus, the objective is to maximize the difference between the hyperplane and the nearest point from either group creating margin between the classified groups.

5.8 Logistic Regression

Logistic Regression is a binary logistic model developed by Cox et al. in 1958 [55] used to assess the likelihood of a binary dependent variable based on a single or multiple independent variables, in our case each of these variables represent the features to identify depression.

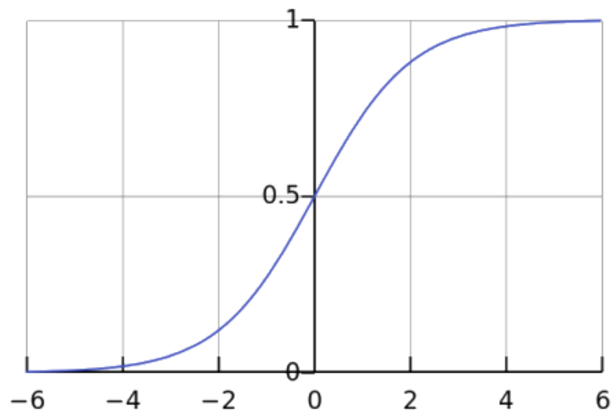

Figure 2. Our standard Logistic Function σ(t); the steeper the curve, the more difficult a diagnosis of depressed can be. Therefore, we aim to modify this curve to optimize for accuracy in diagnosis [60]

The relationship between the binary dependent variable and the features is defined through equation (1).

$$F(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}} \qquad (1)$$

In this equation, $\beta 0 + \beta 1x$ represents the parameters of best fit for the success case, which in this context is 'depression'.F(x) represents the probability of the dependent variable t being equal to the depressed case. It is important to note that F(x) inherits a non-depressed bias.

Applications of Logistic Regression in depression detection have been explored by studies such as the research done by Nguyen, et al. [56] towards classifying depressive posts from online forums.

5.9 Decision Tree

Decision Trees is a classification technique used in depression prediction tasks. The data is split indefinitely based on different attributes to create a tree-like model for prediction. Decision Tree are frequently used in studies detecting depression such as the study by Choudhury, et al. [57], which analyzed the textual data collected from smartphone sensors using Decision Trees to identify the definite symptoms of depression.

5.10 Gradient Boosting

Gradient Boosting is essentially an ensemble learning method that creates a stronger, more accurate model by combining multiple weaker models. It corrects the error of previous ensemble model by training new models. Gradient Boosting has shown promising results at detecting depression in textual data from mental health forums [58].

5.11 Ensemble Model

Ensemble Models combine multiple machine learning algorithms to make predictions. This model helps in improving the overall performance. Ensemble models created using Random Forest, Naïve Bayes and SVM have been effective at classifying depressive posts on social media.

VI. Literature Survey

Castaldelli-Maia, João Mauricio, and Dinesh Bhugra [1] provide an analysis of global data concerning mental and substance use disorders. This examines disparities between geographical regions with regards to sociodemographic characteristics and income levels based on natural language processing. Brigitta, Bondy [2] centers on the investigation of the mechanism of action of antidepressant drugs. It also highlights the influence on our comprehension of neuronal functioning and the potential underlying causes of depression. Dinga, Richard, Andre F. Marquand, et.al [3explains moderate level accuracy is achieved only on the severity of depressive symptoms in an individual patient. This emerged from consistent and noteworthy predictors. This was considered for predicting natural progression of depression. Uddin, Md Zia, Kim Kristoffer Dysthe, et.al [4] described the development of an automatic algorithm for the identification of symptoms of depression in natural language texts. It utilized a sample of young individuals seeking guidance for self-perceived depressive symptoms.This was done through the implementation of the one-hot approach and the deep learning technique of Recurrent Neural Networks (RNN). This approach, which employs natural language to describe the users' concerns, can contribute to the advancement of this research area. Carvajal, Liliana, Katherine Ottman, et.al [5] presented the transcultural translation and adaptation process for the Revised Children's Anxiety and Depression Scale (RCADS) tool in the Belizean context. This facilitated the adaptation of the instrument items to preserve the original clinical relevance.It also ensured that they were acceptable and comprehensible for Belizean adolescents. Moncrieff, Joanna, Ruth E. Cooper, et.al [6] have posited that depression is caused by irregularities in brain chemicals, specifically serotonin (5-hydroxytryptamine or 5-HT).This notion provides a crucial rationale for the usage of antidepressants. In an effort to determine whether the existing evidence supports serotonin's role in the etiology of depression.In particular, if depression is connected to reduced serotonin concentrations or activity, an "umbrella" review was conducted across. Franzen, Peter L., and Daniel J. Buysse [7]examines the correlation between sleep disruption and major depressive disorder (MDD) by analyzing data from different cross-sectional studies. It also investigates the long-term risk factors of insomnia leading to the development of depression. Furthermore, the paper explores the impact of insomnia on the clinical progression, response to treatment, and recurrence of MDD. Lastly, it assesses the effectiveness of specific sleep interventions in enhancing both sleep quality and depression outcomes. In another study Luna Ansari, Shaoxiong Ji, et.al [8] explains that by combining different NLP techniques, it is possible to identify the combination of models and features.This helps in improving the accuracy of depression detection. The experiments include four classifiers, three of which rely on artificial neural networks.The artificial neural network include LR and RNN-based neural networks, such as LSTM and Attention LSTM. Aloshban, Nujud, Anna Esposito, et.al [9] have described a joint analysis of linguistic and acoustic aspects of speech.This allows for the differentiation between depressed and non-depressed speakers with an accuracy rate above 80%. The research was conducted on a corpus of 59 interviews (equivalent to approximately 4 hours of material) involving 29 patients diagnosed with depression and 30 control participants. The results show that multimodal approaches are more effective than unimodal ones. Individuals tend to express their condition through only one modality, thus creating variety across unimodal methods. Additionally, it demonstrates that it is possible to assess the "confidence" of the approach. This automatically identify a subset of the test data in which the performance is above a predetermined threshold. Liu, Hao, Huaming Peng, et.al [10] demonstrates the effectiveness of chatbots as a means of self-help depression treatment in real-world settings. The study showed that the therapy chatbotreduced depression levels as measured by the Personal History Questionnaire (PHQ-9) over a period of 16 weeks. It slightly reduced anxiety levels as measured by the Generalized Anxiety Disorder (GAD-7) during the first 4 weeks. The chatbot intervention was found to be more effective than bibliotherapy. However, a decline in chatbot adherence was observed. This may be attributed to technical and content-related defects. The use of conversational AI was found to help establish a therapeutic alliance. This was indicated by the higher scores in the Working Alliance Inventory-Short Revised (WAI-SR) among chatbot users.Furthermore, feedback on XiaoNan, the chatbot used in the study, suggested that process factors were more influential than content. Babu, Nirmal Varghese, and E. Kanaga [11] have defined sentiment analysis as the process of analyzing and extracting the feelings, opinions, and judgments conveyed in texts or other data. Multi-class classification, is used to achieve accurate classification.As the data is classified into several subclasses based on sentiment polarity.Emoticons and emojis present in social media data also have sentiment score values.This can be utilized for sentiment analysis or classification. In this research study, Priya, Anu, Shruti Garg, and Neha Prerna Tigga [12] applied various machine learning algorithms to categorize anxiety, depression, and stress into five different severity levels. The data was collected using a standardized questionnaire, DASS-21. DASS-21 measured common symptoms of anxiety, depression, and stress. The authors employed five different classification techniques, including Decision Tree (DT), Random Forest Tree (RFT), Naïve Bayes, Support Vector Machine (SVM), and K-Nearest Neighbour (KNN). The study determined that Naïve Bayes exhibited the highest accuracy, whereas Random Forest was found to be the best model. The authors used the f1 score to select the best model due to the imbalanced classes present in the dataset. In the study conducted by Tyshchenko, Yevhen [13] the author aimed to retrieve blogs that were independent of the control and clinical corpora. The author experimented with three different input representations, including BOW, TFIDF, and topic modeling features. This representations where combined with SVM and Random Forest Classifier. The author also trained Convolutional Neural Networks (CNNs) with both randomly initialized and pre-trained word vectors.The impact of the length of the blog posts on the performance of the CNN model was investigated. Al Hanai, Tuka, et.al [14] presented a model that analyzed 142 interactions to detect depression during interviews. The authors conducted three sets of experiments using audio and text modalities. The first set of experiments was conducted without the question that prompted the response. The second set included the context by conditioning on the question asked. The third set analyzed the sequence of responses without conditioning on the questions asked. In the research conducted by Rahimapandi, Hanis Diyana Abdul, et.al [15] a systematic literature review was conducted to predict depression using machine learning algorithms from 2016 to 2021. The authors identified relevant variables for predicting depression using machine learning techniques. The authors determined the latest and most frequent screening types used to detect depression. They also examined state-of-the-art techniques in machine learning to predict depression based on chosen metrics. Li, Chong, Mingzhao Yang, et.al [16] proposed an intelligent method that uses artificial intelligence technologies to evaluate the mental health problems of college students.The aim was to get efficient and accurate psychological diagnosis and treatment. This study employed a mixed-method approach that combined psychological questionnaires with facial emotion analysis. This comprehensively assessed the mental health of students on a large scale. The Depression Anxiety and Stress Scale-21 (DASS-21) was used as the psychological questionnaire. K Iyer, ZA Khan [18] highlighted the significance of understanding the effects, possible triggers, and treatments of depression. Jocelyne Matar Boumosleh, Doris Jaalouk [19] identified several independent positive predictors of smartphone addiction, including depression and anxiety.This research noted, young adults with personality type A, high stress levels, and low mood may lack positive stress coping mechanisms. Thus this indicates that such individuals are more susceptible to smartphone addiction. Sandeep Grover, Venkatesh Raju V, et.al [20] reported that depression does occur in children and adolescents in the Indian context. Maureen Kroning, Kayla Kroning [21] emphasized the importance of developing mental health programs to increase awareness and reach out to teens who may be suffering in silence. These programs can leverage social media.It collaborated with teen support groups and faith organizations to create safe havens for teenagers. In the study conducted by Sandeep Grover, Alakananda Dutt, Ajit Avasthi [22] it was highlighted that depression is a mental disorder among both outpatient clinic populations and individuals receiving medical and surgical treatment. The study further reported that depression is the most common psychiatric disorder in elderly individuals across various settings. Studies conducted in India have also revealed that life events preceding the onset of depression play a crucial role in the development of the disorder. Juan Aníbal González-Rivera, Orlando M Pagán-Torres, et.al [23] employed the DASS-21 questionnaire and found significant psychometric deficiencies. This was particularly in matters relating to construct validity, as well as convergent and discriminatory validity. Their findings demonstrated that the DASS-21 does not accurately replicate the three-dimensional structure of the original instrument within Puerto Rico's Hispanic community. Ezekiel Victor, Zahra M Aghajan, Amy R Sewart, et.al [24] suggested that deep learning methods with minimal human intervention could effectively detect depression using the DASS-21. Therefore, streamlining the process. Gautam Kumar Baboo, Veeky Baths [25] explained that the computerized version of the DASS-21 test eliminates the possibility of anxiety or nervousness. This could arise from paper-based or personal interview methods. This assertion was supported by Robert S Vaughan, Elizabeth J Edwards, Tadhg E MacIntyre [26] findings, which demonstrated that the psychometrics of the DASS-21 were supported.It investigates the implications of COVID-19 in sports. The study provided a substantial addition to the literature on athlete mental health. It also enabled definitive comparisons with the general population as the scale operates equivalently across athletes and non-athletes. Rebecca Beiter, Ryan Nash, Melissa McCrady,et.al [27] emphasize the need for colleges to assess the mental health of their students.Treatment programs were designed that address their specific needs, given the potential of mental health issues.This helps to improve the academic success of college students. According to Burkhardt, Hannah, Michael Pullmann, et.al [28] there are variations in the quality of emotion features extracted through different extraction methods. In their study, the emotion features derived from the GoEmotions BERT-based model accounted for more variance in univariate mixed-effect regressions. It alsocontributed to the prediction of depression and anxiety status by a random forest classifier.GoEmotions model provides clinically relevant nuance not captured by other existing tools. Non-emotion variables from LIWC remain valuable in linguistic modeling tasks. Mokros, Łukasz, Piotr Świtaj, et.al [29] confirm that depression and loneliness are suitable targets for tailored therapeutic programs.This promotes a return to work and work efficiency. In their study, short-term and long-term psychodynamic psychotherapy and psychoanalysis were found. This alleviated depressive symptoms, improve work ability and functional outcomes. In a systematic review, clinical care and work-directed psychological interventions reduce the severity of depression and absence of sickness. Zhou, Zhaohe, Dan Luo, Bing Xiang Yang, and Zhongchun Liu [30] applied machine learning techniques to predict depression symptoms with reasonable accuracy and net benefit. They identified risk exposures previously confirmed in other studies.

VII. Implementation

We begin our research by the analysis of PHQ-9 as a tool for diagnosis.Depression is predicted using PHQ-9 screening tool which consist of nine questions followed by its severity level. The dataset used consist of each question as features and the diagnosis is based on analytic 'phq9' score and actual 'class' diagnosis.

Table 7: Analysis of PHQ-9

Metrics	PHQ-9
Accuracy	0.78
Precision	0.81
Recall	0.78
F1 Score	0.78

It can be seen that the performance of PHQ-9 diagnosis compared with the actual diagnosis of the user. The accuracy of PHQ model was approximately 78% which cannot be deemed reliable as a tool for diagnosing depression. PHQ-9 being an analytical model for depression diagnosing, the inadequate accuracy result can be decomposed by studying the Correlation Matrix.

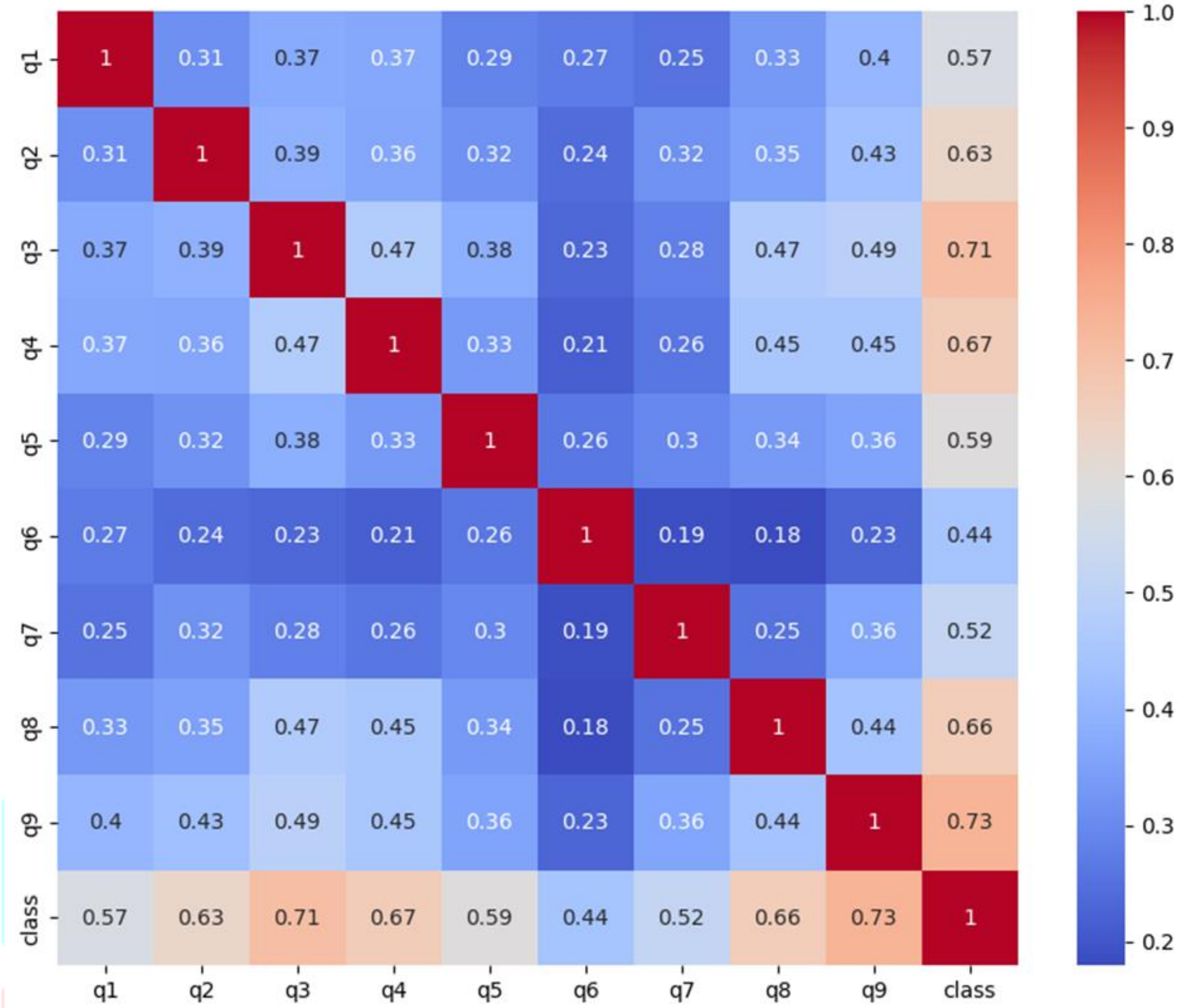

Figure 3: Correlation Matrix

The matrix in Figure 3 represents the correlation of each question having distributed probability with the target class. For example, the question represented by ‘q9’ pertains to whether or not the user is having suicidal thoughts and thus has a higher correlation with the target class. In case of an equal distribution of correlation between the questions and the target class, as assumed by the PHQ-9 questionnaire, diagnosis using analytically methods could have been employed. Since the correlation varies across questions, Machine Learning-based models need to be used to ensure better diagnosis.

7.1 Data Pre-processing

In this particular research study, information was gathered through an anonymous PHQ-9 form, which aided in the execution of a depression prediction model. To guarantee data quality and alignment with the diverse machine learning models employed in the project, a thorough data preprocessing methodology was carried out. The subsequent section presents an overview of the data preprocessing workflow:

Data Collection

The process of collecting data acquires responses from a varied range of participants by means of the anonymous PHQ-9 form.

Data Cleaning

Data cleaning techniques were utilized to handle any instances of missing values present in the gathered dataset. The absence of values could have originated from non-response or other variables. An appropriate approach was implemented to manage these missing values.

Feature Selection and Transformation

Analysis was conducted to assess the importance and relevance of each feature (question) in the PHQ-9 dataset for depression prediction. The specific requirements and preferences of used machine learning models was considered. Features were chosen based on their informational value and adjusted as needed.

Data Splitting

To enable the training, validation, and evaluation of the model, the preprocessed dataset was partitioned into separate sets: training, validation, and test. The training set was employed to train the model. The validation set was crucial in fine-tuning the hyperparameters and assessing the model's performance during the development stage. Ultimately, the test set was used as an independent dataset to evaluate the final model's performance.

7.2 Training Procedure

Model Initialization

The goal of the models is to produce better and more accurate diagnosis of Depression than the analytical PHQ-9 model. In order to achieve this goal, several classification models are initialized, including Gradient Boosting, Logistic Regression, Random Forest, Support Vector Machine, Decision Tree, and Naive Bayes. Each model is trained using the training data.

Training

Models that were used for training are SVM, Gradient Boosting, Random Forest, Decision Tree, Naïve Bayes and Ensemble Model. We have considered SVM, Random Forest, Logistic Regression, Gradient Boosting and Decision Tree models in Ensemble Model and used voting classifier method to make predictions.

Evaluation

Various evaluation metrics were documented during the model training procedure. Metrics such as accuracy, the precision, the recall value and the f1 score were noted for each of the models to determine the adaptability of the models. Similarly, the models were also evaluated by plotting the confusion matrix and the classification report.The confusion matrices for the models were used to take into account the false positives and false negatives with respect to each class prediction. The classification report was studied to further inspect the accuracy, precision and recall rates across all the classes of diagnosis.

Optimization

The models were compared on the basis of their accuracies, precision, recall and f1 scores. The model showcasing the highest validity while taking the accuracy, precision, recall and f1 score into consideration is further optimized by hyperparameter tuning. The optimized model is then deployed for real-time prediction of depression.

VIII. Results and Discussion

8.1 Comparison of Models:

Making Predictions and Calculating Accuracies:

Predictions are made on the test data using each trained model and the accuracy is calculated by comparing the predicted labels with true labels.

Table 8: Accuracies of respective machine learning algorithms

Models	Accuracies
Support Vector Machine (SVM)	0.9535
Ensemble Model (SVM, Random Forest, Gradient boosting)	0.9243
Gradient boosting	0.9086
Random Forest	0.9008
Decision tree	0.8154
Naïve bayes	0.3290

The performance of SVM model for accuracy is 0.9648, followed by its precision (0.9662), recall (0.9677), F1_score (0.9665) respectively. The accuracy of Gradient Boosting (0.8457), Random Forest (0.9131), Decision Tree (0.8782), Naïve Bayes (0.8782) and Ensemble Model (0.9551). On comparing the performance of classification models by evaluating their accuracies, the results indicate SVM model achieved highest accuracy of 0.9648 followed by Ensemble model (0.9551) and Random Forest (0.9131).

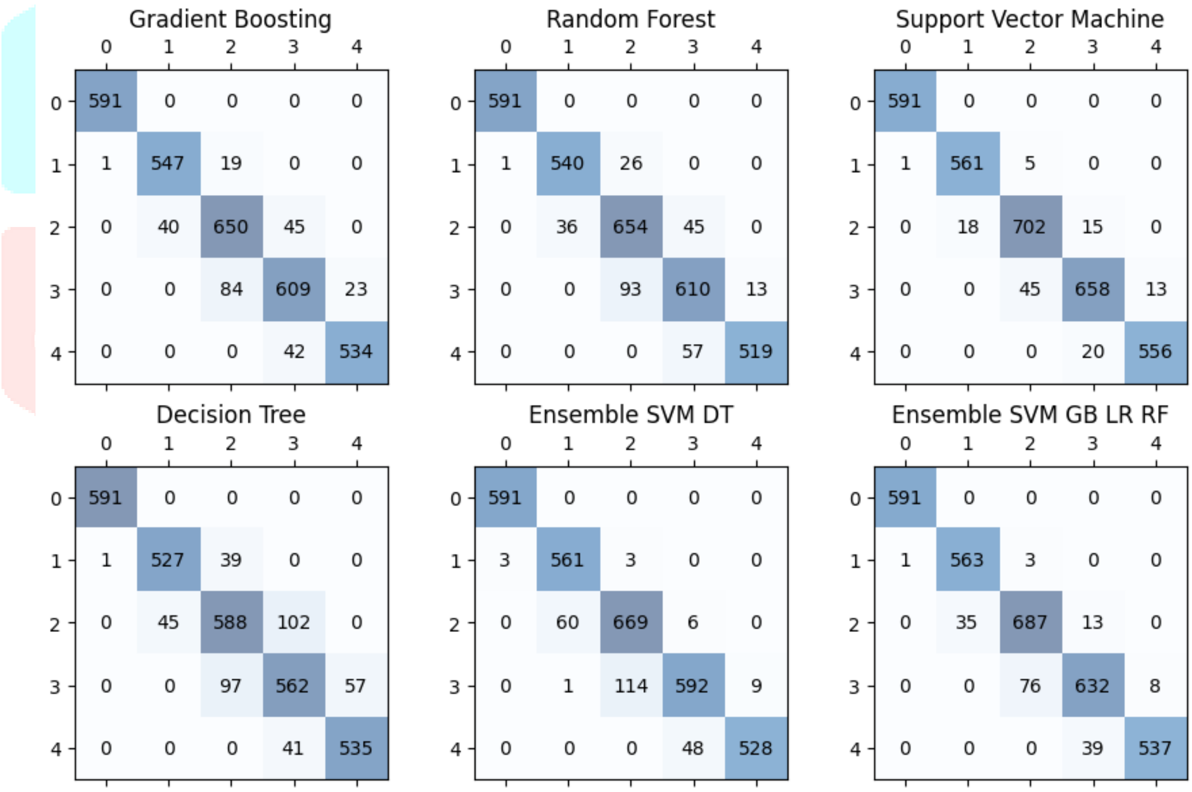

Figure 4: Comparison Matrix

The confusion matrix plot for the different models showcases the leverage SVM Classifier has over other models, especially taking the false positives and false negatives into consideration. The SVM Classifier model display a more uniform distribution of validity across the various classes of diagnosis which is especially crucial in case of healthcare models. All the models display equal proficiency when it comes to identify class ‘0’ which represents ‘No Depression’. SVM surpasses other models in accurately classifying the remaining classes of depression and also the decisive class ‘4’ which represents ‘Severe Depression’. Other models with accuracy and precision scores similar to SVM are other Ensemble models based on SVM substantiating the case for SVM Classifier as the superior model for identifying depression.

8.2 Comparison of Results:

A bar chart is created to visualize and compare the accuracies of different models.

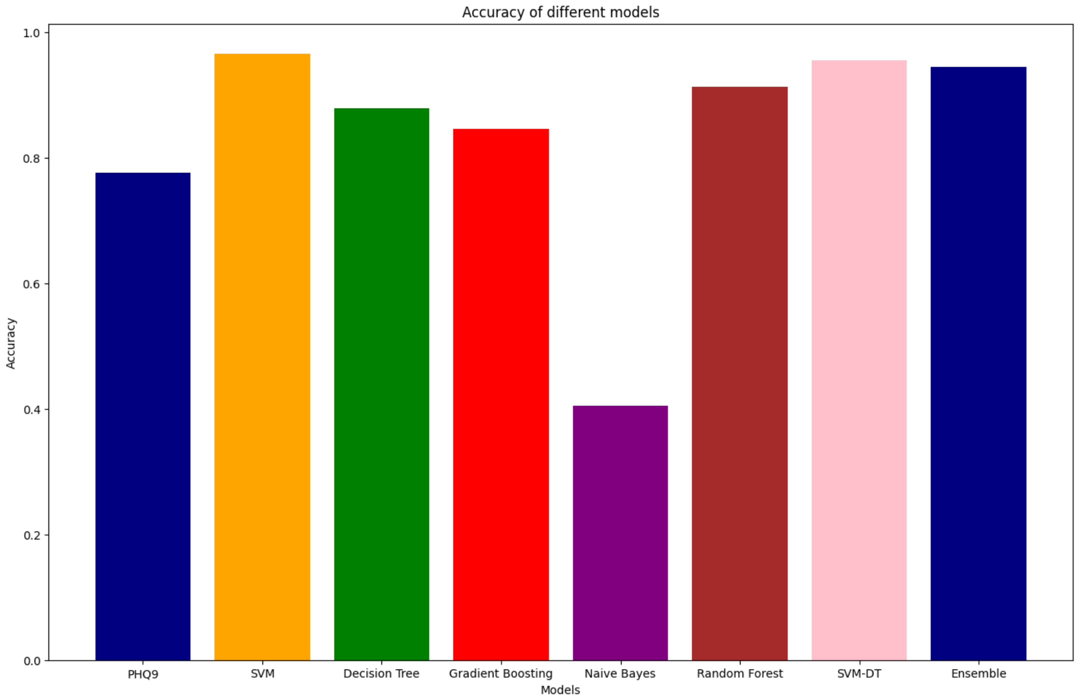

Figure 5: Visual Representation for accuracy of different models

The x-axis represents the model names, while the y-axis represents the accuracy values. SVM model shows best performance with highest accuracy of 0.96.

However, the best model for any healthcare prediction system cannot be determined on the basis of accuracies alone. The false positives and false negatives are equally crucial in healthcare diagnosis. Thus, better accuracy and prediction rate of SVM Model not just for the main depression class, but also across all the alternate classes presents a strong case for its adoption as the best model for Depression Prediction.

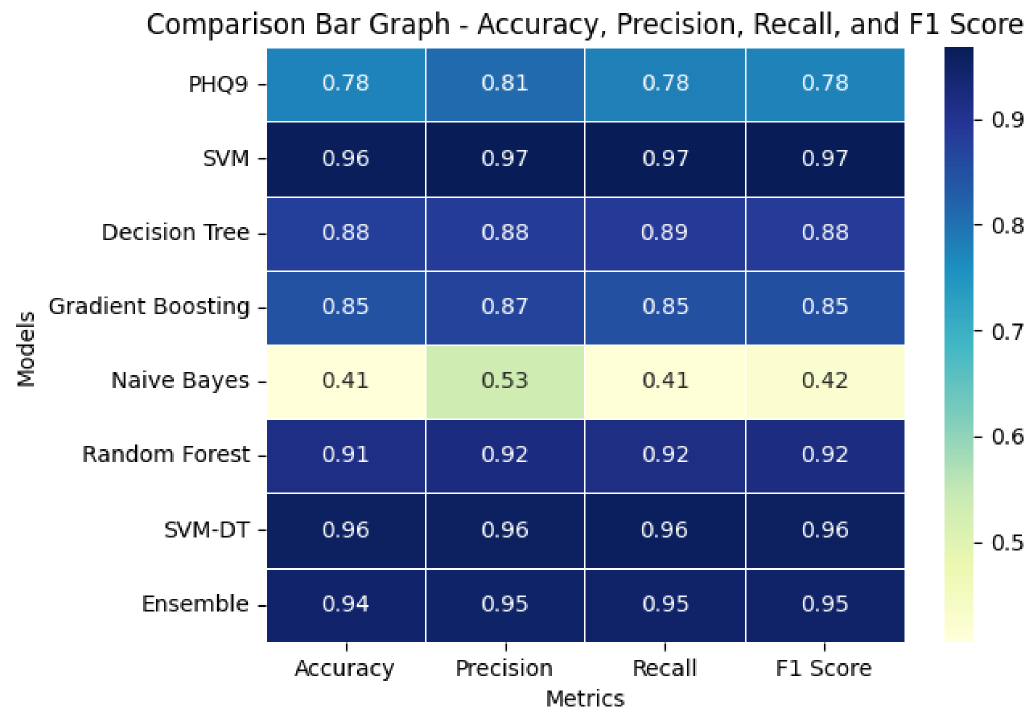

Figure 6: Comparison Bar Graph-Accuracy, Precision, Recall and F1 Score

The comparison results establishedSVM as the best model with the highest accuracy, precision, recall and f1 scorewith the Naïve Bayes model representing the opposite end of the spectrum. The comparison also showcases the efficacy of the SVM Model over the analytical PHQ-9 model.

Hyperparameter tuning

The chosen SVM Model is further optimized using the GridSearchCV Algorithm which stores the best performing parameters after hyperparameter tuning. The accuracy of the model after hyperparameter tuning is 0.9654 which is marginally better than the original model. Thus, our model has been optimized and is now ready for deployment.

8.3 Web Application Deployment

The research then moves ahead with the deployment of the SVM model using a Web Application for predicting depression. It provides real-time prediction or feedback to the end user.

Flask Framework:

The web application was developed using the Flask framework, a lightweight Python webframework. Flask provides a user-friendly interface for handling user requests and integrating the SVM model for classification.

Render.com Deployment:

The web application was deployed on Render.com, a cloud platform that simplifies thedeployment process. Render.com provides a scalable infrastructure to host web applications. It ensures reliable performance and accessibility.

Landing Page:

Upon accessing the web application at “https://depressionprediction.onrender.com/”, users are greeted with the landing page. When the user clicks on the link to start the assessment, they should be taken to a page with the PHQ-9 questionnaire. The questionnaire should consist of nine questions, each with a range of responses from "Not at all" to "Nearly every day." The user selects their response to each question.

IX. Conclusion and Future Enhancements

This study uses machine learning algorithms for predicting depression. The use of these algorithms provides an ultimate goal of facilitating early diagnosis. It also helps intensify the outcomes of mental health of an individual along with improved accuracy and effectiveness for predicting depression.

The deployed Web Application uses the SVM Model which provided promising results in predicting depression. The accuracy and performance metrics achieved are evaluated and compared against existing methods or benchmarks. The findings therefore suggest that machine learning algorithms are valuable tools for identifying the risk of depression on the basis of PHQ-9 responses.

To improve the accuracy for predicting depression using machine learning algorithms, several future advancements can be considered.Firstly, a comprehensive feature engineering which involves selecting relevant input variable that are strongly associated with depression can be conducted. Secondly, deep learning techniques for data augmentation can be incorporated on large or different types of datasets for more generalization of results. Lastly, hyperparameter optimization can also be utilized in conjunction with advance algorithms such as genetic algorithms to get optimal performance.

The ongoing development of these machine learning models is expected to yield greater insight into the underlying factorsand predictors of depression whileenabling the provision for more effective support and care to those at risk of depression.

FiguresandTables

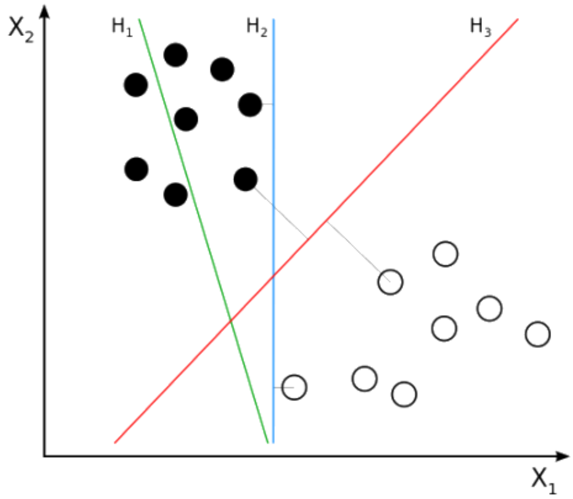

Figure 1. Visualization of a Support Vector Machine: if the white and black dots represent the classes, H1 does not separate the classes, H2 minimally separates the classes, and H3 maximally separates the classes. [60]

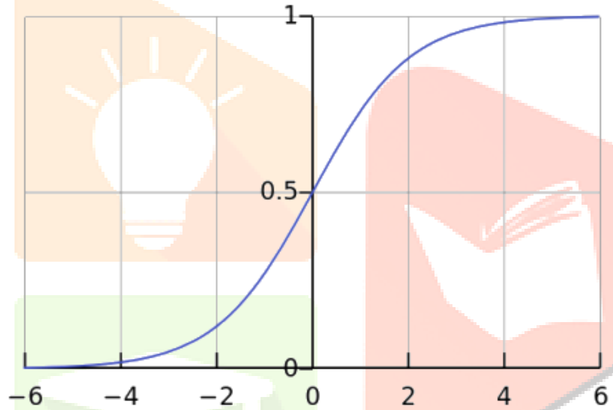

Figure 2. Our standard Logistic Function σ(t); the steeper the curve, the more difficult a diagnosis of depressed can be. Therefore, we aim to modify this curve to optimize for accuracy in diagnosis [60]

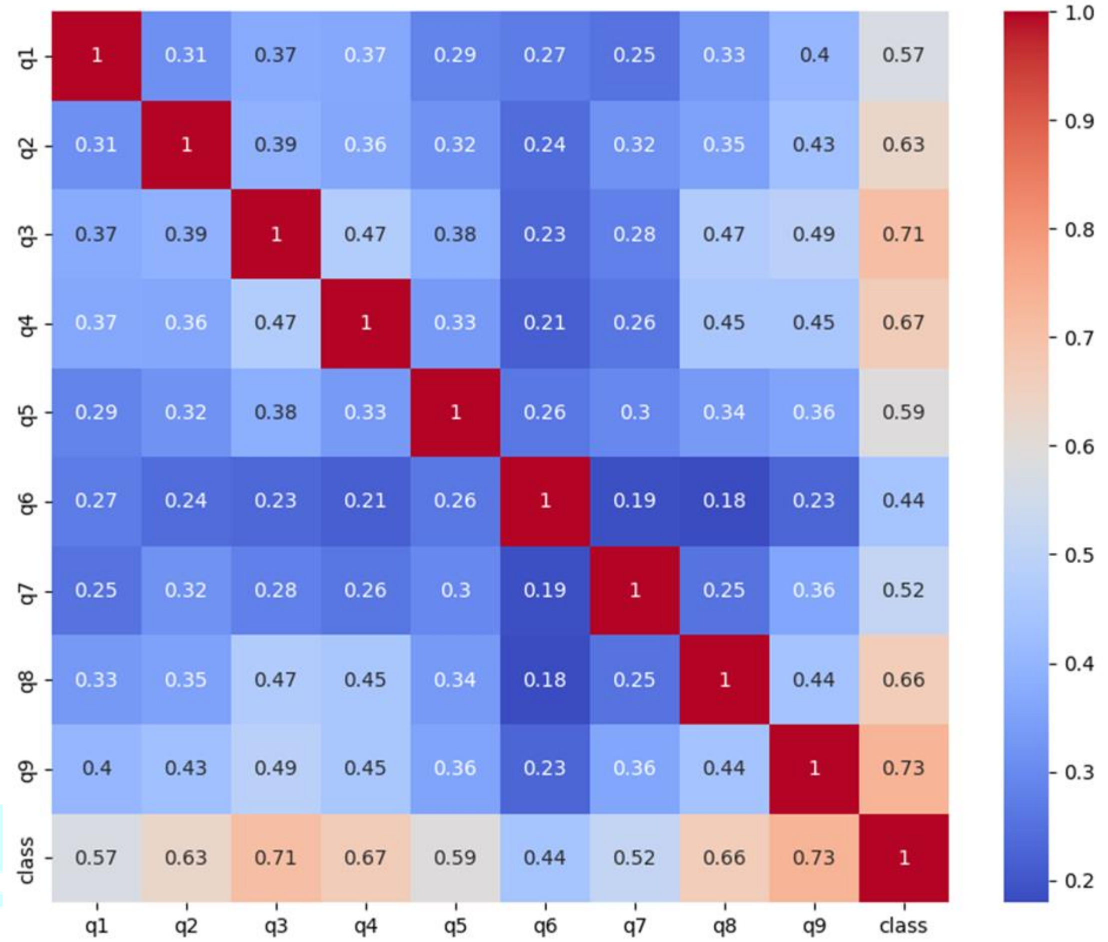

Figure 3: Correlation Matrix

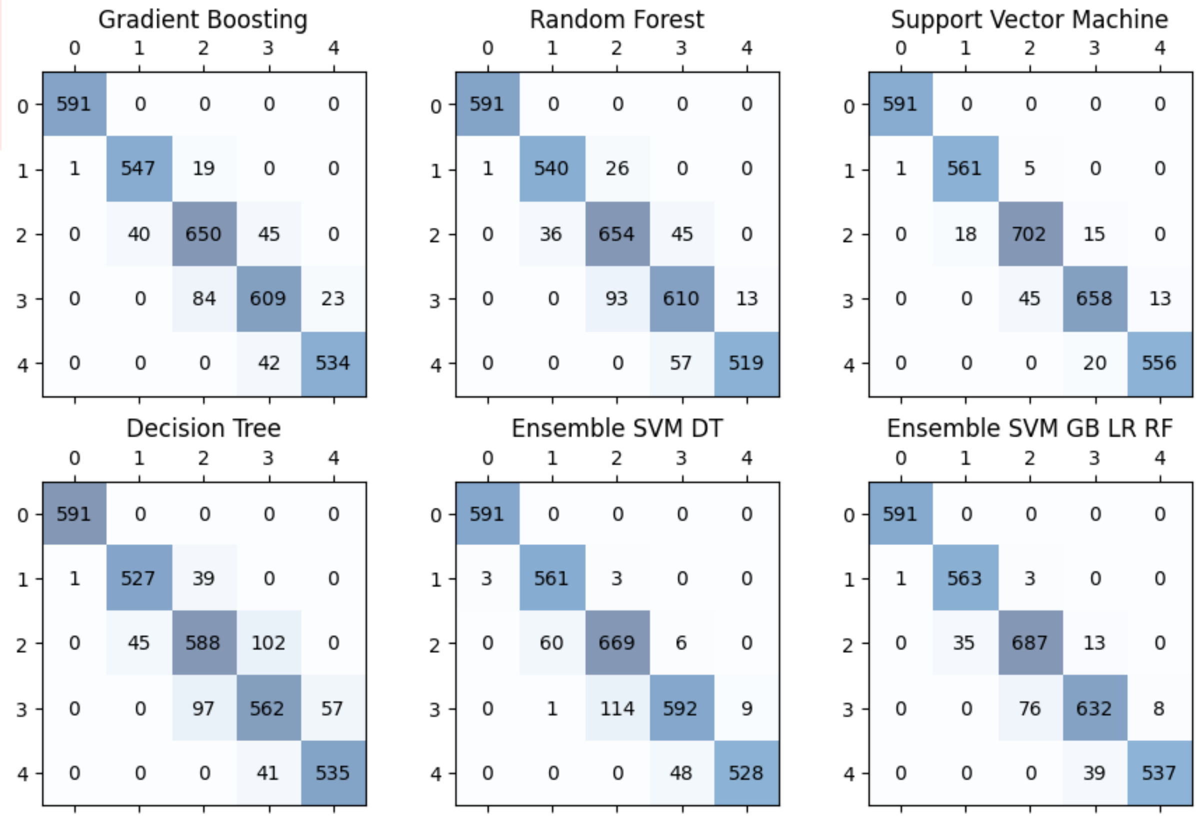

Figure 4: Comparison Matrix

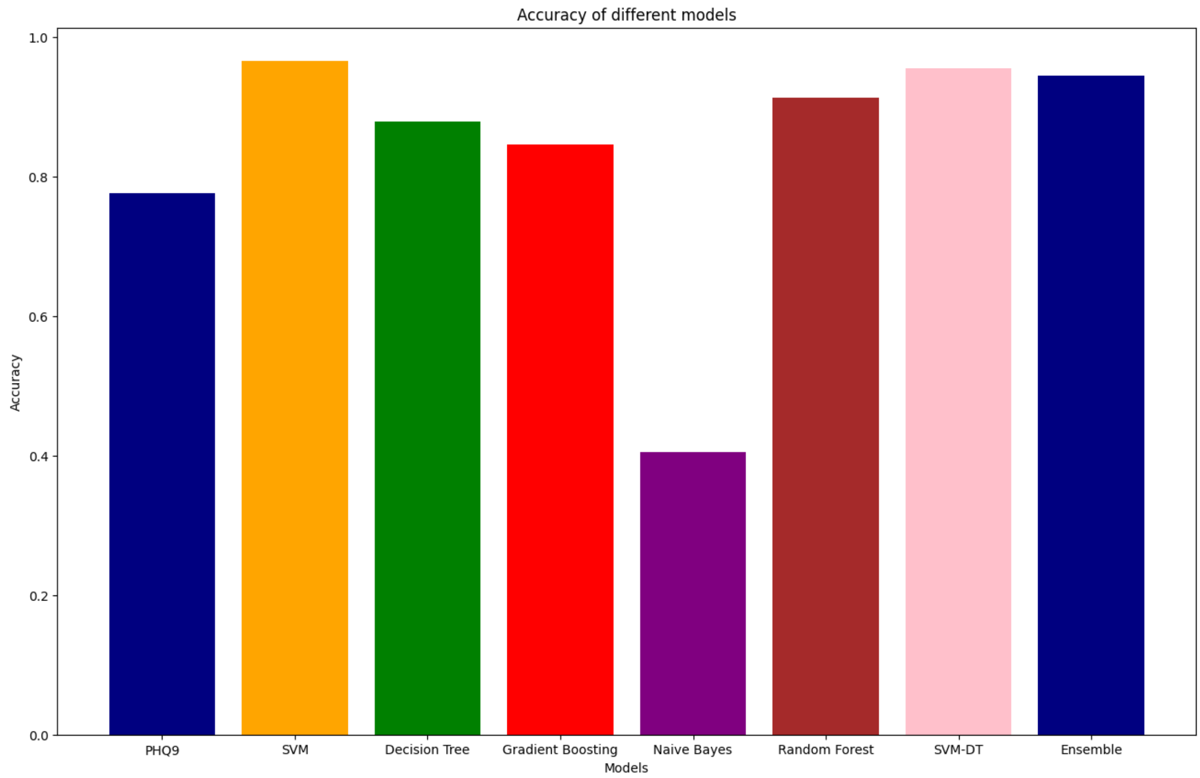

Figure 5: Visual Representation of accuracy of different models

Table 1 GDS Severity

Severity	Depression
Normal	0-4
Mild	5-8
Moderate	9-11
Severe	12-15

Table 2PHQ Severity Level

Severity	Depression
Mild	0-5
Moderate	6-10
Moderate severe	11-15
Severe	16-20

Table 3DASS-21 Severity

Severity	Depression	Anxiety	Stress
Normal	0-9	0-7	0-14
Mild	10-13	8-9	15-18
Moderate	14-20	10-14	19-25
Severe	21-27	15-19	26-33
Extremely Severe	28+	20+	34+

Table 4. PHQ-8 Severity Level

Total Severity Score (PHQ-8)	Depression
0-4	Minimal Depression
5-9	Mild Depression
10-14	Moderate Depression
15-19	Moderately Severe Depression
20-24	Severe Depression

Table 5. PHQ-9 Severity Level

Total Severity Score (PHQ-9)	Depression
0-4	None - Minimal Depression
5-9	Mild Depression
10-14	Moderate Depression
15-19	Moderately Severe Depression
20-27	Severe Depression

Table 6PHQ-9 Questionnaire for Depression

1	Little interest or pleasure in doing things
2	Feeling down, depressed or hopeless
3	Trouble falling asleep, staying asleep, or sleeping too much
4	Feeling tired or having little energy
5	Poor appetite or overeating
6	Feeling bad about yourself - or that you're a failure or have let yourself or your family down
7	Trouble concentrating on things, such as reading the newspaper or watching television
8	Moving or speaking so slowly that other people could have noticed. Or, the opposite - being so fidgety or restless that you have been moving around a lot more than usual
9	Thoughts that you would be better off dead or of hurting yourself in some way

Table 7: Analysis of PHQ-9

Metrics	PHQ-9
Accuracy	0.78
Precision	0.81
Recall	0.78
F1 Score	0.78

Table 8: Accuracies of respective machine learning algorithms

Models	Accuracies
Support Vector Machine (SVM)	0.9535
Ensemble Model (SVM, Random Forest, Gradient boosting)	0.9243
Gradient boosting	0.9086
Random Forest	0.9008
Decision tree	0.8154

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