

Depression Prediction using Machine Learning

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Abstract—In our tech-driven world, where depression affects over 5% of the global population, early detection and intervention are vital. With 1 from both 3 and 5 women and men are expected to be experiencing major depression, machine learning presents promising avenues for prediction and intervention. Depression's complexity challenges accurately diagnosing and accurate treatment, which prompt the development of various machine learning techniques to improve the management. So, this study employs five machine learning algorithms to predict depression, anxiety and stress severity using dataset from the DASS 21 questionnaire across diverse demographics. Despite class imbalances, the forest classifier considered as the most accurate and trusted model, bolstered by the incorporation of the F1 measure. Additionally, the algorithms exhibit sensitivity to negative outcomes, underscoring their potential in enhancing mental health care. This research contributes to advancing predictive models for psychological disorders, facilitating timely interventions and ultimately improving mental health outcomes in our modern society.

Index Terms— Depression analysis, prediction, machine learning, F1 measure, early detection, mental health.

I. INTRODUCTION

Depression is frequently seen in middle-aged and older individuals who also grapple with chronic ailments like obesity, diabetes, and sleep disorders. Indicators such as BMI, WC, CRP, and lipid profile—marked by elevated TC and reduced HDL—signal obesity and metabolic syndrome, heightening susceptibility to heart-related issues. This suggests a bidirectional relationship between depression and concurrent health conditions [1], including HbA1c levels. The study concentrates on sleep-related challenges such as irregular sleep schedules and disruptions in circadian rhythms, as well as the repercussions of EDS and insufficient sleep on inactive habits and diminished physical activity. Its aim is to apply ML techniques to anticipate depressive symptoms in this age bracket, exploring various predictive elements collectively and individually. The objective is to deepen our comprehension of the interplay between mental health, lifestyle choices, and biomarkers in middle-aged and older adults. The text underscores the global health urgency posed by depression, emphasizing its widespread impact and the hurdles in identification and treatment. It draws attention to how common depression is, how closely it is linked to an increased risk of suicide, and how it ranks as the fourth most common cause of death for those aged 15 to 29. The article then delves into the emerging domain of automated depression detection, particularly through sophisticated analysis of speech signals, noting that individuals with depression exhibit unique patterns in facial expressions, body movements, and speech characteristics. Speech signal analysis, due to its non-intrusive nature and relatively low cost, has gained attention. The paper aims to provide a systematic summary of speech-based depression recognition (SDR) [2], covering its historical development, the transition

from traditional to deep learning-based methods, and the integration of multiple features. The main contributions include introducing recent literature, analysing trends, and identifying future research directions. The discussion covers the seriousness of the depression crisis, challenges in current diagnostic methods, and the promise of ML and speech signal analysis for automated depression detection. It provides a detailed overview of the evolution of SDR methods, offering insights into their present state and future potentials. The hurdles in managing Major Depressive Disorder (MDD) are emphasized, especially the limited efficacy of antidepressants, and the increasing interest in predictive models for treatment response using machine learning methods. Findings from a random-effects model involving 758 patients using a restricted maximum likelihood estimator are presented. The model reveals a combined accuracy of 83.93 (95 CI: 78.90–89.29), an Area-Under-the-Curve (AUC) of 0.850 (95 CI: 0.747–0.890), and a partial AUC of 0.779. The average sensitivity and specificity across models are stated as 77.96 (95 CI: 60.05–88.70) and 84.60 (95 CI: 67.89–92.39), respectively. The discussion also mentions the exploration of various ML algorithms and the consideration of neuroimaging techniques, particularly MRI, to improve prediction accuracy[3]. The impracticality of widespread clinical use due to high costs is acknowledged, leading to the proposal of electroencephalography (EEG) as a more cost-effective alternative for predicting treatment response in psychiatry. The challenges in establishing robust individual biomarkers for treatment response are acknowledged, and a meta-analysis indicating moderate sensitivity and specificity in predicting treatment response during a depressive episode is mentioned. The second part of the text shifts focus to depression as a prevalent psychological disorder, particularly exacerbated during the COVID-19 pandemic, affecting 322 million people globally [4]. A detailed study of the problem, depression among the senior citizens helps the health planner and policy maker to design appropriate health care system[5]. In Bangladesh, a significant portion of the population faces mental health challenges, emphasizing the importance of promptly identifying individuals with depression. This paper aims to enhance this effort by pinpointing socio-demographic and psychosocial factors that influence depression. It intends to create a dataset to predict depression risk and to explore machine learning methods and feature selection algorithms for efficient screening. One notable advantage highlighted is the simplified version of the required information for this screening process [6]. The paper's structure is covering related works, methodology, give the result of a comparative study with existing works, and concluding remarks with potential future study scopes.

II. SURVEY

The present study employs the majority of the input variables from the machine learning predictive modelling research on depression in hypertensive populations. Less than 9.0% of these have missing data [7]. Using the Random Forest package's "na.roughfix()" method, the missing values was substituted with the mean for continuous and categorical model data. Descriptive and bivariate analyses evaluate fundamental attributes based on the depression state of the individuals [7].

Clinical Information is used for this depression prediction survey and may include medical history, blood pressure readings, medication use, and other pertinent clinical characteristics. Lifestyle Factors: Information needed regarding lifestyle decisions including nutrition, exercise, and drug usage may be crucial in predicting survey results. Psychosocial factors, such as social support networks and stress levels, may be incorporated into the analysis to forecast depression. The research "Biomarkers" investigates the use of biological markers to collect information for predictive survey models.

This model's overall performance was assessed using the area under the receiver operating characteristic curve (AUC), which is sometimes referred to as the F1-score, precision, accuracy, sensitivity, and specificity. AUC, a commonly used statistic for binary classification issues, offers a summary of the classifier's performance that is representative. For practical models, AUC values between 0.7 and 0.9 are often regarded as good, and values over 0.9 as exceptional [8]. A higher F1-score denotes accurate class identification and is correlated with fewer negatives and fewer complete positives. AUC and F1-score are well-known metrics for assessing classification performance over an imbalanced dataset [9].

986 (11.7%) of the 8,728 persons in the sample who had hypertension also reported having clinical depression according to their PHQ-9 scores. The depressed group was notably younger than the non-depressed group. While non-Hispanic White, non-Hispanic Black, and non-Hispanic Asian persons made up a larger share of the non-depressed categories, this group had a bigger number of people of Mexican, Hispanic, and other background.

PHQ-9 was used in a study to anticipate depression in order to halt heart failure. The patients' mean age was 45–65 years, with 70% of them being men, 55% being white, and 43% being black. Their ejection fraction ranged from 15–45%. Sixty-eight deaths, five transplants, two implantations of ventricular assist devices, 645 admissions for all causes (275 [33.9%] for heart failure), and 374 visits to the emergency department (ED) were

among the 51 (33.7%) important clinical events that occurred throughout a 12-36-month period with a total of 625 person/years [10]. Significantly greater hospital admissions and related admissions were associated with moderate-to-severe depression symptoms. Comparing those with mild symptoms to those without depression, more admissions were observed. The "grey zone" of PHQ-9 scores between 10 and 15 led to additional research to determine the best cut points for determining how depressive symptoms affect hospitalisations [11]. Using a diagnostic methodology, this systematic evaluation of the PHQ-9's diagnostic qualities complies with earlier suggestions to use a bivariate meta-analysis to compile the diagnostic features of the PHQ-9 for various scoring systems.

Functioning features of different PHQ-9 cutoff criteria for major depression diagnosis-

TABLE 1. PHQ-9 POINTS FOR DIAGNOSING MAJOR DEPRESSION

Depression Score(PHQ-9)	Sensibility (%)	Specificity (%)	Likelihood Ratio(1)
≥ 9	95	84	6.0
≥ 10	88	88	7.1
≥ 11	83	89	7.8
≥ 12	83	92	10.2
≥ 13	78	93	11.1
≥ 14	73	94	12.0
≥ 15	68	95	13.6

Based on **Error! Reference source not found.** mental health professional conducted a structured psychiatric interview with 590 patients to ascertain if severe depression was present or absent based on DSM-IV diagnostic criteria. Major depression was associated with a specificity and sensibility of 88% for PHQ-9 scores ≥ 10 [12].

A lot of academics have been using machine learning algorithms to predict anxiety and sadness [13]. Neural Networks, AdaBoost Classifier, and Naïve Bayes. The discussed research focuses on analysing social media posts for detection of emotions and categorizes depression levels based on specific keywords associated with various emotional states. By scrutinizing posts for positive, negative, sadness, anger, and anxiety emotions, the study aims to glean insights into individuals' mental health status via their online expressions. Such analysis holds promise for early detection and intervention strategies, leveraging machine learning's power to bolster mental health monitoring and support in the digital age [14]. This research article entails numerous individual classifiers for predicting emotions accurately and sensitively, providing insights into depression levels.

Depression was diagnosed by Williamson et al. using correlations between formants and spectral data across various time intervals [15], Syed and colleagues created features for audio and video that can record changes over time [16]. The purpose of this study was to model 192 interaction sequences in order to identify depression in participants. In order to predict sadness, we ran three sets of tests utilising attributes that were taken from text and audio data.

By employing 45-fold cross-validation to separate depressed individuals from control participants, we evaluated the overall performance of an SVM classifier on our dataset. Utilising the open-source Scikit-learn toolbox, the principal SVM classifier was trained using several kernel functions, such as linear, polynomial, and radial basis functions [17]. We compared the SVM classifier's performance using different features to classify clinical depression using this voice and speech data in the below Figure 1.

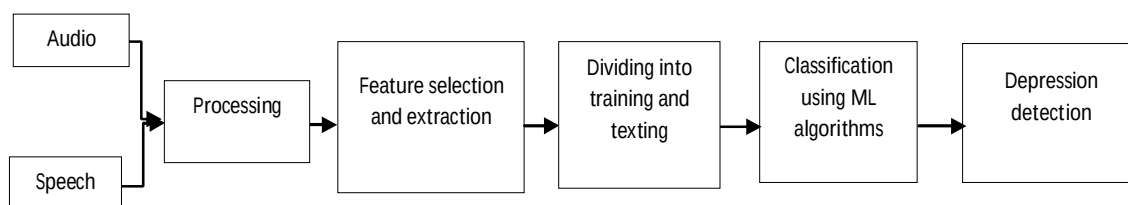


Figure 1. Detecting depression from voice and speech using machine learning

Psychiatry and machine learning have always been studied separately. But now researchers are increasingly employing EEG and machine learning to identify depression. Several contributions are provided by this survey. It offers an organised assessment of machine learning based methods for identifying depression and relapse, as well as clinical and non-clinical instruments including audiovisuals, EEG and self-questionnaires. This will provide academics with a thorough grasp of this area of research. Modern models for diagnosing and forecasting

depression and relapse are covered, along with conventional multi-data and multimodal approaches. The report also suggests a number of worthwhile topics for more research [18].

An individual with depression like unipolar or bipolar may experience depressive episodes after periods of non-depression due to the high risk of relapse or recurrence [19]. A long-term relapsing-remitting syndrome has replaced the unique or episodic condition that depression was once known as, with some individuals achieving partial recovery in between bouts [20]. HAM A and HAM D scores can be used to categorise an individual as "No Anxiety-No Depression," "No Anxiety-Depression," "Anxiety-No Depression," or "Anxiety-Depression." All save the "No Anxiety-No Depression" group required psychiatric therapy for mental health conditions [21].

To get training data, a total of sixty older persons were interviewed using the Geriatric Depression Scale (GDS). Five classifiers are compared using four metrics: Root Mean Square Error (RMSE), Accuracy, ROC area, and Precision. Ten more senior citizens' data sets without decision classes are used to prepare the test data set. The GDS scale is used to manually validate the prediction outcome. The results of these measurements demonstrate that the SMO model is a more precise and accurate way to predict depression in older adults. However, ROC area and RMSE values show that Bayes Net outperforms the other four classification models [22].

The various things about connected to the screening of discouragement subjects compared to solid people, for the most part utilizing meet strategies and surveys, are included within the investigate of Making strides conclusion of Sadness with XGBOOST machine learning demonstrate and the enormous bio markers touch dataset ($n=11081$). In spite of the fact that DSM-IV-based discouragement interviews have been the gold standard for diagnosing discouragement, the things about appear that they may have disadvantages [23].

A comparison of completely structured interviews (MINI) and semi-structured interviews with clinical judgment (CIDI) for the purpose of diagnosing depression. According to Levis et al. (2018), compared to the semi-structured interview (CIDI), more persons were classified as depressive during the fully structured interview (MINI). The study emphasises the necessity of looking into the connection between biomarkers and depression diagnosis in light of the limitations of clinical interviewing methods, such as their dubious sensitivity and specificity. Based on the National Institutes of Health, biomarkers are objectively quantifiable signs of pathological processes, normal biological processes, or reactions to therapeutic interventions self-reported, clinician-administered questionnaires have been the gold standard for diagnosing and assessing depression for the past thirty years [24]. This data is utilised to address biomarker variability. Machine learning has promise in the analysis of biomarker data for depression diagnosis and therapy prediction. ML techniques are being used to predict anxiety and sadness in epilepsy patients in an attempt to better manage the illness [25]. Due to the lack of reliable diagnostic indicators, depression is a global health concern that can have serious repercussions, including suicidal ideation. It is also frequently misdiagnosed and mistreated. In place of back propagation, the particle swarm-cuckoo search (PS-CS) optimisation algorithm is used in this research to provide a novel approach to training deep neural networks. PS-CS in combination with convolutional neural network beats other deep learning architectures and popular classification models, achieving an amazing 99.5% accuracy in depression diagnosis. In contrast, the accuracies of traditional models like decision trees, logistic regression, and K-nearest neighbour (KNN) vary from 69% to 97%. By more precisely and successfully identifying depression, this innovative method may enhance the outcomes of early intervention and therapy [26]. The worldwide effects of depression make the urgent need for easily accessible, precise automatic detection technologies necessary. Individuals display unique physiological and psychological indicators, emphasizing the need for better early identification in order to treat this crippling illness [27]. Depression is a common mood condition that often leads to self-mutilation thoughts. Its symptoms include ongoing sorrow and cognitive deterioration. Although traditional diagnosis is based on interviews conducted by psychiatrists, EEG coherence analysis has potential for diagnosing depression. By identifying neural correlation, this technique analyzes brain activity in sad people. Developing reliable methods for diagnosing depression is the aim of research; deep learning techniques and CNN-based EEG systems have showed promise in this regard. While network analysis evaluates brain connections and reveals problems linked to depression, ERP analysis detects changes in brain function. By describing pertinent research, data collection methods, and recommended processes, the paper emphasises the value of wearable EEG technology and public datasets in practical applications [28].

Among older individuals, anxiety and depression are common but frequently undetected mental health conditions that can cause a number of health problems. Conventional diagnostic techniques are not practicable for diagnosing these illnesses in nations like India where patient loads are high and healthcare resources are scarce. As a result, it is crucial to create a predictive model with machine learning technology. The model for diagnosing anxiety and depression in older individuals proposed by this study is based on sociodemographic and health-related characteristics. By reducing associated morbidities and enhancing overall patient care, machine learning technology may help with the early identification and treatment of depression and anxiety in the elderly.

The mental health of elderly populations throughout the world may be improved if predictive models like RF were more widely accepted and improved upon for use in mainstream clinical practice [29]. Machine learning may now be used to analyse human behaviour thanks to recent advancements in computing power and information processing. In contrast to conventional statistical techniques, machine learning can create prediction models on its own by analysing a variety of interacting variables, combining different kinds of data, and handling variability in datasets. Although there has been promise in identifying predictors of therapy results in mood disorders, no single measure has consistently shown robustness. Although the application of machine learning to predict depression treatment outcomes has gained traction, no comprehensive analysis has examined the subject [30]. Depression is a major global burden that frequently results in chronicity and impairment. Effective therapies depend on early identification of the factors indicating chronicity and remission. While earlier research has connected a number of variables to chronic depression, it has primarily examined group differences rather than developing predicting models. Predictive accuracy can be optimized by merging several data types and utilizing machine learning (ML) techniques. Utilizing information from the Netherlands Study of Depression and Anxiety (NESDA), the study aims to identify critical variables that differentiate depressed individuals who have persistent symptoms from those who do better over a two-year span [31]. In addition to stability selection, machine learning approaches will be applied to find significant predictors of the course of depression. We will pay particular attention to biomarkers that are relevant to the underlying processes of depression. Millions of individuals worldwide suffer from depression, which is becoming a more prevalent mental health issue in the twenty-first century. Depression often presents with a wide range of symptoms that can overlap with those of other disorders. Researchers are utilizing machine learning approaches and investigating several data modalities to improve the identification and categorization of depression. By doing this analysis, the study hopes to shed light on present procedures and offer guidance for next investigations into depression diagnosis [32].

Experts usually agree that factual approaches are more effective when there are fewer indicators, whereas machine learning methods are more useful for larger datasets and when non-linear relationships between the indicators and the predicted outcomes are expected [33].

A high percentage of missing data in an indicator presents problems; counting such problems for analysis might lead to bias. Although the research primarily focuses on predicting ultimate outcomes, it did not take into account the effects of different treatments. Similarly, Austin et al. [34] proposed in a later work that more complex learning techniques would have less advantages and that quantifiable learning strategies should perform significantly better in "large N, little p" scenarios. In the past, however, there has been a push for combining the two methods so that they work in concert rather than against one another [35]. Based on learning, one study showed how meta-learners may effectively combine factual and machine learning models to predict parallel events and perhaps improve overall execution. Thus, the results suggest that it may not always be necessary to select between factual and machine learning models when it comes to predictive tasks in the rehabilitation domain. They used a dataset of depressed patients as an example, pointing to the possibility of suffering severity and the possibility of discontinuing their therapy for a variety of reasons within a maximum of sixty days. For clinical decision-making, or selecting the beginning of treatment, both outcomes are often relevant [36]. In this way, for a moved forward prescient execution, a more progressed meta-learner may be best in hone [37]. It is found that the consolidating quiet covariates as extra meta-learner input may possibly encourage impact and advantage the execution of the meta-learners.

By analyzing pretreatment symptoms and EEG data, the research sought to personalize treatment approaches for major depressive disorder. Baseline symptom scores emerged as critical predictors of symptom improvement, underscoring the significance of initial symptom severity in treatment outcomes [38]. The study also identified associations between specific symptoms and EEG features, suggesting that EEG data could enhance predictive models for treatment response [38].

A major mental health problem associated with notable incapacity and a decreased quality of life may be major depressive clutter [39]. Traditional approaches of the treatment rely on standardized protocols, often resulting in suboptimal results due to the heterogeneity of depressive symptoms and individual responses to medicines [40]. By leveraging advanced computational methods, such as gradient-boosted decision trees, the study by Rajpurkar et al. [41] achieved high discriminative performance in predicting improvement in specific depressive symptoms. By incorporating objective EEG data alongside symptom assessments, clinicians can tailor interventions to address specific symptom domains and improve patient outcomes [39]. This personalized approach aligns with the growing emphasis on precise medicine in mental care, aiming to improve treatment response rates and reduce the burden of trial-and-error approaches in case of the anti-depressant therapy [40].

III. RESULT ANALYSIS

The TABLE presents a comparison of various methods for predicting depression via machine learning techniques in many research. This research uses a variety of machine learning models, including ANN, SVM, and XGBOOST, in conjunction with assessment instruments, including the Geriatric Depression Scale, PHQ-9 evaluation, and facial action coding system (FACS). The need to investigate alternate learning strategies for increased accuracy, solve data constraints including limited sample sizes and self-reported data dependence, and expand feature sets for more reliable predictive modelling are some of the major potential gaps that have been highlighted.

TABLE II. IDENTIFIED RESULTS AND FUTURE GAPS

Sl. No	Name of author	Title	Features	Future Gap
1	Arkaprabha Sau, Bhakta, and Ishita	Using machine learning classifiers to predict depression in older people [4]	The study used the Geriatric Depression Scale to interview sixty older adults between April 1 and April 30, 2016. Data was compared using accuracy, ROC area, precision, and RMSE measures. Five learning approaches were used for predictive modelling, including decision tables, multilayer perceptrons, logistic regression, and SMO.	To improve accuracy in the future, alternative learning approaches might be explored. The illness known as depression has several facets. Optimisation is required because confounding may result in some erroneous associations between various parameters. For a more accurate feature selection of depression prediction, several nature-inspired algo-based optimisation strategies may be applied. It is also possible to do performance analysis with various data sets from throughout the country.
2	Chiyoungand Lee and Heewon Kim	Predictive modelling of depression and hypertension in populations with machine learning [7]	Six different machine learning methods were utilised in this case to complete the classification process: ANN, random forest, AdaBoost, stochastic gradient boosting, XGBoost, and SVM.	Although our ANN and SVM models perform best on a test set with the greatest AUC and F1-score, their future therapeutic utility is questionable. This is because the study only used self-reported data, the sample size was small in comparison to other population studies, and the diagnosis of depression was based only on self-reported questionnaires.
3	Bhatt, Sandra B. Dunbar, Andreas P. Kalogeropoulos, Javed Butler, Kunal N. and Vasiliki V. Georgiopoulou.	PHQ-9 is helpful for depression in heart failure or not [10]	According to the study's findings, a diverse urban sample of stable outpatients with heart failure may be used to predict patient-centered outcomes and healthcare utilisation using the PHQ-9 assessment.	The small number of significant clinical events in our study—such as fatalities, ventricular assist device implantations, or emergency heart transplants—made it difficult to identify any associations between the PHQ-9 score and these kinds of incidents.
4	James R., Thomas F. Quatieri, Williamson, Brian S. Helfer, Rachelle Horwitz, Bea Yu and Daryush D. Mehta.	Motor incoordination-based vocal indicators of depression [15]	The focus of this work is on the facial action coding system (FACS), which makes it possible to code discrete facial gestures called facial action units (FAUs). The main study for this project has shown that 88% of the population may be reliably classified as depressed or not using a manually extracted FAU connected to the buccinator muscle[15].	Future work is necessary to broaden and improve both the array of speech variables we have chosen and their computing approach, even if the preliminary correlation analysis given in this research serves as a guide for our current work in creating automatic classifiers of depression severity.
5.	Willem J.M.I. Verbeke and Amita Sharma	Enhancing depression diagnosis utilising XGBOOST machine learning model and a comprehensive biomarkers dutchdataset (n = 11,081) [23]	A move towards identifying mental diseases with pathological testing in addition to conventional approaches has been brought about by the WHO's comprehensive mental health action plan, which emphasises the critical importance of mental health.	The need for more thorough measuring instruments, such the whole mini-international neuropsychiatric interview questionnaire, and the addition of genetic, epigenetic, and cytokine markers represent the future research gaps in depression studies. Limitations in the study's emphasis on dutch nationals, relevant criteria, and generalisation are highlighted.

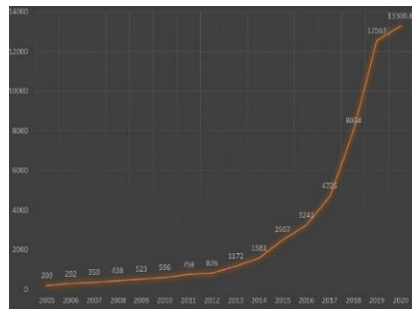


Figure 2. Growth comparison of above studies

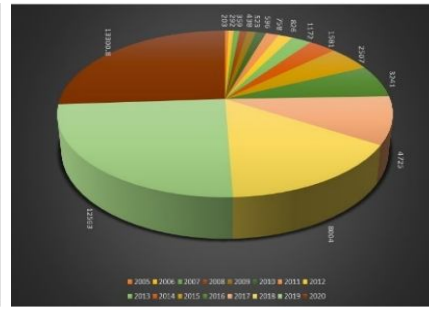


Figure 3. Accuracy comparison of above studies

A. Depression Research Growth Comparison by Individual

The **Error! Reference source not found.** most likely depicts a pattern of increasing research throughout time in the study of depression in individuals. There could not have been as many studies at first, which could indicate a narrow knowledge or narrow emphasis of the study. The number of studies is probably trending upward over time, reflecting a rise in interest in and understanding of the significance of depression research.

B. Pie Chart for Accuracy Comparison

It is likely the case that the Figure 3 contrasts the precision of various techniques or models applied to depression forecasting. A particular approach or model is represented by each segment of the pie, with the size of the section indicating the degree of accuracy. Researchers and practitioners may use this chart to select the best tools for their work by using the insights it offers on whether models or methodologies predict depression more accurately.

Taking these observations together, we can deduce that as knowledge and interest in depression research expand (as shown in the growth comparison picture), researchers are also increasing the accuracy of depression prediction using different techniques or models (as shown in the accuracy comparison pie chart). This all-encompassing strategy calls for a greater level of involvement and skill development while tackling mental health issues

IV. CONCLUSION

Several research on the evaluation and prediction of mental health issues, including anxiety and depression, using machine learning algorithms. It focuses on how well machine learning algorithms predict anxiety and depression in individuals with hypertension, which can aid in the creation of depression screening tools for this population. Using this approach to identify depression risk factors can assist hypertensive individuals in making decisions about their own personal health. The concept, mathematics, and visualization of classification assessment techniques such confusion matrix and resilience against unbalanced data are also covered in the study. It also covers several classification metrics for assessing biometric models and gives examples of ROC, PR, and DET curves. Even while heart failure medicine is effective in treating the condition, overall mortality is still high. Depression has been found to have a significant impact on total mortality, quality of life, and healthcare usage. The PHQ-9 tool has been shown to be reliable in predicting patient-related outcomes and health care usage in a heterogeneous metropolitan sample of stable outpatients with heart failure. In a different research, data gathered via the DASS-21 questionnaire is used to predict five distinct severity levels of stress, anxiety, and depression using machine learning algorithms. While random forest is the best model based on the f1 score, naïve bayes has the highest accuracy.

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