Identifying the Case for The Prediction Of Mental Health Using Adaptive Boosting

Manoj Rishi Nulu†
Department of Computer Science and Engineering
B V Raju Institute of Technology
Narsapur, Telangana, India.
manojrishi777@gmail.com

Sai Sathwik Kosuru†
Department of Computer Science and Engineering
B V Raju Institute of Technology
Narsapur, Telangana, India.
saisathwk363@gmail.com

Koushik Reddy Madhadi
Department of Computer Science and Engineering
B V Raju Institute of Technology
Narsapur, Telangana, India.
koushikmadhadi@gmail.com

Padmanabha Reddy Y C A*
Department of Artificial Intelligence and Machine Learning
Chaitanya Bharati Institute of Technology
Gandipet, Telangana, India.
ananthayc.reddy@gmail.com

Lanke Pallavi
Department of Computer Science and Engineering
B V Raju Institute of Technology
Narsapur, Telangana, India.
pallavi503@gmail.com

M. Venkata Subbarao
Department of Electronics and Communication Engineering
Shri Vishnu Engineering College for Women
Bhimavaram, Andhra Pradesh, India.
mandava.decs@gmail.com

***Abstract*—Cognition has so far failed to provide a clear perspective of the human mental state to the studies by humans for conceiving appreciable results. Worsening the above fact, computers are prevalently reliant on quantitative aspects, and qualitative aspects are dealt with in terms of categorical elements. While mental issues are growing persistently across the population owing to various non-technical factors, Technology is still unable to answer certain research questions about identifying and addressing the mental states of humans. In the current work, we provide an AdaBoost algorithm where we employ Large Language Corpora for consideration of the mental state of the patients. We emphasize the importance and the relevance of these corpora showing an average accuracy of 85% where the work is novel in terms of the studies carried out as a part of it. We implement decision trees to incorporate decision-making logic into the model and involve the use of weak base learners to ensure effective boosting of the model's running rate. As the model is developed, we evaluate the performance in terms of False Positive and False Negative interpretations of the model's predictions. In this way, we propose an algorithm to demonstrate how ML models can transform the mental healthcare sector with their unique applications and designs.**

***Index Terms*—Cognitive, Mental health, Adaboost, Corpus, Questionnaire**

I. Introduction

Artificial intelligence (AI) systems can learn without human intervention as seen through specific examples such as RLHF, RLAIF, etc. A broad spectrum of fields has benefited greatly from machine learning, notably the recognition of speech, CV, and NLP. Similar applications can be used for Mental Illness and trauma prognosis where several findings have had no logical explanations or reasoning for decades. Various questions remain unanswered in mental health studies that require smart inputs which can be made possible through Machine Learning Algorithms.

In many types of inquiry, examinations, and tests, supervised training in machine learning is the most frequently utilized approach. This is particularly valid in the medical industry when forecasting the condition. The categorization technique known as supervised learning, in further detail, uses structured training data. Unsupervised learning doesn't need guidance, though, so it can make predictions. The primary objective of unsupervised learning is the management of data without supervision. Researchers have extremely few opportunities to use unsupervised learning techniques in the clinical setting. To deal with harder medical evaluation issues, strong algorithms, sophisticated neutral networks, tree-based decisions, gradient boosting, and other techniques were developed and put to use. Moreover, Medical evaluations consist of noise and multiple outliers that need to be appropriately addressed and algorithmically explained. Feature Extraction and Feature Engineering is complicated over medical data with diverse feature sets and unrelated classes. According to Miner et al., predictive healthcare statistical analysis will radically alter the medical services sector. Typically, mental illness is identified by a person's self-evaluation, which calls

†These two authors contribute equally to the work.
*Corresponding Author

for the use of a questionnaire designed to uncover particular emotional or interpersonal patterns [11]. With the right care and therapy, it is hoped that many people with mental illnesses or emotional problems will be able to recover. The procedure for diagnosing mental health issues is not simple and cannot be completed quickly. The questionnaire corpus used for such studies is not even uniform and requires careful categorization and classification for aggregating into appropriate based on groups or other abstractive similarities. It is worth mentioning that it is difficult to quantize similarities, differences, results, and performance under such situations, thus making mental health prediction a mere manifestation of probable outputs from the given questionnaire corpus and the associated human responses.

In the current work, we focussed on the fact that an in-depth conversation with questions about signs, history of illness, and inspection of the body will often precede the diagnosis. Furthermore, knowing that the testing for psychology and evaluation methods are available and used to identify an individual's level of mental wellness difficulties, we have employed various existing models and technologies to leverage the accuracy and feasibility of the existing systems for mental health predictions. Many different sorts of mental illnesses go by names like schizophrenia, depression, bipolar disorder, and anxiety. Anxiety disorders, which include panic disorders, appear to involve sudden panic episodes and extreme terror. A racing heart, perspiration, and lightheadedness are some of the physiological signs and symptoms of panic disorder. The hallmark of the psychological disorder post-traumatic stress disorder (PTSD) is emotional numbness brought on by traumatic events. According to surveys, there is a significant delay in obtaining professional therapy for an anxiety problem. So, we aim to address these diseases through well-defined models with increased accuracy using Adaboost optimization in the current study.

II. Literature Survey

It has been demonstrated that psychological illness has an impact on physical health and affects a person's thinking, feelings, and behaviors. With an estimated 450 million sufferers worldwide, the most widespread mental health disorder in today's society is depression [2]. Unfortunately, the above figure is deficient in explaining the actual state of mental health around the world since every ill person may not become a patient or may not officially approach a clinic thus defeating the purpose of completeness of the official figures. All major age groups, including children and teenagers, are susceptible to mental health issues and significant bias can be found towards the young ages with the reasons being attributed to work pressure. There are four significant areas where machine learning has applications in the discipline of mental well-being: (i) the identification and evaluation of behavioral conditions; (ii) prognosis, medication, and assistance; (iii) the welfare of the public; (iv) study as well as medical governance [2]. The instructed model's ML techniques are evaluated using fifty-six samples in the data set [13]. On the given data set, the CatBoost approach outperformed the competition with 89.3% prediction accuracy and 89.0% precision. Estimated reliability of 87.5%, as well as exactness of 84.0%, were achieved by logistic regression, which performed brilliantly [13]. Zhong and Xiao developed a method to enhance health prediction using deep learning algorithms and the improved fusion node. They used machine learning methods like K-Nearest Neighbour and Convolutional Neutral Networks to precisely predict sickness. For accurate disease prediction, this technology considers a person's lifestyle choices and health history. Overall, the CNN algorithm outperformed the k-NN technique with an accuracy of 84.5% [2]. Furthermore, k-NN has a larger time and memory consumption than CNN. A K-mean-based sickness prediction system was introduced by Jamgade and Zade [2]. Overall, ML shows promise for enhancing clinical and research workflow effectiveness and producing fresh perceptions of mental health and well-being. A global mental health emergency has also been brought on by the Coronavirus epidemic. Depending on their situation, people experience sentimental, monetary, tangible, and mental anguish. A surge still exists, moving faster than the initial wave. In some areas, partial restrictions were resumed, and in the badly affected areas, the possibility of even more severe confinement looms large.

In 2017, a study called the National Study on Drug Use and Health was undertaken, with non-institutionalized Americans serving as a sample for analysis. Over a year, some research was conducted on teens (about 1600 students) using RF models to determine whether they were suffering from symptoms related to depression, and it was discovered that approximately 53 percent of teenagers with severe depression sought therapy [7]. According to several studies, sociodemographic characteristics influence the availability of mental health care. For example, certain research studies show that males, single parents, and the relationship between men's race and psychiatric services utilization are stronger for households with lower incomes, and utilization of services is likely caused by externalizing problems instead of depression [7]. Predictive modeling using machine learning approaches is the best way to assess how well individual signs of depression and various sociodemographic characteristics predict teenagers' availability of psychological care.
Madan et al. underscores the significance of real-world healthcare databases in advancing personalized medicine, particularly in mental health. They focus on text mining of psychiatric symptoms and attributes, achieving an 86% F1 score and 91% accuracy in an independent test set using a neural network model. Zhang et al. discuss AI's application in addressing depression, with a focus on children, using deep learning tools for diagnosis and forecasting with high sensitivity and precision ratios, surpassing existing systems.

Researchers highlight the intricate nature of mental illness, which is intertwined with diverse clinical and socioeconomic factors. They note the escalating use of natural language processing (NLP) for early diagnosis and propose further exploration of deep learning for enhanced outcomes [12]. Sharma et al. delve into ML's role in diagnosing mental illnesses, utilizing XGBoost to improve the diagnosis of mental depression with a high accuracy rate of 0.90. Lastly, a study analyzes mental health tech surveys from 2014 and 2016 to predict treatment response rates through aggregation for more insightful outcomes.

III. Existing Work

Machine learning has been used to anticipate numerous aspects of mental health, including diagnosis, risk assessment, and treatment planning. Various ML models are employed for predicting suicidal thoughts among college students [6] and behavioral issues[8]. Some examples of recent work in the area of machine learning-based mental health predictions are shown below: 1) Depression prediction: The application of ML methods to forecast the possibility of depression in individuals based on variables such as speech patterns, social media posts, and physiological markers. For instance, a study that was published in the Journal of Medical Internet Research in 2018 employed NLP techniques to analyze the content of tweets and accurately predict the likelihood of depression. A deep integrated support vector machine model is employed for college students regarding depression diagnosis [4].

2) Schizophrenia prediction: A 2019 study published in Schizophrenia Bulletin employed machine learning algorithms to analyze neuroimaging data and identify patterns of brain connection that were predictive of later schizophrenia onset. The following machine learning (ML) methods have been used: RF, k-NN, and SVM [2]. ML model for predicting readmission risk of patients with this disorder is built and the data is taken from a Spanish region [15]. 3) Prediction of treatment response: Machine learning has been used to foretell the effectiveness of many therapies for mental health issues, including antidepressant drugs and psychotherapy. For instance, a 2019 study that appeared in the American Journal of Psychiatry employed machine learning algorithms to analyze neuroimaging data and forecast the effectiveness of cognitive behavioral treatment in depressed individuals.

4) Early identification of behavioral issues in kids and teens: Machine learning has been utilized to construct predictive models for the early identification of behavioral issues in children and adolescents, such as ADHD or ASD. Research published in the Journal of the American Academy of Child and Adolescent Psychiatry in 2018 employed machine learning algorithms to analyze behavioral data and identify indicators that were predictive of ADHD. ML techniques such as Linear Discriminant Analysis, RF, SVM, and K-NN were applied to study attention deficit hyperactivity disorder [2].

5) Natural language processing is used to examine text-based posts in social media to forecast psychological characteristics like depression [3].

6) An adaptive boosting algorithm is implemented to find anxiety disorders during the Covid-19 pandemic [5]. Another method involves the usage of electronic health records and a novel ML approach with artificial intelligence [9]. A hybrid model is built based on SVM and RF algorithms for anxiety disorders and other psychological traits [14].

7) A single-layer convolutional neural network is used for monitoring the public's mental health that is associated with finance [10].

Work related to ML-based mental health prediction already exists and includes a few instances like these. The discipline of ML is expected to grow in importance in enhancing the efficacy and accuracy of mental health prediction, which can support early detection, intervention, and individualized treatment planning for people with mental health illnesses. However, while machine learning has shown potential in mental health prediction, it is not a replacement for clinical judgment and should be used in conjunction with traditional diagnosis and assessment procedures by competent healthcare professionals.

IV. Methodology

A. Algorithm

*1) **Nature**:* There are abnormalities in generating reliable information about mental disease from the prior available algorithms. As a result of this, we propose a system that employs AdaBoost, also known as Adaptive Boosting, a well-liked ensemble learning algorithm that has significant advantages over other types of ML algorithms and techniques for predicting the outcome of mental health. The algorithm is designed to implement the model training over an in-store/predefined data set where it uses both decision trees and decision stumps, two types of weak-base learners, to generate a much more accurate model. Later, the algorithm will analyze the data provided by the user, and the results will be displayed via the interface. The data provided by the user can be used for RLHF and this data consists of the user responses to the query corpus posed by the system to the user. While the actual queries have a complex implementation of varied inputs, we utilized the concept of categorical feature extraction techniques to quantize the inputs and apply the model accordingly.

*2) **Reason for using AdaBoost Algorithm:**:* The reasons for using the above proposed model, though general are significant in the current work since it demonstrates how model training is important for complex data such as healthcare data. The observations can be inferred not only for mental health applications but also for other generic healthcare technologies.

- The model can overfit over the most dominant pattern in the given input corpus due to the generic similarity tendency of human responses. Hence, there is a need for the training process to be selective and adaptive in its learning so that we can avoid premature overfitting of the model to some extent.

- Data Set may consist of biases, particularly on the training part where the split of data set sizes may adversely favor a single pattern over another causing the model to be partisan which may raise both ethical and performance issues. AdaBoost Algorithm periodically checks the model training for comparison between the expected and observed training outcomes of the model, thereby reducing the risk of losing the model due to unnecessary bias introductions. We can ensure uniform distribution of data through this procedure.

*3) **Steps**:*

- Initialize Sample Weights:
  At the beginning of the algorithm, all training examples are given equal weight $w(i) = \frac{1}{N}$.
  $w(i)$ is the weight of the i-th training example, N is the total number of training examples. These weights are subjected to repeated cycles of training and testing to adapt to the requirement and according to the training data set.
- Calculate Error of Weak Learner:
  This error is typically the sum of the weights of misclassified examples categorizable as False Positives or False Negatives.
  $\varepsilon(t) = \sum(w(i) \cdot I(y(i)\#\ h_t(x(i))))$
  $\varepsilon(t)$ is the error of weak learner t.
  $y(i)$ is the true label of example i.
  $h_t(x(i))$ is the prediction of weak learner t for example i.
  $I(condition)$ is the indicator function that equals 1 if the condition is true and 0 otherwise.
- Compute Weight for Weak Learner:
  $$a(t) = 0.5 \cdot \ln\left(\frac{1-\varepsilon(t)}{\varepsilon(t)}\right)$$
  where $a(t)$ is the weight of weak learner t and $\varepsilon(t)$ is the error of weak learner t.
- Update Sample Weights: Update the weights of training examples for the next iteration. Increase the weight of misclassified examples and decrease the weight of correctly classified samples.
  $$w(i, t+1) = w(i, t) \cdot \exp\left(a(t) \cdot I(y(i) \neq h_t(x(i)))\right)$$
  for all training examples i.
  Here, $I(\text{condition})$ is the indicator function that equals 1 if the condition is true and -1 otherwise.
- Combine Weak Learners' Predictions: Combine the predictions of all weak learners by a weighted majority vote
  $$H(x) = \text{sign}\left(a(t) \cdot h_t(x)\right)$$
  for all weak learners t.
  $H(x)$ is the final strong classifier's prediction for input x.

The methods used in the work are further discussed below:
This goal is to create an accurate model for forecasting mental disease from the user's response to the questionnaire corpus by the system. This paper includes a detailed explanation of the involved approaches as well as the steps for data collection and the modules used. The architecture diagram of our project is shown in detail in figure 1. The approaches are explained in further detail below.

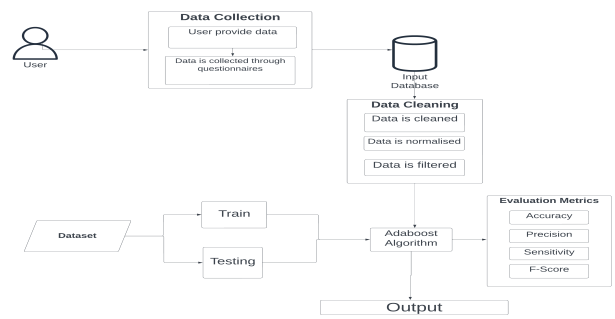

Fig. 1. Proposed flow

B. Data Collection, processing and the Relevance for Data Ethics

We gathered the information from a poll that was carried out in 2014. The dataset we have taken is the same as that used in the reference [12]. This dataset "Survey on Mental Health in the Tech Workplace in 2014" measures attitudes towards mental health and the frequency of mental health disorders in the workplace. This study primarily focuses on workers because, for a variety of reasons, they are more likely to develop mental illnesses. The collection is made up of 27 fields and 1260 records, the majority of which are single-valued attributes. It is advisable to employ a methodical process to compile the information obtained from the user as input and save it in a database or folder. The parameters or attributes used in this project are 'Age',' Gender',' family history', 'benefits',' care options',' anonymity', 'leave', and 'work interfere' with the word distribution as seen in the figures 2 and 3.

1) Data Cleaning and Processing: The collected data contains mainly complex data patterns that need to be considered for training while the critical fact is that the data contains a mixture of clean and unclean data. Hence, category-level and data-level filters are applied to eliminate noise and increase the concentration of usable data. We applied feature engineering to the training data using the equation mentioned below in Fig. 2

Using the mean method:

$$X_i = (X_i + \frac{\sum X}{N})$$

Where: - X - Feature - X_i - Missing value - $\sum X$ - Sum of non missing values - N - Number of non-missing values

We employed the mean method to identify patterns among the data and eliminate all the flaws, unnecessary data points, and associated outliers.

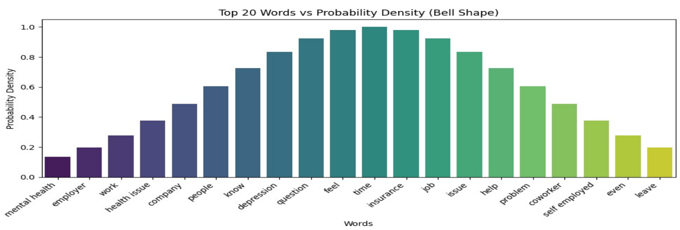

Fig. 2. Probability Word Distribution in the Text Corpus

Fig. 3. Word Cloud obtained on the Text Corpus

2) Importance of Data Ethics: The data associated with the model include sensitive and personal data that may potentially expose user privacy and leak personal details. As an approach towards Responsible AI, we may need to include appropriate filters to avoid the misuse of the models. We ensured that no privacy issue was evident during our work. Parameters such as **'Age',' Gender',' family history', 'benefits',' care options',' anonymity', 'leave', and 'work interfere'** are sensitive and hence, with appropriate flagging, we need to carefully handle such points where we need to implement a separate training process that avoids unnecessary violation of user's rights and privacy through its predictions.

C. Model Development

Data is partitioned for a dual purpose role which is for training the core model and another for implementing the AdaBoost Algorithm. Since this is a common procedure, we used 70% of the data collected to train and 30% to test. Because this approach is an ensemble learning method, it combines numerous weak classifiers to produce a strong classifier. All training examples in the dataset are first given equal weights. To train weak classifiers, decision trees are used. Now we compute the error rate and normalize the weights. Repetition of the method continues until the minimal error rate performance criterion is fulfilled. The recursive approach entails the usage of boosting algorithms that follow dynamic weight and bias initialization and rapid error prevention strategies.

D. Deployment

Creating a user-friendly website in which we can collect input data and predict outputs that are simple to grasp for the user.

1) Possible Product Design Principles: Product Engineers often find the pain points of the user to empathize with their feelings, intervening in their problem space to design universal solutions and design the product according to the requirements. The principles that can be considered are:

- Since the experiment is entirely study-focused, we need not focus on accessibility features and measurements. The desired product is more of the abstraction of the model underneath.
- The questions posed should be as simple as possible and any jargon must be avoided.

2) MLOPs and Model Versioning:

- Data versioning should be too frequent to miss the constantly changing population's mental conditions across the years.
- The deployment is relatively simpler due to the use of simple AdaBoost techniques.

V. Results and Discussion

The evaluation of the ideal solution during this classification model training can be specified using the correlated matrix. To calculate the performance measures, we use the following metrics: TP(number of positive classifications), TN(number of negative classifications), FP(incorrect negative classifications), FN(incorrect positive classifications), P(Number of positive cases), and N(Number of Negative cases). Here, The percentage of test samples that were properly classified out of the total test samples is the accuracy. In our case, positive prediction refers to being mentally ill, whereas negative prediction is the vice-versa. One could consider precision to be a measurement of exactness. A higher precision suggests that the model is effective at identifying those who require assistance. Sensitivity or recall, is a metric for comprehensiveness. Precision and recall are combined into one score by the F-score. The highest and lowest possible values are one and zero respectively.

The obtained results are shown in the table I. The comparison between algorithms as per performance metrics are shown in figure 4.

Overall, ML boosted with AdaBoost techniques is found to show positive results for enhancing the clinical-cum-research workflow effectiveness and producing fresh perceptions of the mental health and well-being domain. It makes sense that there are large gaps in this young discipline where issues are to be addressed appropriately by future research. The majority of the studies considered here lay a significant emphasis on identification and recognition, particularly about depressive symptoms, the possibility of suicide, and dementia. Classifier performance measurements assess the classifier's capacity to make decisions. SVM and K-NN received the highest F-scores among the previously used algorithms [1]. As per the algorithms we used in our present work, AdaBoost leads in accuracy and F-Score, whereas SVM got the highest precision and Decision Tree leads in Recall. Overall, by considering all of the performance metrics, it is observed that the AdaBoost algorithm is the best one compared to other classifiers in predicting the results. Examining the data set, the findings might be improved because a more extensive dataset would increase the model's potential, thus highlighting the need for bringing in new data repositories in the future.

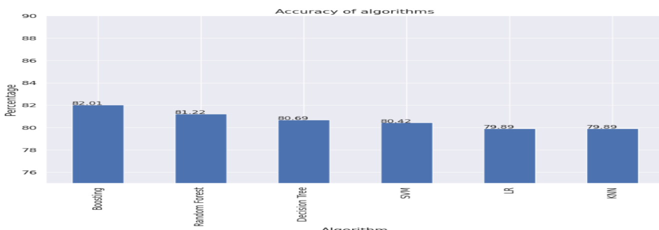

Fig. 4. Graphical representation of accuracies of the algorithms

VI. Conclusions and Future Work

Overall, it is evident that ML may considerably enhance mental health issue identification and diagnosis. Fortunately, we can modify the AdaBoost techniques further to design models that even enable the successful prognosis of various mental ailments and the associated conditions. Generally speaking, the focus of this research study has been on how to employ adaptive boosting in the identification of behavioral health concerns. Additionally, it was revealed that

Classifier	Accuracy	Precision	Recall	F score
Logistic Regression	79.89	76.3	86.1	80.9
Support Vector Machine	80.42	74.04	93.05	82.46
Decision Tree	80.68	74.15	93.58	82.73
K Nearest Neighbour	79.89	74.88	89.3	81.45
Random Forest	81.21	75	93.05	83.05
Adaboost	82.01	76.21	92.51	83.57

TABLE I
Results

using ensemble methods significantly improved mental health prediction. The effectiveness of the features directly affects how reliable the built-in prediction models are. Better real-time data gathering through surveys can help us learn more about patients and their diseases and result in more accurate results when using performance metrics like accuracy, precision, F-score, etc. Based on a survey about employee working circumstances, the current dataset was created. Due to privacy concerns, we are having trouble accessing data. Creating new mental-health-related data sets and data repositories is part of our future tasks.

References

[1] M.Srividya, S.Mohanavalli and N.Balaji. "Behavioral Modeling for Mental Health using Machine Learning Algorithms." Journal of Medical Systems (2018).

[2] Shatte ABR, Hutchinson DM, Teague SJ. "Machine learning in mental health: a scoping review of methods and applications." Psychological Medicine 1–23 (2019).

[3] Alghamdi, Norah, Mahmoud, Hanan and Abraham, Ajith and Alanazi, Samar and Garcia-Hernandez, Laura. (2020). Predicting Depression Symptoms In An Arabic Psychological Forum. IEEE Access. PP. 1-1. 10.1109/ACCESS.2020.2981834.

[4] Ding, Y., Chen, X., Fu, Q., Zhong, S. (2020). A depression recognition method for college students using deep integrated support vector algorithm. IEEE Access, 1–1.

[5] Byeon, H. Predicting High-Risk Groups for COVID-19 Anxiety Using Adaboost and Nomogram: Findings from Nationwide Survey in South Korea. Appl. Sci. 2021, 11, 9865.

[6] Macalli, M., Navarro, M., Orri, M. et al. A machine learning approach for predicting suicidal thoughts and behaviours among college students. Sci Rep 11, 11363 (2021).

[7] Mallory L. Dobias, Michael B. Sugarman, Michael C. Mullarkey, Jessica L. Schleider. "Predicting Mental Health Treatment Access Among Adolescents With Elevated Depressive Symptoms: Machine Learning Approaches." Administration and Policy in Mental Health and Mental Health Services Research (2021).

[8] Md. Sabab Zulfiker, Nasrin Kabir, Al Amin Biswas, Tahmina Nazneen, Mohammad Shorif Uddin, "An in-depth analysis of machine learning approaches to predict depression." Current Research in Behavioral Sciences, Volume 2, 2021, 100044, ISSN 2666-5182.

[9] Nemesure, M.D., Heinz, M.V., Huang, R. et al. Predictive modeling of depression and anxiety using electronic health records and a novel machine learning approach with artificial intelligence. Sci Rep 11, 1980 (2021).

[10] Alanazi, S.A.; Khaliq, A.; Ahmad, F.; Alshammari, N.; Hussain, I.; Zia, M.A.; Alruwaili, M.; Rayan, A.; Alsayat, A.; Afsar, S. Public's Mental Health Monitoring via Sentimental Analysis of Financial Text Using Machine Learning Techniques. Int. J. Environ. Res. Public Health 2022, 19, 9695.

[11] Jetli Chung, Jason Teo, "Mental Health Prediction Using Machine Learning: Taxonomy, Applications, and Challenges", Applied Computational Intelligence and Soft Computing, vol. 2022, Article ID 9970363, 19 pages, 2022.

[12] E. O. Ogunseye, C. A. Adenusi, A. C. Nwanakwaugwu, S. A. Ajagbe, and S. O. Akinola, "Predictive Analysis of Mental Health Conditions Using AdaBoost Algorithm", paradigmplus, vol. 3, no. 2, pp. 11-26, Aug. 2022.

[13] Jetli Chung and Jason Teo. "Single classifier vs ensemble machine learning approaches for mental health prediction." Brain Informatics (2023).

[14] E. Syed Mohamed, Tawseef Ahmad Naqishbandi, Syed Ahmad Chan Bukhari, Insha Rauf, Vilas Sawrikar, Arshad Hussain, A hybrid mental health prediction model using Support Vector Machine, Multilayer Perceptron, and Random Forest algorithms,

Healthcare Analytics, Volume 3, 2023, 100185, ISSN 2772-4425, https://doi.org/10.1016/j.health.2023.100185

[15] Góngora Alonso, S., Herrera Montano, I., Ayala, J.L.M. et al. Machine Learning Models to Predict Readmission Risk of Patients with Schizophrenia in a Spanish Region. Int J Ment Health Addiction (2023).