Nature Journal of Emerging Sciences, Technologies, & Innovations
https://naturerust.com/index.php/njesti
Vol. 6, No. 3, March 2026, pp. 289 - 303
ISSN (Print): 3115-4611, ISSN (Online): 3122-1017

RESEARCH

OPEN ACCESS

A hybrid particle swarm optimization-support vector machine for anxiety prediction among undergraduate students

Opeyemi Aderiike Abisoye[1,3]*, Munir Danjuma[1], Blessing Olatunde Abisoye[2], Sani Alkali Umar[1] , Usoh Ufort Ikouwen, Julius Olajire[1], Oladayo Oluwatosin Akinwande[3],

[1]Department of Computer Science, Federal University of Technology Minna, Nigeria
[2]Department of Computer Engineering, Federal University of Technology Minna, Nigeria
[3]Department of Software Engineering, Veritas University, Abuja, Nigeria

Article Info

Article history:

Received: January 26th 2026
Revised: March 15th 2026
Accepted: March 17th, 2026

Munir Danjuma https://orcid.org/0009-0001-1226-7023
(Munir D.)
https://orcid.org/0000-0003-2750-7883
(Abisoye B.O.)
https://orcid.org/0009-0004-7293-5902
(Umar S.A.)
Oladayo Tosin ,
https://orcid.org/0000-0003-4496-1885
(Akinwande O.T.)
https://orcid.org/0009-0005-6361-7205
(Ikouwen U.U.)
https://orcid.org/0009-0009-8231-9026
(Olajire J.)

Keywords*:*

Anxiety
Particle Swarm Optimization
Support Vector Machine
Hybrid
Undergraduate Student

ABSTRACT

Globally, the prevalence of anxiety disorders is increasing, and this illness have a significant impact on people's mental health, cognitive functions, behavior, and social interactions, among other aspects of their lives. Anxiety disorders throw off the delicate balance of mental health. Exploring how machine learning can be harnessed to combat the decline in life expectancy by addressing anxiety health issues is a vital issue. Novel research demonstrates the revolutionary possibilities of unconventional methods. These methods provide a deeper understanding of mental health issues by analyzing the complexity of these disorders and the underlying causes. Consequently, this research aims to explore the role of Artificial Intelligence (AI) in the assessment of anxiety levels among Nigerians. By leveraging AI technology, we can develop a more accessible and proactive approach to mental health monitoring and support. Metaheuristic algorithm: Particle Swarm Optimization algorithm is being explored as optimization techniques to increase the performance accuracy of these AI methods and overcome some challenges of traditional AI models. Our findings indicate that the Oversampled, PSO-tuned Support Vector Classifier outperformed the other models with 96% Accuracy, 96% Precision, 99.8% Recall, and F1 score of ~~0.833~~. Finally, this study presents a Hybrid Particle Swarm Optimization-Support Vector Machine for Anxiety Prediction among Undergraduate Students and indicates that oversampling increases minority class instances to balance class distribution and overcome imbalanced datasets.

1. INTRODUCTION

Anxiety isn't the same as fear, but they are frequently traded. Anxiety is considered a future-oriented, long-acting reaction broadly centered on a diffuse danger, while fear is a suitable, present-oriented, and short-lived reaction to an identifiable and particular risk" [1], [2]. ~~students' attitudes towards the effect of fear and anxiety on their academic achievement.)~~. Government limitations to moderate the spread of infection have led to far-

*Corresponding Author

Abisoye O.A., Email: o.abisoye@futminna.edu.ng, ORCID: https://orcid.org/0000-0002-7324-2479

reaching social confinement, which can have significant results for mental wellbeing [3]. In Nigeria, a country that faced its unique set of challenges during the pandemic, the toll on mental health was particularly severe. The lockdowns, economic hardship, and uncertainty about the future exacerbated anxiety levels among the population.

Patients benefit from treatment, which prolongs life and make them to enjoy normal, productive lives. But sometimes students suffer from Depression and anxiety, and this affects their studies and social behavior. Previous studies have highlighted the critical importance of a number of essential components in tackling the worldwide problem of anxiety disorders. The necessity of early detection is the most important of these factors. Numerous research, counting those by [4], [5] have shown that early detection of anxiety disorders is crucial for starting prompt interventions and providing individualized support for those who are affected. It lessens the toll that these illnesses make on people's wellbeing and makes more potent treatment plans possible. Simultaneously, the literature review emphasizes how important innovative methodologies are.

1.1 Contribution to Knowledge

Unlike the previous studies, recognizing anxiety as a pervasive and challenging condition to diagnose, this article aims to leverage the power of Artificial Intelligence (AI), specifically employing a Particle Swarm Optimization (PSO)-tuned Support Vector Machine (SVM) approach. By delving into the assessment of anxiety levels among Nigerians, the study seeks to identify influential features contributing to anxiety tendencies, map these features to treatment outcomes, and predict anxiety treatment status using machine learning. The overarching goal is to develop an innovative, AI-driven solution that enhances accessibility, early detection, and intervention for anxiety disorders, thereby contributing to the improvement of mental health, overall well-being, and potentially addressing the decline in life expectancy. The study's significance lies in its potential to overcome minority class instances to balance class distribution with oversampling. This offers a blueprint for the application of AI in combating anxiety-related health challenges, particularly in the aftermath of a major public health crisis.

This article is organized as follows: Section 2 briefly explores various studies on anxiety disorders and the methods undertaken to improve the condition. Section 3 presents the methodology utilized in recognizing the different levels of anxiety. Section 4 unveils the outcomes of the study with metaheuristics algorithms for predicting anxiety. While Section 5 provides a summary of the results obtained, it highlights a discussion of the results, limitations of the study and outlines future directions. Section 6 concludes the study.

2. LITERATURE REVIEW

2.1 Theoretical Overview

(i). AI in Anxiety

Artificial intelligence (AI) is a major field of computer science and engineering that aims to build machines capable of performing tasks that typically require human intelligence. Healthcare is being enhanced by Artificial Intelligence (AI) is to enable efficient, accurate, and personalized clinical decision-making [31]. The ability to achieve early detection is one of the main benefits of AI for anxiety prediction. We can predict anxiety at different levels of severity thanks to machine learning algorithms, as said by [4], [5]. The objective of improving the quality of life for those impacted by anxiety disorders is closely aligned with the early detection that is essential for prompt interventions and customized treatment plans. As is often the case in the literature, it lessens the severity of these conditions and provides access to more potent therapeutic approaches. [6] has explored the use of sophisticated AI models and text data analysis from social media and other sources. These methods offer a more profound understanding of the complex nature of mental well-being issues and mark a significant departure from traditional approaches. At the vanguard of these developments is machine learning, which provides the capacity to extract meaningful information from large amounts of textual data, thereby advancing our understanding of the underlying causes of anxiety disorders. A variety of machine learning algorithms, each with specific advantages and skills in anxiety prediction, will be used in our investigation. Now let's examine the particular algorithms that are workable.

This section presents the theoretical overview of Machine Learning. A review of existing related studies on Anxiety prediction was presented with different with different AI methods they explored.

(ii) Artificial Neural Network

An artificial neural network is a sort of AI method that recognizes patterns in information. It is propelled by the structure and work of the human brain, with interconnected hubs or "neurons" that handle data and transmit signals to other neurons. Mathematical model of neurons is the fundamental building block in an Artificial Neural Network, and it has three (3) basic components: the synapses or connecting links that provide weights,

w_i, to the input values, X_i *for i* = 1, ...*n*; An adder that sums the weighted input values to compute the input to the activation function

$$v = w_0 + \sum_{i=1}^{n} X_i w_i \qquad (1)$$

where w_0 is the bias, which is a numerical value associated with the neuron and; a monotone activation function *or* squashing function maps *v* to *g*(*v*), the output value of the neuron. Numerous study employments counterfeit neural systems as one of the few base learners in an outfit approach to anticipate long-term weakening in anxiety disorder symptoms [7].

(iii) Support Vector Machine

Support Vector machines (SVM) is a binary class algorithm which use hypothesis space of linear functions in a high dimensional feature space from optimization theory that implements a learning bias derived from statistical learning theory. Employing a strategy known as the "kernel trick," SVMs can successfully perform non-linear classification in addition to linear classification by mapping their inputs into high-dimensional feature spaces. The foundations of Support Vector Machines (SVM) have been developed by [8] and gained popularity due to many promising features such as better empirical performance In quintessence, it draws borders between the different classes [9].

If we choose a mapping from the original space X to the higher Dimensional space $D(k: X \rightarrow D)$ then

$$k(x) = d \qquad (2)$$

Where $x \varepsilon X$ and $d \varepsilon D$ then we will maximize

$$W(\alpha) = \sum_{i=1}^{m} \propto_i - \frac{1}{2}\sum_{i=1}^{m} \propto_i \propto_j y_i \propto y_j (k(x_i).k(x_j)) \qquad (3)$$

to find the Lagrangian multipliers under the constraints and calculate the value of the class

$$f(x) = sign(\sum_{support\ vectors} y_i \propto_i^0 (k(x_i).k(x) - b_0) \qquad (4)$$

(iv) Random Forest Classifier

A random forest is a classifier from the family of classifiers

$$h(x/\theta_1),\ldots, \mathrm{h}(\mathrm{x}/\theta_k) \qquad (5)$$

from a classification tree with parameters randomly θ_k selected from a random vector model**.**

For the final classification $f(x)$ (which combines the $\{h_k(x)\}$ classifiers, each tree casts a vote for the most popular class at input X and the class will have the highest votes.

Specifically given data: $D = [\{x_i, y_i\}]_{i=1}^{n}$ (6)

We train a family of classifiers $\{h_k(x)\}$ where each classifier $h_k(x) \equiv \mathrm{h}(\mathrm{x}/\theta_k)$ is in our case a predictor of n and y=±1 which is the target

Random Forest operates by amalgamating tree structures and training on the available sample data to perform classification [10]. To improve prediction accuracy, the Random Forest algorithm provides an ensemble approach that combines several decision trees.This approach works especially well for our task because it is highly accurate and proficient with structured data. Instead of fixed ensemble

$$\{h_k(x)\}_{k=1}^{k} \qquad (7)$$

of classifiers, we have $h(x/\theta)$; specifies classification tree classifier $h(x/\theta)$. We have a fixed probability θ distribution for determining variety of trees.

(v) Logistic Regression

For tasks involving binary classification, logistic regression (LR) is a basic yet effective algorithm. It is a good option for the preliminary investigation of anxiety prediction due to its interpretability and simplicity. According to [11], logistic regression is utilized to portray information and clarify the relationship between one subordinate parallel variable and one or more independent factors that are ostensible, ordinal, interim, or proportion. The most fundamental classification algorithm is LR. In terms of mathematics, LR functions similarly to linear regression. In order to optimize model correctness, LR determines the proper weights or coefficients for each column [12].

(vi) Decision Tree

Decision Tree modeling offers simplicity and transparency. These trees are an effective resource for learning about the elements that lead to anxiety disorders. They will support our efforts to develop novel approaches and deeper comprehension. One of the effective techniques that is frequently applied in many domains, counting machine learning, picture preparing, and design acknowledgment, is the decision tree [13]. DT could be a consecutive show that viably and cohesively combines a number of crucial tests in which a numerical include is compared to a edge esteem in each test. Compared to the numerical weights within the neural network of associations between hubs, the conceptual rules are considerably less complex to make. DT is utilized generally for gathering purposes. Moreover, DT could be a classification show that's habitually utilized in information mining [14]. Each tree is made up of hubs and branches. Each subset indicates an esteem that can be taken by each hub, which speaks to highlights in a category that should be classified [15].

(vii) Deep Learning

Deep learning models are planned to memorize from expansive sums of information and can be utilized to form forecasts or classifications based on modern information inputs [7]. Researcher's as embraces Deep learning models to analyze information from wearable sensors and foresee long-term weakening in anxiety disorder indications.

(a) Convolutional Neural Network

Ahmed *et al*., [16] stated that Convolutional Neural Network (CNN) stands as an essential division inside neural systems specialized in tasks such as picture acknowledgment, classification, object detection, and the acumen of different visual information highlights. In fact, CNN could be a shape of profound learning planned for both preparing and assessment. Each input picture experiences a grouping of layers counting convolution layers utilizing channels (also called Kernels), Pooling layers, completely associated layers (FC), and eventually applies a Softmax function to categorize an object with a probability range between 0 to 1. As the images progress through each layer, they are mathematically represented as multi-dimensional matrices and expressed in terms of input and output volumes [17].

(b) Recurrent Neural Network

A Recurrent Neural Network (RNN) may be a sort of neural organize that's planned to work with consecutive information, such as time arrangement or natural language. Not at all like bolster forward neural systems, which prepare input information in a single pass, RNNs keep up an inner state that permits them to handle groupings of inputs [17]. This inside state is overhauled at each time step, and is utilized to educate the preparing of consequent inputs. One of the key highlights of RNNs is that they can keep up a memory of previous inputs, which permits them to capture worldly conditions within the information. This makes them well-suited for assignments such as discourse acknowledgment, language translation, and estimation examination, where the meaning of a given input depends on the setting in which it occurs [4].

(c) Long Short-Term Memory

Long short-term memory (LSTM) could be a time consideration engineering planned to handle long-term conditions in data. LSTM is outlined to overcome the vanishing angle issue in conventional RNNs[18]. LSTM employs a memory cell and three entryways (input door, disregard entryway, and yield door) to control the stream of data. The input entryway decides how much modern data ought to be put away within the memory cell, the disregard entryway chooses which data to dispose of from the memory cell, the yield entryway controls the yield of the memory cell. Different tasks such as discourse acknowledgment, dialect modeling, and machine translation [19]. The disregard entryway chooses which data to dispose of from the memory cell. LSTM has been effective in different assignments such as discourse acknowledgment, language modeling, and machine translation.

(viii) Metaheuristic Algorithm: Swarm Intelligence

Swarm Intelligence is a nature-inspired metaheuristic optimization calculation established within the collective behavior of social living beings, especially birds and angles. Presented by Kennedy and Eberhart [20], Swarm Intelligence has picked up noticeable quality as a capable optimization procedure broadly utilized in different spaces, counting machine learning. The calculation models the optimization handle as a swarm of particles moving through a multidimensional look space, where each particle represents a potential arrangement. In each emphasis, particles powerfully alter their positions based on their personal encounters and the collective data shared inside the swarm. This collaborative development is impacted by two essential components: personal best (pbest) and worldwide best (gbest). The pbest indicates the leading arrangement a particle has encountered, whereas the gbest speaks to the finest solution identified by any particle in the entire swarm. Through this interplay of personal and global knowledge, PSO aims to explore the solution space effectively [21].

(ix) Particle Swarm Optimizer

The Particle Swarm Optimization (PSO) mimics the social behavior of birds and fish to optimize solutions. Each potential solution, represented by a particle, adjusts its position and velocity iteratively based on its personal best and the best position found by the entire swarm. The algorithm efficiently explores the solution space, seeking the optimal solution to a given problem. PSO is widely used in various optimization tasks, such as parameter tuning in machine learning models, and it is known for its simplicity and effectiveness in finding near-optimal solutions in complex search spaces [22].

The movement of each particle is guided by its current position, velocity, and the influence of the pbest and gbest. The velocity determines the direction and distance of a particle's movement in the search space. The updating of positions and velocities is governed by mathematical equations that incorporate inertia, cognitive, and social components. The inertia term maintains the current velocity, while the cognitive and social components, influenced by the particle's personal best and the swarm's global best, guide the particle toward promising regions. This combination of exploration (global best) and exploitation (personal best) ensures a balanced search for optimal solutions. One of the notable strengths of PSO lies in its simplicity and ease of implementation [21]. The algorithm's ability to adapt dynamically to changing landscapes makes it suitable for optimizing complex, non-linear functions. In the context of machine learning, PSO is employed for hyperparameter tuning, feature selection, and model optimization. Machine learning practitioners favor PSO for its efficiency in navigating high-dimensional spaces, resilience to getting stuck in local optima, and versatility across different optimization problems. Despite its widespread use, ongoing research explores enhancements and hybridizations with other optimization techniques to further improve PSO's performance in addressing diverse and challenging optimization tasks. The algorithm is designed to find the optimal solution to a given problem by iteratively adjusting a population of potential solutions, referred to as particles, based on their individual and collective experiences. Two iterative steps are involved [23].

i. Velocity Update:

$$V_{ij}(t+1) = w.v_{ij}(t) + c_1.r_1.\left(p_{ij} - x_{ij}(t)\right) + c_2.r_2.\left(g_{ij} - x_{ij}(t)\right) \quad (8)$$

Where:

$V_{ij}(t+1)$, is the velocity of particle (i) in dimension (j) at iteration$(t+1)$,

w,is the inertia weight,

c_1,and$c_2$are acceleration coefficients,

r_1 andr_2 are random numbers in the range [0, 1],

$p_{ij}$is the best position of particle (i) in dimension (j) (personal best),

$x_{ij}(t)$is the current position of particle (i) in dimension (j) at iteration (t),

$g_{ij}$is the best position among all particles in dimension (j) (global best).

ii. Position Update:

$$x_{ij}(t+1) = x_{ij}(t) + x_{ij}(t+1) \quad (9)$$

2.2 Related Works

Several studies have highlighted the significance of novel approaches in understanding and managing mental health issues. Numerous studies have shown that students in higher education are especially vulnerable to mental health problems like anxiety and depression. Students in higher education encounter a variety of difficulties, including those related to their changing lifestyles, social adjustments, and academic responsibilities. Finding the factors that contribute to these problems is a difficult task for academics and higher education institutions. These results make it very clear that novel strategies are desperately needed to prevent and treat anxiety disorders. The creation and application of cutting-edge techniques that provide early detection and customized interventions are necessary in this context with the extreme objective of progressing the quality of life for individuals impacted. This objective is in line with the larger global mission to effectively and comprehensively address the growing problem of mental health disorders [4].

Pandit *et al* in [24] introduced factors for examining Anxiety and Depression Prediction. As one of the mental health conditions, and as a open wellbeing concern that has fundamental impacts on all person quality of life, relationship with others, and by and large prosperity. In early inquiries about work machine learning methods and information science have coordinated the imperative devices for early discovery of mental wellbeing related issues. The researcher's objective is to point at given more information on the components driving to anxiety and depression and to develop a predictive modeling for improving the accuracy and efficiency of early mental health diagnoses. Out of the method that is been used Tabular DNN outperformed ANN and other machine learning methods that were used by 30%. Furthermore, the findings were able to proof that deep learning tabular models have the strength to improve the accuracy and efficiency. A diagnosis of mental health at early stage is very important in order to have access and support to all individuals that are in need of this work.

Concurring to [25]. Anxiety disorder as the biggest group and the foremost commonest sort of mental health disorders. Along the line, it has been known that checking patients history and analyze issue impersonation in making coherent choices can be done by the utilize of machine learning approach. The survey of this paper is the most concept and applications of machine learning strategies in anticipating anxiety disorder sorts and Seventeen (17) thinks about were considered that connected machine learning approach for anticipating anxiety disarranges and five (5) extra considers were inspected for anticipating suicide propensities. The precision of the comes about varies agreeing to the sort of uneasiness clutter and the sort of strategies utilized for foreseeing the clutter.

The side effects of anxiety and depression at early stage in children have 4 major impacts on children mental wellbeing development counting their full of feeling advancement. Examining the impact of mental wellbeing issues on emotional advancement has pulled in the intrigued of most researchers' consideration for the final two decades. The objective of this paper, machine learning strategies was utilized to foresee the chance variables related with children in school on depression and anxiety. [26] utilize data consisted of 5685 understudies in grades 5-9, matured 10-17 a long time, examining at open and outcast schools in the West Bank. The information were collected utilizing the wellbeing behaviors school children survey within the 2012-2013 scholarly a long time and analyzed utilizing machine learning to anticipate the hazard components related with understudy mental wellbeing side effects. Five machine learning techniques (Arbitrary Woodland, Neural Arrange, Choice Tree, Bolster Vector Machine, and Naïve Bayes) were utilized for the forecast by the analysts. Out of the five machine learning strategies that was utilized the comes about demonstrated that the Arbitrary Woodland show had the most noteworthy exactness levels (72.6%, 68.5%) for depression and anxiety respectively and it has the most excellent execution in gathering and foreseeing the student's depression and anxiety. The results appeared that school viciousness and bullying, scholarly execution, and family wage were the foremost imperative variables influencing depression and anxiety scales. In general, machine learning demonstrated to be an proficient device for recognizing and anticipating the related components that impact understudy sadness and anxiety. The arrangement of machine learning inside the school data frameworks might encourage the improvement of health prevention and intercession programs that will enhance students' mental health and cognitive improvement.

In the research work of [4] machine learning calculations were utilized to foresee the event of anxiety, depression, and stretch. The analysts collected information from utilized and unemployed people over diverse societies and communities utilizing the Depression, Anxiety, and Push Scale survey. The machine learning calculations precisely anticipated uneasiness, discouragement, and stretch on five diverse seriousness levels. In any case, the classes in the perplexity lattice were imbalanced, so the F1 score degree was included to recognize the finest exactness demonstrate. The Random Forest classifier was found to be the foremost exact among the five calculations utilized. Also, the calculations were particularly sensitive to negative comes about, as shown by the specificity parameter. [27] introduce that mental health problems have become a significant concern in Malaysia. Generally, these problems encompass a range of health issues that impact an individual's emotions, thoughts, behavior, and social interactions. The National Wellbeing and Morbidity Study (NHMS) conducted in 2017 revealed that one out of every five Malaysians suffers from depression, while two out of every five experience anxiety, and one out of every ten faces stress. Notably, higher education students are particularly vulnerable to mental health issues. However, identifying the factors contributing to these problems poses a challenge, hindering effective assistance for individuals affected by them.

[6] introduce that understanding and addressing mental health issues is crucial for overall well-being of society. By analyzing text data from sources like social media, researchers can gain deeper insights into these illnesses and potentially detect them early on. In our research, we aim to detect the mental state of social media users using advanced deep learning models, departing from traditional methods. Through a binary classification task, we successfully predict if a user is suffering from one of nine different disorders. Our hierarchical attention network surpasses previous benchmarks for four of these disorders. Additionally, we investigate the limitations of our model and examine key phrases that contribute to the classification through word-level attention weights analysis [18]. In recent years, there has been a noteworthy rise within the predominance of psychological disorders around the world. This considers points to foresee the event of common mental wellbeing issues, counting anxiety, depression, and stretch, by utilizing eight diverse machine learning calculations. Information from the online DASS42 apparatus was utilized to anticipate five levels of severity for each clutter. The calculations were categorized into probabilistic, closest neighbor, neural organize, and tree-based strategies. Furthermore, a crossbreed classification calculation was utilized to foresee the severity levels. The same methods were connected to another dataset, DASS21, collected by the creators. The results shows that the crossover calculation outperformed person calculations in terms of expectation precision. Strikingly, the spiral premise work arrange, a sort of neural arrange, displayed the most elevated exactness among the calculations utilized. The researcher discusses the significance of early detection and prediction of lung cancer, by

emphasizing on the potential of machine learning-based models, specifically ensemble techniques, to enhance the accuracy in predicting lung cancer.

Based on the research work of [28], the researcher discusses how traditional screening methods for anxiety and depression can be limiting and how the recent advancements in Natural Language Processing (NLP) and speech modeling offer a more effective approach in addressing the situation. The proposal introduces a multi-modal system that combines deep-learned features from audio and text with hand-crafted features rooted in clinical domain knowledge for screening depression and anxiety. However, the experimental results indicate that the integration of deep-learned features with hand-crafted techniques improved the classification performance, which demonstrate the potential of speech-based biomarkers for mental health screening in the realm of digital health, based on the F1 scores increasing from 0.58 to 0.63 for depression and from 0.54 to 0.57 for anxiety.

[29] discusses anxiety as a response to life's stresses and clashes, with over the top signs demonstrating anxiety disorders regularly related to Autonomic dysfunction (ADy). Recognizing ADy inside uneasiness clutter patients utilizing existing strategies is considered as a challenging assignment. The analysts receive machine learning models and properties determined from ECG and respiratory signals to identify ADy in people with anxiety. Factual and recurrence space highlights from these signals are utilized, and administered machine learning calculations, counting SVM, Irregular Timberland, and Slope Boosting. Based on the try conducted the accomplish promising comes about with precision up to 82.2% and AUC values up to 0.84 in 10 and 30 miniature sectioned datasets. Based on the discoveries, the analysts recommended that ECG-derived highlights can serve as successful markers for diagnosing ADy in anxiety clutter patients, and the potential for even better precision with profound neural network-based models is famous for assist investigation. [30] addresses the centrality of screening and diagnosing anxiety and depression in epilepsy patients, given their high predominance as comorbidities. The analysts enlist 480 epilepsy patients and utilize six machine learning models to foresee anxiety and depression. The results collated by the analyst appear that the random forest and multilayer perceptron models are especially compelling in expectation, with stigma being the foremost imperative highlight. The study proposes that the strategies created may be profitable for distinguishing epilepsy patients at risk of anxiety and discouragement, possibly supporting regular, persistent administration. Further research is required to evaluate the commonsense application of this framework in clinical settings.

The importance of this research lies in its potential to address a pressing issue: the decline in life expectancy. More than 1.8 million lives are assessed to have been lost due to COVID-19 around the world in 2020. This estimate, although staggering masks the uneven effect of the widespread over distinctive nations and statistical characteristics like age and sex, as well as its effect on population wellbeing, a long time of life expectancy and life span. By developing an AI-driven approach to assess anxiety and stress levels, we hope to contribute to the improvement of mental health, thereby enhancing overall well-being and life expectancy. This research may serve as a blueprint for utilizing AI technology to combat anxiety-related health problems in the aftermath of a major public health crisis in Nigeria. This aims to predict anxiety in students with the use of a particle swarm optimization-tuned support vector machine approach. The paper will identify predominant features leading to anxiety aggravation, and identify a good model to predict anxiety

3. METHODOLOGY

This section introduces the model description, dataset collection and dataset descriptive analysis for the model algorithm to predict anxiety among undergraduate students.

3.1 Dataset Collection

The datasets were collected from college and university undergraduate students in Lahore, Pakistan, including medical colleges, professional studies departments, and specific institutions like FMH College of Medicine and Dentistry, giving profitable experiences into the predominant issues of depression and anxiety among the student populace. It consists of 787 participants providing a comprehensive view of the mental health landscape among the university's undergraduate population. This dataset is generated from the inspiration of the Beck Depression and Beck Anxiety inventories. The datasets are typically collected via convenience sampling using structured, self-reported online questionnaires, often investigating the relationship between anxiety, depression, and stress. Ethical Approval: Ethical approval was obtained from the Institutional Review Board.

3.2 Dataset Descriptive Analysis

Fig. 1 presents graphic insights of the descriptive statistics of the dataset systematically comparing information between occurrences of anxiety and non-anxiety cases inside the dataset. For occasions classified as non-anxiety cases, the expressive measurements uncover that the 'Amount' highlight ranges from at least esteem of 1.00 to a greatest of 28,948.

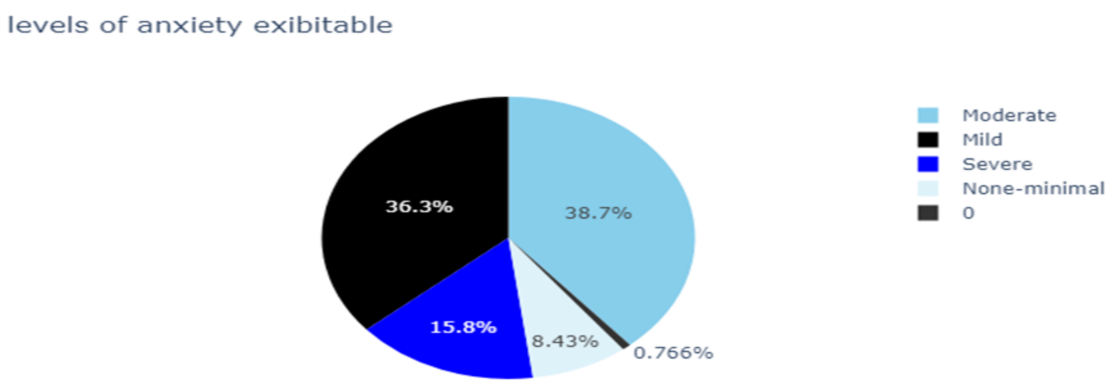

Fig 1: Descriptive statistics of the dataset

This wide extend proposes critical changeability in exchange sums inside the non-anxiety category. On the other hand, anxiety cases show a smaller run, with least and greatest 'Amount' values of 1.18 and 1,371.81, separately. (Beck Sadness Stock: Employments, Unwavering quality, Where to Require the Test. These discoveries give pivotal experiences into the dissemination designs of 'Amount' over uneasiness and non-anxiety cases. Analyzing the measurable rundown encourages a more profound understanding of the characteristics and potential qualifications in exchange sums, shedding light on the relationship between financial exchanges and anxiety levels inside the dataset.

3.3 Model Preprocessing Stages

Description of the model Preprocessing is shown in Fig. 2. It serves as a valuable resource for evaluating machine learning methods, particularly in the realm of classification tasks related to the severity of depression and anxiety [19].

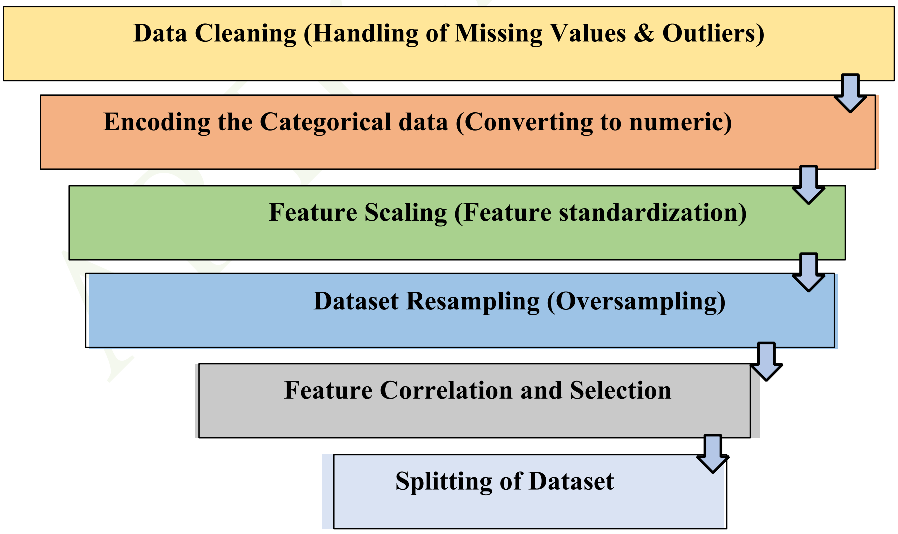

Fig. 2: Data Preprocessing stages

Data preprocessing is a vital task in machine learning to acquire accurate task. It is significant as different models have unmistakable prerequisites and information quality that can essentially affect prescient execution. Data preprocessing serves a few key purposes, counting information cleansing and planning to relieve inclinations, taking care of lost values, and diminishing variety. The dataset includes both numerical and categorical information, requiring the encoding of categorical factors some time recently they can be utilized for modeling purposes. Also, the information experienced exception location and evacuation to dispense with information focuses that might antagonistically influence demonstrate execution. Guaranteeing that autonomous factors are inside the same extend is crucial for show stability; hence, highlight scaling was connected to standardize the factors. This was done to relieve any potential inclinations and overfitting within the preparing of our machine learning model. The execution of these preprocessing assignments was encouraged utilizing the Python information control library, pandas, and the machine learning library, scikit-learn. The step-by-step prepare is outlined in Fig 2..

3.4 Model Description

This study encompassed an exploration of various machine learning models, both supervised and unsupervised, to effectively classify anxiety treatment state. The choice of machine learning models employed in this research is expounded upon in the subsequent subsection. Additionally, the process of model creation and the selection of optimal hyper parameter values for achieving the best model performance are elaborated upon. Selecting an appropriate machine learning model is a critical decision in the modeling process.

Different models possess unique characteristics and are well-suited to specific types of problems. Therefore, a comprehensive evaluation of various models was conducted to ascertain their suitability for the task of classifying anxiety treatment state After completing the dataset preprocessing stage, the information experiences a vital step of dividing into preparing and test sets. This plays a significant part in setting up the model's parameters, for Support Vector Machine. Particle Swarm Optimization was later explored on the SVM to ascertain effectiveness of optimization. Hold Out Cross validation was applied on the models by splitting the datasets in 70:30 training and testing ratio respectively

3.5 Hyperparameter Tunning with the Best Model

To assess the performance of our top-performing algorithms, we conducted hyper parameter tuning, a crucial step in optimizing learning algorithms. Hyper parameter tuning aids in selecting the most effective parameters for machine learning classifiers, enhancing their predictive capabilities

4. RESULT AND DISCUSSION

4.1 Data Preprocessing Results

Earlier to actualizing a machine learning calculation, it is basic to embrace information preprocessing. This step is significant as different models have unmistakable prerequisites and information quality can essentially affect prescient execution. Information preprocessing serves a few key purposes, counting information cleansing and planning to relieve inclinations, taking care of lost values, and diminishing variety. The dataset includes both numerical and categorical information, requiring the encoding of categorical factors some time recently they can be utilized for modeling purposes. Also, the information experienced exception location and evacuation to dispense with information focuses that might antagonistically influence demonstrate execution. Guaranteeing that autonomous factors are inside the same extend is crucial for show stability; hence, highlight scaling was connected to standardize the factors. This was done to relieve any potential inclinations and overfitting within the preparing of our machine learning model. The execution of these preprocessing assignments was encouraged utilizing the Python information control library, pandas, and the machine learning library, scikit-learn.

Hence, the information cleaning prepare was embraced, which included two essential processes:

i. Removing Null and Missing Values: The dataset comprises of 789 instances, and it was found that there were 18 invalid values inside the dataset.

ii. Handling Outliers: This involves distinguishing and overseeing exceptions inside the dataset. Exceptions are information focuses that essentially veer off from the rest of the information, regularly carrying the potential to misshape show execution. To distinguish exceptions, the boxplot method was utilized for all the free highlights. Boxplots are compelling visualizations for recognizing exceptions, with exceptions spoken to as information focuses exterior the boxplot's hairs. For effortlessness, the box plot of a few of the highlights is delineated in Fig. 3.

Whereas the box plots uncovered the nearness of exceptions within the information, a vigorous strategy known as the Interquartile Run (IQR) procedure was connected to handle these exceptions. The IQR strategy is eminent for its versatility to exceptions. In this approach, any information point falling past the boundary of Q3 + 1.5 times the IQR is classified as an exception and along these lines expelled. This prepare was carried out to improve the vigor and exactness of the machine learning models utilized within the venture.

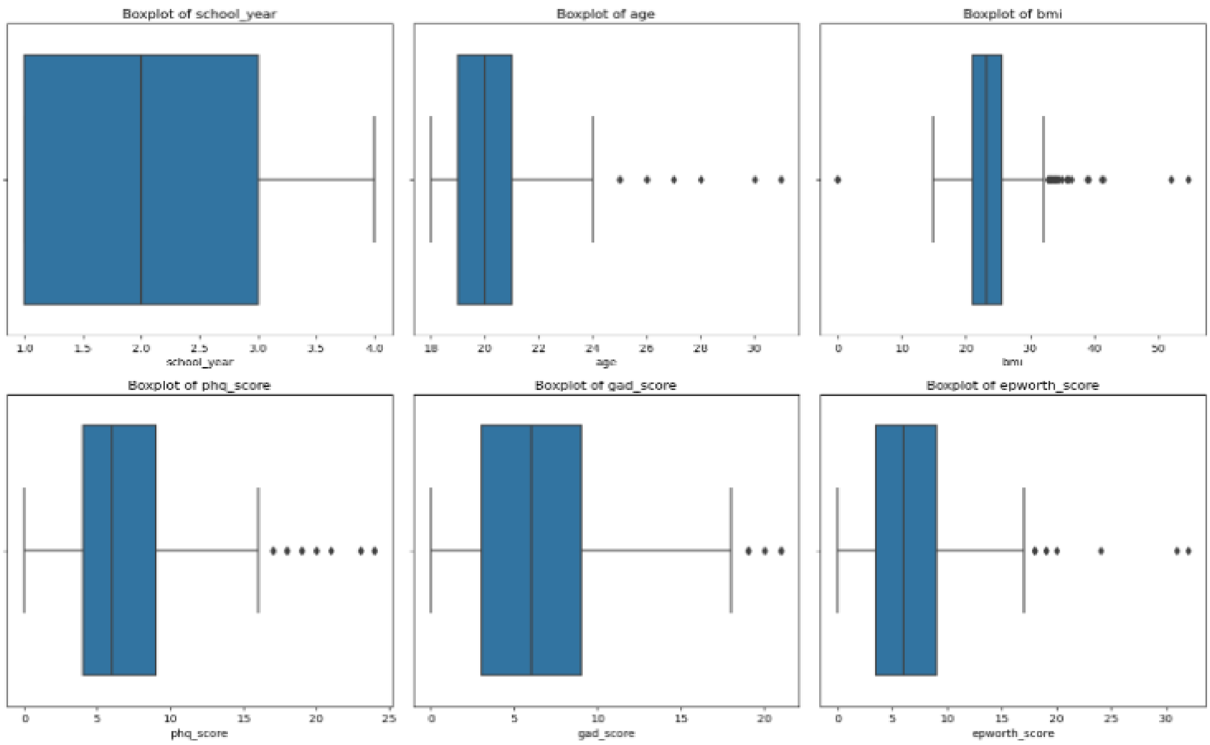

Fig 3: Boxplot of the numerical values

4.2 Feature Scaling

The vital step within the information preprocessing pipeline includes scaling, a method utilized to standardize the run of free factors inside the dataset. Highlight scaling guarantees that the factors are inside a steady extend, which can be centered around or inside the extend of to 1, depending on the chosen scaling strategy. When input variables exhibit widely varying magnitudes, with some having excetionally large values, it can lead to issues such as algorithmic oversight or skewed model performance. To mitigate these issues, feature scaling was performed in this study using the skew function of scipy.stats, also referred to as robust standardization.

The scipy.stats method involves the following steps:

i. Calculation of the median (50th percentile), the 25th percentile, and the 75th percentile for each variable.
ii. Subtracting the middle from the values of each variable.

Separating the result by the interquartile extend (IQR), which is the contrast between the 75th and 25th percentiles. This process guarantees that the factors are changed in a way that creates them strong to exceptions and steady for machine learning calculations. Fig. 4 outwardly outlines the include scaling prepare, delineating how it successfully normalizes the run of autonomous factors inside the dataset

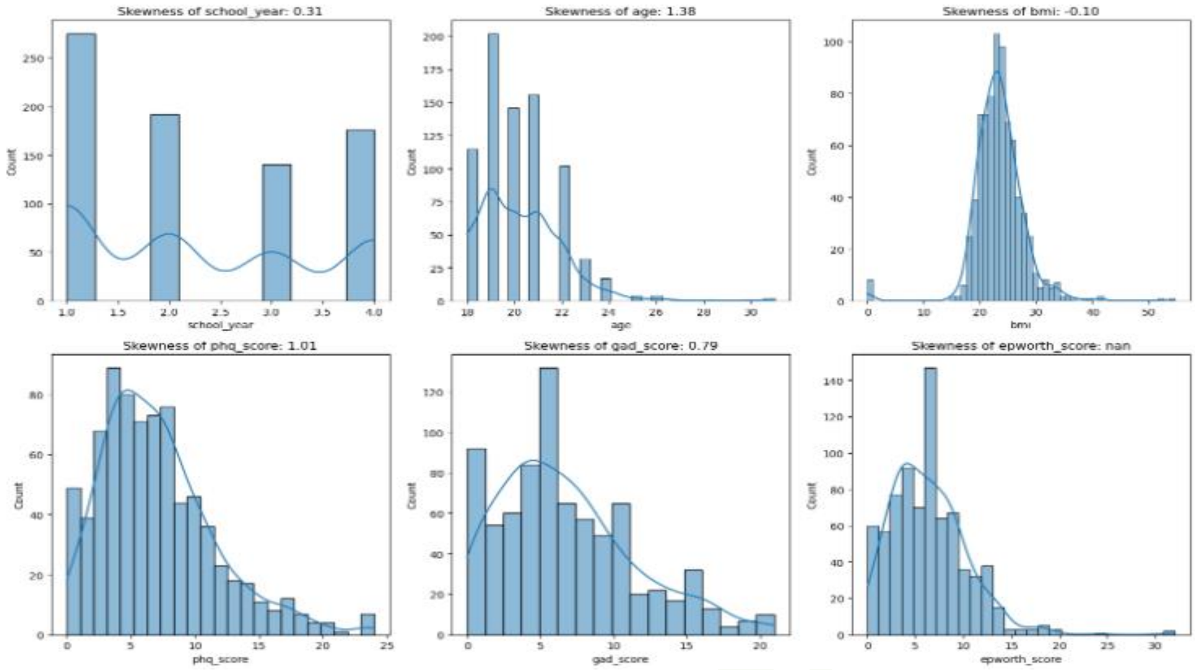

Fig.4: Feature Scaling done using the skew function

4.3 Dataset Re-sampling

In addressing the challenge of imbalanced data, where we have more of the male class over the female hence may be underrepresented, oversampling techniques become a valuable tool to ensure a balanced representation of different classes in the dataset. This is particularly crucial in scenarios where the available data is limited, as a skewed distribution can lead to biased model outcomes, especially for the minority class. Oversampling involves augmenting the instances of the minority class by generating synthetic samples or replicating existing ones. By artificially inflating the representation of the underrepresented class, oversampling aims to mitigate the impact of class imbalance, fostering a more equitable learning environment for machine learning models. In the context of mental health care prediction, such as anxiety treatment outcomes, employing oversampling becomes imperative, especially when dealing with datasets reflecting real-world demographics, as observed in the Federal District where the number of women seeking treatment surpasses that of men. This technique enhances the model's ability to generalize across diverse demographic groups, ensuring that predictions are not skewed toward the majority class and that the model is better equipped to handle the inherent imbalances in the data. Some classifiers may struggle to perform well with imbalanced datasets. To mitigate these concerns and enhance classifier performance, this paper implemented resampling technique; oversampling to balance the dataset.

4.4 Feature Correlation and Selection

In predictive machine learning pipeline, selecting the most relevant features is a pivotal step in the data preprocessing pipeline. Not all features within a dataset contribute significantly to building an accurate predictive model. Therefore, feature selection is employed to identify and retain only those features that have a substantial impact on improving prediction accuracy. One crucial aspect of feature selection is assessing feature correlation. Features that exhibit a high degree of correlation are likely to be linearly dependent and have a similar influence on the dependent variable. Consequently, when two features are highly correlated, it is often prudent to retain only one of them, reducing redundancy in the dataset.

To gain insights into feature correlations, heat maps were generated to visualize the correlation patterns within the original dataset and later the oversampled datasets. These heat maps, displayed in Fig.5 provide a graphical representation of feature correlations. However, due to the dataset's size, the heat maps may not reveal intricate details. Consequently, feature selection was undertaken to identify and retain the most pertinent features. This process aids in capturing essential features that contribute significantly to building an effective machine learning model for predictive purposes.

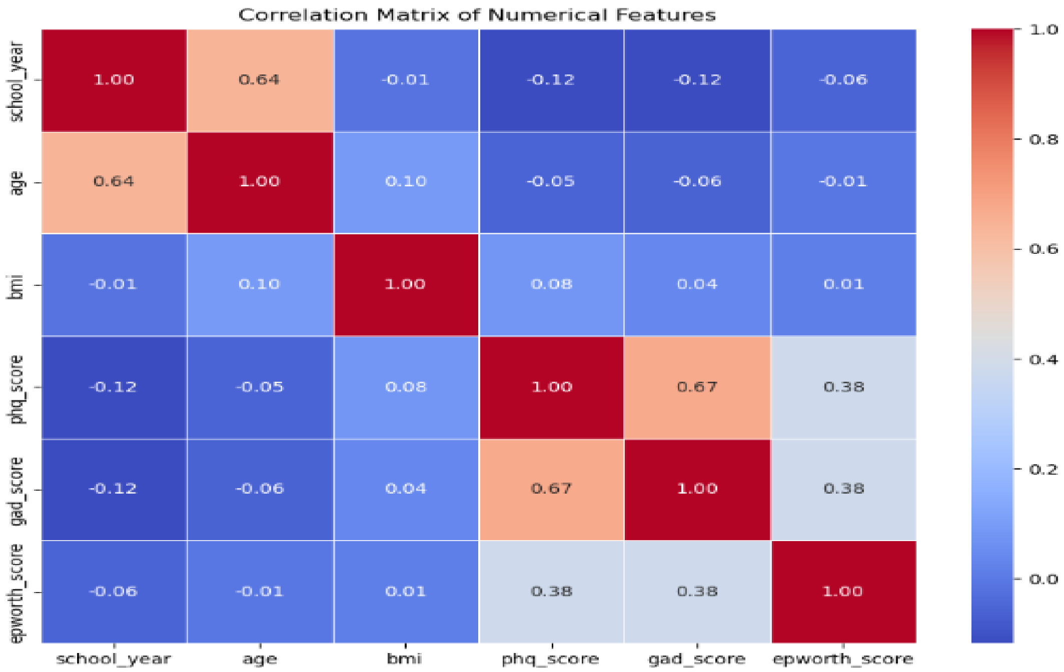

Fig. 5: The correlation map of the various features

4.5 Comparative Analysis

Our evaluation considered the original dataset, under sampling, and oversampling datasets, utilizing the AUC score, accuracy, precision, recall, and F1-score for comparison. The SVM, PSO tuned SVC, SVC on oversampled data, PSO-tuned SVC on oversampled data are all evaluated. The PSO-tuned SVC on oversampled data consistently outperformed other models on all evaluation metrics

Table 1: Accuracy, Precision and AUC score after hyper parameter tuning

Methods	Accuracy	Precision	AUC score	Recall	F1 score
Support Vector Classifier	0.862	0.822	0.500	0.000	0.000
PSO-tuned Support vector classifier	0.960	0.960	0.998	0.998	0.833

Table 1 displays Accuracy, Precision and AUC score after hyper parameter tuning. It reveals that PSO tuned SVC on oversampled data correctly identified the anxiety or non-anxiety cases. It shows the performance of Support vector Machine with the PSO-tuned SVC on oversampled data respectively. The matrix reveals that out of all sample cases, PSO-tuned SVC on oversampled data identified all targets correctly. The exploration of machine learning models, particularly Support Vector Machines (SVMs), in predicting anxiety treatment outcomes holds promise for advancing mental health research and personalized intervention strategies. The utilization of various features, including psychological scores, demographic information, and treatment history, contributes to a holistic understanding of factors influencing treatment efficacy.

The models developed in this study, particularly the optimized model with hyperparameter tuning techniques like Particle Swarm Optimization (PSO), exhibit the potential to enhance predictive accuracy and guide clinicians in tailoring treatment plans. As we navigate the complex landscape of mental health, the integration of advanced machine learning methodologies not only aids in prognosis but also opens avenues for gaining deeper insights into the intricate interplay of variables affecting anxiety treatment outcomes. Ultimately, the strides made in this study underscore the transformative potential of machine learning in mental health, offering a glimpse into a future where predictive analytics can contribute meaningfully to personalized and effective anxiety treatment strategies. This suggests that oversampling can be a valuable approach in real-world scenarios to improve classification without losing critical information.

5. CONCLUSION

The primary aim of this study is to explore the application of machine learning models, with a specific focus on Support Vector Machines (SVMs) in predicting anxiety treatment outcomes. The foundation of the research lies in the recognition of the complex nature of mental health and the potential for personalized intervention strategies. The study employs a holistic approach by incorporating various features, including psychological scores, demographic information, and treatment history, to comprehensively understand the factors influencing treatment efficacy. Notably, the models developed undergone optimization through hyperparameter tuning techniques such as Particle Swarm Optimization (PSO), showcasing the potential to enhance predictive accuracy.

The study emphasizes the transformative role of advanced machine learning methodologies in gaining deeper insights into the intricate interplay of variables affecting anxiety treatment outcomes. The methodology employed in this research involves the development and optimization of predictive models, particularly the Support Vector Classifier, using oversampling techniques and PSO for hyperparameter tuning. The findings revealed that the Oversampled, PSO-tuned Support Vector Classifier outperforms other models, especially when applied to oversampled data. The study recommends further exploration in key areas for future research, including alternative sampling methods to enhance classifier models without introducing redundant observations. Additionally, it proposes the integration of advanced hyperparameter tuning options, such as metaheuristic algorithms like PSO or Genetic Algorithms, and ensemble methods to improve the efficiency and robustness of SVMs in predicting anxiety treatment outcomes.

Additionally, leveraging Bayesian optimization methods could provide a probabilistic framework that not only tunes hyperparameters but also models the optimization process, adapting to the system's response and iteratively refining the search space. Another area worth exploring is ensemble methods in hyper parameter tuning. The study underscores the importance of collaboration between data scientists, clinicians, and mental health professionals for the responsible deployment of machine learning models in clinical settings. Overall, the research lays the foundation for future endeavors in refining and advancing predictive analytics for personalized and effective anxiety treatment strategies.

Declaration

Ethical Statement: The authors of this paper hereby give declaration of competing interest that this paper is our original work and has not been published in any media

Competing Interest: This article has no competing interests

Funding: There is no external funding received by the authors

Availability of data and material: **https://www.kaggle.com/datasets/shahzadahmad0402/depression-and-anxiety-data**

Consent to participate: Not Applicable

REFERENCES

1. Roller, L., & Gowan, J. (2019). The anxious person. *Australian Journal of Pharmacy*, *100*(1181).
2. Gutoreva, A., & Olin, S. L. (2024). Cognitive causes of the mental state of terror and their link to mental health outcomes. *Journal of Health Psychology*, *29*(14), 1704-1718.
3. Magson, N. R., Freeman, J. Y., Rapee, R. M., Richardson, C. E., Oar, E. L., & Fardouly, J. (2021). Risk and protective factors for prospective changes in adolescent mental health during the COVID-19 pandemic. *Journal of youth and adolescence*, *50*(1), 44-57.
4. Priya, A., Garg, S., &Tigga, N. P. (2020). Predicting Anxiety, Depression and Stress in Modern Life using Machine Learning Algorithms. *Procedia Computer Science*, *167*, 1258–1267. https://doi.org/10.1016/j.procs.2020.03.442
5. Nemesure, M. D., Heinz, M. V., Huang, R., & Jacobson, N. C. (2021, January 21). Predictive modeling of depression and anxiety using electronic health records and a novel machine learning approach with artificial intelligence. *Scientific Reports*, *11*(1). https://doi.org/10.1038/s41598-021-81368-4
6. Sekulić, I., & Strube, M. (2019, November). Adapting deep learning methods for mental health prediction on social media. In *Proceedings of the 5th Workshop on Noisy User-generated Text (W-NUT 2019)* (pp. 322-327).

7. Jacobson, N. C., Lekkas, D., Huang, R., & Thomas, N. (2021, March). Deep learning paired with wearable passive sensing data predicts deterioration in anxiety disorder symptoms across 17–18 years. *Journal of Affective Disorders*, *282*, 104–111. https://doi.org/10.1016/j.jad.2020.12.086
8. Stitson, M. O., Weston, J. A. E., Gammerman, A., Vovk, V., & Vapnik, V. (1996). Theory of support vector machines. *University of London*, *117*(827), 188-191.
9. Mahesh, B., & Amanullah, M. (2025, June). Analysis of K neighbors classifier algorithm compared for improved accuracy with logistic regression for predicting depression. In *AIP Conference Proceedings* (Vol. 3267, No. 1, p. 020114). AIP Publishing LLC.
10. Saifullah, S., Fauziyah, Y., &Aribowo, A. S. (2021, February 24). Comparison of machine learning for sentiment analysis in detecting anxiety based on social media data. *JurnalInformatika*, *15*(1), 45. https://doi.org/10.26555/jifo.v15i1.a20111
11. Widodo, S., Brawijaya, H., &Samudi, S. (2022, October 3). Stratified K-fold cross validation optimization on machine learning for prediction. *Sinkron*, *7*(4), 2407– 2414. https://doi.org/10.33395/sinkron.v7i4.11792
12. Wade, T. D., Allen, K., Crosby, R. D., Fursland, A., Hay, P., McIntosh, V., ... & Byrne, S. (2021). Outpatient therapy for adult anorexia nervosa: Early weight gain trajectories and outcome. *European Eating Disorders Review*, *29*(3), 472-481.
13. Stein, G., Chen, B., Wu, A. S., & Hua, K. A. (2005, March). Decision tree classifier for network intrusion detection with GA-based feature selection. In *Proceedings of the 43rd annual ACM Southeast Conference-Volume 2* (pp. 136-141).
14. Rana, M. S. R., & Kabir, M. R. (2020, December). Determining Clinical Depression From The Analysis of Socio-Economic Attributes. In *2020 23rd International Conference on Computer and Information Technology (ICCIT)* (pp. 1-6). IEEE.
15. Charbuty, B., &Abdulazeez, A. (2021, March 24). Classification Based on Decision Tree Algorithm for Machine Learning. *Journal of Applied Science and Technology Trends*, *2*(01), 20–28. https://doi.org/10.38094/jastt20165
16. Ahmed, S. T., Singh, D. K., Basha, S. M., Abouel Nasr, E., Kamrani, A. K., & Aboudaif, M. K. (2021). Neural network based mental depression identification and sentiments classification technique from speech signals: A COVID-19 Focused Pandemic Study. *Frontiers in public health*, *9*, 781827.
17. Nasir, J. A., Khan, O. S., &Varlamis, I. (2021, April). Fake news detection: A hybrid CNN-RNN based deep learning approach. *International Journal of Information Management Data Insights*, *1*(1), 100007. https://doi.org/10.1016/j.jjimei.2020.100007
18. Kumar, P., Garg, S., & Garg, A. (2020). Assessment of Anxiety, Depression and Stress using Machine Learning Models. *Procedia Computer Science*, *171*, 1989–1998. https://doi.org/10.1016/j.procs.2020.04.213
19. Zhang, L., Wang, S., & Liu, B. (2018, March 30). Deep learning for sentiment analysis: A survey. *WIREs Data Mining and Knowledge Discovery*, *8*(4). https://doi.org/10.1002/widm.1253
20. Eberhart, Russell C., Yuhui Shi, and James Kennedy. *Swarm intelligence*. Elsevier, 2001.
21. Zhang, Yan, Bingdong Li, Wenjing Hong, and Aimin Zhou. "MOCPSO: A multi-objective cooperative particle swarm optimization algorithm with dual search strategies." *Neurocomputing* 562 (2023): 126892.
22. Kong, Yunfeng. "An iterative local search based hybrid algorithm for the service area problem." *Computational Urban Science* 1, no. 1 (2021): 19.
23. Zhao, ZiYan, MengChu Zhou, and ShiXin Liu. "Iterated greedy algorithms for flow-shop scheduling problems: A tutorial." *IEEE Transactions on Automation Science and Engineering* 19, no. 3 (2021): 1941-1959.
24. Pandit, M., Azwaan, M., Wani, S., Abubakar Ibrahim, A., AbdulmollaAbdulghafor, R. A., &Gulzar, Y. (2023, January 28). Examining Factors for Anxiety and Depression Prediction. *International Journal on Perceptive and Cognitive Computing*, *9*(1), 70–79. https://doi.org/10.31436/ijpcc.v9i1.368
25. Kotsilieris, T., Pintelas, E., Livieris, I. E., & Pintelas, P. (2020). Predicting anxiety disorders and suicide tendency using machine learning: a review. *International Journal of Medical Engineering and Informatics*, *12*(6), 599-608.
26. Qasrawi, R., Polo, S. P. V., Al-Halawa, D. A., Hallaq, S., & Abdeen, Z. (2022). Assessment and prediction of depression and anxiety risk factors in schoolchildren: machine learning techniques performance analysis. *JMIR formative research*, *6*(8), e32736.
27. Khaiyom, J. H. A., Mukhtar, F., & Oei, T. P. S. (2021). Anxiety Disorders in Malaysia from 2005 To 2015: A Scoping Review of their Prevalence Rates, Associated Factors, And Predictors: Received

2020-04-05; Accepted 2021-03-08; Published 2021-09-16. *Journal of Health and Translational Medicine (JUMMEC)*, *24*(2), 31-47.

28. Diep, B., Stanojevic, M., & Novikova, J. (2022). Multi-modal deep learning system for depression and anxiety detection. *arXiv preprint arXiv:2212.14490*.
29. George, A. S., Kurup, A. V., Balachandran, P., Nair, M., Gopinath, S., Kumar, A., &Parasuram, H. (2021, July 2). Predicting Autonomic Dysfunction in Anxiety Disorder from ECG and Respiratory Signals Using Machine Learning Models. *International Journal of Online and Biomedical Engineering (IJOE)*, *17*(07), 143.
30. Wei, Z., Wang, X., Ren, L., Liu, C., Liu, C., Cao, M., Feng, Y., Gan, Y., Li, G., Liu, X., Liu, Y., Yang, L., & Deng, Y. (2023, September). Using machine learning approach to predict depression and anxiety among patients with epilepsy in China: A cross-sectional study. *Journal of Affective Disorders*, *336*, 1–8. https://doi.org/10.1016/j.jad.2023.05.043
31. Ikegwu, Anayo Chukwu, James Onyilo, and Henry Friday Nweke. "Artificial intelligence-based clinical decision support systems: enhancing modern healthcare for smart diagnosis and prognosis." *Nat J Emerging Sci Technol Innovations* 1, no. 1 (2025): 17-34.