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Article

A mental health monitoring system based on intelligent algorithms and biosensors: Algorithm behaviour analysis and intervention strategies

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Abstract: Introduction: Mental health monitoring encompasses the systematic observation and assessment of an individual's psychological well-being, aiming to detect, understand and manage mental health conditions. It involves various techniques and interventions tailored to support individuals in achieving and maintaining optimal mental wellness. Recent advancements include the use of biosensors and biomechanics to analyze physiological signals that correlate with mental states, providing a more comprehensive understanding of psychological well-being. **Aim:** The aim of this research is to construct an innovative mental health monitoring system established on intelligent algorithms and biomechanical data through behaviour analysis and intervention strategies. **Methodology:** We propose a novel Snow Ablation-driven Bi-directional Fine-tuned Recurrent Neural Network (SA-BFRNN) to identify the state of mental health. In addition to behavioural data, biosensors are employed to collect real-time physiological signals such as heart rate variability, skin conductance, and muscle tension, offering objective markers of mental stress and anxiety. These biomechanical inputs are integrated into the system for multi-modal analysis. We employ the SA algorithm, iteratively removing less influential connections and nodes based on their impact on model performance. This process enhances network efficiency and generalization capabilities, refining the BFRNN for mental health state identification. Utilizing a questionnaire with 25 questions, administered to a selected group of 756 individuals, we validate our proposed model. Biosensor data is synchronized with questionnaire responses to improve the precision of mental state identification. Clustering-derived labels are validated with mean opinion score. These labels inform classifiers for individual mental health prediction, aligning with our objective of robust mental health assessment through data-driven approaches. SA-BFRNN integrates both forward and backward temporal information, enhancing its ability to discern subtle patterns in behaviour. Through iterative fine-tuning, our network learns to adapt to diverse datasets, enabling precise identification of mental health states. **Research findings:** In the result evaluation phase, we thoroughly examine how well our proposed SA-BFRNN model recognizes various states of mental health across different parameters. Our findings also highlight the significance of incorporating biomechanics, where biosensor data showed a strong correlation with mental health indicators, thereby augmenting the accuracy of the system. Our findings emphasize the efficacy of the SA-BFRNN technique, as demonstrated by its overall performance in terms of recall (92.56%), accuracy (90.13%), F1-score (88.16%) and precision (89.23%). Our experimental results unequivocally demonstrate that our proposed model performed better than other traditional approaches in classifying contents from multimodal data, showing notable enhancements in accuracy and robustness, particularly under dynamic conditions.

Keywords: mental health monitoring system; biosensors; biomechanics; intelligent algorithms; mental health prediction; snow ablation-driven bi-directional fine-tuned recurrent neural network (SA-BFRNN)

1. Introduction

Mental health is a critical issue of overall well-being, impacting human's thoughts, emotions and movements in everyday breathing [1]. It additionally affects our capability to manage stress, interact with human beings and make selections. Mental health issues have grown to be a primary public fitness situation, impacting millions of humans globally in the current decades [2]. The persistent sensitivity around intellectual health issues and the restrained availability of professional assistance makes those problems. Innovative methods of tracking and intervening in mental health are therefore additionally acceptable but also essential.

An important development in the connection of technology and healthcare is the creation of the MHMS. This system uses statistical knowledge and customized approaches for intervention to effectively analyse, forecast and manage mental health disorders [3]. Recent advancements include the integration of biosensors and biomechanical data to offer deeper insights into physiological signals such as heart rate, skin conductance, and muscle tension, providing a more holistic view of mental well-being.

Mental health encompasses numerous components, each playing a vital position in influencing a person's universal well-being. It consists of our emotional balance, psychological resilience and the ability to create and hold fulfilling relationships. Moreover, mental fitness influences essential lifestyle capabilities together with decision-making, stress control and the capacity to conform to alternate or face adversity [4].

The spectrum of intellectual fitness stages from flourishing well-being, wherein people realize their talents, address contribute to their communities, work productively and ordinary stresses of life, to diverse levels of intellectual health problems along with melancholy, tension, schizophrenia and bipolar sickness. These disorders can particularly impair a person's potential to perform daily responsibilities, interact in productive interactions and sense a feeling of connection and value [5].

Globally, mental health conditions are a major contributor to the load of disease. According to worldwide fitness assessments, depression is a main purpose of incapacity internationally, affecting thousands and thousands of people [6]. Anxiety problems, substance use problems and other psychiatric situations also pose significant health challenges and they are often connected to different serious fitness outcomes, which include cardiovascular sickness, diabetes and weight problems [7].

The conduct of intellectual health refers to the signs and symptoms of mental health conditions manifest in regular lifestyles and they can be objectively measured and monitored [8]. Usually, mental health experts depend upon self-mentioned signs and observable conduct in the course of medical exams to diagnose and treat mental health issues [9]. However, behaviours related to intellectual fitness can be delicate and range substantially among individuals, which pose demanding situations in correct and timely diagnosis.

Advancements in technology have brought the improvement of mental fitness monitoring structures that use diverse tools, together with mobile apps, wearable devices and information analytics, to gather as well as analyze behavioural records [10]. These systems can track patterns including sleep, physical hobbies, and social interaction and mood fluctuations. Wearable devices equipped with biosensors can further measure biomechanical responses, such as gait analysis, heart rate variability, and galvanic skin response, providing more accurate indicators of stress and mental health changes.

Limitations of mental health monitoring systems consist of reliance on self-reporting, restricted accuracy in detecting diffused behavioural adjustments, capacity privacy concerns with statistics sequence and demanding situations in integrating multiple sources of information [11]. This study aims to develop a novel algorithm-based mental health monitoring system using behaviour analysis and intervention techniques. We propose an innovative Snow Ablation-driven Bi-directional Fine-tuned Recurrent Neural Network (SA-BFRNN) to determine mental health status.

Contribution and motivation of the work

The motivation and contribution of the study are discussed in this part. The motivation for the use of an SA-BFRNN in mental health monitoring is its functionality to capture subtle temporal and contextual changes in mental health states through advanced bi-directional recurrent neural architectures. Snow ablation complements the model's dynamic fine-tuning ability, which enhances accuracy and responsiveness. This precision is crucial for detecting shifts in mental situations, enabling well-timed interventions. SA-BFRNN's sophisticated learning mechanisms adeptly handle the complexity and variability in mental health statistics. Finally, this principle leads to better personalized and effective monitoring, coupled with support systems. Thus, the contributions of this study could be summarized as follows:

The dataset consists of 756 samples, selected from groups 1 and 2, respectively. The initial stage of creating a model involves creating training and testing sets from the dataset. Min-max normalization is used to ensure standardized and reliable information. We used K-Means clustering to cluster the pre-processed data. Clustering-derived labels are validated with mean opinion scores. We propose a novel Snow Ablation-driven Bi-directional Fine-tuned Recurrent Neural Network (SA-BFRNN) to identify the state of mental health.

This work is structured as follows: Part 2 related work. The methods and materials are described in part 3. Part 4 presents the results, while Part 5 concludes the study. Abbreviations part give the meaning of all abbreviations.

2. Related work

Utilizing the use of advanced analytics and AI, the research [12] created a DSS that can accurately identify and diagnose a variety of mental health conditions. To construct the assessment tool and determine which questions participants must answer, the DSS improvement procedure first used the NEPAR algorithm. To predict the presence and kind of a person's mental disease, several machine learning models were trained utilizing the responses provided by the participants to these questions as well as other existing data. Based on 28 questions and without human intervention, the result demonstrated that the proposed DSS can accurately identify mental diseases with 89% accuracy.

The suggested technique operated in connection with research on AI-based predictive modelling and aimed to improve the use of subjectively self-reported indicators of mental health issues with more reliable measurements. The method may help mental health professionals identify patients more swiftly and precisely and it was usually relevant to everyone who experienced significant levels of stress during the COVID-19 epidemic. In consideration of the significant suffering during the COVID-19 pandemic, study [13] aimed to address the issue of early identification for individuals at a higher risk of later developing chronic mental health illnesses.

The global increase in mental health issues and the need for quality MHC were addressed in the study [14] by utilizing ML. The datasets used in the study were presented from the Kaggle repository "Mental Health Tech Survey". Additional machine learning models, including RF, KNN, bagging and a few more, were applied to the data. The indicated accuracy of these models ranged from 81.22% to 75.93%, which was sufficient for making decisions. AdaBoost was the model with the greatest accuracy among all those used to forecast the results of mental health treatments.

Study [15] created the DL-MHMS for college students. Utilizing the most effective CNN available, the model utilized EEG information from college students to categorize their mental health condition as positive, negative, or normal. The simulation analysis has obtained the greatest F1 score and classification accuracy.

In terms of the type of therapy offered and degree of personalization, mental health chatbots were restricted in the research [16] and practice presently in distribution. For example, the majority of chatbots incorporate CBT into established conversational directions, which were unproductive when used repeatedly. In the study, they predicted that AI and BA treatment can more successfully materialize in a chatbot scenario to offer ongoing emotional support, tailored help and remote mental health monitoring. They described the architecture and development process of the AI chatbot, which was based on BA and then they implemented a participatory evaluation of it in a pilot research environment to validate its efficacy in helping people with mental health concerns.

The sentimental analysis of economic text information, mostly released on digital media, represented the study's [17] main tools for monitoring the public's mental health to determine the general state of mental health and the effects of national and international financial policy. The Guardian app programming interface was used to gather the dataset, while AdaBoost, a single-layer CNN and the SVM were used for processing. When contrasting with different techniques, such as SVM and AdaBoost, which have associated classification accuracies of 0.677 and 0.761, respectively, the single layer CNN, which has a classification accuracy of 0.939, was thought to have produced the best results during the stages of training and testing. To monetary and other institutions, public health would gain from the results of the study.

Utilizing the specially designed internet platform "Mind Turner," study [18] aimed at tackling the issue of early mental health condition prediction. By incorporating innovative techniques in the process, chronic mental health diseases can be prevented in the future. From the Question-Answer-based evaluation, they employed the RF to determine the participants' stress levels and SVM was utilized to identify the participants' facial expressions. Finally, both were integrated using Interval Type-2 Fuzzy Logic to forecast an individual's expected mental state, acute depression, mild depression, or not distressed.

Based on a variety of accuracy criteria, study [19] determined and assessed the efficacy of ML algorithms, particularly KNN, RF and LSTM, in identifying mental health disorders. Kaggle provided a dataset on mental health disorders. The applied methods yielded data indicating that the KNN model scored an accuracy of 95%, whilst the RF technique achieved 100% accuracy. In terms of accuracy metric, the LSTM model attained 99% accuracy. The area under the curve for the RF model is 100%. The goal of the system was to detect and forecast mental health illnesses early on using AI model approaches.

Employing 32 criteria and ML, study [20] proposed to predict the mental health of medical workers. Through an online questionnaire, they gathered the 32 qualities of 5108 Chinese healthcare providers, and the self-evaluation results were utilized to measure mental health. It offered a novel prediction model that made use of NN and optimization algorithms to identify and prioritize the most significant parameters influencing the mental health of healthcare professionals. The findings indicated that the suggested model outperformed the current methods in terms of prediction accuracy, with a 92.55% accuracy rate. The mental health of worldwide medical workers can be predicted using the strategy.

Table 1 presents recent literature detailing methods employed, datasets utilized and the corresponding benefits and findings, offering a comprehensive overview of current research trends and insights.

Table 1. Description of recent literature.

Study No.	Methods Used	Dataset Used	Findings	Benefits
12	NEPAR algorithm, various ML models	Participant responses	89% accuracy in identifying mental diseases	Improved diagnosis speed and precision
13	ML (RF, KNN, bagging, AdaBoost)	Mental Health Tech Survey from Kaggle	AdaBoost showed the highest accuracy	Quality mental health care
14	Deep learning, CNN	EEG data from college students	High classification accuracy and F1 score	Accurate mental health monitoring
15	AI, Behavioural Activation (BA)	Chatbot Feedback	Chatbot efficacy	Personalized Assistance
16	AdaBoost, CNN, SVM	Data from The Guardian API	Highest accuracy	Improved public mental health monitoring
17	RF, SVM, Type-2 Fuzzy Logic	Mind Turner platform	Mental state forecasting	Early prediction of mental health issues
18	KNN, RF, LSTM	Mental health disorders data from Kaggle	RF and LSTM showed nearly perfect accuracy	Early detection of mental health disorders

3. Methods

- Data collection: The sample of 756 individuals was selected through stratified random sampling to ensure a balanced representation of various mental states. Group 1 consisted of 350 participants, while Group 2 had 406. Data collection involved both behavioural observations and biosensor data (heart rate variability, skin conductance), capturing diverse physiological and psychological indicators to enhance the accuracy of mental health assessments.
- Data splitting: The initial stage of creating a model involves creating training and testing sets from the dataset, with training data as the initial set and testing sets

as the finalized model fit, which consists of 80 training and 20 testing. Biosensor readings were included in both training and testing sets for improved model generalization.

- Data processing using min-max normalization: The process of min-max normalization integrates mental health measures into an identical range, which makes it easier to compare and combine data from various sources. This includes biomechanical data, such as muscle tension, ensuring consistent integration with other mental health indicators.
- Clustering: It is the process of grouping related items into significant and useful groupings to ensure the parts in one group are more comparable than the items in other groups. We used K-Means clustering. It is the most often utilized clustering algorithm. Biomechanical signals, including movement patterns from biosensors, were also clustered to detect physical manifestations of mental states.
- Labelling: Clustering-derived labels are validated with mean opinion score.
- Classifiers: We propose a novel Snow Ablation-driven Bi-directional Fine-tuned Recurrent Neural Network (SA-BFRNN) to identify the state of mental health. **Figure 1** demonstrates the overall performance of mental health monitoring.

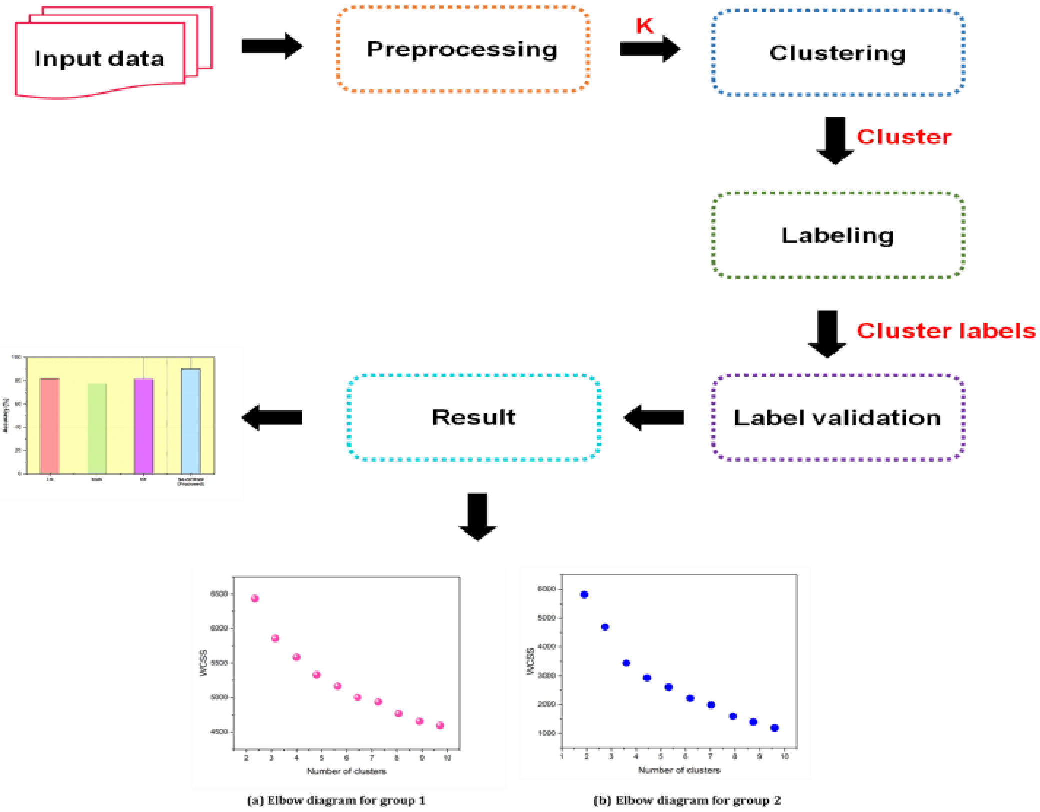

Figure 1. Overall process for mental health monitoring.

3.1. Experimental data

The dataset consists of 756 samples, of which 350 and 406 samples were selected from groups 1 and 2, respectively. It also includes 20 characteristics and three class labels (Mentally distressed, neutral, happy). The group under evaluation has a mean age of 22 years. The ratio of the training set to the test set was set at 80:20. There are

180 samples in the testing set and 576 samples in the training set.

3.2. Data processing

The process of min-max normalization integrates mental health measures into an identical range, which makes it easier to compare and combine data from various sources. It produces predictions and information about mental health trends and requirements that are more reliable.

Min-max normalization: One of the most popular methods for normalizing data involves changing the values of the characteristics under consideration to new, smaller values within a predetermined range; typically, [0–1] is used. It has been established that all of the associations in the examined data are preserved by min-max normalization. Every value in the feature under evaluation is related to a unique standardized value using the subsequent equation.

$$v' = \frac{v - \mathrm{min}_A}{\mathrm{max}_A - \mathrm{min}_A}(\mathrm{new\_max}_A - \mathrm{new\_min}_A) + \mathrm{new\_min}_\mathrm{A} \tag{1}$$

here max_A is the maximum value for the given feature, v is the original value, and v' is the new normalized value. While $\mathrm{new\_max}_A$ and $\mathrm{new\_min}_A$ denote the highest and lowest values for the newly examined range, A, min_A is the minimal value for the provided feature A.

3.3. Clustering

It is the process of grouping related items into significant and useful groupings to ensure the parts in one group are more comparable than the items in other groups. Cluster analysis improves comprehension of information and determines prospective groups that need to be processed further. The term used for unsupervised learning is clustering. It is a structure for learning that enables the use of particular object functions, including a capability that maintains a cluster compact by minimizing the distances inside it. In the fields of psychology, pattern recognition, information retrieval, ML and data mining, cluster analysis has been of great significance. A variety of conditions can be combined to form an illness. To differentiate between various illnesses kinds, clustering is employed.

Several kinds of clustering techniques may be used, including grid-based, partitional, hierarchical, density-based and model-based approaches. A basic exploratory data analysis technique called clustering divides data into groups without providing any background information or knowledge. It is mostly used for information discovery rather than forecasting. The construction of taxonomies and class labels is done using the clustering result. The process of allocating suitable class labels is facilitated by the variety of clusters that are produced. The number of clusters that are produced is only a representation of the potential class labels; it is unable to demonstrate that the class label and the representative clusters are mapped. Clustering is a process that can be used to identify naturally existing groupings, which can then be utilized to construct classifiers.

Verifying the number of clusters found by simulation is crucial. The specific data collection and the intended application of the findings determine which clustering technique and related parameters are acceptable. Determining the number of clusters requires several experiments. If the outcome reaches the required qualities, data preparation and model parameters must be adjusted. To verify that the number of clusters obtained is accurate, a wide range of cluster validity measures are employed. Both high and low intra-class similarity is required for the data point. Within the cluster, there should be strong cohesiveness between the data indications and there should be loose coupling between neighboring clusters.

K-Means clustering: K-means clustering is the most often utilized clustering algorithm. The K-Means clustering method is an iterative technique that is popular and works well in a variety of real-world scenarios.

Let n be the total amount of data points and K be the number of clusters. Each of the "K" is allocated to each of the "n" points of data. The primary objective is to maximize the variances among the clusters and minimize the disparities between data points within each cluster. However, the application identifies locally optimum solutions using a heuristic method. It indicates that the cluster assignments are initially calculated, and then the positions are gently altered to determine whether the modifications enhance the homogeneity within the clusters. The items are clustered using a centroid-based method, which minimizes the twisted reserves among the objects and the closest cluster centre. Implementing the K-means clustering method over a variety of K values and comparing the outcomes enables the user to determine the number of clusters in the data.

3.4. Cluster validation

To determine if the cluster produced by using the K-means algorithms is accurate, cluster validation is necessary. Compactness and separation are the two factors that determine which cluster validity indices are accessible. Also known as intra-class similarity, compactness quantifies that connected data points are inside a cluster.

Separation, which is also known as interclass similarity, quantifies the difference among clusters. When a cluster has low interclassed similarities and high intra-class similarities, the clustering outcome is considered effective. The elbow technique employing within-cluster sum of squares (WCSS) is the most often utilized cluster validity.

The definition of WCSS, or Within-Cluster-Sum-of-Squares, is provided by Equation (2):

$$\text{XDTT} = \sum_{j=1}^{m} \left(W_j - Z_j\right)^2 \tag{2}$$

In the above instance m is the number of characteristics used to define the observation, and Z_j is the centroid associated with observation W_j. One of the most often used techniques is the elbow approach, utilizing WCSS. It is based on the concept that, although clustering performance determined as WCSS improves with an increase in k, the rate of growth is typically decreasing. An "elbow" that indicates a notable decline in the rate of development could be detected for plotting the WCSS versus rising k. A reasonable performance is obtained by choosing the number of clusters that match the elbow point. The amount of clusters is repeatedly changed while utilizing the WCSS Elbow-Method. Three clusters were confirmed to be present in groups 1 and 2 by the experiment.

3.5. Validation of labels

We evaluated the mean opinion score (MOS) using the Quality of Experience concept to further validate the group's labels. The arithmetic mean over an individual's single judgments for a specific stimulation in a subjective quality evaluation test is the MOS provided in Equation (3).

$$\mathrm{MOS} = \frac{\sum_{m=0}^{M} Q_m}{M} \tag{3}$$

where *R* represents each subject's unique rating for a certain stimulation over *N* trials. This score indicates that the obtained value reflects the real value that the person provided.

3.6. Classifiers

Using a collection of characteristics, classification is a supervised SA-BFRNN approach that classifies data as belonging to a certain class or group. **Figure 2** lists the general procedures for developing classifiers using various classifier models.

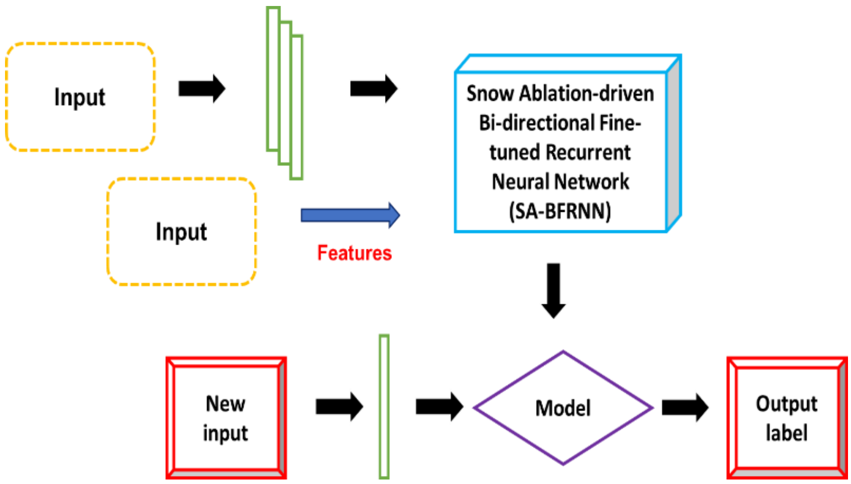

Figure 2. Construction of classifier.

3.6.1. Snow ablation optimizer (SAO)

For mental health monitoring, snow ablation metaphorically refers to the technique of selectively diminishing the effect of assured statistics inputs or network weights, comparable to that snow melts away. This technique permits the model to recognize more applicable or seasonally affected features which are essential for detecting shifts in mental health states.

Three basic natural phenomena melting, evaporation and sublimation serve as inspiration for SAO. The phases of the SAO algorithm exploration, exploitation, initialization stage and dual-population mechanism will be protected in detail in the following parts.

Initialization phase

The population is initialized via the SAO method utilizing the dimensions, size of the population and border range in the solution space. The initial population is produced randomly by Equation (4). Usually, a $N - by - dim$ matrix, wherein N is the population's size and dim is the solution's surface dimension, is used to initialize the whole population. The population initialization example is as follows:

$$W = ka + \text{rand} \times (va - ka) \tag{4}$$

where rand is a random number in the interval $[0, 1]$, W is the initialized population, as well as ka and va are the resolution area's upper and lower boundaries, correspondingly.

Exploration phase

During the exploration phase, water vapour generated from snow or liquid water sublimates or evaporates, irregularly moving in space to explore. Incorporating the randomness and irregularities of BM into the SAO algorithms makes an easier for members of the population to identify worthwhile and possible areas during the stage of exploration. The density function of probability of an average distribution with a single variation and zero mean is used by the SAO approach to determine the particle's step measurement for traditional BM. The BM mathematical expression is as follows:

$$e_A(w; 0,1) = \frac{1}{\sqrt{2\pi}} \times \exp\left(-\frac{w^2}{2}\right) \tag{5}$$

The following is the position updating equation for the SAO algorithm's exploration phase:

$$W_{j_{\text{new}}} = Elite_{\text{pool}}(l) + QA_j(i) \times \left(q_1 \times \left(A(i) - W_j(i)\right) + (1 - q_1) \times \left(\overline{W}(i) - W_j(i)\right)\right. \tag{6}$$

Where $W_{j_{\text{new}}}$ represents the person's position following an update; The randomized number vector for BM is denoted by $QA_j(i)$; the random integer in [0,1] is represented by q_1. The position of the current individual is represented by $W_j(i)$; $A(i)$is the ideal solution for the current population.

In this location update, $\overline{W}(i)$ denotes the position of the population's centre of gravity; l is a random number within the interval $[1, 4]$ and $Elite_{pool}(l)$ denotes the random selection of one individual from the set $Elite_{pool}$.

The mathematical equation for $\overline{W}(i)$and $Elite_{pool}(l)$ is as follows:

$$\overline{W}(s) = \frac{1}{M}\sum_{j=1}^{M} W_j(s) \tag{7}$$

$$\text{Elite\_pool}(s) \epsilon [A(s). W_{\text{second}}(s), W_{\text{third}}(s), Y_d(s)] \tag{8}$$

$A(s)$ Represents the best option for the current population, $Y_d(s)$ represents the average score of those in the top 50% of the population's physical scores and the individuals with the 2nd and 3rd greatest fitness scores are represented by $W_{second}(s)$, $W_{third}(s)$, respectively. Elite people are those in the population that score in the top 50% of fitness, as determined by the SAO method, to facilitate the computation of $Y_d(s)$.

$$Y_d(s) = \frac{1}{M_1}\sum_{j=1}^{M_1} W_j(s) \tag{9}$$

where M_1 is the number of elite persons; that is, M_1 is equivalent to half of M quantitatively. The $best$ solution, the 2nd best solution, the 3rd best solution, and the median solution of the elite people in the general population make up $\text{Elite}_{\text{pool}}(l)$. An arbitrary number is selected at random after this collection provided with the position update for every exploration location update.

Exploitation phase

The SAO algorithm's exploitation stage primarily presents the behaviour of snow melting and turning into water. The snowmelt process is represented in the SAO algorithm via the degree-day approach, with the following equation:

$$N = \text{CCE} \times (S - s_1) \tag{10}$$

here N is the snowmelt rate, a crucial variable for modeling melting behaviour throughout exploitation. The temperature on a daily average is S. The zero-base temperature is denoted by s_1. The following is how N is represented in the SAO algorithm:

$$N = \text{CCE} \times S \tag{11}$$

The value of the CCE curve, which varies from 0.35 to 0.6, denotes the degree—day factor. The CCE curve modifies the measured equation in every assessment in the format shown below:

$$\text{CCE} = 0.35 + 0.25 \times \frac{f^{\frac{EF_t}{EFs_{max}}} - 1}{f - 1} \tag{12}$$

here EF_s is the maximum number of assessments and EF_t is the total quantity of current assessments. The following formula is used in the SAO method to determine the snowmelt rate:

$$N = \text{CCE} \times S(s) = \left(0.35 + 0.25 \times \frac{f^{\frac{EF_t}{EFs_{max}}} - 1}{f - 1}\right) \times S(s) \tag{13}$$

$$S(s) = f^{\frac{-EF_t}{EF_{max}}} \tag{14}$$

The following is the SAO algorithm's exploitation phase location update equation:

$$W_{j_{\text{new}}} = N \times A(s) + QA_j(s) \times \left(q_2 \times \left(A(s) - W_j(s)\right) + (1 - q_2) \times \left(\overline{W}(s) - W_j(s)\right)\right) \tag{15}$$

In this case q_2 is the random number chosen in $[-1, 1]$ and N is the snowmelt rate in the SAO method. Based on the present ideal location, this formula increases the probability that non-optimal members of the population come with more value ideas.

Dual-population mechanism

In the SAO algorithm, a new two-population technique is used. In conclusion, the SAO algorithm's position update equations are presented as follows: index1 represents the set of people who were chosen at random from the whole population and index2 represents the set of individuals who were left over after extraction.

$$W_{j_{\text{new}}} = \begin{cases} \text{Elite}_{\text{pool}(s)} + QA_j(s) \times \left(q_1 \times \left(A(s) - W_j(s)\right)\right) + (1 - q_1) \times \left(\overline{W}(s) - W_j(s)\right)) j \in \text{indes1} \\ N \times A(s) + QA_j(s) \times \left(q_1 \times \left(A(s) - W_j(s)\right)\right) + (1 - q_2) \times)\left(\overline{W}(s) - W_j(s)\right)) j \in \text{indes2} \end{cases} \tag{16}$$

3.6.2. Bi-directional fine-tuned recurrent neural network (SA-BFRNN)

Neural network

RNN analyzes temporal information by incorporating information from prior time steps. BDRNN combines two RNNs to include data from subsequent stages. The first RNN is a conventional rearward directional RNN that combines information from the past and present times; the second RNN, is positioned to combine information from the present and future times, which is accomplished by rearranging the sequence of the input time steps.

Recurrent neural network

For mental health monitoring, RNNs can be particularly useful for studying time-series statistics, which include temper logs, speech styles, or behavioural modifications over time, approving the model to capture temporal dependencies and styles that could suggest adjustments in mental health status.

The solid lines represent the RNN. The equation for each layer k of an RNN with K layers is as follows:

$$b_0^k(s) = e_k\left(b_0^{k-1}(s)X_0^k + \beta\left(b_0^k(s-1)W_0^k\right) + a_0^k\right) \tag{17}$$

Therefore, when $k = K$, $\beta = 0$; otherwise, $\beta = 1$. The weight matrices are X and W, the bias matrices a, layer K and output b. The layer determines the transfer function, which has the following equation:

$$e_k(w) = \begin{cases} 2/(1 + f^{-2w} - 1, k \neq K \\ z = \dfrac{f^w}{(\sum f^w)}, k = K. \end{cases} \tag{18}$$

Bi-directional recurrent neural network

The following equation employs each hidden layer k in a BDRNN with K layers:

$$b_m^k(l) = ek\left(b_m^{s-1}(s)X_m^1 + b_m^k(s-1)V_m^k + b_{(1-m)}^{s-1}Y_{(1-m}^{k=1} + a_m^k\right) \tag{19}$$

where $m = 0$ and $m = 1$, respectively, determine the layer's forward and backward directions. Y represents an extra weight matrix. At time s, the output layer can be characterized as follows:

$$b_0^K(s) = e_K(b_0^{s-1}(s)X_0^K + b_1^{K-1}(s)X_1^K + a^K) \tag{20}$$

3.6.3. Snow ablation-driven bi-directional fine-tuned recurrent neural network (SA-BFRNN)

The Snow Ablation-driven Bidirectional Fine-tuned Recurrent Neural Network (SA-BFRNN) represents a pioneering technique for assessing mental health states. Leveraging the SA algorithm, the version refines itself iteratively by selectively casting off much less impactful connections and nodes. This strategic pruning enhances both the performance and generalization skills of the network, resulting in a far better and more accurate tool for assuming out mental health situations. By quality-tuning the Bidirectional Fine-tuned Recurrent Neural Network (BFRNN) via this process, the SA-BFRNN achieves maximum sensitivity and specificity in spotting diverse states of mental health. Through its modern technique, this novel framework promises to contribute considerably to the advancement of mental health assessment, probably revolutionizing diagnostic practices and enhancing affected person care consequences (Algorithm 1).

Algorithm 1 SA-BFRNN

```
Initialize parameters for the snow ablation mechanism
Define parameters for the bi-directional RNN layers
Define parameters for fine-tuning mechanism
for each time step t
Input_data = current_time_step_data
Forward_pass = SA_BFRNN_forward(Input_data)
def SA_BFRNN_forward(Input_data)
Input_data = snow_ablation(Input_data)
bi_rnn_output = BiDirectional_RNN(Input_data)
final_output = fine_tune(bi_rnn_output)
return final_output
def snow_ablation(Input_data)
return Input_data
def BiDirectional_RNN(Input_data)
forward_output = forward_RNN(Input_data)
backward_output = backward_RNN(Input_data)
bi_rnn_output = concatenate(forward_output,backward_output)
return bi_rnn_output
def fine_tune(bi_rnn_output)
return bi_rnn_output
```

4. Results

4.1. Experimental setup

Use Tensor-Flow (version 2.5 or later) and Keras for deep learning model development with Python (version 3.8 or newer) on a machine with at least 32 GB of RAM to experimentally set up the Mental Health Monitoring for SA-BFRNN.

4.2. Confusion matrix

A 3 × 3 confusion matrix is a tool used to show and examine the accuracy of predictions produced by a classification system in the framework of mental health monitoring. This matrix contributes to evaluating the effectiveness of the technique or system and classifies items into three predetermined groups in this case, “mentally distressed,” “happy” and “neutral”. This matrix helps in visualizing the accuracy of predictions across these three mental states by comparing the predicted labels against the true labels. The confusion matrix can be organized and explained in **Figure 3**.

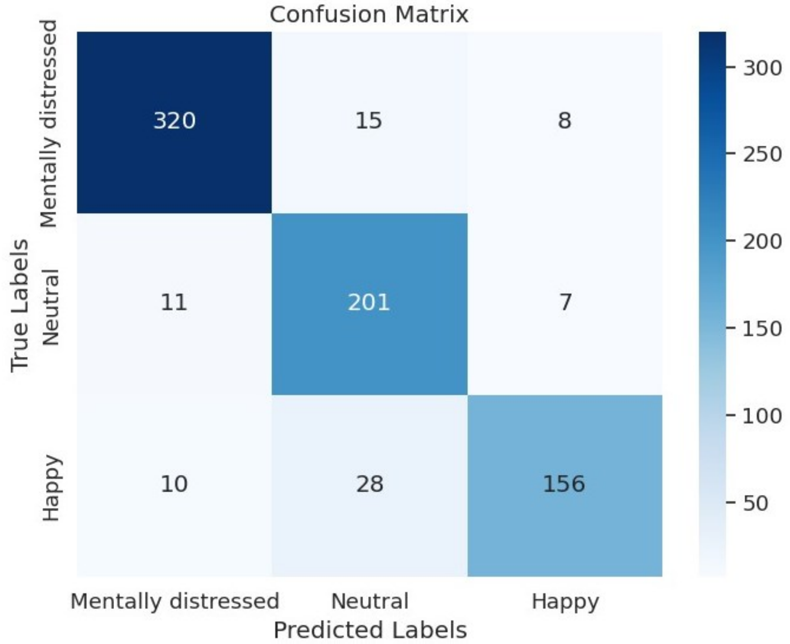

Figure 3. Confusion matrix obtained using SA-BFRNN.

4.3. Outcome of the model evaluation

Initially, two target groups, group 1 in the 18–21 age range and group 2 in the 22–26 age range, were the primary goals of the study. The most effective method for determining groupings within groups 1 and 2 was considered to be clustering. The clustering techniques K-Means are applied.

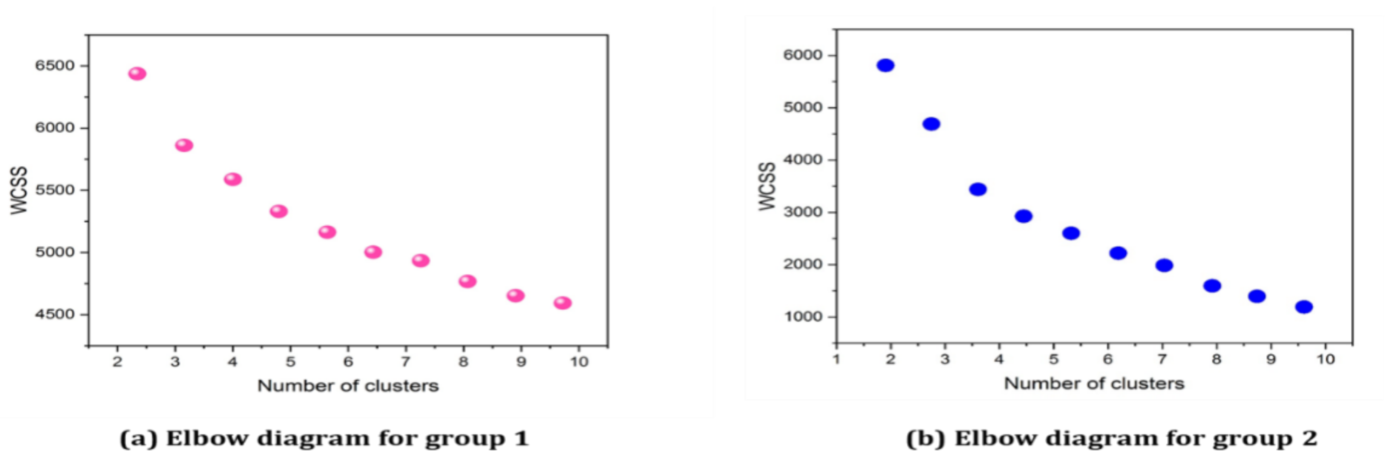

Figure 4. The Elbow method's use for groups 1 and 2.

Different values of K were used for performing additional tests in K-Means clustering. First, 350 group 1 data samples are used to execute the algorithm, and findings are recorded for various values of K ranging from 1 to 10. Compared to the previous rounds, the K-Means clustering for $K = 3$ produced superior results. To determine whether the actual number of clusters K is correct, cluster validation is utilized. We have validated the value of K using the elbow approach with WCSS. The number of clusters obtained has been validated using the WCSS technique and the elbow approach. For both the samples of group 1 and group 2, the validation of the cluster yields an output of 3. **Figure 4** depicts the elbow method's use for groups 1 and 2, respectively.

4.4. Comparative analysis

Classifier performance measures

The metrics of precision, accuracy, F1-score, and recall are examined in this section. The effectiveness of traditional and suggested methods is being compared. The classification performance of the LR, KNN and RF models is compared [21].

This metric assesses the model's general accuracy. It is the proportion of all observations to properly anticipated observations (true positives and true negatives combined). Accuracy in the framework of mental health monitoring would be the percentage of all analyzed cases that were accurately recognized as having a mental health issue or not [22,23].

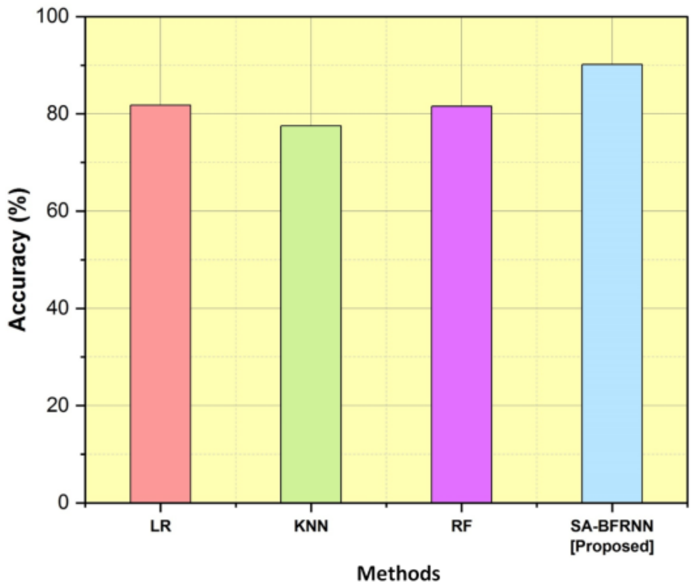

Figure 5. Results of accuracy.

Figure 5 illustrates the accuracy rate achieved by the proposed methodology. Compared to other traditional methods LR (81.78%), KNN (77.54%), and RF (81.52%), the suggested model SA-BFRNN achieves an accuracy rate of (90.13%). SA-BFRNN has superior outcomes compared to the traditional method.

Precision, also referred to as positive predictive value, evaluates the reliability of positive forecasts. The percentage of individuals accurately recognized as having a mental health condition compared to all cases classified as such would be known as accuracy in mental health monitoring.

The precision rate obtained by the suggested technique is shown in **Figure 6**. When compared to other traditional methods LR (79.89%), KNN (76.27%), and RF (80.80%), the proposed model SA-BFRNN achieves a precision rate of (89.23%). When compared to the traditional method, SA-BFRNN produced better results.

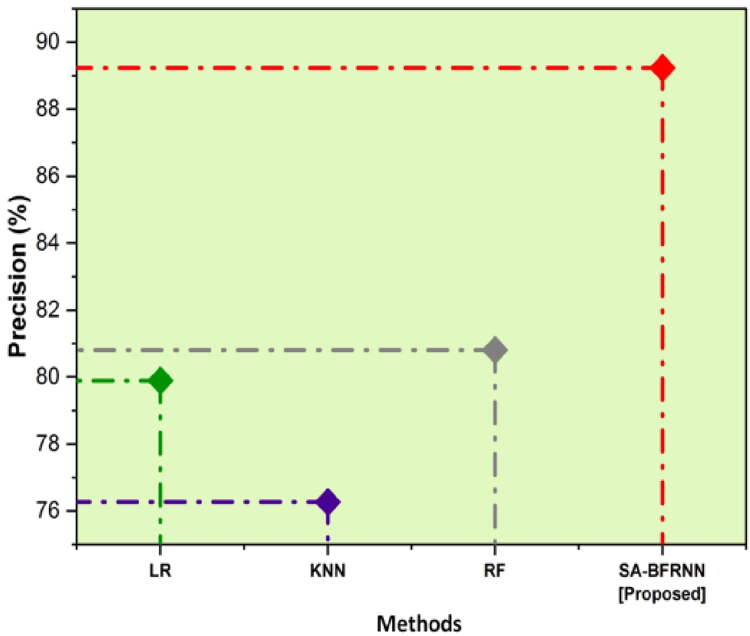

Figure 6. Results of precision.

Recall evaluates the model's capacity to identify every pertinent incident. Recall in mental health monitoring refers to the percentage of real instances with a mental health issue that the model accurately identifies.

Figure 7 illustrates the recall achieved by the proposed methodology. Compared to other traditional methods LR (85.1%), KNN (79.95%) and RF (85.87%), the suggested model SA-BFRNN achieves a recall rate of (92.56%). When SA-BFRNN was compared to the traditional method, better results were obtained.

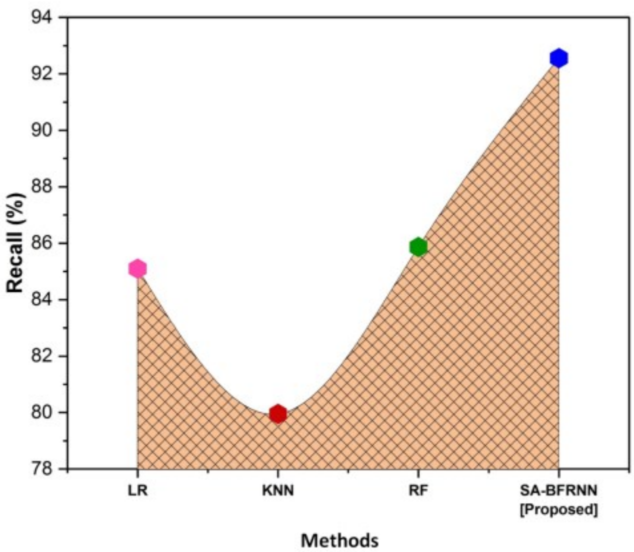

Figure 7. Results of recall.

The harmonic mean of recall and accuracy is known as the F1-score. It is a method of combining recall and accuracy into one measurement that encompasses both characteristics. A higher F1 score in mental health monitoring indicates a better-balanced approach to memory and accuracy, which is essential for reducing false positives and ensuring that the majority of real cases are identified.

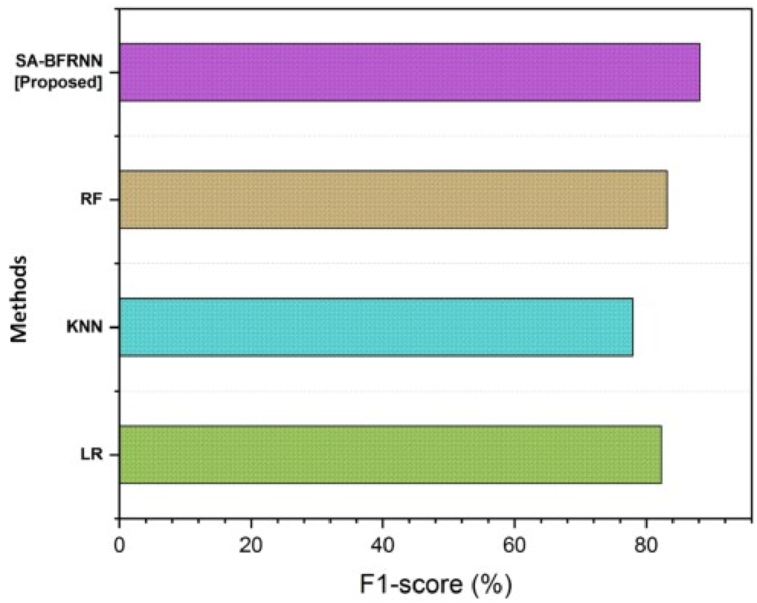

Figure 8. Results of F1-score.

The F1-score rate obtained by the suggested technique is shown in **Figure 8**. When compared to the traditional methods LR (82.35%), KNN (77.99%) and RF (83.17%), the proposed model SA-BFRNN achieves an F1-score rate of (88.16%). Better results were observed when SA-BFRNN was compared to the traditional method. **Table 2** depicts the values of recall, accuracy, F1-score, and precision.

Table 2. Outcome value of parameters.

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
LR	81.78%	79.89%	85.1%	82.35%
KNN	77.54%	76.27%	79.95%	77.99%
RF	81.52%	80.80%	85.87%	83.17%
SA-BFRNN [proposed]	90.13%	89.23%	92.56%	88.16%

The SA-BFRNN achieves higher accuracy and precision due to its bidirectional learning, which captures complex temporal dependencies in mental health data. The integration of biosensor data enhances prediction reliability, while fine-tuning optimizes the model for mental health classification. Additionally, clustering optimization ensures better feature selection, leading to superior performance compared to traditional methods like LR, KNN, and RF. The SA-BFRNN model's improved accuracy and precision in detecting mental health conditions could lead to earlier, more reliable diagnoses. This allows healthcare providers to intervene promptly, offering more personalized and effective treatments. Additionally, the integration of biosensor data enables continuous, non-invasive monitoring, which can be utilized in real-time applications, improving patient care and potentially reducing the burden on mental health professionals. This system could be adapted for use in various settings, including clinics, schools, and workplaces, to promote mental well-being.

5. Conclusion

This study advanced the Snow Ablation-driven Bi-directional Fine-tuned Recurrent Neural Network (SA-BFRNN), a novel method of mental health monitoring. Our approach iteratively modified the community by way of casting off much less extensive connections and nodes with the use of the Snow Ablation (SA) set of rules, improving the version's effectiveness and generalizability. The SA-BFRNN's ability to understand minor behavioural patterns connected to diverse mental health conditions turned into substantially more suitable with the aid of its potential to integrate each forward and backward temporal input. A comprehensive investigation of the SA-BFRNN's efficacy was conducted with 756 participants utilizing a questionnaire. The responses were clustered to produce labels, which were then used to train the model for accurate mental health status predictions and verified by MOS. Our approach to mental health evaluation is accurate and uses data-driven approaches to produce significant improvements over previous methods, as demonstrated by the validation process findings.

5.1. Findings

Based on performance measurements, the SA-BFRNN obtained an F1-score of 88.16%, recall of 92.56%, accuracy of 90.13%, and precision of 89.23%**.** These findings illustrate not only that the model performs in terms of correctly identifying mental health states from multimodal data, but also show significant enhancements in terms of accuracy and resilience, particularly in dynamic environments.

5.2. Limitation and future scope

Limitations of SA-BFRNN might include possible biases in data gathering and scalability issues with huge datasets. Future work will focus on improving interpretability, resolving data privacy concerns and confirming its efficacy.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

Abbreviations

Mental Health Monitoring System = MHMS	Mental Health Care = MHC
Artificial Intelligence = AI	Random Forest = RF
Decision Support System = DSS	K-Nearest Neighbor = KNN
Network Pattern Recognition = NEPAR	Deep Learning-Based Mental Health Monitoring System = DL-MHMS
Convolutional Neural Network = CNN	Electroencephalogram = EEG
Cognitive Behavioural Therapy =CBT	Behavioural Activation = BA
Long Short-Term Memory = LSTM	Neural Networks = NN
Brownian Motion = BM	Recurrent Neural Networks = RNN
Bi-Directional Neural Networks =BDRNN	Logistic Regression = LR

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