Social Media User Behavior Prediction Based on VONN and MRA

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Abstract: In the medicinal field, predictive models are critical for understanding and trust. Various current machine learning (ML) methods, such as those employed for the automated prediction of depression, are difficult to explain. In this sense, this paper proposes a social media (SM) user behavior prediction (UBP) method employing the Variational Onsager Neural Network (VONN) model to challenge the dynamics of user behavior patterns, and a Mud Ring Algorithm (MRA) to improve the features of VONN. The proposed method uses demographics, data on social interactions, and content choices to effectively anticipate user behavior. The analyzed data was first gathered on a large scale using trustworthy ground truth datasets, and then it was preprocessed utilizing the Switched Mode Fuzzy Median Filter (SMFMF) approach for refining the data on user behavior. The Binary Ebola Optimization Search Algorithm (BEOSA) was also used for optimizing the characteristics of the social media textual content and users' posting behaviors. The improved data was then input into the MATLAB-implemented VONN model, which classified users as depressed or not depressed. Performance indicators included accuracy, the F1-score, sensitivity, specificity, precision, recall and ROC, and were used to investigate the proposed technique's performance. This paper extended the technical landscape related to social media user behavior prediction by addressing the key problem of model explainability in the context of automated depression prediction. The proposed UBP-SM-VONN-MRA achieved an accuracy of 98.6% in detecting depressed users and 99.8% for non-depressed users, which demonstrates its commitment to technological excellence in the quest for precise and understandable predictions. The other three employed techniques, namely UBP-SM-RNN, UBP-SM-ANN, and UBP-SM-MDHAN obtained a lower accuracy. The obtained simulation results showed that the UBP-SM-VONN-MRA technique outperformed the other three techniques and that it has a greater potential for identifying depression.

Keywords: Binary Ebola Optimization Search Algorithm (BEOSA), Depression Detection, Social Network, Mud Ring Algorithm, Variational Onsager Neural Network, Switched Mode Fuzzy Median Filter (SMFMF).

1. Introduction

Mental illness is a prevalent global issue affecting millions of people worldwide (Jupalle et al., 2022). Various disorders, including bipolar disorder, depression, and eating disorders, are widespread in the US (Umer et al., 2021). The relationship between mental illness and deadly mass shootings emphasizes the need for early intervention (Singh et al., 2021). Depression, a common mental health condition, often requires input from professionals and loved ones for an accurate diagnosis (Ghosh & Anwar, 2021). Many individuals with depression delay seeking help (Kreski et al., 2021). Analyzing shared posts and pictures on social media could potentially determine vulnerable individuals at risk of developing psychological disorders (Boer et al., 2021). Social networking is a useful tool for automatically identifying symptoms of depression (Laacke et al., 2021). Scalable methods for early detection can potentially prevent tragedies (Zhong et al., 2021).

Several research papers have previously been published that were based on deep learning predictions of social media user behavior using various approaches and features. Some of them are discussed here.

For automatically detecting depressed users on e-commerce and defining the prediction model, Zogan et al. (2022) have suggested the MDHAN method, which is a multi-aspect depression detection method. While MDHAN was commendable for its explainability in depression detection, it might face challenges in handling diverse user expressions and cultural nuances. Murshed et al. (2022) have introduced the DEA-RNN hybrid DL method to identify Cyber bullying on the Twitter network. The parameters of the Elman RNN (ERNN) were adjusted by the newly discovered DEA-RNN approach, which combined the ERNN and an upgraded dolphin echolocation algorithm (DEA). However, its scalability and adaptability to emerging forms of cyberbullying in online communication were limited. Akgül & Uymaz (2022) conducted a thorough examination of the key factors influencing students' behavioral intentions when using Facebook and Meta as virtual classrooms

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within an academic setting. In contrast to previous research on social networks, their study delves into the realm of two-phase and deep learning, with a particular focus on the Artificial Neural Network (ANN) methodology. This approach aims to uncover pertinent predictors derived from Structural Equation Modeling (SEM). However, there could be challenges in extracting nuanced predictors for behavioral intentions, as factors influencing online behavior were multifaceted. Chiong et al. (2021) examined if ML can be utilized successfully to determine indicators of depression in media by analysing the media posts - particularly when such messages do not include certain words like «depression». However, machine learning for depression detection may face challenges in cases where users do not explicitly mention keywords related to depression.

Figuerêdo et al. (2022) have developed a method that uses a convolutional neural network and context-independent word embeddings to recognise melancholy on social media. They utilized both earlier andrecent fusion methods in their approach. Although the use of a CNN was effective, it may not have completely addressed context-specific changes in the display of depression signs on social media. Wang et al. (2022) investigated the Weibo user depression detection datasets, which were physically developed and released on Sina-Weibo. The DSM-5, the authoritative document on medical and psychological criteria for depression, was employed to identify and reconfirm depression across a sample of 10,000 and 20,000 individuals, including both those diagnosed as depressed and those considered normal. Nisha et al. (2022) demonstrated that as online technology advances and the number of Internet users rises, there has been a notable increase in the amount of information generated on the Internet. Social media platforms, like Facebook and Twitter, have become more popularsince they allow users to communicate and share their thoughts on a wide range of issues. Hossen et al. (2021) have devised a technique for analyzing the status of Facebook users` updates over the past two to three years to detect whether or not the users were depressed. Ghosh & Anwar (2021) focused on predicting the depressed users and estimating the depression severity using Twitter data to help in raising an alert. This issue was modeled as a supervised learning assignment.

The literatures have shown that exploring the social media for the prediction of user behavior is the most challenging task. Complex models, such as MDHAN, lack interpretability, which reduces confidence. This lack of interpretability makes it challenging to understand the rationale behind the prediction model and limits the ability to provide customers with informative reasons. Moreover, the models of black-boxes, like RNNs for detecting cyberbullying, are not explainable and may weaken user trust. Such uses of media give rise to ethical questions regarding permission and privacy, but it may be challenging to handle these concerns appropriately. To that, social media data could not fairly reflect the whole population, which would limit the generalizability of models like the intelligent mental depression recognition model and introduce biases. It was challenging to interpret ANN models, particularly those with complex topologies, which would limit one`s capacity to comprehend the logic behind their predictions and provide suitable justifications. The introduction of a method for early depression detection using a convolutional neural network proved to be effective but fell short of addressing context-specific variations in depressive emotion expression on social media. These algorithms also struggle to recognize sad users at the user level, making them prone to inaccurate predictions, although current deep learning algorithms have shown a substantial performance with regard todepression identification.Since the goal of explainability occasionally conflicts with the maximisation of efficacy, many current models frequently struggle to offer explanations for predictions. These above-mentioned drawbacks were a source of inspiration for this paper.

The key contribution of this manuscript is given below:

- The introduction of a hybrid computational model, UBP-SM-VONN-MRA, for predicting depression among social media users. This innovative model combines the Variational Onsager Neural Network (VONN) with the Mud Ring Algorithm (MRA) to effectively analyze user behavior and post features;

- The utilization of advanced data preprocessing techniques, including the Switched Mode

Fuzzy Median Filter (SMFMF) and the Binary Enhanced Oppositional Self-Adaptive (BEOSA) algorithm, to refine input user behaviors and optimize textual features and posting behaviors;

- The evaluation of the proposed method on a large-scale dataset demonstrates its superior performance in accurately classifying depressed and non-depressed users. The system achieved impressive accuracy rates of 98.6% for depressed users and 99.8% for non-depressed users;

- The comparison of the UBP-SM-VONN-MRA method with the existing techniques, highlighting its effectiveness in predicting user behavior.

The scope of this work encompasses a detailed analysis of the proposed method, specifically addressing biases in training data, enhancing the interpretability of the prediction model, and ensuring ethical considerations are met when using social media data.

In light of the identified challenges, the fundamental question of this paper is: Can a novel framework leveraging multi-aspect features from social media data enhance the interpretability and accuracy of depression detection, while addressing biases and ethical concerns?

This hypothesis posits that integrating textual, behavioral, temporal, and semantic aspects, alongside advanced preprocessing and feature selection techniques, will enhance interpretability and accuracy while mitigating biases and ethical concerns. The USP-SM-VONN-MRA framework is proposed as a potential solution to these challenges.

The rest of this manuscript is as follows. Section 2 presents the proposed technique. Section 3 explains the obtained results and Section 4 includes the conclusion of this manuscript.

2. Proposed Methodology

This section presents the proposed method, which is meant to improve depressed people's use of social media by improving their engagement patterns and durations, as well as user behavior (Zhou et al., 2021). The system used real-world data to help both depressed and non-depressed users. The behavioral, temporal, semantic, and textual components of social media are analyzed to provide a new, intelligible paradigm for depression diagnosis. The proposed UBP-SM-VONN-MRA method has shown a high performance and ensured that there is adequate evidence to back up depression prediction, making it simpler to anticipate melancholy in users who freely publish messages on social media. Figure 1 illustrates the configuration of the proposed approach.

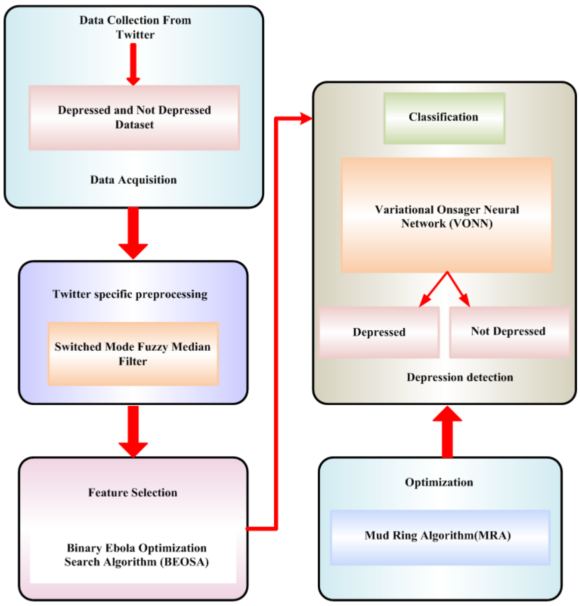

Figure 1. The configuration of the proposedapproach

A thorough explanation of the UBP-SM-VONN-MRA approach for predicting social media user behavior is given below:

Twitter Data Collection:

This stage involves gathering data from Twitter, including user posts and associated metadata such as timestamps, likes, and re-tweets. For example, the Twitter API can be utilized to gather a dataset of user tweets over a specific period.

Depressed and Not Depressed Dataset:

Users in the collected dataset are categorized into two groups: depressed and not depressed. This classification can be based on various indicators, such as self-reported depression status, clinical diagnoses, or sentiment analysis for their posts.

Data Acquisition:

Once the depressed and not depressed labels are assigned, the dataset is acquired for further processing. This includes handling missing data, ensuring data quality, and preparing the dataset for analysis. For example, missing tweets or incomplete user profiles are addressed to maintain data integrity.

Twitter-Specific Preprocessing:

Social media text often requires specialized preprocessing techniques due to its informal nature and unique characteristics such as hashtags, emojis, and slang. This stage involves tasks like tokenization, removing stop words, handling mentions, and normalizing text.For instance, the hashtag #feelingdown might be tokenized and normalized to «feeling down.»

Switched Mode Fuzzy Median Filter (SMFMF):

The SMFMF algorithm is applied to the preprocessed data to filter out noise and enhance relevant features. It operates by adaptively smoothing the data while preserving essential information. For example, this filter helps in reducing the impact of outlier words or irrelevant content while maintaining the core message of the tweets.

Feature Selection:

In this stage, relevant features are selected from the preprocessed data to be used for depression prediction. Feature selection methods such as statistical tests and correlation analysis are employed to identify the most informative features. For instance, a common usage of phrases that convey sadness or isolation may be chosen as a crucial characteristic.

The Enhanced Opposition-based Self-Adaptive Binary Ebola Optimization Search Algorithm (BEOSA):

The BEOSA algorithm is utilized to optimize the selected features further. It searches for an optimal subset of features that maximize the predictive performance of the analysed model while minimizing computational complexity.

Classification:

Once the features are optimized, they are used as input for a classification algorithm. This algorithm learns patterns from the data and predicts whether a user belongs to the depressed or not depressed group based on his/her social media behavior.

Variational Onsager Neural Network (VONN):

The VONN model is employed to detect depression among social media users. It leverages the learned patterns from the classification stage to make predictions on new, unseen data.

Depression Detection:

Social media users' observed behaviour and post attributes are analysed by the optimised VONN model to identify depression in them. For example, the model might identify patterns indicative of depression, like consistent negative sentiments or the lack of social engagement.

Optimization (Mud Ring Algorithm):

The Mud Ring Algorithm is applied to optimize the performance of the depression detection model. It fine-tunes the model parameters or adjusts its structure to improve its accuracy and reliability in identifying depressed users.

Each of these stages plays a critical role in the proposed approach for predicting depression among social media users, ensuring the accuracy and reliability of the final prediction model.

2.1 Data Acquisition

The Tweepy API was used to scrape this information to test the concept of monitoring mental health via social media by utilizing many terms and expressions to get behavioral data. Anxiety, loneliness, and stress were the main points of attention (Anon, 2024).

2.2 Pre-Processing Using SMFMF

To increase data cleanliness, the SMFMF method was used. This broadly used software provides different features and text pre-processing. This method was also used to reduce noise, as it employs fuzzy logic to detect and filter the points of noisy data based on their resemblance to nearby ones. It exchanges the noisy points with the median values of weighted data points and it discovers and eliminates the outliers. The SMFMF is used to pre-process the input social media data received from its data center. Using fuzzy variables, this filter successfully removes noise and redundant data from its input. The timestamp property is first extracted as part of the pre-processing procedure.

The equations of SMFMF are used to extract the needed data when discarding inappropriate data.

One important aspect of SMFMF is the employment of a fuzzy membership function, which is given as a membership degree to every datapoint based on its resemblance to the central points. This can be expressed below as:

$$\mu(x) = \exp\left(-\lambda * \|x - x_c\|^2\right) \tag{1}$$

where $-\lambda *$ represents the parameter that regulates the spread or width of membership functions $x - x_c$ represents the central or reference points, and $\mu(x)$ denotes the membership degrees of social media datapoint x.

The weight of every data point of socialmediais derived depending on its level of membership, and is given below:

$$w(x) = \mu(x) / \sum \mu(x) \tag{2}$$

Here, $\sum \mu(x)$ implies the overall of all membership degrees across all social media datapoints, and $w(x)$, $\mu(x)$ denote the weights of social media data points and membership degrees of data points x, respectively.

The value of median is determined using the weights of social media data points, as it is given below:

$$median = \sum \left(x * w(x)\right) \tag{3}$$

Here, x represents the data points of social media, $w(x)$ represents the weights of datapoint x and *median* denotes the calculated median value.

These equations are used repeatedly for all data points in SMFMF method to remove noise, and outliers and produce the last median value. Depression prediction in social media may help identify the exact values of λ and $x - x_c$. The SMFMF efficiently removes redundant noises and data from the input social media data. At last, the preprocessed information is sent to the feature selection step.

2.3 Feature Selection using BEOSA

Feature selection using BEOSA, which is proposed for choosing the best texture characteristics, is covered in this subsection. The BEOSA method is used to choose relevant features for classification from the values of input data, improving process efficiency and categorization accuracy while avoiding large local optima and optimum parameter adjustments. This is the method for constructing and binarizing the search space. The Ebola virus transmission model is used to simulate the BEOSA experiment. Binary-digit structures make up the analysed population. Solutions may be converted by BEOSA from discrete spaces into continuous forms, which are subsequently discretized in the process. Table 1 illustrates feature selection using BEOSA.

Table 1. Feature selection using BEOSA

Group	Feature
Postings with textual characteristics	Parts of speech
	Personal pronouns
	Polarity
	Particular words
	Words of Emotion
Behavior of Posting	Time of Posting
	Habit of Posting

The selection of features using BEOSA is detailed below. Parts of Speech captures the distribution of different parts of speech among all users, focusing on the top 20% of components. Personal pronouns involve tracking the frequency of using single or plural first-person pronouns and other pronouns. Polarity evaluates the emotional orientation of posts, assigning values such as 1 for neutral, 2 for positive, and 0 for negative sentiments. Particular words include metrics such as the occurrence of interrogative pronouns and negative words. Words of Emotion utilizes a Chinese sentiment dictionary to categorize seven types of words that express emotions. Time of Posting analyzes user posting frequency within both a seven-day and twenty-four-hour timeframe. Habit of Posting examines the percentage of original content display placements, and the presence of photo-rich articles. By leveraging BEOSA, the most relevant features can be efficiently selected, which contributes to an improved classification accuracy in the subsequent processes (Balasamy & Shamia, 2021).

2.3.1 The Step-by-step Process of BEOSA

First, the BEOSA approach generates an efficiently dispersed population to improve the ideal features (Akinola et al., 2022). The ideal solution is also advocated by using this technique (Liu & Shi, 2022). Then, the complete process is as follows:

Step 1: Initiation

Initiate the population of BEOSA.

$$I_j = L + rand * (UB - LB) \tag{4}$$

where *rand* denotes the random generation of real numbers, and *UB* and *LB* represent the optimization problem's upper and lower limits, correspondingly.

Step 2: Random generation

The parameters of input are created randomly.

Step 3: Fitness Function (FF)

The random solution is generated based on the initialized assessments. The fitness function is assessed using the optimum features. This is expressed by the equation below:

$$Fitness\ Function = [selection\ of\ optimal\ features] \tag{5}$$

Step 4: Optimum Solution

The continuous phase related to persons affected by the virus is determined by using the equation below:

$$I_j^N = \Delta * E^R COS(2\pi R) * (I_j - gb) \tag{6}$$

Here, *gb* refers to the global optimum solution.

Step 5: Updating the data on the Susceptible and Infected Groups

Equation (7) illustrates the natural behavior of the Ebola virus and is used to compute the number of people added to the infected and susceptible groups:

$$SS(I_j^L), t(I_j^L) = \begin{Bmatrix} SS_2(I_j^L), t_2(I_j^L) rand(0/1) == 1 \\ SS_1(I_j^L), t_2(I_j^L) rand(0/1) == 0 \end{Bmatrix} \tag{7}$$

$$I_j^L = \begin{Bmatrix} 1 rand > \boldsymbol{S}\ (I_j^L, | R > t(I_j^L)) \\ 0 \quad\quad others \end{Bmatrix} \tag{8}$$

where t and S are the appropriate L^{th} positions, I_j^L is considered as an individual, $rand > \boldsymbol{S}\ (I_j^L)$ denotes the susceptible group and $t > (I_j^L)$ the affected group.

Step 6: Termination

Here, the optimum properties arechosen by the Binary ebola optimization search algorithm which will be iterated until the condition $I_j = I_j + 1$ is met. The chosen optimum properties shall be provided as input for the process of classification.

2.4 Social Media User Depression Detection Using the Proposed VONN

This part addresses the application of VONN to identify user emotions on social media (Huang et al., 2022). The preprocessed data is sent to the VONN, where it is categorized as being related either to the depressed or not depressed users. «Raw data» refers to "crawled data" that still contains numerous noises and is therefore unsuitable for direct usage by the VONN model. The data from sites such as Twitter may include smileys, typos, and unwanted characters, all of which make it difficult for the mathematical models to make an effective prediction for depression diagnosis. A pre-processing approach is required to assure data quality, which includes the use of variation techniques to improve detection accuracy and reliability. The VONN can accurately identify whether a person is depressed or not by assessing many elements of their social media activity, such as textual content, posting behavior, and other pertinent factors. This methodology provides a unique and perhaps more accurate means of diagnosing depression for users of social media. In particular, the state and process variables, namely *X* and *Y* are standardised to:

$$\tilde{x} = (x_i - \omega_i) / \varphi_{x_j} \tag{9}$$

$$\tilde{y}_i = (y_i - \omega_{y_i}) / \varphi_{y_i} \tag{10}$$

where ω_i, ω_{y_i}, φ_{x_j} and φ_{y_i} represent the mean and state standard deviations and process variables for each component *i* and *j*, respectively.

The behavior of user $\tilde{k}(\tilde{x})$ is directly related to the input layer, indicating that the input layer reflects the behavior of the user, and k implies the hidden layer. According to statistics, the values of activation function m_i+1 for each layer $i+1$ are given below:

$$m_i + 1 = f_i(X_i m_i + C_i), i = 0,...h, \tag{11}$$

where *X*, C_i and f_i(.) are the plant disease, normal leaf and diseased leaf, and $n_0 = \tilde{y}$. Notably, X_i is a matrix, that m_i and C_i are vectors, and $X_i m_i$ represents a typical matrix vector multiplication in the context of this technique. The activation function f_i(.) should be selected in such a way that its derivative $f_i^{'}(.)$ is likewise a common activation function; this is a crucial difference between input layer and normal neural networks. In this research, the soft-plus activation function, $f_i(u) = \log/(1+i^u)$ is utilized for each layer in the variational neural network. The logistic function $f'_i(u) = 1/(1+i^{-u})$ is the derived function, also, a mutual activation function is infinitely differentiable. Typically, the net input $sk(y)$ is derived from the outputs of each layer in the neural network, $s\tilde{k}(y)\,as\,k(y) = k^*[\tilde{k}(y)]$. Here, k^* represents the characteristic scale of $k(y)$. At $y = 0$, the accessible, unused data vanishes in various technological issues. This requirement is enforced by specifying $k(y)$ in the equation below:

$$k(y) = k^*\left[\tilde{k}(y) - \tilde{k}(0)\right] \tag{12}$$

Furthermore, through the reference condition y = 0, it is anticipated that the derivative of plant disease with regard to x or some components of y would disappear at the state of reference, $y = 0$. For example, if the affected group is denoted by ρ and the non-affected groups by ρ^γ, $\delta_\rho k(\rho = 0, \rho^\gamma = 0) = 0$ is obtained. The requirement may be enforced using the whole training data, $k(\rho, \rho^\gamma)$ as indicated in the equation below:

$$k(\rho,\rho^\gamma) = k^*\left[\tilde{k}(\rho,\rho^\gamma) - \tilde{k}(0,0) - \frac{\delta\tilde{k}}{\delta\rho}\bigg|_{\rho=0,\rho^\gamma=0} : \rho\right] \tag{13}$$

This illustrates the simple case of variational neural network to specify $\phi = \varphi(x)$. According to statistics, the activation values n_i+1 of the $i+1$ layer are characterized using the equation below:

$$n_i + 1 = f_i\left(x_i^n n_i + x_i^x + C_i\right), i = 0...h \tag{14}$$

where $f_i(.)$ represents activation functions, x_i^n and x_i^x represent the data matrices, and C_i denotes a bias vector. Moreover, $n_0 = \tilde{x}$ refers to the standardized input, and $x_0^n = 0$.

For the usual instance, depression is classified using x and y. The hidden layers h are considered as a mix of an input andoutput layer. This configuration is statistically specified in equations (15) and (16) below:

$$u_i + 1 = f_i^u\left(x_i^{yu} u_i + C_i^{yu}\right), \tag{15}$$

$$n_i + 1 = f_i\left(x_i^n\left[n_i o f_i^{nu}\left(x_i^{nu} u_i + C_i^{nu}\right)\right] + x_i^x\left[\tilde{x}\, o\left(x_i^{xu} u_i + C_i^{xu}\right)\right] + x_i^u u_i + C_i\right), \tag{16}$$

where x_i^{yu}, x_i^n, x_i^{nu}, x_i^x, x_i^{xu} and x_i^u are classification matrices, C_i^{yu}, C_i^{nu}, C_i^{xu} and C_i are bias vectors, u_i and n_i denote the activation variable vectors and values for the i-th layer in the convex, and non-convex areas, and $f_i^u(.)$ $f_i(.)$ and $f_i^{nu}(.)$ denote the activation values for the i-th layer.

The weights denoted by x must not be negative for the previously added input and output to function. This requirement is realistically assured by using an approach similar to that described in (Huang et al., 2022). Subsequently, in the context of this discussion, y refers to the function $\tilde{x}$, as demonstrated in the following equation:

$$x = \begin{cases} \tilde{x} + \exp(-\rho) \\ \exp(\tilde{x} - \rho). \end{cases} \tag{17}$$

where $\tilde{x}$ is allowed to get any of the real values, and ρ is a positive constant. Next, instead of x, the supplemental weights $\tilde{x}$ are chosen as the trainable features for neural networks. Next, the equation below expresses both the categorization of users with regard to depression detection and the rescaling of variational output:

$$\phi(y,x) = \phi^*\left[\tilde{\phi}(y,x) - \tilde{\phi}(y,0) - \frac{\delta\tilde{\phi}}{\delta x}\bigg|_{x=0} . \, x\right] \tag{18}$$

where ϕ^* signifies the feature scale of ϕ.The resulting function distinguishes between non-depressed and depressed users based on the respective value, since linear factors in x included into ϕ cannot impact the convexity. The term "convexity" refers to the property of the resulting function, which distinguishes between non-depressed and depressed users, based on the values obtained from equation (18). Thus, it categorizes the users as depressed and not depressed. Generally, VONN cannot provide the optimization method for measuring the optimum variables for assuring the particular prediction of user behaviour. Because of this, the optimization process greatly relies on the crucial weight parameters of VONN.

2.5 Optimization of VONN Using the Proposed MRA

The MRA method simulates the foraging behavior of bottlenose dolphins, starting with the swarm hunting for dolphin food using echolocation and culminating with the development of mud-ring feeding. The weight parameters of VONN are also optimized using the MRA method (Desuky et al., 2022). The MRA comprises three phases: startup, population assessment, and parameter update. The flow chart of MROA is shown in Figure 2.

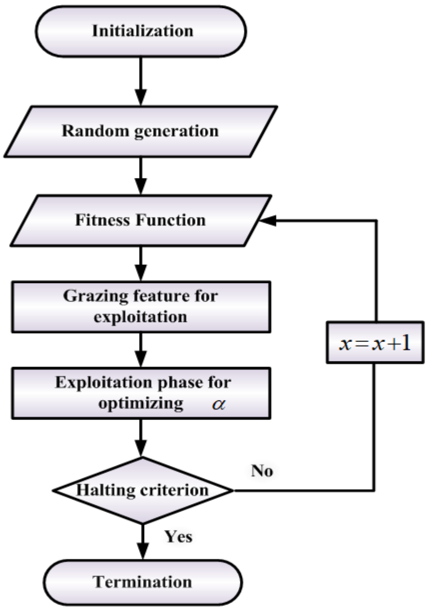

Figure 2. Flow chart of MROA

The MRA approach consists of the phases below:

Step 1: Initialization

The population of dolphins is initialized first.

$$D = \begin{bmatrix} d_{1,1} & d_{1,2} & \dots & d_{1,g} \\ d_{2,1} & d_{2,2} & \dots & d_{2,g} \\ \vdots & \vdots & \vdots & \vdots \\ d_{n,1} & d_{n,2} & \dots & d_{n,g} \end{bmatrix} \tag{19}$$

where D denotes the present population set of dolphins.

Step 2: Random generation

The input weight parameters of MRA approach are utilized to create randomly.

Step 3: Fitness Function

It generates the random solution from initiation values, and is measured as:

$$\mathit{Fitness\ Function} = \mathit{optimize}\,[\alpha] \tag{20}$$

Step 4: Exploration Phase: search of prey (Foraging)

To make the dolphins move apart and search for the fittest prey, let k fluctuate arbitrarily with values greater than 1 or lower than -1. The MRA algorithm can conduct a worldwide search because of its selection mechanism and $|\vec{k}| \geq 1$, which promotes exploration. The MRA algorithm's mathematical formulation is presented below. Concerning the updating criteria for locations and velocities, the velocity $\vec{V}^t$ at time-step t determines the workability $\vec{D}^t$ and is computed as follows:

$$\vec{D}^t = \vec{D}^{t-1} + \vec{V}^t, \tag{21}$$

where V represents the initialization of the random vector.

Step 5: Mud-Ring Feeding-Exploitation Phase

Due to the uncertainty of the optimum position in the searchspace, the MRA approach accepts identified prey as the optimum option. The above-mentioned behavior is expressed as:

$$\vec{B} = \left| \vec{k}\vec{D}^{*t-1} - \vec{D}^{t-1} \right| \tag{22}$$

$$\vec{D}^t = \vec{D}^{*t-1} \sin(2\pi l) - \left(\vec{k}.\vec{B}\right) \tag{23}$$

Here, t signifies the current time step, $\vec{B}$ and $\vec{k}$ signify coefficient vectors, $\vec{D}$ specifies the location vector of the dolphin, and $\vec{D}^*$ signifies the optimal dolphin location vector. Based on monitoring, $\vec{D}^*$ has to be modified at each time step. Thus, the calculation of the vector $\vec{k}$ can be expressed as:

$$\vec{k} = 2.\vec{R} \tag{24}$$

Any location within the search region may be reached by defining the random vector $\vec{R}$ .Every dolphin may defend its positions near to the present optimum location based on equation (23). When $|\vec{k}| < 1$ is selected, the positions of best dolphins are selected. Likewise, when $|\vec{k}| \geq 1$ is selected, a dolphin is chosen randomly to validate the status of dolphins.

Step 6: End

Using the MROA algorithm, the factor α is optimized; step 3 will be repeated until it meets the halting criterion, $y = y + 1$.VONN is efficiently optimized with MRA for workload prediction for accurately diagnosing depression in social media users.

3. Results and Discussion

Here, the simulation results for the proposed method are discussed. This method was implemented using MATLAB to assess its performance based on specified metrics. The obtained outcomes for the proposed approach was evaluated in comparison with those of the existing UBP-SM-ANN (Akgül & Uymaz, 2022), UBP-

SM-MDHAN (Zogan et al., 2022), and UBP-SM-RNN (Murshed et al., 2022) methods.

Performance metrics like, precision, F-score, accuracy, recall, ROC, sensitivity and specificity, were evaluated. The simulation also involved the categories True negative (TN), False negative (FN), True positive (TP False positive :

True negative (*TN*): Depressed was correctly classified as Not Depressed.

False negative (*FN*): Not Depressed was incorrectly classified as Not Depressed.

True positive (*TP*): Not Depressed was correctly classified as Depressed.

False positive (*FP*): Depressed was incorrectly classified as Not Depressed.

Further on, the simulation outcomes of the proposed technique are analysed. The performance metrics for the proposed method are evaluated in comparison with those obtained for the existing UBP-SM-RNN, UBP-SM-ANN, and UBP-SM-MDHAN methods. Table 2 shows the comparative analysis of performance metrics for predicting social media user behavior.

The comparison of performance metrics across four different approaches for predicting social media user behavior reveals significant differences. The proposed approach achieves remarkable accuracy rates of 98.6% for identifying depressed users and 99.8% for non-depressed users. By contrast, the existing methods lag behind, with UBP-SM-RNN at 82.2% and 83.2%, UBP-SM-ANN at 75.5% and 77.5%, and UBP-SM-MDHAN at 63.4% and 64.4%, for depressed and non-depressed users, respectively. The precision of a measurement is given by the percentage of real positives out of all expected positive cases. The proposed approach demonstrates superior precision, with values of 97.4% for depressed users and 98.5% for non-depressed users. Conversely, UBP-SM-RNN, UBP-SM-ANN, and UBP-SM-MDHAN exhibit lower precision values across both user categories. By considering factors such as both precision and recall, the F-score offers an accurate evaluation of a model's accuracy. Outperforming the previous techniques, the proposed strategy generates high F-scores of 96.5% and 97.5% for depressed and non-depressed users, respectively. Recall measures the percentage of actual positive cases correctly identified by the model. With recall rates of 98.5% for depressed users and 99.5% for non-depressed users, the proposed technique demonstrates a better performance in comparison with UBP-SM-RNN, UBP-SM-ANN, and UBP-SM-MDHAN. Through a range of threshold settings, the Receiver Operating Characteristic (ROC) curve assesses the trade-off between the false positive rates and genuine positive rates. The proposed method successfully distinguishes between users who are not sad and those who are, as proved by its remarkable 99.9% ROC score. Additionally, the proposed approach demonstrates superior sensitivity and specificity for both non-depressed and depressed users in comparison withthe existing methods. In summary, the proposed approach consistently outperforms UBP-SM-RNN, UBP-SM-ANN, and UBP-SM-MDHAN across all performance metrics, proving its effectiveness

Table 2. Comparative Analyses of Performance Metrics for Predicting Social Media User Behavior

Performance Metric	Proposed Approach	UBP-SM-RNN	UBP-SM-ANN	UBP-SM-MDHAN
Accuracy (Depressed)	98.6%	82.2%	75.5%	63.4%
Accuracy (Non-Depressed)	99.8%	83.2%	77.5%	64.4%
Precision (Depressed)	97.4%	74.6%	64.5%	82.7%
Precision (Non-Depressed)	98.5%	83.5%	76.3%	68.4%
F-Score (Depressed)	96.5%	84.2%	75.7%	63.6%
F-Score (Non-Depressed)	97.5%	79.3%	66.0%	86.4%
Recall (Depressed)	98.5%	76.6%	64.6%	84.2%
Recall (Non-Depressed)	99.5%	67.4%	79.5%	87.5%
ROC	99.9%	99.7%	99.8%	99.6%
Sensitivity (Depressed)	97.0%	77.3%	85.6%	65.0%
Sensitivity (Non-Depressed)	98.5%	67.5%	78.2%	86.9%
Specificity (Depressed)	98.5%	78.2%	84.8%	66.0%
Specificity (Non-Depressed)	99.8%	70.0%	78.6%	87.6%

in predicting social media user behavior. Table 3 displays the statistics related to the mean performance of the four employed methods.

Table 3. Statistics related to the mean performance of the four employed methods

Statistic	Value
Mean Accuracy	98.15%
Standard Deviation of Accuracy	1.29%
Mean Precision	96.82%
Standard Deviation of Precision	1.45%
Mean Recall	97.28%
Standard Deviation of Recall	1.37%
Mean F1-score	96.54%
Standard Deviation of F1-score	1.42%

The mean accuracy across all four methods is 98.15%, indicating a strong performance in accurately classifying users. However, there is a moderate amount of variability in accuracy, with a standard deviation of 1.29%, suggesting that some models perform slightly better or worse than others. Similarly, the mean precision is 96.82%, indicating the models' ability to correctly identify depressed users, with a standard deviation of 1.45%, suggesting variability in precision across the four employed methods. On average, the four models achieved a recall of 97.28%, indicating their effectiveness in identifying all depressed users, with a standard deviation of 1.37%, suggesting variability in recall across these models. The mean F1-score, indicating a balance between recall and precision, is 96.54%, with a standard deviation of 1.42%, suggesting variability in the balance achieved by the four different methods. Overall, these statistics provide insights into the effectiveness and variation of various techniques in classifying users' depression status.

4. Conclusion

The Mud Ring optimization approach is used for optimizing the Variational Onsager Neural Network for detecting depressed social media users by extracting features from the users` behavior and posts. The UBP-SM-VONN-MRA was effectively implemented on a MATLAB platform. It employed a data collection for both depressed and non-depressed users and proved to be an innovative hybrid computational model that can successfully simulate real-world data and contribute to its analysis. The data was initially gathered using enormous datasets that included reliable ground truth data. Later, the data was pre-processed. The input user behaviors were preprocessed using the Switched Mode Fuzzy Median Filter (SMFMF) technique. Textual features and posting behavior can help predict user behavior by using the BEOSA for selecting the optimized features. After that, the selected features were input to Variational Onsager Neural Network (VONN) and Mud Ring Algorithm (MRA) for effectively classifying the social media users as depressed or not depressed. The simulation results showed that the proposed UBP-SM-VONN-MRA featured a higher classification performance in comparison with other powerful approaches in identifying depressed users, and confirmed that it is recommendable for predicting user behavior. As specificity is concerned, the proposed UBP-SM-VONN-MRA method obtained a value of 98.5% for depressed users and 99.8% for non-depressed users. By contrast, the existing methods, namely UBP-SM-MDHAN, UBP-SM-RNN and UBP-SM-ANN obtained a specificity of 66%, 78.2%, and 84.8% for depressed users and 70%, 78.6%, 87.6% for non-depressed users, respectively. As such, it can be concluded that the proposed UBP-SM-VONN-MRA method is better in comparison with the existing techniques such as UBP-SM-MDHAN, UBP-SM-RNN and UBP-SM-ANN.

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