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Molecular & Cellular Biomechanics 2024, 21(4), 814.
https://doi.org/10.62617/mcb814

Article

Research on the construction of biosensor-assisted mental health monitoring system and talent training strategy

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CITATION

Li Y. Research on the construction of biosensor-assisted mental health monitoring system and talent training strategy. Molecular & Cellular Biomechanics. 2024; 21(4): 814. https://doi.org/10.62617/mcb814

ARTICLE INFO

Received: 16 November 2024
Accepted: 28 November 2024
Available online: 31 December 2024

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Abstract: In recent years, mental health monitoring has become increasingly crucial due to the rising awareness of mental health issues and the demand for effective interventions. In this field, a biosensor-assisted mental health monitoring system is an important development that utilizes technology to distribute real-time information on physiological reactions connected to psychological and emotional conditions. The study intends to increase a talent training strategy and a biosensor-assisted mental health monitoring system using deep learning (DL) techniques. This investigation contains 453 participants enrolled in talent training programs that incorporate problem-solving games and theoretical understanding. After the training programs, the data is gathered from biosensors to monitor mental health. The sensor data is preprocessed using bandpass filtering to eliminate noise from the obtained data. The preprocessed data features are extracted using a Convolutional Neural Network (CNN). This study proposed an innovative Refined Prairie Dog-Optimized Poly-Kernel Support Vector Machine (RPDO-PSVM) model to predict mental health after talent training programs. RPDO optimizes the features selected from data, and PSVM predicts mental health. In a comparative analysis, the research determines the different evaluation metrics like accuracy (96%), precision (93.8%), recall (92.1%), and *F*1-score (94.4%). The conclusion indicates that the suggested method performs better than the forecast for monitoring mental health. The research highlights that the combination of advanced biosensor technology and strategic training offers a promising pathway for improving mental health outcomes.

Keywords: biosensor; mental health monitoring; talent training; Refined Prairie Dog Optimized Poly-Kernel Support Vector Machine (RPDO-PSVM)

1. Introduction

A person's mental health is a crucial component of overall welfare, which affects their social operation, emotional state, and psychological condition. The importance of mental health monitoring for preventing the provocation of mental health disorders and ensuring on-time responses has come to light more and more [1]. In mental health treatment, early diagnosis is necessary since it enables quick action and tentative progression of moderate symptoms into more serious problems. For diseases such as depression, anxiety, and psychosis, early treatment improves outcomes. Interventions include medication executive, psycho-education, and therapy [2]. Continuous monitoring makes it easier for medical providers to keep tabs on mental health changes and spot state changes quickly. Stress, life events, medicine, and social support are some of the variables that cause symptoms to change. Regular monitoring allows medical professionals to adjust treatment regimens and offer ongoing assistance, ensuring quality care [3]. **Figure 1** shows the workflow for the mental health monitoring system.

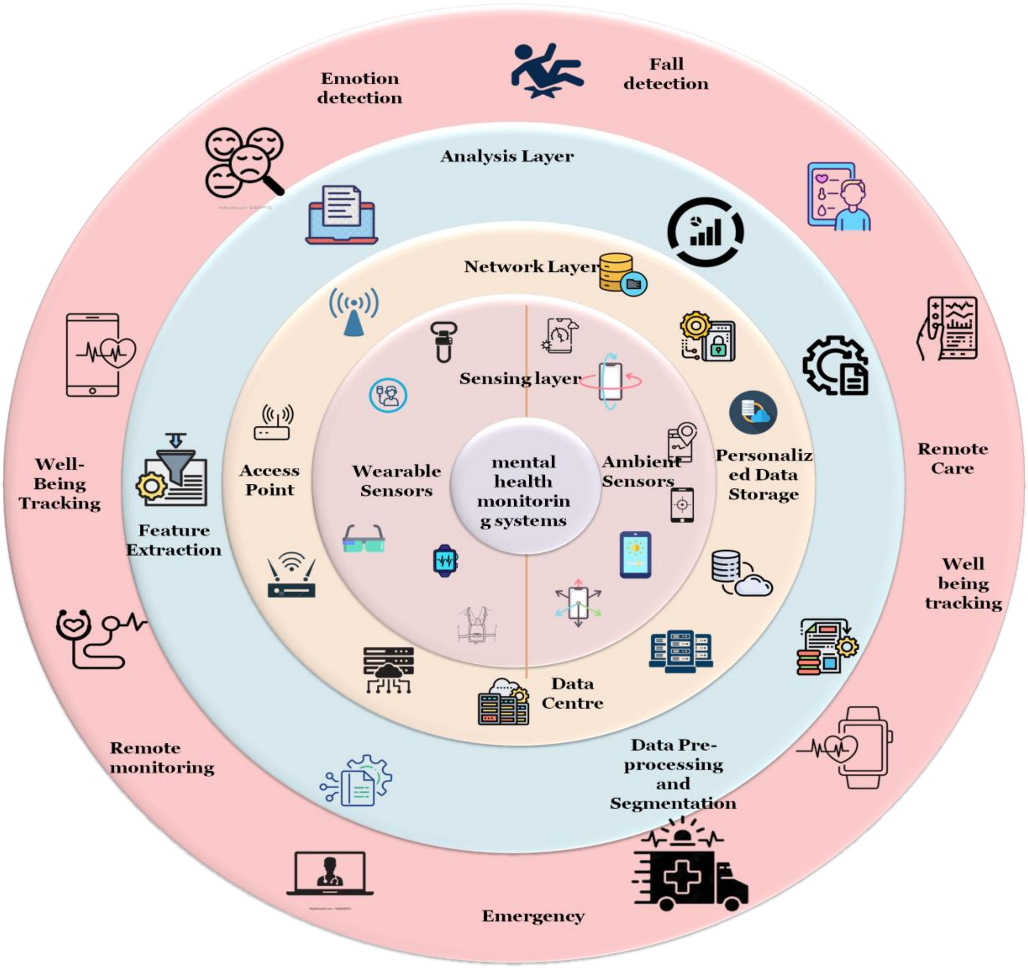

Figure 1. Mental health monitoring system workflow.

Clinical interviews, self-report questionnaires, and observational methods are examples of biased evaluations used in traditional mental health monitoring. These techniques frequently require ongoing monitoring, are automatic, and are subject to biases. They are controlled by accessibility and stigma, and they overlook modifications in mental health situations. Practical, concurrent, and objective monitoring solutions are provided by technological innovations like biosensor-assisted systems [4]. Biosensors are logical tools that use a biological constituent in concurrence with a physicochemical detector to quantify an existing chemical or biological substance. The framework of mental health monitoring determines physiological actions that signify mental conditions, like stress or anxiety, such as skin conductance, brainwave patterns, and heart rate variability [5]. Biosensors have benefits for tracking mental health, such as the objective dimension of physiological markers, non-invasive and accessible design, and concurrent, constant data collecting. By enabling the early diagnosis of mental health situations such as stress and anxiety, these sensors enhance overall mental health care by providing perceptive information for individualized interventions [6]. Limitations of biosensor systems for mental health observation include the prospect of data inaccuracy from outside sources, complexity in ensuring continuing user observance, and challenges in perfectly interpreting complex physiological signals. Widespread adoption is also hampered by privacy issues and the requirement for specific training to analyze sensor data [7].

The study aims to create a talent training strategy and a biosensor-assisted mental health monitoring system using DL techniques. The study aims to leverage a Novel Refined Prairie Dog Optimized Poly-Kernel Support Vector Machine (RPDO-PSVM) model to predict mental health outcomes following a talent training program.

Contribution of the study:

- The study objective is to develop a talent training program and biosensor-assisted mental health monitoring system using the DL method.
- The study gathers data from 453 participants through biosensors. The utilization of bandpass filtering to remove noise from sensor data and conventional neural network (CNN) to extract applicable characters for prediction tasks.
- The study establishes the original RPDO-PSVM, which optimizes and selects features from sensor data to predict mental health outcomes after training programs.
- The study determines the effectiveness of the RPDO-PSVM approach in predicting mental health outcomes, showing superior performance over other methods.
- The study emphasizes the possibility of combining biosensor technology with tactical talent training as a talented method for improving mental health outcomes, providing a scalable and tailored system for mental health monitoring.

2. Related work

This section evaluates the utilization of biosensors and artificial intelligence (AI) for mental health monitoring, with approaches varying in model complexity and sensor integration, to predict mental health outcomes based on physiological data.

The work optimized a system for tracking mental and physical wellness. The artificial fish school approach Zhang and Liu [8] introduced and tested K-means clustering. Findings indicate that effectiveness with advanced test samples was improved, with a 1% gain in classification accuracy and a shorter time for data completion.

The research utilized keyboard inputs from users' social media accounts to track mental health using federated culture and Deep Learning (DL) techniques [9]. A Recurrent Neural Network (RNN)has been evaluated to measure depression levels. By updating a global sentiment vocabulary with anonymized user data, the global model improved, and on day 60, it achieved 93.46% accuracy.

With the reference of Singh et al. [10], depression recognition (DR) DL that employed Bi-Directional Long Short-Term Memory (Bi-LSTM) and CNN to recognize depression in signal data. By segmenting, normalizing, augmenting, and assembling signal data, the model categorized them into four sadness levels. DRDL improved results for low-performing patients by achieving 90.12% accuracy for quaternary classifications and 91.31% accuracy for binary classifications.

As stated in Fei et al. [11], five databases and recognized facial expressions using deep quality from Alex Net and Linear Discriminant Analysis (LDA). With its advanced accuracy and effectiveness over advanced techniques, it has been an affordable and easy-to-use tool for mental health monitoring.

The work evaluated the posts from an online mental health platform and applied DL to recognize and express mental health feelings, as well as anxiety, despair, and obsessive-cleaning disorder (OCD). The recommended Multi-Head Attention with Bilinear CNN (MHA-BCNN) approach Dheeraj and Ramakrishnudu [12], outperformed earlier models and performed superior in identifying mental health disorders by handling uncertainty and long-term dependency.

As mentioned in Liu and Wang [13], the psychological strain experienced by students to generate a model for identifying mental health stress using emotional analysis. A particular dataset was produced for learning by operate DL advance. The accomplishment of the advance had been maintained by comparative trials, which exposed that college students on the test had good mental health and refused apparent symbols of stress.

An energy-efficient memristive sequencer network (EMSN) for classifying human emotions using two-dimensional (2D) materials and inexpensive, environmentally friendly technology. A core sequencer block of LSTM, normalization, and multi-layer perception modules was part of EMSN. The advanced accuracy and computational efficiency of EMSN, as established by experimental findings of Ji et al. [14], enhanced consumer health monitoring.

As stated in Chakraborty et al. [15], COVID-19-exacerbated mental health problems in smart cities that impact a variety of populations, including healthcare professionals and students. Using an online platform called Mind Turner, it predicts mental health problems by combining image dispensation, the Internet of Technology (IoT), and machine learning (ML). Stress levels were detected by Random Forest (RF), emotions were identified by Support Vector Machine (SVM), and depression levels were private with a combination of results from fuzzy logic.

A hybrid outlined method stated by Song et al. [16], for creating clinically from social media timelines that mutual a hierarchical Variation Auto encoder(VAE) and Large Language Model (LLM). It provided factual, coherent, and temporally susceptible outputs that surpass the therapeutic significance of the LLM-only advance by fusing a first-person timeline summarized with third-person clinical insights.

According to Batterham et al. [17], the preferences of employees, clients, and families to build an efficient effect monitor classification for a mental health program for veterans of the armed services. A client-led, customized organization that provides improvement feedback ensures effectiveness and accessibility and permits confined information substitute has been essential.

A wearable gadget that incorporated temperature, accelerometer, and pulse sensors to gather data that was sent to a non-relational database. The data was analyzed using an ML model that used RF and linear regression (LR) to manage mental stress. The model developed by Jayanthi et al. [18] can be used for remote monitoring in everyday situations, healthcare settings, and educational institutions.

The work combined quantum computation, and transfer learning to present a quantum LSTM-based contrastive learning system for incomplete mental health monitoring. The surpassed predictable technique by Padha and Sahoo [19], operating a quantum-guided LSTM encoder and fine-tuning with a tiny labeled dataset, attaining an $F1$-score of 0.99 on heart rate unpredictability data.

A quantum-enhanced ML model by Padha and Sahoo [20], that is effective for ongoing mental health monitoring. Principal component analysis (PCA) was used to improve data patterns, classical models were analyzed, and a meta-approach that integrated many quantum models was developed. The highest $F1$-score of 0.9 obtained from experiments on seven datasets outperformed that of individual models.

The research introduced LAPoMM for tracking mental health metrics in low-resource languages using data from social media. In identifying mental cues like emotions and suicidal thoughts, it performed more advanced than other techniques by utilizing cross-lingual methodologies and a language-agnostic approach. The model by Noraset et al. [21], demonstrated its prospective for worldwide mental health monitoring by showing a strong correlation with actual depression and suicide data.

The work suggested Arousal-valence Networks (ArvaNets), a deep recurrent architecture that combined recurrent and graph convolutional neural networks (GCNN) attentively. To assemble emotions that were mapped to a 2D inspiration valence method, it extracted learnable spatial representation. The approach by Zhu et al. [22], effectively identified emotions and mental states for daily monitoring by utilizing an LSTM unit and a spatiotemporal attention mechanism.

The CNN classification for mental health states based on signal data in a DL-based mental health monitoring method for college students. With improvements in sleep problems, depression, individuality growth, suicide consideration, and self-esteem, the approach by Du et al. [23], attained excellent classification accuracy (97.54%) and $F1$ score (98.35%).

Adiscrepancy in private federated transfer learning architecture by Wang et al. [24], for mental health monitoring that addresses imbalance, insufficiency, and data privacy by integrating relocation education and disparity isolation. A stress recognition case study was used to evaluate the process, which established a 10% enlarge in accuracy and a 21% improvement in recall while maintaining anonymity.

As presented in Mazumdar et al. [25], a dataset for tracking mental health in metaverse settings, with a particular emphasis on post-traumatic stress disorder (PTSD) and escapism. It contains demographics in sequence from Twitter, chat logs, fundamental performance, and user-generated material. By annotating the data collection, mental health professionals made it possible to research mental health trends in virtual environments, particularly PTSD and escapism.

Atrack design for a hierarchical absorption system used in multimodal emotional computing for mental health tracking. It employed an industrial albumen protein-based memristor, incorporated with wearable and flexible electronics. The system by Dong et al. [26], offered low isolation invasiveness, energy utilization, and expenditure, promoting next-generation healthcare equipment in smart cities.

An IoT-enabled mental health framework by Liu [27], for individualized English instruction. It composed educational and mental health data to support teachers, evaluating a variety of data to generate customized tactics and feedback. With excellent accuracy (91.6%), $F1$-score (0.921), and MCC (0.829), the approach performed better than the conservative technique.

3. Methodology

The study collects biosensor data from 453 participants to track mental health after a training program. The data is pre-processed using a bandpass filter and CNN is utilized for feature extraction to find pertinent patterns. By optimizing feature selection and efficiently managing complicated, non-linear biosensor data, the RPDO-PSVM model advances prediction accuracy for mental health. **Figure 2** shows the methodological flow.

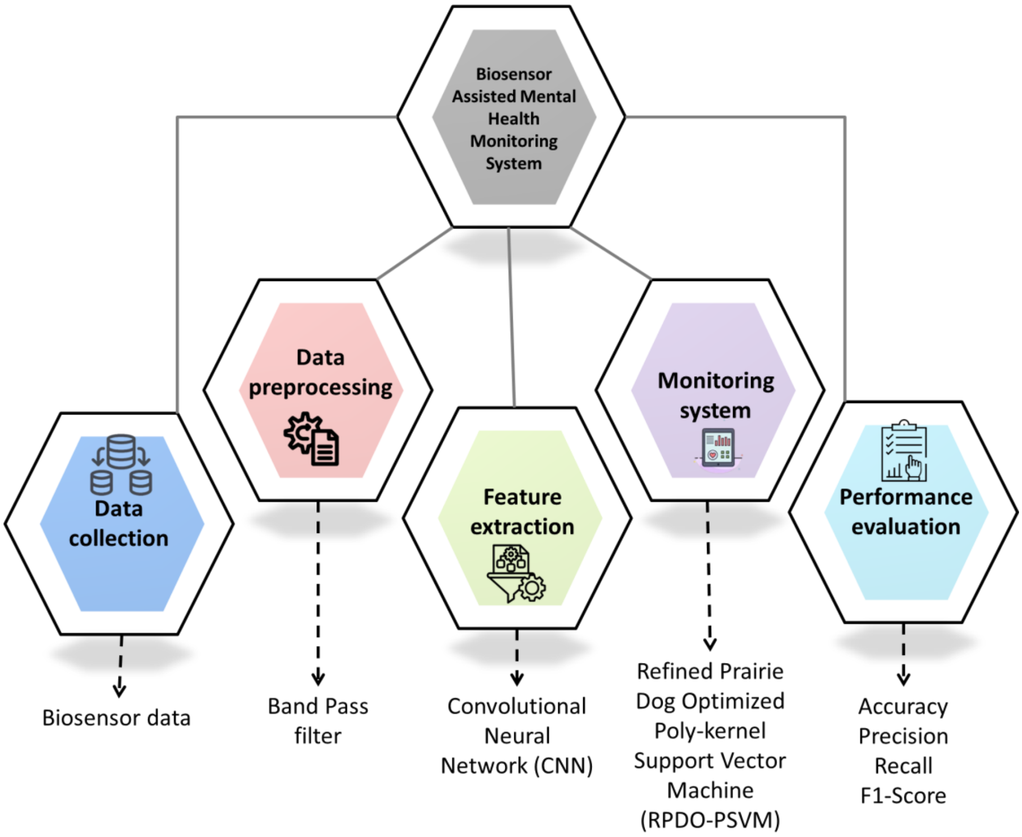

Figure 2. Proposed flow for mental health monitoring system and talent training strategy.

3.1. Dataset

The participants consisted of 453 individuals who were in talent development programs that integrated problem-solving games along with theoretical knowledge. Such participants were continuously monitored on mental health parameters using biosensors before and after the implementation of the talent development programs. These biosensors captured other physiological signals like heart rates, skin conductance, etc., and even brain signals. All this data collection was continuous in the real-time process during the training phases. The sensor data collected was then analyzed after completing all the training programs. The collected data reflected on the mental health status of the participants along with the cognitive responses. Calibration of biosensors was made to obtain precise readings. Physiological signals in the final dataset included those required to analyze the impact of the training program on mental health.

3.2. Data pre-processing

The gathered signal data is preprocessed using a bandpass filter. It diminishes wavelengths outside the specified variety while permitting signals within that range to stream throughout. Its transfer function $G(e)$is given by Equation (1).

$$G(e) = \frac{e_{high} - e_{low}}{e^2 + (e_{high} + e_{low})^2} \tag{1}$$

where $e_{high} and e_{low}$symbolize the upper and lower cutoff frequencies, respectively; this filter passes frequencies betweene$e_{high} and e_{low}$, allowing relevant signal to pass while blocking unnecessary noise. It isolates specific physiological signals and removes irrelevant noise or disturbances, improving the quality of data used for further analysis.

3.3. Feature extraction

A key component of the monitoring system for digital learning environments is CNN-based feature extraction. CNN is used to process the gathered data to extract pertinent features.

Input layer: Raw data values from the input are handled by this layer. Improving pattern resolution in multi-modal data helps to shorten training times without sacrificing data integrity.

Convolutional layer: A collection of adaptive filters with dimensions less than the input data is present in this layer. As these filters run through the input data, their weights are used to perform dot product operations. For example, an input with 12 filters applied yield return attributes with dimensions of 224 × 224 × 12. This operation is represented in Equation (2) asase_1:

$$e_1(W) = h(X_1 \times W + A_1) \tag{2}$$

whereA_1 and X_1 stand for the biases and filter weights, respectively, and '∗' indicates the convolution process. $X_1$is made up of m_d filtering of size$e \times e \times d$, where e is the spatial extent of a sort and d is the integer of avenues in the input W. X_1Createsm_d feature maps by applying m_d convolutions to the input. Each member of the d-dimensional vector A_1 is connected to a filter. The activation function (·), like Tanh or Rectified Linear Unit (ReLU), transforms the filter responses in a nonlinear way.

Pooling layer: To reduce the dimensions of the input data to mitigate overfitting and improve computational efficiencies. To accomplish this reduction, every slice of the depth of the original data is subjected to a tiny filter. Above and below are two common pooling operations: max pooling is used here to choose the maximum values inside the filters.

ReLU layer: Each element is given an activation function by the ReLU layer, which amplifies the disorder of the data patterns. The important features must be extracted using this nonlinearity.

Fully connected layer: In typical neural networks, stimulation in the preceding layer is fully associated with all units in this level. As demonstrated in operatione_2, the activations are calculated by first performing matrix multiplication and then bias offset is given in Equation (3)

$$e_2(w) = g(X_{2^w} + A_2) \tag{3}$$

where,w is the input value, X represents the weight matrix, and A is the bias value. Like$g(\cdot)$ the activation function, $h(\cdot)$functions similarly.

It is important since they do not require manual feature engineering; instead, they automatically extract hierarchical patterns from raw data. In applications like mental health monitoring, CNNs improve model accuracy by identifying temporal and spatial patterns. This allows for automatic, effective feature extraction from complex data, which improves performance.

3.4. Mental health monitoring using refined prairie dog optimized poly-kernel support vector machine (RPDO-PSVM)

This study employs the RPDO-PSVM model to improve mental health monitoring. To increase prediction accuracy, the RPDO-PSVM incorporates a novel optimization technique that maximizes feature selection and is motivated by the social behavior of prairie dogs. The model efficiently handles intricate, non-linear patterns in biosensor data due to the PSVM component.

3.4.1. Poly-kernel support vector machine (PSVM)

After the feature extraction, the signal is classified using PSVM. A PSVM is a deviation of the SVM method that handles complex, non-linear relationships between data points by transforming data into a higher-dimensional space using a polynomial kernel function. It is used for instance, for training in a binary classification problem as given in Equation (4).

$$(y_1, x_1), (y_2, x_2), \ldots\ldots, (y_m, x_m), y_1 \in \Re^c, y_1 \in \{+1, -1\} \tag{4}$$

wherex_ja feature is a vector in the j^{th}example's D-dimension space, and $y_j$is its label, which can be either positive or negative. PSVM is trained by minimizing the following Equation (5).

$$mim: V(\alpha) = \frac{1}{2} \underset{V}{\rightarrow} . \underset{V}{\rightarrow} + D \sum_{j=1}^{m} loss(\underset{V}{\rightarrow} y_j, x_j) \tag{5}$$

The loss function shows how much training error has been lost. In most cases, the hinge-loss is employed. Trading off training error and margin is possible with the parameter D in Equation (5). An increase in training errors results from a small value for$D$. By using the following Equation (6), one can determine if an example y belongs to a class($+1$ or -1).

$$x(y) = sign\left(\sum_{x_j \in SV} \alpha_j, y_j L(y, y_j) \right) + a \tag{6}$$

a represents a threshold, and $\alpha_j$is the weight of the training example y_j ($\alpha_j > 0$). The support vectors (SV) in this case should be represented by$y y_j$, which is typical of training samples. The kernel mapping function, or kernel function$L$, maps from $\Re^c\, to \Re^{c'}$. The dot-product is simply used by the natural linear kernel (Equation (7)).

$$L(y, y_j) = dot((y, y_j) \tag{7}$$

By using Equation (8), a polynomial kernel of degree dot is obtained.

$$L(y, y_j) = (1 + dot(y, y_j))^c \tag{8}$$

For specific purposes, off-the-shelf kernel types are used or designed. It demonstrates that the most effective kernels for numerous natural language processing (NLP) difficulties are those based on polynomial kernels. It is well known that the most effective kernel computing is represented by the dot-product (linear form), which generates the output value by linearly merging all support vectors in Equation (9).

$$x(y) = sign(dot(y, v) + a) \quad where\ v = \sum_{x_j \in SV} \alpha_j, x_{j,} y_j \tag{9}$$

By combining Equations (6) and (8), the determination of an example of x using the polynomial kernel is demonstrated as follows in Equation (10).

$$x(y) = sign\left((\sum_{x_j \in SV} \alpha_j, y_j (dot(y, y_j) + 1)^c \right) + a \tag{10}$$

Degree c is typically set greater than 1. The polynomial kernel switches to a linear kernel when $c$is set to1. Despite the polynomial kernel's efficacy, it is not demonstrated to linearly aggregate all support vectors into a single weight vector; instead, each support vector y_j must have its kernel function (8) computed. When there are a lot of support vectors, the situation gets considerably worse. Consequently, the cost of kernel computations is significantly higher than that of linear kernels, whether in training or testing. Non-linear correlations between psychological states and physiological responses are analyzed by PSVM. The polynomial kernel allows the model to evaluate subtle patterns in biosensor data that correlate with mental health factors, resulting in more accurate predictions than a simple linear model.

3.4.2. Refined prairie dog optimization (RPDO)

The classified data are optimized using RPDO for better detection. Prairie dog foraging actions are simulated by the PDO algorithm. Prairie dogs participate in social activities such as foraging, cave construction, cave maintenance, and predator protection.

At the spatial level, one × dim represents each prairie dog's foraging activity. Upper-bound (UB) and lower-bound (LB) are designated to restrict the range of movement of prairie dogs to impede them from straying from their path during foraging. A difficulty can be solved by placing each prairie dog in its own set at various places. During the initial phase, the location of randomly synthesized prairie dogs, the quality of food at the moment, and the food sources ρ all influenced the prairie dogs' foraging behavior. A fixed food source warning at 0.1 kHz is represented byρ. The efficiency of the evaluation currently achieved the best solution that defines the quality of the current food in the mathematical model. As $fDBest_{j,i}$is the random cumulative effect, and$DPD_{j,i}$ define the position of the randomly synthesized prairie dog. This is the calculation by Equations (11) and (12).

$$fDBest_{j,i} = HBest_{j,i} \times \Delta + \frac{PD_{j,i} \times mean(PD_j)}{GBest_{j,i} \times (VA_i - KA_i) + \Delta} \tag{11}$$

$$DPD_{j,i} = \frac{HBest_{j,i} - qPD_{j,i}}{HBest_{j,i} + \Delta} \tag{12}$$

When the locations of the random solutions of prairie dogs are indicated by $GBest_{j,i}$the global ideal solution found thus far is denoted by$GBest_{j,i}$and Δ is a very small value showing the differences between both. Accordingly, the following Equation (13) can be used to update the location of prairie dogs that are looking for food:

$$PD_{j+1,i+1} = HBest_{j,i} - fDBest_{j,i} \times \rho - CPD_{j,i} \times Levy(m) \tag{13}$$

Levy is a levy distribution in Equation (13) with discontinuous leaps. Prairie dogs dig and construct new caverns around new food sources they discover. The prairie dogs' current location is correlated with the depth of their Digging Strength (DS). Equation (14) for DS updates is as follows:

$$DS = 1.5 \times q \times (1 - \frac{s}{S})^{(2\frac{s}{S})} \tag{14}$$

s is the current iteration number, S is the maximum iteration number, and q is changed between -1 and 1 based on the parity of the current iteration number. The position of prairie dogs is updated throughout the second period, as indicated by Equation (15):

$$PD_{j+1,i+1} = HBest_{j,i} \times qPD \times DS \times Levy(m) \tag{15}$$

The quality of the available food supply ε and the total effect of all prairie dogs are used by the dogs to update their positions at random during the third period. Within the mathematical model, the food source quality is represented by a small number,ε which stands for the quality of the current food source. Using the following Equation (16), the position of prairie dogs can be updated:

$$PD_{j+1,i+1} = HBest_{j,i} - fDBest_{j,i} \times \varepsilon - CPD_{j,i} \times rand \tag{16}$$

where the random number, $q$and, ranges from 0 to 1.

Prairie dogs are frequently attacked by predators while they are foraging. Consequently, the predatory effect (PE) is used to define the predator attack. The following is the Equation (17) used to calculate PE:

$$PE = 1.5 \times (1 - \frac{s}{S})^{(2\frac{s}{S})} \tag{17}$$

Using Equation (18), update the prairie dog positions during the fourth period.

$$PD_{j+1,i+1} = HBest_{j,i} \times PE \times rand \tag{18}$$

Prairie dogs constantly adjust their position to find better food sources during these four time periods, as determined by diverse variables like the DS, the quality of food sourcesε, the cumulative effect of $CPD_{j,i}$ on all prairie dogs, and the PE. The revised locations of prairie dogs at four different times are summed up in Equation (19).

$$\begin{cases} PD_{j+1,i+1} = HBest_{j,i} - fDBest_{j,i} \times \rho - CPD_{j,i} \times Levy(m) \forall s < \frac{S}{4} \\ PD_{j+1,i+1} = HBest_{j,i} \times qPD \times DS \times Levy(m) \forall < \frac{S}{4} \leq s \frac{S}{2} \\ PD_{j+1,i+1} = HBest_{j,i} - fDBest_{j,i} \times \varepsilon - CPD_{j,i} \times rand \forall < \frac{S}{2} \leq 3\frac{S}{4} \\ PD_{j+1,i+1} = HBest_{j,i} \times PE \times rand \forall 3 < \frac{S}{4} \leq sS \end{cases} \tag{19}$$

By maximizing feature selection and model parameters, RPDO improves accuracy and effectiveness when used for event detection. Event detection becomes more reliable and scalable as an outcome of its improved convergence speed, decreased processing costs, and good background adaptation. This reliable method makes it possible to make accurate, concurrent predictions from complex, non-linear biosensor data, which is necessary for evaluating mental health.

By utilizing DL methods with biosensor data, the RPDO-PSVM model offers a complicated method of mental health monitoring. This system combines a PSVM that handles intricate, non-linear patterns with a novel optimization technique inspired by prairie dogs, which improves feature selection for increased prediction accuracy. By optimizing these retrieved traits, the RPDO algorithm keeps only the most pertinent data for prediction. The adaptability and resilience of the model are improved by RPDO, which dynamically adjusts parameters depending on patterns in training data. Algorithm 1 shows the RPDO-PSVM algorithm.

Algorithm 1 Refined Prairie Dog Optimized Poly-Kernel Support Vector Machine (RPDO-PSVM)

Start
Step 1: Initialize data, features, and labels
X, y= load data, load features x and y
Step 2: Train SVM with polynomial kernel
Def train PSVM (features, labels, degree = 3)
    Implement PSVM with polynomial kernel function
    Define the polynomial kernel function
    Poly kernel ($x, y,$ degree = 3): return ($1 + dot(x, y)$) degree
    Train the PSVM model with the polynomial kernel
    PSVM model = Train PSVM (features, labels, kernel = poly kernel)
Step 3: Implement RPDO for parameter tuning
(RPDO (PSVM model, max iteration = 100, Population size = 50)
  Initialize prairie dog position and parameters
 Position = Initialize position (Population size)
 Best position = None
 Best value = Float (‘info)
 For iteration in range (Max iteration):
 For $j$in range (Population size):
 Evaluate position (fitness function) based on model accuracy
 Fitness = Evaluate fitness (PSVM model, positions)
Update best position and value
If fitness < best value:
Best value = fitness
Best position = positions[j]

Algorithm 1 (*Continued*)

Update prairie dog positions based on RPDO logic (Equations (11)–(19))
For j in range (Population size):
Position sj = update position (position sj, best position)
Return the best-optimized model parameters
Return to the best position
Step 4: Event Detection using optimized PSVM
    Event detection (features, PSVM model):
    Predictions = PSVM model. Predict (features)
    Return predictions
    Main Execution Flow features = extract features(X)
    PSVM model = train PSVM (features, x and y)
    Optimized parameters= RPDO (PSVM model)
    Final model = retrain PSVM with optimized parameters (PSVM model, optimized parameters)
    Classify events using the final model
    predictions = event detection (features, final model)
END

4. Result

This study uses the RPDO-PSVM model in Python 3.11 to create a biosensor-assisted mental health monitoring system that predicts mental health outcomes following talent training programs. The evaluation metrics include $F1$-score, accuracy, recall, and precision. For evaluation purposes, the existing approaches, RF (Rescio et al. [28]), Decision Tree (DT) (Rescio et al. [28]), and Local Binary Patterns Histogram (LBPH) (Alrasheedi et al. [29]), are compared to the suggested method.

Accuracy: Accuracy is a measurement of how well the entire model performs, given that it computes the number of correct predictions divided by total predictions. It makes sure all classes have an equal representation in testing the effectiveness of the model. A good accuracy level will result in strong predictive power. But if the datasets are imbalanced, other measures like precision and recall can also be equally important. Accuracy is calculated by the given Equation (20). **Figure 3** and **Table 1** demonstrate the outcomes of accuracy.

$$Acc = \frac{True_{positive} + True_{negative}}{True_{positive} + True_{negative} + False_{positive} + False_{negative}} \tag{20}$$

Table 1. Comparison of accuracy for different classification methods.

Methods	**Accuracy (%)**
LBPH (Rescio et al. [28])	68
DT (Alrasheedi et al. [29])	84.5
RF (Alrasheedi et al. [29])	91
RPDO-PSVM [Proposed]	96

The suggested RPDO-PSVM model outperforms LBPH (68%), RF (91%), and DT (84.5%) with an accuracy of 96%. This is because of the PSVM capabilities and sophisticated feature selection of RPDO-PSVM, which efficiently handles complicated data and makes it ideal for mental health prediction.

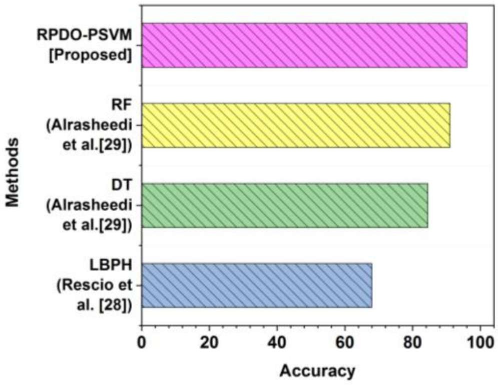

Figure 3. Accuracy comparison of various classification methods.

Precision: Precision measures the accuracy of a model's positive predictions, dividing true positive instances by all predicted positives, including false positives. Higher precision reduces false positives, especially when false positives are costly. It's useful when capturing all positive instances is less important than ensuring positive predictions' relevance. **Table 2** and **Figure 4** show the evolution of precision.

$$Pre = \frac{True_{positive}}{True_{positive} + False_{positive}} \tag{21}$$

Table 2. Comparison of precision for different classification methods.

Methods	Precision (%)
LBPH (Rescio et al. [28])	75
DT (Alrasheedi et al. [29])	84.3
RF (Alrasheedi et al. [29])	91.5
RPDO-PSVM [Proposed]	93.8

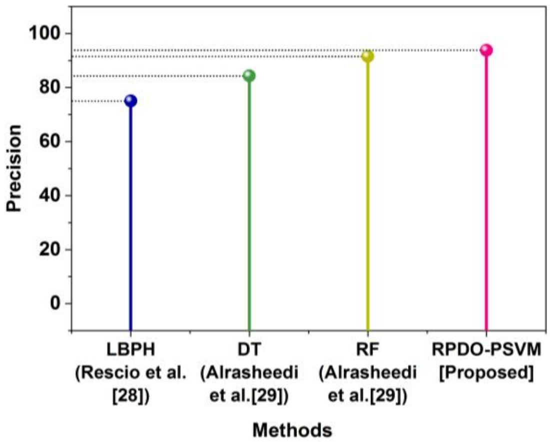

Figure 4. Comparison of precision performance across different methods.

The suggested RPDO-PSVM model outperforms the existing methods, with a precision of 93.8%, compared to 75% for LBPH, 84.3% for DT, and 91.5% for RF. This illustrates how RPDO-PSVM achieves greater accuracy than the other models, making it the best model for accurate mental health monitoring.

Recall is a performance metric used to measure how accurately a model can correctly identify positive cases. Recall is defined as the number of true positives divided by the sum of true positives and false negatives. The greater the recall, the better it is, because the model successfully detects most of the positive cases. This score becomes useful when there is more of a need to retrieve as many positive instances as possible, even at the sacrifice of some false positives. This recall is useful in ascertaining the sensitivity and efficiency of the model about positive results. Recall is calculated using Equation (22). **Table 3** and **Figure 5** denote the outcomes of recall.

$$Recall = \frac{True_{positive}}{True_{positive} + False_{negative}} \tag{22}$$

Table 3. Comparison of recall performance for different classification methods.

Methods	Recall (%)
LBPH (Rescio et al. [28])	71
DT (Alrasheedi et al. [29])	82.5
RF (Alrasheedi et al. [29])	88.5
RPDO-PSVM [Proposed]	92.1

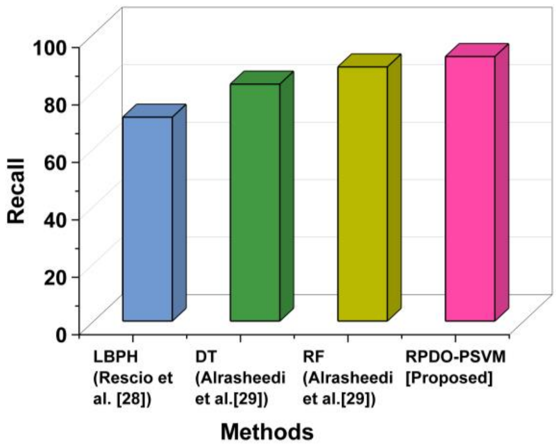

Figure 5. Comparison of recall performance across different methods.

With a 92.1% recall, the suggested RPDO-PSVM model outperforms the other methods, like DT (82.5%), RF (88.5%), and LBPH (71%),in detecting positive cases. This demonstrates that, in contrast to conventional techniques, RPDO-PSVM is efficient at producing precise, real-time forecasts about mental health.

The $F1$ score is a measure of performance that combines precision and recall into one value. Precision is the percentage of accurate positive predictions, whereas recall refers to the ratio of correct identification of all positive instances. The $F1$-score is the harmonic mean between precision and recall, ensuring that there is a proper balance between the two. The $F1$ score is mostly used when there is an issue with class imbalance. Therefore, this score considers precision and recall to give more detailed performance information. It is evaluated using Equation (23). **Figure 6** and **Table 4** demonstrate the evaluation of the $F1$-score.

$$F1 = 2 \times \frac{precision \times recall}{precision + recall} \tag{23}$$

Table 4. Comparison of $F1$-score for different classification methods.

Methods	$F1$-Score (%)
LBPH (Rescio et al. [28])	73
DT (Alrasheedi et al. [29])	84.4
RF (Alrasheedi et al. [29])	90.9
RPDO-PSVM [Proposed]	94.4

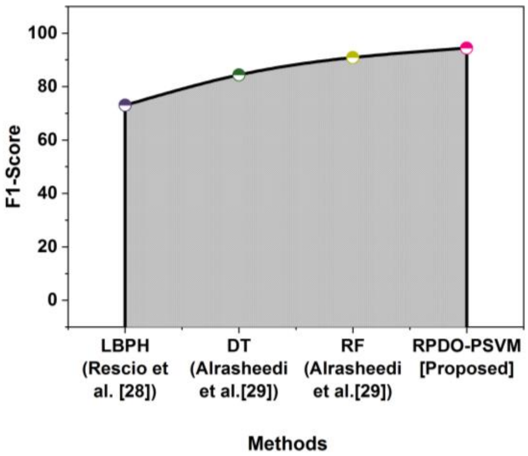

Figure 6. $F1$ score performance for different methods.

With scores of 73% for LBPH, 84.4% for DT, and 90.9% for RF, accuracy is becoming better. With an $F1$-Score of 94.4%, the RPDO-PSVM scored better than all other models, demonstrating its superior performance in mental health monitoring, making it the most accurate model in the comparison.

Figure 7 shows the training accuracy of this study. The training accuracy graph illustrates how the RPDO-PSVM model's performance improves as it processes more data. Initially, the accuracy is low because the model is still in the early stages of learning, struggling to identify patterns in the data. As optimization methods, such as RPDO and PSVM, are applied, the accuracy steadily increases, indicating that the model is becoming more proficient in making predictions. Eventually, the accuracy stabilizes when the model converges, signaling that the learning process has reached an optimal point. However, if overfitting occurs, the graph may show a steep increase in accuracy followed by a sudden drop, suggesting the model has become too specialized in the training data. Overall, the training accuracy graph reflects the model's learning progress and its ability to make accurate predictions over time.

Figure 8 demonstrates the training loss of the study. The graph of the training loss indicates how the error of the model reduces over time as it learns from biosensor data. Initially, the loss is high and indicates how much the model is misunderstood and needs to be optimized. As the RPDO-PSVM model goes through data processing and the adaptation of the parameters, loss decreases as the model performs well. This decline, with consistency and steadiness, is in the training loss. Hence, the model has been learned well regarding the underlying pattern in the data. Since the drop in the loss hints at increasing the correctness of model predictions, when it declines very steeply, then a good sign arises as it manifests that optimization techniques applied to fine-tune the model have performed well. This can be summarized by saying that the lower value to which the training loss eventually stabilizes reflects the optimal nature of the model's parameters in terms of task-specific optimality. Reductions in training loss are directly linked with enhanced performance in predicting mental health as the model becomes more competent at interpreting and classifying the biosensor data.

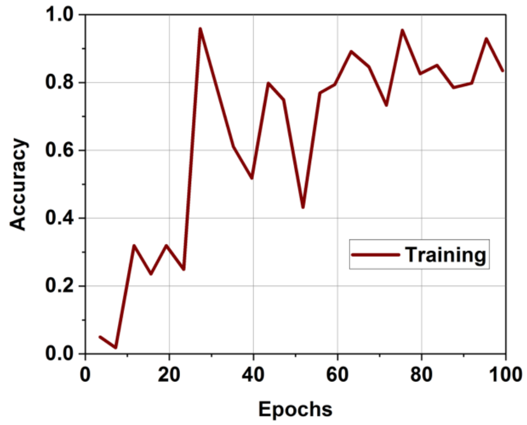

Figure 7. Training accuracy indicating model performance.

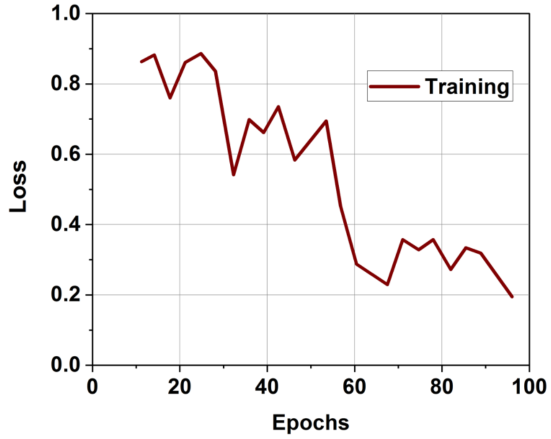

Figure 8. Training loss for model performance.

5. Discussion

Random Forest is good for dealing with large datasets but may overfit if the number of trees is not optimized, thereby reducing generalization. Decision Trees are simple and interpretable but easily overfit, especially in complex datasets with noisy or irrelevant features. LBPH, commonly used for facial recognition, relies heavily on pixel intensity patterns and may not work well with variations in lighting or facial expressions.

The proposed RPDO-PSVM offers several improvements in overcoming these weaknesses. RPDO-PSVM includes the strength of SVMs combined with the optimized poly-kernel for improving its ability to classify points in high-dimensional spaces, especially when working with biosensor data. It makes use of the prairie dog optimization algorithm for hyperparameter fine-tuning in the SVM to ensure that the model is accurate and robust, especially when handling complex biosensor measurements. This also improves the flexibility of the model in capturing the non-linear relationships in biosensor data, hence more efficient for complicated classification tasks. Overcoming overfitting issues inherent in Random Forest and Decision Trees and improving beyond the pattern recognition capabilities of LBPH, RPDO-PSVM offers a more accurate and reliable alternative when applied to biosensor data. It is particularly useful in scenarios involving noisy, high-dimensional, or complexly patterned biosensor data where traditional models are unable to capture such detail. In the end, adding prairie dog optimization guarantees that this model is well-optimized in accuracy as well as efficiency when dealing with biosensor data.

6. Conclusion

Mental health monitoring is essential for quick interventions and improved awareness of mental health disorders. By utilizing DL methods to predict mental health outcomes from biosensor data, this study aimed to create a biosensor-assisted mental health monitoring system with the RPDO-PSVM system. The outcomes showed how well the system performed, which is superior to traditional techniques with 96% accuracy, 93.8% precision, 92.1% recall, and 94.4% $F1$-score. These outcomes demonstrated how well the RPDO-PSVM model provided accurate, advanced forecasts for mental health monitoring. However, limitations were noted, including the reliance on an exacting dataset and potential overfitting during training. Probable information for more scalable and flexible mental health solutions includes future studies on developing concurrent feedback systems for individualized mental health interventions, adding multimodal data for enhanced accuracy, and raising the dataset to enlarge model generalisability.

Ethical approval: Not applicable.

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

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