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Article

Emotional intelligence and biological perception: A new approach to mental health ideological and political education

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Abstract: In recent years, the combination of emotional intelligence (EI) and biological perception has emerged as a significant strategy in mental health, notably in ideological and political education. EI, which involves understanding and managing emotions, fosters self-awareness, empathy, and interpersonal relationships. The purpose was to explore a novel approach integrating EI with biological perception to enhance mental health and ideological and political education. The dynamics of EI and its effects on mental health are examined by analyzing patterns in biological data and emotional reactions using a machine learning (ML) algorithm. The research presents a novel Intelligent Sailfish Optimized Driven Categorical Boosting (ISO-CatBoost) to predict mental health based on emotional outcomes and biological signals. It uses biological data, behavioral reactions, and EI to predict mental health outcomes. The data was preprocessed using data cleaning and normalization from the obtained data. Fast Fourier Transform (FFT) was used to extract the data collection. The results demonstrate that the ISO-CatBoost model effectively predicts mental health outcomes by performance metrics such as accuracy (88.8%), precision (87.5%), recall (98.5%), F1-score (93.2%), and specificity (85.7%). This method advances customized mental health education by providing ways for more effective emotional resilience training within ideological and political frameworks.

Keywords: emotional intelligence; biological data; mental health; ideological and political education; intelligent sailfish optimized driven categorical boosting (ISO-CatBoost)

1. Introduction

The fundamental ideas and techniques of dialectical materialism and ancient materialism are taught in ideological and political guidance, which students can use to address present-day problems. By combining that approach with contemporary political education, youngsters can better connect with own political, cultural, and monetary subsists, which include socialist ideals at an early age, and strive toward socialism [1]. Ideological and political educational innovation and student quality will be improved by integrating mental health education into its curriculum. Both disciplines aim to help students develop moral behavior and principles for growth and community integration while focusing on developing a group of high-quality abilities. Psychology serves as the foundation for mental health education, but the fundamental knowledge of both disciplines differs [2]. Combining political and ideological concerns with psychological education can enhance the understanding of complex ideological and political theories and values to ensure that learners can participate in mental health education, and enhance the overall educational experience [3]. Stress or anxiety is experienced mostly by college students because college education requires lots of academic commitment. It results in eating disorders, sleeplessness, and physical exhaustion. These include physiological, psychological, and environmental factors to learning concerns [4]. According to physiological and psychological research, severe anxiety or anxiety neurosis may have inherited components but acquired elements account for a larger portion. Educational anxiety is influenced by psychological development, physiological maturation, and non-intellectual elements [5]. Factors like rigid family education, achievement-only learning, economic and social growth, and news media can influence learning anxiety. To reduce anxiety, modifiable variables like self-relaxation can be controlled, allowing proper treatment of anxiety disorders without causing psychological strain or stress [6]. Confidence builds through self-belief, inferiority complex eradication and pleasure from small issues in life. Doing enjoyable activities when feeling anxious is called self-occupation. Students who undergo ideological and political instruction can easily manage pressure in college, time management and the transition from classroom into the social stage [7]. The learning process is primarily controlled by themselves, and the educational material is difficult, in contrast to the basic education level. While some students struggle to adjust to college life and experience discomfort, the campus's dynamic and diverse extracurricular events require them to find a balance between education and practice [8]. It incorporates mental health education into the required ideological and political course in an attempt to help college students manage studying anxiety and reduce it from a certain point of view [9]. The integration of political and ideological instruction into mental health education aims to integrate analytical thinking with psychology to effectively address psychological issues, to resolve negative emotions, and to confront real-world problems, thereby facilitating a smooth transition from mental health to social psychology, thereby redefining and innovating the course [10].

1.1. Research objective

The goal was to investigate an innovative approach that combines biological perception and emotional intelligence (EI) to improve mental health and political and ideological instruction.

- To forecast mental health by utilizing biological signals and emotional effects. It introduces a unique Intelligent Sailfish Optimized Driven Categorical Boosting (ISO-CatBoost) method.
- EI, behavioral responses, and biological data are gathered to forecast mental health consequences.
- To preprocess the biological data, cleaning and normalization were utilized, and the Fast Fourier Transform (FFT) approach was used to extract the features of the data.
- Through the provision of strategies for more efficient emotional resilience instruction within political and ideological systems, this approach promotes specific mental health instruction.

The research has six sections. Phase 2 represents related work, phase 3 presents methodology, phase 4 provides results for the research, phase 5 describes discussion, and finally, phase 6 gives a conclusion.

2. Related work

The influence of biomechanics-based optimization techniques in school sports and implications on mental health were examined by Han and Wang [11]. It included information from students who were split into two groups, the experimental group, was enrolled in a biomechanics-based sports program, and the control group, was enrolled in a traditional sports curriculum. Along with instructional strategies intended to promote both mental and physical growth, the biomechanics-based curriculum included an evaluation of body biomechanics and efficiency of movement. The internet has driven development and had a profound impact on people's lives and careers. However, there were drawbacks to its openness and propagation, especially when it comes to political and ideological instruction in educational institutions. Students who received political and ideological education were better able to form moral principles and ideals. Innovative thinking in these fields, however, was a significant issue for these organizations. Also determined the best methods for advancing these topics in higher education institutions are discussed by Gao [12].

College students have been significantly impacted by the digital world, which offered them a variety of ways to access information and challenged in ideological commitments. It was crucial to move away from a particular instructional subject with the objective of supporting students' mental and physical developed by Li et al. [13]. Traditional data was improved by the efficient cloud-based online course administration platform and methods for organization, making it a viable online learning activity. The latest concentration of physical education in higher education institutions on socialism with Chinese characteristics and fundamental principles was discussed by Shaoliu and Tongbai [14]. It highlighted how critical it was to support college graduates' humanistic care, scientific advice, ideological work, and active involvement in anti-epidemic initiatives. Additionally, it addressed the potential and difficulties of fostering the ideological work of college students and proposed theoretical and systematic changes to enhance instruction and provide fresh concepts for ideological education.

Rapid information and technology advancements have had a significant influence on students' educational achievement. Zhang et al. [15] introduced a multimedia-assisted ideological and political education system using deep learning techniques (MIPE-DLT) to enhance the quality of training. Students' ability to gather information and employ multimedia techniques was evaluated by the model, which produced better accuracy and processing speeds in addition to a high-order performance score with minimal latency. Tang [16] investigated the biomechanics of endurance and strength movements used by athletes during the competition process with the basic principles of kinesiology and related conceptual understanding in order to guarantee that athletes may fully utilize their subjective thinking and maximize their value in physical activities. Finally, specific implementation strategies were proposed on how to use the rules of biomechanics to enhance athletes' skills.

Italy found that the association between reduced inflammation and cognitive wellbeing was significantly influenced by one's conduct. Gialluisi et al. [17] looked at three measures of psychological resilience, mental health, and depressive symptoms in a sample of individuals. The findings revealed that Patient Health Questionnaire 9-item, 6-Item Version (PHQ9-6), and 36-Item Short Form Health Survey – Mental Component Summary (SF36-MCS) had substantial correlations with Inflammation (INFLA) score, accounting for 81% and 17% of the correlations, respectively. Nevertheless, the correlations with particular inflammatory biomarkers were somewhat uncorrelated and might be accounted for by biological variables. Although curriculum ideological and political education, or CIPE, has drawn attention in China, its impact is still up for debate. Wang et al. [18] focused on quantifying the CIPE effect in engineering education in China. Based on the prerequisites for each student's graduation, it suggested a CIPE effect assessment approach to higher education. The technology gave teachers and students graphical information to help them find their majors and improve their teaching strategies over time.

Xiuzhi [19] focused on the relationship between students' mental health and their political and ideological education, as well as the investigation of mental health issues in higher education. The findings indicated that while mental health issues were on the rise among college students, the present educational system did not adequately promote psychological treatment. Improving mental health education, deepening acceptance, improving management systems, and expanding the ability of faculty to provide theoretical guidance and useful resources for psychological support in higher education were some of the solutions suggested. Social economy and education have greatly benefited from the quick development of internet technology, but students' mental health education was not given enough consideration. Website material that was inappropriate might have a detrimental effect on pupils' morals and capacity for discriminated by Jiang [20]. To support students' holistic development, political and ideological instruction needed to be combined with mental health education in college.

3. Methodology

The use of biological data as well as behavioral and emotional signals, which are key indicators of mental health. These signals undergo preprocessing steps, including data normalization to standardize values, data cleaning to remove inconsistencies, and Fast Fourier Transform (FFT) to extract relevant frequency-domain features. By leveraging machine learning (ML) algorithms and optimization techniques, the proposed ISO-CatBoost approach effectively predicts mental health outcomes. This model processes the biological, behavioral, and emotional inputs, offering insights into how these factors influence mental well-being. The integration of these methods facilitates a more accurate and comprehensive understanding of mental health within the context of Ideological and Political Education. **Figure 1** shows the overview of methodology.

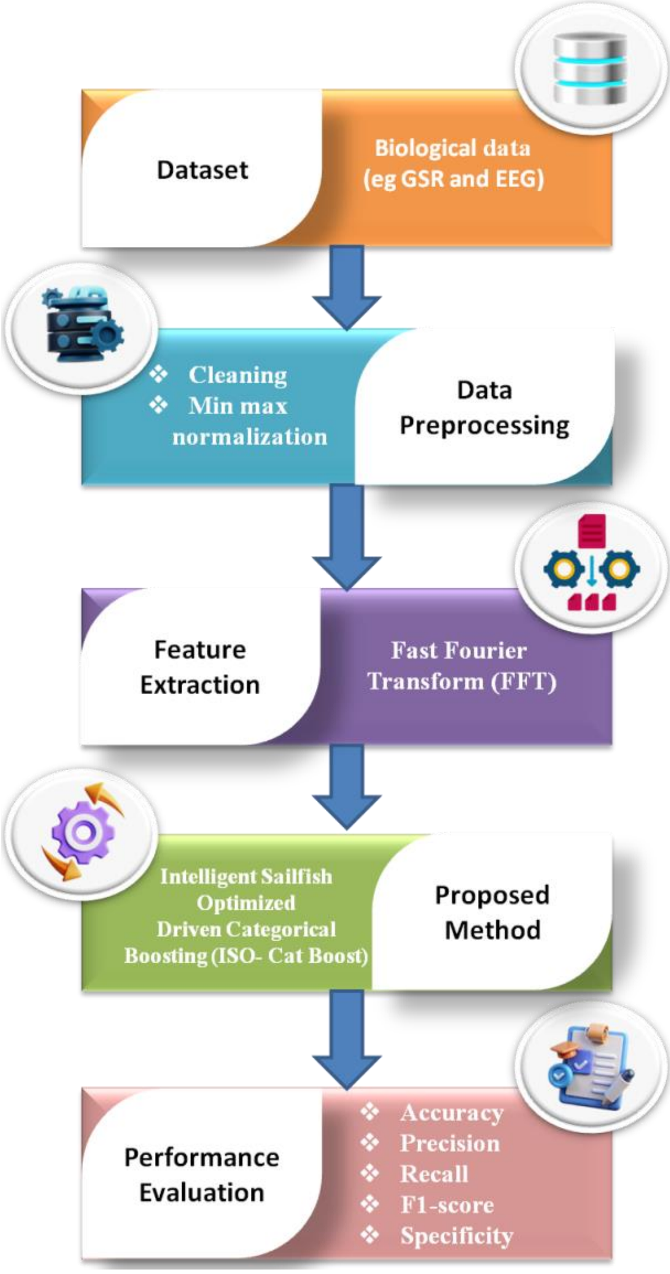

Figure 1. Overview of suggested ISO-CatBoost methodology.

3.1. Data collection

The data set was gathered from open source [21]. It has been generated for emotion monitoring and feedback technologies that are especially suited for biosensor-based political and ideological education at educational institutions. To evaluate students' levels of involvement in learning environments, it attempts to replicate their physiological and emotional reactions.

- Heart Rate: It is a measure of their emotional and physical health; lower heart rates are associated with absorption and tranquility, whereas higher heart rates are associated with stress or disengagement.
- Skin conductance: Increased skin conductance is generally termed GSR, in which skin conductance rises due to the activity of sweat glands, which is normally linked with emotional or physiological activity. When a person is

more involved emotionally, stressed, or nervous, their autonomic nervous system increases the activity of sweating through skin conductance. Therefore, skin conductance helps to assess parameters of the mental state during various stimuli or situations, as well as psychological engagement, stress, and emotions intensity.

- EEG: It measures frequencies of brain waves and is a method of recording the electrical activity of the brain. Higher frequencies are usually associated with increased activity of the brain and better concentration, which means that the brain deals with new material. In contrast, frequencies by lower band are related to distracted, tired, or bored states and these states indicate less cognitive activation or engagement during a task.
- Temperature: Elevated body temperature can be an indicator of physical strain or stress because the body has reacted to stress. A rise in internal temperature may be a sign of higher levels of mental or emotional stress and is associated with the autonomic nervous system's functioning. Higher temperature, in Celsius, may also be interpreted as removal or discomfort since the physical shell of a person responds to stress.
- Pupil Diameter: Larger pupils indicate greater focus or emotional reaction. Pupil width, measured in millimeters, is a crucial indicator of an individual's mental strain and emotional involvement.
- Smile Intensity: It assesses a student's level of attention and positive emotional reactions by measuring their smile intensity, which ranges from 0.0 to 1.0.
- Frown Intensity: The intensity of a student's frown, which ranges from 0.0 to 1.0, is a representation of their unpleasant feelings and frequently indicates disinterest.
- Cortisol Level: Micrograms per deciliter is the unit of measurement for the stress hormone cortisol; higher levels indicate tension or separation, while lower levels indicate relaxation or interest.
- Activity Level: It calculates the intensity of a student's physical activity that can reveal their stress levels or emotional involvement.
- Ambient Noise Level: A student's ability to concentrate and participate emotionally and cognitively can be greatly impacted by the ambient noise level, which is expressed in decibels.
- Lighting Level: Low lighting levels can cause people to pay less attention, hence the lighting intensity, expressed in lux, can have a big impact on retention.

3.1.1. Data preprocessing

- Cleaning: This step involves checking the dataset for inconsistencies, which include missing values, outliers, and variances that might impact the analysis. The columns that no longer contribute to the prediction of mental health consequences have been discarded. Furthermore, columns regarded as unrelated to the research were eliminated, especially the ones that had nothing associated with biological signals and EI. By ensuring that only the most pertinent attributes were kept, this procedure improved the data's quality and interpretability.

- Min-Max Normalization: A normalizing technique called min-max normalization creates an equilibrium of value assessments between data before and after the procedure by executing linear modifications on the original data. The Equation (1) that follows can be applied with this technique. To ensure comparability across various data types, min-max normalization scales input characteristics such as GSR, EEG, and emotional comprehension to a standard range. Avoiding higher values from controlling the training process and accelerating convergence enhances model performance. Additionally, it maintains feature distribution, which keeps significant data patterns preserved.

$$W_{new} = \frac{W - min\ (W)}{max\ (W) - min\ (W)} \tag{1}$$

where W_{new}—The modified value derived from the normalized outcomes, W - Previous value, $max\ (W)$—The dataset's highest possible value, and $min\ (W)$—The lowest value of the data collection.

3.1.2. Feature extraction using FFT

An effective feature extraction technique for examining time-series data, such as EEG and GSR signals, includes FFT. To find important frequency components associated with mental health disorders, it transforms signals into the amplitude-phase from the duration region. By extracting spectrum information such as peak frequencies and spectral power in particular frequency regions, FFT improves signal interpretations and model accuracy. Removing unnecessary frequencies also helps to reduce variability. The FFT algorithm begins with Equation (2).

$$W_l \triangleq \sum_{m=0}^{M-1} w_m e^{-i2\pi \frac{ml}{M}} \tag{2}$$

where the frequency of sampling must be consistent and w_m means input data. The dependency is achieved by using biological signals like EEG, GSR, and EI metrics for predicting mental health and following consistent sampling for feature elevation and model training. The expression for globalization index m in Equations (3)-(6) is expressed as follows:

$$m = Ok + \beta \tag{3}$$

$$W_l \triangleq \sum_{m=0}^{M-1} w_{(Ok+\beta)} e^{-i2\pi \frac{(Ok+\beta)l}{M}} \tag{4}$$

$$\sum_{\beta=0}^{O-1} e^{-i2\pi \frac{\beta l}{M}} \left(\sum_{k=0}^{\frac{M}{O}-1} w_{(Ok+\beta)} e^{-i2\pi \frac{kl}{\frac{M}{O}}} \right) \tag{5}$$

$$\widetilde{W}_l = \sum_{k=0}^{\frac{M}{O}-1} w_{(Ok+\beta)} e^{-i2\pi \frac{kl}{\frac{M}{O}}} \tag{6}$$

It implements the well-known Cooley-Tukey method to compute FT locally on different cores. The collection of input among the cores is necessary before the local transform, and this is due to global indexing as it is illustrated in Equation (3). The phase correction is represented by matrix multiplications similar to those seen in the above equations and needs to be applied following the local transform.

Further, it is possible to obtain improved dimensional FFT such as two-dimensional FFT (2D-FFT) and three dimensional FFT (3D-FFT) by extending this 1D technique along the required dimensions. This is especially useful for decoding intricate biological and emotional information and patterns in the body of research for frequency-domain functions needed to make accurate mental health predictions.

3.2. Prediction using ISO-CatBoost

The proposed ISO-CatBoost technique integrates two efficient strategies, ISO and Cat Boost. It is used in tuning the hyperparameter of the Cat Boost version with the aim of achieving higher usual overall performance through the exploring the parameter constituency efficiently. Cat Boost is a gradient-boosting set of rules that is especially good at solving categorical competencies; hence, the algorithm is ideal for handling complex emotional and biological situations. The sum of these strategies enables development of a strong predictive version to deal with multi-dimensional inputs, coupled with GSR, EEG indicators, and behavioral information. ISO-CatBoost utilizes the instrumentality of both approaches, improving version accuracy and the learning procedure as a whole.

3.2.1. Categorical Boosting (Cat Boost)

It is an ML technique which has publicly apparent advancement in the recent years in dealing with both the regression and the classification problems. It includes developing an ensemble predictive model by way of descending gradients in a practical area and shows how a sturdy predictor can be produced with the aid of greedily combining more than one base predictor or susceptible models iteratively. As the understanding of boosting advances, data distribution is changed. This causes forecast modification, which can result in over fitting issues or erroneous forecasts. Second, categorical variable processing is quite time-consuming. The number of statistics rises, for instance, when Extreme Gradient Boosting (XG Boost) and Light Gradient Boosting Machine (Light GBM) add new basic variables; consequently, calculation time and memory consumption also increase. Cat Boost is designed to handle categorical features without needing extensive preprocessing, making it ideal for biological and emotional data that may include categorical variables. It has shown itself effective in several domains, handling complicated dependencies, uncertain information, and heterogeneous characteristics.

The experimental collection can be expressed as $C = \{(w_l, z_l)\}_{l=1,\ldots,m}$, where $z_l \in \mathbb{R}$ is the goal and $w_l = \left(w_l^1, \ldots, w_l^m\right)$ is supposed to be a random vector containing the n characteristics. The objective of the model's supervised training phase is to train a function $F: \mathbb{R}^n \to \mathbb{R}$that minimizes the predicted loss in Equation (7). With L being a smooth loss function, $\mathcal{L}$ is defined as $\mathcal{L}(F) \coloneqq K(z, F(w))$. In this context, CatBoost's ability to handle complex feature interactions and efficiently process categorical data enhances the prediction accuracy, particularly when the data involves biological and emotional variables. Using a function F^{s+1}, the gradient boosting process enhances the prediction of z,

$$F^{s+1} = F^{s} + \alpha \cdot g^{s+1} s = 0,1, \ldots \quad (7)$$

The function of loss is minimized by choosing g^{s+1}as the base prediction and α as the step size from a collection of functions G in Equation (8).

$$g^{s+1} = \underset{g \in G}{argmin} \mathcal{L}(F^{s} + g) = \underset{g \in G}{argmin} \mathbb{E}K(z, F^{s}(w) + g(w)) \quad (8)$$

Utilizing either the negative gradient step technique or the Taylor approximation in Equation (9).

$$g^{s+1} = \underset{g \in G}{argmin} \mathbb{E}(-h^{s}(w, z) - g(w))^{2} \quad (9)$$

Having defined:

$$-h^{s}(w, z): \frac{\partial K(z, t)}{\partial s} |_{t=F^{s}(w)}$$

The CatBoost method, which may prevent prediction distortion and target leakage, can be used in place of conventional gradient boosting. By using unaware decision trees, which have the same split criteria at every tree level, CatBoost creates a more balanced architecture and expedites the test process. To leverage its ability to handle and analyze category features automatically, while also providing tools for model interpretation, such as feature importance plots, which help explain how input features affect mental health predictions. Since it uses an internal algorithm to improve hyperparameter rather than a unique hyperparameter optimization procedure, it is simpler to use than other gradient boost techniques.

3.2.2. Intelligent sailfish optimization (ISO)

The ISO algorithm effectively increases population diversity and avoids deficiencies related to population diversity by using two parameters in its analysis. The purpose of this is to ensure that the optimization process explores a broad solution space, improving the model's ability to predict mental health outcomes accurately. The initialization of sardine and fish sailing populations is accomplished at random. Fish and sardine sail minimums are denoted by t^{min} and c^{min} , respectively. The structure of the method ISO is shown in **Figure 2**.

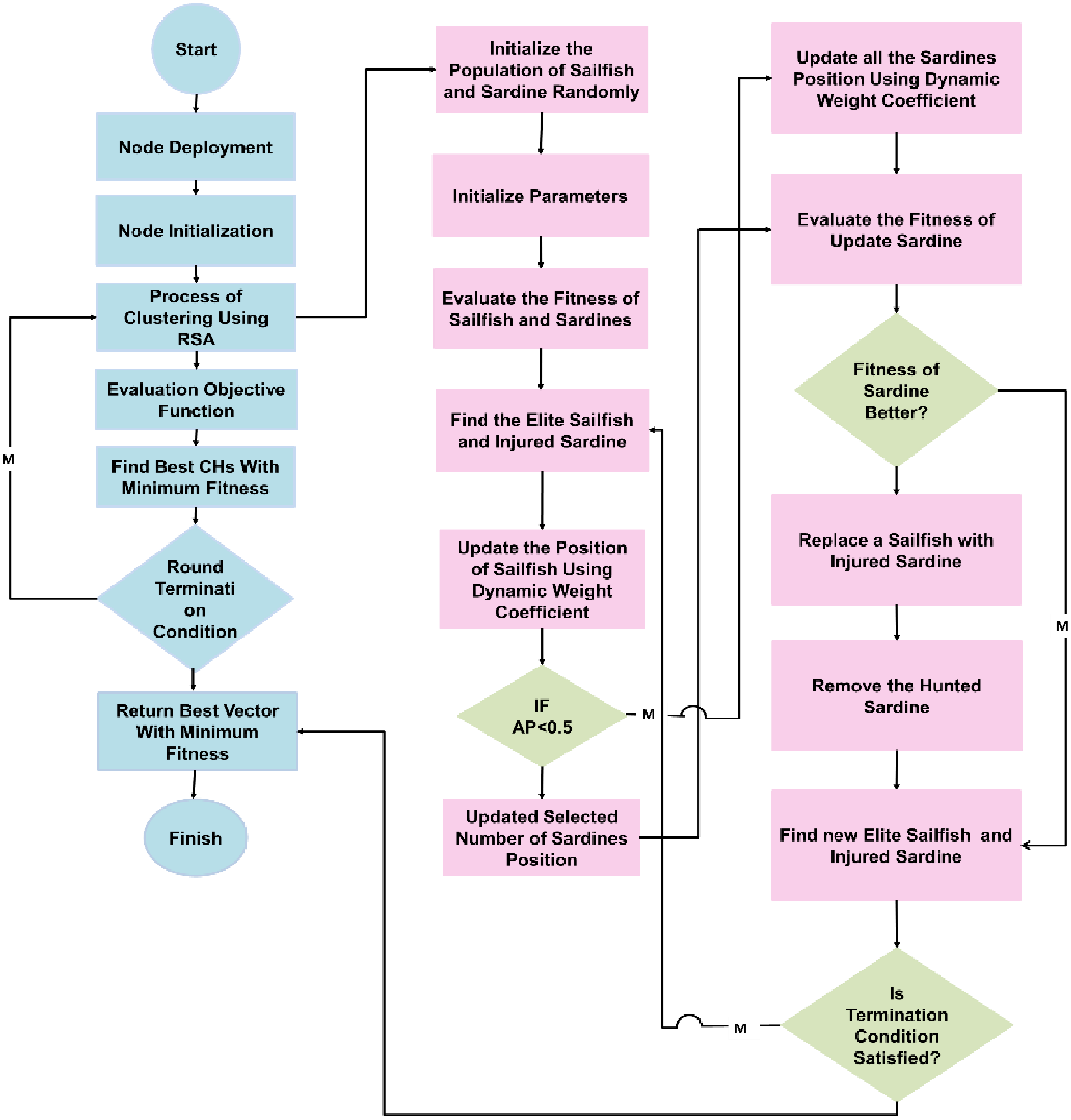

Figure 2. The architecture of the proposed ISO Model.

Both of their values reflect the bare minimum of sensor nodes. Likewise, t^{max} *and* c^{max} stand for sail and sardine maximum values, respectively, which are equivalent to the maximum number of sensor nodes in Equation (10).

$$\begin{gathered} t_{j,i} = t^{min} + rand \times \left(t^{max} - t^{min}\right) \\ c_{j,i} = c^{min} + rand \times \left(c^{max} - c^{min}\right) \end{gathered} \tag{10}$$

The vectors with a large residual energy of Clustering Heads (CHs) are considered to be the most effective. Equation (10) used for updating the sailfish's position continuously enters the dynamic weight coefficient, which in the beginning is higher than w and promotes global investigation. At the absolute least of all, w's value falls relative to the above, making it more helpful for local searches. Thus, in iteration I, the new orientation of the sailfish $\left(W^{j}_{new_{SF}}\right)$is modified by Equation (11). The purpose of this approach is to optimize the hyperparameter of the CatBoost model and enhance its predictive accuracy by efficiently exploring the hyperparameter space.

Through balancing the search process in the problem space, weighting among the first stage reduces the impact of unpredictability. Agent positions demonstrate higher quality when adaptive weighting is used. In general, it accelerates the rate of convergence and allows units to arrive at ideal positions more quickly. ISO enables CatBoost to accurately predict mental health outcomes by capturing complex non-linear relationships between emotional responses, biological signals, and EI, ensuring the effective integration of multiple data types.

$$W^{j}_{new_{SF}} = \omega \times W^{j}_{elite_{SF}} - \lambda_j \times \left(rand(1,0) \times \left(\frac{W^{j}_{elite_{SF}} - W^{j}_{injured_{S}}}{2} \right) - W^{j}_{old_{SF}} \right) \tag{11}$$

where λ_j is a variable in the $j\ th$ iteration that is generated using Equation (12), and $W^{j}_{elite_{SF}}$ location of elite sail, $W^{j}_{injured_{S}}$ ideal position of harmed sardine, and $W^{j}_{old_{SF}}$current position of sail are all included. The model's accuracy in predicting mental health outcomes is enhanced by efficiently integrating diverse biological and emotional data.

$$\lambda_j = 2 \times rand(0,1) \times PD - PD \tag{12}$$

The total amount of baits for each repetition is indicated by PD. The PD variable is crucial to enhancing the sailfish's location around the bait because the quantity of bait decreases when they hunt in groups. PD aids in optimizing by simulating the collective behavior of sailfish, enhancing exploration efficiency, and enhancing predictive accuracy by mirroring the model's adaptation to emotional and biological data changes. Equation (13) defines the formula for the PD metric.

$$PD = 1 - \left(\frac{M_{SF}}{M_{SF} + M_T} \right) \tag{13}$$

Equation (14) defines the new position of sardine $W^{j}_{new_{S}}$ in in the ISO approach. The parameter x creates the environment's searching equilibrium and speeds up the process of finding the best answer. By improving the search equilibrium, x contributes to faster convergence and more accurate predictions in the mental health outcomes model.

$$W^{j}_{new_{S}} = q \times \left(\omega \times W^{j}_{elite_{SF}} - W^{j}_{old_{S}} + BO \right) \tag{14}$$

here defines the integer value of ω. The highest iteration is denoted by j_{max} in Equation (15).

$$\omega = \frac{e^{2\times(1-j/j_{max})} - e^{-2\times(1-j/j_{max})}}{e^{2\times(1-j/j_{max})} + e^{-2\times(1-j/j_{max})}} \tag{15}$$

The positions of $W_{injured}$ and W_{elite} were altered by the weight factor(x). In other words, the agents' new location in the problematic space is closer to the ideal answer. The ISO needs to balance exploration and exploitation, just like previous population-based optimization methods. Since the position-updated equation only uses the target point's location information to randomly calculate its distance to the next searching zone, fundamental ISO leans toward exploration. The model's dynamic balance between exploration and exploitation allows it to adjust its search process when integrating diverse biological and emotional data, enhancing its efficiency in predicting mental health outcomes. Furthermore, the ISO's multi-modal issue results indicate that its exploitation capabilities are deficient. The greatest sailfish in the present group of fish are used by the ISO model to finish learning. The agent learning is directly impacted by the ISO model's alternative method of updating sail and sardine.

The rendition provides valuable insights into the mental fitness levels of individuals by forecasting mental fitness outcomes through the analysis of biological signals and emotional responses. By ensuring that the model's parameters are dynamically modified, ISO reduces over fitting and increases prediction accuracy. This hybrid technique allows for the creation of extra individualized and sensitive intellectual health education structure, in particular, in political and ideological conditions. Additionally, this technique's combination of EI and biological statistics affords a unique manner to research the results of mental health, providing more expertise on the interaction between emotional and physiological states. Algorithm 1 explores the method ISO-CatBoost. Below **Table 1** shows the hyperparameter of the counseled technique.

Table 1. Hyperparameter for the proposed method.

Hyperparameter	**Typical Range**
Learning rate ($\propto$)	0.01 to 0.3
Number of estimators ($N_{estimzators}$)	100 to 1000
Depth	6 to 12
L2 regularization (λ)	1e-5 to 10
Loss function (L)	
Weight factor (ω)	0.1 to 1.0
Exploration–exploitation balance (W)	0.1 to 1.0
Population size (M_{SF})	20 to 100
Elite selection rate (λ_j)	0.05 to 0.5
Search range (t^{min},t^{max})	[0, 10]
Step size (x)	0.1 to 1.0
Sardine position ($W_{injured_S}$)	[−10, 10]
Elite sailfish position ($W_{elite_{SF}}$)	[0, 1]
Target Metric (PD)	0 to 1
Search Equilibrium (x)	0.1 to 1.0
Sardine Update (W_{new_S})	[−10, 10]
Convergence Factor (j_{max})	100 to 1000 iterations

Algorithm 1 ISO-CatBoost

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from boost import CatBoostClassifier
from scipy.fft import fft
import random
1. Load and preprocess dataset
data = pd.read_csv('emotional_monitoring.csv') # Load dataset
data_cleaned = preprocess_data(data) # Custom data cleaning function
2. Min − Max Normalization
def min_max_normalization(df):
   return (df − df.min()) / (df.max() − df.min())
normalized_data = min_max_normalization(data_cleaned)
3. Feature extraction using FFT for time − series data (e.g., EEG, fMRI)
 def extract_fft_features(data_column):
  fft_result = fft(data_column)
  return np.abs(fft_result)
Apply FFT to biological signal columns
fft_features = normalized_data[['EEG','fMRI']].apply(extract_fft_features)
Combine FFT features with other data
final_data = pd.concat([normalized_data, fft_features], axis = 1)
4. Train − test split
X = final_data.drop('mental_health_label', axis = 1)
y = final_data['mental_health_label']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 42)
5. ISO − CatBoost Model (Sailfish Optimization + CatBoost)
class ISO_CatBoost:
def __init__(self, population_size, max_iter, learning_rate, depth, n_estimators):
self.population_size = population_size
self.max_iter = max_iter
self.learning_rate = learning_rate
self.depth = depth
self.n_estimators = n_estimators
self.catboost_model = CatBoostClassifier(iterations = n_estimators, depth = depth, learning_rate = learning_rate, cat_features = [])
def sailfish_optimization(self, X, y):
Initialize population
population = np.random.rand(self.population_size, X.shape[1]) # Random initialization
best_solution = None
best_score = float('inf')
for iter in range(self.max_iter):
for individuals in the population:
Train the CatBoost model with the current individual (hyperparameters)
self.catboost_model.set_params(learning_rate = individual[0], depth = int(individual[1]), n_estimators = int(individual[2]))
self.catboost_model.fit(X, y)
self.catboost_model.fit(X, y)
score = self.catboost_model.score(X_test, y_test)
Check if the current solution is better
if score > best_score:
best_score = score
best_solution = individual
Update population based on best solution found
population = self.update_population(population, best_solution)
return best_solution
def update_population(self, population, best_solution):
Simple random walk or elite selection mechanism (for example)
updated_population = []
```

Algorithm 1 (*Continued*)

```
for i in range(self.population_size):
new_individual = best_solution + (np.random.rand(3) − 0.5) * 0.1
updated_population.append(new_individual)
return np.array(updated_population)
6. Running ISO − CatBoost with Sailfish Optimization
iso_catboost_model = ISO_CatBoost(population_size = 20, max_iter = 50, learning_rate = 0.05, depth =
8, n_estimators = 100)
best_hyperparameters = iso_catboost_model.sailfish_optimization(X_train, y_train)
7. Train the final model with optimized hyperparameters
iso_catboost_model.catboost_model.set_params(learning_rate = best_hyperparameters[0],
depth = int(best_hyperparameters[1]),
n_estimators = int(best_hyperparameters[2]))
iso_catboost_model.catboost_model.fit(X_train, y_train)
8. Evaluate model
accuracy = iso_catboost_model.catboost_model.score(X_test, y_test)
print(f"Final Model Accuracy: {accuracy}")
Helper function for data preprocessing
def preprocess_data(data):
Remove irrelevant columns and handle missing values
data_clean = data.dropna(axis = 1, how = 'any') # Example: dropping columns with missing values
return data_clean
```

4. Experimental result

This section describes the research's experimental setup and comparison phase, where significant parameters are used to assess how well the suggested ISO-CatBoost approach performs.

4.1. Experimental setup

For ML operations, **Table 2** shows a system configuration with an Intel i7 processor, 16 GB of RAM, and a GPU such as the NVIDIA GTX 1060. The version of the operating system should be Ubuntu 20.04+ or Windows 10, and the storage should be on a 512 GB SSD. The version of the programming language is Python 3.8.

Table 2. Experimental setup specifications overview.

Component	Specification
RAM	16 GB or higher
CPU	Intel i7 or higher
GPU	NVIDIA GTX 1060
Storage	SSD with at least 512 GB
Operating system	Windows 10/Ubuntu 20.04+
Programming language	Python 3.8+

4.2. Comparison phase

To evaluate the effectiveness of the suggested ISO-CatBoost, performance indicators, including accuracy, precision, recall, F1-score, and specificity, are used, and compared with KNN Optimizer [22] and the Random Forest model [23]. This comparison determines the performance of the models in predicting mental health outcome based on EI and biological inputs. These measures and statistics help to understand the results of models depending on efficiency, ability to make predictions and accuracy of classification. The evaluations show how ISO-CatBoost outperforms the other in multiple related performance categories.

- Accuracy: Its score is one of the measures used to determine how many of the scenarios in the database were classified correctly. It determines the percentage of instances among all of the model's predictions that are correctly classified. Also, it evaluates the overall correctness of the model in predicting mental health outcomes shown in **Figure 3**. It can be mentioned mathematically in Equation (16).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{16}$$

where, TP- True Positive; TN-True Negative; FN-False Positive; and FP-False Negative

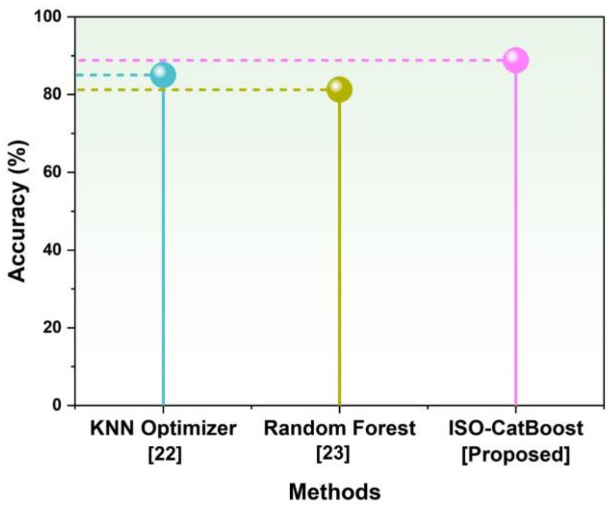

Figure 3. Accuracy Comparison of Proposed ISO-CatBoost with Traditional Approaches.

Table 3. Outcome values of accuracy.

Methods	Accuracy (%)
KNN Optimizer [22]	85
Random Forest [23]	81.25
ISO-CatBoost [Proposed]	88.8

Table 3 indicates the accuracy of different models for forecasting events concerning mental health. The RF model achieved an accuracy score of 81.25%, while the KNN-optimized model was slightly better with an accuracy of 85%. However, the proposed ISO-CatBoost model performed both, reaching an accuracy of 88.8%. This superior performance underscores the ISO-CatBoost model functioning in the context of predicting the further mental health and shows its potential for even better results.

- Precision: It calculates the proportion of accurately forecasted positive observations to all of the predictions. The model's efficacy in preventing false positives is crucial for accurately identifying individuals based on emotional and biological signals illustrated in **Figure 4**. The formula in Equation (17) is used to compute it.

$$Precision = \frac{TP}{TP + FP} \tag{17}$$

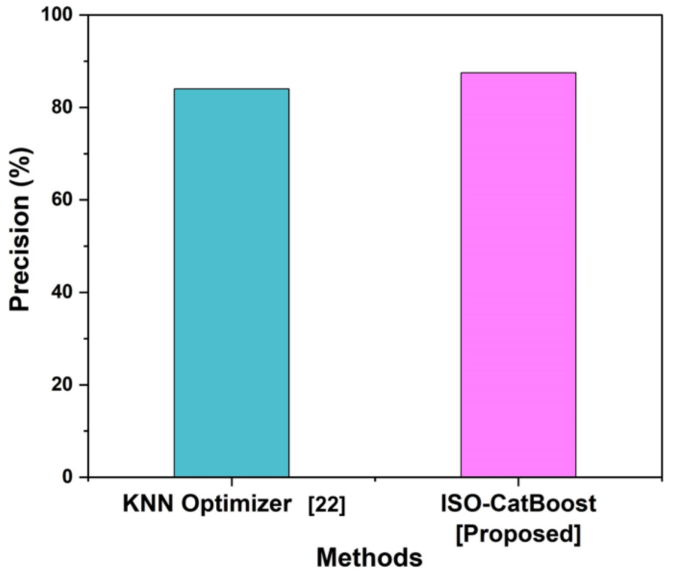

Figure 4. Precision Comparison of Proposed ISO-CatBoost with Traditional Approach.

Table 4. Result values of the metric precision.

Methods	Precision (%)
KNN Optimizer [22]	84
ISO-CatBoost [Proposed]	87.5

Table 4 illustrates the precision of various models in forecasting results associated with mental health. The proposed ISO-CatBoost model outperformed others, demonstrating superior precision in accurately identifying positive instances. It achieved a precision of 87.5%, reflecting its improved ability to correctly classify relevant cases. The KNN optimizer model yielded a precision of 84%, highlighting a slight yet significant difference in performance. This superior performance highlights the ISO-CatBoost model's effectiveness in predicting mental health outcomes in this specific instance and demonstrates its potential for more accurate predictions.

Recall: It measures the percentage of real positive outcomes that the classifier properly predicts and is frequently referred to as sensitivity or true positive rate. **Figure 5** shows the model's capacity to identify true positives, ensuring it accurately captures mental health from EI and biological data. It is computed using Equation (18).

$$Recall = \frac{TP}{TP + FN} \tag{18}$$

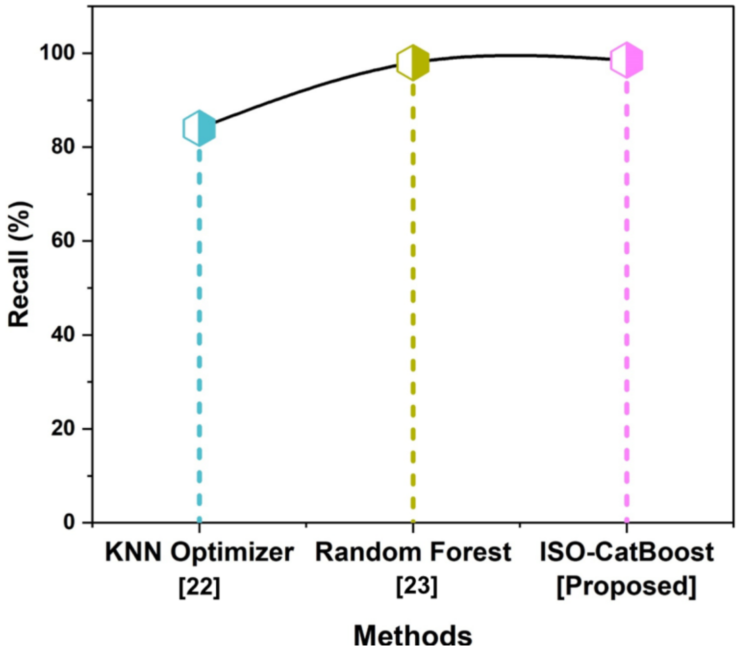

Figure 5. Recall Comparison of Proposed ISO-CatBoost with Traditional Approaches.

Table 5. Numerical outcome of recall.

Methods	**Recall (%)**
KNN Optimizer [22]	84
Random Forest [23]	98
ISO-CatBoost [Proposed]	98.5

Table 5 illustrates the recall values of various models, highlighting the performance of the ISO-CatBoost model, which achieves a recall of 98.5%. This indicates its strong ability to correctly identify important occurrences, demonstrating superior value compared to other models. RF achieves a recall value of 98%, showing its competitive performance in detecting relevant events. In contrast, the KNN-optimized model exhibits a lower recall of 84%, suggesting relatively less efficiency in identifying key instances.

- F1-score: It provides an equilibrium between precision and recall by combining both into a single statistic. It is the harmonic mean of precision and recall. An F1 score of 0 to 1 denotes excellent precision and recall, whereas a score of 0 denotes subpar performance. It is essential for evaluating the model's overall performance in predicting mental health outcomes without bias, as shown in **Figure 6**. Equation (19) is used to determine the F1 score.

$$F1 - score = 2 \times \frac{Precision\ \times Recall}{Precision + Recall} \tag{19}$$

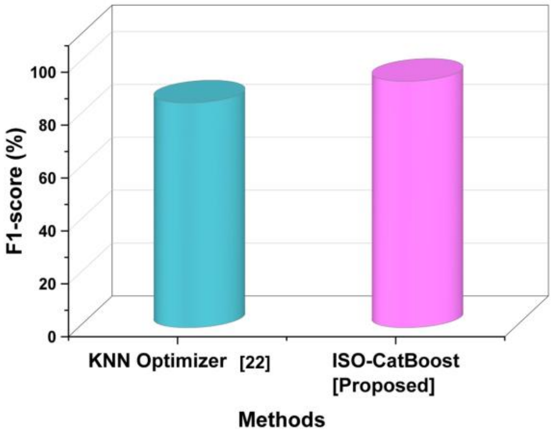

Figure 6. F1-score comparison of proposed ISO-CatBoost with traditional approach.

Table 6. Result values for F1-score.

Methods	F1 score (%)
KNN Optimizer [22]	85
ISO-CatBoost [Proposed]	93.2

The F1 scores for the methods are presented in **Table 6**, which demonstrates the performance comparison between the ISO-CatBoost and KNN Optimized models. The ISO-CatBoost model achieves an F1-score value of 93.2%, while the KNN Optimizer model achieves an F1-score value of 85%, highlighting its superior ability to balance recall and precision. This superior performance underscores the ISO-CatBoost model functioning in the context of predicting the further mental health and shows its potential for even better results.

- Specificity: The capacity of the framework to incorrectly estimate the stress level is known as specificity, shown in Equation (20). It shows how well the model can identify people who don't have mental health difficulties, reducing false negatives.

$$Specificity = \frac{TN}{TN + FP} \quad (20)$$

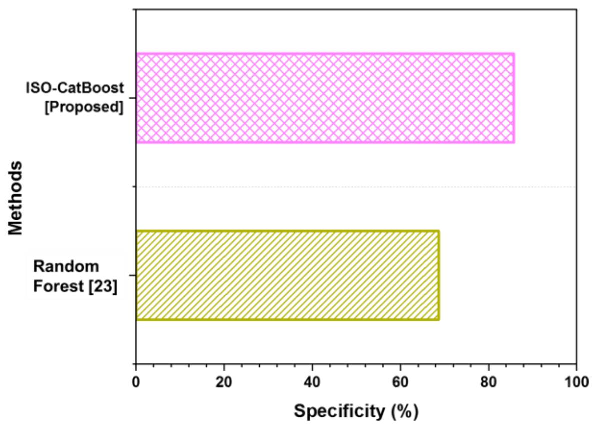

Figure 7. Specificity comparison of proposed ISO-CatBoost with traditional approach.

Table 7. Specificity outcome values.

Methods	Specificity (%)
Random forest [23]	68.65
ISO-CatBoost [Proposed]	85.7

The specificity of the models is displayed in **Table 7** and **Figure 7**. With an efficiency of 85.7%, the suggested ISO-CatBoost model considerably outperformed the RF model, which had a specificity of 68.65%. This shows that the proposed ISO-CatBoost outperforms other models in accurately classifying negative consequences. The higher number of unique features of the ISO-CatBoost model indicates that correctly classifying the true negatives, thus minimizing false positive compared to RF model.

5. Discussion

Mental health forecasting based on the emotional and biological information like GSR and EEG signal is challenging despite the several RF and KNN optimizers in the ML framework. Consequently, RF shows merits when applied to large datasets and to continuous time-series data; however, it has some disadvantages linked to interpretability as well as to computational cost which increases notably when handling large datasets. The KNN, which depends on the distance calculations, has issues when dealing with high dimensional, complex biological data and then performs poorly. Both of the methods are likely to be over-fitted when the training data is noisy or imbalanced, a situation that is common in mental health prediction. In particular, it is found that RF and KNN algorithms can be inadequate in capturing high non-linearity present in the emotional and biological data and hence they cannot give accurate and useful predictions in this field. In contrast, the suggested approach, the ISO-CatBoost method, is a hybrid optimization approach that enhances model robustness and interpretability in significant, high-dimensional biological datasets by fusing ML and optimization techniques. To address these issues, it includes aspects of intelligent optimization, non-linear relationship, and feature extraction involving biomarkers. This approach seems to offer a clearer, efficient and, therefore, comprehensible means of estimating mental wellness outcomes within biological perception and EI.

6. Conclusion

The research explores an innovative mental health education approach by integrating biological comprehension and EI, using an ML algorithm to identify patterns in biological data and emotional reactions. Based on biological indicators and emotional results, it introduced a novel ISO-CatBoost method for predicting mental health. To forecast mental health consequences, the research made use of behavioral responses, EI, and biological data (such as GSR and EEG). Data normalization and data cleaning were used to preprocess the data that was collected. Data was extracted using the FFT. Through the analysis of biological data and EI, the findings show that the ISO-CatBoost model accurately predicts mental health outcomes of the performance metrics such as precision (87.5%), specificity (85.7%), accuracy (88.8%), f1-score (93.2%), and recall (98.5%). Through the provision of strategies for more efficient emotional resilience instruction within political and ideological frameworks, this technique promotes personalized mental health education. The dependence on particular biological signals, such as GSR and EEG, which could not adequately represent mental and emotional aspects across a range of groups, is one of the limitations. Future studies should increase the dataset, investigate real-time applications, and incorporate genetic or physiological data in real-time. They should additionally look into individualized mental health interventions.

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