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Article

Research on enhancing the accessibility of psychological health services by using media communication technology and biomechanical biosensors

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Abstract: Access to mental health services remains a global challenge, particularly for marginalized groups. This research endeavors to enhance the accessibility of mental health services by integrating media communication technology with biomechanical biosensors, including electrodermal activity sensors and heart rate monitors. The proposed approach leverages mobile communication platforms and wearable biosensors for real-time biomechanical parameter monitoring (including heart rate, blood pressure, respiratory rate, body temperature, and galvanic skin response, etc.) and remote interventions. Judge the impact on the brain and neuroendocrine system through the changes in biomechanical indicators, and use this as a basis for judging mental health. The objective is to develop a telehealth model that merges bio-data-driven alerts with communication tools to deliver prompt psychological support. This study underscores the deficiencies of traditional health systems in ensuring comprehensive mental health monitoring and emphasizes the potential of media communication technologies as scalable and accessible tools for early interventions in underserved areas, and also emphasizes the relationship between the physiological indicators measured by biosensors and the biomechanical mechanisms of mental health. Despite the existence of online methods for detecting mental health issues, early detection remains problematic. This research presents a framework for integrating pre-processed biosignal data with user-generated content to facilitate proactive monitoring. To address the limitations of conventional classifiers, the study introduces a Fitness-Dependent Optimizer-tuned Upgraded Decision Tree (FDO-UDT) model, which enhances the early identification of at-risk individuals using personalized thresholds and real-time event detection based on biomechanical data, it is helpful to provide an early warning before the clinical symptoms of mental health problems occur. The results indicate that automated alerts triggered by biomechanical sensor thresholds improve responsiveness and engagement, ensuring timely interventions for those in need. The FDO-UDT model achieves performance metrics of 90.21% accuracy, 98.01% recall rate, and 86.38% precision, outperforming traditional methods. The study concludes that the integration of media communication technologies with biomechanical sensors offers scalable solutions to improve the delivery of mental health services, especially for rural and underserved populations.

Keywords: media communication; biomechanical biosensors; mental health services; Fitness-Dependent Optimizer Tuning Upgraded Decision Tree (FDO-UDT); biosignal monitoring

1. Introduction

The two components of the human condition are mental as well as physical health. Physical health is a state of the body, taking into account anything from the degree of activity to the lack of sickness. Everyone's psychological and social well-being is positively correlated with their psychological state [1]. Although the concept varies according to the culture, it often relates to the satisfaction of life, the achievement of objectives and potential, the capacity to handle stress and sorrow, and the final makes sense to establish connections with people on several levels. Health is defined as a state of entire psychological, social, and bodily wellness, rather than the absence of a sickness or disease [2]. Physically healthy people have traits like balanced strength in their muscles, a high degree of cardiac fitness, a low heart rate at rest, a high level of lipoprotein cholesterol, and happiness at work and home. People in good psychological condition can make changes, feel important and worthwhile, and have a strong sense of self-worth [3]. They largely rely on their initiative to address their problems and make their own decisions; they feel safe both individually and collectively. This demonstrates that others are understood. They are capable of tolerating dissatisfaction in their day-to-day activities, they respect other people, they have a feeling of duty, and they behave emotionally maturely [4]. A person in good psychological condition is capable of managing daily stress and achieving their objectives. Mental health can be impacted by a variety of factors, including anxiety, trauma, and sleep issues [5]. Although a person cannot prevent mental disease from happening, they can safeguard their mental well-being all of their life. To create a wireless body area network that can support contemporary mental health treatment, they want to investigate biosensors [6]. Several physiological illnesses, disabilities, and abnormalities are growing more common as the world’s population ages, with major societal and economic consequences. Both the people and the country’s healthcare institutions will benefit from the prevention and proper management of such illnesses [7]. Benefits from intelligent information and communication technologies include enhancing life quality and assisting seniors and other populations with illnesses that are chronic or acute in leading lives that are independent. A component of an active biological system that can be a digestive enzyme, an antibody, or something similar, is positioned on top of a transducer in biosensors, which are comprehensive tests that can identify the presence of a specific analytic [8]. There is a constant supply of medical information that can yield valuable insights into an individual’s mental health when incorporated into an intelligent analytics system. Smart biosensors in health use the latest developments in wireless technology and micro-technology to gather and send data, and when combined with sensors, can improve therapy and surveillance [9]. For instance, wearable biosensors are particularly useful in preventing and controlling health risks and offer monitoring of vital signs for all age groups, including youngsters, seniors, and hospitalized. Smart biological sensors can help those who need mental health services or care, and also individuals who experience a progressive loss of their mental, physical, and other abilities as they age [10]. Finally, biosensors facilitate advanced, economical, and effective medical detection applications [11]. Using cutting-edge and micro-technological advancements, biosensors offer efficient and real-time monitoring, particularly in health services [12].

Aim of the study

The objective is to develop a telehealth technology approach that offers instant psychological support through communication tools with bio-data-driven notifications. By employing personalized criteria and real-time event detection, the study suggests an FDO-UDT algorithm to address the shortcomings of traditional classifications and enhance the early identification of people at risk.

2. Related work

The potential and challenges associated with using intelligent biological sensors for medical purposes were discussed in the article, along with several cutting-edge approaches to using smart biosensors in the setting [13]. The initial project was an infrastructure and the second described an Internet of Things, or IoT setting with sensors and devices that might be used to make customized suggestions to increase worker productivity and workplace safety. The final result was a sophisticated non-invasive bio-signal monitoring system that might identify possible pathological problems in infants while they were asleep.

The wireless sensing techniques for psychological surveillance were thoroughly reviewed in the article [14]. It examined recently released research that used noninvasive sensing techniques to forecast mental health conditions. It also identified the current problems with contactless sensing techniques and suggested ways to address them in future studies.

They provided a thorough analysis of psychological services and their significance to human living in the research [15]. An investigation and discussion of various biosensors for monitoring psychological wellness have been conducted. Additionally, they plan to create a Wireless Body Area Network (WBAN) prototype that would assist mental health practitioners in managing clients, guaranteeing their confidentiality, and averting unintentional fatalities.

Following the approach, they worked on sensors intended to assess the physical surroundings, interactions between people, and physiological processes in the study [16]. Smart technologies for healthcare and monitoring of people could be designed and implemented using a wide range of sensors, both natural and man-made, including those found in plants. To clear up, automated systems and sensing technology could be used to improve AN called Anxiety Neurosis care and lessen the workload for medical personnel.

The mechanism of disease of mental illnesses with high rates of disabilities, morbidity, and deaths was described in the article in a way that implied biomarkers [17]. From advancements in psychological biosensors with biometric data components, generating principles, and flexible information to the development of Big Data networks used to share difficult psychological indicators and cases, it was expected that mental health services could be progressively improved from several angles.

The assessment techniques have been divided into five subdivisions of biological sensors that include eyesight, EEG denoted Electroencephalogram signal, Electrooculogram called EOG signal, and multi-signal. The study examined the use of biosensors in the diagnosis of mental illnesses [18]. There was also discussion of a potential use in healthcare diagnosis.

The scientific proof supporting the application of medical equipment to facilitate early mental disease diagnosis and prevention was explained in the article [19]. In disadvantaged areas, connected health systems and patients could receive seamless, coordinated, and ongoing care by utilizing technological innovations to improve mental healthcare treatments. A summary of several health technology applications, as well as the benefits and drawbacks of technological acceptance and scale-up, were provided in the research. A thorough analysis of the most recent advancements, patterns, and studies in wearable biosensor devices for health surveillance was the goal of the research [20]. Paper the requirement of multifunctional sensing technologies for immediate action for health tracking systems while dealing with technological concerns such as implementations, flexibility, and satisfaction among users was discussed [21]. Similarly, the need for portable and handheld biosensor solutions for guaranteeing reliability and user acceptance was focused on dealing with the technical barriers and improved performance [22]. Particular attention was paid to the difficulties multi-parameter physiological measurement systems encounter in their technical construction.

3. Proposed system

This section details the dataset employed in the study and describes the proposed FDO-UDT method, highlighting its relevance to the research objectives. It successfully lays the basis for comprehending the methodology that was used in the study.

3.1. Dataset

The data gathering of this study involved monitoring the participant's pulse rate variability (PRV) derived from photoplethysmography (PPG) plays, an important role in detecting mental stress. It is the alternative solution to heart rate variability (HRV)obtained from the electrocardiography (ECG). Mental stress is a normal reaction to daily activity. However, both acute and chronic stress can lead to psychological and cardiovascular problems. HRV is thought to be a good indication of both mental stress and health. The conventional method for determining HRV is to use ECG as the time difference that separates successive R peaks. The PPG is regarded as an option for detecting mental stress by measuring PRV, the time gap between two consecutive PPG peaks. This study included 27 healthy bachelor students fifteen males and twelve females with an average age of 21 ± 2 years to gather PRV data. Data is collected from the subject's earlobes using a highly responsive, affordable, low-powered PPG sensor that is RoHS-exempt the data was recorded from the earlobes. The simulated technique included two phases at the beginning and throughout the entire Stroop challenge. During the beginning phase, every student is asked to sit in an acceptable spot in the classroom during campus hours, with the sensor attached to their earlobe. The individuals are then asked to write down their colored terms. During the Stroop test stage, the participants were engaged with an Android operating system app to induce cognitive class. The dataset was sourced from an open-access platform on Kaggle, which was used to feed the FDO-UDT contributing to its improved ability to detect the mental health with superior performances [23].

Integrating sensors with telehealth

Sensors that can be worn have made major advances in detecting physiologic parameters for telehealth. Biosensors, which measure heart rate, have a huge capacity for illness identification. Biosensors will be connected with the telecommuting platform via Application Programming Interfaces (APIs). The teletherapy platform may generate alerts that notify the medical professional and offer specific treatments, such as exercises for breathing, to assist the user in efficiently managing their physiological condition.

- APIs for monitoring psychological wellness: APIs can be used to track mental health information such as mood, anxiety, and sleep behaviors. These APIs enable people to track their psychological health and communicate the results with medical professionals.
- APIs for connecting mental health services: There are APIs that allow users to access psychological resources like treatment and therapy. These APIs can help people connect with medical professionals and obtain the treatment they require.

3.2. Using FDO-UDT to improve early detection of at-risk people

The suggested method integrates the FDO and UDT model with real-time biosensor data and media communication technologies to enhance psychological health service delivery. The FDO-UDT model employs a hybrid approach, utilizing optimization techniques to personalize thresholds for bio signal alerts, enabling accurate identification of at-risk individuals. This model processes electrodermal activity and heart rate data, leveraging machine learning (ML) algorithms to detect significant changes indicative of psychological distress.

3.2.1. UDT

Using examples of weighted data, the method creates UDT structures. $S = \{j_1, j_2, \ldots., j_m\}$ is a set of m training examples, assuming that have it. These examples belong to a group of classes, $D = \{D_1, D_2, \ldots \ldots, D_l\}$. The crisp instances of a class, where each of them has a complete weight allocated to a single class. The weighted situations, in which every instance's weight is divided across different classes. In other words, the strength of each instance j's participation in class D_i and $\sum_{i=1}^{l} \delta_{Di}(j) = 1$ is represented by its weight, $\delta_{Di}(j)$. The weighted examples are now to be used in the application of the data concept. To leverage the UDT method to improve the accuracy of identifying individuals at risk for psychological health issues by effectively utilizing weighted biosensor data, thus enhancing the overall monitoring and intervention framework. This is how the likelihood of class D_i might be stated.

$$\hat{o}_i(S) = \frac{\sum_{j \in S} \delta_{Di}(j)}{|S|} \tag{1}$$

The total amount contributed by each of the training cases to class D_i is shown by the numerator in Equation (1). Observe that $\sum_{j \in S} \delta_{Di}(j) = |D_i(S)|$in the case of sharp categories. The objective is to utilize the contributions of each training case, considering their weights, to enhance the identification of individuals at risk for psychological health issues. By adapting Equation (1) to account for these weighted contributions, the model aims to improve the accuracy of classifying at-risk individuals based on biosensor data. Using Equation (1) has an impact when taking the weighted classes into account. In this instance, each class's trained example's contributions will be considered. Consequently, in the following way shown in Equation (2).

$$O(S) = \left(o_1(S) = \frac{\sum_{j \in S} \delta_{D1}(j)}{|S|}, \dots \dots .., \hat{o}_l(S) = \frac{\sum_{j \in S} \delta_{Dl}(j)}{|S|} \right) \quad (2)$$

The complexity of $\hat{O}(S)$, and the data that this distribution conveys, can be written in the form of Equation (3).

$$Info_{W\ DT}\left(\hat{O}(S)\right) = -\sum_{i=1}^{l} \hat{o}_i(S) \times log_2\left(\hat{o}_i(S)\right) \quad (3)$$

This is the expression for the details of S based on attribute A, which contains n values in Equation (4).

$$Info_{W\ DT} * (B, S) = \sum_{k=1}^{n} \frac{|S_k|}{|S|} Info\ \left(\hat{O}(S_k)\right) \quad (4)$$

The following is how the information gain is expressed as Equation (5).

$$Gain_{W\ DT}(B, S) = Info_{W\ DT}(S) - Info_{W\ DT}(B, S) \quad (5)$$

The following Equation (6) is the expression for the gain proportion, which serves as the selection criteria.

$$GainRatio_{W\ DT}(B, S) = \frac{Gain_{W\ DT}(B, S)}{SplitInfo(B, S)} \quad (6)$$

The method is not to be mistaken with the fuzzy decision tree model a collection of overlapping subspaces makes up a fuzzy decision tree. This is done by fuzzily dividing a node into two overlapped subdivisions that contain objects using an individually linear discriminator function. Certain items are solely given to the left replacement, some to the right, and others to both. In line with such a concept, a test instance could connect to several terminal nodes. A defuzzification approach is used to aggregate the output estimates of these terminal nodes to get the test instance's final projected participation. The method, in comparison, uses the traditional DT model, which assigns a certain class to every test example. In contrast, the study employs a traditional DT model that assigns a specific class to every test example to enhance the classification accuracy for individuals at risk of psychological health issues.

3.2.2. FDO

FDO is dynamic, has a rapid convergence percentage, and can solve linear issues. To improve psychological health by biosensors and communication technology allowing for real-time monitoring and early intervention for individuals at risk. FDO consists of the points that are listed below. A randomly selected collection of scout bees is started in the field of search space, $W_l(l = 1,2,3, \dots \dots m)$. The scout honey bees are haphazardly looking for an improved residence. When a better position is discovered, the old one is abandoned.

Consequently, the algorithm identifies a new optimal solution at each place. This capability is crucial for detecting physiological signals indicative of psychological distress, thereby enabling timely support for users. However, the present forward path will return to its previous direction in search of the optimum answer if it does not yield any optimum alternative. As they hunt for the best response, the scout bees add pace to their present location and instant, which might be displayed in the following Equation (7).

$$W_{l,s+1} = W_l + O \tag{7}$$

where W stands for the scout bees, L for their current location, s for their repetition, and O for their direction and forward momentum pace. The speed is determined by a parameter called fitness weight (FW). The pace's growth, however, is completely arbitrary. The expression for the FW is in Equation (8). The FDO method utilizes biosensor data to guide the scout bees' movements, optimizing the monitoring of psychological health and enabling timely support for at-risk individuals.

$$FW = \left|\frac{W^*_{L,s,e}}{W_{l,s,e}}\right| - \gamma \tag{8}$$

The fitness value for the present resolution is represented by $W^*_{L,s,e}$, the weighting factor that controls the FW, and the value of the fitness functional for the entire optimal solution is indicated by $W_{l,s,e}$. If 1 indicates a strong rate of convergence, and if 0 indicates doesn't impact the calculation above. For a stable search, is typically 0 in many situations. This condition is problematic, though. Depending on it. The spectrum of [0, 1] is where the FW must reside. If the values of $W^*_{L,s,e}$, and $W_{l,s,e}$are equal, then FW will be 1. FW's value will be 0 when $W_{l,s,e}$ is zero. Equations (9) and (10), is essential to maintain an optimal FW to ensure effective guidance of the biosensor-based monitoring, facilitating timely interventions for at-risk individuals. Applying the following guidelines prevent $s\ W^*_{L,s,e} = 0$, Wherein is an arbitrary number between −1 and 1. The following **Table 1** displays the hyperparameters for the proposed method.

$$O = \alpha W_{L,s,e}\text{: } If\ WF = 0,\ \ OR\ \ \ WF = 0,\ \ OR\ \ \ W_{l,s,e} = 0 \tag{9}$$

$$O = \begin{Bmatrix} WF\left(W_{l,s,e} - W^*_{l,s,e}\right) - 1;\ If\ WF < 1\ AND\ WF > 0\ AND\ \alpha < 0 \\ WF\left(W_{l,s,e} - W^*_{l,s,e}\right) - 1;\ If\ WF < 1\ AND\ WF > 0\ AND\ \alpha \leq 0 \end{Bmatrix} \tag{10}$$

Table 1. Hyper parameters of FDO-UDT.

Hyperparameter	**Description**	**Range**
Population Size (*m*)	Number of scout bees in the search space	50−100
Max Iterations (*s*)	Maximum number of optimization iterations	100−500
Fitness Weight (*FW*)	Controls momentum and convergence	[0,1]
Threshold Value	Personalized threshold for biosignal alerts	0.01−0.1
Direction (*o*)	Forward momentum of Scout bees	−1 to +1
Learning Rate (∝)	Regulates parameter updates in the decision tree	0.01−0.1

Table 1. (*Continued*).

Hyperparameter	Description	Range
Decision Tree Depth	Maximum depth of the decision tree	5−15
Minimum Split Size	The minimum number of samples required to split the anode	2−10
Gain Ratio Threshold	Threshold for selecting the optimal split in UDT	0.1−0.9
Biosignal Sampling Rate	Frequency of collecting data from biosensors	1Hz−100Hz
Optimization Convergence	Convergence rate of FDO algorithm	<0.001 (error margin)

By combining these biosensors with mobile communication platforms, the method facilitates immediate data transmission and remote intervention capabilities. Additionally, user-generated content is incorporated to enrich the contextual understanding of each individual's psychological state. Automated alerts triggered by the FDO-UDT model ensure timely responses, increasing engagement and responsiveness from healthcare providers. This hybrid framework not only addresses the limitations of traditional health systems but also promotes scalable and accessible psychological support for underserved populations. Ultimately, it aims to create a proactive monitoring system that significantly improves early intervention efforts in mental health care. Algorithm 1 shows the proposed method FDO-UDT.

Algorithm 1 FDO-UDT

```
import numpy as np
FDO Parameters
def fitness_weight(W_star, W, γ):
return abs((W_star / W) − γ)
Scout bee movement
def scout_bee_movement(W_l, O):
return W_l + O
UDT with weighted data
def calculate_weighted_probability(S, D):
probabilities = {}
For d in D:
probabilities[d] = sum(δ_Di(j) for j in S) / len(S)
return probabilities
Information gain calculation
def info_gain(S, B):
return info(S) − info(B, S)
def info(S):
prob = np.array([o_hat_i(S) × np.log2(o_hat_i(S)) for i in range(len(S))])
return −sum(prob)
Main execution
if __name__ == "__main__":
Example initialization
S = [j1, j2, ..., jm]
D = [D1, D2, ..., Dl]
W_star = np.Random.rand()
W = np.Random.rand()
```

Algorithm 1 (*Continued*)

```
γ = 1.0
O = np.Random.rand()
Calculate fitness weight
FW = fitness_weight(W_star, W, γ)
Update scout bee position
new_position = scout_bee_movement(W, O)
Calculate class probabilities
probabilities = calculate_weighted_probability(S, D)
```

4. Experimental result

The result section efficiently describes the experimental setup and comparison phase using the performance metrics for the study of psychological healthcare.

4.1. Experimental setup

Table 2 presents a clear and structured overview of the experimental setup including the types of programming language, processor, libraries, memory, and implementation system used in the proposed method. This organized format facilitates easy reference and understanding of the implementation process, ensuring efficient execution of the method.

Table 2. Experimental setup.

Category	**Specification**
Programming Language	Python 3.x
Libraries Required	numpy, pandas, sci − kit − learn, matplotlib, deep, scipy, seaborn
Operating System	Windows, macOS
Processor	Minimum: Intel Core i5/AMD Ryzen 5
	Recommended: Intel Core i7/AMD Ryzen 7
RAM	Minimum: 8 GB
	Recommended: 16 GB
Storage	Minimum: 2 GB free space
Python Environment	Jupyter Notebook/Anaconda/Vs Code

4.2. Comparison phase

The approach that is suggested is contrasted with the existing Gradient boosting and the method of Random Forest denoted by RF based on performance standards including accuracy, recall, and precision [24, 25]. It highlights the advantages of the proposed method, presenting its greater ability to effectively identify at-risk individuals and improve psychological health service delivery.

Evaluation metrics

Accuracy**:** The likelihood of correct classification for mental health is referred to as accuracy, which is defined in Equation (11).

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{FP} + \text{TP} + \text{FN}} \times 100\% \tag{11}$$

- True-negative (TN) refers to the number of clean signals correctly identified as clean.
- True-positive or TP: Hidden signals are those that are appropriately identified among all those transmitted.
- FN called False-negative is the proportion of those signals mislabeled as clean.
- False positive defined as FP refers to the number of instances where the classifier incorrectly labels the communication as a mental illness.

Figure 1 illustrates that the suggested method FDO-UDT achieves higher accuracy at 90.21% compared to the other existing methods gradient boosting [24] and RF [25] which are 88.80% and 83.23% which displays the FDO-UDT is more effective in accurately predicting mental health risks and robust detection.

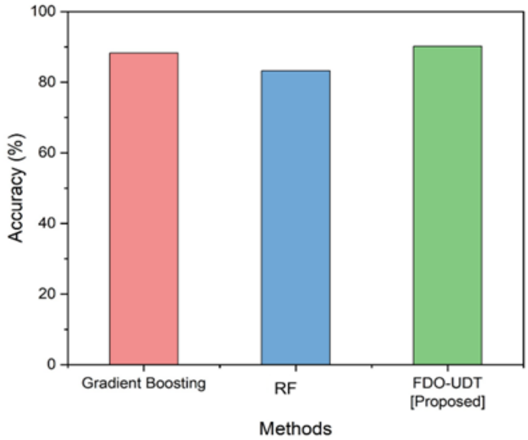

Figure 1. Comparative analysis of FDO-UDT accuracy with existing approaches.

Precision: It is defined in Equation (12), as the number of accurately detected positive instances among all expected positive results. This method is beneficial when false positives are significant. It plays a crucial role in the context of the study's objective, as high precision ensures that the alerts generated for psychological distress are reliable, reducing the likelihood of unnecessary interventions.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{12}$$

Figure 2 displays the evaluation of the metric precision. The existing gradient boosting methods and RF get lower values of 84.21% and 78.02%, respectively. In contrast, the proposed method FDO-UDT performs better, demonstrating a precision of 86.38% in making precise predictions reinforcing its potential for improved accuracy.

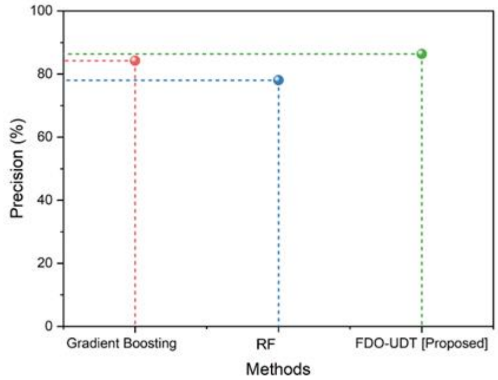

Figure 2. FDO-UDT precision outcome with existing approaches.

Recall: This metric measures the proportion of accurately detected positive instances among all positive instances. When false negatives are prohibitive. The model indicates its effectiveness in accurately identifying at-risk individuals, ensuring that those who need immediate psychological support are promptly detected and assisted. The following Equation (13) is used to compute recall.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{13}$$

Figure 3 describes the performance metric recall, indicating that FDO-UDT achieves greater values of recall of 98.01% than the other existing methods RF [25], and gradient boosting [24] which are 89.87% and 96.97% it indicating the accurate instances identification in mental health in large data by minimizing the possibilities of incorrect estimations. In comparison, the existing methods, gradient boosting and RF show lower recall rates of 79.66% and 83.53% respectively. The following **Table 3** shows the performance of the proposed FDO-UDT with the existing methods. According to the comparison, the method performed greater than the other methods.

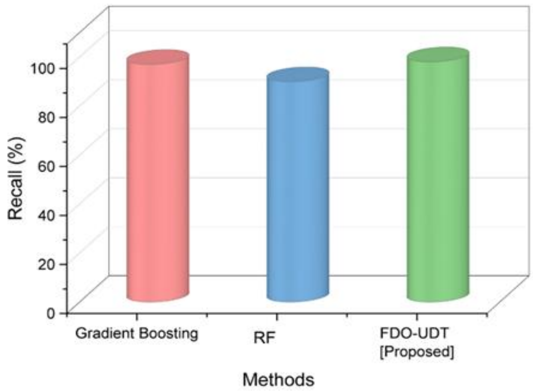

Figure 3. Performance evaluation of the metric recall.

Table 3. Value of the metrics.

Methods	Accuracy (%)	Precision (%)	Recall (%)
Gradient Boosting [24]	88.80	84.21	96.97
RF [25]	83.23	78.02	89.87
FDD-UDT [Proposed]	90.21	86.38	98.01

5. Discussion

The suggested FDO-UDT method demonstrates superior performance compared to existing methods such as Gradient Boosting and RF. It outperformed the traditional methods in terms of recall, accuracy, and precision demonstrating its enhanced ability to detect psychological factors. The gradient Bosting model with effective but still it struggles with higher misclassification rates due to its reliance on fixed constraints making it less adaptable to fluctuations in data. RF though more reliable does not match the broader optimization capabilities of FDO-UDT. Incorporating FDO-UDT significantly improves all key metrics delivered in its ability to identify at-risk individuals with greater reliability. This flexibility allows for better detection and timely interventions making FDO-UDT a more robust and effective solution for enhancing health service, particularly in remote and limited areas. Overall, this method is highly encouraged for its ability to integrate into fitness-dependent optimization which enhances the adaptability and early identification leveraging the dynamic threshold conditions that are important considerations for telemedical services.

6. Conclusion

The purpose is to develop a telehealth model that uses bio-data-driven alerts and means of communication to provide instant psychological aid. This study emphasizes the limitations of traditional healthcare systems in offering comprehensive mental wellness monitoring, and underlines the limitations of traditional healthcare systems in providing comprehensive mental wellness monitoring, highlighting the need for communication through media technologies to be adaptable and accessible instruments for early treatments in marginalized communities. Although existing internet technologies can assist diagnose psychological health disorders, early diagnosis is a significant challenge. This study proposes a system for combining pre-processed biosignal data with user-generated material to enable proactive monitoring. To overcome the limitations of conventional classifiers, the paper offers an FDO-UDT framework that uses specific thresholds and real-time detection of events to enhance the early identification of at-risk people. The findings showed that automated warnings based on sensor parameters improve awareness and engagement criteria, resulting in prompt action for persons in need. FDO-UDT outperforms standard approaches in terms of accuracy (90.21%), recall (98.01%), and precision (86.38%). The study finds that media communication tools, when integrated with biosensors, provide scalable alternatives for improving psychological health treatment delivery by accurate and timely identification of individual risk, particularly among rural and underserved groups. The study is limited by potential challenges in data privacy, integration issues with existing telehealth platforms, and reliance on wearable biosensors that may not be accessible to all users. Further research can explore advanced machine learning models for improved prediction accuracy, wider adoption of affordable biosensors, and integration with diverse healthcare systems to enhance scalability.

Ethical approval: Not applicable.

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

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