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Article

Research on the biological mechanism and biosensing monitoring of sports promoting ideological and political education

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Abstract: The biological mechanism and biosensing monitoring of sports are examined in this research that looks at how physical activity not only improves physical health but also raises political involvement and ideological consciousness. Research in this area has received less attention in the context of sports education. The investigation on how physical exercise influences brain function, mood regulation, and cognitive processes, which are crucial for shaping political and ideological awareness, is performed. Biosensing technologies are used to monitor physiological sports responses while performing activities, which include heart rate variability (HRV), skin conductivity, and brainwave patterns. The data obtained was-processed to remove noise from the signals, normalize the signals, and prepare them for analysis. Wavelet Transform (WT) is applied to identify relevant physiological markers that would correlate with emotional and cognitive states, which could influence ideological perspectives among students. A hybrid intelligent model of Enhanced Adam optimized Intelligent Decision Tree (EAO-IDT) is implemented to predict the sports activity and outcomes of political education. EAO is used to optimize the hyperparameters of IDT, while classification and prediction capability of influencing various physiological responses on ideology and political development was further improved. The results found that certain physiological responses were significantly associated with the changes in political attitudes and participation. This approach shows the potential of combining biosensing technologies and machine learning (ML) models to monitor and improve the educational effects of sports-related activities.

Keywords: biological mechanism; ideological and political education; heart rate variability (HRV); Enhanced Adam-Optimized Intelligent Decision Tree (EAO-IDT)

1. Introduction

World Health Organization (WHO) formally encouraged the usage of the phrase exercise prescription in 1969. Physical examinations and health checks are the foundation of exercise prescription, which is then paired with lifestyle factors and athletic inclinations. The prescription content for the individuals comprises exercise mode, frequency, and time, in which people can schedule their workouts on a regular basis to improve their fitness and cure illnesses [1]. A history has been accompanied by reform, which have led to the formation, growth, and prosperity in political and ideological training. It is especially true at present when the political and ideological work of universities is getting unprecedented attention, the primary responsibility for establishing moral education, which is the core mission of education. The enjoyment in performing physical activity, altering their personalities, and improving teamwork are all essential, as it involves the development of both theoretical knowledge and motor abilities. To improve the training procedures, especially in the development of physical culture and educational sectors, the need for imparting knowledge and skills related to sports is crucial. It includes the body's movements and forms while optimizing the effectiveness of the several organs. Additionally, medical diagnostics incorporates sports physiology, especially when it comes to cardiovascular health and exercise stress testing. In addition to improving athletic performance, this highlights the field's vital role in protecting athletes' health and lifespan [2]. The advancement of sports physiology has had a significant impact on modern training techniques and our comprehension of the physiological, biomechanical, and psychological elements that underpin athletes' abilities. Sports physiology's historical development can be linked to early research on exercise and human mobility. Sports physiology has grown over the years to encompass a wide spectrum of research, including the coracoacromial ligament's function in shoulder biomechanics and joint stability, which has consequences for athletes' injury management and prevention [3].

The exercise performance is significantly influenced by human physical attributes, organ function, tissue structure, energy storage, and metabolic status. Many individuals in the sports industry tend to emphasize their skills and techniques based on the physical training methods. For both professional sportsmen and regular people, sports training have a significant impact on their performance. Specifically, monitoring daily activities for excellent training helps in the identification of any motor abnormalities. Traditional methods involved in detecting and analysing sports performance include the involvement of professional trainers. But the accuracy of predicting the movements is complex and might be inaccurate in some instances [4]. This necessitates the significance of using advanced detection methods. These applications include developments in computer vision that are used to evaluate athletic abilities, prevent injuries, and give critical performance indicators for a variety of sports. The most widely used application is the wearable intelligent monitoring systems. Sensor fusion is specifically used in health and sports monitoring to measure body reaction and exercise parameters, classify activities and movement patterns, estimate energy expenditure, and evaluate sleep patterns. Efforts have recently been undertaken to improve performance using efficient biological methods [5].

A vital component of maintaining peak physical performance throughout sports is the real time monitoring of physiological change. The recent developments in wearable technologies and wireless sensors have completely changed how body markers are measured and interpreted. Lactate is one of these that is essential for evaluating the body's physiological responses. Athletes' degree of physical fitness is a reflection of their overall health, which encompasses both intrinsic and exercise-related aspects [6]. The body's structure, the efficiency of its organ systems, and other elements play a part in the conversion and storage of energy. Human physical attributes such as energy storage, organ function, and metabolic status have a major impact on exercise performance. The significance of physical training has not been properly acknowledged by many in the sports industry, who instead prioritize skill development [7]. Conventional physical training frequently has issues including a dull training regimen, low participant engagement, and trouble motivating and engaging them [8]. To solve these problems, new alternatives in the field of physical training have been made possible by the recent development of sensing devices and digital entertainment technologies that are developing and implementing flexible technology [9]. These devices were initially developed for medical health monitoring and are characterized by their portability, flexibility, remote operation, lightweight, intelligent design, and real-time data processes capabilities. Their use has broadened, and are currently crucial in helping to track their level of exhaustion and make customized training modifications [10]. **Figure 1** shows the improvements in human body parts after the sports.

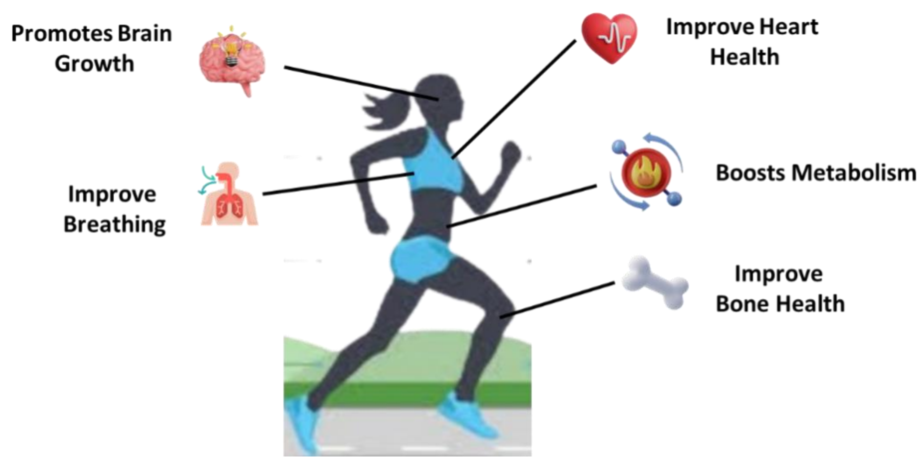

Figure 1. The human body parts are improving after the sports.

1.1. Research objective

The research indulges in the investigation of biological mechanics, biosensing monitoring, and how physical exercise affects political engagement and ideological consciousness. Additionally, the results of sports-related political education efforts are predicted using a hybrid intelligence model called the Enhanced Adam optimized intelligence Decision Tree (EAO-IDT). Investigating the effects of physical activity on brain function, emotional control, and cognitive processes, all of which are critical in forming political and ideological function.

1.2. Key contributions

The key insights of this research are as follows:

- To collect data comprising of sports person, to accurately detect the physiological improvement.
- To apply preprocessing method to remove noise from the signals, normalize the signals, and prepare them for analysis.
- To use feature extraction method called Wavelet Transform to identify the most important feature of the input data.
- To implement EAO-IDT model to predict the sports activity and outcomes of political education.

1.3. Structure of the research

The research presents the relevant studies in Section 2 based on the ideas of applying various methods of machine learning (MI) in sports to improve the physical activity. Section 3 discusses the methodologies used in this research. Additionally, Section 4 and 5 delivers the results produced by the proposed model. Finally, Section 6 discusses the conclusion, including its limits and potential future applications.

2. Related work

Bioelectric signals are crucial indicators of human health in sports monitoring, where players' performance and level of fatigue in real-time must be observed to create an efficient exercise plan. It was challenging for recording dynamic bioelectrical signals of human body during movement. The most recent developments in sports bioelectric monitoring were analyzed utilizing durable Intelligent Garment Systems (IGS) [11]. The scientific community continued to struggle with the kinematic estimate of continuous motion in electroencephalography (EEG)-based BCI systems. Two artificial neural network (ANN)-based decoders were compared in [12] for estimating three lower-limb kinematic parameters and the location of the ankle and knee joint angles during pedaling activities. Using deep learning (DL)-based methods, the results showed lower-limb kinematic properties during pedaling activities estimated from EEG signals. The portable and flexible biosensor on the tester's skin was investigated [13]. Real-time tracking of exercise intensity in sports was possible through the use of piezoelectric signals. Sweat from the skin followed the predefined course through the guide channel of the personal-disclosure mutual-sharing (PDMS) substrate and obtained at the modified Nanowire (NWs). It also monitored changes in the concentration of lactic acid in sweat to gauge the degree of physical effort in a sport because the output piezoelectric voltage depends on the concentration of sweat. To establish an accurate system can recognize various physical activity like running and jumping [14]. The raw sensor data was preprocessed using a Butterworth filter for inertial sensors and a median filter for the Global Positioning System (GPS). The filtered data was then segmented using Hamming windowing techniques. The variance threshold feature selection approach was utilized [15] to choose pertinent characteristics after extracting features from the raw GPS and inertial sensors. Using the piezoelectric effect, the PVDF transformed mechanical energy from the body into electrical energy. The flexible device was secured to the hand or arm in a conforming manner.

Piezoelectric signals were actively output by the sensor, which may function without a power source and provide sports information. The talent in volleyball was interpreted [16] by the sensors to detect the minuscule and delicate spiking movement. The sensor can also track language and pulse changes in real time during a volleyball match. Big sports data was created by connecting the self-powered sensors to a wireless transmitter and uploading sports data. Although these devices can record a number of data types and were worn on the human body, it concentrated on wearable use for risk assessment and performance enhancement in biomechanical applications related to sports and industries. The consequences of these environmental elements, technology developments, and customized training methods on injury treatment and prevention are also covered in the conversation. Additionally, it looks at the future possibilities of sports physiology research, emphasizing new fields like metabolomics and genomics as well as the significance of bridging the gap between theory and practice. These observations are summarized in the article's conclusion, which highlights their significant ramifications for sports physiology and athletic performance going forward.

Key technologies that aid human factors practitioners, ergonomists and safety and health professionals enhanced user performance and track risk, including wearable devices like exoskeletons, inertial measurement units (IMUs), force sensors, and surface electromyography (EMG) [17]. It analyzed the application of flexible wearable technology with life signal monitoring in the sports industry. Furthermore, the categorization of applications, the present state, and the advancement tendencies of comparable equipment and goods were assessed. Academics anticipated receiving useful references and direction for connected studies and the growth of the sports sector. The influence of perspiration on typical sports movements was lessened, and the problem of discomfort during extended use was resolved by using microfluidic detection to gather biomarkers. To improve performance and monitor athletes in real time, [18] investigates the use of wearable nano biosensors. It created a model of sensor use, examines pertinent algorithms, and carries out comparisons. The suggested method increased the efficacy of sports development by 7.83%. Both diversified athlete demographics and long-term validation are lacking. A Deep Learning-Based Innovative Ideological Political Education Platform is suggested by [19] study to improve instruction and reduce political hazards in the classroom. It strengthens economic links and supervision for better interventions through the use of a Radial Basis Function Neural Network. The results demonstrate an 86.55% teaching quality performance rate; nevertheless, the results are limited by the reliance on political and economic stability.

Research gaps

Despite notable progress in the application of wearable technology and bioelectric signals for sports monitoring, a number of research gaps still exist. The first is the need for more precise and dependable techniques that are dynamic bioelectrical signals during different bodily motions, particularly in real-time settings. There are issues with precision and continuous motion tracking with the existing dependence on electroencephalography (EEG)-based devices for kinematic estimate. Piezoelectric sensors and inertial measurement units (IMUs) are two examples of many sensor types that still need to be optimized for better data synchronization and noise reduction. The development of more comfortable and user-friendly wearable technology that can reliably track athletes' health over long stretches of time without interfering with performance is another gap. Furthermore, despite the promise that AI/ML approaches have demonstrated, their use in the real-time analysis of multivariate physiological data in sports is still in its infancy and needs further research before it can be applied practically and for risk assessment and performance enhancement.

3. Methodology

A brief explanation of the processes comprised in this research is provided in this section to compute the overall efficiency of improving the educational effects of sports-related activities. A hybrid intelligent model of EAO-IDT, to predict the sports activity and outcomes of physiological improvement and political education, is elaborated in detail. **Figure 2** illustrates the steps in the suggested method.

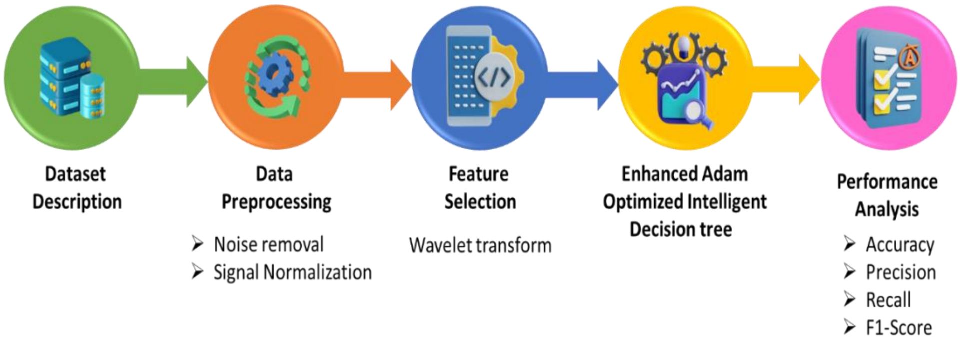

Figure 2. Overall process flow diagram.

3.1. Dataset description

The data was collected from Biosensor-Student Health Fitness Data and was utilized for analysis of physiological improvement for sports. It was collected from a publicly available platform called Kaggle (https://www.kaggle.com/datasets/ziya07/biosensor-studenthealthfitnessdata). A comprehensive set of real-time health metrics was gathered from students by wearable biosensors. This dataset uses cutting-edge ML techniques to make it easier to analyze and forecast students' levels of fitness and health.

3.2. Data preprocessing

The data obtained was pre-processed to remove noise from the signals, normalize the signals, and prepare them for analysis.

- Noise Removal

The Wiener filter is utilized to reduce noise present in the input biosensor signals. It treats both the desired signal and the noise as stochastic processes with linear properties as shown in Equations (1) and (2), using their respective spectrum characteristics to filter out noisy signals.

$$m(x) = h(x) + s(x) \tag{1}$$

Here, coefficients $m(x)$, the linear filter is applied with the estimated signal. The input signal, $h(x)$consists of noise $s(x)$.

$$h(x) = \sum_{s=0}^{y=1} v_a(l(b-q) \times w(b-q) \tag{2}$$

Here, h is a discrete Wiener filter that uses the following equation to find the value of $h(x)$.

- Signal Normalization

Min-max normalization, which is specified in Equation (3), is used in this investigation to produce the improved prediction.

$$A(s) = \frac{h(s)-min(w(o))}{max(w(o))-min(w(o))}, S = 1,2,3,..N \; (\tag{3}$$

where, $min(w(o))$ and $max(w(o))$ represent the min and max of a sample data $w(o)$; this formula can map an original value $A(s)$ to a value in the interval [0, 1] through min-max normalization.

3.3. Feature selection using wavelet transform

Wavelet transformations are one of the mathematical functions that produce a time-scale representation and the particular time series to the relationships. Wavelet transformations can be used to identify data trends such as the points, discontinuities, and local minimum and maximum that would be missed by other signal analysis techniques. Another useful tool for de-noising the given data collection is wavelet analysis. The ability to select the mother wavelet flexibly based on the properties of the time series under investigation is another benefit of wavelet analysis. The first step in wavelet analysis is choosing a mother wavelet (ψ) and is expressed in Equation (4).

$$\psi_{i.n}(n) = \frac{1}{\sqrt{|T_0^i|}} \sum_l \psi\left(\frac{l - n\tau_0 t_0^i}{t_0^i}\right) w(l) \tag{4}$$

where n and w is an integer that control the scale and translation, and $w(l)$ is a fixed dilation step and τ_0 is a factor of translation.

3.4. Prediction using Enhanced Adam Optimized Intelligent Decision Tree (EAO-IDT)

IDT learning algorithms and EAO method are used for enhancing the prediction rate of sports activity. It leverages the strengths of both DT algorithms and the AO method. IDTs are made up of inner nodes with functions and leaf nodes with forecasts, and node splitting is done using one-dimensional or multidimensional predicates. The tree construction procedure entails increasing a quality function. The AO algorithm, which was created for stochastic objectives that adaptively adjusts network weights.

3.4.1. Intelligent Decision Tree (IDT)

A DT is one of binary tree with inner and leaf nodes of two different kinds. The leaf node has enhancing the physiological activity for sports. To whereas every leaf node has a forecast, every inner node has a function. When comparing the values of one of the attributes to a threshold, one-dimensional predicates are usually employed. However, there are also multidimensional predicates. Although multivariate predicates make it possible to construct even more intricate dividing surfaces, their application in practice is uncommon, partly due to their tendency to retrain judgment. Like other ML algorithms, tree learning techniques have a number of parameters and variables, and the decision tree root node. The IDT implementation is represented in **Figure 3**.

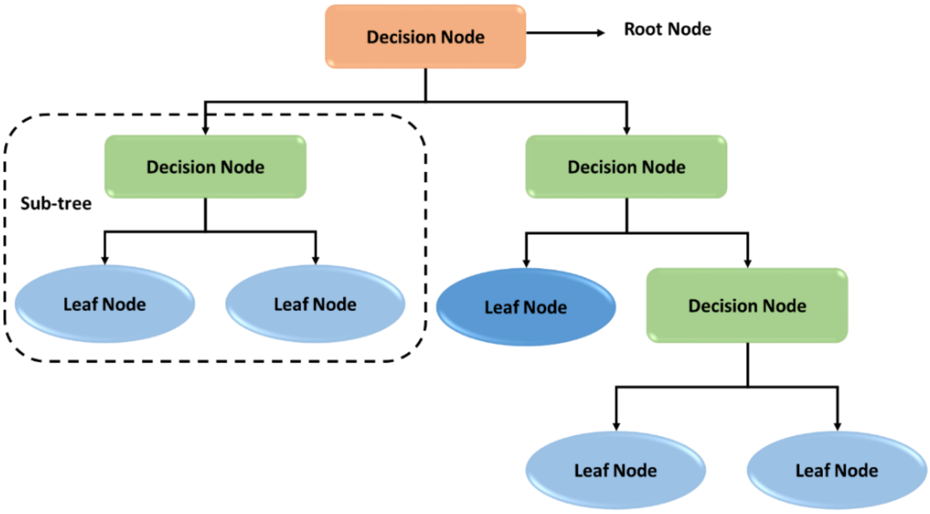

Figure 3. Improved decision tree implementation.

An IDT cannot be created until the quality function has been established. At each node, the sample is split according to the chosen quality function. To discuss the collection of objects in the set of nodes and the items represented in left and right sub-trees for a given predicate are identified using the following Equation (5).

$$G(Q) = -\sum_{l=1}^{L} o_l \log o_l \tag{5}$$

The information criteria $G(Q)$ evaluates the target distributed variable and quality among G objects. Less diversity in the target variable results in a lower value for the information criteria. Simultaneously maximizing the function of quality $\log o_l$ and L is the attribute and l threshold value.

The IDT algorithm terminates if the observations of a single class remain or if the depth of the DT is limited, which was unrestricted in depth. The information criterion is given by Equation (6).

$$G(Q) = \sum_{l=1}^{L} o_l(1 - o_l) \tag{6}$$

where G is the number of classes and $G(Q)$ is the percentage and the class are fallen into node Q. The Gini criterion is used the CART algorithm.

To maximize information, standard criteria are used to conduct a thorough search of the original data set. This procedure is time-consuming and is reflected in an IDT learning process since the information criteria values need to be computed for each attribute value for each observation in the training set.

3.4.2. Enhanced Adam Optimization (EAO) algorithm

Adam is a popular adaptive optimization algorithm used for improving the physical activity for the sports person and predict the overall performance. That are replaces the conventional stochastic gradient reduction technique because of its high efficiency. It is believed to have low memory needs and to be computationally efficient, dynamically updating the learning rate for every parameter. Adam uses a gradient descent-style parameter update technique with momentum. The exponential moving the average of the gradient a_o and the squared gradient b_o are used, the advantages of the EAO and momentum are thus combined. To update parameters, the following Equations (7–10) are utilized.

$$a_o = \beta_1 a_{o-1} + (1 - \beta_1) y_o \tag{7}$$

$$b_o = \beta_2 b_{o-1} + (1 - \beta_2) y_o^2 \tag{8}$$

$$a_o^{\wedge} = \left(\frac{a_o}{1-\beta_1^o}\right) b_o^{\wedge} = \left(\frac{b_o}{1-\beta_2^o}\right) \tag{9}$$

$$\theta_{o+1} = \theta_o - \frac{\eta}{\sqrt{b_o^{\wedge} + \in}} a_o^{\wedge} \tag{10}$$

here, β_1 is the exponential decay rate. The default values for β_1 and β_2 are 0.9 and 0.999, respectively. $a_o^{\wedge}$ and $b_o^{\wedge}$ are correction biases for a_o and b_o respectively.

When comparing the steep and soft parts of the error surface, the derivative is larger in the former. Therefore, it is identified that there are noticeable upgrades in the specific regions. The little gradient in these areas means that it takes longer to emerge from the fat surface. The conventional Adam optimization moves in two directions, one toward history and the other toward the gradient $\eta \hat{g}_s$, as demonstrated in Equations (11) and (12).

$$u_s = \gamma u_{s-1} + \eta \hat{g}_s \tag{11}$$

$$\hat{g}_s = \nabla_{\theta_{s-1}} \sum_j \mathcal{L}(e(w; \theta_{s-1}), z) \tag{12}$$

This method naturally enables the algorithm to go slowly with characteristics and quickly with low curvature. However, since the momentum step is independent $\nabla_{\theta_{s-1}}$ of the current gradient, it provides a high-quality gradient step by updating the parameters using to calculate the moment and the steps are measuring the performance. The suggested method overcomes the limitation of traditional Adam to evaluating the gradient to applying the current velocity, which improves the momentum term of Adam. Thus, Adam's momentum term is resolved. Equations (13) and (14) use the present velocity g_s to determine the gradient at a temporary position θ_{temp} certain amount of distance has been traveled.

$$u_s \quad \gamma u_{s-1} \quad \left(\theta_{temp}\right) \quad (u_s) \tag{13}$$

$$g_s = \nabla_{\theta_{temp}} \sum_j \mathcal{L}(e\left(w; \theta_{temp}\right), z) \tag{14}$$

here, the gradient determined at point θ_{temp} is used to update the parameters' velocity.

A different problem with the sigmoid function's traditional optimization methods is that some inputs are negative; the corresponding derivative goes to zero. As a result, the learning rate to adjust the present element and decreasing the learning rate for parameters in proportion to their update history is the aim. The exponentially decaying average is used to update history of the gradients that are accumulated, the model does not blow Equation (15) when the parameters of the objective functions are changed because of the decay rate β_2.

$$n_s = \beta_2 * n_{s-1} + (1 - \beta_2)(\hat{l}_s)^2 \tag{15}$$

here, the gradient of starting parameters n_s determines whether the learning rate increases or decreases based on history n_{s-1}, which is expressed by Equations (16) and (17).

$$\hat{n}_s = \frac{n_s}{1-\beta_1^s} \tag{16}$$

$$\hat{u}_s = \frac{u_s}{1-\beta_2^s} \tag{17}$$

here, the model is nearing convergence $\hat{n}_s$, which keeps it from being trapped at the local minima, and guarantees that the sum does not grow exponentially. The learning rate drastically changed the conclusion of the training process by employing the participants; instead of the earlier updates, the approach may rather change orientation in $\hat{u}_s$. This result is more accurate fine-grained.

The use of EAO-IDT component can adapt better to complex decision-making processes by incorporating domain-specific knowledge, heuristics, or more refined splitting criteria. IDT ensures that the model can make more informed and accurate decisions at each node. While, EAO fine-tunes the IDT's parameters, ensuring that the splits made by the tree are optimal for minimizing prediction errors. By adjusting the learning rate dynamically, Adam helps in achieving better convergence, reducing bias and variance in predictions. Hyperparameter tuning, early stopping to conserve resources, parallel tree construction for efficiency, boosting or bagging, and other sophisticated methods are also improved by the model. **Table 1** illustrates the hyperparameters used to increase the accuracy of the analysis process.

Table 1. Details of Hyperparameters for (EAO-IDT).

Hyperparameters	**Values**
SNR Threshold	1.5–3
Dilation Factor	1.5–2.0
Learning Rate (η)	0.001–0.01
Weight Decay	1–5
Validation Split	0.2–0.3

The procedures and techniques used in the suggested EAO-IDT for improving the physiological activity for sports using MI are deliberated in Algorithm 1.

Algorithm 1 EAO-IDT for Improving the Physiological Activity in Sports

```
Step 1: Data Preprocessing
def apply_wiener_filter(signal):
  filtered_signal = []
  for i in range(len(signal)):
     filtered_signal.append(estimate_signal(signal[i]))
  return filtered_signal
normalized_data = min_max_normalization(filtered_data)
Step 2: Feature Selection Using Wavelet Transform
def wavelet_transform(data, mother_wavelet):
  transformed_features = []
  For signal in data:
     transformed_signal = apply_wavelet(signal, mother_wavelet)
     transformed_features.append(transformed_signal)
```

Algorithm 1 (*Continued*)

```
    return transformed_features
mother_wavelet = 'db1'
wavelet_features = wavelet_transform(normalized_data, mother_wavelet)
Step 3: Model Training with Hybrid Enhanced Adam Optimized Intelligent Decision Tree (EGO-IDT)
class DecisionTree:
    def __init__(self, criterion='gini'):
        self.criterion = criterion
    def fit(self, data, labels):
        pass
Class AdamOptimizer:
    def __init__(self, beta1=0.9, beta2=0.999, learning_rate=0.001,epsilon=1e-8,):
        self.beta1 = beta1
        self.beta2 = beta2
def train_model(data, labels):
    dt = DecisionTree (criterion = 'gini')
    adam_optimizer = AdamOptimizer()
    dt.fit(data, labels)
    parameters = dt. parameters
    for epoch in range (1000):
        gradients = calculate_gradients (dt, data, labels)
        For param in parameters:
            param = adam_optimizer.update(gradients[param], param)
return dt
End
```

4. Results and discussion

This section delivers the outcomes procured by the proposed EGO-IDT model implemented in improving physiological action for sports. Certain performance metrics are involved to evaluate the performance and are also discussed. Additionally, a comparative approach is offered to determine how effective the suggested approach is in comparison to other cutting-edge techniques.

4.1. Experimental setup

The system described is equipped with an Intel i7 CPU, offering strong multi-core performance and making it well-suited for demanding computation tasks with 16 GB of RAM, and NVIDIA GTX 1050ti GPU are the components of a computer system environment that uses Python to perform its operations.

4.2. Experimental outcomes

The experimental outcomes are derived by using number of evaluation criteria, including accuracy, precision, recall, and f1-score. This is done to analyze the performance and the description of these measures is as follows:

- Accuracy

The percentage of accurate forecasts among all predictions is known as accuracy, and it is a frequently used indicator to assess a model's effectiveness. It gauges how accurately the model can categorize or forecast results. Generally represented as a percentage, accuracy is the ratio of correctly anticipated outcomes to total predictions. It is expressed by using Equation (18).

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{18}$$

here, TP stands for true positive and TN is a true negative. FP and FN illustrates a false positive and negative. To improve the physical activity for tracking performance or optimizing movement, the model might predict whether an action was performed correctly. Accuracy would tell the overall percentage of correctly identified actions compared to all actions evaluated.

- Precision

Precision is defined as the percentage of pertinent instances among the retrieved instances to increase physical activity in sports. Put more simply, it quantifies the proportion of actions that the model determined to be positive that were, in fact, pertinent or accurate. It is given by Equation (19).

$$Precision = \frac{TP}{TP+FP} \tag{19}$$

- Recall

A statistic called recall is employed to measure how a classification model performs better, particularly when applied with unbalanced input datasets. Out of all the real positive examples in the data, it gauges how successfully the model detects positive instances and is represented by Equation (20).

$$Recall = \frac{TP}{TP+FN} \tag{20}$$

- F1-Score

A model's precision and recall are combined into a single metric called the F1-score, which yields genuine positive results for every anticipated positive case. When working with datasets that are unbalanced, when one kind may be more prevalent than the other, it is extremely beneficial. Furthermore, the model is a harmonic mean of precision and recall performances Equation (21).

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{21}$$

The model identifies pertinent events, such as an improvement in movement performance or the possibility of injury prevention, and the F1-score can assist in assessing the performance of physical activity. The model is examined and the outcomes are shown in **Table 2** using the performance metrics.

Table 2. Outcomes of the proposed model.

Metrics	**EAO-IDT [Proposed]**
Accuracy	88%
Precision	79.8%
Recall	82.3%
F1-Score	80.2%

As inferred from the table, the proposed EAO-IDT produces accuracy (88%), precision (79.8%), recall (82.3%), and F1-score (80.2%). This demonstrates that the proposed model procures high performance and improves the physiological moment.

Comparative analysis based on existing studies such as Extreme XGBOOST [20], Decision Tree [20], CatBoost [20], and the proposed EAO-IDT is implemented. Thus, the following discussion is held regarding the outcomes generated by each approach depending on evaluation variables. **Table 3** indicates the accuracy outcomes generated by the proposed and existing model and a graphical illustration of produced values is represented in **Figure 4**.

Table 3. Outcomes of accuracy.

Method	Accuracy
XGBOOST [20]	79.2%
Decision Tree [20]	77.2%
CatBoost [20]	77.9%
EAO-IDT [Proposed]	88%

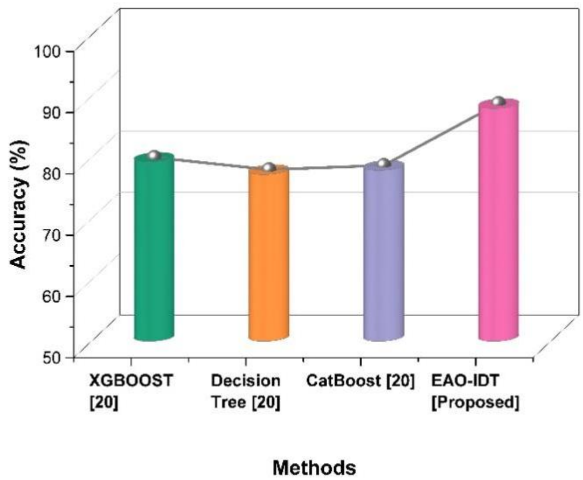

Figure 4. Results based on accuracy.

Table 3 highlights the accuracy of several ML techniques by comparing their performance. With an accuracy of 79.2%, XGBoost is followed by Decision Tree and CatBoost, which have respective accuracy rates of 77.2% and 77.9%. With an accuracy of 80.4%, the suggested model, EAO-IDT, performs better than the other three. This suggests that the EAO-IDT model is enhanced in accurately predicting outcomes than XGBoost, Decision Tree, and CatBoost, providing a promising solution for the targeted application, whether in sports, physical activity, or another domain. It also shows that the EAO-IDT model offers the best classification performance among the tested methods. The proposed EAO-IDT model enhances prediction accuracy by optimizing hyper parameters through Enhanced Adam, leading to improved decision-making efficiency and better adaptation to physiological variations. In addition; analysis based on precision is performed by the proposed system, as shown in **Table 4**. Additionally, **Figure 5** displays the results of precision.

Table 4. Results based on precision.

Method	Precision
XGBOOST [20]	78%
Decision Tree [20]	76.7%
CatBoost [20]	75.9%
EAO-IDT [Proposed]	79.8%

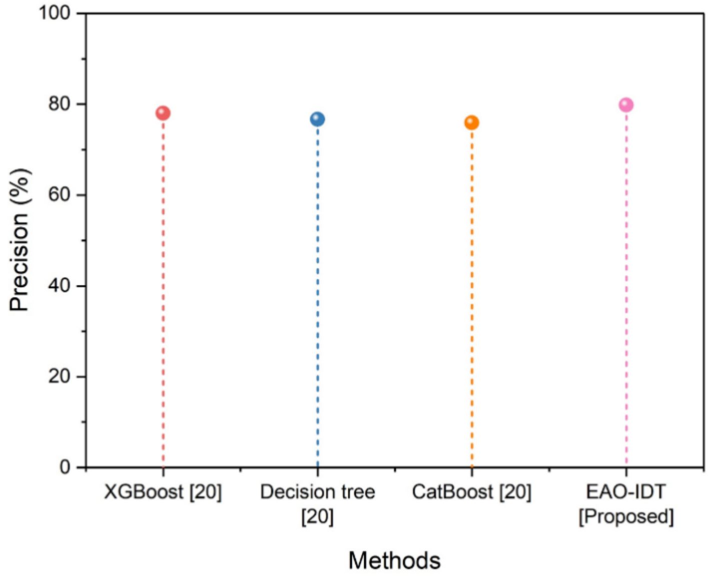

Figure 5. Outcomes of precision.

From **Table 4**, it is inferred that CatBoost has a lesser precision of 75.9%, XGBoost obtains 78%. When it comes to accurately recognizing positive instances among those anticipated to be positive, the suggested model, EAO-IDT, procures precision of 79.8%. Thus, EAO-IDT appears to be a more dependable option because it is better at reducing false positives than both XGBoost, Decision Tree and CatBoost. **Table 5** indicates the recall outcomes generated by the proposed and existing models and graphical values are represented in **Figure 6**.

Table 5. Outcomes of recall.

Method	Recall
XGBOOST [20]	81.2%
Decision Tree [20]	78%
CatBoost [20]	81.5%
EAO-IDT [Proposed]	82.3%

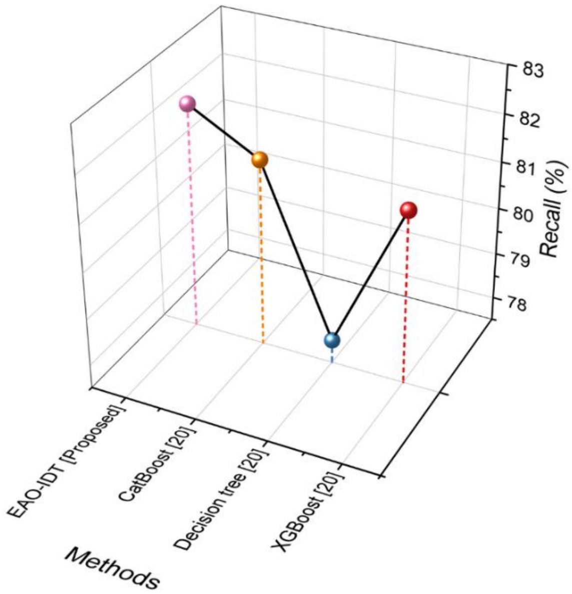

Figure 6. Outcomes of recall.

The recall of three ML techniques is contrasted in the table, indicating how well each can detect true positive cases. With an 81.2% recall, XGBoost accurately detects 81.2% of the dataset's real positive occurrences. With a much lower recall of 62.1%, SVM misses a sizable percentage of true positives. With an 82.3% recall, the suggested EAO-IDT model outperforms both XGBoost, Decision Tree and CatBoost, proving its capacity to accurately detect more positive cases. This increased recall shows that EAO-IDT is especially good at reducing false negatives, which makes it a better model for jobs where it's important to record all relevant positive instances, such as tracking physical activity in sports or health applications. The analysis based on F1-Score performed by the proposed system is shown in **Table 6**. Additionally, **Figure 7** represents the outcomes obtained by the F1-Score parameter.

Table 6. Results of F1-Score.

Method	F1-Score
XGBOOST [20]	79.6%
Decision Tree [20]	77.3%
CatBoost [20]	78.6%
EAO-IDT [Proposed]	80.2%

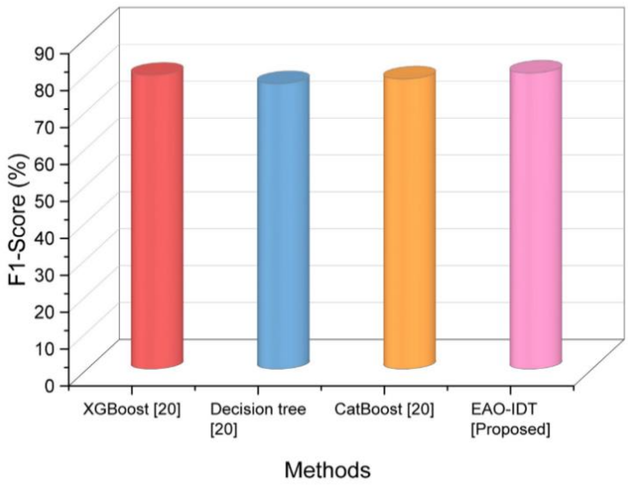

Figure 7. Outcomes of F1-score.

The comparison based on F1-scores for three ML methods, which balance precision and recall in evaluating model performance, is performed. With an F1-score of 79.6%, XGBoost strikes a respectable mix between recall and precision. Decision Tree performs less when compared with overall algorithms in reducing false positives and detecting true positives, as seen by its lower F1-score of 77.3%. The F1-score of the suggested EAO-IDT model is 80.2%, demonstrating improved performance than XGBoost, Decision Tree and CatBoost. According to this, EAO-IDT provides the best overall performance by optimizing the trade-off between recall and precision. For sports-enhanced activity and physiological improvement detection or recognition, where accuracy depends on both precision and recall, a higher F1-score suggests that EAO-IDT is more robust, capturing more true positives while maintaining fewer false positives.

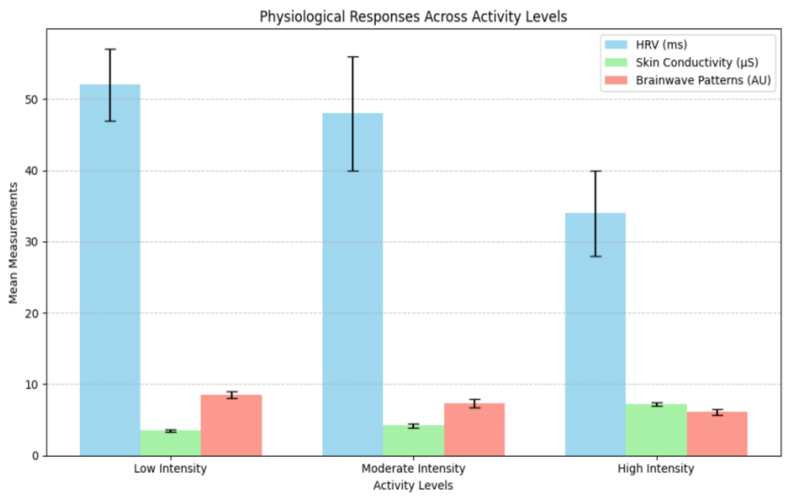

Figure 8. Physiological responses across activity levels.

The physiological responses including HRV, skin conductivity, and brainwave activity at varying physical demand levels from low to high intensity activities are depicted in the **Figure 8**. The blue bar chart demonstrates that physical activity intensification leads to reduced HRV and increased error bar indicators. Physiological indicators of skin conductivity and brainwave activity rise minimally based on intensity changes yet maintain small differences between each condition. The error bars represent measurement uncertainties which indicate that greater physiological fluctuations mainly affect HRV during activities with increased intensity.

5. Discussion

The proposed EAO-IDT model exhibits notable gains in the various metrics when compared to the other conventional methods. Despite being widely utilized in sports and physiological monitoring, SVM and XGBoost have several drawbacks, especially in precision and recall, which affect their capacity to correctly detect positive cases. For instance, XGBoost obtains precision and recall, suggesting an opportunity for growth, whereas SVM suffers from low precision and recall. Alternatively, the EAO-IDT model performs better than conventional techniques with greater accuracy, recall, and precision, making it more efficient at identifying pertinent physiological events and athletic activities. The improved F1-score (80.9%) further illustrates the model's capacity to strike a balance between recall and precision, which is essential for uses such as injury prevention and sports performance tracking. More varied datasets and additional tuning could enhance the model's performance even with current enhancements. For even more accurate, real-time forecasts, future research should concentrate on incorporating cutting-edge methods like deep learning and testing EAO-IDT in a variety of sporting scenarios. Therefore, the EAO-IDT model presents a promising improvement over conventional techniques, offering a more precise and dependable instrument for tracking physical activity and enhancing performance.

6. Conclusion

The objective of this research is to investigate the biological mechanics and biosensing monitoring of how physical exercise affects political engagement and ideological consciousness. Additionally, the results of sports-related political education efforts were predicted using a hybrid intelligence model called the EAO-IDT. Research investigating the effects of physical activity on brain function, emotional control, and cognitive processes, all of which are critical in forming political and ideological function. Various metrics are used to measure and access the EAO-IDT model's abilities to track physical activity and optimize athletic actions. Based on all measures, the results demonstrated that EAO-IDT performed better than models such as XGBoost, Decision Tree, and CatBoost, with an accuracy (88%), precision (79.8%), recall (82.3%), and F1-Score (80.2%). These results demonstrate the model's efficacy in injury prevention, performance improvement, and real-time physical activity tracking. Nevertheless, the research has shortcomings, including the requirement for additional verification in dynamic and real-world sports environments. Future studies should concentrate on integrating other sensor types, enhancing real-time processing, and addressing power consumption to guarantee portability to adapt the model to various sports. The system's usefulness might also be increased by adding DL for improved damage prediction and creating customized models. Field testing and cooperation with sports experts would also aid in improving the model for real-world sports science applications.

Ethical approval: Not applicable.

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

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