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Article

Biosensing technology based on biomechanics in psycho analysis: Improving the efficiency of ideological and political education

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Abstract: In recent years, advancements in technology have significantly transformed educational paradigms, particularly through the integration of biomechanics in teaching methodologies. The incorporation of biomechanical analysis in educational settings provides valuable insights into students' physical engagement and motor skills development. This study aims to leverage biomechanical data to enhance the effectiveness of physical education and sports training. Biomechanical sensors, such as motion capture systems and wearable devices, collect critical data on parameters like gait, balance, and muscle activity. By analyzing this data, educators can gain a deeper understanding of students' physical performance and identify areas for improvement. We propose a novel biomechanical optimization framework utilizing a multi-kernel support vector machine (MK-SVM) to assess students' physical strain levels during activities. In the preprocessing stage, a median filter is employed to eliminate noise from the motion data. Features are extracted using power spectral density (PSD) analysis to evaluate students' physical responses during instructional activities. The proposed method utilizes algorithms to create personalized training environments, identifying physical responses and facilitating real-time feedback for enhanced engagement in sports and physical education. The MK-SVM algorithm is applied for feature selection, effectively categorizing student strain levels to refine personalized learning strategies. Results indicate that our approach outperforms traditional methods, achieving high accuracy (92%), Recall (98%), precision (80%), and F1-Score (88%) in assessing students' physical strain. This study demonstrates how biomechanics and technology can revolutionize physical education, fostering more adaptive and responsive learning environments.

Keywords: psycho-analysis; biosensing; ideological; political education, electroencephalography (EEG); advanced kookaburra optimizer with poly-kernel support vector machine (AKO-PSVM); biomechanics

1. Introduction

The role of ideological and political education has never been more critical in a progressively more complex and interconnected world. Educational institutions strive to cultivate informed citizens capable of engaging thoughtfully with societal issues, yet traditional methods often struggle to foster genuine interest and critical thinking. Students frequently disengage from ideological discussions, hampering the development of their political consciousness. As educators seek innovative solutions to enhance the effectiveness of their curricula, there is a growing need to explore new methodologies that can provide deeper insights into students' emotional and cognitive engagement [1].

In the modern period, placing a strong emphasis on pupils' daily political and ideological education and consistently advancing standards like scientific, standardized, and student projects that are institutionalized help to enhance the relevance and potency of political and ideological guiding the youth and providing education at colleges and institutions in the modern period to go on a fresh adventure and make a fresh input in the modern age [2]. Psychoanalysis plays an important role in considering the underlying motivations and emotions that shape individuals' beliefs and behaviors. By integrating biosensing technology within psychoanalytic frameworks, educators can better assess and address the psychological dynamics at play in ideological and political education. This integration not only enhances the understanding of students' responses but also facilitates the development of strategies that cater to their unique psychological profiles [3,4].

Political and ideological education that develops pupils' high levels of contemporary political and ideological knowledge. Surveys, interviews, and oral presentations by class informants are frequently used by college student management professionals to better understand the emotional conditions of their students [5]. The main problems with these methods are as follows: first, some students can be reluctant to tell the truth out of concern for unfavorable outcomes or for other reasons, which could result in the gathering of inaccurate data. Second, some students fill out the questions at random because they are either repelled by them or don't want to spend the time reading them, which might provide inaccurate findings. Third, since some students conceal their emotions, it is hard to gather accurate information by watching professors and other pupils. Therefore, the ideal foundation for creating precise and useful emotional data is objective physiological data. The rising objectivity of these results has led to the expansion of additional biosensor-based physiological signal-based emotion recognition systems throughout time [6]. These physiological signals are easily acquired, and safe, and reflect the effects of emotion on the autonomic nervous system. Electrocardiograms (ECGs), electromyograms (EMGs), Galvanic-skin resonances (GSRs), respiratory rates (RRs), and electroencephalograms (EEGs) are commonly used in stress recognition often provide biomechanical data that can reflect physiological responses expression of stress states also plays a role. EEG signals are commonly used as physiological cues for stress recognition. EEG signals have been widely used in conjunction with biomechanical data in studies of swallowing, mental status assessment, and the diagnosis of neurological depression [7].

Blink rate, heart rhythm variability, cortisol levels, and EEG patterns all changed, suggesting that these data can be used in the diagnosis of stress and that multiple aspects should be carefully considered when using technology as they are worn to detect stress. Measurements such as electr-oculography (EOG) readings, EEG readings, EMG readings, plethysmography (PPG) readings, heart rate variability, blood pressure, respiratory rate, skin temperature, and GSR, can be used to measure stress quantitative and emotional Subject's emotional development, employee motivation. The subject's emotional growth, executive motivation, and present external circumstances may all be evaluated and interpreted with the aid of these physiological changes [8].

The information on biosensing technology, specifically as it relates to psychoanalysis and its application for improving political and ideological education effectiveness. The intend to solve this by enhancing the way biosensors, in conjunction with EEG, GSR, and HRV, can offer real-time information on cognitive and emotional states during educational activities. In the of ideological education, this would enable a more sophisticated understanding of how biosensing might optimize engagement and learning outcomes. To properly demonstrate the capabilities of the biosensing technology.

The use of advanced technology in educational frameworks offers new prospects for improving the efficacy of ideological and political education. Among these advancements, bio-sensing technology provides a transformative strategy by offering real-time insights into college students' emotional and cognitive states, overcoming constraints inherent in traditional techniques. These technologies enable educators to understand subtle physiological changes that are frequently difficult to detect via interviews, delivering more objective and comprehensive images of college students' participation. Using biosensors such as electroencephalograms (EEGs), galvanic skin response (GSR), and heart rate variability (HRV), educators can evaluate stress, motivation, and emotional responses, adjusting their tactics to stimulate critical thinking and active engagement [9,10].

The use of biosensing technology supports psychoanalytic frameworks by bridging the gap between internal mental processes and observable behaviors in ideological education. For example, emotional responses to political discourse or ideological can be quantitatively assessed, allowing instructors to adjust coaching strategies in real time. This integration of psychoanalysis and technology opens up possibilities for addressing underlying emotional barriers to increasing political awareness, such as indifference, anxiety, or resistance to ideological issues [11].

Aim and contribution of the study

This study aims to integrate biosensing technology into psychological research to improve the study of ideological and political education. The main contribution is the extension of the Kookaburra optimizer with a multi-kernel support vector machine (KO-PSVM), which enables accurate analysis of student stress levels and improves individual learning strategies.

2. Related works

Combining machine learning with increased sensitivity, selectivity, and accuracy to improve biosensor performance was developed by Anapanani [12]. The examination covers a variety of machine learning methods in addition to data pre-processing, feature extraction, and classification. The result highlights challenges to data availability and sensor performance while also offering a prediction of new advancements like artificial intelligence and deep learning for bio-sensing systems of the future.

Williamson [13] investigated the collections that include social, material, and institutional components and attempted to conceive academic neuroscience and genomics as bio-informational schooling technical know-how. It demonstrated the integration of biological and virtual technologies in influencing educational research, coverage, and exercise by examining neural and genetic techniques to determine how biodigital method generate knowledge about academic problems.

Sethia and Indu [14] examined to identify real-time stress detection using a wearable system and evaluate how well meditation audio reducing stress following exposure to instruction. The approach combined Bayesian optimization for machine learning hyperparameter tuning with Genetic Algorithm and Mutual Information for function selection. The results demonstrated the importance of electrodermal activity (EDA), Blood Volume Pulse (BVP), and HRV for stress identification and emphasized the strain-relieving effects of meditation. They also indicated great type accuracy (98.28%).

Bakker and Schumacher [15] encourage the upcoming creation of political psychology researchers to self-reports and embrace ideas and methodologies that improve understanding of the affective-cognitive, unconscious processes that lead to political judgments. A summary of research utilizing eye tracking, neuroimaging, and psychophysiological metrics was presented.

Pao and Yan [16] examined the effect of political and ideological education on college students' mental health. A separate convolutional neural network (CNN) was utilized to identify faces in images, and a deep learning (DL) student emotion detection model was created. The findings indicated that while social practices and campus society had a beneficial collision on political entity individuality, demographic features had a substantial impact. When compared to conventional machine learning (ML) techniques, the strategy increased classification accuracy by 8.036%.

Juárez Varón et al. [17] examined the effects of both in-person and online university instruction on learning process factors using neurotechnology. Using galvanic skin response, eye tracking, and EEG were used and indicated that students who attended in-person sessions had more emotional intensity, higher positive brain activity, and lower stress levels.

Mukherjee and Halder [18] introduced a DL-based method for measuring human stress levels based on pulse rate and EEG. The method detects mental stress levels using a CNN-tanh long short-term memory (CNN-TLSTM) model based on anconsiderationmethod. To improve classification accuracy, the model incorporates an attention layer.

Chen and Lee [19] carried out several tests to assess students' stress levels. Physiological signals gathered such as ECG, PPG, and EEG were examined to evaluate stress levels, through improved models like self-supervised CNN and Long-term Recurrent Convolutional Network (LRCN).

Pabreja et al. [20] used information from 650 respondents to examine stress among students. A forecast of stress level was produced with an R-squared value of 0.8042 after 15 important elements were found using the revelation method and the random forest regressor (RFR) model.

Tang et al. [21] cautioned a Spatial-Temporal Information Learning Network (STILN) to extract discriminative traits from EEG-based total emotion popularity. The community employed a Bidirectional Long Short-Term Memory Network (Bi-LSTM) for sequential context mastering and 2-dimensional (2D) strength topographic maps to document electrode dependencies.

Sharma et al. [22] examined the effectiveness of ML procedures in decreasing the chance of pressure prediction and better early remedy. The researchers hired category algorithms together with Naive Baye's (NB), MLP, Linear Regression (LR), Bayes Net, J48, and RF on more than 2 hundred college student statistics.

3. Methodology

This section explains the dataset used in this study and explains the pre-processing technique using a median filter for noise reduction, extracting features using Power spectral density (PSD), and the proposed method KO-PSVM in detecting the psycho-stress level of students. The methodology framework is given in **Figure 1**.

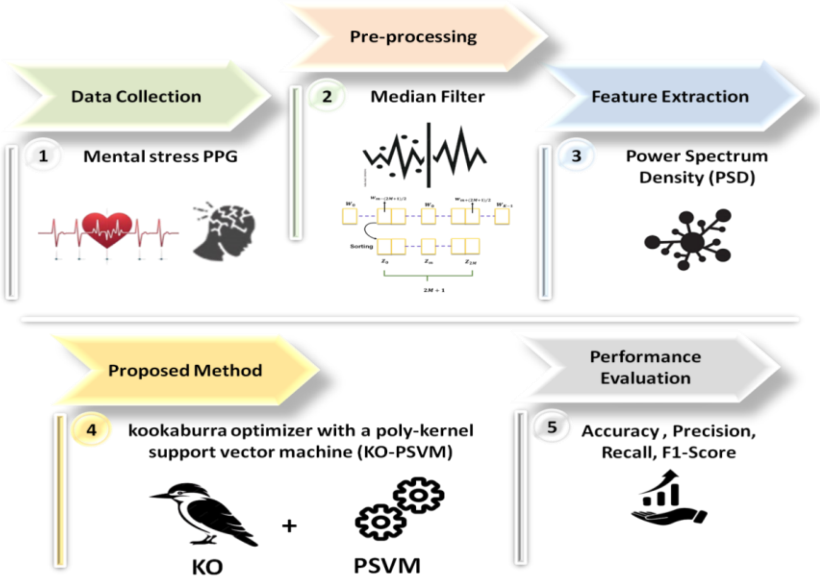

Figure 1. Overall process of KO-PSVM method.

3.1. Dataset

In this study Mental Stress PPG dataset from Kaggle is used to detect the students' emotional and cognitive engagement during educational activities [23].

Mental stress is a typical response to life's experiences. However, both acute and long-term stress can cause psychological and cardiac problems. Heart rate variability (HRV) is thought to be a gauge of stress levels and physical fitness. Usually, HRV is calculated by timing the separation of two consecutive R-peaks on an Electrocardiogram (ECG). Photoplethysmogram (PPG), which employs pulse rate variability (PRV), or the time between two consecutive PPG peaks, is another technique for identifying mental stress. This study gathered 27 healthy bachelor's students (15 men and 12 women, ages 21 ± 2) who participated in two phases: A baseline phase and a Stroop test phase. The baseline phase involved participants sitting comfortably in a controlled classroom environment while a sensitive, low-power, RoHS-compliant PPG sensor was attached to their earlobe to monitor PRV for a specific amount of time and record baseline coronary heart rate data. The Stroop test phase had participants using an Android app to engage in a color-word association task that was intended to cause mental stress. During this phase, the equal PPG sensor recorded PRV data to evaluate changes brought on by stress. The data collection included continuous PRV monitoring, followed by analysis to determine the effect of stress on heart rate variability, providing information about the physiological response to cognitive stress. To ensure a comprehensive assessment of physiological reactions, the data were subsequently processed using specialized software to compute PRV and examine variations in heart rate variability before and after the Stroop task.

3.2. Noise removal using a median filter

The median filter is well-suited for preprocessing psycho-stress level data, particularly ECG signals, as it effectively removes noise while preserving important features. By maintaining the integrity of signal characteristics, this technique enhances the accuracy of subsequent analyses, enabling more reliable assessments of students' psycho-stress levels.

Figure 2 illustrates the operation of the median filter, which replaces a point in a segment with the median value of the series. The whole date series is denoted as $W_0 \sim W_{K-1}$, and the segment ($W_{m-(2M+1)/2 \sim W_{m+2(2M+1)/2}}$) subjected to a window of length 2N + 1. Sorting segment ($W_{m-(2M+1)/2 \sim W_{m+2(2M+1)/2}}$) in either ascending or descending order yields the temporary array $z_0 \sim z_2$. The temporary array's middle point is denoted by Z_m . Z_m replaces the center point W_m in the segment ($W_{m-(2M+1)/2 \sim W_{m+2(2M+1)/2}}$). When the next temporary array Z_m is received, the median filter is continued by deleting the earliest point and adding the most recent (new) point to the proper location of the first temporary array. $Z_0 \sim Z_{2M}$. This reduces the amount of time needed to compute the subsequent sorting process. The window travels across the complete data series $W_0 \sim W_{K-1}$ to smooth out ECG.

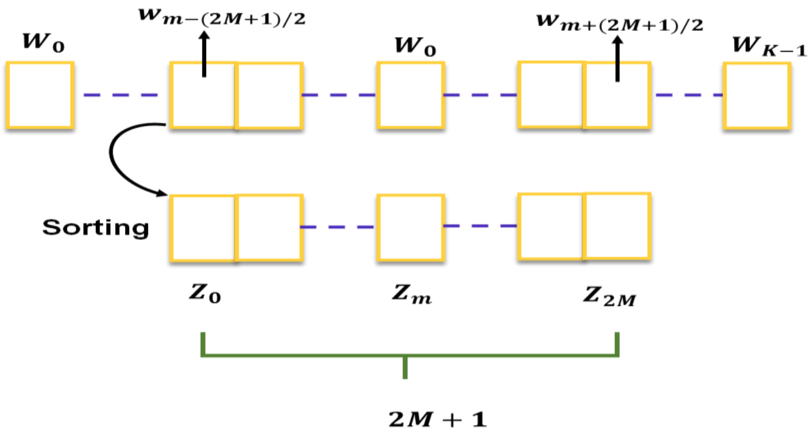

Figure 2. Visual representation of Median filtering steps.

3.3. Feature extraction using PSD

Feature extraction using PSD is highly suitable for analyzing psycho-stress levels in students. Quantifying the power distribution of HRV signals facilitates the identification of stress-related patterns and enhances the accuracy of subsequent analyses, leading to a more reliable assessment of students' psychological states.

The assessment of a power distribution of signal over frequency is known as the PSD. Equation (1) can be used to describe the PSD of a stationary random process w_n.

$$O_{ww}(e) = \sum_{n=-\infty}^{n==\infty} Q_{ww}(n) f^{-2mifm/e_t} \tag{1}$$

In this case, e_t is the sampling frequency, and $Q_{ww}(n)$ is the signal's autocorrelation. One may determine the signal's power in a specific frequency range by integrating over both positive and negative frequencies (Equation (2)).

$$O(e1, e2) = \int_{e1}^{e2} O_{ww}(e)ce + \int_{-e1}^{-e2} O_{ww}(e)ce \tag{2}$$

For every one-minute segment, the HRV signal was a series of RR intervals. For feature extraction, every epoch with fewer than 30 data points was disqualified. It was examined after elimination. The beat number was the signal's index. All signals were normalized by computing their z-score (i.e., $(w - \mu)/\sigma$, where μ is the average of the signal and σ is its standard deviation to remove the bias of the signal's mean and variance on feature extraction. Welch's method for calculating PSD.

3.4. Proposed method KO-PSVM

The combination of the KO and PSVM is explained in this section to analyze the psycho-stress level of students. The KO combined with PSVM provides an effective framework for analyzing students' psycho-stress levels. KO optimizes PSVM hyperparameters, enhancing classification accuracy by exploring and exploiting potential solutions.

3.4.1. Poly-kernel support vector machine (PSVM)

The PSVM is suitable for forecasting psycho-stress levels in students by effectively handling non-linear relationships within complex data. Its integration of polynomial kernels enhances model accuracy and adaptability, making it ideal for evaluating individual stress responses based on various input features, thereby improving personalized intervention strategies.

SVM

The fundamental theories of SVM are introduced in this part. SVM maximizes the distance between positive and negative instances to create an ideal separating hyper-plane as the decision plane. With a training dataset $R = \{w_i, z_i\}_{i=I}^{m}, (w_i \in Q^m, z_i \in Q), W_i$ is the $i - th$ input feature vector, z_i is the class label of w_i and m is the whole numeral of samples.

Following the completion of the training sample, the following ideal hyper-plane may be determined (Equation (3)).

$$o(w) = x^S \times \emptyset(w) + a \tag{3}$$

Where x is a hyper-plane vector, a is a bias term, and the input characteristic vector is mapped into high-dimensional characteristic space using the function of $\emptyset(w)$. The following quadratic programs can be solved to determine the estimated values of a and$x$. The quadratic program's Varangian in Equations (4)–(6) is given in Equation (7).

$$\min S(x, a, \varepsilon) = \frac{1}{2}||x||^2 + D\sum_{i=I}^{m} \varepsilon_i \tag{4}$$

$$s.t. z_i(x^S \times \emptyset(w_i) + a) \geq 1 - \varepsilon_i i = 1, .., m \tag{5}$$

$$\varepsilon_i \geq 0, i = 1, .., m \tag{6}$$

$$K(x, \varepsilon, a; \alpha) = S(x, \varepsilon, a) - \sum_{i=1}^{m} \alpha_i \{z_i(x^S \emptyset(w_i) = a) + \varepsilon_i - 1\} \sum_{i=1}^{m} \mu_i \, \varepsilon_i \tag{7}$$

For the dual formulation of the SVM (Equations (8)–(10)), partial derivatives of $K(x, \varepsilon, a; \alpha)$ concerning the primal variables are taken, and the results are then substituted into $K(x, \varepsilon, a; \alpha)$ in Equation (7).

$$maxK(x, \varepsilon, a; \alpha) = \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{j,i=1}^{m} \alpha_j \alpha_i z_j z_i L(w_j, w_i)\} \tag{8}$$

$$s.t. \sum_{i=1}^{m} z_i \alpha_i = 0 \tag{9}$$

$$0 \leq \alpha_i \leq di = 1, .., m \tag{10}$$

Where the kernel function is the inner product function $L(w_j,\ w_i)$, and α_i is the Lagrange multiplier of observation i. The dual optimization problem is solved to get the linear decision function, and the SVM problem may be made simpler as in Equation (11).

$$o(w) = sgn \sum_{i=1}^{m} \alpha z_i L(w_i, w) + a) \tag{11}$$

PSVM

The choice of the model' s kernel function is crucial. Different prediction models will be created by using SVM with various kernel functions, leading to varying prediction efficiency and accuracy. Global and local kernels are the two kinds of kernel functions that are frequently utilized in SVM. One common type of local kernel is the radial basis function (RBF) kernel. Equation (12) is the definition of its mathematical form. The kernel's parameter is denoted byσ. One common type of global kernel is the polynomial kernel, which has the following Equation (13). The kernel parameter is denoted by where$c$.

$$L_{\mathrm{RBF}}(w_j, w_i) = \exp\left(-\frac{1}{2\sigma^2} ||w_j - w_i||^2\right) \tag{12}$$

$$L_{poly}(w_j, w_i) = (w_j^S w_i + 1)^c \tag{13}$$

To increase SVM's prediction accuracy and generalization capacity, aPSVM is suggested. Both the local and global kernel functions make up the PSVM kernel function (Equation (14)).

$$L_{new} = \tau L_{RBF} + (1 - \tau) L_{poly} (0 < \tau < 1) \tag{14}$$

Where τ is the coefficient of weight. Mercer's theorem must be satisfied by the kernel function for it to be utilized as the SVM kernel. Mercer's theorem is also satisfied by the poly-kernel function L_{new}, which is created by the convex arrangement of L_{RBF} and L_{poly}. The poly-kernel function offers better distribution performance across various datasets and combines all the features of a conventional single kernel.

3.4.2. Kookaburra optimizer (KO)

The KO is well-suited for optimizing psycho-stress evaluation methods in students. Its dual-phase approach, combining exploration and exploitation, enhances the search for effective parameters. This adaptability allows KO to efficiently identify optimal solutions in complex problem spaces, improving stress assessment accuracy and intervention strategies.

Inspiration of KOA

Kookaburras are carnivorous birds found in Australia and New Guinea, weighing 300 g and 28–47 cm. They feed on mice, insects, snakes, frogs, reptiles, and birds. Their open beak allows them to dive and seek prey, and they repeatedly strike victims to ensure their safety. The KOA strategy was designed to protect prey.

Initialization of the algorithm

Using a population of kookaburras, the KO methodology is an iterative optimization technique that finds appropriate solutions for optimization issues. Based on where it is located in the problem-solving space, each kookaburra chooses its decision variables, creating a matrix that may be represented by a vector. At the start of the KO implementation, the kookaburras' positions are initialized at random (Equations (15) and (16)).

$$W = \begin{bmatrix} W_1 \\ \vdots \\ W_j \\ \vdots \\ W_M \end{bmatrix}_{M\times n} = \begin{bmatrix} W_{1,1} \dots W_{1,c} \dots W_{1,n} \\ \vdots \quad \ddots \quad \vdots \quad ⋰ \quad \vdots \\ W_{j,1} \cdots W_{j,c} \cdots W_{j,n} \\ \vdots \quad ⋰ \quad \vdots \quad \ddots \quad \vdots \\ W_{M,1} \cdots W_{M,c} \cdots W_{M,n} \end{bmatrix}_{M\times n} \tag{15}$$

$$w_{j,c} = ka_c + q.(va_c - ka_c) \tag{16}$$

The KO population matrix, W_j, represents the jth kookaburra, $w_{j,c}$ represents its cth dimension in search space, M represents the numeral of kookaburras, n represents the numeral of decision variables, q is a random number, and ubd and lbd represent the upper and lower bounds of the cth decision variable. The problem's function can be assessed using Equation (17).

$$E = \begin{bmatrix} E_1 \\ \vdots \\ E_j \\ \vdots \\ E_M \end{bmatrix}_{M\times 1} = \begin{bmatrix} E(W_1) \\ \vdots \\ E(W_j) \\ \vdots \\ E(W_M) \end{bmatrix}_{M\times 1} \tag{17}$$

The superiority of potential explanation and inhabitants members is gauged by the assessed objective function, E, which is a vector based on the jth kookaburra. The greatest member is represented by the best-assessed value, while the worst member is represented by the worst-estimated value. The goal function is reassessed and the best member is updated in tandem with the kookaburras' shifting locations.

KO mathematical modeling

- Phase1: Exploration (hunting strategy)

As carnivorous birds, kookaburras consume a wide range of creatures, such as frogs, insects, mice, reptiles, and birds. Their powerful necks help them hunt, which causes them to shift positions a lot. To avoid being mired in local optimal, this method embodies global inquiry and exploration. To replicate their hunting technique, the KO design uses the position of other kookaburras with superior objective function (OF) values as prey locations. Equation (18) determines each kookaburra's accessible prey set.

$$DO_j = \{W_l : E_l < E_j and l \neq j\}, where j = 1,2,..,M and l \epsilon \{1,2,..,M\} \quad (18)$$

Here, DO_j is the set of potential prey for the jth bird W_l is the bird that has a higher OF value than the jth bird, and E_l is the OF value. The KO proposes to assume that every bird chooses a victim at random and attacks it. Equation (19) is used to calculate the kookaburra's new position foundation on the imitation of its movement towards the prey in the hunting strategy; if the OF value in the new position is improved, Equation (20).

$$w_{j,c}^{O1} = w_{j,c} + q.\left(SCP_{j,c} - J.w_{j,c}\right), j = 1,2,..,M, and c = 1,2,...n \quad (19)$$

$$W_j = \begin{cases} W_j^{O1}, E_j^{O1} < E_j \\ W_j, else \end{cases} \quad (20)$$

The text describes a KO model with $W_j^{O1} W_{j,c}^{O1}$, E_j^{O1}, r, $SCP_{j,c}$, J, and M, as decision variables, based on a random number from sets 1, and 2.

- Phase 2: (Exploitation) Making certain the prey is dead

When attacking, kookaburras repeatedly strike their prey against a tree before crushing and devouring it. This activity, which is similar to local search with exploitation, causes minor shifts in their location close to hunting sites. The algorithm's capacity to adjust to local conditions is demonstrated by its goal of achieving better solutions close to achieved solutions and promising locations.

The KO design uses Equation (21) to determine a random location to emulate kookaburra behavior. The displacement takes place in a neighborhood whose radius, originally set to the maximum value, is equal to $\frac{(va_c - ka_c)}{s}$. To increase the accuracy of local searches, the radius gets smaller as iterations go on. Equation (22) states that each kookaburra's new position replaces its old one if it increases the objective function value.

$$w_{j,c}^{O2} = w_{j,c} +)(1 - 2q).\frac{(va_c - ka_c)}{s}, j = 1,2,...,M, c = 1,2,...,n, and s = 1,2,...,S \quad (21)$$

$$W_j = \begin{cases} W_j^{O2}, E_j^{O2} < E_j \\ W_j, else \end{cases} \quad (22)$$

W_j^{O2} represents the new recommended location of the jth bird based on stage 2 of KO, where $w_{j,c}^{O2}$ is its cth element, E_j^{O2} is it OF value, s is the algorithm's iteration timer, and S is the most numeral of iterations.

KO-PSVM: This hybrid approach captures complex relationships in the data, yielding robust predictions and actionable insights to support interventions in educational settings. The KO-PSVM algorithm 1 initializes a population of kookaburras and iteratively updates their positions based on exploration and exploitation strategies to optimize the objective function. After training a PSVM using the optimized parameters, it predicts the psycho-stress levels of new student data.

Algorithm 1 KO-PSVM

$Initialize\ KO\ parameters$
$\quad Input: Population\ size\ M, Number\ of\ decision\ variables\ n, Maximum\ iterations\ S$
$\quad W = Randomly\ initialize\ a\ population\ matrix$
$Evaluate\ initial\ objective\ function\ values$
$\quad For\ each\ kookaburra\ W_j\ in\ W:$
$E_j = ObjectiveFunction(W\_j)$
$For\ iteration\ t = 1\ to\ S:$
$\quad a. Exploration\ Phase\ (Hunting\ Strategy)$
$\qquad For\ each\ kookaburra\ W_j:$
$DO_j = \{W_l: E_l < E_j and l \neq j\}, where j = 1,2,.., M and l \epsilon \{1,2,.., M\}$
$\qquad\quad Choose\ a\ random\ prey\ W_j from\ DO\_j$
$\qquad\quad Update\ position\ based\ on\ prey\ location$
$w_{j,c}^{O1} = w_{j,c} + q.\left(SCP_{j,c} - J.w_{j,c}\right), j = 1,2,.., M, and c = 1,2, \ldots n$
$\qquad\quad If\ E_j^{O1} < ObjectiveFunction(W_j^{O1}):$
$W_j = W_j^{O1}$
$\quad b. Exploitation\ Phase\ (Ensuring\ Prey\ Is\ Killed)$
$\qquad For\ each\ kookaburra\ W\_j:$
$w_{j,c}^{O2} = w_{j,c} +)(1 - 2q).\frac{(va_c - ka_c)}{s}, j = 1,2, \ldots, M, c = 1,2, \ldots, n, and s = 1,2, \ldots, S)$
$\qquad\quad If\ E_j^{O2} < ObjectiveFunction(W_j^{O2}):$
$W_j = W_j^{O2}$
$Train\ Polynomial\ Support\ Vector\ Machine$
$\quad Construct\ the\ training\ dataset\ R = \{W_i, Z_i\}$
$\quad Solve\ the\ quadratic\ program\ to\ find\ a\ and\ x$
$\quad Calculate\ the\ decision\ function\ using\ the\ dual\ formulation$
$Predict\ psycho\ stress\ level\ using\ trained\ PSVM\ model$
$\quad Input: New\ student\ data$
$\quad Output: Predicted\ psycho - stress\ level$

4. Experimental result

This section discusses the system configuration for detecting mental stress, evaluation metrics, and performance results of the proposed KO-PSVM model. It also compares the KO-PSVM with existing methods highlighting its superior performance.

4.1. System configuration

The system designed for detecting mental stress through Pulse Rate Variability (PRV) analysis features an Intel Core i7-1200K processor with 32 GB of DDR4 RAM and a 1 TB NVMe SSD, supported by a 2 TB HDD for data storage. It utilizes an NVIDIA RTX 3080 GPU to accelerate ML tasks and operates on Ubuntu 22.04 LTS. Key software includes Python 3.10, along with libraries like NumPy, pandas, and sci-kit-learn for data processing and ML.

4.2. Evaluation metrics

The performance of the suggested methods in detecting the psycho-stress level of students is estimated using various metrics including F1-Score, precision, accuracy, and recall.

- Accuracy: It represents the ratio of every result to precisely anticipated observations. The whole sample size is separated by the sum of the True negative (TN) and True positive (TP) values to regulate accuracy (Equation (23)). False Positive (FP) and False Negative (FN).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FN} + \text{FP}} \tag{23}$$

- Precision: The measure expresses the degree of accuracy of the positive forecast as the proportion of TP to the whole of FP and TP. This is crucial for applications where false positives can lead to significant issues (Equation (24)).

$$Precision = \frac{TP}{TP + FP} \tag{24}$$

- Recall: It is calculated to assess a model's capacity to recognize all pertinent cases. It is essential for applications where missing a positive occurrence is critical.

$$Recall = \frac{TP}{TP + FN} \tag{25}$$

- F1-Score: It is the precision and recall's harmonic mean considering, that a single score stability both objectives. It is available in extremely helpful while working with unbalanced datasets.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{26}$$

4.3. Output phase

The KO-PSVM model demonstrated strong performance in stress detection, with a superior accuracy of 92%. It achieved 80% precision, indicating a reliable proportion of TP predictions. The recall rate was high at 98%, indicating its ability to identify nearly all stress cases. The F1-Score of 88% balanced precision and recall, making the KO-PSVM a highly effective model for identifying emotional and cognitive states in educational contexts (**Table 1**).

Table 1. Output of the proposed method.

Method	Precision (%)	Accuracy (%)	F1-Score (%)	Recall (%)
KO-PSVM [Proposed]	80	92	88	98

4.4. Comparison phase

The suggested method is compared with the traditional methods including Naïve Bayes [18] and Sequential Minimal Optimization (SMO) [19] in detecting the psycho-stress level of students.

Table 2 and **Figure 3** present a comparison of the accuracy of three different methods used in the study. They NBattained an accuracy of 90.00%, demonstrating a strong performance in correctly classifying instances. The SMO method, however, performed significantly lower, with an accuracy of 69.23%, indicating its limitations in this context. In contrast, the proposed KO-PSVM surpassed both; attaining an impressive accuracy of 92%. This result indicates the effectiveness of the KO-PSVM method in accurately detecting stress levels based on the data, positioning it as a superior choice compared to the other methods evaluated.

Table 2. Accuracy comparison.

Method	Accuracy (%)
Naïve Bayes [24]	90.00
SMO	69.23
KO-PSVM [Proposed]	92

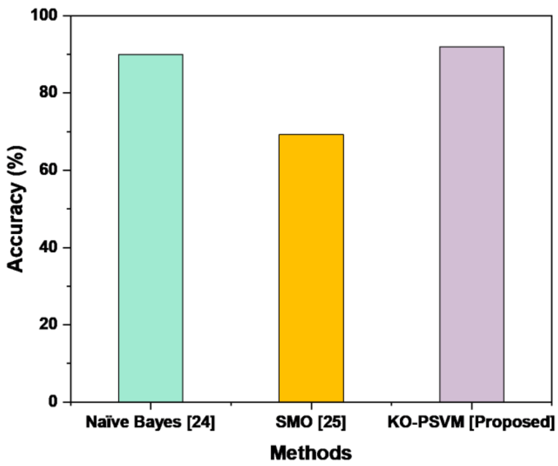

Figure 3. Comparison of model performance in terms of accuracy.

Table 3 and **Figure 4** compare the precision of the three classification methods. Precision measures the ratio of TP results between all positive forecasts, which is crucial for assessing the reliability of the classifiers. The NB achieved a precision of 78.41%, indicating that it properly identified an important number of positive cases but still had room for improvement. The SMO method lagged with a precision of 69.20%, suggesting the rate of false positives. Conversely, the proposed KO-PSVM achieved a precision of 80%, representing its enhanced capability to correctly identify TP cases while minimizing false positives, thereby reinforcing its effectiveness in stress detection tasks.

Table 3. Precision comparison.

Method	Precision (%)
Naïve Bayes [24]	78.41
SMO	69.2
KO-PSVM [Proposed]	80

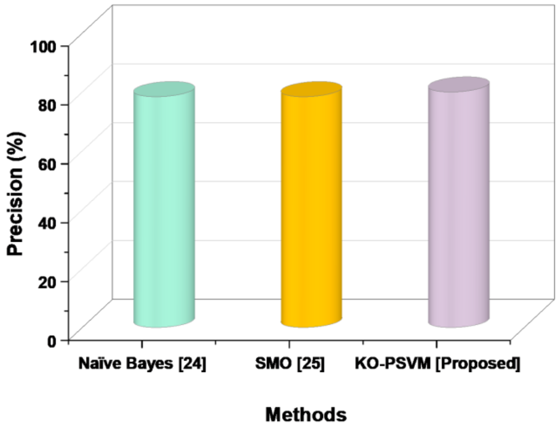

Figure 4. Comparison of model performance in terms of precision.

Table 4 and **Figure 5** outline the recall rates of the three classifiers, which measure the ratio of definite positive cases that were properly recognized. The NB demonstrated a high recall of 97.18%, suggesting it was very effective in detaining most of the TP instances. In contrast, the SMO method exhibited a much lower recall of 69.20%, indicating it missed a considerable number of TP cases. The proposed KO-PSVM outperformed both, achieving a recall rate of 98%, which indicates its exceptional ability to identify nearly all actual stress cases in the dataset. This performance emphasizes the KO-PSVM's effectiveness in scenarios where detecting as many true positives as possible is critical.

Table 4. Recall comparison.

Method	Recall (%)
Naïve Bayes [24]	97.18
SMO	69.2
KO-PSVM [Proposed]	98

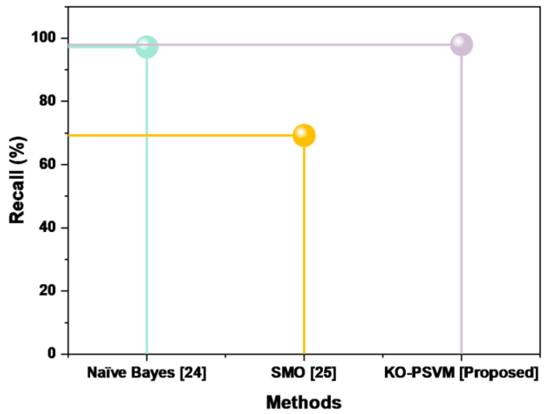

Figure 5. Comparison of model performance in terms of recall.

Table 5 and **Figure 6** offer a contrast of the F1-Scores for the different category techniques. This metric is especially functional for comparing models whilst there may be an uneven class distribution. The NB classifier recorded an F1-Score of 86.79%, reflecting a very good balance between precision and recall. The SMO approach, however, demonstrates a lower F1-Score of 81.8%, highlighting its weaknesses in both precision and recall. The proposed KO-PSVM performed the highest F1-Score of 88%, illustrating its strong overall performance in preserving a high stage. This superior F1-Score suggests that the KO-PSVM no longer excels at identifying real positives but also does so reliably, making it a distinctly powerful approach for stress detection.

Table 5. F1-Score comparison.

Method	F1-Score (%)
Naïve Bayes [24]	86.79
SMO	81.8
KO-PSVM [Proposed]	88

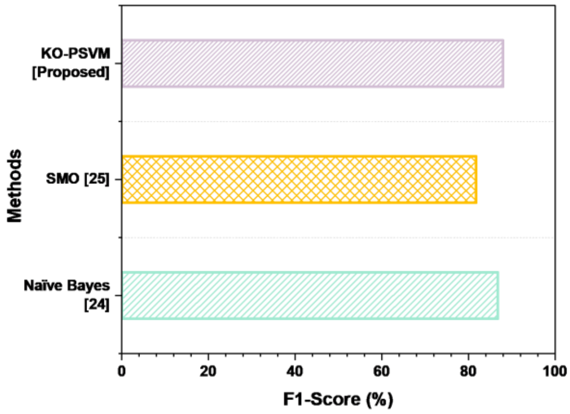

Figure 6. Comparison of model performance in terms of F1-Score.

5. Discussion

There are many limitations with the Sequential Minimal Optimization (SMO) and Naïve Bayes (NB) methods. Although SMO works well for training, Support Vector Machines (SVM) have struggled with large, noisy datasets that are typical of biosensing applications. This results in higher computing costs and slower processing speeds. Its total performance also depends heavily on selecting the appropriate kernel, which can be challenging when dealing with complex biosensing data. In difference, NBassumes feature independence, which is unrealistic in psychoanalytical data since physiological signals (e.g., skin conductivity, heart rate) are often interdependent. Naïve Bayes makes the improbable assumption that features are conditionally unbiased in many real-world situations, which could severely reduce its predicting accuracy when features are correlated. Although NB is effective for categorical data, it has trouble with non-stop variables until they are roughly represented by a distribution such as Gaussian, which may not always accurately reflect reality. Additionally, NB suffers from poor performance on minority training due to its sensitivity to elegance imbalances, which frequently favor the greater approach in imbalanced datasets. Lastly, given short datasets, either strategy may exhibit poor generalization, with SMO perhaps failing to identify an effective decision boundary because of constrained data and Naïve Bayes failing to accurately estimate probabilities. The limitations of NB and SMO in biosensing applications are addressed by the KOO-PK-SVM. In addition to SVM optimization, the Kookaburra Optimizer improves computing performance and handles larger, noisier datasets than SMO. Because of its independence assumption, Naïve Bayes is unable to recognize the distinctive interdependencies in biosensing data that the Poly-Kernel addresses. Additionally, KOO-PK-SVM effectively manages class imbalances, enhancing the overall performance of minority classes. It improves psychoanalytical predictions in education by providing greater generalization on limited datasets, ensuring precise decision boundaries, and providing reliable possibility estimation.

6. Conclusion

This examination highlights the transformative function of the biosensing era in psychoanalysis, specifically in the context of enhancing ideological and political training. By utilizing the KO-PSVM, the studies efficiently recognized and analyzed students' emotional and cognitive states, accomplishing excessive performance metrics, which include 92% accuracy, 98% recall, 80% precision, and 88% F1-Score. These findings underscore the potential of biosensing devices to create greater personalized and powerful learning surroundings, facilitating deeper engagement with complicated ideological content material. The integration of real-time statistics analysis not only enriches educational methodologies but also additionally educators to reply greater dynamically to students' psychological needs. Ultimately, this examination paves the way for destiny improvements in instructional practices that leverage the era to foster meaningful learning reviews.

Limitation and future work: The limitations include an undersized sample size of 27 participants, which affects the generalizability of the result, and the reliance on a single biosensor type, probably overlooking different physiological signs. Future research must aim to amplify the pattern size and contain numerous biosensing technologies, such as EEG and ECG, to create a more comprehensive expertise on mental pressure. Additionally, exploring the mixing of actual-time information processing and system mastering strategies should decorate the adaptability of instructional techniques, fostering a greater responsive mastering environment tailored to male or woman pupil desires.

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