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Article

Construction of machine learning based psychological crisis warning model for college students integrating biomechanics indicators

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Abstract: College students these days are under a great deal of psychological stress. This stress, whether originating from academic demands or personal life challenges, triggers a cascade of biological responses within the body. Physiologically, stress can disrupt the normal functioning of the endocrine system, leading to abnormal secretion of stress hormones like cortisol, affecting neurotransmitter levels and neural plasticity, thereby impacting mental health. If left unaddressed, this psychological stress can have severe and lasting negative effects on their well-being. In this context, it is crucial to quickly identify students experiencing mental health crises. However, the manual verification method has significant constraints and cannot effectively ascertain the mental state of the students. To address these challenges, this research proposes a Machine Learning-based Psychological Crisis Warning (ML-PCW) framework, integrating biomechanical indicators to provide unique insights into students' psychological states. For instance, changes in gait patterns can be associated with different emotional states, where abnormalities in walking speed, stride length, or body sway may indicate increased stress or anxiety. In the digital age, college students are more inclined to express their emotions through online platforms. Big Data analytics has emerged as a powerful tool for analyzing this digital footprint, providing valuable insights into their psychological states. Additionally, statistical techniques are employed to establish an emotional assessment paradigm that considers not only traditional psychological factors but also biological and biomechanical cues. In this research, the honey badger search-joint adaptive kernelized support vector machine (HBS-AKSVM) technique is developed. This technique is designed to handle the labeling process of the initial data, which includes both psychological and biological data. By incorporating biomechanical indicators, the HBS-AKSVM can more accurately categorize and analyze the data while minimizing the computational load during the development of the PCW system. Research findings show that the suggested approach operates more effectively than current approaches in terms of supplying professionals with a psychological supplementary assessment that is dependable. By integrating biomechanical indicators, the ML-PCW framework offers a more comprehensive and accurate understanding of college students' psychological states, enabling early detection and timely intervention in mental health crises.

Keywords: Psychological crisis warning (PCW); machine learning (ML); college students, big data (BD); internet; honey badger search-joint adaptive kernelized support vector machine (HBS-AKSVM); artificial intelligence (AI); biomechanics indicator

1. Introduction

The physical and mental growth of college students is undergoing significant changes, making them a unique social group. They are susceptible to changes in behaviors, cognitive processes, interpersonal connections, values, ethics, employment notions, personality characteristics, etc. These changes can quickly result in psychological imbalance and psychological crises [1]. Colleges and universities are currently paying more attention to the problem of psychological crises and crisis intervention among college students several have established specialized counseling and guidance centers and given courses on mental health education. This is a consequence of both the restructuring of higher education and the unavoidable advancement of positive psychology [2]. The growth of university automation has resulted in the collection of a substantial quantity of data about student academic performance, which is crucial for fostering innovation and improvement in education. The large data that has been gathered also offers a solid basis for using data-driven methods in academic warning. Big data in education has enormous social benefits an increasing number of scholars are researching academic caution [3]. Colleges and institutions frequently make a concerted effort to develop web-based learning environments by using pertinent learning materials and platforms. Furthermore, these universities make an effort to improve student outcomes by offering a range of learning management systems that enhance instructional strategies. These feelings consist of trepidation, concern, and fear [4]. Education professionals, administrators, and counselors are increasingly concerned about the growing prevalence of anxiety and depression among students. Recognizing these mental health challenges significantly disrupt tached emic engagement, higher learning process and impact overall well-being [5].

The mental health crisis among college students and the need for immediate action has surfaced globally in the last ten years. This narrative is frequently believed to involve official campus-based behavioral or psychiatric intervention. Students have been portrayed as anxious, unhappy, and suicidal by this "crisis narrative," which may have given the idea that improving the mental wellness of learners is one of the top global concerns in educational institutions [6].

Patients with mental health illnesses experience difficulties with emotion, thought, and behavior, among other elements of their lives. The development of behavioral indicators of mental health is made possible by mobile health (mHealth) and electronic health (eHealth) technology, which make it possible to gather enormous amounts of data inconspicuously [7]. When combined with health-related information on psychiatric symptoms, questionnaire data alone may not provide a complete and accurate image of a patients for anxiety and depression disorder. However, mobile sensed data are often noisy, fragmentary, and contain a substantial number of missing observations. Therefore, creating strategies to address these data challenges is essential to realizing the therapeutic potential of mHealth solutions [8]. Both the general public and particular worker groups, including healthcare professionals, have been shown to experience high levels of psychological discomfort. The frequency of anxiety and depression has also been focus of numerous research. The students have seen a significant shift in their daily routines due to the closing of educational institutions and the shift to online instruction. According to earlier research, college students are more vulnerable to mental health issues including anxiety and despair [9]. By concentrating on first-year students, an especially vulnerable demographic, by using longitudinal data and assessing the effects of various Covid-related stresses, to builds on previous research. For several reasons, using longitudinal data represents a significant expansion. It first specifically looks at how survey participation changed before and during the outbreak; It can have an impact on the inner power of the frequent cross-section designs. Furthermore, imperfect remembering problems are resolved when individuals are asked to contrast their present psychological state with that of a previous era in cross-sectional designs. Second, after controlling for important variables like pre-existing mental health and psychosocial resources, it enables us to look into fundamental reasons [10].

1.1. The aim of this research

One disadvantage is that leveraging big data and AI to evaluate students' psychological states through their online conversations without their knowledge or agreement raises significant ethical questions about privacy and consent. The objective of the research by the novel honey badger search-joint adaptive kernelized support vector machine (HBS-AKSVM)) strategy is proposed. These findings verified the resonant Construction of the based PCW Model for College Students.

1.2. Contribution of the research

The primary contribution is listed as follows.

1) The ML-PCW framework combines a variety of datasets gathered from university students to enable thorough analysis and precise detection of psychological crises.
2) The system uses big data analytics to extract valuable insights from the information, enabling proactive interventions and support plans that are customized to each student's unique requirements.
3) The dataset validates the efficacy of the HBS-AKSVM methodology, showing it to be better than conventional techniques in terms of giving dependable additional psychological evaluations.

1.3. Organization of the paper

The article is arranged in the following order of organization: Section II evaluates the previous author's studies. Section III provides the materials and methods for the PCW model for college students. Section IV focuses on the experimental findings. Section V concludes the article with a few observations and recommendations for future policy research.

2. Related work

Academic stress may be the most significant factor affecting college students' mental health, so enhancing the monitoring of mental health issues among college students is an important area of research. To forecast students' mental health, information is gathered from the stress data. The Heuristic Fuzzy C means Clustering Algorithm (HFCA) is suggested in the research to analyze the academic performance, psychological health, and stress levels of college students. The HFCA assists in determining important elements that impact academic achievement, such as satisfaction with learning and involvement. To avoid mental health issues and guarantee that at-risk students receive the assistance they require, the project intends to create policies and approaches [11].

A psychological crisis person identification model based on the bipartite graph convolution network model (B-GCN) was developed to solve the inadequacies of conventional spotting approaches [12]. The model was based on the psychological questionnaire data and aimed to fully utilize the relationship information between students. Two sets of arrangements were made for the dimension facts. Subsequently, SNK-q check, chi-square test, descriptive analysis variance assessment, and unbiased pattern t-test were carried out using valid data. Finally, the impact and change in the well-being ranges of individuals with undesirable emotional indications after two years were examined [13]. It analyzed susceptibility variables using machine learning (ML) techniques. The world's higher education system must prioritize addressing the pupils' mental health education, enhance their psychological well-being, and improve their mental health condition. To interview individuals, determine risk and protective variables, and estimate the likelihood of school violence, it designed a risk assessment program. The attention of the research was to automate the possibility valuation process by creating ML and natural language processing (NLP) technologies. The impact of school violence was extensive, affecting not only the people and their families but also the staff members [14]. Studies have shown that students attending the most violent schools had less academic attainment, greater dropout rates, and low attendance. It suggested a remote supervision and deep learning (DL) architecture to build a textual commenting system that can automatically recognize high-risk suicide text messages. Common people have an anonymous and quick way to express their feelings on web-based social media platforms. In a specific Chinese social media data source, there were around 2 million messages, and thousands more were created daily [15].

Psychiatric models were widely used to understand mental health issues among students. According to these theories, there is a crisis since recognized anxiety and mood problems are so widespread. Seldom has it been acknowledged how important developmental processes like distinctiveness construction and determination are in accepting the kinds of discomfort University students can experience. To address the gap, it evaluates concurrently if developmental and psychological characteristics predict students' likelihood of experiencing emotional distress, which manifests as a propensity to feel too worried, unhappy, or overwhelmed to research [16]. An early investigation to determine whether models for predicting mental health symptoms created by combining data from longitudinal studies can be applied to other publicly available data sources. It integrated information from student life (students at universities) and cross-checked (individuals living with schizophrenia) investigations. Apart from evaluating generalizability, it investigated whether tailoring models to match mobile sensing data and increased model performance by oversampling severe symptoms that occurred less frequently, and the outcomes of leave-one-subject-out cross-validation (LOSO-CV) were presented [17].In outpatient treatment sessions, ML models for Natural Language Processing (NLP) were evaluated to determine the risk of suicide by utilizing a Smartphone app. Language samples, scores on standardized measures of depression and sociality, and the therapist's assessment of the client's mental health were all used in the data-gathering process. Suicidal risk was predicted using models that had previously been created. There was a need for innovation in risk detection given the rising incidence of teenage suicide. Suicidal people can be identified by ML using linguistic samples. The possibility trial was determined to measure the efficacy of ML models and investigate the usage of this technology in teenage therapy sessions [18]. The mixed-methods pilot experiment set out to find the way graduate medical psychology learners were acquainted with informal and informal artificial intelligence (AI) and ML over their academic careers. The usage of psychotherapy apps in mental health treatment was growing [19]. The objective was to assess several methods of script feature demonstration for public broadcasting positions and assess how well they performed when used in conjunction with automated ML (Auto ML) technologies [20]. This top system frequently overlooks signs of despair, according to error analyses. Furthermore, we have included visual aids that facilitate comprehension of the learnt classifiers.

The research used big data mining to provide a psychological crisis warning system for college students. The technique enhances the Random Forest (RF) algorithm by labeling and particle swarm optimization [21]. The technique could effectively evaluate complicated data and offer practitioners trustworthy psychological supplemental diagnoses, resolving the problem of noise in psychological sample data from college students. It evaluated the algorithms' capacity to give postings that a moderator would flag for quick attention priority.

3. Research methodology

The main objective of this investigation is to test the construction of an ML-based model for college students. In this research, a descriptive method was employed to systematically examine and characterize the characteristics, behavior, and perspective of college students regarding psychological crises. The exploration aimed to gather comprehensive data on different factors causal to psychological well-being, such as scholastic stress, financial pressures, and social interactions using formal questionnaires and data collection techniques. By avoiding any adjustment or amendment of the natural situation of the response, spearman's rank correlation and lasso regression analysis enable the estimate of elements and how they interact in the university environment, giving a complete picture of the perspectives and experiences of the students. Building a strong ML-based model to expect and administer PCW in college students requires this in-depth knowledge.

3.1. Dataset

HBS-AKSVM tested on the larger records, structured to estimate the psychological well-being of college students. The dataset comprises demographic and behavioral data collected from 1000 college students, evenly distributed across age groups and reflecting the gender distribution typical in higher education (600 males and 400 females) assists the model to efficiently identify the risk at individuals. Each student profile includes age, academic performance metrics, history of medical issues and medications which greatly influence the mental health of participants, experiences with college intimidation and leave requests, details of eating patterns, and assessments of sleep quality are generally cause higher possibilities of mental health issues. A total of 500 sample Psychological Crisis Warning (PCW) indicators were collected to ensure high-quality data. Psychological crisis indicators like depression symptoms, anxiety symptoms, stress reactions, suicidal ideation, Substance use and abuse, eating disorders, and psychotic symptoms were assessed using an HBS-AKSVM model because they had a strong correlation in assessing the mental crises and applied to responses from psychometric questionnaires administered to all participants. This dataset serves as the basis for exploring age and gender differences in construction and validating a predictive model to proactively identify at-risk college students and intervene effectively.

3.2. Questionnaire design

A questionnaire was used to gather information. For analyzing data, inferential as well as descriptive statistics were employed. The questionnaire was designed to gather information on specific factors related to PCW Model for college students. **Table 1** represents the sample questionnaire for PCW Model for college students and the research's questionnaire used a 5-point Likert-type scale and changed from previous investigations. A rating system that is used to ask respondents the degree to which they agreed with the assertions. The questionnaire ensured sophisticated input for assessment by offering a wide range of participants to provide their perspectives and expressions on several retirement-related issues.

Table 1. Sample questionnaire for physiological crises assessment.

S. No	Questions	Response
1.	How would you rate your academic performance?	1) poor 2) fair 3) good 4) very 5) Excellent
2.	How often have you felt overwhelmed or stressed in the past month?	
3.	How often have you experienced persistent sadness or loss of interest in activities recently?	1) Never 2) Rarely 3) Sometimes 4) Often 5) Always
4.	How often do you feel anxious, restless, or on edge?	
5.	Do you have any chronic medical conditions?	
6.	Have you experienced bullying or harassment at college in the past year?	(Yes/No)
7.	Have you had thoughts of self-harm or suicide in the past month?	
8.	How often do you consume alcohol or use recreational drugs?	1) Never 2) rarely3) Occasionally 4) frequently 5) very frequently
9.	How would you rank the quality of your sleep throughout the previous month?	1) very poor 2) poor 3) Fair 4) Good 5) Excellent
10.	How would you describe your eating habits?	1) Balanced 2) Mostly balanced 3) Irregular 4) Unhealthy 5) balanced

3.3. Statistical analysis

The predictive value data matrix and the whitened independent variable are entered into the analytic tool, SPSS 28.0.1.0 software. SPSS software defines the 2 methods Spearman's rank correlation and lasso regression analysis. These analyses are used for data preprocessing in the described method. Here is a more detailed explanation of how each is applied.

- Spearman's rank correlation

A non-parametric version of the rank relationship called Spearman's rank correlation is utilized to assess how well a monotonic function can define the correlation between two variables. It does not assume a linear relationship or normally distributed variables, making it more robust to outliers and non-linear relationships. The following formula for Spearman rank correlation coefficient$\rho_t = 1 - \frac{\delta \sum c_1^2}{m \times (m^2 - 1)}$. Where, C_j is the difference between the ranks of the j^{th} observation, and m is the number of observations.

- Lasso regression

Lasso regression selects variables and relates regularization to improve the statistical model it generates' predictability and interpretability. It reduces the residual sum of squares provided that the total of the coefficients' absolute values is less than a constant. The objective function for Lasso regression is $\min \left(\sum_{j=1}^{m}(Z_j - \beta_0 - \sum_{i=1}^{o} \beta_i w_{ji})^2 + \lambda \sum_{i=1}^{o} |\beta_i|\right)$, where,$\lambda$ is a tuning parameter that controls the strength of the regularization.

Table 2 presents the p-values for various influencing factors in the context of the ML-based PCW model for college students. Each factor's *p*-value indicates the statistical significance of its impact on predicting a psychological crisis. Factors such as personality characteristics learning pressure, sleep media use, stress coping strategies, economic situation, and emotional relationship all have threshold *p*-values less than 0.05 suggesting that they are statically significant contributors. Specifically, personality characteristics and emotional relationships have the lowest *p*-values (0.001), indicating a particularly strong influence on the likelihood of a psychological crisis. The low *p*-values for all these factors underscore their importance in developing accurate and effective predictive models for psychological crises among college students.

Table 2. Results of lasso regression analysis for handling participants' mental health assessment.

Influencing factor	*P*-value
Qualities of personality	0.001
Learning pressure	0.002
Physical health Statius	0.008
Academic performance	0.009
Social media	0.006
Family support	0.003
Sleep media use	0.011
Stress coping strategies	0.013
The state of the economy	0.004
Relationships on an emotional level	0.001

3.4. Predicting psychological crises using honey badger search-joint adaptive kernelized support vector machine (HBS-AKSVM)

- Honey Badger Search (HBS)

The honey badger Search (HBS) finds its inspiration in the behavior of the badger, an animal species that is known for its ability to locate honey**.** Updated expression processing equations replicate the dynamic search behavior of mining and hunting for honey by a honey badger. Some traits that honey badgers have are listed below. When faced with situations that prevent them from fleeing, their fearless nature will not stop them from engaging larger predators. The honey badger aggressively searches for food by moving slowly and discovering 50 holes throughout a 40-kilometer radius every day using the rat-smelling technique. Although honey badgers are fond of honey, they are not very adept at finding beehives to collaborate with birds. Together, they reap the rewards of cooperation as the bird leads the badger to the honeycomb and uses its strong claws to pry open the hive. The population initialization, updating the search agent's position, prey attraction, and density factor are all included in the HBS process model for the optimization method as shown in **Figure 1**.

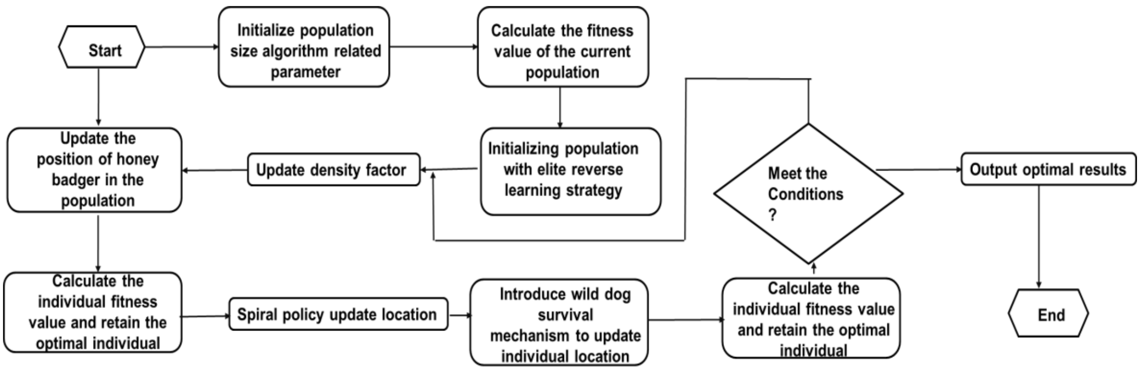

Figure 1. Methodological flowchart of HBS for psychological crisis detection.

Initialization: The following Equation (1) is an expression for initialization using the matric X solution.

$$W = \begin{pmatrix} W_{11}W_{12}W_{13}W_{14} \dots \dots W_{1c} \\ W_{21}W_{22}W_{23}W_{24} \dots \dots W_{2c} \\ W_{31}W_{32}W_{33}W_{24} \dots \dots W_{3c} \\ W_{41}W_{41}W_{43}W_{44} \dots \dots W_{4c} \\ \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \\ W_{m1}W_{m2}W_{m3}W_{m4} \dots \dots W_{mC} \end{pmatrix} \quad (1)$$

If C is a dimension, W_i is the position of the i^{th} person among the M candidate individuals, and W is a population made up of M honey badger individuals. The starting location of a honey badger is produced at random using the space search issue boundaries in the manner described In Equation (2).

$$w_{ji} = ka + q_1 \times (va - ka) \quad (2)$$

where $LbandUB$ represents the upper and lower bounds of the optimization space, respectively, and Q_1 is a random integer uniformly distributed over [0,1].

The mining and joining honey stages are the two phases involved in updating the search agent's location. A few aspects are taken into consideration, such as the density factor and the attractiveness of prey, to define the expressions before diving right into updating position expressions of the honey badgers mining and joining honey stages. Prey's concentration intensity and distance from the honey badger are key factors in determining the attractiveness of prey.

L_iIs the prey's odor intensity; a higher number indicates that the i^{th} honey badger can locate the prey more precisely and get there more quickly. It can be written mathematically as Equation (3).

$$L_i = q_2 \times \frac{T}{4\pi c_i^2} \tag{3}$$

where the terms source intensity and the separation between the target and theW_i honey badger are T andT_i, respectively. The following is the expression for two variables as shown in Equations (4) and (5).

$$T = (W_i - W_{i+1})^2 \tag{4}$$

$$c_i = W_o - W_i \tag{5}$$

where W_o is the prey's location that the algorithm considers to be the position of the ideal individual. The attraction between a honey badger and its victim increases with proximity. To facilitate a seamless transition from exploration to development, the density factor gradually drops with the number of repetitions. To lessen randomness, the decreasing factor is updated with the excess number of rounds, which can be stated mathematically as Equation (6).

$$\alpha = D_0 \times exp\left(\frac{-k}{k_{max}}\right) \tag{6}$$

where k is the current iteration count, K_{max} the number of iterations that can be reached at most, and $D_o$is a constant greater than or equivalent to one, and the default value of D_o is 2.

The way honey badgers search for prey is expressed in the mining stage as follows in Equation (7).

$$W_{new} = W_o + E \times \beta \times L \times W_o + E \times q_3 \times c_i \times |\cos(2\pi r_4)[1 - \cos(2\pi r_5)\ ]| \tag{7}$$

In this case, C_i Indicates the separation between the target and the i^{th}honey badger, W_O represents the ideal prey position and β higher than or equal to 1 indicates how well honey badgers can acquire food. Three distinct random values between $0\ and$ 1 are denoted by the letters Q_3, Q_4, and Q_5. Prey odor intensity is$L$. The agent uses E as the search direction to rigorously shift the search direction in Equation (8).

$$E = \begin{cases} 1, q_6 \leq 1/2 \\ -1, q_6 > 1/2 \end{cases} \tag{8}$$

Due to the innate cooperation and mutual benefit of birds, the honey stage is the second location update procedure with the honey guide. The honey guide searches a variety of locations for the hive. It will give a piercing scream when it locates the hive. The following is the updated expression as Equation (9).

$$W_{new} = W_o + E \times q_7 \times \alpha \times c_i \quad (9)$$

where $E$and α are papers that are computed in updating the honey badger searches at a spot near the W_O position; W_{new}Indicates the new position of the honey badger, and indicates where the prey is W_O.HBS finds its inspiration in the behavior of the badger as shown in Algorithm 1.

- Adaptive kernelized support vector machine (AKSVM)

Utilizing ASKSVM architecture, the student performance prediction model is put into practice. Generally speaking, it has an output layer and several hidden SVM layers. AKSVM offers several advantages over other architectures, including the ability to manage the problem of very large input vectors and small training datasets, more flexible kernel function design, and strong regularization power in the output layer SVM to prevent over-fitting. **Figure 1** depicts the AKSVM flow. List the following integers: $C, K, N, M, andO$. It is important to note that there is no set number of concealed layers. Analysis of the number of layers selected using grid search will be done. To lower the processing power required for the best search, authors have proposed using grid search. In real-world applications, a small number of hidden layers are often attained; however, adding more hidden layers might make the model perform worse. AKSVM often uses the linear, sigmoid, O^{th} order polynomial, and radial basis function (RBF) kernel functions. The primary concern is that these kernels could not produce the optimal outcomes in every application. Customizing the kernel for each application is beneficial, which is why Multiple Kernel Learning (MKL) has garnered a lot of attention. In this research, the typical kernel functions are combined by the AKSVM using MKL. To construct the final kernel function, the combination of kernel functions must adhere to Mercer's theorem. By using the benefits of each kernel, the classifier can perform better. The authors take into account sigmoid, linear, RBF, and O^{th} order polynomial kernels. To conform to the main focus of comparable publications. They are defined using kernel function $L(w_1, w_2)$ with inner products(w_1, w_2), respectively, using notation (10–13).

$$L_1(w_1, w_2) = \langle w_1, w_2 \rangle \quad (10)$$

$$L_2(w_1, w_2) = exp(||w_1 - w_2||^2 / 2\sigma) \quad (11)$$

$$L_3(w_1, w_2) = (w_1, w_2 + d)^o \quad (12)$$

$$L_3(w_1, w_2) = tang(w_1, w_2 + d) \quad (13)$$

where o is a positive integer and σ and d are real values.

For MKL, a heuristic method is used. Here is a summary of the fundamental formulations as shown in Equation (14). Describe the kernel alignment $E(L_j, r)$ between the label set y and the kernel matrixL_j.

$$E(L_j, r) = \langle L_j, rr^S \rangle E / \sqrt{\langle L_j L_j \rangle E \langle rr^S, rr^S \rangle E} \quad (14)$$

Essentially, a high contribution to the final kernel exists if L_j has a large alignment to y. Consequently, the definition of the F-heuristic is Equation (15).

$$\mu_j = E(L_j, r) / \sum_{j=1}^{4} E(L_j, r) \quad (15)$$

The mean square error (MSE) might be taken into consideration to further integrate it. Affirmative becomes an M-heuristic as shown in Equation (16).

$$\mu_j = \sum_{j=1}^{4} (N_j - N_i) / \sum_{i=1}^{4} \sum_{j=1}^{4} (N_j = M_i) \quad (16)$$

The use of HBS-ALSVM for predicting psychological crises shows promise in enhancing accuracy and reliability. This advanced approach integrated adaptive kernelization with efficient search strategies, aiming to optimize predictive models based on complex psychological data. By leveraging to techniques, the model aims to provide robust insights into potential crises, thereby facilitating proactive interventions and support for college students' mental health needs.

Algorithm 1 HBS-AKSVM

Initialize:
Require: W and Z loaded with training labeled data $\propto \Leftarrow 0$ or $\propto \Leftarrow$ partially trained HBS-AKSVM
D $\Leftarrow$ some values
Return
    For all $\{w_i, z_j\}$, $\{w_i, z_j\}$ do
            Optimize α_i and α_i
        End for
  Until mo changes in $\propto$ or resource constraints criteria met
Ensure: Retain only the support vector $(\alpha_i > 0)$
Return
Establish parameters$s_{\max}$, M, β, and D.
Start the population at random places
Assess each honey badger position's fitness w_j using the goal function and assigning to e_j, $j \in [1,2, \dots, M]$
Save the best spot $w_{prey}$and determine the suitability ofe_{prey}.
While$s \leq s_{max}$do
Refresh the component that is dropping α.
    For $j = 1$ to M do
            Determine the intensity I_j.
    If$q < 0.5$ then
            Revise the position w_{new}.
    Else
            Revise the position.
    end if
            Assess the new role and designate a new one.
    if$e_{new} \leq e_j$ then
            Set $w_j = w_{new}$and$e_j = e_{new}$
    End if
    if$e_{new} \leq e_{prey}$ prey then
    Set $w_{prey} = w_{new}$and$e_{prey} = e_{new}$
    end if
end for
conclude with the Stop criterion met
return w_{prey}

4. Result

4.1. Experimental setup

To confirm the viability of the suggested detection technique, the psychological warning analysis investigation uses Python. In the meanwhile, the approach displayed is followed in the construction of further experimental settings. This equipped with robust hardware and software configurations to support advanced computational tasks. It features AMD Ryzen 7 5800X processor and 32GB of DDR4 memory, ensuring high-speed processing and efficient multitasking. Graphics-intensive tasks are managed by the NVIDIA GeForce RTX 3080 GPU, supported by a 1TB NVMe (nonvolatile memory express) SSD for fast data access. Operating on Ubuntu 20.04 LTS, development is facilitated through Python 3.9 leveraging TensorFlow 2.7 for GPU- GPU-accelerated DL tasks and OpenCV 4.5.3 for image processing. CUDA 11.4 and CUDNN 8.2.1 provide optimized frameworks for GPU computing, enhancing performance and scalability.

4.2. Performance evaluation

The experimental assessment index consists of two main components: model fitting performance and consideration. The model fitting factor is the goodness of fit index (GFI). The GFI index, which takes into account the major influence of sample size on test findings, can be described as the square sum of the variances among the matrix of observations and the correlation coefficient of the replicating matrix of the gathered data, as well as the recorded variance. The following is the Equation (17) expression for GFI.

$$GFI = 1 - \frac{tr((\sum(\hat{\theta})^{-1}(T\sum(\hat{\theta})))^2)}{tr(((\hat{\theta})^{-1}T)^2)} = 1 - \frac{tr((\sum(\hat{\theta})^{-1}T - J)^2)}{tr(((\hat{\theta})^{-1}T)^2)} \tag{17}$$

where w^2 the model's chi is the square value and $\sum(\hat{\theta})$ is the covariance matrix suggested by the psychological assessment model for college students. It should be noted, however, that $tr((B^2)) = tr(AA')$

- Goodness of Fit Index (GFI): GFI is a statistical measure used to assess how well an ML model fits the observed data in predicting psychological crises among college students. It evaluates the proportion. The equation for GFI is Equation (18).

$$GFI = \frac{\sum(\hat{z} - \hat{z})^2}{\sum(z - \bar{z})^2} \tag{18}$$

where z are actual values, $\hat{z}$ are predicted values and $\hat{z}$ is the mean of z. A GFI closer to 1 indicates the model fits the data well, suggesting that it effectively predicts psychological crises among college student.

- Root Mean Square Error (RMSE): According to the PCW model, RMSE measures the average difference between observed and projected values and actual values for college students. It provides a measure of the model's accuracy in predicting outcomes. Mathematically, it is calculated as Equation (19).

$$RMSE = \sqrt{\frac{1}{m}\sum_{j=1}^{m}(Z_j - \hat{Z}_j)^2} \tag{19}$$

where, Z_j represents actual psychological crisis indicators, $\hat{Z}_j$ represents predicted values and m is the number of annotations. A lower RMSE indicates a better fit of the model of the data, implying more accurate predictions of potential psychological crises among college students.

- Mean Absolute Error (MAE): MAE measures the typical degree of faults in a set of predictions, without considering their direction. It is less sensitive to outliers compared to RMSE. Mathematically, it is represented as Equation (20).

$$MAE = \frac{1}{m}\sum_{j=1}^{m}|Z_j - \hat{Z}_j| \quad (20)$$

where Z_j represents observed indicators of psychological crisis, $\hat{Z}_j$ is predicted values and is the number of observations. A lower MAE indicates that the model predictions are closer to actual outcomes, suggesting a more accurate identification of potential psychological crises in college student.

4.3. Outcomes of analysis

In evaluating methods for a PCW for college students, GFI values like 249.21 for HBS-AKSVN indicate robust fir compared to 94.23 for PSO-RF and 38.57 for the traditional method. These values highlight HBS-AKSVM's potential to improve predictive accuracy and early intervention strategies for mental health crises among students. GFI predictive accuracy values are as shown in **Figure 2**.

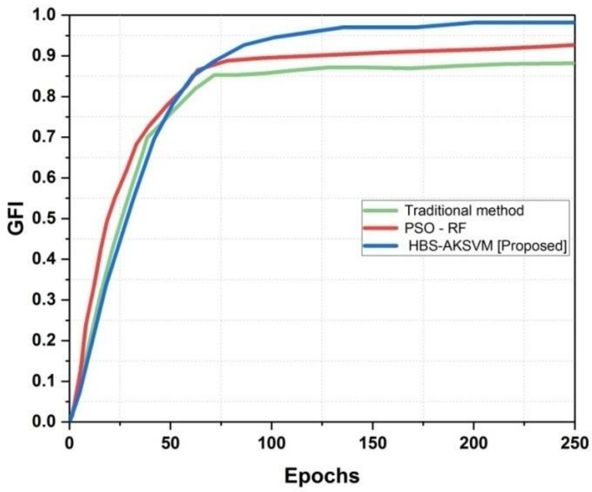

Figure 2. GFI performance of the HBS-AKSVM method over existing approaches.

In the proposed HBS-AKSVM method against traditional linear scaling, significant differences in RMSE values are observed. The traditional methods show increasing RMSE values ranging from 1.21 to 246.65, indicating varied accuracy across scales. In contrast, the HBS-AKSVM method demonstrates more consistent performance with RMSE values stabilizing around 30.36 to 36.01, suggesting enhanced reliability in predicting psychological severity. These results underscore the methodological superiority of HBS-AKSVM in providing precise and consistent assessments, crucial for developing a robust PCW model tailored to college students. RMSE predictive accuracy values are as shown in **Figure 3**.

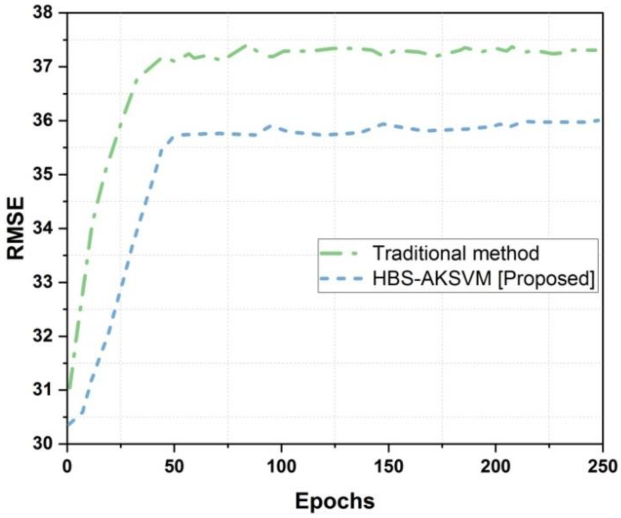

Figure 3. HBS-AKSVM RMSE outcomes compared with the traditional method.

In evaluating the efficacy of the proposed HBS-AKSVM against traditional methods using MAE, significant improvements are evident. For instance, the HBS-AKSVM achieves MAE values as low as 0.023, outperforming traditional methods which exhibit higher errors exceeding 100. This indicated the potential of HBS-AKSVM in accurately predicting psychological crises among college students, offering a robust tool for early intervention and support**.** MAE predictive accuracy values are as shown in **Figure 4**.

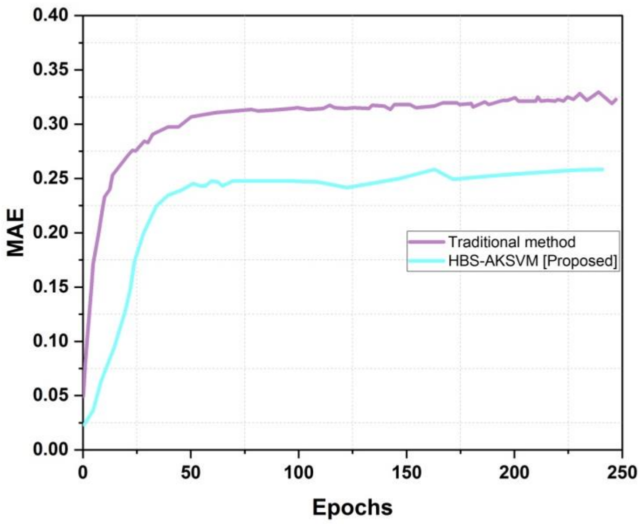

Figure 4. Comparative analysis of HBS-AKSVM, MAE outcome over the conventional method.

4.4. Outcomes of the proposed method

The effectiveness of a suggested method is contrasted with those of modern techniques such as the Singular Spectrum Analysis - Partially Periodic Regression

(SSA-PPR), Particle swarm optimization and Random Forest (PSO-RF) by calculating performance measures like RMSE and MAE.

- RMSE

In evaluating models for PCW, various methods were compared based on their RMSE performance as shown in **Table 3** and **Figure 5**. SSA-PPR exhibited an RMSE of 38.5, indicating its predictive limitations. The PSO-RF showed improved performance with An RMSE of 37.3, suggesting better predictive accuracy than SSA-PPR. The HBS-AKSVM approach, demonstrated the lowest RMSE at 36.12, highlighting its potential as an effective predictive tool for identifying and managing psychological crises among college students. These results underscore the significance of advanced hybrid models in enhancing early crisis detection and intervention strategies.

Table 3. Evaluation of RMSE values of HBS-AKSVM in crisis detection.

Methods	RMSE
SSA-PPR	38.5
PSO-RF	37.3
HBS-AKSVM [Proposed]	36.12

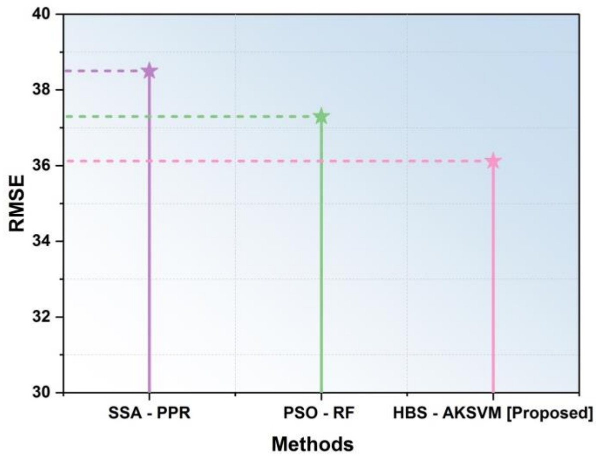

Figure 5. Overall RMSE outcome of HBS-AKSVM over two existing approaches.

- MAE

Table 4 and **Figure 6** illustrate that different approaches were evaluated in terms of their MAE performance when evaluating models for PCW. With an RMSE of 40, SSA-PPR demonstrated its predictive limits. The PSO-RF showed improved performance with An MAE of 32, suggesting better predictive accuracy than SSA-PPR. The HBS-AKSVM approach, demonstrated the lowest RMSE at 30, highlighting its potential as an effective predictive tool for identifying and managing psychological crises among college students. These results underscore the significance of advanced hybrid models in enhancing early crisis detection and intervention strategies.

Table 4. Assessing the MAE values of HBS-AKSVM for effective detection.

Methods	MAE
SSA-PPR	40
PSO-RF	32
HBS-AKSVM [Proposed]	30

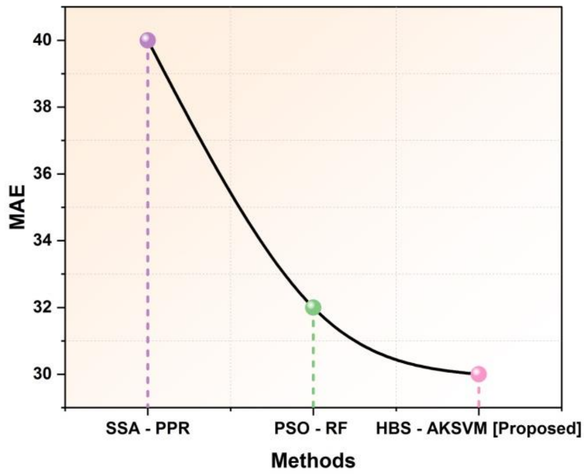

Figure 6. MAE evaluation of HBS-AKSVM over two established approaches.

4.5. Overall proposed method

These matrices RMSE and MAE indicate the model's prediction accuracy. An RMSE of 36.12 suggested the average error in predicting PCW scores, while an MAE of 30 indicated the average magnitude of these errors. Lower values in both matrices would significantly higher prediction accuracy, crucial for effectively identifying and intervening in student mental health crises as shown in **Table 5** and **Figure 7**.

Table 5. Performance values of HBS-AKSVM method parameters.

Parameters	Percentage
RMSE	36.12
MAE	30

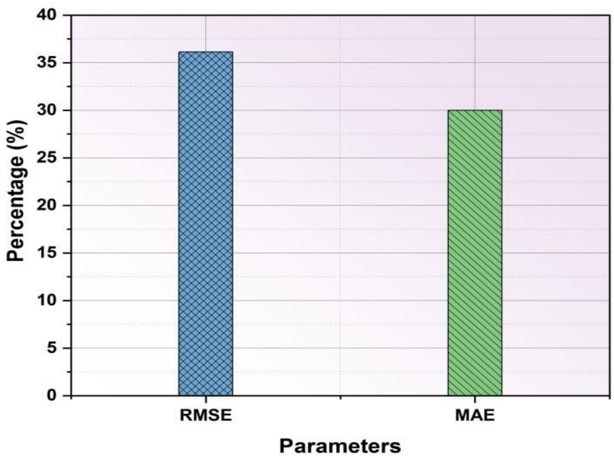

Figure 7. Evaluation of HBS-AKSVM effectiveness.

5. Discussion

The research offered an HBS-AKSVM model as a perfect solution for detecting and predicting physiological crises among students. By integrating an advanced hybrid model, the HBS-AKSVM approach adapts to the complexity of gathered information derived from online platforms and larger data analytics. This suggested approach demonstrated superior performance in evaluation metrics such as RMSE and MAE estimated with traditional methods like PSO-RF and SSA-PPR. Both the existing approaches are effective but, failed to deal with complicated trends in physiological data, leading to varying and greater degrees of error. The HBS-AKSVM technique resolves these restrictions by enabling adaptation in analyzing different patterns of data while ensuring stable reductions in errors. The greater stability and accuracy of the HBO-AKSVM method make it an important tool for early prevention strategies in health crises. In addition, the improved performances and decreased error rates emphasized the trustworthiness of the model, promising more accurate detection of psychological issues. Continuously the HBS-AKSVM offered a robust effective solution for developing a prior detection system tailored to the needs of individuals.

6. Conclusion

This research aimed to develop an ML-PCW framework for college students to promptly identify those experiencing psychological stress. This framework addresses the significant limitations of manual verification methods in effectively assessing the mental states of students, proposing an AI and ML approach to enhance to evaluate the psychological state of students, leveraging the authenticity of their online expressions. An emotional para diagram is established using statistical techniques to assess mental crisis HBS-AKSVM technique is introduced to label initial information and reduce the computational load during the development of the PCW system. The discoveries indicate that the proposed HBS-KSVM approach significantly outperforms in terms of RMSE (36.12%) and MAE (30%) than existing methods by providing professionals with a reliable supplementary psychological assessment tool that proved to the better model performance. This improved efficiency is critical in timely identifying and assisting students in psychological distress, thereby mitigating the negative impacts on their well-being and academic performance. However, the research has certain limitations. One major constraint is the reliance on data sourced from online platforms, which might not comprehensively represent the mental states of all students, especially those less active on the internet. Additionally, the model performance is reliant on the quality and quantity of the data available, posing challenges in generalizing the findings across different demographics and institutions. Future research should focus on integrating diverse data sources, including offline interactions, to enhance the robustness of the ML-PCW framework. Furthermore, exploring the applicability of the proposed techniques across educational contexts and incorporating advanced AI methodologies could cover the manner for a further accurate and inclusive mental health crisis detection system.

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