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The cultivation methods of humanistic spirit in college English teaching and its influence on students' mental health based on deep learning

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The observation of the reform and progress in English language instruction reveals a discernible pattern characterised by a focus on proficiency, excellence, and expertise. Since the inception of prioritising knowledge transmission, there has been a gradual shift towards recognising the need of inclusive skills training and development. This has further evolved to place a strong emphasis on fostering excellence in English instruction, with a special focus on nurturing artistic proficiency. Therefore, enhancing the development of humanistic traits in college English instruction is not merely a component of English teaching reform, but rather emerges as the primary concern that English educators must confront. The present study introduces a novel approach, namely the swallow swarm optimisation with a stacked autoencoder (SSOA-SAE) model, to investigate the mental health of college students in the context of English language education. The objective of the SSOA-SAE model is to ascertain the approach to fostering the cultivation of the humanistic spirit in the domains of English instruction and mental health. The SSOA-SAE model is implemented by first executing the SAE model in order to perform the classification process effectively. Furthermore, the Single-Source Optimisation Algorithm (SSOA) is employed to successfully adjust the hyperparameters associated with the Stacked Autoencoder (SAE) model. This study investigates a comprehensive series of simulations conducted on the SSOA-SAE model, and afterwards compares the findings with those of other established models. The

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predictive accuracy of SSOA-SAE in assessing the mental well-being of students enrolled in English courses with a humanistic approach is evaluated to be 99.88%. The simulation results indicated that the SSOA-SAE model demonstrated superiority above contemporary methodologies.

1. Introduction

The establishment of prestigious institutions of higher education is increasingly regarded as a matter of great significance within the realm of advanced education. Many scholars contend that an essential component in the creation of an exceptional university lies in the provision of humanities education. Moreover, humanistic education is not solely contingent upon one or a few subjects within the curriculum, but rather encompasses a comprehensive cultural education. Since the 1980s, there has been significant support from various experts for the investigation of the underlying reasons behind the evolution of university campus culture (Wang, 2022). China's educational system, spanning from primary school to university, has consistently emphasised the importance of sports. Sports education goes beyond showcasing athletic prowess and physical fitness; it encompasses a wide range of knowledge including logic, art, history, and literature. Sports education encompasses concepts related to sports, the essence of sports, and the ethical principles that shape students' character. It also contributes to philosophical and moral development, cultivates a contemporary cultural sensibility, and explores the inner spiritual realm. Individual socialisation holds significant educational value and is of utmost importance (Li, Lu, & Gong, 2021; Mody & Bhoosreddy, 1995).

The Chinese country has a superb custom of giving significance to the humanistic soul. Confucius, a renowned educator in ancient China, espoused the belief that the purpose of education is to equip pupils with the necessary skills and knowledge to effectively manage and conduct affairs. Confucius imparted to his disciples a comprehensive education in the six disciplines of rites, music, calligraphy, numeracy, archery, and eloquence. This ancient Chinese educational system aimed to instill in students the virtues of excellence, knowledge, character, and aesthetic refinement. According to Mr. Cai Yuanpei, an esteemed educator, it is acknowledged that the purpose of education is to cultivate the development of individuals' moral character (Wang, 2015). The prevailing perception regarding Chinese traditional educational philosophy is that individuals are classified or stratified. Despite a lengthy duration, the undeniable trajectory of industrialization and modernization, coupled with the global prevalence of pragmatism, has established utilitarianism as the dominant ideology. The growing proliferation of telematics services in the daily activities has given rise to the availability of digital data associated to different activity types generated in the devices (de Arriba Pérez, Santos Gago, & Caeiro Rodríguez, 2016). The progressive advancement of science and technology education has had a detrimental impact on the cultivation of humanistic values in higher education. This has resulted in a neglect of fostering students' ethical and moral development, as well as their ability to form well-rounded and informed opinions. Additionally, the emphasis on scientific and technological education has overshadowed the importance of providing enlightenment and broader perspectives to college students (Rider et al., 2018).

In our nation, over the course of time, our primary education system has failed to eradicate the dominance of test-oriented instruction. A considerable proportion of university students arrive on campus with an inherent deficiency in humanistic attributes (Garg, 2021; He, 2016). Similarly, in advanced education, there is a greater emphasis on specialisation rather than general knowledge, a greater emphasis on practicality rather than the study of humanities, a greater emphasis on vocational education rather than holistic education, and a greater emphasis on science and technology education rather than humanities education. These shifts have transformed traditional institutions of higher learning into institutions focused on developing specific skills and preparing individuals for professional careers. The disparity between science and humanities education gives rise to a dissonance between the rigour of scientific knowledge and the more subjective nature of humanities studies among college students (Ahmed & Ali, 2021; Wald et al., 2015). In the realm of collegiate English education, English instructors primarily focus on the fundamental skills of English acquisition and perceive English instruction as a purely linguistic endeavour, disregarding the cultivation of students' humanistic traits (Yan, Y., & Singh, M. K. M., 2023). By explicitly articulating the concept of humanistic education, it is suggested that educators have the potential to cultivate students as "gifts" rather than merely developing their skills (Musa, 2015). In a similar vein, the importance of English instruction is firmly established.

Language serves as a vehicle for transmitting culture, playing a pivotal role in the advancement of human civilization and intellectual development. The curriculum includes a wide range of humanistic elements, necessitating that college English instructors possess strong skills in analysing the humanistic significance of English education (O'Reilly & Lester, 2017; Usman, Shaharuddin, & Abidin, 2017). This approach aims to enhance students' awareness, promote their inclinations, foster character development, and integrate foreign language learning into their overall educational experience. The English teaching curriculum should ideally foster a positive and enriching experience for both educators and learners (Lonn & Dantzler, 2017). By means of diligent communication, educators and learners have the opportunity to enhance their disposition, cultivate their humanistic values, and improve the effectiveness of college English instruction.

An effective approach to assessing the effectiveness of a teaching reform that is rooted on humanistic principles is examining the psychological well-being of the pupils. The assessment of students' mental health can be conducted through the use of direct interviews, a method that requires a significant investment of time. Consequently, there is a pressing need for the development of an automated mechanism to evaluate a student's emotional well-being. Researchers believe that deep learning (DL) could potentially serve as a beneficial tool for making precise predictions regarding an individual's mental health. Conventional deep learning (DL) techniques have diminished efficacy when employed for the purpose of predicting mental health conditions. Therefore, it is necessary to employ an optimal deep learning technique for the purpose of this prediction.

The present study proposes a novel approach, namely the Swallow Swarm Optimisation with a Stacked Autoencoder (SSOA-SAE) model, to investigate the mental health of college students in the context of English education. The objective of the SSOA-SAE model is to ascertain the approach to fostering the cultivation of the humanistic spirit in the domains of English instruction and mental health. The SSOA-SAE model is implemented by first executing the SAE model to perform the classification procedure. Furthermore, the Single-Source Optimisation Algorithm (SSOA) is employed to successfully adjust the hyperparameters associated with the Stacked Autoencoder (SAE) model. This study conducts a comprehensive analysis of a series of simulations pertaining to the SSOA-SAE model, and subsequently compares these simulations with previously established models.

2. Related Works

The scholars in the cited works (Cai, 2022; Shahabaz & Afzal, 2021) investigate the state of college students' engagement with the historical culture in the context of "Internet +". This article examines the strategies for enhancing college students' proficiency in old cultural practises through the lens of "Internet +". It focuses on various aspects such as the curriculum system, educational methodologies, educational resources, the integration of traditional culture and campus culture, offline and online practical activities, as well as scale and personalization. Finally, this study presents techniques aimed at enhancing the traditional cultural competencies of college students in the contemporary day. The study conducted by Hidayati et al. (2022) primarily examined the governance of several characteristics observed within the Islamic Muhammadiyah Boarding College (MBS) (Hidayati et al., 2022). The educational institution is situated in Bantul, a specific region within the city of Yogyakarta, Indonesia. This research is classified as a case study. The author conducted a thorough examination of a time-limited activity, programme, event, or individual, employing a qualitative approach to inform decision-making. The data has been analysed via a descriptive research methodology.

In their study, Li (2021) and Tavares (2022) examines the many effects of the natural speaker ideal on the personalities of English as a Second Language (ESL) students, specifically focusing on the influence of language and cultural achievement. This study presents a case analysis of two English as a Second Language (ESL) students hailing from Brazil and Colombia, who are now enrolled at a Canadian university. The focus lies on the manner in which the attributes of students underwent changes as they implemented their approaches within the progressive neoliberal and individualistic environments prevalent in Canadian higher education. The findings illustrate instances of contradictory examples, as the students demonstrated a novel approach of individualistic uniqueness in constructing their conscious identities. The present study, as outlined in reference (Guo et al., 2020), presents a comprehensive examination of the impact of a ceremonial event dedicated to body contributors on the development of humanistic and ethical attitudes among medical students. The study encompasses a thorough introduction, description, and evaluation of these impacts. A comprehensive evaluation was conducted to ascertain the perspectives of third-year medical students regarding self-perceived changes, respect for healthcare providers and their families, and their connection with patients.

In his study, Chang (2020) examines the policies of education and culture in the context of physical education (PE) instruction at institutions of higher education. This article examines the cognition of culture and education in physical education (PE) teaching among 110 students and teachers in a university, utilising a combination of mathematical statistics and questionnaire review. The recent study conducted by Pant and Srivastava (2019) and Salihu and Iyya (2022) aims to investigate the correlation between mental health and spiritual intelligence. Additionally, the study seeks to identify any differences in mental health and spiritual intelligence based on educational background (science and arts) and gender. The present study used the goal-directed selection strategy to pick a sample of 300 college students majoring in arts and science disciplines. The participants are chosen from four distinct government degree campuses or colleges located in Haridwar.

In Shen and Gadekallu (2022) the authors introduced a resource search approach for mobile intelligent education systems, utilising a distributed hash table. The initial stage in developing an effective approach for resource discovery involves the utilisation of a distributed hash table and a vector space model. The issue of similarity between query vectors and vectors of location resources is resolved by establishing a vector link between location resources and user queries in order to identify multi-attribute resources. Ultimately, the identification of the most pertinent resources is determined based on the facts pertaining to resource similarity. In order to enhance the efficacy of the education system, a study conducted by Xiang, Fu, and Gadekallu (2022) employed the utilisation of K-means clustering technique to identify the most suitable allocation of resources. Table 1 presents a comprehensive summary of the conclusions gathered from previous studies.

Table 1

Summary of the related works

Reference	Methodology used	Advantages	Limitations
(Cai, 2022; Shahabaz &	Internet +	It promotes the college student's cultural	Students get more addicted to this

Afzal, 2021)		education quality and cultivates high-quality talents	approach
(Hidayati et al., 2022)	Character Education	Implementing character values such as independence, religious character, social character, team building, and ta'zim benefits students' mental health.	Obstacles to character education are parent's support and the school environment
(Li, 2021; Tavares, 2022)	Native-speakerism, Individualism, and Neoliberalism	Identities of high school students changed positively as the students navigated their experiences in the new individualist and neoliberal contexts	Some conflicting instances occur when students adopted a new individualist identity.
(Guo et al., 2020)	Combination of anatomy teacher's experience and honor ceremony in the context of humanism and ethics.	Gratitude ceremony positively promotes humanism in medical students	Lack of multi-centered survey including in-depth interviews and longitudinal follow-ups.
(Chang, 2020)	Cultural education strategies in physical education teaching	75.4% of the teachers and students think that culture and education can improve the performance of physical education	3.9% of the students think that physical education has negative impacts on culture and education
(Pant & Srivastava, 2019; Salihu &	Spiritual Intelligence Scale and Mithila Mental Health Status Inventory (MMHSI)	Female students are better compared to male students in terms of spiritual intelligence and	The scale of mental health and MMHSI, is not so good for the

Iyya, 2022)		mental health	present scenario, because some items are confusing in the scale.
(Shen & Gadekallu, 2022)	A mobile intelligent education system based on the distributed hash table	Provides resources with the greatest relevance to the search content	Complex process
(Xiang et al., 2022)	Educational resource matching using K-means Clustering	Accurately matches the required resources for users according to their needs, and has high practicability.	Consumes more time for the matching process.

3. Problem Statement

Enhancing the implementation of humanistic-oriented pedagogical reforms in college English courses represents a highly effective approach towards advancing educational progress and cultivating individuals who possess the requisite skills and competencies to meet the demands of the job market. Numerous challenges exist within contemporary education, necessitating a conscientious approach to the college English curriculum. Enhancing students' mental well-being and fostering their humanistic development can be achieved through the implementation of alternative teaching methodologies and the incorporation of diverse and comprehensive curriculum content. This process can be initiated by establishing a clear understanding of curricular orientation. The assessment of teaching reform based on humanistic literacy includes the evaluation of students' mental health as a significant indicator. Self-report questionnaires are frequently employed as a means of assessing the mental well-being of individual students. The process of manual assessment is intricate and lacks efficiency. Therefore, it is imperative to develop a mechanism for accurately predicting a student's mental health automatically. Deep learning is often regarded as a highly valuable technology in the realm of mental health prediction. The current state of deep learning models used for mental health prediction is characterised by their complexity, inefficiency, and time-consuming nature.

4. The Proposed SSOA-SAE Model

This study utilises a novel SSOA-SAE model to investigate the mental health of college English students. The objective of the SSOA-SAE model is to ascertain the approach to fostering the cultivation of the humanistic spirit in English instruction and mental well-being. The suggested Single Sign-On Authentication-Self-Attention Encoder model (SSOA-SAE) begins by implementing the Self-Attention Encoder (SAE) model to perform the categorization process with high efficiency. Furthermore, the Single-Source Optimisation Algorithm (SSOA) is employed to efficiently adjust the hyperparameters associated with the Stacked Autoencoder (SAE) model.

4.1. Process involved in SAE based Classification

The SSOA-SAE model is implemented by first executing the SAE model in order to perform the classification process with optimal efficiency. The autoencoder (AE) is trained in an unsupervised manner to generate the corresponding input with fewer construction errors during the result phase. Moreover, the autoencoder (AE) primarily experiences challenges in learning to integrate the input inside the feature space, which is diminished when it is linked to the input space (Hodashinsky et al., 2019). The selection of the code space dimension is typically based on maximising the classifier's speed of event optimisation by utilising the interconnected input space.

The autoencoder (AE) is now capable of producing efficient outcomes for the given input vector by utilising suitable coding techniques. The input dataset's dimension can be characterised, and the number of neurons in the hidden state is represented as, where and signify the set of positive integers. The links between the output and input of the encoder can be represented and expressed using Equation (1).

$$c = f(b + W^Z u)$$
(1)

The activity function of encoding neurons is described by f in Equation (1). The weight of the encoder can be characterised by matrix W, which relates the input of hidden states, while the vector b represents the bias. The equation (2) provides the relationship between the encoding units for output and input.

$$\hat{u} = \hat{f}(\hat{b} + \widehat{W} c$$
(2)

Eq. (2), $\hat{f}$ indicates the activation function of decoder neurons. The input - output relationships of the decoder should be implemented by $\hat{u} = g_D(\widehat{W}, \hat{b}; c)$. In the following, AE can be expressed by Eq. (3).

$$E_{sparse} = E_Z + \beta \sum_{q=1}^{N} KL(\rho \| \hat{\rho})$$
(3)

The current cost function consists of two distinct stages. The goal function of the neural network is denoted as E_Z. The symbol β is represented as the weight assigned to the sparsity penalty in Equation (4).

$$E_Z = \frac{1}{Z}\sum_{k=1}^{Z} e_k^2 + \frac{\lambda}{2}\left(\|W\| + \|\widehat{W}\|\right)$$
(4)

The regularisation term, denoted by λ in Equation (4), is primarily employed to mitigate the issues of overfitting. The error vector is defined as the differences in variances between the fundamental output and novel output, as stated in Equation (5).

$$e_k = \|u^{(k)} - \hat{u}\|$$
(5)

In Eq. (5), $k = 1, 2, \ldots Z$. It is easier for observing that E_Z is a formulation that represents the interior weight of AE and it is defined by Eq. (6).

$$E_Z = E_{AE}(W, b, \widehat{W}, \hat{b})$$
(6)

The SAE methodology can be identified as the encoding step of training an autoencoder (AE). The decoder component of the autoencoder (AE) is not utilised in the generation of the stacked autoencoder (SAE) as it is specifically selected for training the AE. Figure 1 depicts the organisational framework of the Society of Automotive Engineers (SAE). SAE, or Stacked Autoencoder, is a type of unsupervised learning architecture consisting of three layers: the input layer, hidden layer, and output layer. The encoder is utilised to transform the input data provided to the input layer into a hidden representation. Once all the concealed layers have undergone training, the decoder is employed to reconstruct the input data based on the hidden representation. The output layer is responsible for projecting the mental health status of the student.

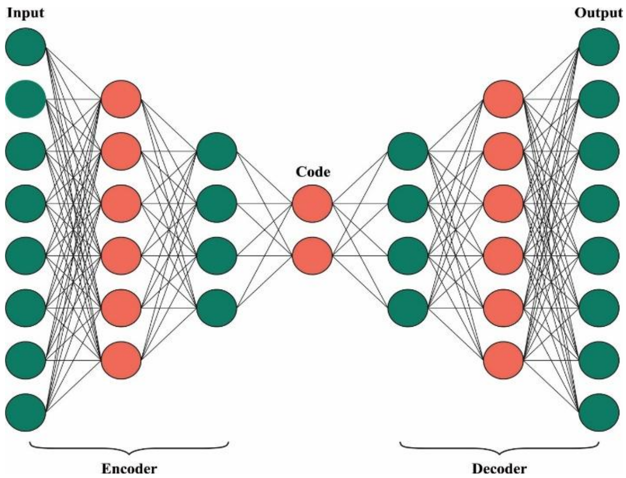

Figure 1. *Structure of SAE*

4.2. Process involved in SSOA based Hyperparameter Optimization

In this study, the Single-Source Optimisation Algorithm (SSOA) is employed to effectively adjust the hyperparameters associated with the Stacked Autoencoder (SAE) model. In their study, Neshat, Sepidnam, and Sargolzaei (2013) introduced a population-based Metaheuristic technique known as the SSO model (Zhou et al., 2019). Typically, within each iteration, the population exhibits a high degree of organisation in accordance with the aim function. In the current version, the process of HL shifting is not implemented, which serves as a guiding signal for investigating particles that afterwards examine the searching agent located between the neighbouring HLs and LL. The explorer particle adjusts its position with the help of Eq. (7).

$$\theta_e(t+1) = \theta_e(t) + V(t+1) \tag{7}$$

The term V(t+1) in Eq. (7) is defined by Eq. (8).

$$\mathrm{V}(t+1) = \mathrm{VHL}(t+1) + \mathrm{VLL}(t+1) \tag{8}$$

The terms VHL(t+1) and VLL(t+1) in Eq. (8) are defined using Eq. (9) and (10) respectively.

$$VHL(t+1) = VHL(t) + rand(0,1)(\theta_e^{best}(t) - \theta_e(t)) + rand(0,1)(\theta_{HL}(t) - \theta_e(t)) \tag{9}$$

$$VLL(t+1) = VLL(t) + rand(0,1)(\theta_e^{best}(t) - \theta_e(t)) + rand(0,1)\,(\theta_{LL}(t) - \theta_e(t)) \tag{10}$$

From the expression, θ_e defines the explorer position, θ_{HL} stands for the HL position, θ_{LL} indicates the LL place adjacent to the explorer, θ_e^{best} indicates the finest position, V refers to the velocity vector, VHL denotes the velocity vector that goes towards HL, and VLL indicates the velocity vector that goes towards the adjacent LL. The equation used to modify the position of the random particle is reformulated into a new equation that allows for exploration beyond the boundaries of the search zone. In order to modify the position of the stochastic particle, Equation (11) is utilised.

$$\theta_O(t+1) = rand(0.5, 2) \cdot VSS \tag{11}$$

The term VSS in Eq. (11) is defined by Eq. (12).

$$VSS = \frac{\sum_{j=1}^{N-k} \theta_e^j(t)}{N-k} \tag{12}$$

In this context, the symbol θ_O represents the stochastic position of the particle, θ_j identifies the location of the j-th particle, N represents the total number of particles, and k signifies the quantity of randomly positioned particles. In order to enhance the effectiveness of the proposed strategy, the utilisation of Opposition Based Learning (OBL) is incorporated into the Single-Source Optimisation (SSO) methodology to enhance the rate at which convergence occurs. The opposite amount x is denoted as a novel value within the range $x \in [lb, ub]$. The opposite value of x is denoted by $\tilde{x}$ which is determined using Eq. (13).

$$\tilde{x} = lb + ub - x$$
(13)

In general, each search agent and opposite solution are determined using Eq. (14) and (15) respectively.

$$x = [x_1, x_2, x_3, \ldots x_D]$$
(14)

$$\tilde{x} = [\tilde{x}_1, \tilde{x}_2, \tilde{x}_3, \ldots, \tilde{x}_D]$$
(15)

The value of all the components in $\tilde{x}$ is represented by Eq. (16)

$$\tilde{x}_j = lb_j + ub_j - x_j \; where \; j = 1,2,3, \ldots, D$$
(16)

Once the fitness value $f(\tilde{x})$ of the opposite solution is superior to $f(x)$ of the original solution x, next $x = \tilde{x}$; then $x = x$. This operation attains X&Y vectors and the number p that describes the effect of X on Y which lies in the interval of [0,1]. The operation *merge* generates the vector Z each the element is determined according to Eq. (17): once the value X_i & Y_i overlaps next it comprises equivalent value; otherwise, Z_i considers the values X_i with the possibility p or assume the value Y_i through the possibility $(1\text{-}p)$.

$$merge\,(\mathrm{X}, \mathrm{Y}, p)_i = \begin{cases} X_i, & if\; rand\;(0,1) < p \\ Y_i, & or\; else \end{cases}, i = 1,2, \ldots, D \qquad (17)$$

This discrepancy in classifier accuracy is attributable to the distinct nature of the solutions. Once the characteristics have been incorporated into a precise solution of higher classification, it is quite likely that the features will be relevant. In contrast, many approaches are employed to address the impact of uncertainty during the assessment of a novel solution. Consequently, these methods exhibit slower convergence rates and are less susceptible to becoming confined within local optima. Figure 2 presents the flowchart illustrating the Single Sign-On (SSO) process.

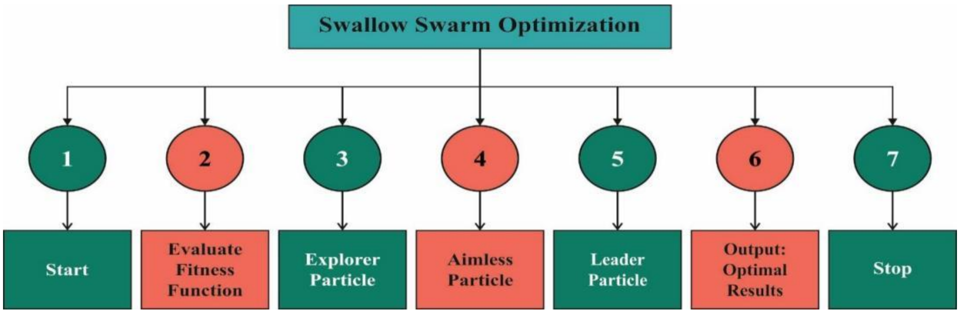

Figure 2. *Flowchart of SSO*

The proposed methodology involves representing the solution as a vector that encapsulates the feature. At the onset, a vector population is created, either through random selection or alternative methods. The population vector quantity is a constant value, specifically determined by the size of the population. In each cycle, all vectors are arranged in a descending series. The initial component transforms the high-level (HL) aspect. The solution identified by a Local Leader (LL) is the least optimal vector referred to as random particles, while other vectors are characterised as explorer particles. The values of the parameters "numbers" and "are" have been previously mentioned. The explorer particle adjusts its position based on the leader's location, but the random particle moves in a more arbitrary manner as dictated by Equation (18).

$$\mathrm{S}_e(t+1) = merge(\mathrm{V}(t+1), \mathrm{S}_e(t), p_{ve}) \quad (18)$$

Where V(t+1) is defined by Eq. (19).

$$\mathrm{V}(t+1) = merge(\mathrm{VHL}(t+1), \mathrm{VLL}(t+1), p_{vhl}) \quad (19)$$

Where VHL(t+1) and VLL(t+1) are defined by Eq. (20) and (21) respectively.

$$VHL(t+1) = merge(merge(SHL(t), \mathrm{S}_e(t), p_{he}), rand\,\{0,1\}^D, p_{her}) \quad (20)$$

$$VLL(t+1) = merge(merge(SLL(t), \mathrm{S}_e(t), p_{le}), rand\,\{0,1\}^D, p_{ler}) \quad (21)$$

5. Results and Discussion

The SSOA-SAE model is subjected to experimental analysis utilising a dataset consisting of 800 samples from students, which is categorised into four distinct class labels (Harrison & Wang, 2020). The participants in this study were selected from two high schools located in Hong Kong. The predominant demographic of the student population consisted of individuals from middle-class socioeconomic backgrounds, all of whom had a Chinese heritage. In order to be included in the study, participants had to meet two criteria: first, they had to be at least 14 years of age; second, they had to be actively enrolled in secondary school and maintain a minimum attendance rate of 85%. The class labels serve as indicators of the degree to which a humanistic approach influences the mental well-being of students. The information pertaining to the dataset is presented in Table 2.

Table 2

Dataset details

Label	Class Name	No. of Instances
Class 1	No Impact	200
Class 2	Slight Impact	200
Class 3	Noticeable Impact	200
Class 4	Severe Impact	200
Total Instances		**800**

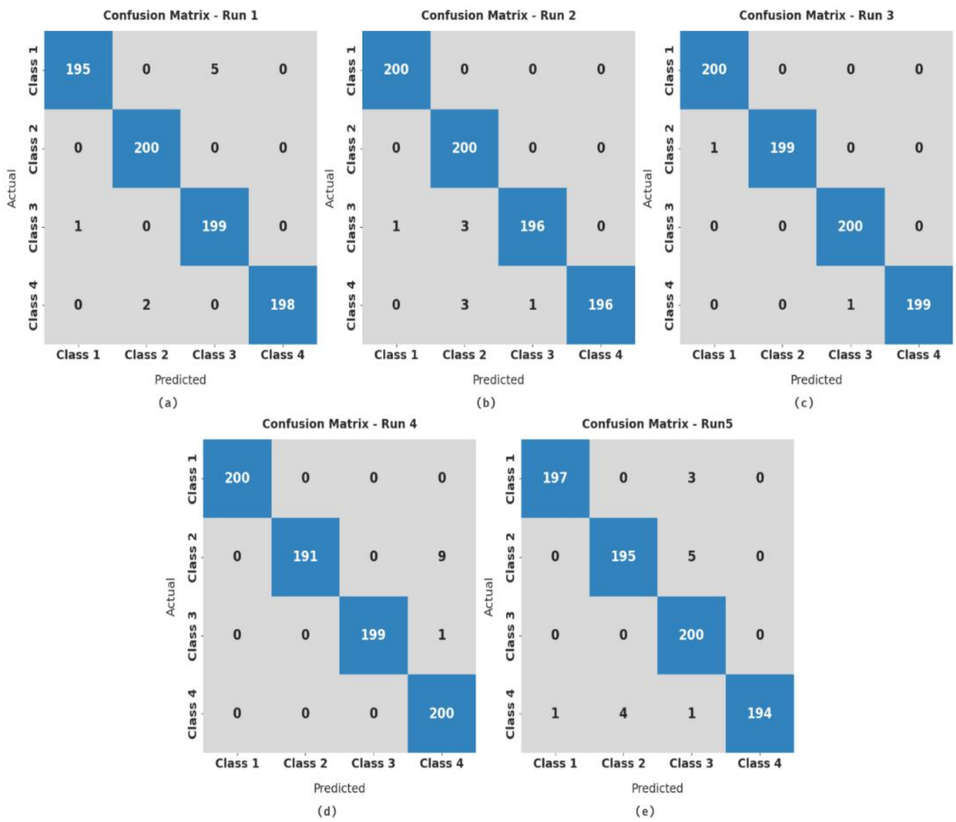

Figure 3. *Confusion matrices of SSOA-SAE technique (a) run-1, (b) run-2, (c) run-3, (d) run-4, and (e) run-5*

Figure 3 depicts the confusion matrix derived from the SSOA-SAE model across five distinct iterations. The SSOA-SAE model has successfully classified 195, 200, 199, and 198 samples into classes 1-4 using run-1. The SSOA-SAE method has successfully classified 200, 199, and 199 samples into classes 1-4, respectively, using the run-3 approach. Additionally, utilising the run-4 method, the SSOA-SAE methodology has successfully classified a total of 200, 191, 199, and 200 samples into classes 1-4, respectively. Furthermore, the SSOA-SAE system has successfully classified 197, 195, 200, and 194 samples into classes 1-4 using the run-5 method.

Table 3 and Figure 4 demonstrate the comprehensive classification results of the SSOA-SAE model throughout multiple iterations. Based on the experimental data, it can be concluded that the SSOA-SAE model has demonstrated superior performance compared to other models. For instance, on run-1, the SSOA-SAE model has reached average accuracy ($accu_y$), F-measure (F_{score}), False Negative Rate (FNR), False Positive Rate (FPR), False Discovery Rate (FDR), and FOR of 99.50%, 99%, 1%, 0.33, 0.99, and 0.33 respectively.

Table 3

Result analysis of SSOA-SAE technique with various measures and runs

Class Labels	Accuracy	F-Score	FNR	FPR	FDR	FOR
			Run-1			
Class 1	99.25	98.48	02.50	00.17	00.51	00.83
Class 2	99.75	99.50	00.00	00.33	00.99	00.00
Class 3	99.25	98.51	00.50	00.83	02.45	00.17
Class 4	99.75	99.50	01.00	00.00	00.00	00.33
Average	**99.50**	**99.00**	**01.00**	**00.33**	**00.99**	**00.33**
			Run-2			
Class 1	99.88	99.75	00.00	00.17	00.50	00.00
Class 2	99.25	98.52	00.00	01.00	02.91	00.00
Class 3	99.38	98.74	02.00	00.17	00.51	00.66
Class 4	99.50	98.99	02.00	00.00	00.00	00.66
Average	**99.50**	**99.00**	**01.00**	**00.33**	**00.98**	**00.33**
			Run-3			
Class 1	99.88	99.75	00.00	00.17	00.50	00.00
Class 2	99.88	99.75	00.50	00.00	00.00	00.17
Class 3	99.88	99.75	00.00	00.17	00.50	00.00
Class 4	99.88	99.75	00.50	00.00	00.00	00.17
Average	**99.88**	**99.75**	**00.25**	**00.08**	**00.25**	**00.08**
			Run-4			
Class 1	100.00	100.00	00.00	00.00	00.00	00.00
Class 2	98.88	97.70	04.50	00.00	00.00	01.48

Class 3	99.88	99.75	00.50	00.00	00.00	00.17
Class 4	98.75	97.56	00.00	01.67	04.76	00.00
Average	**99.37**	**98.75**	**01.25**	**00.42**	**01.19**	**00.41**
			Run-5			
Class 1	99.50	98.99	01.50	00.17	00.51	00.50
Class 2	98.88	97.74	02.50	00.67	02.01	00.83
Class 3	98.88	97.80	00.00	01.50	04.31	00.00
Class 4	99.25	98.48	03.00	00.00	00.00	00.99
Average	**99.13**	**98.25**	**01.75**	**00.58**	**01.71**	**00.58**

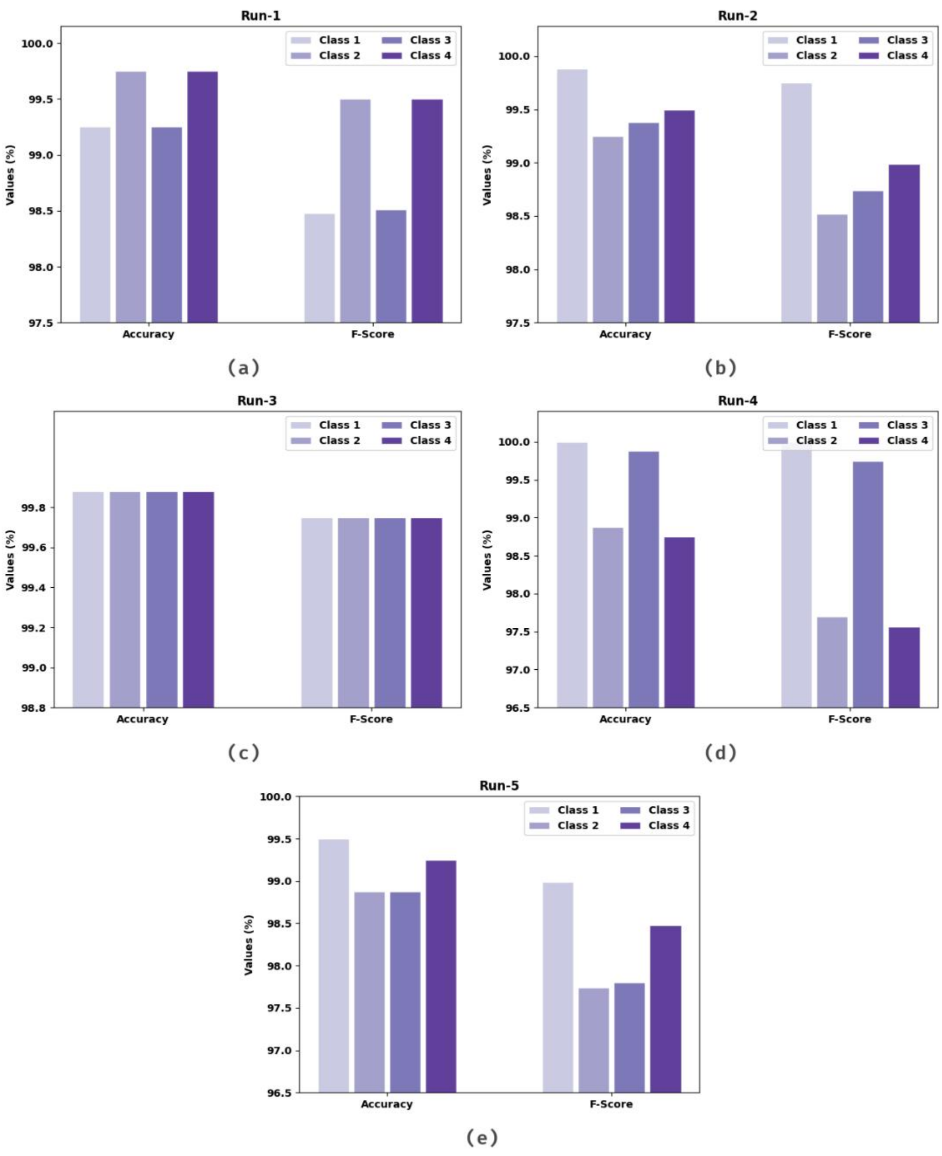

Figure 4. *Result analysis of SSOA-SAE technique (a) run-1, (b) run-2, (c) run-3, (d) run-4, and (e) run-5*

Followed by, on run-3, the SSOA-SAE approach has gained average $accu_y$, F_{score}, FNR, FPR, FDR, and FOR of 99.88%, 99.75%, 0.25%, 0.08, 0.25, and

0.08 correspondingly. In line with, on run-4, the SSOA-SAE model has reached to average $accu_y$, F_{score}, FNR, FPR, FDR, and FOR of 99.37%, 98.75%, 1.25%, 0.42, 01.19, and 0.41 correspondingly. Next to that, on run-5, the SSOA-SAE technique has attained to average $accu_y$, F_{score}, FNR, FPR, FDR, and FOR of 99.13%, 98.25%, 1.75%, 0.58, 01.71, and 0.58 correspondingly.

Figure 5. *TA and VA analysis of SSOA-SAE technique*

The figure depicted in Figure 5 showcases the achieved training accuracy (TA) and validation accuracy (VA) of the SSOA-SAE technique on the test dataset. The experimental results suggest that the SSOA-SAE model has achieved the highest values for both TA and VA. Specifically, the value added (VA) appeared to be greater than the total assets (TA).

The figures in Figure 6 depict the training loss (TL) and validation loss (VL) obtained by the SSOA-SAE system on the test dataset. The experimental results suggest that the SSOA-SAE algorithm has achieved the lowest values for TL (Total Loss) and VL (Validation Loss). Specifically, the vocabulary level (VL) appeared to be lower than the target language (TL).

Figure 6. *TL and VL analysis of SSOA-SAE technique*

Finally, Table 4 presents a comprehensive comparison analysis of the SSOA-SAE model in relation to other current models. Figure 7 depicts a thorough evaluation of the SSOA-SAE model in comparison to other models. The data suggests that the SSOA-SAE model has demonstrated a high level of effectiveness, with a maximum outcome of 99.88%. Subsequently, it has been observed that both the LR and CNN models have exhibited suboptimal performance, with the LR model achieving a minimum accuracy of 96.14% and the CNN model achieving a minimum accuracy of 96.17%. Linear regression is subject to a significant limitation due to the assumption of linearity in both the dependent and independent variables (Corcoran et al., 2018). Additionally, it has been observed that CNN exhibits a longer processing time in the context of predictive analytics (Zhang et al., 2021). Furthermore, the utilisation of the Deep Neural Network (DNN) model has resulted in a marginal improvement of 96.40%. However, it has been shown that deep neural networks (DNNs) exhibit improved processing capabilities when trained on larger datasets (Baek & Chung, 2020). In accordance with this, the Naive Bayes (NB) and bagging models have achieved satisfactory accuracies of 97.23% and 97.83%, respectively. The bagging model introduces the concept of interpretability loss. If the prescribed procedures are not adhered to, the resultant bagging model may exhibit various errors. Bagging, although it exhibits high accuracy, is characterised by its computational intensity, which may potentially hinder its widespread use in the field of mental health prediction (Zulfiker et al., 2021). Nevertheless, the SSOA-SAE model has demonstrated superiority over alternative approaches. The effectiveness of the SSOA-SAE model in predicting the mental well-being of students engaged in English courses with a humanistic approach surpasses that of established models like as DNN, NB, LR, bagging, and CNN.

Table 4

Comparative analysis of SSOA-SAE technique with existing approaches

Methods	Accuracy	F-Score	FNR	FPR	FDR	FOR
DNN Model (Baek & Chung, 2020)	96.40	96.06	0.28	1.92	0.35	1.48
LR Model (Corcoran et al., 2018)	96.14	97.45	0.35	1.85	0.34	1.70
NB Model (Srividya, Mohanavalli, & Bhalaji, 2018)	97.23	97.43	0.39	1.62	0.33	1.87
Bagging (Zulfiker et al., 2021)	97.83	98.76	0.29	1.75	0.34	1.72
CNN Model (Harrison & Wang, 2020)	96.17	97.27	0.36	1.46	0.35	1.87
SSOA-SAE (proposed)	99.88	99.75	0.25	0.08	0.25	0.08

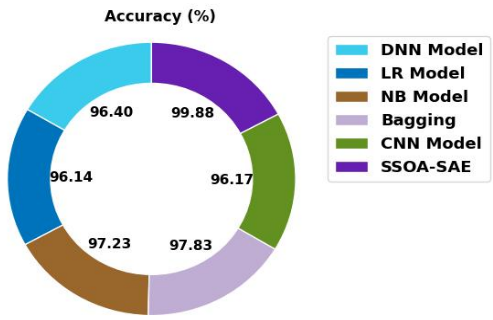

Figure 7. $Accu_y$ *analysis of SSOA-SAE approach with existing algorithms*

Figure 8 provides a complete analysis of the F-score performance of the SSOA-SAE technique in comparison to other models. The figure revealed that the SSOA-SAE algorithm has gained an effectual outcome with a maximal F_{score} of 99.75%. Also, the LR and CNN models have outperformed ineffectual performance with lower F_{score} of 97.45% and 97.27% correspondingly. Besides, the DNN approach has obtainable slightly increased F_{score} of 96.06%. In line with this, the NB and bagging models have reached a reasonable F_{score} of 97.43% and 98.76%. But, the SSOA-SAE model has surpassed other methods.

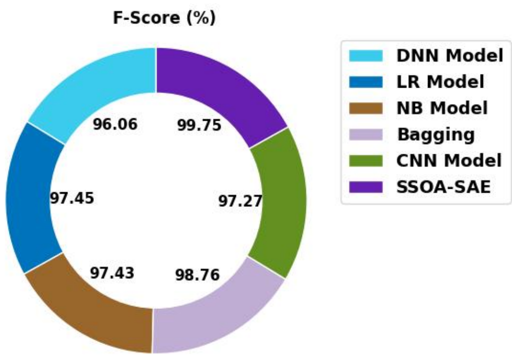

Figure 8. F_{score} *analysis of SSOA-SAE approach with existing algorithms*

Figure 9 presents a comprehensive analysis of the False Negative Rate (FNR) for the SSOA-SAE model compared to other models. The illustration suggests that the SSOA-SAE model achieved favourable results with a higher FNR of 0.25%. Conversely, both the LR and CNN models exhibited suboptimal performance, displaying lower FNR values of 0.35% and 0.36% respectively. Additionally, the DNN approach yielded a slightly improved FNR of 0.28%. Similarly, the NB and bagging models demonstrated reasonable FNR values of 0.39% and 0.29% respectively. Ultimately, the SSOA-SAE model outperformed other methodologies in terms of FNR.

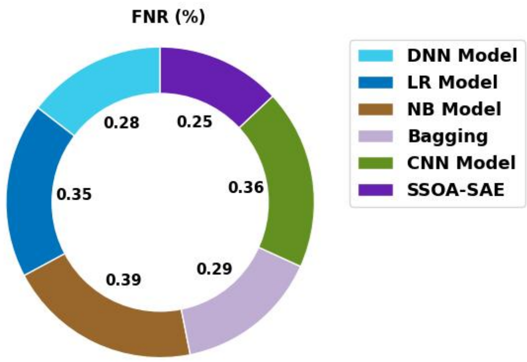

Figure 9. *FNR analysis of SSOA-SAE approach with existing algorithms*

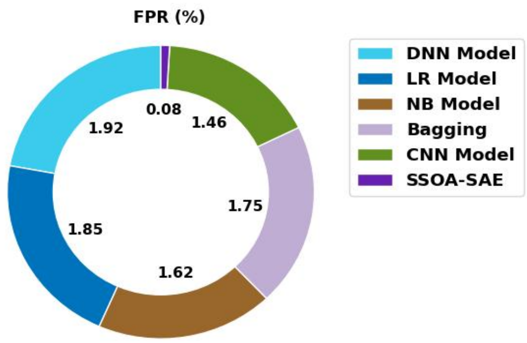

Figure 10. *FPR analysis of SSOA-SAE approach with existing algorithms*

Figure 10 depicts a comprehensive examination of the False Positive Rate (FPR) involving the SSOA-SAE model in comparison to alternative methods. The illustration highlights that the SSOA-SAE technique achieved favorable results, demonstrating a maximum FPR of 0.08%. In contrast, both the LR and CNN models displayed less effective performance, registering minimal FPR values of 1.85% and 1.62%, respectively. Additionally, the DNN approach showed a somewhat improved FPR of 1.92%. Similarly, the NB and bagging models attained reasonable FPR values of 1.62% and 1.75%, respectively. Notably, the SSOA-SAE algorithm outperformed other methods in terms of FPR.

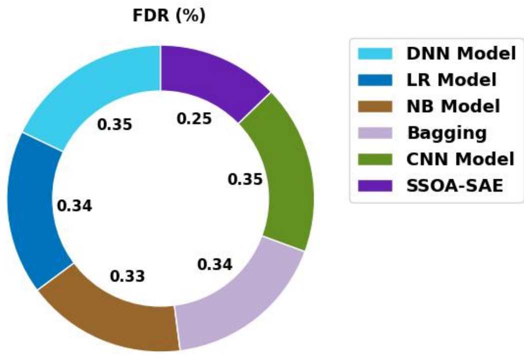

Figure 11. *FDR analysis of SSOA-SAE approach with existing algorithms*

Figure 11 portrays an extensive analysis of the False Discovery Rate (FDR) for the SSOA-SAE system in comparison to alternative approaches. The illustration suggests that the SSOA-SAE model achieved favorable results, showcasing a maximum FDR of 0.25%. In contrast, both the LR and CNN algorithms exhibited less effective performance, indicating the lowest FDR values of 0.34% and 0.35%, respectively. Additionally, the DNN model demonstrated a slightly higher FDR of 0.35%. Furthermore, the NB and bagging models attained a reasonable FDR of 0.33% and 0.34%, respectively. Ultimately, the SSOA-SAE system outperformed other methods in terms of FDR.

6. Conclusion

This study utilises an innovative SSOA-SAE model to investigate the mental health of college students in the context of English education. The objective of the SSOA-SAE model is to ascertain the approach to fostering the cultivation of the humanistic spirit in the domains of English instruction and mental health. The suggested Single Sign-On Authentication-Self-Attention Encoder (SSOA-SAE) model begins by implementing the Self-Attention Encoder (SAE) model in order to perform the categorization process with optimal efficiency. Furthermore, the Single-Source Optimisation Algorithm (SSOA) is employed to efficiently adjust the hyperparameters associated with the Stacked Autoencoder (SAE) model. This study investigates a comprehensive series of simulations conducted on the SSOA-SAE model, with a focus on comparing its performance against other established models in the field. The simulation results indicated that the SSOA-SAE model demonstrated superiority compared to other contemporary techniques. Hence, the utilisation of the SSOA-SAE model might be employed as a means to examine the mental well-being of college students in the context of English education. Therefore, In subsequent iterations, the efficacy of the SSOA-SAE model may be augmented through the implementation of feature selection techniques. The presence of a wider range of mental diseases among the target population will result in an increased number of class designations. When this situation occurs, there is a tendency for class labels to have a higher degree of overlap. The approach under consideration exhibits a high level of complexity when it comes to processing data that contains a larger number of class labels. Fuzzy rules can be employed to address this problem in cases where the occurrence of overlap is anticipated.

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