Educational Administration: Theory and Practice
2024, 30(5), 1611-1622
ISSN: 2148-2403
https://kuey.net/

Research Article

"Mind Matters: An Evaluation and Effectiveness Study of Student Mental Health Education Programs"

Xiuzhen Chen[1*]

[1*]College of Humanities and Arts, Hainan College of Economics and Business, Haikou, Hainan, 571127, China

***Corresponding Author:** Xiuzhen Chen
E-Mail: chenxiuzhen76@163.com

Citation: Xiuzhen Chen, (2024), "Mind Matters: An Evaluation and Effectiveness Study of Student Mental Health Education Programs", *Educational Administration: Theory and practice 30*(5), 1611-1622
Doi: 10.53555/kuey.v30i5.3133

ARTICLE INFO

ABSTRACT

This study investigates the impact and efficacy of student mental health education programs, aiming to assess their effectiveness in enhancing well-being and promoting mental health awareness. Utilizing a mixed-methods approach, the research combines quantitative surveys, qualitative interviews, and pre-post assessments to comprehensively evaluate the outcomes of mental health education initiatives implemented within educational settings. Key objectives include measuring changes in students' knowledge, attitudes, and behaviors related to mental health, as well as assessing the overall effectiveness of various program components such as curriculum content, delivery methods, and support systems. The study also explores the influence of demographic factors and pre-existing mental health perceptions on the outcomes of these educational interventions. The findings of this research hold significant implications for educational institutions, policymakers, and mental health practitioners. A nuanced understanding of the strengths and limitations of current mental health education efforts can inform the development of evidence-based strategies to cultivate resilient, well-informed, and mentally healthy student populations. The study contributes to the ongoing discourse on mental health in educational settings and provides actionable insights to enhance the overall well-being of students.

Keywords: students mental health analysis, education program, data analysis, deep learning models, feature extraction, classification

1. Introduction:

Technological advancements like wearables, social media, cellphones, and neuroimaging have made it possible for mental health researchers as well as practitioners to gather a tremendous amount of data at a very fast pace. Machine learning (ML), a powerful technology that has arisen to examine this data, attempts to build methods that can automatically enhance through experience utilizing sophisticated statistical as well as probabilistic methods. AI, computer vision, speech recognition, natural language processing, other fields have benefited greatly from ML. This is because ML enables researchers and developers to extract important from data, offer personalised experiences, create intelligent methods [1]. Because machine learning (ML) makes it possible to analyse complicated data quickly and efficiently, it has significantly advanced health-related sectors like bioinformatics. Such insightful procedures are additionally being investigated with emotional wellness information, with the expansive capability of both working on persistent results and improving comprehension of mental circumstances and their administration inside the more extensive local area. Psychological well-being is both a condition of mind and a general atmosphere of a person. Psychological instability results from anomalies in mind science [2]. The psychological state of an individual serves as a proxy for how best to treat their illnesses. It is essential to keep an eye on the emotional well-being profiles of different groups in order to spot any disparities connected to wellbeing. Working specialists, undergrads, and secondary school understudies make up the people group. It is an unavoidable belief that stress as well as suffering affect people of all ages and socioeconomic backgrounds. Differentiating between the psychological well-being of different classes at different periods is essential to avoiding serious illness. Medical service providers will soon be expected to take a patient's mental health profile into account in order to provide better prescriptions and aid in a quicker recovery [3]. Some of the most serious mental health disorders, such as chronic diseases, bipolar disorder, schizophrenia, don't just happen overnight; they often develop over time and have early symptoms. Such problems could be avoided or managed even more skillfully. In the unlikely event that abnormal mental states are discovered early on in the illness, more treatment as well as attention can be provided. Therefore, evaluating people's psychological states based only on their appearance or mannerisms is a sophisticated mental science that is currently unmotorized. Despite the existence of screening test arrangements, large populations cannot use them due to financial and time constraints. Furthermore, there is a chance that determination-based methods will discourage sick people from taking part. Mental health problems frequently go unnoticed or untreated [4]. The created expectation framework will help the clinicians in leading mental testing and in foreseeing the psychological wellness of a person. The clinician and specialist work couple to treat patient side effects from both a social and clinical viewpoint. The areas of brain science and psychiatry are both fundamental in exploring and creating treatment for working on mental and close to home wellbeing. As indicated by WHO, 50 million Indians are experiencing misery which is one of the pervasive results of psychological maladjustment. India has a sum of just 898 clinical clinicians, one for each 1.3 million individuals and a sum of 3800 therapists, one for each 3,30,000. At this crossroads it is exceptionally fundamental to give psychological well-being administrations accessible to bigger local area of populace. A few factors that influence the overall mental prosperity of an individual incorporate globalization, working environment pressure, contest at concentrate on place, and so forth. The proposed framework is supposed to perform conduct profiling of people trying to make mental medical services more open. Machine learning is a procedure that expects to build frameworks that can work on through experience by utilizing progressed measurable and probabilistic strategies. It is accepted to be a fundamentally valuable device to help in foreseeing emotional wellness [5]. It is permitting numerous analysts to secure significant data from the information, give customized encounters, and foster robotized wise frameworks. The broadly involved calculations in the field of ML, for example, support vector machine, irregular woodland, and fake brain networks have been used to conjecture and sort the future occasions. Directed learning in ML is most broadly applied method in many sorts of exploration, studies, particularly in foreseeing sickness in clinical field. In regulated learning, the terms, properties, and values ought to be reflected in all information occurrences. All the more definitively, managed learning is an order method utilizing organized preparing information. In the mean time, solo learning needn't bother with oversight to anticipate. The fundamental objective of solo learning is taking care of information without oversight. It is extremely restricted for the scientists to apply solo learning strategies in the clinical field [6].

2. Related works:

As of now, the significance of training informatization is deficient, and there is no inside and out comprehension of positive job of college informatization development on improvement of advanced education. Customary administration idea as well as method of reasoning have truly limited development as well as improvement of college informatization. Hypothetical examination results are separated from the real world. This is predominantly in light of the fact that the vast majority of the specialized staff participated in plan are not the cutting edge faculty of training, which prompts the disengagement between the planned works and schooling [7]. A psychological wellness sickness is characterized as a medical problem that influences the prosperity and how an individual feels, thinks, acts, speaks with others [8]. According to American Mental Affiliation, psychological wellness sickness is close to home and conduct or a mix of the two kinds of an ailment that is related with family, social, or business related issues [9]. It tends to be additionally said that psychological well-being sickness is a medical problem that influences the profound and conduct prosperity of an individual further prompting physiological impacts [10]. It has been displayed in a concentrate by [11] that emotional well-being sickness is additionally delegated uneasiness jumble, burdensome confusion, and Schizophrenia problem. The vast majority of these are displayed by the two grown-ups and young people in different age gatherings. This study centers principally around the emotional well-being of understudies. In the concentrate by [12], they showed that undergrads experience the ill effects of tension problem and burdensome issue, and these sicknesses are profoundly connected with their social, work, and family issues. In this review, we think about two sicknesses that lead to understudy's emotional wellness issues. Following the exploration by [13], we consider nervousness confusion and burdensome problem as two kinds of psychological maladjustment among understudies. However Schizophrenia problems are similarly significant contrasted with other three problems, it is seen as seldom present among undergrads [14]. According to the American Psychiatric Association (APA), anxiety is characterised by apprehension, uneasiness, and overwhelming terror. Physiological symptoms ensue after these emotions and last for a while before recurring cyclically when anxiety flares up again [15]. Three primary categories of anxiety disorders exist: panic disorder, social anxiety disorder, generalised anxiety disorder (GAD). We have limited our research to these three anxiety kinds in this study, even though the APA taxonomy specifies a few more. Pupils suffering from Generalised Anxiety Disorder (GAD) often experience extreme anxiety or tension related to social and ordinary aspects of life, such as work, social interactions, personal safety, and routine events [16]. Typically, GAD causes people to avoid or seek comfort from situations where the conclusion is uncertain and to worry needlessly about things that might not turn out well for them. In terms of decision trees (0.705), random forests (0.755), extreme gradient boosting (0.765), multilayer (0.782), simple perceptrons, Hopfield and convolution learning networks, and logistic hidden neural networks (0.783), results were appropriately assessed. In their study [17], the authors offered conventional classification approaches and tree-based models as AI methodology. The three steps proposed by the authors [18] for analysing mental health were: using the Student Attribute Matrix (SAM) to quantify attributes; estimating using a classification Back Propagation Neural Network (BP-NN); using the BP-NN student progress indicators and attribute casual relationships. The results of the estimation process were perfect (49.72), and the accuracy increased on other parameters. The method of selecting and classifying features was altered in a variety of ways by the addition of machine learning algorithms. In order to anticipate student conduct in an e-learning environment, the authors [19] used methods of ML, CF (collaborative filtering), RS (recommendation system), and ANN (artificial neural network). Writers of study [12] determined stress utilizing heart rate, EMG, GSR hand and foot data, and respiration. They came to the conclusion that respiration is an important stress-related metric. The authors of the study [20] predicted stress using electrocardiogram (ECG) data. Data obtained from every sensor is compared to index value in order to identify any stress. In paper [21], creators applied J48 calculation, SMO, Bayesian Organization calculation for anticipating weight on information gathered from 16 people groups under 4 various distressing circumstances. In paper [22] utilized HRV highlights and EEG sign to anticipate the anxiety. Different highlights like HRV, pulse, ECG are utilized to foresee the anxiety. In paper [23], creators utilized choice tree calculation is applied on a dataset gathered from two test finished that these test to be unsuitable. Understudies anxiety is determined in the beginning of the semester and in the remainder of the semester. Work [24] imagine that music itself has a power that different expressions can't coordinate and outperform, and this power contains extremely strong feelings. This is likewise an exceptionally clear confirmation of the capability of music in various written works. Creator [25] imagines that the "nervousness" brought about by the tension of study, business and contest has turned into a significant mental issue that plagues higher professional understudies. Running against the norm, latent music appreciation should be ventured into dynamic music mood and intuitive and helpful music-themed exercises, so understudies can rediscover their own qualities and capacities, reconfirm themselves as well as acknowledge themselves during time spent tuning in, talking about and communicating music, with the goal that they can play music actually.

3. System model:

Add individual fundamental data in the information, and utilize the BP brain organization to lay out emotional well-being appraisal methods. Through planning connection between affecting variables as well as mental issues, info test tests are considered; just continually enter and finish preparing to accomplish the reason for the model laid out. The examination course is displayed in Figure 1. The information of school, first and foremost, understudies' emotional wellness is gotten from three parts of text, picture and organization assessment. Among them, text information neds text pretreatment, text information cleaning, word. Picture information requires picture pretreatment, picture information cleaning, standardization. Network information needs preprocessing, arrangement information cleaning, modular handling. Example is then stamped, examples are partitioned into preparing tests and test tests. In the wake of, preparing tests should be prepared to work out the profound propensity esteem in the model lastly joined with the three close to home estimations for the assessment and examination of psychological well-being.

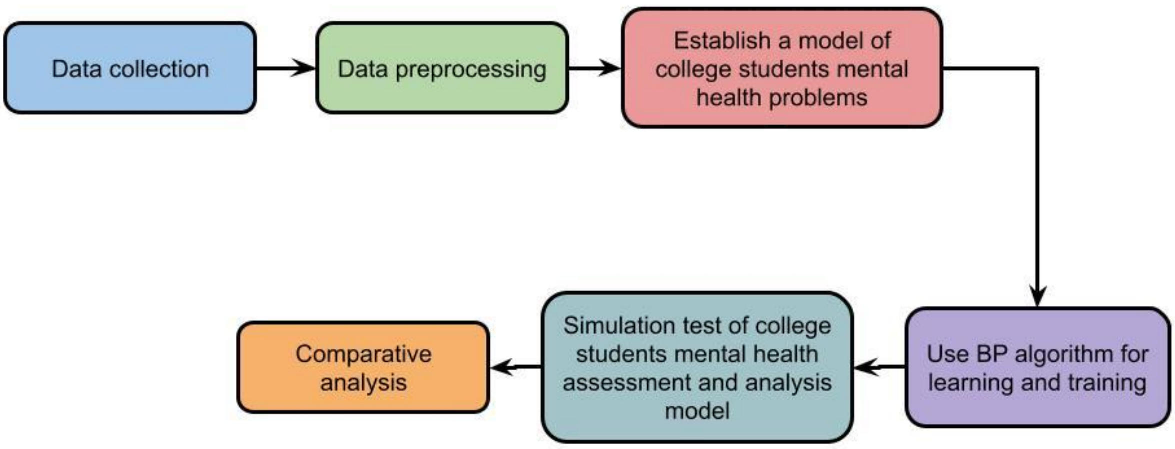

Figure-1 proposed students mental health analysis model

For schools and colleges, it is of positive importance to allow understudies to get training, guarantee their psychological wellness, and oversee and break down their profound state. Schools and colleges are spots to convey gifts to the nation and society. Schools and colleges ought to cause understudies to have no mental weight, attempt to invigorate all their true capacity and understand their self-esteem, in order to develop into helpful individuals for society. Up to now, there are numerous hypothetical explores on understudies' psychological wellness and profound state in training. However, these are somewhat fundamental hypothetical information. This paper is advanced under this reason. Focusing on understudies' mental and profound acknowledgment, we to begin with built an acknowledgment system. In view of the variety of human mental feelings, we have planned a wide range of examples for feelings, and we really want to recognize the examples of feelings first. Then, at that point, a progression of acknowledgment handling are done, lastly the feeling investigation capability is added rather than a solitary acknowledgment capability.
the activity, first and foremost, design and handling method of convolutional brain organization as well as multi-facet neuron self-coding brain network are utilized to investigate emotional well-being of undergrads, then, at that point, the information structure got from the examination is organized, and the enormous information investigation hypothesis and strategy are utilized to lead auxiliary examination, to find the ordinariness of most understudies' emotional well-being. Some undergrads' emotional wellness information that are not normal are separated and exceptionally handled, and the accompanying articulation is acquired by eqn (1)

$$R(x) = \frac{\sqrt{P_1 c^{\delta\beta x}/(c-1)^{\alpha x}}}{\sum_{i=0}^{k} P_2 x_i} \tag{1}$$

The mental health data of college students are represented by P2, whereas P1 represents special data. Analysis attribution is c, discrete variable is Θ, standard quantitative value is 1. To achieve required function at this moment in DL analysis technique, it is important to visually operate as well as process specific data:

$$R'(x) = \left| \sum_{i=1}^{k} P_i - \frac{\sqrt{P_1 c^{\beta x}/(c\phi-1)^{\alpha x}}}{\sum_{i=0}^{k} P_2 x_i} \right| \tag{2}$$

The symbol α represents the generalised mental health data information of college students, while β represents specialised data information. c contains all of the data; its standard quantitative value is 1, and its dispersion coefficient is υ. To reduce the impact of some unsettling elements and inaccurate data, discrete analysis on pertinent data must be done in conjunction with big data analysis theory following a separate data processing step. The role is by eqn (3)

$$R''(x) = \left| \frac{\sum_{i=1}^{k} (P_i - x)^{i\phi}}{\sqrt{(c^{11}\phi + c^{22}(1-\phi))}} - \frac{\sqrt{P_1 c^{\beta x}/(c\phi-1)^{\alpha x}}}{\sum_{i=0}^{k} P_2 x_i} \right| \tag{3}$$

Determining the type of data structure is also required when discrete transformation analysis and processing is finished. Figure 2 illustrates assessment as well as analysis method development process of DL theory on the mental health of college students. While the existing method as well as data structure are capable of doing superficial analyses and evaluations of mental health of typical college students, reasonable processing as well as deepening will be required if a more thorough analysis is to be conducted. Certain features of data structure as well as method must be limited and distinguished from others, and on a certain basis, suitable error analysis and data evaluation must be performed on data structure as well as method. The resulting comprehensive data analysis as well as processing correlation analysis method has a deeper application level.

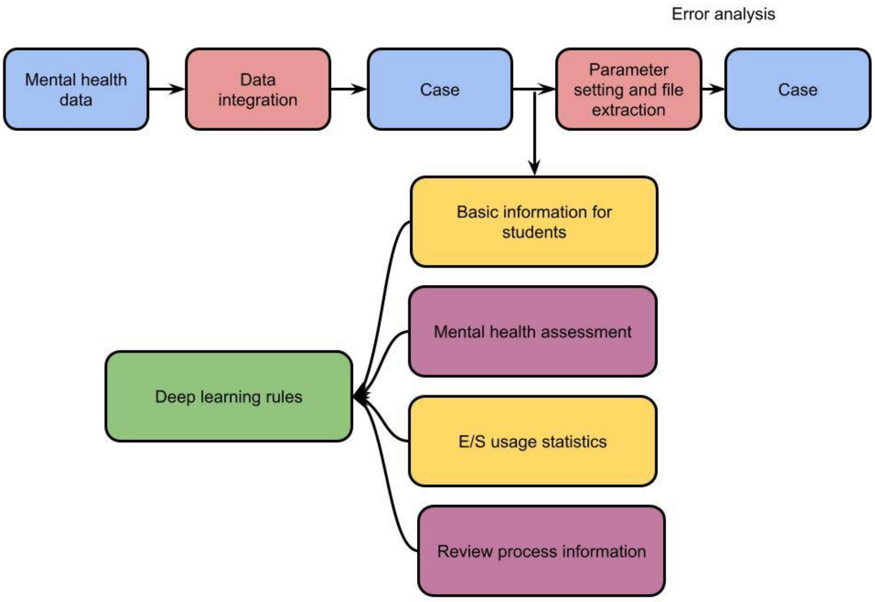

Figure 2: students' mental health status analysis

4. Stochastic Q- component with spatio regressive gradient neural network (SQCSRGNN) based data feature extraction and classification:

Formula for gradient descent is as follows. Assume that objective function to be minimised is f:R^N→R^t. One iteratively updates an initial point, x^((0))∈R^N, utilizing objective function's steepest descent at current point by eqn (4)

$$\mathbf{x}^{(t+1)} = \mathbf{x}^{(t)} - \eta \nabla f\left(\mathbf{x}^{(t)}\right) \quad (4)$$

By accounting for curvature datra, or second derivatives of objective function, at every step, Newton's technique expands on this method. Consequently, objective function's Hessian matrix H is included in iterative update by eqn (5)

$$\mathbf{x}^{(t+1)} = \mathbf{x}^{(t)} - \eta \mathbf{H}^{-1} \nabla f\left(\mathbf{x}^{(t)}\right) \quad (5)$$

Without any nonlinearities, a given unitary gate Ui (θi) acts sequentially on output of preceding unitary gate Ui−1(θi−1) in QNNQG14. In computations pertaining to gradient computations and error derivation, classical side data of QNNQG is employed, allowing side information to propagate freely throughout network structure. The unitary operator U(θ⃗) is formed by applying L unitaries sequentially by eqn (6)

$$U(\vec{\theta}) = U_L(\theta_L) U_{L-1}(\theta_{L-1}) \ldots U_1(\theta_1), \quad (6)$$

For a given input system ψ φ, evolution of QNNQG system is by eqn (7)

$$|Y\rangle = U(\vec{\theta})|\psi\rangle|\phi\rangle = U(\vec{\theta})|z\rangle|1\rangle = U(\vec{\theta})|z,1\rangle$$

$$f_i = \left\{\sum_{\mu,\nu}^{K} \left(\theta_\mu^* \theta_\nu - \bar{\theta}_\mu^* \bar{\theta}_\nu\right) \mathrm{Tr}\left(B\sigma^\mu \rho_{\text{in}}^i \sigma^\nu\right) + \eta\right\}^2$$

$$f_{ik}(X) = \frac{1}{(2\pi)^{p/2} |\Sigma_k|^{1/2}} \exp\left(-\frac{1}{2}(X - X_{ik})^T \Sigma_k^{-1} (X - X_{ik})\right) \quad (7)$$

using which we compute by eqn (8):

$$\left(\frac{\partial f_i}{\partial \theta_\zeta}\right) = \left\{\sum_{\mu,\nu,\delta,\gamma}^{K} \left(\theta_\mu^* \theta_\nu - \bar{\theta}_\mu^* \bar{\theta}_\nu\right)\left(\bar{\mathcal{G}}_\zeta^\delta \theta_\gamma + \mathcal{G}_\zeta^\gamma \theta_\delta^*\right) \mathrm{Tr}\left(B\sigma^\mu \rho_{\text{in}}^i \sigma^\nu \otimes B\sigma^\delta \rho_{\text{in}}^i \sigma^\gamma\right) + 2\eta \sum_{\delta,\gamma}^{K} \left(\bar{\mathcal{G}}_\zeta^\delta \theta_\gamma + \mathcal{G}_\zeta^\gamma \theta_\delta^*\right) \mathrm{Tr}\left(B\sigma^\delta \rho_{\text{in}}^i \sigma^\gamma\right)\right\}$$

$$\left(\frac{\partial f}{\partial \theta_\zeta}\right) = \Big\{\sum_{\mu,\nu,\delta,\gamma,j,k,p,q}^{K} 2A_{j'kp'q}^{\infty} \left(\theta_\mu^* \theta_\nu - \bar{\theta}_\mu^* \bar{\theta}_\nu\right)\Big(\bar{\mathcal{G}}_\zeta^\delta \theta_\gamma + \mathcal{G}_\zeta^\gamma \theta_\delta^*\Big)\Big) \mathrm{Tr}\left(B\sigma^\mu \sigma^j |0\rangle\langle 0| \sigma^k \sigma^\nu \otimes B\sigma^\delta \sigma^p |0\rangle\langle 0| \sigma^q \sigma^\gamma\right) + 2\eta \sum_{\delta,\gamma,j,k}^{K} A_{j'k}^{\infty} \Big(\bar{\mathcal{G}}_\zeta^\delta \theta_\gamma + \mathcal{G}_\zeta^\gamma \theta_\delta^*\Big) \mathrm{Tr}\left(B\sigma^\delta \sigma^j |0\rangle\langle 0| \sigma^k \sigma^\gamma\right)\Big\}$$

$$\mathcal{G}_\nu^\mu = \left(\frac{\partial \theta^\mu}{\partial \theta^\nu}\right) = \begin{cases} \sum_{l \in \{L(\nu)\}} \left(\frac{\partial g^\mu(w)}{\partial w_l}\right)\left(\frac{\partial w_l}{\partial g^\nu(w)}\right) & \mu \neq \nu \\ 1 & \mu = \nu \end{cases} \quad (8)$$

where {L(ν)} is collection of indexes l for which $\frac{\partial g^\nu(w)}{\partial w^l} \neq 0°$.

It is significant to remember that, just as weights vary over time, G also does. Dependence between various parameters that are represented as coordinates is measured by matrix G. Dirac-delta function, represented as matrix G, implies that parameters are independent as well as that parameter space is equal to Euclidean space. From standpoint of a dynamical system, matrix G controls how one parameter depends on other factors, which modifies original parameter. This situation can be correlated with long-range hopping manybody interactions, in which the amplitude of the matrix G j i corresponds to hopping energy from lattice site i to j. Ergodicity occurs when magnitude of each element in matrix G is sufficiently large, resulting in a significant hopping energy and a drop in the disorder strength. However, when the size of each element in matrix G is sufficiently tiny, the hopping energy is low, increasing the disorder strength and leading to the emergence of localization and the loss of ergodicity. Consider an individual ι ∈ f ∗ and an agent f, denoted by the function f: → -n is by eqn (9)

$$\mathcal{C} \equiv \begin{cases} C_\iota : \forall \iota \in \tilde{I} : \chi(v, f(\iota)) = 0, \\ C_{\iota_*} : \iota^* \in \mathcal{I}\tilde{I} : \chi(v^*, f^*(\iota^*)) = 0, \end{cases} \quad (9)$$

where v* and f * (γ*) denote vertex and function at γ*, respectively, and χ(·) is a compact constraint function. Additionally, * denotes a specific individual, vertex, or function. The process of creating the conventional linear PCA in a high-dimensional space using a kernel function is known as kernel principal component analysis.

Self-adjoin operator for trace class G is implemented in the Hilbert space H by eqn (10).

$$\operatorname{tr}(T) := \sum \langle \psi_i, T\psi_i \rangle$$

$$c_1 \parallel f \parallel^2 \leq \sum_{\alpha \in A} |\langle h_\alpha, f \rangle|^2 \leq c_2 \parallel f \parallel^2 \ \text{ for all } f \in \mathcal{H} \quad (10)$$

Let $(h_\alpha)_{\alpha \in A}$ be a frame in H. Set $L: \mathcal{H} \to l^2$ by eqn (11)

$$L: f \mapsto (\langle h_\alpha, f \rangle)_{\alpha \in A} \quad (11)$$

Then . $L^*: l^2 \to \mathcal{H}$ represented by eqn (12),

$$L^*((c_\alpha)) = \sum_{\alpha \in A} c_\alpha h_\alpha \quad (12)$$

where $(c_\alpha) \in l^2$; and by eqn (13)

$$L^*L = \sum_{\alpha \in A} |h_\alpha\rangle\langle h_\alpha|$$

$$\sum_{i,j=1}^{N} \bar{c}_i c_j K(v_i, v_j) \geq 0 \quad (13)$$

for all I $\{x_i\}_{i=1}^N \subset S, \{c_i\}_{i=1}^N \subset \mathbb{C}$, and $N \in \mathbb{N}$.

$$K(x, y) = \langle \Phi(x), \Phi(y) \rangle_{\mathcal{H}(K)} \quad (14)$$

Additionally, replicating characteristic that follows is true by eqn (15):

$$f(x) = \langle K_x, f \rangle_{\mathcal{H}(K)}$$

$$\operatorname{span}\{K_x := K(\cdot, x)\} \quad (15)$$

H (K)-inner product by eqn (16)

$$\left\langle \sum c_i K_{x_i}, \sum d_j K_{x_j} \right\rangle_{H(K)} := \sum \bar{c}_i d_j K(x_i, x_j) \quad (16)$$

The following posterior probability distribution can be maximised to predict the label field for any feature extraction challenge.

$$\hat{x}_t = \arg \max_{x_t} P(X_t = x_t \mid Y_t = y_t)$$

$$\hat{x}_t = \arg \max_{x_t} \frac{P(Y_t = y_t \mid X_t = x_t) P(X_t = x_t)}{P(Y_t = y_t)} \quad (17)$$

where the estimated labels are indicated by $\hat{x}_t$. Since (18) reduces to, the prior probability $P(Y_t = y_t)$ is constant.

$$\hat{x}_t = \arg \max_{x_t} P(Y_t = y_t \mid X_t = x_t, \theta) P(X_t = x_t, \theta) \quad (18)$$

where θ is the parameter vector connected to xt's clique potential function. The MAP estimate in this case is x^t. $P(X_t = x_t)$is prior probability, $P(Y_t = y_t \mid X_t = x_t, \theta)$ is likelihood function, which make up equation (19).

Prior probability $P(X_t = x_t)$ is given as

$$P(X_t = x_t, \theta) = \frac{1}{z} e^{\frac{-U(x_t)}{T}} = \frac{1}{z} e^{\frac{-\{\sum_{c \in C} V_c(x_t)\}}{T}} \quad (19)$$

where U(X_t) is energy function, and z is partition function, written as $z = \sum_{x_t} e^{\frac{-U(x_t)}{T}}, U(X_t)$. The clique potential function in spatial domain is represented by $V_c(x_t)$. It is characterised by the bonding parameter of the MRF model as

$$V_c(x_t) = \begin{cases} +\alpha \text{ if } x_{st} = x_{qt} \\ -\alpha \text{ if } x_{st} \neq x_{qt}, \end{cases}$$

$$V_{sc}(x_{st}, x_{qt}) = \begin{cases} +\alpha \text{ if } x_{st} \neq x_{qt} \text{ and } (s,t),(q,t) \in S \\ -\alpha \text{ if } x_{st} = x_{qt} \text{ and } (s,t),(q,t) \in S. \end{cases} \quad (20)$$

Data argumentation is required to preserve input-output mapping in MLPs or CNNs permutation equivariant. It differs from ridge regression in some subtle but crucial ways. Eq. (21) describes the Lasso estimate:

$$\hat{\beta}^{\text{Lasso}} = \min_{\beta} \sum_{i=1}^{N} \left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j\right)^2 \quad (21)$$

$$\text{s.t. } \sum_{j=1}^{p} |\beta_j| \leqslant t \quad (22)$$

Equation (23) gives the Lagrangian version of the Lasso issue.

$$\hat{\beta}^{\text{Lasoo}} = \min_{\beta} \sum_{i=1}^{N} \left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j\right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \quad (23)$$

$$\min_x \frac{1}{2} \parallel x - y \parallel_2^2 + \lambda_1 \parallel x \parallel_1 + \lambda_2 \parallel Dx \parallel_1 \quad (24)$$

where $\|\cdot\|_1$ is l_1 norm, and $D \in R^{(n-1)\times n}$ is given as eq. (25)

$$D = \begin{bmatrix} 1 & -1 & 0 & \dots 0 & 0 \\ 0 & 1 & -1 & \dots 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 1 & -1 \end{bmatrix} \qquad (25)$$

The derivative of x 1 is one if x i is greater than zero and one in all other circumstances, although it is not defined at zero. As a result, eq (26) is written.

$$w_i = \begin{cases} \lambda_1 & \text{if } x_i > 0 \\ \in [-\lambda_1, \lambda_1] & \text{if } x_i = 0 \\ -\lambda_1 & \text{if } x_i < 0. \end{cases} \qquad (26)$$

To repeat the criteria in (27), utilise the well-known projection operator, represented as eq(30).

$$w = P_{\lambda_1}(w + x) \qquad (27)$$

$$P_{\lambda_1}(a_i) = \begin{cases} \lambda_1 & \text{if } a_i > \lambda_1 \\ \in [-\lambda_1, \lambda_1] & \text{if } |a_i| \le \lambda_1 \\ -\lambda_1 & \text{if } a_i < -\lambda_1. \end{cases} \qquad (29)$$

Projection equation for z is obtained in the same way and is denoted by eq (30).

$$z = P_{\lambda_2}(z + Dx) \qquad (30)$$

$$\begin{cases} x - y + w + D^T z = 0 \\ w = P_{\lambda_1}(w + x) \ \dots\dots\dots. \\ z = P_{\lambda_2}(z + Dx).\ . \end{cases} \qquad (31)$$

First eqn in (31) clearly shows that x = y − $w - D^T z$. When it is substituted in the second equation, the outcome is $x = y - D^T z - P_{\lambda_1}(y - D^T z)$. As a result, the criteria in (31) can be rewritten as eq (32)

$$z = P_{\lambda_2}\left(z - DP_{\lambda_1}(y - D^T z) - Dy + DD^T z\right) \qquad (32)$$

Based on the equation in (33), NN is proposed with dynamic equation as being given by

State Equation

$$\frac{dz}{dt} = P_{\lambda_2}(z - h(z)) - z$$

Output Equation

$$x = y - D^T z - P_{\lambda_1}(y - D^T z) \qquad (33)$$

5. Experimental analysis

Following data analysis in this phase, we utilized Python to extract and visualise our findings so that we could see trends in student grade performance across various courses as well as helpful information. To help instructors enhance their students' academic performance so they can make better decisions in future, data visualisation makes it possible to find all features as well as insightful information in student dataset. To further comprehend results, we also compare each of the outcomes of our suggested method utilizing a more pictorial method.

Dataset description:

The experience API (xAPI) of a learner activity tracker programme provided the data set used in this paper. The learning and training architecture (TLA) offered by xAPI makes it easier to track how much a learner has improved and to keep track of their actions, such as writing articles, watching videos, or reading articles. Learning platform facilitator can identify learner, activities, any other relevant elements that could aid in addressing learning practice by using xAPI. There are 16 attributes and 480 student records in the dataset. Three primary categories are used to group these attributes: (1) Features relating to demographics, such as nationality and gender. (2) Academically connected characteristics such as section, grade level, educational stage. (3) Characteristics associated with behaviour, such as raising one's hand in class, accessing resources, conducting surveys among peers, and feeling satisfied with school. The sample includes 175 female and 305 male participants, respectively. Two academics are involved in the dataset collection. For example, in Europe, the European Commission funds two networks: Network of Experts on Social Aspects of Education and Training (NESET) and European Expert Network on Economics of Education (EENEE). These networks write reports for the Commission, which then informs its official communications. The OECD disseminates brief notes titled Pisa in Focus that offer policy recommendations based on data analyses of its Programme for International Student Assessment (PISA).

Table-1 Comparative based on various dataset

Dataset	Techniques	Accuracy	Precision	Recall	F1_Score	RMSE	MAP
EENEE	LMS	75	66	54	45	42	33
	SVM	82	68	59	49	45	39
	SQCSRGNN	85	71	62	52	47	42
NESET	LMS	79	69	55	53	51	45
	SVM	83	72	62	55	53	47
	SQCSRGNN	85	75	65	59	57	49
PISA	LMS	87	72	61	61	55	51
	SVM	92	75	63	63	59	53
	SQCSRGNN	95	77	65	65	62	55

The next step is information cleaning, which is the most popular method for identifying information that is incomplete, inaccurate, superfluous, or missing and then replacing, modifying, or discarding it in accordance with the specific requirement. We discovered that the missing data is present in three segments. Not a Number, or NaN, is a special value in Numpy and Information Edges displays that deals with a valueless cell. The encoding of information comes next. We use this direct information encoding scheme at the moment when the absolute element is identified as ordinal. Holding the sequence is important in this case. As a result, the succession should be encoded. During name encoding, each mark will be converted into a whole numeric value. We'll look for the covariance lattice from that point on. It is most likely of the primary lattice in information science and machine learning. It provides information about co-development (relationship). The mean vector in the network of fluctuation covariance comprises the technique for each variable, while the differences of the factors will be in the primary corner to corner and the covariances between each set of factors of the other lattice places. We place the information's free highlights into a predetermined reach in element scaling. When processing pre-processed information, it manages completely altering attributes, sizes, and units. We then divided the dataset into two categories: informative collecting preparation and testing. The next phase is called emphasise significance. Since highlight determination is a key process for directing variable use to what is typically productive and powerful for a particular machine learning framework, it is fundamental to machine learning. Tuning is the next step. The process of improving a model's presentation while avoiding overfitting or needless variation is known as tuning. Choosing appropriate hyperparameters in machine learning is how this is implemented. Hyperparameters can be thought of as the "dial" or "handles" of a machine learning model.

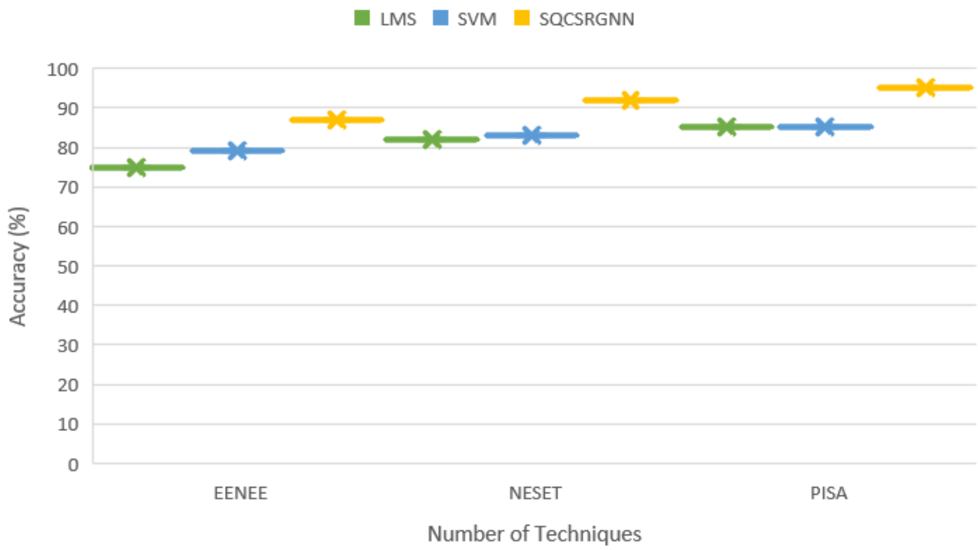

Figure-3 Comparative analysis of accuracy for EENEE, NESET, PISA datasets

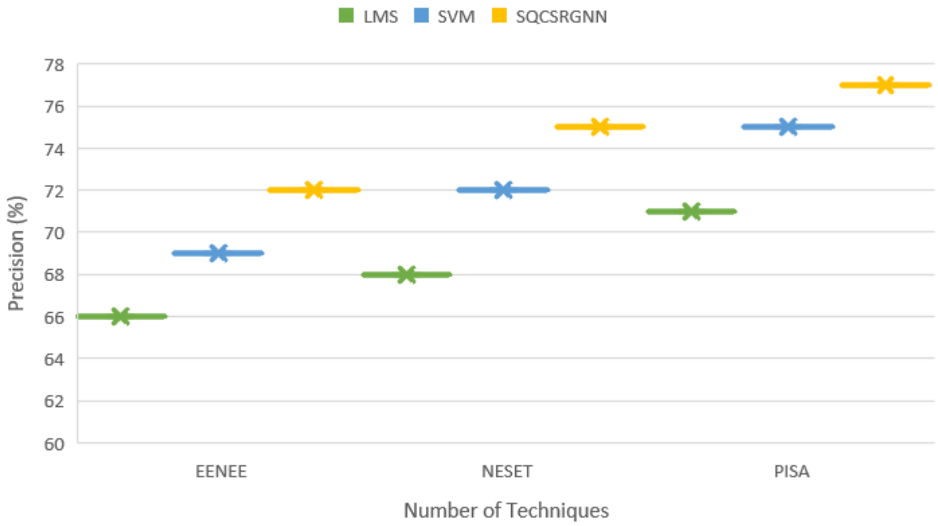

Figure-4 Comparative analysis of Precision for EENEE, NESET, PISA datasets

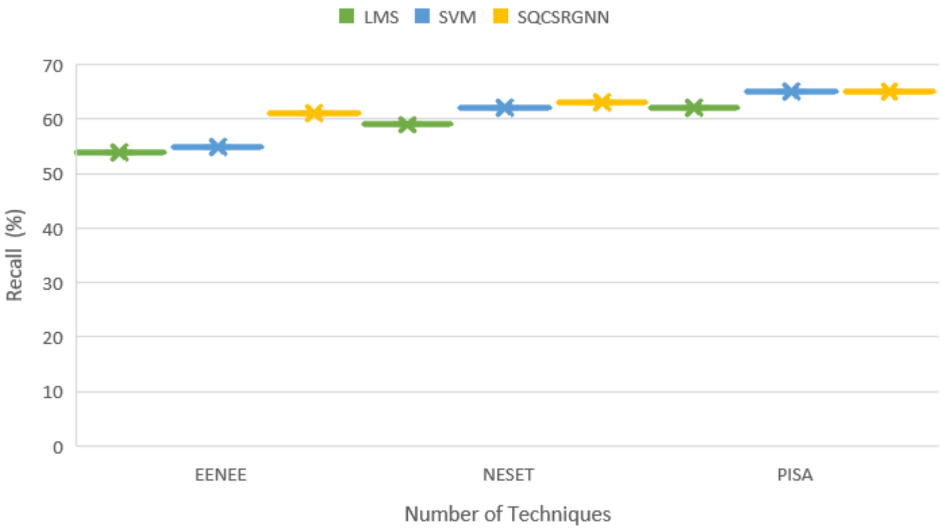

Figure-5 Comparative analysis of recall for EENEE, NESET, PISA datasets

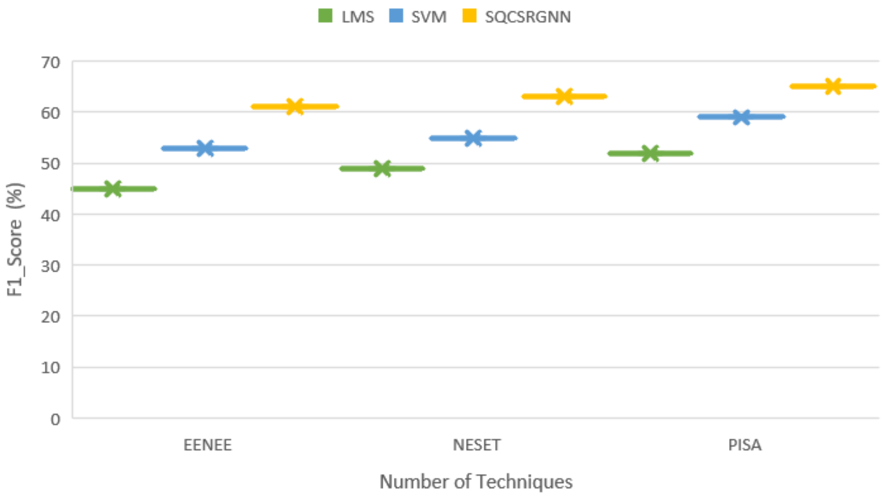

Figure-6 Comparative analysis of F-score for EENEE, NESET, PISA datasets

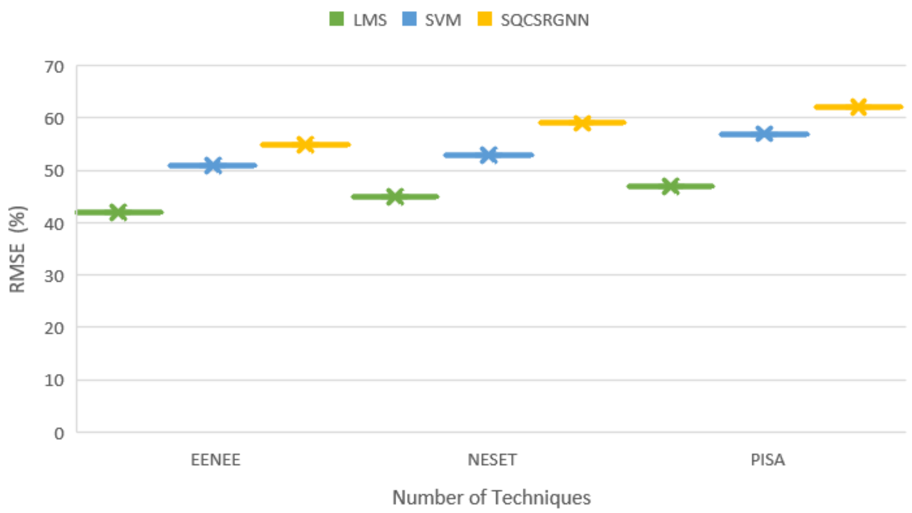

Figure-7 Comparative analysis of RMSE for EENEE, NESET, PISA datasets

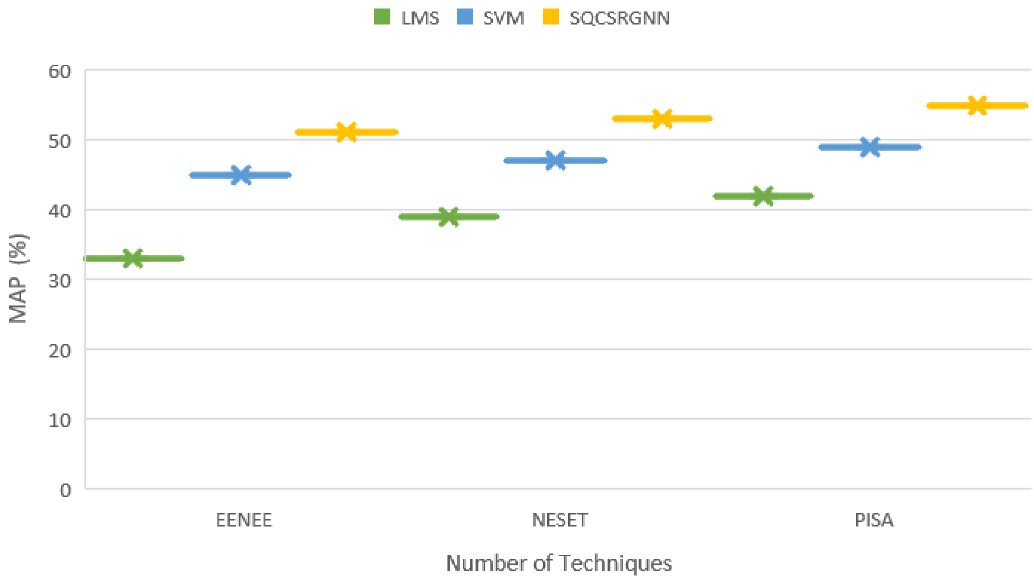

Figure-8 Comparative analysis of MAP for EENEE, NESET, PISA datasets

Table 1 and Figure 3-8 above present a comparative comparison of existing and proposed techniques based on different datasets. The EENEE, NESET, and PISA datasets have all undergone parametric analysis in terms of accuracy, precision, recall, F-1 score, RMSE, and MAP. In this case, the suggested method achieved 85% accuracy, 71% precision, recall 62%, F-1 score of 52%, RMSE of 47%, and MAP of 42%; the current method, SVM, achieved 82% accuracy, 68% precision, recall 59%, F-1 score of 49%, RMSE of 45%, and MAP of 39%; for the EENEE dataset, LMS achieved 75% accuracy, 66% precision, recall 54%, F-1 score of 56%, RMSE of 43%, and MAP of 53%. The suggested method achieved 85% accuracy, precision of 75%, recall of 65%, F-1 score of 59%, RMSE of 57%, and MAP of 49% for the NESET dataset; the current method, LMS, achieved 79% accuracy, precision of 69%, recall of 55%, F-1 score of 53%, RMSE of 51%, and MAP of 45%; and the SVM achieved 83% accuracy, precision of 72%, recall of 65%, F-1 score of 59%, RMSE of 57%, and MAP of 49%. The suggested method achieved 95% accuracy, 77% precision, recall 65%, F-1 score of 65%, RMSE of 62%, and MAP of 55%; the current method, LMS, achieved 87% accuracy, 72% precision, recall 61%, F-1 score of 61%, RMSE of 55%, and MAP of 51%; for the PISA dataset, SVM achieved 92% accuracy, 75% precision, recall 63%, F-1 score of 63%, RMSE of 59%, and MAP of 53%. It takes as information the information focuses i.e., the quantity of tests and the quantity of bunches K. Rehashed tests were controlled by shifting the upsides of K. The aftereffects of the runs executed were recorded for additional handling to discover the quantity of groups K in the two populaces viable. We have utilized the agglomerative methodology of various leveled grouping. A granular perspective at first considers each datum point as a bunch and afterward finds closeness between useful pieces of information by utilizing the Euclidean distance technique. The 300 and 356 information tests of populace 1 and populace 2 were individually dependent upon various leveled bunching. The contribution for various leveled grouping is the information tests and the distance to consolidate bunches in the agglomerative methodology. To approve the names got by grouping we have utilized the idea of MOS. As a piece of this cycle we imparted the class name to every one of the people who partook in the trial to track down the singular pleasantness with their condition of emotional wellness. The fitting number of bunches and its comparing marks were distinguished. The subsequent stage is to fabricate a classifier models with the elements and the marks got through bunching. The objective populace 1 and populace 2 brought about similar number of groups, instinctively we have chosen to blend them into a solitary populace with 656 examples. Prior to applying the emotional wellness model, we really want to pre-dissect the psychological healthrelated information of undergrads. In the wake of building the information model and information structure, the important models and information calculations are altered by the exploratory outcomes. (harsh the testability analyze, it is found that the relationship and dependability of the applicable exploratory information increment straightly with the increment of how much information examination. After further dissecting the information qualities, it is found that the qualities of the information likewise digress somewhat.

6. Conclusion:

Undergrads are in a significant phase of entering the general public, and the psychological wellness of understudies is likewise a significant issue confronting our schooling. Step by step instructions to precisely assess and examine the psychological wellness of understudies is subject of this research. In this research, top to bottom restudy of viewpoint of undergrads' psychological wellness assessment and examination model works on the precision and pace of assessment and examination and further develops work productivity. A wide range of methods and calculations had been acquainted and proposed with test and take care of the emotional well-being issues. There are as yet numerous arrangements that can be refined. Furthermore, there are as yet numerous issues to be found and tried involving a wide assortment of settings in machine learning for the psychological wellness space. As ordering the emotional well-being information is for the most part an extremely difficult issue, the highlights utilized in the machine learning calculations will essentially influence the exhibition of the grouping. The e-learning wellbeing mediations relating to time spend in learning, interruption, sluggishness, states of e-learning making undesirable, pressure in secure circumstance made understudies to have a redirection from learning as well as understanding. With proposed method circumstances in elearning is effectively noticed and broke down in like manner. Likewise, the significance among the chose ascribes. In this examination work we examined about the e-emotional well-being mediations as well as relationship that exists among characteristics. Fuse of element examination best portrays fluctuation, among connected properties as well as assists with deciding joint varieties for unnoticed dormant level factors. We have figured out an instrument for the best assurance of variables that contribute towards virtual learning climate. This peculiarity is figured out ahead of time, can make the learning climate easy to use and intuitive among the understudy's local area.

Acknowledgement:
Fund project：Ministry of Education and UNICEF project on "Improve core competencies" for young people （2021-2025）

Reference:

1. Shafiee, N. S. M., & Mutalib, S. (2020). Prediction of mental health problems among higher education student using machine learning. *International Journal of Education and Management Engineering (IJEME)*, *10*(6), 1-9.
2. Baba, A., & Bunji, K. (2023). Prediction of Mental Health Problem Using Annual Student Health Survey: Machine Learning Approach. *JMIR Mental Health*, *10*, e42420.
3. Mutalib, S. (2021). Mental health prediction models using machine learning in higher education institution. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, *12*(5), 1782-1792.
4. Du, C., Liu, C., Balamurugan, P., & Selvaraj, P. (2021). Deep learning-based mental health monitoring scheme for college students using convolutional neural network. *International Journal on Artificial Intelligence Tools*, *30*(06n08), 2140014.
5. Nanda, A., Tuteja, S., & Gupta, S. (2022). Machine learning based analysis and prediction of college students' mental health during COVID-19 in India. In *Artificial Intelligence, Machine Learning, and Mental Health in Pandemics* (pp. 167-187). Academic Press.
6. Ahuja, R., & Banga, A. (2019). Mental stress detection in university students using machine learning algorithms. *Procedia Computer Science*, *152*, 349-353.
7. Muzumdar, P., Basyal, G. P., & Vyas, P. (2022). An empirical comparison of machine learning models for student's mental health illness assessment. *arXiv preprint arXiv:2202.13495*.
8. Abdullah, A. S., Abirami, R. M., Gitwina, A., & Varthana, C. (2021). Assessment of academic performance with the e-mental health interventions in virtual learning environment using machine learning techniques: A hybrid approach. *Journal of Engineering Education Transformations*, *34*(SP ICTIEE), 79-85.

9. Herbert, C., El Bolock, A., & Abdennadher, S. (2021). How do you feel during the COVID-19 pandemic? A survey using psychological and linguistic self-report measures, and machine learning to investigate mental health, subjective experience, personality, and behaviour during the COVID-19 pandemic among university students. *BMC psychology*, *9*(1), 1-23.
10. Mendoza, N. B., King, R. B., & Haw, J. Y. (2023). The mental health and well-being of students and teachers during the COVID-19 pandemic: Combining classical statistics and machine learning approaches. *Educational Psychology*, *43*(5), 430-451.
11. Huang, H., & Xiao, H. (2023). The cultivation methods of humanistic spirit in college English teaching and its influence on students' mental health based on deep learning. *Eurasian Journal of Educational Research*, *104*(104), 87-105.
12. Shen, Y., Zhang, W., Chan, B. S. M., Zhang, Y., Meng, F., Kennon, E. A., ... & Zhang, X. (2020). Detecting risk of suicide attempts among Chinese medical college students using a machine learning algorithm. *Journal of affective disorders*, *273*, 18-23.
13. Zhou, L. (2022). Applications of deep learning in the evaluation and analysis of college students' mental health. *Discrete Dynamics in Nature and Society*, *2022*.
14. Liang, Y. (2024). Research on the Prediction and Intervention Model of Mental Health for Normal College Students Based on Machine Learning. *International Journal of Intelligent Systems and Applications in Engineering*, *12*(6s), 369-385.
15. Nayan, M. I. H., Uddin, M. S. G., Hossain, M. I., Alam, M. M., Zinnia, M. A., Haq, I., ... & Methun, M. I. H. (2022). Comparison of the performance of machine learning-based algorithms for predicting depression and anxiety among University Students in Bangladesh: A result of the first wave of the COVID-19 pandemic. *Asian Journal of Social Health and Behavior*, *5*(2), 75.
16. Chen, T. (2023). Investigating the mental health of university students during the COVID-19 pandemic in a UK university: a machine learning approach using feature permutation importance. *Brain Informatics*, *10*(1), 27.
17. Wang, Y., & Ma, C. (2022). Evaluation and analysis of college students' mental health from the perspective of deep learning. *Wireless Communications and Mobile Computing*, *2022*, 1-11.
18. Rois, R., Ray, M., Rahman, A., & Roy, S. K. (2021). Prevalence and predicting factors of perceived stress among Bangladeshi university students using machine learning algorithms. *Journal of Health, Population and Nutrition*, *40*, 1-12.
19. Wang, T., Zhao, Y., & Yin, M. (2022). Analysis and research on the influence of music on students' mental health under the background of deep learning. *Frontiers in Psychology*, *13*, 998451.\
20. Liu, J., & Wang, H. (2022). Analysis of educational mental health and emotion based on deep learning and computational intelligence optimization. *Frontiers in Psychology*, *13*, 898609.
21. Gurusamy, D., Chakrabarti, P., Midhunchakkaravarthy, Chakrabarti, T., & Jin, X. B. (2022, September). Machine Learning, Wearable, and Smartphones for Student's Mental Health Analysis. In *Congress on Intelligent Systems* (pp. 327-341). Singapore: Springer Nature Singapore.
22. Sun, Y., & Jen, T. H. (2023). The Impact of the Teaching Mode of Physical Activities Independent Courses in Arts Education on the Physical Changes and Mental Health of College Students Based on Deep Learning Analysis. *Eurasian Journal of Educational Research*, *105*(105), 140-158.
23. Krishnan, R., Kumari, S., Badi, A. A., Jeba, S., & James, M. (2023). Predictive machine learning model for mental health issues in higher education students due to COVID-19 using HADS assessment. *Arab Gulf Journal of Scientific Research*.
24. Venkatachalam, B., & Sivanraju, K. (2023). Predicting Student Performance Using Mental Health and Linguistic Attributes with Deep Learning. *Revue d'Intelligence Artificielle*, *37*(4).
25. Gao, Q., & Wei, Y. (2023). Understanding the cultivation mechanism for mental health education of college students in campus culture construction from the perspective of deep learning. *Current Psychology*, 1-18.