

# The Impact of the Teaching Mode of Sports Independent Courses on the Physical Changes and Mental Health of College Students Based on Deep Learning Analysis

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## ABSTRACT

Common mental disorders are increasing among the populations of western industrial countries. There is a strong connection between physical health and mental health but somewhat well-known regarding the pathways from one to another. After directing for co-founders, previous studies only discovered strong cross effects among mental and physical health. But few are well-known regarding the potential pathways via which mental health influences physical health and in reverse (i.e., known as "indirect effects"). These are robust risk criteria for ill health and levy more risk on the college student's health which may be simply neglected with lower cost interferences. This manuscript develops an effective Tunicate Swarm Optimization Algorithm with Deep Belief Network (TSOADB) model to determine the impact of the teaching model of sports on the mental health status of college students. To attain this, the proposed TSOADB model majorly investigates the input data to determine the patterns related to the mental health condition. The proposed TSOADB model primarily applies an effective classification model called DBN to examine the input data. The TSOA is employed to choose the hyperparameters linked with it for enhanced results properly. A series of simulations were performed to showcase the betterment of the TSOADB model, and the experimental results were investigated under several measures. The experimental results highlighted the superior outcomes of the TSOADB model over other models.

**Keywords:** Deep Learning, Mental Health, Tunicate Swarm Optimization, College Students, Teaching Mode, Sports.

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## INTRODUCTION

Education is the fundamental component of advancing the social turn of events and the most direct method for working on personal quality (Ma, 2021). In this way, school education is becoming increasingly more significant with the advancement of society. With the improvement of science and innovation, school education is continually changing and refreshing. Among them, the main one is the change of the teaching mode (Y. Zhang, 2022). Data education shows up in the ongoing school education driven by the improvement of science and innovation. Even though data education isn't promoted totally, numerous important investigations have offered adequate specialized help for its turn of events. Education is significant in advancing the thriving and advancement of a country (Harris & Bacon, 2019). For people, it can work on their social characteristics and assist them with turning into the abilities required. For the country, it can improve inventiveness and advance its revival. It likewise can work on the characteristics of residents and understand the legacy of development.

Present-day college students have increasingly high prerequisites for their quality's inside and out advancement (X. Wang, 2014). Whenever their lives are firmly connected with sports, the prerequisites for the utilization of basic education will be higher and more unambiguous. In college students' games cognizance, the

primary factor is fortifying preparation, the most immediate and viable method for further developing competitors' cutthroat levels (P. Li & Meng, 2022). A little games contest is coordinated by the class or students, which cannot just control review, life musicality, and amicable mindset. It develops feeling to empower college students to have a good rest, consequently continually altering the method of sports comprehension and further developing games perception capacity in this interaction (X. Wang, S. Zhao, J. Liu, & L. Wang, 2022; Mody & Bhoosreddy, 1995). College students are the future mainstays of the nation's turn of events, bearing the memorable assignment of building the country and rejuvenating the country, fostering a healthy propensity for a logical work-out while in school, and giving an actual good establishment to future social help. Individuals are, as of now, not content with the quest for material components and, on second thought, go to sports wellness, sports relaxation, sports diversion, and different angles as their games discernment moves along (H. S. Lee & J. Lee, 2021).

Exact factual examination discoveries might be procured by deep mining and investigation of the data in the current database, which can give data support for mentors to assemble preparing programs, evaluate preparing quality, and change on-the-fly techniques (Kosholap et al., 2021; Garg, 2020). Thinking performance in sports mental exercises: believing is a fundamental mental viewpoint for grasping data and capacities, and appreciation is the result of reasoning exercises; it is the main mental perspective in creative learning; the law of inward solidarity of reasoning and discernment gives a hypothetical establishment to internal impersonation of sports perception (Gunawan, Firmansyah, & Widiastuti, 2019); the law of shared advancement among thinking and issues gives a hypothetical establishment to the assimilation of sports insight, and the law of common advancement among thinking and issues gives a hypothetical establishment to the assimilation of sports cognizance. Students' games' mental limit fosters their capacity to assess and tackle issues while partaking in sports, and an unmistakable utilization of the real thinking and issues progress one another. Numerous mental, epidemiologic, and financial investigations have utilized intercession examination; however, none regarding the connection between physical and mental health and the pathways that we consider (Ho, Cheong, & Weldon, 2021). A gathering of these examinations has dissected immediate and roundabout impacts of tension and youth injuries on mental health. Second, mental health might influence people's dynamic interaction, weakening their capacity to get data on their health, counteraction, and the nature of healthcare suppliers, affecting their actual health.

X. Zhang and Luo (2021) suggested Deep Learning (DL) studies mention the help of data mining approaches in providing open problems, computer software and hardware recommendations, and recently associated solutions. The suggested outcomes underlined the significance of utilizing innovative educational method mining approaches for data relevant to the emotional assessment of students. Educational mindset has collected few explanations in computational students. Conversely, psychology is related to computer education and underlines various subjects relevant to distinct mental education stages to debates DL. The researchers in Security and Communication Networks (2021), and Shahabaz and Afzal (2021) elaborate on the present condition of tennis teaching, after which studies the appropriate context of DL and argue the typically utilized neural network method in the domain of DL. The researchers in Xiao (2021) focused on learning the influences of healthy physical fitness depending on huge data mining technologies in aerobics teaching. Based on examining the composition of healthy physical fitness, the role of aerobics and data mining is utilized for testing students in some varsity via statistical methodologies and experimental methodologies.

Mendoza Torralba (2020) and Z. Li (2022) suggest a conceptual structure of "Sports Ed 3.5" for varsities and collegiate athletic links for developing an athlete data system for sports analytics. Moreover, the structure focuses on elaborating the philosophy that would direct every stakeholder in using the information of athletes for elastic decision making. Yang, Oh, and Y. Wang (2020) and Salihu and Iyya (2022) accomplishment of artificial intelligence (AI) educational robot-related voice interaction; a hybrid physical education (PE) teaching mode is made for realizing personalized education for students. Firstly, the speech recognition system is devised from 3 prospects of speech synthesis, speech recognition, and interaction management, and the precision of identification is enhanced by the method. Secondly, a new model of hybrid PE teaching is made. With intelligent information technology, the benefits of old PE teaching are compiled for improving the classroom proficiency of PE teaching and personalized education capability for students. H. Wang and M. Chen (2022) learned the implementation of the flipped classroom teaching method depends on limited shot learning in public PE in usual varsities and academies. It examines the theoretical merits of the flipped classroom teaching method depending on few-shot learning, compiling its advantages with the recent typical college atmosphere. Xiang, Fu, and Gadekallu (2022) presented a distributed hash table-based resource search strategy for mobile intelligent education systems. The first step in creating an efficient method for finding resources is employing a distributed hash table and a vector space model. Then the similarity problem between query vectors and vectors of location resources is addressed by constructing the vector link between location resources, and user queries, to locate multi-attribute resources. Finally, based on the resource similarity findings, the most relevant resources are

identified. For a more intelligent education system, Bibi et al. used K-means clustering to find the greatest match for resources. Krishnan et al. (2022) propose a Concept-based and hierarchical clustering unsupervised learning approach for Twitter sentiment analysis. Single linkage, full linkage, and average linkage are serially ensembled. Two feature representation approaches are investigated: Boolean and TF-IDF. The author also compared well-known classifiers (Naive Bayes, Neural Network) Understudied approaches are evaluated on accuracy (percentage of right predictions). Umamaheswari and Parthiban (2021) employ Object-Oriented Programming and Data Communication Network to construct and analyse case studies. The example course has two plug-ins, local and log storage, and reports are shown. This study tracked the activities of each pupil. This research shows the distribution of material access, from which we may deduce the number of engaged students and their activities. The study shows how many assignments and quiz submissions were on time. The figure also shows hit distribution. Deep learning and reinforcement learning were used to predict COVID-19. This article uses Recurrent Neural Networks (RNN), specifically the Modified Long Short-Term Memory (MLSTM) model, to estimate new cases, losses, and cures in the next several days. This research offers deep learning reinforcement to improve COVID-19's symptom prediction. Real-world data was used to evaluate the system.

The key contribution of this work is to develop an effective Tunicate Swarm Optimization Algorithm with Deep Belief Network (TSOADB) model to determine the impact of the teaching model of sports on the mental health status of the college students. To attain this, the proposed TSOADB model majorly investigates the input data to determine the patterns related to the mental health condition. The proposed TSOADB model primarily applies an effective classification model called DBN to examine the input data. The TSOA is employed to choose the hyperparameters linked with it for enhanced results properly. A series of simulations were performed to showcase the betterment of the TSOADB model. **Table 1** depicts the summary of recent works.

**Table 1.** Summary of Recent Works

References	Methodology Used	Advantage	Disadvantage
X. Zhang and Luo (2021)	Deep Learning	More accurate	Extremely expensive
T. Zhao (2021)	RBF neural network	Strong tolerance to input noise	Classification is slow
Xiao (2021)	Big data mining technology	Quicker and Better Decision Making	Not distinguish the specific meaning of the data, and the data field it targets is also not specific,
Mendoza Torralba (2020)	Machine learning	Generates predictive models	Require large amounts of hand-crafted, structured training data
Yang et al. (2020)	Hybrid Teaching Mode of Physical Education	Individualized education ability of physical education teaching is improved.	The plagiarism and credibility problem
H. Wang and M. Chen (2022)	Flipped classroom	More efficient	There is significant work on the front-end
Shen and Gadekallu (2022)	Mobile intelligent education system based on 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 matching process.
Bibi et al. (2022)	Concept-based sentiment analysis (CBSA)	More advanced and more accurate	Incorrectly Targeted Sentiment
Krishnan et al. (2022)	Object-Oriented Programming course and Data Communication Network	Files can easily be shared between users.	Requires more time
Umamaheswari and Parthiban (2021)	Cooperative Particle Swarm Optimization (CPSO) with Multilayer Perceptron (MLP), called CPSO-MLP model	Computational efficiency	Requires large amount of data

## MATERIALS AND METHODS

In this section, the impact of the teaching mode of sports independent courses on the physical changes and mental health of college students based on deep learning analysis is discussed.

### Mental Health Classification Using DBN Model

At the initial stage, the proposed TSOADBN model primarily exploited an effective classification model called DBN to examine the input data. Generally, the major variance among the MLP and DBN is that the DBN can able to perform the learning mechanism by layer-wise unsupervised training procedure. But, the MLP technique failed to carry out feature learning tasks and is broadly employed in the classifier model. The similarities between the MLP and DBN are that they are FC (Fully connected) networks and the applied BP (Back propagation) methodology for supervised learning is implemented in the classification layer of DBN (J. Guo et al., 2019). The RBM is a probability-based graphical network comprehended by the stochastic NN (Neural network) whereby 2 output units of the neuron are involved. It depends on the BM methodology and a FE methodology depends on the energy mechanism and optimization takes place using the unsupervised training. The RBM methodologies involve 2 groups of layers that are, visible layer  $v=(v_1, v_2, \dots, v_n)$  denotes the observation dataset, and hidden state  $h=(h_1, h_2, \dots, h_m)$  described by the FE layer. At first, the uppermost 2 layers are signified as the joint distribution of output, and the final hidden ( $h_1$ ) layers are named the related memory components. The learning procedure of the DBN model undergoes separation into 2 stages such as unsupervised learning (pretraining) and supervised learning (fine-tuning). Initially, unsupervised learning is realized by contrasting deviance to the stacked RBM training in a hierarchical way. Next, supervised learning is motivated by the BP methodology for fine-tuning the earlier bias and weight. A most important objective of unsupervised training in DBN is the optimization of RBM to extract the feature from the dataset. For a collection of  $(v, h)$ , the  $E(v, h|\theta)$  energy function can be described by:

$$E(v, h|\theta) = -\sum_{i=1}^n a_i v_i - \sum_{j=1}^m b_j h_j - \sum_{i=1}^n \sum_{j=1}^m v_i w_{ij} h_j \quad (1)$$

In Eq. (1),  $\theta = \{w_{ij}, a_i, b_j\}$  indicates the variable in RBM, while  $w$  signifies the weight of the connectivity layer, and  $a$  &  $b$  symbolize the bias of visible and hidden neurons, correspondingly. The joint possibility distribution is defined by Eq. (2):

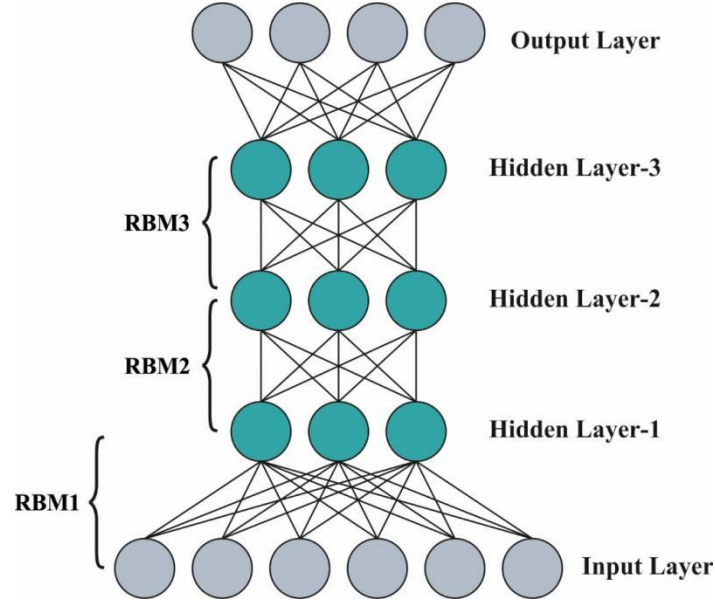
$$P(v, h|\theta) = \frac{e^{-E(v, h|\theta)}}{z(\theta)}, z(\theta) = \sum_{v, h} e^{-E(v, h|\theta)} \quad (2)$$

In the Gibbs sampling process, the restrictive probability distribution of the hidden and visible neurons is denoted as Eq. (3) and Eq. (4):

$$P(h_i = 1|v, \theta) = \text{sigmoid}(b_j + \sum_i v_i w_{ij}) \quad (3)$$

$$P(v_i = 1|h, \theta) = \text{sigmoid}(a_i + \sum_j h_j w_{ji}) \quad (4)$$

The likelihood  $h_j$  signifies an active state. Meanwhile, RBM has symmetric features for the hidden neuron  $h$ , the activation layer probability of all the neurons in the visible layer is demonstrated in the above equation. The procedure is applied for obtaining the respective weight  $w$  of RBM, and the unsupervised learning of DBN training the RBM in a hierarchical means to attain the earlier weight  $W=(w_1, w_2, \dots, w_l)$ . **Figure 1** depicts the structure of DBN. Supervised learning involves fine-tuning the connection weight generated from unsupervised learning. The BP methodology determines the gradients by labeling the trained dataset and modifies the network parameters among the layers to decrease the gradients. In conclusion, the deep network architecture with minimum prediction error is proposed.



**Figure 1.** Framework of DBN

### Hyperparameter Adjustment Process

Here, the TSOA is employed to properly choose the hyperparameters linked with it for enhanced results. The scientific and motivation modeling of the TSOA method is briefly discussed. Tunicate can discover the position of the feed source in the ocean. However, it is unknown regarding the feed source in the searching region (El-Sehiemy, 2022). In TSOA, 2 activities of tunicates are exploited for determining the feed source and they are SI and jet propulsion. For methodically processing the jet propulsion activity, the tunicate might satisfy three scenarios i.e., motion nearby the location of the optimal searching agent, continued near the optimal searching agent, and prevent the fights between the searching regions. Meanwhile, the swarm behavior upgrades the position of other searching agents on the optimal solution. **Figure 2** showcases the flowchart of the TSO technique. The arithmetical procedure of the TSOA is shown below.

To avoid the fights amongst searching agents,  $\vec{A}$  vector is exploited to calculate the new searching agent position as Eq. (5), Eq. (6), and Eq. (7).

$$\vec{A} = \frac{\vec{G}}{\vec{M}} \quad (5)$$

$$\vec{G} = c_2 + c_3 - \vec{F} \quad (6)$$

$$\vec{F} = 2 \cdot c_1 \quad (7)$$

However,  $\vec{F}$  portrays the water flow advection in the Deep Ocean and  $\vec{G}$  indicates the gariab less. The  $c_1, c_2,$  and  $c_3$  parameters are arbitrary values ranging from zero and one,  $\vec{M}$  indicates the social force between search agents. The  $\vec{M}$  vector was evaluated by Eq. (8):

$$\vec{M} = [p_{\min} + c_1 \cdot p_{\max} - p_{\min}] \quad (8)$$

In Eq. (8),  $p_{\min}$  and  $p_{\max}$  indicates the prime and secondary speeds for creating social interfaces. Here,  $p_{\min}$  and  $p_{\max}$  values are regarded as 1 and 4. Next, to prevent the fight between nearby ones, the searching agent is travelling toward the optimal neighbors.

$$\vec{PD} = |\vec{FS} - r_{\text{and}} \cdot \vec{P}_{p(x)}| \quad (9)$$

In Eq. (9),  $\vec{PD}$  indicates the distance between the feed search and feed source, for example, tunicate,  $x$  symbolizes the existing iteration,  $\vec{FS}$  indicates the position of the feed source. The  $\vec{P}_{p(x)}$  vector characterizes the tunicate position and  $r_{\text{and}}$  indicates the arbitrary amount lies within the interval of zero and one. The searching agent is remaining the position nearby the optimal searching agent\*

$$\vec{P}_{p(x)} = \begin{cases} \vec{FS} + \vec{A} \cdot \vec{PD} & \text{if } r_{\text{and}} \geq 0.5 \\ \vec{FS} - \vec{A} \cdot \vec{PD} & \text{if } r_{\text{and}} < 0.5 \end{cases} \quad (10)$$

In Eq. (10),  $\vec{P}_{p(x)}$  embodies the upgrading tunicate position concerning the  $\vec{FS}$  feed source position. To arithmetically imitate the tunicate behavior of swarm, initialized 2 optimal solution is to save and upgrade the position of another searching agent depending on the position of an optimal searching agent. The succeeding formula is indicated to define the swarm behavior of tunicate:

$$p_p(x + 1) = \frac{p_p(x) + p_p(x+1)}{2 + c_1} \quad (11)$$

The flowchart and steps presented are given below.

Tunicate initialize population  $\vec{P}$

Choose the maximal count of iterations and prime parameters.

Calculate the fitness values of each searching agent.

After evaluating the fitness values, the optimal search agent is traveled in a given search region.

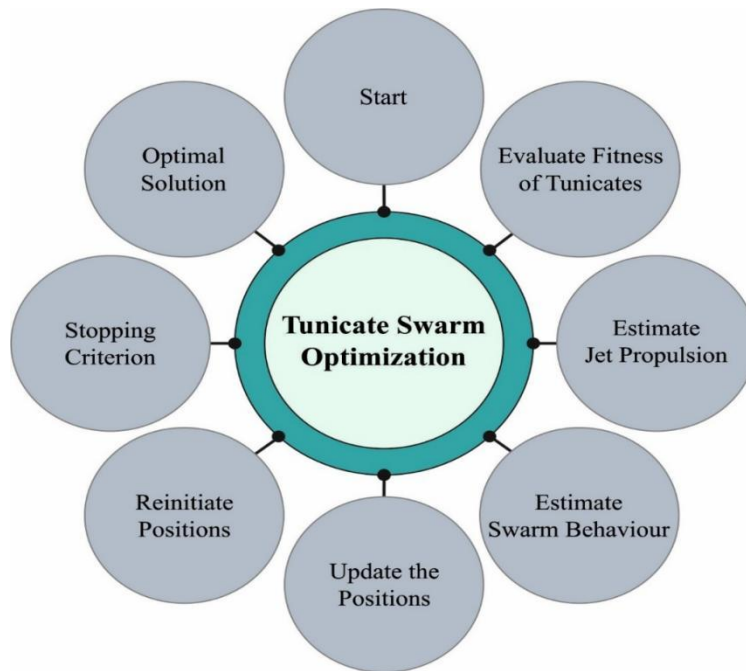
Upgrade the location of each searching agent through Eq. (11).

Adjust the upgraded searching agent that chases off from the edge in the searching region.

Evaluate the upgraded search agent fitness value. The optimal solution compared to the prior optimal solution, then upgrade  $p_p$

Once the ending criteria are met, the TSOA gets stopped and repeats Steps 5-8.

Attain optimal solution.



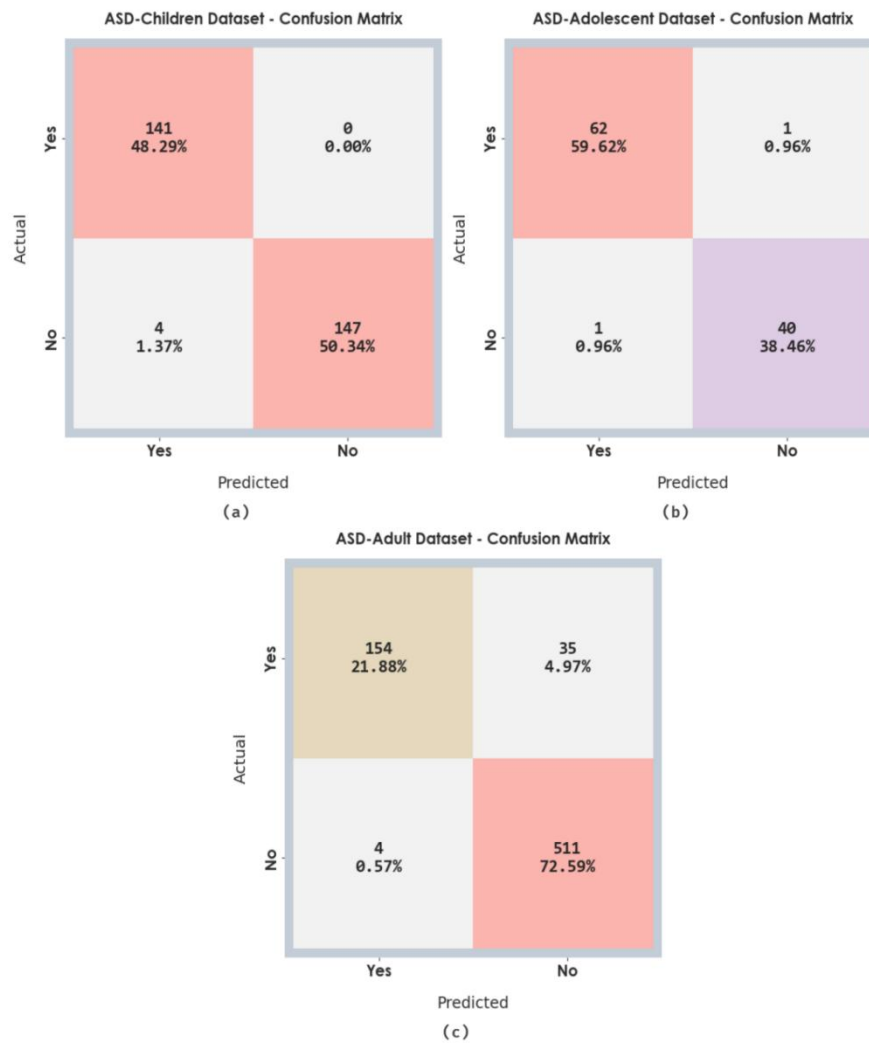
**Figure 2.** Flow Chart of TSO Technique

## RESULTS AND DISCUSSION

Neurodevelopmental abnormalities in the brain are the primary cause of autism spectrum disorder (ASD). Autism Spectrum Disorder (ASD) is a developmental disorder characterised by difficulties in social interaction and repetitive or limited actions or interests. There aren't many chances for physical exercise for people with autism spectrum disorders (ASD). The experimental validation of the proposed model is inspected on three datasets namely ASD-Children Dataset (dataset 1), ASD-Adolescent Dataset (dataset 2), and ASD-Adult Dataset (dataset 3).

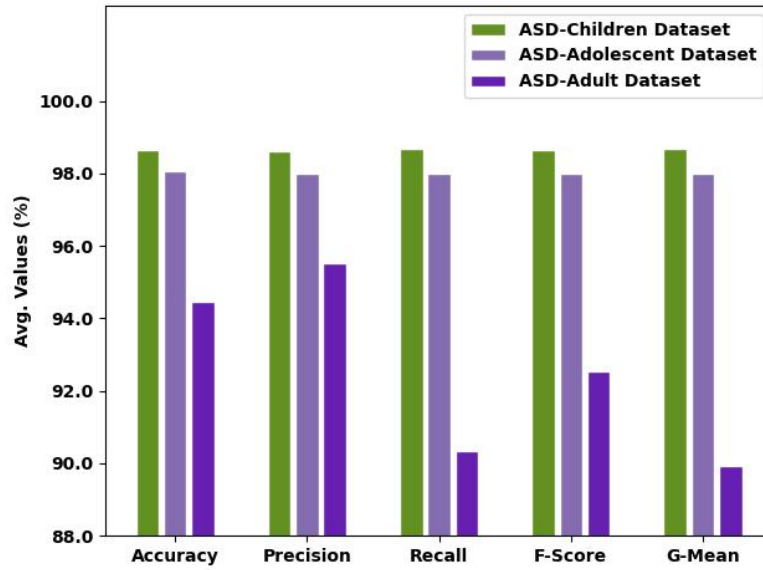
**Figure 3** reports a set of three confusion matrices created by the use of the TSOA-DBN model on the test data. With dataset-1, the TSOA-DBN model has recognized 141 samples in the Yes class and 147 samples in the No class. On the other hand, with dataset-2, the TSOA-DBN methodology has recognized 62 samples in the Yes class and 40 samples in the No class. Next to that, with dataset-3, the TSOA-DBN algorithm has recognized 154

samples in the Yes class and 511 samples in the No class.



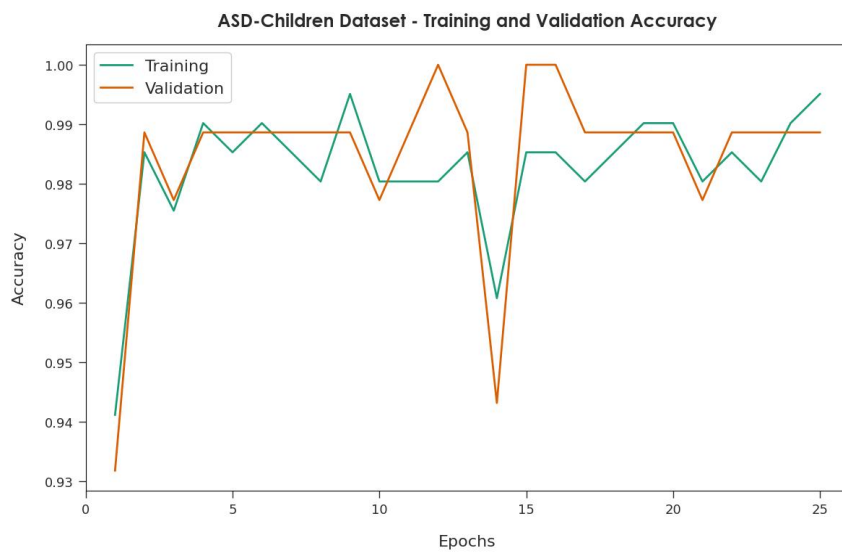
**Figure 3.** Confusion Matrices of TSOA-DBN Technique (a) Dataset-1, (b) Dataset-2, and (c) Dataset-3

**Figure 4** depicts an in-depth analysis of the TSOA-DBN model carried out on three different datasets. The findings demonstrated that the TSOA-DBN model provided improved outcomes across all datasets.



**Figure 4.** Result Analysis of TSOA-DBN Technique under Three Datasets

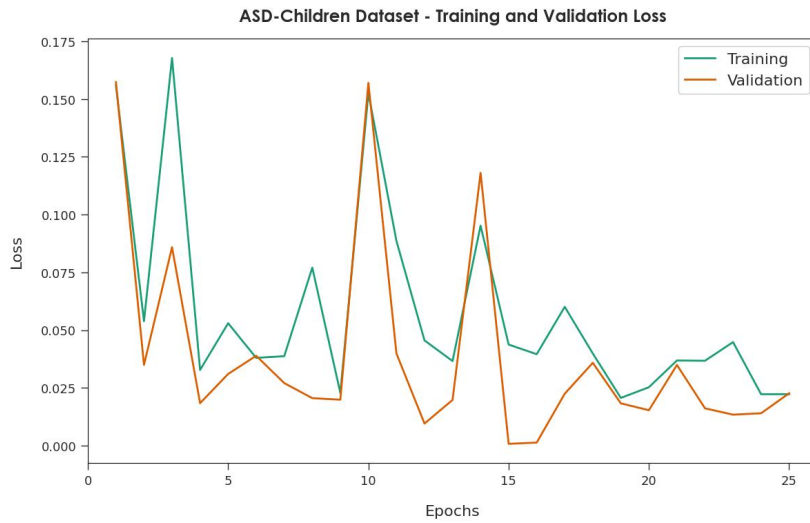
For instance, on dataset-1, the TSOA-DBN model has attained average  $accu_y$ ,  $prec_n$ ,  $reca_l$ ,  $F_{score}$ , and  $G_{mean}$  of 98.63%, 98.62%, 98.68%, 98.63%, and 98.67% respectively. Moreover, on dataset-2, the TSOA-DBN system has gained average  $accu_y$ ,  $prec_n$ ,  $reca_l$ ,  $F_{score}$ , and  $G_{mean}$  of 98.08%, 97.99%, 97.99%, 97.99%, and 97.99% correspondingly. Furthermore, on dataset-3, the TSOA-DBN methodology has gained average  $accu_y$ ,  $prec_n$ ,  $reca_l$ ,  $F_{score}$ , and  $G_{mean}$  of 94.46%, 95.53%, 90.35%, 92.54%, and 89.92% correspondingly.



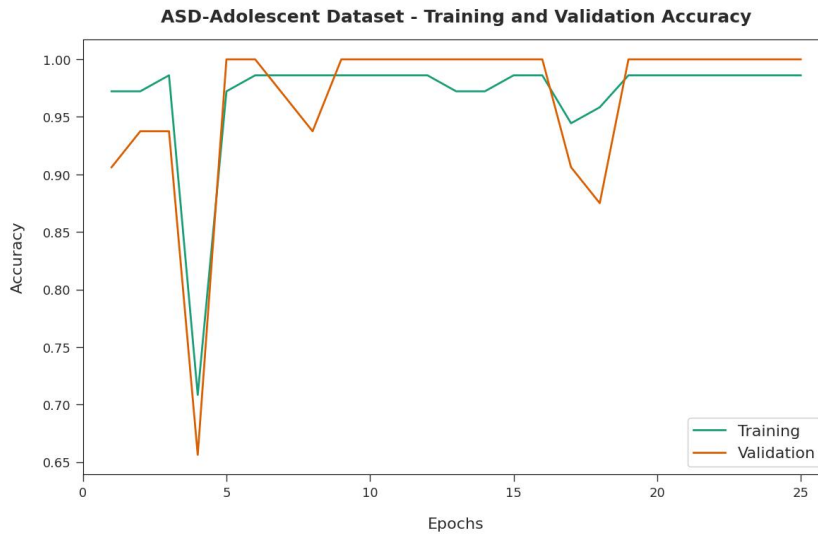
**Figure 5.** TA and VA Analysis of TSOA-DBN Technique under Dataset-1

The training accuracy (TA) and validation accuracy (VA) attained by the TSOA-DBN approach under dataset-1 is demonstrated in **Figure 5**. The experimental outcome implied that the TSOA-DBN model has gained maximum values of TA and VA. In specific, the VA seemed to be higher than TA.

The training loss (TL) and validation loss (VL) achieved by the TSOA-DBN model under dataset-1 are established in **Figure 6**. The experimental outcome inferred that the TSOA-DBN system has accomplished the least values of TL and VL. In specific, the VL seemed to be lower than TL.



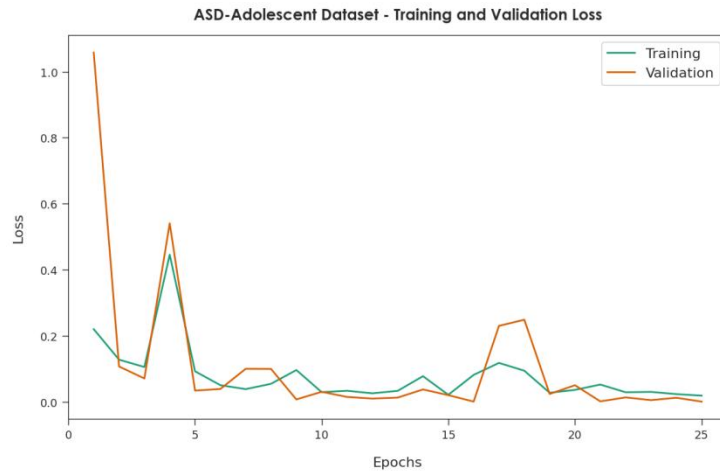
**Figure 6.** TL and VL Analysis of TSOA-DBN Technique under Dataset-1



**Figure 7.** TA and VA Analysis of TSOA-DBN Technique under Dataset-2

The TA and VA gained by the TSOA-DBN method under dataset-2 are illustrated in **Figure 7**. The experimental outcome implied that the TSOA-DBN system has obtained maximal values of TA and VA. Particularly, the VA seemed to be higher than TA.

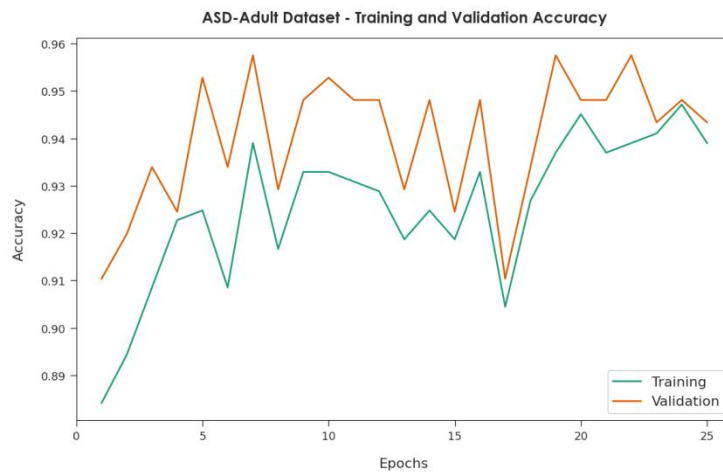
The TL and VL achieved by the TSOA-DBN system under dataset-2 are established in **Figure 8**. The experimental outcome inferred that the TSOA-DBN system has established the least values of TL and VL. In particular terms, the VL seemed to be lower than TL.



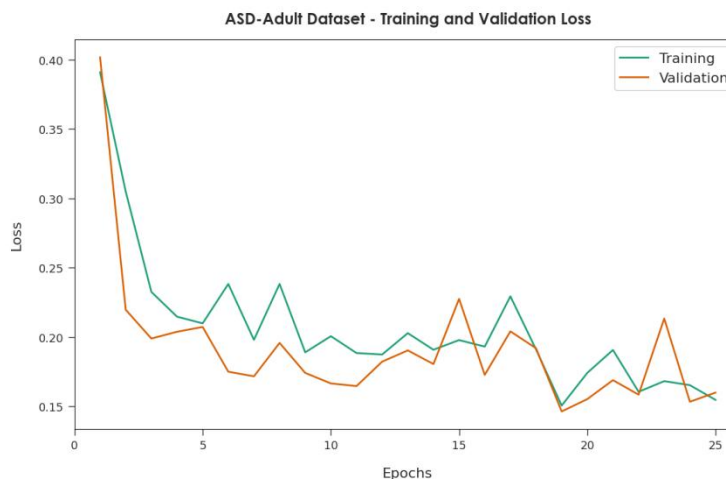
**Figure 8.** TL and VL Analysis of TSOA-DBN Technique under Dataset-2

The TA and VA gained by the TSOA-DBN approach under dataset-3 are illustrated in **Figure 9**. The experimental outcome implied that the TSOA-DBN model has gained maximum values of TA and VA. In specific, the VA seemed to be higher than TA.

The TL and VL achieved by the TSOA-DBN system under dataset-3 are established in **Figure 10**. The experimental outcome inferred that the TSOA-DBN system has accomplished the least values of TL and VL. In specific, the VL seemed to be lower than TL.

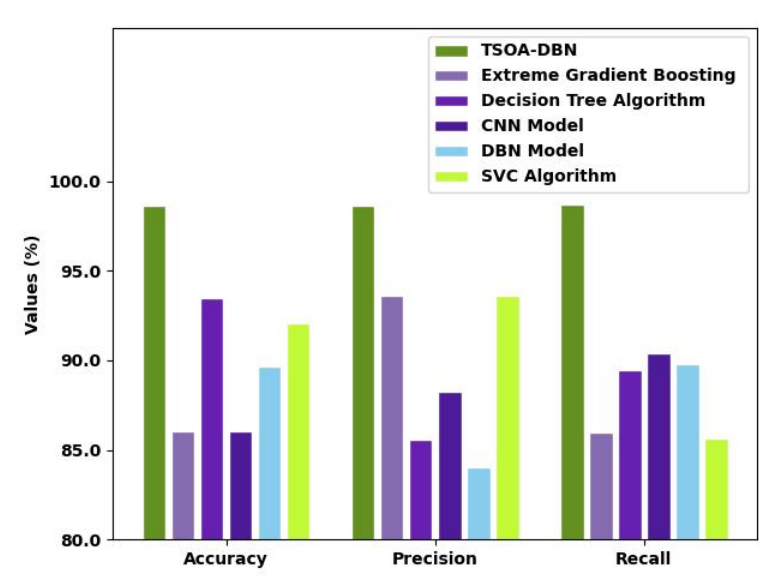


**Figure 9.** TA and VA Analysis of TSOA-DBN Technique under Dataset-3



**Figure 10.** TL and VL Analysis of TSOA-DBN Technique under Dataset-3

At last, the comparative classification performance of the TSOA-DBN model is studied in **Figure 11**. The experimental values portrayed that the TSOA-DBN model has shown enhanced performance over all other methods. For instance, concerning  $accu_y$ , the TSOA-DBN model has offered an enhanced  $accu_y$  of 98.63% whereas the XGBoost (Z. Zhang, Z. Zhao, & Yeom, 2020), DT (L. Liu, 2021), CNN (Y. Guo & X. Wang, 2021), DBN (X. Wang, 2009), and SVC (Shen & Gadekallu, 2022) models have attained reduced  $accu_y$  of 86.03%, 93.49%, 86.04%, 89.64%, and 92.05% respectively.



**Figure 11.** Comparative Analysis of TSOA-DBN Technique with Existing Algorithms

In line, concerning  $prec_n$ , the TSOA-DBN method has provided enhanced  $prec_n$  of 98.62% whereas the XGBoost, DT, CNN, DBN, and SVC systems have attained reduced  $prec_n$  of 93.61%, 85.55%, 88.25%, 84.05%, and 93.61% correspondingly. Along with that, concerning  $reca_1$ , the TSOA-DBN model has offered enhanced  $reca_1$  of 98.68% whereas the XGBoost, DT, CNN, DBN, and SVC models have gained decreased  $reca_1$  of 85.95%, 89.47%, 90.37%, 89.82%, and 85.62% correspondingly. Therefore, the proposed TSOA-DBN model has gained effectual performance over other methods.

## CONCLUSION

In this article, a new TSOADB N model has been introduced to determine the impact of the teaching model of sports on the mental health status of college students. To attain this, the proposed TSOADB N model majorly investigated the input data to determine the patterns related to the mental health condition. The proposed TSOADB N model primarily exploited an effective classification model called DBN to examine the input data. Followed by, the TSOA is employed to properly choose the hyperparameters linked with it for enhanced results. To showcase the betterment of the TSOADB N model, a series of simulations were performed and the experimental results are investigated under several measures. The experimental results highlighted the superior outcomes of the TSOADB N model over other models. There is a problem with the suggested experiment since it uses a basic system. That's why a more sophisticated system and non-linear difficulties must be investigated to see how the suggested solution performs. In the future, the presented TSOADB N model can be extended to the use of dimensionality reduction approaches.

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