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College Students' Mental Health Prediction Model Based on Time Series Analysis

Abstract: - Social attention has long been focused on students' mental health, and forecasting mental health may be compared to a time-series classification challenge. The psychological health education programs at all of the colleges are now addressing the same problem, despite the fact that the number of schools is expanding quickly and the demand for students is always rising. In this Manuscript, College Students' Mental Health Prediction Model Based on Time Series Analysis (CS-MHP-CSTGCN) is proposed. Initially, the data is collected from Students Mental Health Assessments dataset. Then, the collected data is fed into pre-processing utilizing Implicit Bulk‐Surface Filtering (IBSF). The IBSF is used for data cleaning and data normalization. Then the preprocessed data are given to Continual Spatio-Temporal Graph Convolutional Networks (CSTGCN) for predicting a Mental Health of College Student's and classify as normal and abnormal. CSTGCN does not express adapting optimization strategies to determine optimal parameters. Hence, the Multiplayer Battle Game-Inspired Optimizer (MBGIO) to optimize CSTGCN which accurately predict the Mental Health of College Student's. The proposed CS-MHP-CSTGCN approach is implemented in Python. The suggested method's effectiveness was evaluated using performance measures such as MSE, F1-score, accuracy, precision, and recall. The suggested CS-MHP-CSTGCN approach contains 27.26%, 29.41% and 13.26% higher accuracy ,26.26%, 21.41% and 23.26% higher precision and 19.29%, 14.31% and 21.26% less mean squared error likened with current methods, like Student Behavior Prediction of Mental Health Based on Two-Stream Informer Network (SBP-MH-TSIN), Research on the Prediction and Intervention Model of Mental Health for Normal College Students Based on Machine Learning (PMH-NCS-RPMM) and Mental Disorder Prediction Model With the Ability of Deep Information Expression Using Convolution Neural Networks Technology (MDP-ADI-CNN) respectively.

Keywords: College Student's, Continual Spatio-Temporal Graph Convolutional Networks, Implicit Bulk‐Surface Filtering, Mental Health and Multiplayer Battle Game-Inspired Optimizer.

I. INTRODUCTION

Schools, colleges and society as a whole have been quite worried about the mental health issues that students are facing [1]. In recent years, there has been an increase in the number of mental health cases involving students, which has an impact on their grades and can result in dropout or even suicide. Based on psychological testing and investigations, the State Education Commission found that 20.23% of 126,000 college students exhibited evident psychological issues [2-3]. Thus, it is believed that by anticipating kids' mental health conditions, identifying children who have mental abnormalities beforehand, and enabling educators and schools to engage in by psychological interventions with kids, disaster might be avoided and the chance of harmful occurrences reduced. [4-6]. The majority of current approaches are grounded on qualitative research and gather and analyze student mental health data through the use of questionnaires and self-evaluations. Significant subjectivity is frequently evident in the research findings since many students are unwilling to disclose their genuine psychological state [7-9]. In the current rigorous and fast-paced educational environment, students' mental health has become a major issue that requires careful consideration. The quest of academic brilliance can have a negative impact on students' psychological health when combined with personal struggles and social pressures [10-11]. The more intricately they must manage their schoolwork, relationships with their peers, and goals for the future, the more critical it is to prioritize and treat their mental health. In addition to helping students achieve academic success, a supportive atmosphere that recognizes and meets their emotional needs can help them lead well-rounded, satisfying lives [12-15].This delves into the complex aspects of pupils' mental health, illuminating the different elements that influence it and investigating methods to foster their emotional fortitude and general welfare. Students' emotional, psychological, and social states are all part of their general health, and their psychological health is a critical component [16]. The move to a higher education can be thrilling and daunting at the same time, exposing students to a wide range of obstacles that may negatively affect their mental health. Academic stress is frequently brought on by tight schedules and difficult assignments.Students' mental resources may be further taxed by the desire to participate in extracurricular activities, work part-time, and keep up social

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relationships [17-19]. A number of variables, including interpersonal problems, homesickness, financial worries, and worry about the future, complicate their emotional environment [20].

A drawback of the research is the narrow range of behavioral information taken into account when assessing students' mental health. While academic success, social contacts, and extracurricular activities are all significant parts of student life that may have an impact on mental health, the study primarily focuses on students' canteen intake, Internet access, and daily routine behaviors. Although students with aberrant mental health disorders frequently exhibit learning disabilities in real life, only took into account a portion of their daily behavioral data when gathering student data. Considered every student as an individual when predicting their mental health status since students who have typically, People around someone with abnormal mental health conditions usually have some sort of influence. Furthermore, the TSIN method of prediction ignores the possibility that friends with mental health disorders may have an impact on each other, thus compromising the classification model's accuracy. The intricacies of mental health expressions may be difficult for the RPMM model to adequately represent, which could result in oversimplification or incorrect data interpretation.Although the CNN-based model has significant limitations, it shows promise in diagnosing common mental problems among college students. The diversity and quality of the training data, which may not accurately reflect the complex range of mental health conditions

To overcome the limitations the primary objectives of this research are to detect pupils with psychological abnormalities, analyze and anticipate students' psychological conditions, and use a combination of qualitative and quantitative research approaches to link students' everyday activities to their psychological conditions. Additionally, the research aims to effectively gather information from the vast amounts of data produced by college students' daily lives.A lot of behavioral data is being gathered as the consequence of the intellectualization and digitization of campuses, including information about meals, travel, study habits, and Internet usage.An organized framework for comprehending the components, composition, and aesthetic quality of Normal College Students' Mental Health is provided by CSTGCN, thanks to data processing techniques and integration technologies. Its efficacy in improving the packaging design process for Normal College students is demonstrated by the analytical results of the CSTGCN. Based on this data, this research suggests a CS-MHP-CSTGCN detentions the dependency among students' actions also time cycle tendency. Lastly, classification prediction is performed using a CSTGCN method.For experimental investigation, the results of the studies indicate that the CSTGCN performs well.

II. LITERATURE SURVEY

Several works have presented previously in literatures were depending on the College Students' Mental Health Prediction using deep learning. Few of them were mentioned here,

Xu et al. [21] have presented a SBP-MH-TSIN. Student mental health has received a lot of social attention over the years, and mental health prediction may be viewed as a time-series classification job. It proposes an informant network based on a two-stream structure (TSIN) to determine how dependent students were on one another. A filtering mechanism was used to achieve the mental health prognosis made by layering in behaviors, time cycle trends, and intermediate variables. This method attains high accuracy and low precision.

Liang [22] has presented a PMH-NCS-RPMM. This study looked at using fuzzy recognition technology to analyze the mental health of typical college students in an effort to increase the efficacy of package design for these types of schools. To systematically investigate and evaluate the creative and aesthetic elements included in the representations of mental health among typical college students, the study's approach consists of a number of crucial procedures. With the help of fuzzy identification algorithms and Direction Point Cluster (DPC) segmentation techniques, the suggested algorithm extracts and selects features from mental health datasets with accuracy. The study examines the nuanced facets of the mental health of normal college students using fuzzy logic and image processing by using the Random Probabilistic Markov Model (RPMM) for characteristic selection. This method attains high precision and low recall.

Huang [23] has presented a model for predicting mental disorders that uses convolution neural networks technology and can represent deep information. Despite the fast growing number of colleges and the rising demand for students, the psychological health education programs at all of them were currently dealing with the same issue: there aren't enough teachers in this sector to address the urgent demands of the majority of students. Students at universities struggle to finish their coursework on time due to mental health issues, which hinders their personal growth. These kinds of things happen one after the other. The research develops a CNN-based approach for identifying mental disorders that uses university students' common diagnosis of mental disorders as an example. Because of its capacity for self-learning, the model can recognize psychological disorders in university students and provide support. to the psychological health team and college psychological counsellors. This method attains high recall and low f1-score.

Guo[24] has presented a Mental Health State Prediction Method of College Students Based on Integrated Algorithm. Conducting pertinent research is crucial since psychological health was a significant issue that college students must deal with. In order to effectively exploit the information in the data from mental health tests, the prediction accuracy of the classifier may be boosted by combining the decision tree approach with the Adaboost algorithm for ensemble learning. The C4.5 decision tree method has been chosen as the foundational algorithm for this study since identifying and classifying samples according to feature properties is possible with this popular classification approach.. Having chose the experiment's sample of 2780 students' mental health evaluations from a certain university in 2020 in order to confirm the efficacy of this approach. This method attains high MSE and low f1-score.

Huang [25] has offered a K-means clustering algorithm-based analysis and prediction of the mental health of college students. The psychological management system presented in this study is based on the K-means clustering analysis technique. Based on the core functions of the conventional system, the idea of data mining was applied to the students' psychological data. The pertinent elements of a vast amount of psychological data about the pupils were taken out by optimizing the iterative K-means method. In order to help managers scientifically oversee students' mental health processes, a data model is developed. The system builds the data mining model as the study is being conducted, keeps mining the psychological information of the students in the database, and looks at a variety of aspects related to the mental health of college students, and offers the appropriate remedy. This method attains high F1-score and low accuracy.

Pei [26] has presented a Prediction and analysis of contemporary college students' mental health based on neural network. Interpersonal communication also performance evaluation on campus provides a significant difficulty for a typical high school graduate. Many college students suffer from mental health issues in an attempt to cope with the pressures and competition that modern college student's experience. This study evaluates, predicts, and investigates the mental health state of contemporary college students using a neural network algorithm. A computer technique used to predict the mental health of contemporary college students was neural network algorithms. Neural network-based data mining technology was used to collect data sources. Low accuracy and a high MSE are achieved by this approach.

Sheng [27] has presented a Simulation Application of Sensors Based on Kalman Filter Algorithm in Student Psychological Crisis Prediction Model. Many relevant people have become aware of the severely abnormal state of some Chinese college students' crises in mental health and psychology. Chinese university students have a very unfavourable psychological construction for a variety of external factors. The Kalman filter was a data processing technique for calculating regression. Recursive access to pertinent data was possible since the typical computation filter has lowest information error. This calculation approach may choose appropriate filters to compute high-dimensional and low-dimensional system data with accuracy within the relevant time domain. The primary purpose of the research was to resolve various issues and demonstrate the efficacy of the Kalman filter calculation method. This approach achieves a low f1-score and excellent accuracy.

III. PROPOSED METHODOLOGY

In this section, CS-MHP-CSTGCN is proposed. The approach involves five steps: Data Acquisition, Pre-processing, feature extraction, prediction and optimization. The process begins with the acquisition of Students Mental Health Assessments dataset, a crucial step in guaranteeing the availability of trustworthy and pertinent data for examination. Following Data acquisition, the data's undergo pre-processing using an Implicit Bulk‑Surface Filtering (IBSF) for data cleaning and data normalization. Then the pre-processed data are then input into a CSTGCN for the purpose of prediction. The CSTGCN, known for its robustness and ability to handle complex data, is tasked with the critical role of prediction. By leveraging its deep learning capabilities, the CSTGCN predict the Mental Health of College Student's and classify as normal and abnormal. To further enhance the performance of the CSTGCN and optimize its parameters for improved accuracy and efficiency, the

Multiplayer Battle Game-Inspired Optimizer (MBGIO) technique is employed. Block Diagram of the suggested CS-MHP-CSTGCN is shown in figure 1.

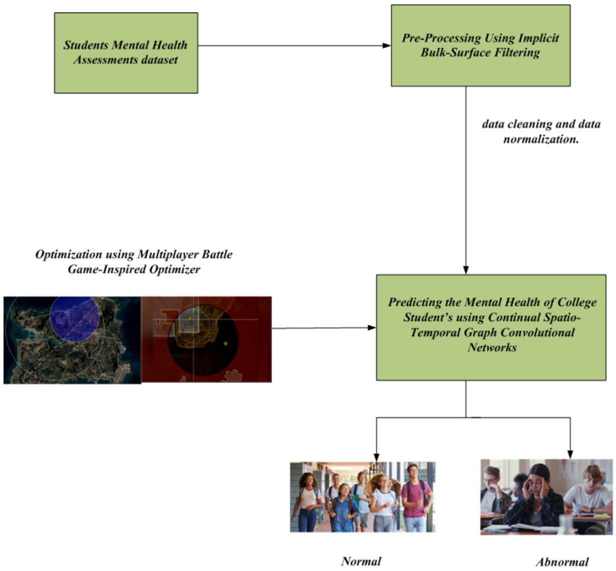

Figure 1: Block Diagram of the proposed CS-MHP-CSTGCN

A. Data Acquisition

The input data's are collected by Students Mental Health Assessments dataset [28]. Student assessments of their mental health are included in the dataset. By collecting a variety of variables that could have an impact on students' mental health, this dataset aims to offer insightful information about the mental health of students. The data set is made up of a wealth of records that have been meticulously chosen to maintain secrecy and privacy from a variety of anonymous sources. Recognizing that no dataset is ever 100% accurate is crucial since there are many potential causes of inaccuracy and ambiguity. Look through older dataset versions for listings from the past.

B. Pre-Processing Using Implicit Bulk‑*Surface Filtering*

In this section, pre-processing using Implicit Bulk‑Surface Filtering (IBSF) [29] is discussed. In the preprocessing, IBSF is used for data cleaning and data normalization.IBSF can handle the massive amount of data that is usually gathered in mental health research involving college students since it can process a big number of data efficiently. Its bulk-surface methodology enables the examination of numerous data sources quickly. IBSF lowers complexity of the information while preserving pertinent information by concentrating on the bulk-surface interaction. This is important for mental health prediction because it allows important predictors to be identified without being overtaken by unimportant factors.

$$-(r_\Omega^H)^2 \nabla . \sigma + y = s, \quad in\ \Omega \tag{1}$$

Where r_Ω^H represent the Helmholtz bulk filter radius, ∇ represent the traditional spatial gradient operator, σ represent a second order tensor like the continuum mechanics Cauchy stress tensor, y represent the generalized Robin boundary condition and s represent the partial differential equation.

$$\sigma = \lambda tr(\varepsilon(y))I + 2\mu \varepsilon(y) \tag{2}$$

Where tr represent the trace worker, λ and μ are the Lame coefficients, I represent the individuality tensor, ε is the strain tensor acting on geometry.

$$\Pi(y) = \frac{1}{2}(r_\Omega^H)^2 \int_\Omega \sigma : \varepsilon\, d\Omega + \frac{1}{2}(r_\Gamma^H)^2 \int_\Gamma \nabla_\Gamma y^T . \nabla_\Gamma xyd\Gamma \tag{3}$$

Where $(r_\Omega^H)^2$ and $(r_\Gamma^H)^2$ represent the corresponding weights, Ω represent the geometry's overall strain energy, $d\Gamma$ considering a constant distribution over the integration domains and $\nabla_\Gamma y^T$ represent the smoothness of the design boundary. Data normalization is determined in equation (4).

$$(r_{\Omega}^{H})^{2} = \beta \frac{(r_{\Gamma}^{H})^{2} \int_{\Gamma} \nabla_{\Gamma} y^{T} . \nabla_{\Gamma} y d\Gamma}{\int_{\Omega} \sigma : \varepsilon \, d\Omega}, \; 0 < \beta \leq 1 \tag{4}$$

Where β represent the weighting factor. r_{Ω}^{H} represent the Helmholtz bulk filter radius, $\nabla_{\Gamma} y^{T}$ represent the smoothness of the design boundary. σ Represent a second order tensor like the continuum mechanics Cauchy stress tensor and $d\Omega$ is the geometry's overall strain energy. Data is cleaned in equation (5)

$$K_{\Omega} = \sum \int_{\Omega^{e}} \left(r_{\Omega^{e}}^{H} \right)^{2} B^{T} C B \, d\Omega \tag{5}$$

Where C represent the linear-elastic isotropic constitutive Matrix. The bulk shape functions N spatial gradients are contained in B. $r_{\Omega^{e}}^{H}$ Represent the rudimentary Helmholtz bulk filter range. Finally, the IBSFnormalize and cleaned the data. Then, the pre-processed output is fed toContinual Spatio-Temporal Graph Convolutional Network (CSTGCN) for predicting theMental Health of College Student's.

C Student's Mental Health Prediction using Continual Spatio-Temporal Graph Convolutional Networks

The prediction using CSTGCN [30] is discussed. CSTGCN is used for expecting theMental Health of College Student's and classify as normal and abnormal.CSTGCNs can demonstrate the intricate relationships and interactions between individuals by utilizing the graph structure seen in social networks between college students. This enables a greater sympathetic of the ways in which social ties impact mental health consequences. As new data becomes available, CSTGCNs can update their predictions continually, hence supporting constant learning. Since that there are many variables that might affect mental health and that these factors can vary over time, this is especially advantageous for mental health prediction models. Ongoing education guarantees that the model is still applicable and flexible in the face of changing conditions.

$$y^{(t)} = w_{0} + \sum_{k=1}^{k} \sum_{v=1}^{v} W_{k,v} \cdot X_{v}^{(t-k-1)} \tag{6}$$

Where $X^{(t)}$ represents the input slice which is convolved with the kernel weight W in the same time-step it is conventional. After then, the intermediate findings are stored in memory m. w_{0} represents the bias andthe output of a standard convolution would be $y^{(t)}$. t represents the time-step.

$$m^{(t)} = \left[\sum_{v=1}^{v} W_{k,v} \cdot X_{v}^{(t)} : k \in 1, K \right] \tag{7}$$

Where K values stored in time-step. $X^{(t)}$ Represents the input slice. W represents the kernel weight. $y^{(t)}$ represents the output of a standard convolution.

$$y^{(t)} = w_{0} + \sum_{k=1}^{K} m_{k}^{(t-k-1)} \tag{8}$$

Where $y^{(t)}$ represents the output of a standard convolution. w_{0} represents the bias and m represents the memory.

$$k_{T} + (k_{T} - 1)(d_{T} - 1) - p_{T} - 1$$

(9)

Where k_{T}, d_{T} and p_{T} represents the equivalent regular convolution's zero-padding, dilation, and temporal kernel size.The effective network stride is determined by

$$s_{NN} = \prod_{t=1}^{L} s_{t} \tag{10}$$

Where a neural system with L layers and s represents the temporal stride. The Mental Health of College Student's is classified as normal and abnormal in equation (11)

$$H_l^{(t)} = \sigma\left(Delay(\mathrm{Re}\,s\left(H_{l-1}{}^{t}\right)\right) + BN\left(C_0 TC\left(GC\left(H_{l-1}^{t}\right)\right)\right) \tag{11}$$

Where, the delayed residual is output by $Delay(\mathrm{Re}\,s\left(H_{l-1}{}^{t}\right)$ in a first-in, first-out manner that corresponds to the Continual Temporal Convolutional. l represents the characteristics in layer at time t. GC represents the Graph Convolutional. Finally, CSTGCN predicted the Mental Health of College Student's and classify as normal and abnormal. In this research, Multiplayer Battle Game-Inspired Optimizer (MBGIO) is assigned to enhance CSTGCN. Here, MBGIO is assigned for turning weight parameter of CSTGCN.

D Optimization using Multiplayer Battle Game-Inspired Optimizer

In this section, Optimization using Multiplayer Battle Game-Inspired Optimizer (MBGIO) [31] is discussed.Here the proposed CSTGCNweight and bias parameters $y^{(t)}$ *and* $H_l^{(t)}$ are optimized using MBGIO. The strategy may be more successful in engaging college students if it presents the mental health prognosis as a cooperative battle game. Multiplayer games are popular among students, which may make them more receptive to taking part in mental health exams. By investigating novel approaches for prediction and intervention, cutting edge methods such as MBGIO can propel progress in the field of mental health research. This may provide discoveries that help larger groups of people dealing with mental health issues in addition to college students.

Step 1: Initialization

The starting population of MBGIO is generated randomly. Then the initialization is derived in equation (16).

$$y = \begin{bmatrix} y_1^1 & y_1^2 & y_1^1 & \cdots & y_1^D \\ y_2^1 & y_2^2 & y_2^3 & \cdots & y_2^D \\ \vdots & \vdots & \vdots & \vdots & \\ y_N^1 & y_N^2 & y_N^3 & \cdots & y_N^D \end{bmatrix} \tag{12}$$

Where y represent the uniform distribution that generates D is the dimension's initial value, then N represent the neutral for population size.

Step 2: Random Generation

After initialization the input fitness purpose industrialized randomness via MBGIO.

Step 3: Fitness Function

The initialized limits is based on current best location are resolute. Calculate the suitability value for each individual.

$$Fitness\ Function = Optimizing\ \left[y^{(t)}\ and\ H_l^{(t)}\right] \tag{13}$$

Where $y^{(t)}$ represents the increasing accuracy and $H_l^{(t)}$ signifies the lowering mean square error.

Step 4:Movement Phase $y^{(t)}$

The Movement Phase is primarily in charge of the exploitation capabilities and directs people into possible regions by using the idea of the "safe zone." the equivalent regular convolution's zero-padding, dilation, and temporal kernel size.

$$y^{(t)} = \left(\left|Y_{best} - Y_{worst}\right| + eps\right) \times rand\left(0.8,1.2\right)$$

(14)

Where $y^{(t)}$ represent thesafety radius. The safe area's radius must not be zero, so eps is a tiny non-negative value. $rand\left(0.8,1.2\right)$ yields a random integer between 0 and 1 and fulfils the uniform distribution.

$$y_{new}^{k} = \begin{cases} y_i^k + normal(\ ), & if\ rand(0,1) < 0.5 \\ y_i^k + \left(y_{best}^k - y_i^k\right) \times rand(0,1), & otherwise \end{cases}$$

(15)

Where the moved discrete and its updated value in the k^{th} dimension are represented by y_{new} and y_{new}^{k} respectively, and $normal(\ )$ yields a random amount that follows the conventional normal delivery.

Step 5: Battle Phase $H_l^{(t)}$

The main function of the Battle Phase is to replicate various clash behaviors that occur when users of the game come across each other at random and to enable exploration. When playing against opponents of different skill levels, players may use diverse tactics, but their common goals are to avoid enemy attacks to reduce damage taken and to deal maximum damage to the opponent to win.

$$y_{new}^{k} = \begin{cases} y_i^k + rand(0,1) \times dir^k, & if\ rand(0,1) < 0.5 \\ y_{opponent}^{k} + rand(0,1) \times dir^k, & otherwise \end{cases}$$

(16)

Where dir represents the vector among the i^{th} individual and casually selected opponent individual. $y_{opponent}$ representstheopponent individual. y_i representsthe original individual.

$$H_l^{(t)} = Y_i + dir \times \cos\ (2 \times \pi \times rand\ (0,1)) \tag{17}$$

Where dir represents the vector between the i^{th} individual and the randomly selected opponent individual. $rand\ (0,1)$ satisfies the uniform spreading and returns a random amount between 0 and 1.

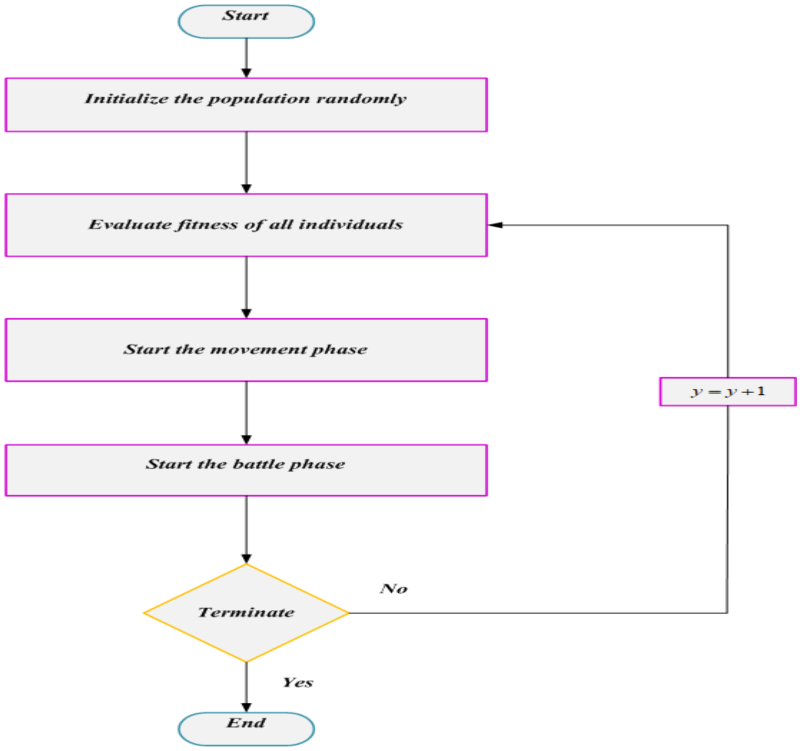

Figure 2: Flowchart for MBGIO

Step 6: Termination Condition

In this stage, the weight parameter ($y^{(t)}$ and $H_l^{(t)}$) of Continual Spatio-Temporal Graph Convolutional Network are optimized with the help of MBGIO, repeatedly recurrence the step 3 until the halting is $y = y + 1$ met. Then finally proposed CS-MHP-CSTGCN classifies Mental Health of College Student's with higher accuracy.

IV. RESULT AND DISCUSSION

This section discusses the results of the proposed technique. The suggested CS-MHP-CSTGCN method is then simulated in Python and compiled utilizing Jupiter notebook and executed in Mac Book Pro along Intel core i7 processor of 2.7 GHz, 8GB of RAM speed. The obtained outcome of the proposed CS-MHP-CSTGCN approach is analysed with existing systems like SBP-MH-TSIN, PMH-NCS-RPMM and MDP-ADI-CNN individually.

A Performance Measures

This is a vital step for selecting the optimal classifier. Performance events are measured to assess presentation like correctness, precision, recall, F1-score and MSE. To scale performance metrics, the performance metric is deemed. To scale the performance metric, the True Negative, True Positive, False Negative and False Positive samples are needed.

- True positive (TP): Accurately predicting College Students' Mental Health and classify as normal
- True Negative (TN): Accurately predicting College Students' Mental Health and classify as abnormal
- False Positive (FP): Inaccurately predicting College Students' Mental Health and classify as normal
- False Negative (FN): Inaccurately predicting College Students' Mental Health and classify as abnormal

1) Accuracy

Accuracy is defined as the percentage of right forecasts. It is quantified by the following equation (18)

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{18}$$

2) Precision

The ratio of correctly predicted positive observations to all positively expected observations is known as precision. The following stated equation (19) is used to measure it.

$$\Pr ecision = \frac{TP}{(TP + FP)} \tag{19}$$

3) Recall

The ratio of correctly anticipated positive observations to all of the class's observations is known as recall. That's provided in equation (20)

$$\operatorname{Re} call = \frac{TP}{(TP + FN)} \tag{20}$$

4) F1-Score

The F1-score is designed as the weighted regular of recall and precision. Here is the F1-Score found in equation (21)

$$F1 - Score = \frac{2 * precision * recall}{precision + recall} \tag{21}$$

5)Mean Square Error

Mean square error (MSE) is calculated by averaging, or taking the mean, of all squared errors determined from data in relation to a function. The MSE is given in equation (22)

$$Mean\,Square\,Error = \frac{1}{n} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 \tag{22}$$

B Performance Analysis

The imitation results of the suggested CS-MHP-CSTGCN method are shown in Figure 3 to 7. The proposed CS-MHP-CSTGCN techniques linked to the SBP-MH-TSIN, PMH-NCS-RPMM and MDP-ADI-CNN techniques, in that order.

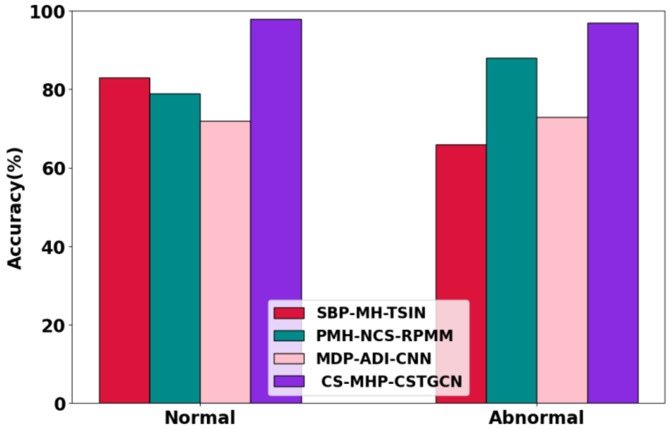

Figure 4: Analysis of Accuracy

Figure 3 shows examination of accuracy.The correctness graph shows how well the CSTGCN model performs in comparison to other benchmark models. Understanding each model's relative effectiveness and applicability for forecasting mental health effects based on student actions and time cycles is aided by this. The proposed CS-MHP-CSTGCN technique reaches in the range of 26.36%, 28.42% and 19.27% higher accuracy for normal and 27.26%, 29.41% and 13.26% higher accuracy for abnormal compared to existing techniques such as SBP-MH-TSIN, PMH-NCS-RPMM and MDP-ADI-CNN respectively.

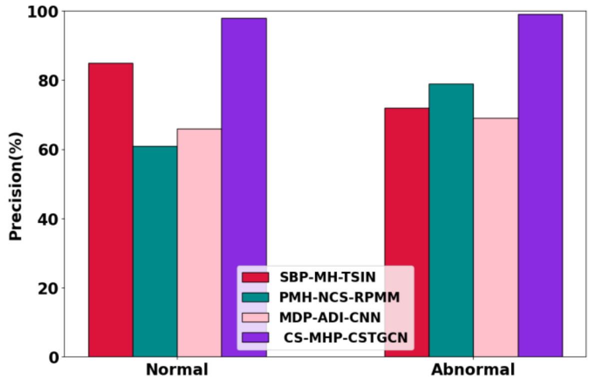

Figure 4: Analysis of Precision

Figure 4 shows analysis of precision. A visual comparison of the accuracy with which various models detect affirmative instances may be made thanks to the precision graph. Based on the precision findings displayed in the graph, you may quickly determine which models are more accurate and make wise selections. The proposed CS-MHP-CSTGCN technique reaches in the range of 21.36%, 22.42% and 19.27% higher precision for normal and 26.26%, 21.41% and 23.26% higher precision for abnormal compared to existing techniques such as SBP-MH-TSIN, PMH-NCS-RPMM and MDP-ADI-CNN individually.

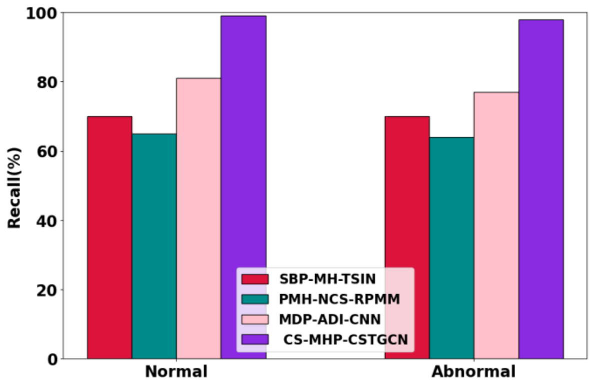

Figure 5: Analysis of Recall

Figure 5 shows examination of recall. On the graph, each model or dataset is represented by a data point that shows the recall level. To demonstrate trends or patterns in the recall of various models across datasets, lines may be drawn connecting the data points. The proposed CS-MHP-CSTGCN technique reaches in the range of

21.36%, 26.42% and 18.27% higher recall for normal and 28.26%, 24.41% and 23.26% higher recall for abnormal compared to existing techniques such as SBP-MH-TSIN, PMH-NCS-RPMM and MDP-ADI-CNN respectively.

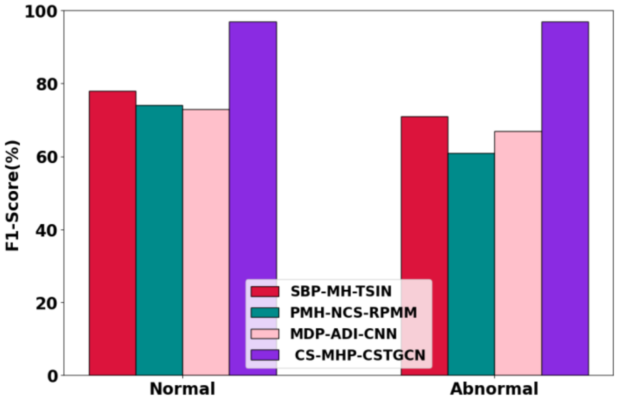

Figure 6: Analysis of F1-score

Figure 6 shows analysis of F1-score. Everyone can determine which models have higher F1-scores a sign of a favourable trade-off between precision and recall by examining the data points and trend lines. Data points on the Y-axis would be higher for models with higher F1-scores. With the F1-score findings displayed in the graph, you can quickly determine which models have higher F1-scores and make defensible decisions. The proposed CS-MHP-CSTGCN technique reaches in the range of 22.36%, 35.42% and 28.27% higher F1-score for normal and 27.26%, 23.41% and 23.26% higher F1-score for irregular compared to current techniques such as SBP-MH-TSIN, PMH-NCS-RPMM and MDP-ADI-CNN respectively.

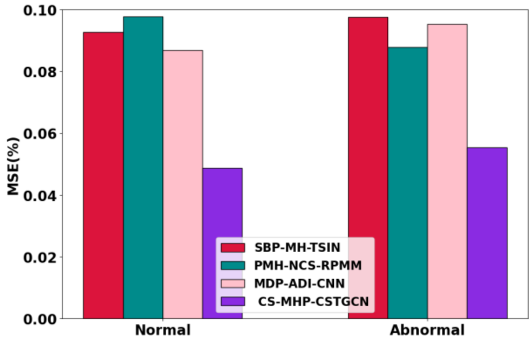

Figure 7: Analysis of Mean Squared Error

Figure 7 shows analysis of Mean Squared Error. The MSE graph makes it possible to compare the prediction abilities of various models or configurations visually. With ease, you can determine which models have lower MSE values and use the MSE data displayed in the graph to inform your selections. The proposed CS-MHP-CSTGCN technique reaches in the range of 26.26%, 17.22% and 25.27% lower mean squared error for normal and 19.29%, 14.31% and 21.26% lower mean squared error for abnormal compared to current techniques such as SBP-MH-TSIN, PMH-NCS-RPMM and MDP-ADI-CNN respectively.

C Discussion

In this section, CS-MHP-CSTGCN is developed in this research. Promising outcomes are seen when sophisticated deep learning models, like the CSTGCN, are used to analyze daily behavior data from kids in order to forecast their mental health condition. Time cycle patterns and behavioral dependencies are efficiently captured by the CSTGCN. The better performance of CSTGCN over other deep learning models is demonstrated by experimental assessments on a Students Mental Health Assessments dataset comprising 11 benchmark datasets and 8213 students. There are restrictions, though, like the emphasis on small amounts of behavioral data and the examination of individual students. Improvements might include adding more detailed behavioral traits of students, using graph structures to represent student interactions, and taking into account the effects of abnormal mental health on others in the immediate vicinity. Overall, the CSTGCN model shows promise for precise mental health status prediction grounded in time cycles and student activities. An intriguing method for examining the psychological health of typical college scholars in relation to wrapping design is provided by the CSTGCN built in this research. A methodical framework for understanding the elements, structure, and aesthetic value of Normal College Students' Mental Health is provided by CSTGCN through data processing techniques and integration technologies. The outcomes of the CSTGCN investigation show how well it works to improve the way Normal College students develop cases.

V. CONCLUSION

In this section, CS-MHP-CSTGCNis successfully implemented. The proposed CS-MHP-CSTGCN approach is applied in Python. The presentation of the suggested CS-MHP-CSTGCN approach contains 27.26%, 29.41% and 13.26% higher accuracy, 26.26%, 21.41% and 23.26% higher precision and 19.29%, 14.31% and 21.26% lower mean squared error when analysed to the existing methods like SBP-MH-TSIN, PMH-NCS-RPMM and MDP-ADI-CNN methods respectively.In the future, researchers will concentrate on collecting more detailed behavioral data from students, especially when it comes to their classroom and library learning experiences. The goal is to create a network that captures the relationships between students by utilizing graph topologies. To improve prediction accuracy, this network will give connections with kids who have abnormal mental health statuses higher weights. In addition, one can plan to incorporate the psychological professionals' assessments of students' psychological deviations into the model so that it can efficiently allocate resources toward psychological counselling. This strategy makes sure that educators and schools can more effectively and completely distribute resources to serve all children who require it. The long-term goal is to develop a strong predictive framework that supports proactive mental health care in educational environments.

REFERENCES

[1] Hou, Z. (2024). A Neural Network Evaluation Model for College Students' Mental Health.

[2] Liu, H., &Xu, J. (2022). Research on the use of neural network for the prediction of college students' mental health. *Scientific Programming*, *2022*, 1-8.

[3] Lu, N. (2024). Mental health rehabilitation of college students based on self-regulated music psychotherapy. *Entertainment Computing*, 100636.

[4] Jin, Q. (2024). Analysis of Psychological Health Data for College Students Based on Data Mining. In *Artificial Intelligence, Medical Engineering and Education* (pp. 222-231). IOS Press.

[5] Lifelo, Z., Ning, H., &Dhelim, S. (2024). Adapting Mental Health Prediction Tasks for Cross-lingual Learning via Meta-Training and In-context Learning with Large Language Model. *arXiv preprint arXiv:2404.09045*.

[6] 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.

[7] Sahu, B., Kedia, J., Ranjan, V., Mahaptra, B. P., &Dehuri, S. (2023). Mental Health Prediction in Students using Data Mining Techniques. *The Open Bioinformatics Journal*, *16*(1).

[8] Roche, A. I., Holdefer, P. J., & Thomas, E. B. (2024). College student mental health: Understanding changes in psychological symptoms in the context of the COVID-19 pandemic in the United States. *Current Psychology*, *43*(14), 13041-13050.

[9] Jiang, L., & Zhang, Y. (2022). Prediction and influencing factors of big data on college students' positive psychological quality under mobile wireless network. *Mobile Information Systems*, *2022*.

[10] Saito, T., Suzuki, H., &Kishi, A. (2022). Predictive modeling of mental illness onset using wearable devices and medical examination data: Machine learning approach. *Frontiers in digital health*, *4*, 861808.

[11] Wang, M. (2022). Prediction Analysis of College Students' Physical Activity Behavior by Improving Gray Wolf Algorithm and Support Vector Machine. *Advances in Multimedia*, *2022*.

[12] Zhang, M., Yan, K., Chen, Y., & Yu, R. (2024). Anticipating interpersonal sensitivity: A predictive model for early intervention in psychological disorders in college students. *Computers in Biology and Medicine*, *172*, 108134.

[13] Huang, Q., Wang, X., Ge, Y., &Cai, D. (2023). Relationship between self-efficacy, social rhythm, and mental health among college students: a 3-year longitudinal study. *Current Psychology*, *42*(11), 9053-9062.

[14] Zając, T., Perales, F., Tomaszewski, W., Xiang, N., &Zubrick, S. R. (2024). Student mental health and dropout from higher education: an analysis of Australian administrative data. *Higher Education*, *87*(2), 325-343.

[15] Wilson, L. C., &Liss, M. (2022). Safety and belonging as explanations for mental health disparities among sexual minority college students. *Psychology of sexual orientation and gender diversity*, *9*(1), 110.

[16] Atlam, E. S., Ewis, A., Abd El-Raouf, M. M., Ghoneim, O., & Gad, I. (2022). A new approach in identifying the psychological impact of COVID-19 on university student's academic performance. *Alexandria Engineering Journal*, *61*(7), 5223-5233.

[17] Rutkowska, A., Cieślik, B., Tomaszczyk, A., &Szczepańska-Gieracha, J. (2022). Mental health conditions among E-learning students during the COVID-19 pandemic. *Frontiers in public health*, *10*, 871934.

[18] Mingyu, Z., Sutong, W., Yanzhang, W., &Dujuan, W. (2022). An interpretable prediction method for university student academic crisis warning. *Complex & Intelligent Systems*, *8*(1), 323-336.

[19] Nasrullah, S., &Jalali, A. (2022). Detection of types of mental illness through the social network using ensembled deep learning model. *Computational Intelligence and Neuroscience*, *2022*.

[20] Liu, J., Xu, Z., Li, X., Song, R., Wei, N., Yuan, J., ...& Su, H. (2024). The association between the sense of relative deprivation and depression among college students: gender differences and mediation analysis. *Current Psychology*, 1-10.

[21] Xu, J., Ding, X., Ke, H., Xu, C., & Zhang, H. (2023). Student Behavior Prediction of Mental Health Based on Two-Stream Informer Network. *Applied Sciences*, *13*(4), 2371.

[22] 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.

[23] Huang, P. (2022). A mental disorder prediction model with the ability of deep information expression using convolution neural networks technology. *Scientific Programming*, *2022*, 1-8.

[24] Guo, N., 2024. Mental Health State Prediction Method of College Students Based on Integrated Algorithm. In *Artificial Intelligence, Medical Engineering and Education* (pp. 205-212). IOS Press.

[25] Huang, P. (2022). A mental disorder prediction model with the ability of deep information expression using convolution neural networks technology. *Scientific Programming*, *2022*, 1-8.

[26] Pei, J. (2022). Prediction and analysis of contemporary college students' mental health based on neural network. *Computational Intelligence and Neuroscience*, *2022*.

[27] Sheng, C. (2024). Simulation Application of Sensors Based on Kalman Filter Algorithm in Student Psychological Crisis Prediction Model. *Measurement: Sensors*, 101190.

[28] https://www.kaggle.com/datasets/sonia22222/students-mental-health-assessments

[29] NajianAsl, R., &Bletzinger, K. U. (2023). The implicit bulk-surface filtering method for node-based shape optimization and a comparison of explicit and implicit filtering techniques. *Structural and Multidisciplinary Optimization*, *66*(5), 111.

[30] Hedegaard, L., Heidari, N., &Iosifidis, A. (2023). Continual spatio-temporal graph convolutional networks. *Pattern Recognition*, *140*, 109528.

[31] Xu, Y., Zhong, R., Zhang, C., & Yu, J. (2024). Multiplayer battle game-inspired optimizer for complex optimization problems. *Cluster Computing*, 1-25.