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Survival Study on Student Academic Performance Classification based on Mental Health

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ABSTRACT

Educational Data Mining (EDM) is used to extract the important information from educational data. EDM identifies the trends from educational data to enhance the student academic performance. EDM uses the machine learning conceptsto recognize the learning, to improve teaching and to optimize the educational systems. Mental health issues are prevalent among students. Depression has significant obstacle for performing the long-term learning in educational system. Student dropout prediction is an important event for educational institutions and policymakers around world. Early student academic performance prediction is an essential research topic in educational data mining. Different deep learning and artificial intelligence methods are introduced to forecast the student academic performance. However, the existing prediction techniques failed to handle the student mental health and their mood changes. In order to address the existing issues, different artificial intelligence and deep learning methods is introduced for student academic performance classification based on mental health.

Keywords: Educational data mining, student academic performance prediction, machine learning, classification, mental health, artificial intelligence

1. INTRODUCTION

Student academic performance prediction has become important for educational institutions seeking to implement targeted interventions and support systems. The mental health problems of students are highly concerned by schools and society. The State Education Commission conducted psychological tests and investigations on 126,000 college students, and the results showed that 20.23% of those students had obvious psychological problems. Therefore, it is important one for predicting the mental health status of students, identifying the students with mental abnormalities in advance, and allowing schools and teachers to interfere psychologically with students.

Student performance forecasting in educational institution is an essential one to increase the learning efficiency. Student performance prediction model handled the multi-dimensional academic data classification. The student performance prediction helps the educational stakeholders for increasing the education quality and addressing society demands. Artificial Intelligence (AI) and Deep learning (DL) methods are used for forecasting student performance depending on diverse factors like study habits, attendance, and past academic records.

The main contribution of survey article is given as:

- To predict the student academic performance based on mental health status from input database with minimum time and higher accuracy
- To discuss different student academic performance prediction methods for reducing the error rate
- To evaluate the conventional student academic performance for attaining better results.

The contents of this paper are organized as follows: Section 1 presents the introduction to the student academic performance and the challenges faced by existing methods. Section 2 presents the review of various machine learning concepts for student academic performance. Section 3 describes the student academic performance datasets used in this study. Section 4 explains the description of different student academic performance techniques. Section 5 explains different

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performance metrics employed for student academic performance. The experimental results are presented and discussed in the Section 6. Section 7 concludes the work with future direction.

2. LITERATURE SUVERY

The fully embedded bi-order network (FE-BiON) model was introduced in [1] with deep learning based mental health evaluation. However, FE-BiON model failed to provide accurate and comprehensive solution for college student entrepreneurial mental health. Multi-dimensional Student Performance Prediction Model (MSPP) was introduced in [2] with data preprocessing and feature engineering methods. Though the classification accuracy was improved, the time complexity was not minimized by MSPP. An explainable AI technique failed to guarantee the transparency and interpretability of MSPP model to educators and administrators.

An explainable AI-based approach was introduced in [3] for forecasting the undergraduate student performance. Machine learning (ML) classifiers with hyper-parameter tuning performed the student academic performance prediction. But, SHAP and LIME failed to contribute variable for student result prediction and policymakers to improve student academic performance. A multi-factor machine learning framework was designed in [4] to predict and profile the student academic performance. An unsupervised clustering technique was used to partition the students into academic and stress-risk profiles. But, the designed framework failed to incorporate controlled calibration protocols for uniform device selection with higher data reliability.

A variable reduction with optimal deep recurrent neural network (VR-ODRNN) approach was introduced in [5] for student performance analysis. However, VR-ODRNN model failed to improve the model ability to handle missing or noisy data. VR-ODRNN model failed to improve adaptability. Multilayer Perceptron was introduced in [6] to predict the student suspension and dropout. But, feature augmentation and cost-sensitive learning was not carried out to improve the prediction precision.

A detection framework called CASTLE was introduced in [7] for identifying the student mental health. The representation learning was carried out to combine the data on social life and physical appearance. But, the CASTLE framework failed to combine the features like students' Internet access patterns and life orderliness. A multi-graph spatial-temporal synchronous network (MGSTSN) was introduced in [8] to enhance the prediction performance. However, MGSTSN failed to integrate the broader data spectrum of finer temporal granularity and additional contextual variables.

A multi-source sparse attention convolutional neural network (MsaCNN) was introduced in [9] to forecast the course grades in formulation. MsaCNN determined the relationship between courses and multiple heads to combine multi-source features. However, the computational complexity was not reduced by MsaCNN. An innovative strategy was designed in [10] with Virtual Reality (VR) and Augmented Reality (AR) technologies. But, he designed framework failed to construct the inclusive and effective educational support networks.

Psychological Snapshot Guided Pairing (PSGPair) model was introduced in [11] for psychological support to improve query-response pairing in Community Question Answering for Psychological Wellness (CQA-PW). However, PSG-Pair model failed to improve the accuracy and efficiency. The student performance prediction approach was introduced in [12] for addressing the student samples division issues under multi-dimensional discrete data. But, the student performance prediction approach failed to minimize the experimental effects.

The social-emotional learning and character development (SECD) approach was introduced in [13] based on learning skills and academic grades. But, SEL failed to navigate the diverse challenges of school system. A machine learning-based approach was introduced in [14] to predict and assess student mental health. The designed approach recognized the early symptoms of mental distress with psychological and behavioral data. However, the time complexity was not reduced by machine learning-based approach. Partial least squares–structural equation modeling (PLS-SEM) was designed in [15] for Chinese university students. The smart learning was carried out with positive mediating variable and beneficial effects on academic performance. But, PLS-SEM failed to enhance the robustness and generalizability.

An association rule mining (ARM) was carried out in [16] to compute relationship between educational and personal factors and student mental health status.

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But, the universities failed to provide stress-management retreats, outdoor learning activities and structured social engagement programs to build resilience and reduce isolation. An artificial neural network (ANN) was introduced in [17] to forecast the student self-reported mental health dimensions. ANN performed the student depressive state prediction with higher accuracy and f-1 score. ANN improved the prediction performance with student depressive state. But, ANN failed to produce diversified evidence.

A student-specific AI-powered mental health assessment and intervention platform termed MindLift was carried out in [18] to perform real-time multimodal system. But, MindLift failed to encourage healthier and emotionally conscious academic communities in mental healthcare. An integrated learning algorithm and Xgboost model was introduced in [19] to recognize key factors influencing student well-being. However, the computational time complexity was not minimized by designed model. A comprehensive machine learning (ML) and explainable AI (XAI) based methodology was introduced in [20] for addressing the data imbalance problem. But, the designed methodology failed to provide scalable and adaptable to different educational context for policymakers and educators.

An evolutionary intelligent multiple neural networks (EIMNN) was introduced in [21] for college student mental health analysis. EIMNN framework used cooperative co-evolution plan to optimize the multimodal representation. But, EIMNN failed to improve psychological interpretability and therapeutic responsiveness. A multi behavior type association framework and dropout prediction model was introduced in [22] to examine learning behavior of temporal behavior. But, the designed framework failed to improve the effectiveness of dropout prediction and the adaptability of decision feedback.

A multimodal data fusion algorithm was introduced in [23] to forecast the college student academic performance in accurate manner. BERT model extracted the deep features from assignment feedback. However, the BERT-GCN failed to provide stronger technical support for improving the quality of education. Artificial Intelligence (AI)-driven Educational Data Mining (EDM) system was introduced in [24] to categorize the student academic performance and explainable AI for explainability. But, EDM system failed to provide personalized and effective support tailored to each student's unique needs and challenges.

The data mining technique was introduced in [25] to examine pupil behavior patterns and predict how well they would perform academically. The designed technique was used to forecast the student performance analysis based on previous and current semester data. An informer network based on a two-stream structure (TSIN) was introduced in [26] to compute interdependence between student behaviors and time cycle. But, the time complexity was not reduced by data mining technique.

A machine learning (ML) model was introduced in [27] to forecast the student mental health issues in 1 year and following year with the health survey content. Automated Machine Learning (AutoML) was introduced in [28] for predicting the student academic performance in medical academic institutions. AutoML employed decision makers in admission systems for selecting students. But, the precision level was not enhanced.

A novel Student Academic Performance Predicting (SAPP) system was introduced in [29] to improve the prediction accuracy. SAPP system employed 4-layer stacked Long Short Term Memory (LSTM) network to predict student pass or fail outcomes. PsyGraph-SSL model was introduced in [30] to join the graph convolutional networks (GCN), and self-supervised learning (SSL) for analyzing the student mental health risks. However, the accuracy was not enhanced by PsyGraph-SSL model.

3. DATASET DESCRIPTION

The first dataset used is Student Mental Health Analysis. URL of the dataset is given as https://www.kaggle.com/datasets/utkarshsharma11r/student-mental-health-analysis. The dataset comprised the responses from students regarding mental health status during online learning. The data points is collected through survey and aimed on different psychological and behavioral aspects influenced by remote education. The dataset is used for exploratory data analysis (EDA), data visualization and predictive modeling to understand the online education impacts on student mental health. The dataset comprised 1,000 entries and 10 columns (i.e., features) with the demographic details, lifestyle habits and mental health indicators.

Table 1 Feature Description of Student Mental Health Analysis Dataset

Features	Description
Name	Student's first name
Gender	Gender of the respondent (Male/Female)
Age	Age in years
Education Level	Academic level (e.g., Class 8, BTech, MSc)
Screen Time	Average screen time per day during online learning (hrs/day)
Sleep Duration	Average daily sleep duration (hrs)
Physical Activity	Weekly exercise time (hrs/week)
Stress Level	Stress level (Low, Medium, High)
Anxious Before Exams	Whether student feels anxious before exams (Yes/No)
Academic Performance Change	Self-assessed change in academic performance

The second dataset used is Mental Health of Students Dataset. The URL of the given dataset is given as https://www.kaggle.com/datasets/aminasalamat/mental-health-of-students-dataset. Student Mental Health Dataset is employed to determine the relationship between academic life and mental well-being among the university students. Mental health challenges, namely depression, anxiety and panic attacks are prevalent among students across worldwide. Student Mental Health Dataset is connected with the academic pressure, social isolation and personal factors. The dataset presented the snapshot of diverse features, namely gender, age, course of study, academic performance (CGPA) and marital status. The data is collected through anonymous online survey taken by university students from different academic disciplines and year. Every record represents a student's self-reported information, including demographic details, academic standing, and mental health status. The questions identified whether student experienced depression, anxiety, or panic attacks. The dataset comprised 11 columns and multiple entries. Every column denotes the individual student response.

Table 2 Feature Description of Mental Health of Students Dataset

Features	Description
Gender selection	Gender identity of respondent
Age	Student age
Course Name	The academic program student enrolled in
Current year of Study	Indicates student year (e.g., first, second, etc.)
Cumulative Grade Point Average (CGPA)	Academic Performance Measure
Marital status	Student is single, married, or otherwise
Do you have Depression / Anxiety / Panic attack?	Self-reported presence of each mental health condition
Did you seek any specialist for a treatment?	Professional help was sought

The dataset is employed for exploratory data analysis to identify the patterns and correlation between the mental health and academic factors. Machine Learning models are used for forecasting the mental health risks among the students depending on academic and demographic inputs. Statistical studies are carried out on student well-being, helping institutions design better support systems and awareness programs.

4. METHODOLOGY

With fast growth of society and academic pressure, student mental health issues are receiving large attention. Depression is considered as important mental illness that affects 3.8% of adults across worldwide. Mental health affects the student academic performance and impacts the physical and mental development, social interaction and future careers. Student mental health risks are important topic in education and psychology field. The risk factors for mental health problems, namely depression and anxiety disorders among students are identified. Different machine learning models are employed to forecast the patient mental health status. Student performance classification is carried out using different techniques through pre-processing, feature selection and classification.

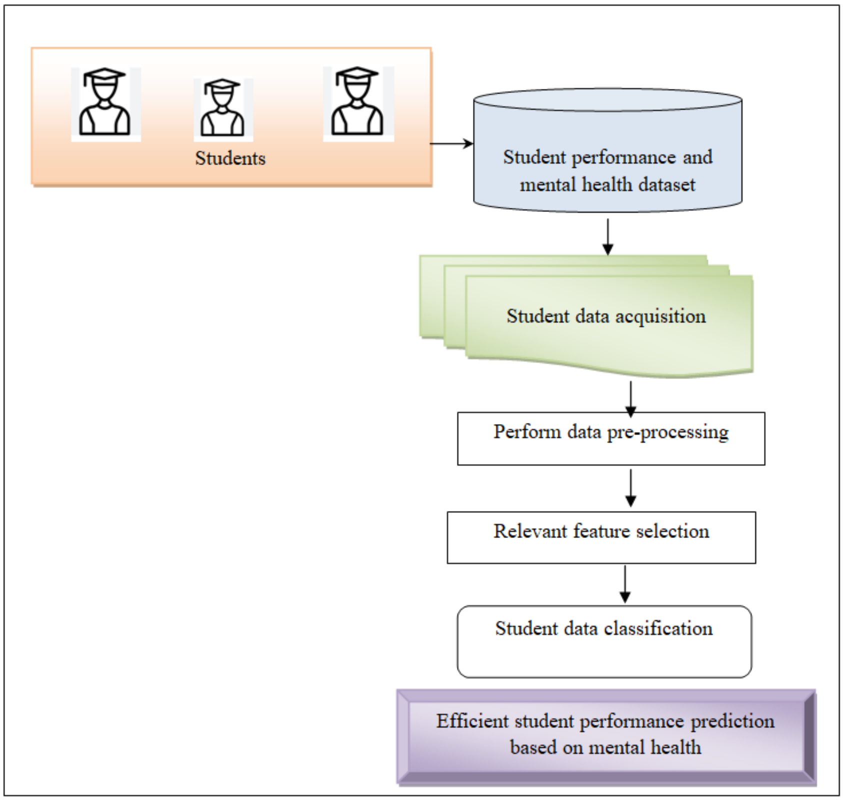

Figure 1 Architecture Diagram of Student Performance Classification

Figure 1 illustrates the architecture diagram for performing student academic performance classification based on mental health. The architecture performed data collection, data pre-processing, feature selection and classification for student academic performance classification.

4.1 Multi-dimensional Student Performance Prediction Model

Multi-dimensional Student Performance Prediction Model (MSPP) is introduced with data preprocessing and feature engineering method. MSPP model is introduced to extract the sparse and heterogeneous academic data in structured training record. MSPP performed data preprocessing with multi-class classification mechanism to increase the precision and recall performance across multiple categories. MSPP model comprised contextual information and multi-layered analysis to improve the prediction accuracy. MSPP model is introduced for student prediction into different performance classes, namely distinction, pass, fail or withdrawn. MSPP addressed problems linked with educational dataset over temporal settings with AI features. MSPP model is employed to

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perform the dense representation for efficient prediction to attain accurate classification results. An adaptive hyper-parameter tuning and graph neural network layers are used for performing efficient prediction. MSPP model reduced the false positive rate for attaining reliable student classification.

4.2 Explainable AI-based Approach

An accurate student academic achievement prediction has received large attention in research community. The student prediction increased their importance in understanding student' progress and helped in achieving success. Explainable AI-based Approach is introduced for forecasting the undergraduate student performance in Bangladesh. The dataset comprised 872 student records from different institutions. The dataset performed data-preprocessing methods, namely one-hot encoding, column remaining and missing values handling. Synthetic Minority Oversampling Technique (SMOTE) and normalization algorithms are employed to achieve data balance and feature scaling correspondingly. The machine learning (ML) classifiers with hyperparameter tuning are used to improve the student academic prediction performance. A custom stacking ensemble classifier is introduced to improve the accuracy. eXplainable Artificial Intelligence (XAI) algorithms like SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) are used to carry out efficient prediction based on significant factors. Explainable AI-based Approach increased the transparency, fairness and reliability for attaining improved student performance in classroom and anticipation.

4.3 Deep Learning Model for Psychological Support

A deep learning-based mental health evaluation tool termed fully embedded bi-order network (FE-BiON) model is introduced to estimate the mental health of college students FE-BiON model is introduced for launching their individual businesses. FE-BiON model joined fully embedded feature engineering and parallel network structure. FE-BiON model is used for improving the recognition ability and psychological characteristics accuracy. The national health and nutrition inspection is carried out in United States. The national health and nutrition inspection survey is conducted in South Korea for behavioral risk factor monitoring system. FE-BiON model increased the accuracy and F1 value for attaining improved prediction performance. The fully embedded feature processing method is employed for gathering the complex relationship between features to attain improved performance. FE-BiON model is introduced for mental health prediction of college students. FE-BiON model presented the scientific basis for entrepreneurship education development in colleges and universities. FE-BiON model presented the practical guidance for increasing the success rate of college student entrepreneurship.

4.4 Multi-Factor Machine Learning Framework

A multi-factor machine learning framework is introduced for performing student academic performance prediction with the behavioral, financial and wearable data. The student data is gathered from higher education students in India. The designed framework combined lifestyle behaviors, financial variables and physiological data for efficient prediction. The designed framework performed structured preprocessing and feature engineering based on financial stress metric. The designed framework joined composite stress index with financial and physiological data points. Multiple regression method is introduced to achieve highest accuracy. The wearable-related features are examined to perform correlation and t-tests to examine their relationship with academic outcomes. K-Means and Agglomerative Clustering are employed to partition the students into interpretable academic and stress-risk profiles. The designed framework performed early student risk detection. The designed framework presented adaptable blueprint for educational institutions to employ predictive academic analytics.

4.5 Variable Reduction Approach with Deep Recurrent Neural Network

The deep learning model identified the complex patterns and relationships for accurate educational outcome prediction. A new variable reduction with optimal deep recurrent neural network (VR-ODRNN) approach was introduced to carry out the student performance outcome analysis. VR-ODRNN model computed the student data to recognize the course grades attained by students. Min-max normalization is employed to measure the input data uniformly. VR-ODRNN model employed the coot optimization algorithm (COA) for selecting the optimal feature subset. In addition, the student performance is predicted by through DRNN. The hyper-parameter

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selection of DRNN approach is carried out by Dwarf Mongoose Gannet Optimization Algorithm (DMGOA).

4.6 Counseling Resource Optimization using Multilayer Perceptron

Multilayer Perceptron Classifier is introduced to forecast the student suspension and dropout. The main objective of multilayer perceptron classifier is to assist schools in monitoring situations and counseling resources. The schools increased the efficiency of interventions through improving the precision of resource allocation.

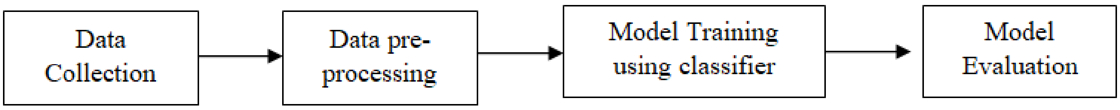

Figure 2 Process of Counseling Resource Optimization

The dataset comprised student records from Chaoyang University of Technology spanning five academic years (2017–2021). The data from second semester of 2021 academic year is used for model testing. The data from remaining semesters are employed for efficient training and validation. The designed model increased the accuracy to provide better classification results. The designed model is employed in real-world applications for resource allocation and institutional decision-making.

4.7 Multimodal Educational Data Fusion for Students' Mental Health Detection

Mental health issues are resulted in diverse consequences like depression, self-mutilation and worse for university students. A detection framework is introduced for identifying the student mental health termed CASTLE. The designed framework is introduced with the educational data fusion for mental health detection. The representation learning is carried out for mental health detection. The representation learning is employed to combine the data on social life, academic performance and physical appearance. A multi-view social network embedding algorithm (MOON) is introduced to determine student social life in widespread way. The designed framework combined student heterogeneous social relations in effective manner. Figure 3 illustrates the process diagram of student mental health detection.

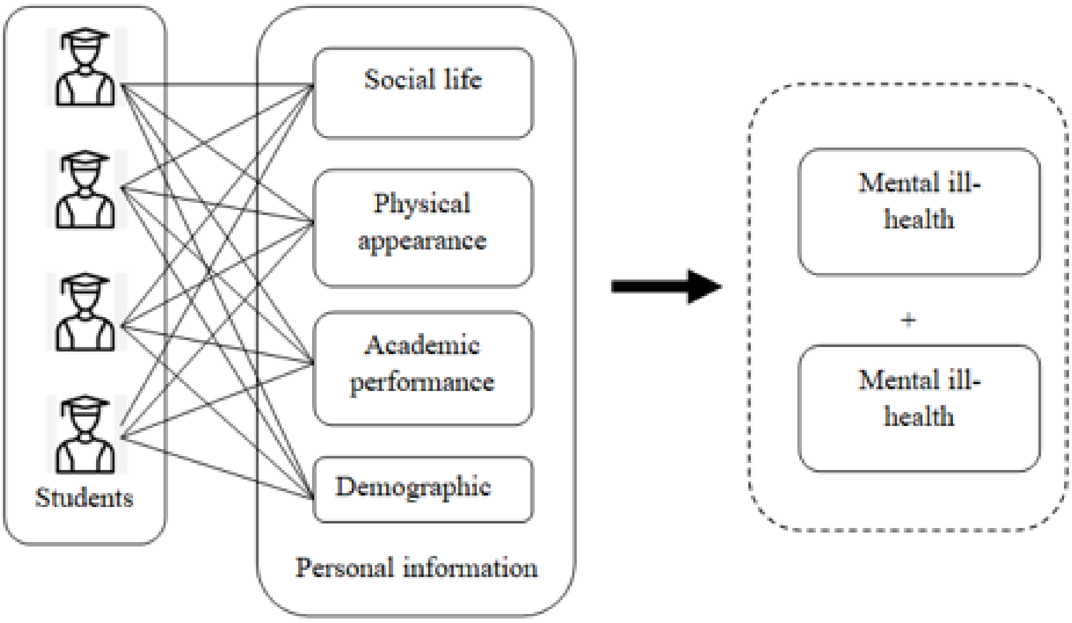

Figure 3 Student Mental Health Detection

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A synthetic minority oversampling technique algorithm (SMOTE) is used to address the label imbalance problems. A deep neural network (DNN) model is employed for efficient student mental health detection.

4.8 Multi-Graph Spatial-Temporal Synchronous Network

A multi-graph spatial-temporal synchronous network (MGSTSN) is introduced to enhance the precision of prediction performance. MGSTSN performed holistic representation of different spatial-temporal dynamics through the spatial trend and pattern graphs. The dual spatial-temporal synchronous graphs and synchronous modules are employed for learning the interplay between spatial and temporal factors affecting student performance. MGSTSN improved the capability in gathering the multi-faceted nature of student performance data.

5. PARAMETER ANALYSIS

The result analysis of existing student performance prediction methods is carried out using four different parameters, namely student performance prediction time, precision, recall and student performance prediction accuracy. Student performance classification accuracy '$SPCA$' is defined as the ratio of number of student data that are correctly classified the academic performance based on mental health to the total number of student data. 'tp' symbolizes the true positive, 'tn' indicates the true negative, 'fp' symbolizes the false positive, 'fn' denotes false negative. The prediction accuracy is computed in terms of percentage (%). Student performance classification time '$SPCT$' refers to as an amount of time consumed by algorithm to predict the academic performance as pass or fail. 'DS' represent the student data and the actual time consumed in academic performance prediction denoted by '$Time(PP)$'. Student performance classification time is measured in milliseconds (ms). Precision 'Pre' is defined as the ratio of classifying the true value in academic performance from the data samples. The precision is computed in terms of percentage (%). Recall 'Rec' is known as sensitivity. It is used to correctly identify all the positive instances in dataset. The recall is computed in terms of percentage (%). Table 3 provides the parameter description.

Table 3 Parameter Description

Parameter	Formula
$SPCA$	$\left(\frac{tp+tn}{tp+tn+fp+fn}\right)*100$
$SPCT$	$\sum_{i=1}^{n} DS_i * Time(PP)$
Pre	$\frac{tp}{tp+fp}*100$
Rec	$\frac{tp}{tp+fn}*100$

6. RESULTS AND DISCUSSION

The result analysis is carried out based on student academic performance classification through different machine learning and deep learning techniques. The performance measurement is carried out depending on student academic performance classification in social media platform. Performance evaluation metrics are used to determine the efficiency and performance of student academic performance classification. The performance of existing student academic performance classification methods is discussed with help of table and graphs.

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Table 4 Tabulation on Student Academic Performance Classification Accuracy, Student Academic Performance Classification Time, Precision and Recall for Student Mental Health Analysis Dataset

Method Name	Student Academic Performance Classification Accuracy (%)	Student Academic Performance Classification Time (ms)	Precision (%)	Recall (%)
MSPP	85	57	82	80
Explainable AI-based Approach	92	32	91	90
FE-BiON model	84	48	82	83
Multi-factor machine learning framework	89	42	90	89
VR-ODRNN approach	90	40	89	88
Multilayer Perceptron Classifier	91	35	90	89
Detection framework	86	55	84	82
MGSTSN	88	43	86	83

Table 5 Tabulation on Student Academic Performance Classification Accuracy, Student Academic Performance Classification Time, Precision and Recall for Mental Health of Students Dataset

Method Name	Student Academic Performance Classification Accuracy (%)	Student Academic Performance Classification Time (ms)	Precision (%)	Recall (%)
MSPP	87	55	83	82
Explainable AI-based Approach	94	30	92	91
FE-BiON model	85	46	84	84
Multi-factor machine learning framework	91	42	90	89
VR-ODRNN approach	92	40	91	90
Multilayer Perceptron Classifier	93	33	90	89
Detection framework	88	52	86	84
MGSTSN	90	41	88	86

Table 4 and table 5 explain the student academic performance classification results for eight different methods with four performance metrics and three datasets respectively. From the above tables, it is clear that the Explainable AI-based Approach attained improved student academic performance classification results than other existing methods for two datasets. For Student Mental Health Analysis Dataset, Explainable AI-based Approach attained 92% of student academic performance classification accuracy, 32ms of student academic performance classification time, 91% of precision and 90% of recall. For Mental Health of Students Dataset, Explainable AI-based Approach attained 94% of student academic performance classification accuracy, 30ms of student academic performance classification time, 92% of precision and 91% of recall. Figure 4 and figure 5 demonstrate performance analysis of student academic performance classification results Dataset.

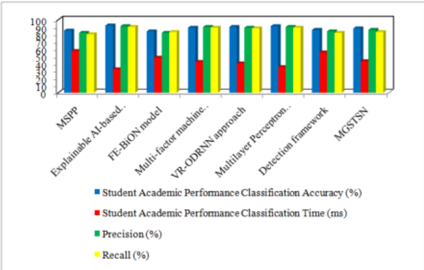

Figure 4 Performance Analysis of Student Academic Performance Classification Results for Student Mental Health Analysis Dataset

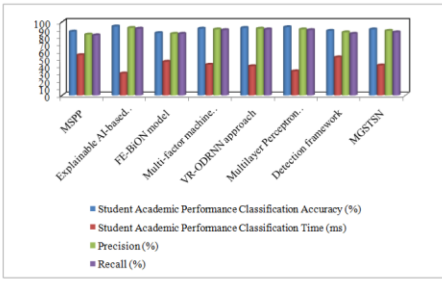

Figure 5 Performance Analysis of Student Academic Performance Classification Results for Mental Health of Students Dataset

Figure 4 and figure 5 shows the performance metric comparison of eight different existing methods for three different datasets correspondingly. From graphical analysis, it is observed that performance of Explainable AI-based Approach is higher than any other methods for three datasets. This is because of using SMOTE and normalization algorithms to attain the data balance and feature scaling. The machine learning (ML) classifiers with hyperparameter tuning increased the student academic prediction performance. A custom stacking ensemble classifier increased the student academic performance classification accuracy. An eXplainable Artificial Intelligence (XAI) algorithms performed efficient prediction depending on significant factors. Explainable AI-based Approach increased transparency, fairness and reliability for achieving the improved student performance in classroom and anticipation. For Student Mental Health Analysis Dataset, Explainable AI-based Approach improved student academic performance classification accuracy by 5%, reduced student academic performance classification time by 28%, increased precision by 6% and increased recall by 6% when compared to other existing techniques. For Mental Health of Students Dataset, Explainable AI-based Approach improved student academic performance classification accuracy by 5%, minimized student academic performance classification time by 30%, increased precision by 5% and increased recall by 6% when compared to other existing techniques.

7. CONCLUSION AND FUTURE WORK

In the survey, student academic performance classification analysis is carried out using different techniques. Different performance metrics are employed to analyze the student academic performance classification with help of number of student data points. When the student academic performance classification result is compared with another study, explainable ai-based approach has attained improved performance results. In this work, Explainable Artificial Intelligence-based Approach attained higher accuracy during student academic performance classification for two different datasets. Explainable Artificial Intelligence has attained highest student academic performance classification accuracy result than all the other existing methods. These results strongly suggest Artificial Intelligence concepts can be implemented in future for efficient student academic performance classification instead of the other conventional methods.

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