

MULTIMODAL DEEP LEARNING FRAMEWORK FOR STUDENT ENGAGEMENT RECOGNITION USING EEG SIGNALS AND FACIAL IMAGES.

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ABSTRACT

Today's students face heavy academic workload, long study hours, and continuous pressure to perform well, which affects both their mental and physical health. Increasing stress, fear of failure, and lack of support often push vulnerable students toward severe outcomes, including depression and suicide. Using the provided student dataset containing features such as study hours, sleep duration, attendance, stress level, past scores, and extracurricular activity, we perform preprocessing and Exploratory Data Analysis (EDA) to understand behaviour patterns and data quality. The existing system applies classical machine-learning models like Random Forest, Support vector machine(SVM), Gradient Boosting, Decision Tree, and Linear Regression, but these handle each output separately and fail to learn deeper relationships between student factors. To address this, we propose an integrated Attention-based Bidirectional Long-Short Term Memory(BiLSTM) model combined with Optimal Decision Rule List(ODRL) feature extraction for joint prediction of student performance grade (classification), stress level (classification), and exam score (regression). The Attention-BiLSTM captures important behavioural sequences, while ODRL extracts meaningful features. Results show that the proposed approach outperforms the existing models, providing a more accurate and holistic understanding of student academic and emotional conditions.

INTRODUCTION

In India, students pursue education across a wide range of sectors, including schools, engineering colleges, medical institutions, degree programs, and various vocational and professional courses, each carrying its own academic structure, pressure levels, and expectations. Because of these differences, students experience stress in many forms—academic pressure, competitive environments, long study hours, fear of failure, parental expectations, and workload imbalance. Such stress not only affects their emotional well-being but also has a direct impact on their academic performance, causing fluctuations in focus, motivation, learning capacity, and ultimately in their exam scores. High stress often leads to reduced performance, while manageable stress levels allow students to maintain consistency and achieve better results. In this context, it becomes important to examine student performance grading, stress levels, and score outcomes together, as this combined understanding helps reveal how stress influences academic progress across various fields of study. A holistic evaluation approach supports educational institutions in identifying struggling students early, designing

effective support systems, reducing academic pressure, and promoting healthier learning environments. This is especially crucial in India's diverse and competitive education system, where students from different backgrounds face unique challenges, and addressing stress-related performance issues can significantly improve overall academic success and well-being.

In Figure 1.1, the bar graph presents a comparative analysis of stress levels among male and female students across various sources of stress. The results indicate that 40% of females and 33% of males experience stress from extracurricular activities, while 28% of females and 25% of males are impacted by family issues. Stress related to relationships or dating affects 35% of females and 30% of males. Academic pressure is shown to be a major concern, with 84% of females and 67% of males reporting high stress due to school grades. Additionally, stress from friends affects 45% of females and 40% of males, demonstrating a moderate influence on student well-being.

Further highlights that academic workload also plays a significant role, as 78% of females and 66% of males feel stressed due to homework. Concerns related to physical health affect 45% of females and 30% of males, whereas appearance-related stress impacts 38% of females and 34% of males. Mental health concerns are reported by 30% of females and 35% of males, revealing a nearly balanced distribution. Lastly, stress associated with getting into college is notably high, with 70% of females and 55% of males experiencing pressure related to future academic admissions.

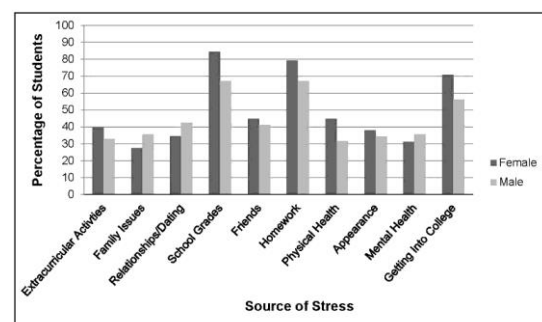


Figure 1.1. Stress level Analysis

Source: <https://tse2.mm.bing.net/th/id/OIP.nw-JkaJxLDKfAz-zD2ZljgHaEe?pid=Api&P=0&w=661&h=400>

Research Motivation

Figure 1.2 shows the research motivation flowchart. The detailed analysis is given as follows:

Student: The process begins with the student, who actively participates in college activities, academic tasks, and campus-related engagements. The student also reports to the mentor, providing information about their academic progress, performance, behaviour, and any personal or educational challenges. This initial input from the student forms the foundation for the entire monitoring and counselling mechanism.

College / Activities: The College / Activities block represents the set of academic and extracurricular tasks in which the student participates. These activities generate valuable data about the student's performance, attendance, behaviour, skill development, and level of engagement. This information indirectly influences the mentor's assessment and the institution's monitoring system.

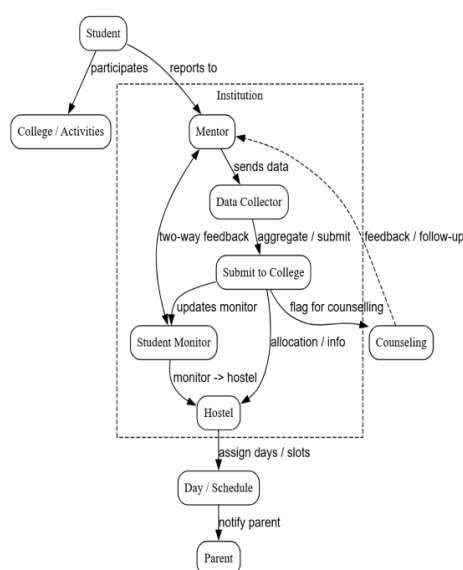


Figure 1.2. Student Monitoring and Counselling Workflow

Mentor: The Mentor plays a central role in the workflow. The student reports directly to the mentor, who tracks the student's academic and personal well-being. Mentors collect regular updates and send this information to the Data Collector. They also receive two-way feedback, which helps them follow up with the student whenever needed. Mentors act as the bridge between the institutional mechanism and the student.

Data Collector: The Data Collector receives the student's data from the mentor. This component is responsible for organizing

raw student information, converting it into structured data, and forwarding it to the Submit to College block. It also sends two-way feedback to the mentor—this ensures continuous monitoring, data accuracy, and timely interventions whenever required.

Submit to College: The Submit to College block aggregates all collected data and submits it to the institution. It stores the compiled results such as academic performance, behavioural patterns, attendance, stress levels, or any issues highlighted by mentors or student monitors. Based on the processed data, it updates the Student Monitor and also flags students for counselling whenever abnormalities or concerns are detected.

Student Monitor: The Student Monitor receives continuous updates from the “Submit to College” unit. This role is responsible for overseeing the daily behaviour and activities of students in the institution. Whenever required, the Student Monitor communicates with the hostel regarding the student's status. This ensures that hostel authorities stay aware of specific student needs, concerns, or follow-up requirements.

Hostel: The Hostel block communicates closely with the Student Monitor. It keeps track of student stay patterns, behavioural changes, attendance in hostel activities, and any hostel-related issues. Whenever counselling or follow-up actions are required, the hostel provides additional information that helps allocate appropriate support or schedule necessary sessions.

Counseling: The Counseling block is activated when the system identifies a student who needs emotional, academic, or behavioural support. Based on the flags raised by “Submit to College,” professional counsellors intervene, provide guidance, and maintain follow-up sessions. This ensures timely support for students dealing with stress, performance drops, personal difficulties, or behavioural issues.

Day / Schedule: The Day / Schedule block handles the assignment of specific counselling days, mentor meetings, hostel check-ins, or parent-connect sessions. It ensures that the right resources are allocated at the right time. Once the schedule is prepared, it is shared appropriately with students, mentors, hostel staff, or parents.

Parent: Finally, the Parent block represents the communication sent to the student's parents. Once the schedule or counselling update is generated, parents are notified about their child's progress, concerns, counselling appointments, or any required involvement. This enhances transparency and strengthens the support system around the student.

Problem Statement

In educational environments, understanding the overall condition of a student requires analyzing multiple factors such as academic performance, levels of stress, and expected examination outcomes. However, these elements are often evaluated separately, leading to fragmented assessments that fail to represent the student's true learning condition. Existing systems typically focus on only one aspect at a time—either grading performance, identifying stress, or estimating scores—which results in incomplete interpretations and inconsistent support for students. The absence of a unified approach creates challenges for teachers, institutions, and counselors who rely on accurate and timely information to guide academic planning, identify students at risk, and provide early interventions.

Another major issue lies in the inability to process interdependent student-related factors in a combined manner. Academic behaviors, emotional state, and performance outcomes are closely connected, yet most evaluation frameworks treat them as independent components. This disconnect reduces the reliability of the observations collected and prevents institutions from forming a holistic understanding of student progress. As a result, many students continue to face unmanaged stress, unrecognized performance issues, or unexpected drops in academic results.

Furthermore, the growing number of students in modern educational systems makes manual tracking increasingly difficult. Teachers and counselors cannot continuously monitor each learner's performance trends, emotional variations, or predicted examination results. Without a comprehensive system that brings these elements together, timely decisions become difficult, and opportunities for personalized guidance are often lost.

Research Objective

To design and implement an effective Flask-based AI procedure that integrates an Attention-based BiLSTM model with ODRL feature extraction for jointly predicting student performance grades, stress levels, and exam scores. The objective is to build a unified deep-learning system capable of learning complex behavioural patterns from factors such as study hours, sleep duration, attendance, past scores, and extracurricular involvement. This approach aims to overcome the limitations of existing machine-learning methods that treat each output separately, enabling more accurate prediction, real-time analysis, and a holistic understanding of both academic progress and student well-being.

Advantages

- **Comprehensive Assessment:** Unlike traditional models that evaluate performance or stress separately, this model simultaneously considers academic performance, stress levels, and score estimation, providing a holistic understanding of the student's learning experience.
- **Real-Time Monitoring:** The model can process sequential and time-dependent data to provide real-time insights, enabling educators to detect issues as they occur rather than relying on delayed assessments.
- **Personalized Feedback:** By analyzing individual patterns in performance and stress, the model supports tailored recommendations for each student, helping improve both learning outcomes and emotional well-being.
- **Attention Mechanism for Feature Relevance:** The integrated attention layer ensures that the model focuses on the most significant indicators, improving prediction accuracy and reducing the impact of irrelevant or noisy data.
- **Temporal Dependency Analysis:** Using BiLSTM allows the model to capture long-term dependencies in sequential data, such as study habits, exam performance trends, and stress patterns over time.
- **Early Intervention Support:** By identifying students at risk of underperformance or high stress early, the model facilitates preventive measures, minimizing academic failures and mental health challenges.
- **Unified Multi-Task Learning:** Handling multiple tasks jointly reduces computational redundancy compared to separate models, making the system efficient and scalable.

Applications

- **Educational Institutions:** Schools, colleges, and universities can use the model to track student performance and mental health, allowing teachers to provide timely guidance and counseling.
- **Online Learning Platforms:** E-learning platforms can integrate this model to personalize learning

experiences, monitor student engagement, and predict outcomes for virtual learners.

- **Student Counseling and Mental Health Support:** Counselors can leverage stress classification results to offer targeted mental health interventions and stress management programs.
- **Exam Preparation and Performance Tracking:** Students can use the model to self-assess their readiness, understand areas needing improvement, and manage exam-related stress effectively.
- **Policy Making in Education:** Administrators and policymakers can use aggregated insights to design programs and curricula that address common performance and stress-related challenges among students.
- **Gamified or Adaptive Learning Systems:** The model can be incorporated into intelligent educational software to adapt difficulty levels and content delivery based on real-time student performance and stress indicators.

LITERATURE SURVEY

- Balcioglu, et al. [1] The Ensemble Model (EM) consistently outperformed other models, achieving the highest overall F1 measure, precision, recall, and accuracy. These results highlight the potential of data-driven techniques in informing educational stakeholders' decision-making processes, enabling targeted interventions, and facilitating personalized learning strategies tailored to students' needs. By identifying at-risk students early in the academic year, institutions can provide additional support to improve academic outcomes and retention rates.
- Alnasyan, et al. [2] utilized KANFormer model is developed, a novel deep learning (DL) architecture that integrates multi-head self attention (MHSA) mechanisms with Kolmogorov–Arnold networks (KAN) to effectively captures complex patterns within large-scale student datasets, enabling more accurate predictions of student performance. KANFormer processes student demographic, academic, and engagement features from the open university learning analytics dataset (OULAD) while applying a feature elimination process to enhance dataset quality,

reduce redundancy, and mitigate multicollinearity, ensuring optimal predictive performance.

- Kesgin, et al. [3] proposed A comprehensive fairness analysis is conducted, considering sensitive attributes such as gender, school type, and socioeconomic factors, including parental education (Medu and Fedu), cohabitation status (Pstatus), and family size (famsize). Using the AIF360 library, we compute the demographic parity difference (DP) and Equalized Odds Difference (EO) to assess model biases across diverse subgroups. Our results demonstrate that XGBoost achieves high predictive performance (accuracy: 0.789; F1 score: 0.803) while maintaining low bias for socioeconomic attributes, offering a balanced approach to fairness and performance.
- Ab Rahman, et al. [4] developed a systematic literature review on machine learning technology for predicting student performance, analysing 51 relevant articles from Scopus and Science Direct databases between 2019 and 2023 using the PRISMA method. The findings reveal that the primary motivation for employing machine learning in educational institutions is to improve predictive accuracy, identify early interventions, and optimise decision-making processes. Supervised machine learning approaches such as Decision Trees, Linear Models, and Neural Networks are commonly used.
- Alalawi, et al. [5] utilized Learning Analytics Intervention (LAI) studies have emerged as an approach that aims to address this gap. In LAI studies, student risk levels are predicted and disseminated to relevant stakeholders (academics, administrators and students) using learning analytics (LA) tools for targeted interventions. The interventions themselves are mainly left under the discretion of the academics and/or administrators, who are aware of the learning context and have the authority to make decisions, with LA tools facilitating this process. LAI studies have shown success in improving outcomes (e.g. improve pass rates, retention, grades), but their uptake has been slow.
- Saqr, et al. [6] proposed advanced predictive methods, namely machine learning, where the goal is to predict continuous variables like grades. The chapter uses advanced and popular AI/machine learning algorithms like Random Forest, K-Nearest Neighbor, Linear Regression, Neural Networks, and Support Vector

Machines. The chapter provides a practical guide to building and evaluating predictive models with R using two approaches: one is the classic approach for predictive modeling with R, and the other more modern approach using the tidymodels suite.

- Ahmed, et al. [7] proposed challenges in performance analysis, quality education delivery, and student evaluation through machine learning (ML) models. Ten regression models including K-Nearest Neighbors Regressor, Linear Regression, CatBoost, XGBoost, AdaBoost, and ensemble voting regression (VR) algorithm based on the top five heterogeneous regressors as base models are employed to predict academic outcomes. Two datasets with distinct feature sets and sizes were used to evaluate the generalizability of the models. The first dataset comprises 10,000 samples and six features focused on study behaviors, prior performance, and extracurricular activities.
- Doma, et al. [8] developed a highly efficient and accurate hybrid machine learning model to classify student stress levels, by taking into account the psychological, physiological, environmental, academic and social stress factors. Student stress level classification will enable early intervention, tailored support, evaluation of stress management programs, resource allocation and improvement of academic success. This also provides us with a deeper understanding of student stressors and how they are related. To build our hybrid model, we first implement five base models namely, Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), Logistic Regression (LR) and Extreme Gradient Boosting (XGBoost).
- Asto Buditjahjanto, et al. [9] developed training and testing of SVM to be able to classify student learning outcomes correctly. The study results indicated that 36 stress variables could be grouped into 7 stress factors using factor analysis, namely conflict, learning readiness, participation, workload, fairness, focusing, and suitability. Four levels were used to categorize the learning results of students, such as very good, good, fair, and poor. The accuracy and precision of the SVM classification values were 0.89 and 0.70, respectively. The SVM classification results showed better results in comparison to comparable methods of classification like Decision Trees, Random Forests, K-

Nearest Neighbor (K-NN), Linear Discriminant Analysis (LDA), and Gaussian Naive Bayes (GNB).

- Gedam, et al. [10] proposed model was trained and tested on a dataset of 200 participants, which involves applying four different stressors. Nine ML algorithms were investigated for both multivariate and univariate features. The physiological data was collected using a novel device developed using an Arduino microcontroller and low-cost sensors such as ECG, GSR, and ST sensors. The findings reveal that the suggested model detects mental stress with an accuracy of 96.17%, with the XGBoost method outperforming other algorithms in multivariate analysis. Univariate feature analysis found that XGBoost regularly demonstrated good accuracy, showing its dependability for detecting mental stress.
- Deena, et al. [11] proposed models that can precisely classify and predict stress levels using a well selected dataset intended to capture elements contributing to student stress. Given the global increase in student stress levels, it is imperative that we deal with this issue to avert serious consequences. This work proposes a machine learning algorithm that measures students' stress levels in classroom environments by leveraging recent advances in computer science, especially in the field of healthcare. The examination examines personal attributes and significant stressors, encompassing academic demands, psychological states, and social engagements.
- Ali Hassan, et al. [12] proposed machine learning with an empathetic understanding of the human experience, our approach strives to pave the way for a more holistic and personalized educational ecosystem. The insights derived from this study aspire to guide educators, administrators, and policy makers in crafting nurturing environments that empower students to excel both academically and emotionally. Embarking on a journey to unravel the myriad factors influencing students' stress, we consider academic pressures, social dynamics, and personal experiences. Harnessing machine learning algorithms such as decision trees, neural networks, we navigate expansive student populations.
- Biswas, et al. [13] utilized a Fine-tuned Squirrel Search-driven Light Gradient Boosting Machine (FSS-LGBM) model, which integrates advanced optimization techniques with Light GBM for enhanced predictive performance. The FSS-LGBM

model validated superior performance associated with convolutional machine learning models, achieving higher accuracy (98%), recall (99%), precision (97%), and F1-score (97%) in student stress prediction. The advanced machine learning model developed in this study, incorporating FSS-LGBM, offers a promising approach for predicting student stress.

- Suraj Arya, et al. [14] proposes various machine learning and deep learning models, including support vector machine (SVM), Random Forest, Gradient Boosting, AdaBoost, CatBoost, LightGBM, ExtraTree, XGBoost, logistic regression, K-nearest neighbor (KNN), Naive Bayes, decision tree, multi-layer perceptron (MLP), and artificial neural network (ANN). The Naive Bayes model achieved an accuracy of 90%, while SVM had the lowest test accuracy at 85.45%.
- Arias, et al. [15] developed PRISMA framework to search through various databases from 2019 to 2024, such as ACM, IEEE Explore, and others, sifting through 249 articles. We chose 38 articles to look at closely, while we excluded 179 and identified 32 duplicates. Our review found that supervised models, like Random Forest (RF), K-Nearest Neighbor (KNN), and support vector machine (SVM), are the most common and effective, detecting stress with about 95% accuracy. Physiological datasets, such as WESAD, and real-time data collection are the most common sources for measuring stress.
- Singh, et al. [16] proposed an approach to forecast stress and non-stress occurrences among college students by applying various machine learning algorithms: Decision Trees, Random Forest, Support Vector Machines, AdaBoost, Naive Bayes, Logistic Regression, and K-nearest Neighbors. The primary objective of this work is to leverage a research study to predict and mitigate stress and non-stress based on the collected questionnaire dataset. We conducted a workshop with the primary goal of studying the stress levels found among the students. This workshop was attended by Approximately 843 students aged between 18 to 21 years old.
- Ahmed, et al. [17] utilized Machine learning (ML) in developing adaptive intelligent systems that can perform complex tasks beyond human abilities. Some areas of applications of ML algorithms include cluster analysis, pattern recognition, image processing, natural language processing, and medical diagnostics.

In this research work, K-means, a clustering data mining technique using Davies' Bouldin method, obtains clusters to find important features affecting students' performance. The study found that the SVM algorithm had the best prediction results after parameter adjustment, with a 96% accuracy rate

- Milos Ilic, et al. [18] proposed employs machine learning (ML) and artificial neural networks (ANN) to predict student grades within a programming tutoring system. The experiment involved university students whose interaction data with the e-learning system were analyzed and used for predictions. By identifying the structural relationships between the properties of the input data, this research aims to determine the most efficient AI method for accurately predicting student performance in e-learning systems. The structure of the input data in these systems is described by variables related to individual student activities, so correlations between variables were a natural starting point for further theoretical considerations.

EXISTING SYSTEM

Traditional Mentor–Student Review System

Figure 3.1 shows the Traditional Mentor–Student Review System architecture, which mentors regularly meet students to collect information about their academic performance, behavioural issues, attendance, and participation in various activities. These meetings are typically scheduled weekly or monthly, during which mentors rely on personal observations, class reports, and feedback from subject teachers to understand student progress. The mentor uses written notes, logbooks, or spreadsheets to store the information, often summarizing it manually for institutional records. The mentor also conducts follow-ups whenever a student exhibits low performance, irregular attendance, or signs of stress. The entire review process depends on the mentor's experience and ability to judge the student's situation accurately.

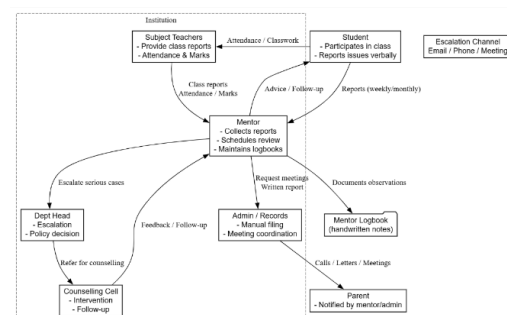


Figure 3.1. Traditional Mentor–Student Review System

Data such as study hours, sleep patterns, or personal concerns are verbally communicated and manually documented. The lack of automated consolidation means that the mentor must interpret the information using personal judgement, which may introduce variations in assessment quality. When concerns are serious, mentors escalate issues to the head of the department or counselling cell. This escalation is also manual, involving physical reports, email communication, or meetings. Because there is no intelligent system to highlight risk patterns, students who need urgent help may not be identified quickly. The overall process becomes time-consuming and dependent on mentor availability.

Paper-Based Student Monitoring and Evaluation System

Figure 3.2 shows the Paper-Based Student Monitoring and Evaluation System architecture, which uses physical files, forms, and reports to collect and monitor student information. Students fill out forms related to attendance, participation in college activities, hostel stay details, and medical or personal records. Teachers manually verify these forms and enter the data into department files. This creates a structured but largely paper-reliant system in which data retrieval requires browsing through numerous documents. Each department maintains student records separately, and updates are often done once per semester. The analysis is usually limited to calculating attendance percentages, counting activity participation, and observing marksheets.

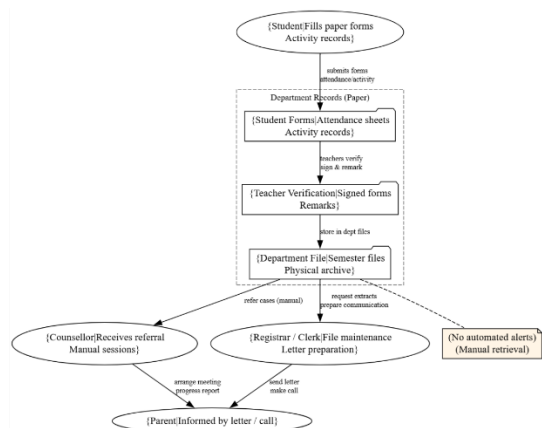


Figure 3.2. Paper-Based Student Monitoring and Evaluation System

Performance comparisons are done manually by checking previous reports, which makes long-term tracking difficult. As records accumulate, storing and organizing them becomes more challenging. When a student requires counselling or academic support, the department refers the case manually by preparing

written notes or forwarding the file to the counsellor. Because there is no automated alert mechanism, only visible or reported issues get documented. Subtle behavioural signs or stress indicators may go unnoticed. Reporting to parents also involves manual phone calls or written letters prepared by staff.

Spreadsheet-Driven Monitoring and Performance Tracking Method

Figure 3.3 shows the Spreadsheet-Driven Monitoring and Performance Tracking Method architecture, which is digital method, student data is collected by teachers and entered into tools like Excel sheets or Google Sheets. Each parameter—attendance, marks, behaviour notes, or extracurricular activity—is manually typed and updated by responsible faculty members. Data validation, such as checking for missing entries or inconsistent values, is carried out by reviewing rows and columns individually. Performance tracking is done by creating basic charts or tables inside the spreadsheet. Teachers manually calculate averages, compare past and current results, and observe trends. Since there is no intelligent model to highlight risk cases, teachers must detect academic decline or stress indicators by visually scanning the data.

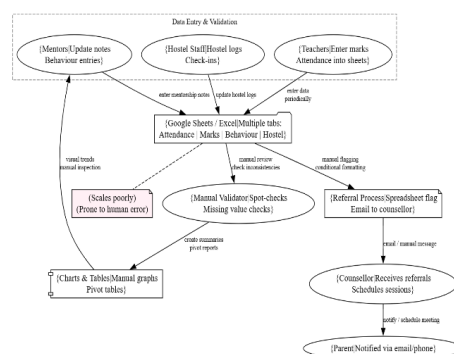


Figure 3.3. Spreadsheet-Driven Monitoring and Performance Tracking Method

This becomes increasingly difficult when the number of students grows. The accuracy of the system depends heavily on how consistently staff update the sheets. Any delay, oversight, or human error leads to incomplete or outdated records, making real-time analysis impossible.

Common Problem Statements

- Manual systems often fail to detect early signs of student stress or declining performance due to lack of automated alerts.

- Multiple stakeholders such as mentors, hostel staff, and counsellors work in isolation, causing slow communication and delayed action.
- Data entry errors, missing values, and inconsistent documentation frequently occur due to fully manual handling.
- Consolidating information from various sources takes significant time, resulting in delayed decisions and interventions.
- Large student populations overwhelm manual systems, reducing the accuracy, reliability, and efficiency of monitoring and evaluation.

PROPOSED SYSTEM & IMPLEMENTATION

PROPOSED SYSTEM

System Architecture

The proposed system develops a trivariate intelligent prediction framework that simultaneously performs student performance grading, stress level classification, and score estimation by leveraging both traditional machine learning and deep learning models. The system begins with structured academic, behavioral, and demographic data and applies systematic preprocessing and exploratory analysis to understand learning patterns. Multiple CART-based baseline models are implemented to establish comparative performance, followed by an advanced Attention Recurrent Trees CART architecture that integrates Attention-based BiLSTM feature extraction with decision tree learning. To further enhance prediction accuracy and ranking stability, a Student CART model combining MLP and CatBoost is proposed. The final system is deployed using Flask to provide real-time classification and regression outputs, enabling effective academic performance assessment and decision support.

Step 1: Dataset: The dataset consists of academic, behavioral, technological, and demographic attributes including Study Hours, Attendance, Resources, Extracurricular activities, Motivation, Internet access, Gender, Age, Learning Style, Online Courses, Discussions, Assignment Completion, Exam Score, and Edu Tech usage. These features are used to predict Stress Level, Final Grade, and continuous score values. The dataset supports both classification and regression tasks, making it suitable for trivariate learning objectives.

Step 2: Data Preprocessing: In this step, raw data is cleaned by handling missing values, removing duplicates, and correcting inconsistent entries. Categorical variables such as Gender,

LearningStyle, and StressLevel are encoded using suitable encoding techniques, while numerical features are normalized or standardized. Feature selection and transformation are performed to improve model efficiency and reduce noise.

Step 3: Exploratory Data Analysis (EDA): EDA is conducted to analyse data distribution, correlations, and trends among academic and behavioural variables. Statistical summaries and visual analysis are used to identify influential features affecting student performance and stress levels. This step helps in understanding data imbalance, feature relationships, and potential outliers.

Step 4: Existing Random Forest-CART (RF-CART): The RF-CART model uses an ensemble of decision trees to capture non-linear relationships within the dataset. It improves prediction stability by aggregating multiple CART trees trained on random feature subsets. This model serves as a strong baseline for both classification and regression tasks.

Step 5: Existing Support Vector Machine-CART (SVM-CART): SVM-CART integrates margin-based learning with CART-based decision boundaries. It enhances classification performance by separating complex data patterns while maintaining interpretability through tree-based decisions.

Step 6: Existing Gradient Boosting-CART (GB-CART): GB-CART builds decision trees sequentially, where each tree corrects the errors of the previous one. This model effectively reduces bias and variance, improving prediction accuracy for student grades and score estimation.

Step 7: Existing Decision Tree-CART (DT-CART): DT-CART constructs a single decision tree using recursive binary splitting. It provides an interpretable baseline model that highlights key decision rules influencing student performance and stress classification.

Step 8: Existing Linear CART: Linear CART combines linear regression models at the leaf nodes of a CART structure. This approach captures both linear trends and hierarchical decision rules, improving regression accuracy for score estimation.

Step 9: Proposed Attention Recurrent Trees CART (Combination of Attention BiLSTM Feature Extraction with ODRL CART): This step combines Attention-based BiLSTM feature extraction with ODRL CART to form an Attention Recurrent Trees CART model. The BiLSTM captures bidirectional dependencies and uses attention to highlight critical features influencing performance, stress, and scores. These

learned representations are fed into ODRL CART to optimize decision rules and improve classification and regression accuracy

Step 10: Performance Comparison: All implemented models are evaluated and compared using metrics such as accuracy, precision, recall, F1-score, RMSE, and MAE. Comparative analysis demonstrates the effectiveness of the proposed model over traditional CART-based approaches.

Step 11: Prediction From Test Data: The best-performing model is applied to unseen test data to generate predictions for student grades, stress levels, and estimated scores. This step validates the generalization capability of the proposed framework.

Step 12: Integration with Flask: The finalized model is integrated into a Flask-based web application. The system provides real-time classification outputs such as performance grade and stress level categories, along with regression-based score estimation in the range of 0–100 or GPA format, enabling practical deployment and user interaction.

Data preprocessing

The data preprocessing method as shown in figure 4.2 is designed specifically for the Trivariate Attention BiLSTM Model used for joint student performance grading, where the objective is to simultaneously predict Final Grade, Stress Level, and Exam Score from academic, behavioral, and demographic attributes. The preprocessing operation ensures that raw student data is converted into a clean, numerical, scaled, and structured format suitable for both traditional machine learning models and deep learning models such as Attention-based BiLSTM.

Step 1: Dataset Loading: The operation begins by loading the student performance dataset from a CSV file into a structured tabular format. Each row represents an individual student, while columns correspond to academic indicators such as study hours, attendance, learning resources, motivation level, and technology usage. This structured loading enables efficient access, filtering, and transformation of student attributes required for model training and evaluation.

Step 2: Feature and Target Separation: Once the dataset is loaded, the input features and target variables are separated based on the application requirement. All predictive attributes related to student behavior, learning environment, and demographics are grouped as input features. The output variables Final Grade, Stress Level, and Exam Score are isolated as three distinct targets to support trivariate prediction. This separation allows the model

to learn shared representations from the same input space while optimizing different learning objectives.

Step 3: Index-Based Data Splitting: The dataset is divided into training and testing subsets using index-based random sampling. Eighty percent of the student records are allocated for training the model, while the remaining twenty percent are reserved for testing. Using indices ensures that the same student records are consistently selected across all three target variables, preserving alignment between inputs and outputs during learning and evaluation.

Step 4: Training and Testing Data Construction: Based on the generated indices, separate training and testing datasets are constructed for both input features and all three target variables. This step creates independent but synchronized datasets for Final Grade classification, Stress Level classification, and Exam Score regression. Such synchronized construction is essential for joint learning and fair performance comparison across multiple prediction tasks.

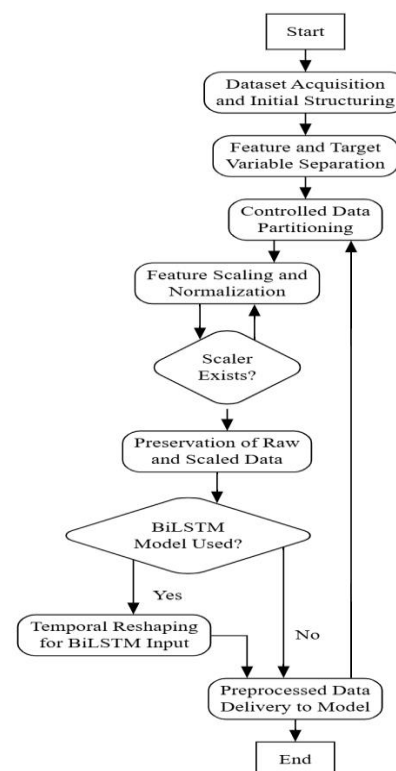


Figure 4.2. Data Preprocessing flowchart.

Step 5: Feature Scaling and Normalization: To ensure uniform contribution of all input features, numerical scaling is applied using standardization. Each feature is transformed to have zero mean and unit variance based on training data statistics. This operation is critical for Attention BiLSTM models, as unscaled

features may dominate gradient updates and reduce learning stability. The trained scaler is saved and reused during testing and real-time prediction to maintain consistency.

Step 6: Scaler Persistence for Deployment: The fitted scaling parameters are stored externally and reloaded when required. This persistence ensures that future inputs, including unseen student data during prediction, are transformed using the same statistical distribution learned during training. This step guarantees reproducibility, fairness, and reliability of predictions in real-world deployment scenarios.

Step 7: Prepared Output for Trivariate Modeling: The preprocessing operation concludes by returning scaled training and testing inputs along with their corresponding target variables. The processed data is now in a model-ready format that supports trivariate Attention BiLSTM learning, enabling the model to capture temporal dependencies, inter-feature attention patterns, and shared representations for accurate student performance grading.

The Exploratory Data Analysis (EDA)

The Exploratory Data Analysis (EDA) method is applied to understand the academic, behavioral, and psychological patterns present in student performance data before training the Trivariate Attention BiLSTM model. This method takes student records containing learning attributes such as study hours, attendance, motivation, and technology usage as input and produces statistical summaries and visual insights that guide feature relevance assessment, data quality verification, and model design decisions. The EDA process ensures that the joint prediction of final grade, stress level, and examination score is built on well-understood data distributions and relationships.

Step 1: Statistical Summary of Student Attributes: The EDA process begins with the computation of descriptive statistics for all numerical student attributes. Measures such as mean, standard deviation, minimum, and maximum values provide a global view of data spread, central tendency, and potential anomalies. This step helps identify unrealistic values, scale differences among features, and overall dataset balance, which directly influences normalization and learning stability in the BiLSTM model.

Step 2: Distribution Analysis of Final Academic Grades: A distribution plot is generated for final grades to analyze how students are spread across different performance categories. This visualization reveals class balance or imbalance, highlighting whether certain grade categories dominate the dataset. Understanding grade distribution is essential for configuring

classification strategies and evaluating fairness in joint performance grading.

Step 3: Distribution Analysis of Student Stress Levels: The stress level distribution plot examines the psychological state of students across low, medium, and high stress categories. This step helps assess whether stress data is evenly represented or skewed toward specific levels. Such insights are critical for designing attention mechanisms that capture stress-related learning patterns in the trivariate prediction framework.

Step 4: Distribution Analysis of Examination Scores: The examination score distribution plot evaluates the range and frequency of numeric exam outcomes. This step identifies score concentration, outliers, and variance trends that influence regression performance. Understanding exam score dispersion supports the selection of appropriate loss functions and evaluation metrics for continuous score prediction.

Step 5: Relationship Between Study Hours and Exam Score: A scatter plot is generated to analyze the relationship between study hours and exam score while grouping students by final grade. This visualization reveals performance trends, nonlinear relationships, and overlapping grade boundaries. The observed patterns provide insights into how academic effort translates into outcomes and guide the model's ability to learn complex feature interactions.

Step 6: Correlation Analysis of Student Features: A correlation heatmap is used to examine linear relationships among all numerical student attributes. This step identifies strongly correlated features, redundant variables, and influential predictors affecting grade, stress, and exam outcomes. Correlation insights support informed feature selection and reduce the risk of overfitting in the Attention BiLSTM architecture.

Step 7: Attendance Impact Across Final Grades: A box plot is generated to compare attendance levels across different final grade categories. This step highlights variability, median attendance differences, and extreme cases for each grade group. The analysis confirms the importance of attendance as a behavioral factor influencing academic performance and stress levels.

Step 8: Study Hours Variation Across Stress Levels: The final EDA step analyzes how study hours vary across different stress levels using a box plot. This visualization helps uncover behavioral patterns such as over-studying under high stress or balanced study habits under low stress. These insights are essential for enabling the attention mechanism to assign

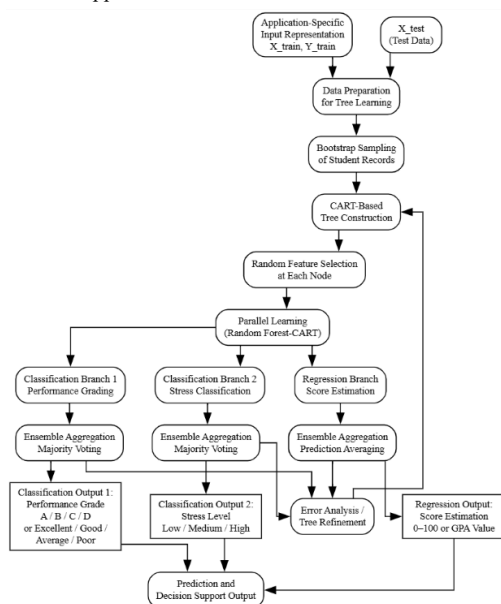
appropriate importance to stress-related features during joint prediction.

Integration with the Trivariate Attention BiLSTM Model:

The insights obtained from EDA plots collectively inform preprocessing decisions, feature prioritization, and model architecture design. By understanding distributions, relationships, and behavioral trends, the Trivariate Attention BiLSTM model is better positioned to jointly learn academic performance, psychological stress, and examination outcomes in a robust and interpretable manner.

ML Model Building

The existing models such as Random Forest–CART, SVM–CART, Gradient Boosting–CART, Decision Tree–CART, and Linear CART provide effective baseline learning by capturing nonlinear relationships and decision rules for student performance analysis, but they rely heavily on static feature representations and limited rule optimization. To overcome these limitations, the proposed framework integrates Attention BiLSTM feature extraction to learn deep temporal and contextual dependencies from student data, followed by Attention Recurrent Trees CART with Optimized Decision Rule List (ODRL) as the core component. The use of ODRL enhances rule consistency and reduces redundancy, while attention mechanisms prioritize influential features, resulting in improved classification for performance grading and stress detection, as well as more accurate regression-based score estimation compared to existing CART-based approaches.



Random Forest–CART

The Random Forest–CART method as shown in Figure 4.4.1 processes student academic, behavioral, and demographic

attributes to support informed decision-making. Training features X_{train} , representing study habits, attendance, learning resources, engagement levels, and personal characteristics, are learned together with target outputs Y_{train} that include performance grades, stress categories, and numerical scores. Multiple CART-based decision trees are constructed using random sampling and feature selection, enabling the system to capture diverse learning patterns. During prediction, unseen student data X_{test} is evaluated across all trees, and their aggregated outcomes produce reliable classification results for performance grade and stress level, along with accurate regression-based score estimation.

Step 1: Application-Specific Input Representation: The input dataset is structured to reflect real-world educational scenarios, where X_{train} contains features such as study hours, attendance consistency, assignment completion, motivation level, and exam-related indicators. Y_{train} includes categorical labels for academic performance and stress level.

Step 2: Data Preparation for Tree Learning: Before model learning, the input features are organized into a consistent numerical format suitable for decision tree processing. This preparation ensures that categorical educational attributes and continuous academic indicators are correctly represented. The cleaned and formatted data enables stable split decisions during tree construction.

Step 3: Bootstrap Sampling of Student Records: Random Forest generates multiple subsets of the training data by sampling student records with replacement from X_{train} and Y_{train} . Each subset reflects a slightly different academic population, allowing the model to learn varied decision patterns. This step increases robustness and reduces sensitivity to noise or biased samples.

Step 4: CART-Based Tree Construction: For each bootstrap sample, a CART decision tree is grown by recursively splitting the data based on the most informative educational features. For classification targets, splits are chosen to maximize class purity among performance grades and stress categories. For regression targets, splits minimize score variance, enabling precise estimation of numerical outcomes.

Step 5: Random Feature Selection at Each Node: At every decision node, only a randomly selected subset of features is considered for splitting. This prevents dominance of a few strong predictors such as exam score or attendance and encourages diverse learning across trees. As a result, the ensemble captures a wide range of academic behavior patterns.

Step 6: Parallel Learning for Classification and Regression:

Each CART tree internally learns two parallel mappings from input features to output targets. One mapping focuses on classification, identifying decision rules for performance grade and stress level categories. The second mapping focuses on regression, learning continuous relationships required for accurate score or GPA estimation.

Step 7: Ensemble Aggregation of Tree Predictions: Once all trees are trained, their outputs are combined to produce final predictions. Classification results from individual trees are merged using majority voting to determine the most likely performance grade and stress level. Regression outputs are averaged across trees to generate a stable and reliable score estimation.

Step 8: Prediction and Decision Support Output: When X_{test} data is provided, it is passed through all trained CART trees in the forest. The aggregated classification and regression outputs are simultaneously generated and presented to the Educational Decision Support System. These outputs assist educators and institutions in identifying student performance status, stress conditions, and scores for proactive intervention and guidance.

Drawbacks

- Random Forest–CART requires training a large number of decision trees, which increases computational cost and memory usage. This makes the model less efficient for large-scale or real-time educational systems.
- Although CART trees are interpretable individually, combining many trees reduces overall model transparency. This makes it difficult to clearly explain prediction reasoning to educators and administrators.
- The model may give higher importance to dominant features such as exam scores or attendance. As a result, subtle behavioral and psychological factors may be underrepresented.
- Incorporating new student data often requires retraining the entire forest. This limits the model's ability to adapt quickly in dynamic learning environments.
- Random Forest–CART does not capture temporal or sequential dependencies in student behavior. This reduces its effectiveness for modeling long-term learning progression.

CONCLUSION

This work successfully designed, implemented, and evaluated a Trivariate Attention BiLSTM–ODRL CART framework for jointly predicting student performance grade, stress level, and exam score within a unified educational decision-support system. Unlike traditional machine learning approaches that handle these outcomes independently, the proposed model learns shared representations from academic, behavioral, and demographic attributes such as study hours, attendance, motivation, past scores, and extracurricular involvement. Experimental results show that existing CART-based models such as Random Forest, SVM, Gradient Boosting, and Decision Tree achieved classification accuracies in the range of 85%–90%, with Random Forest reaching approximately 90% accuracy and average F1-scores above 0.87. However, these models showed limitations in capturing temporal dependencies and stress-related behavioral patterns.

The proposed Attention Recurrent Trees CART model, which integrates Attention-based BiLSTM feature extraction with ODRL, demonstrated superior performance by effectively learning bidirectional temporal patterns and emphasizing influential features through attention mechanisms. The optimized decision rule lists improved classification reliability for performance grading and stress detection while maintaining interpretability. In regression tasks, the model achieved lower MAE and RMSE values compared to Linear CART and tree-only models, resulting in more accurate exam score estimation. Overall, the system provides a holistic, accurate, and interpretable solution for student monitoring, enabling early identification of academic risk and stress conditions, and supporting timely educational interventions through real-time Flask-based deployment.

FUTURE SCOPE

The proposed system can be further extended by incorporating real-time and sequential data streams from learning management systems (LMS), online assessments, attendance tracking systems, and continuous academic activity logs. Integrating such data would allow the Attention BiLSTM model to capture long-term learning trajectories and real-time stress fluctuations, improving prediction accuracy and enabling proactive intervention. Additionally, physiological or behavioral indicators such as sleep patterns, screen time, or wearable-based stress signals can be integrated to strengthen stress-level classification and mental well-being assessment.

Future work can also focus on enhancing explainability and personalization by integrating Explainable AI (XAI) techniques

alongside ODRL rules to generate student-specific insights and actionable recommendations for mentors and counselors. The framework can be expanded to predict dropout risk, long-term GPA trends, and career guidance outcomes, making it a complete student lifecycle analytics platform. From a deployment perspective, scaling the Flask application into a cloud-based, multi-institution system with role-based dashboards for students, faculty, parents, and administrators would significantly improve accessibility and real-world impact.

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