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Early Detection of Academic Burnout Using Student Interaction Logs and Machine Learning

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***Abstract:** Academic burnout is a growing concern in today's digitally driven education system. The prolonged stress of online learning, frequent assessments, and lack of physical interaction has increased the risk of mental fatigue among students. This paper presents a machine learning–based approach to detect early signs of academic burnout using student interaction logs collected from online platforms. The proposed model analyses behavioural data such as login frequency, study time, quiz performance, and emotional feedback to predict burnout risk levels. Early detection allows timely intervention from educators and counsellors, improving student well-being and academic performance.*
***Keywords:** Academic Burnout, Machine Learning, Student Logs, Mental Health, Learning Analytics, Emotion Detection, Early Intervention*

I. INTRODUCTION

In the last few years, education has changed a lot. Because of new digital tools and the COVID-19 pandemic, many schools and colleges started teaching online or in a mix of online and offline methods.

While online learning gave students more flexibility and access to study materials from anywhere, it also brought some problems especially emotional and mental stress [1]. Many students found it hard to stay motivated without regular face-to-face interaction with teachers and classmates.

One big issue that came up is something called academic burnout. This means a student feels very tired, mentally drained, and starts losing interest or confidence in their studies. Burnout can lead to poor concentration, lower grades, and even mental health problems like anxiety. If not handled early, it might cause students to give up on their education [2].

Until now, burnout was usually noticed by teachers or counsellors through one-on-one talks or surveys. But these methods take time and don’t always work well specially when learning is online and there are too many students. That’s why we need smart systems that can detect early signs of burnout automatically, using student data and without bothering the student directly[3].

Today, online platforms and learning apps collect a lot of useful information like how long a student studies, how often they log in, and what kind of questions they answer. These are called student interaction logs. If we use Machine Learning (ML) to study this data, we can find patterns that show when a student might be feeling stressed or close to burnout [4].

This paper introduces a smart system that looks at these interaction logs and uses ML to predict whether a student is at risk of burnout. The idea is to catch the problem early so that teachers or support staff can help the student in time.

By using this approach, we can make learning not just smarter but also more caring where the system looks out for students' well being and helps them succeed both academically and emotionally.

II. LITERATURE REVIEW

Many researchers have explored how to detect academic burnout in online learning:

1) One recent study introduced a smart system that checks for stress by using tools like automatic question generation and facial expression analysis to understand how students are feeling [1].
2) Another research used data from students' phones and their online activity to predict mental fatigue. They used machine learning techniques like SVM and Random Forest and got good results [2].
3) A third study looked at students’ interaction time, quiz scores, and emotional responses. Their system could catch early signs of students losing interest—before it turns into full burnout [3].

All of these studies show that machine learning can help us understand students’ mental health better, give early warnings, and possibly prevent students from dropping out or feeling overwhelmed.

III. METHDOLOGY

A. Data Collection

Data was collected from a simulated online learning platform including:

1) Login/logout timestamps: This tells us when a student logs into the learning platform and when they log out. It helps us understand their daily study routine and whether they're attending regularly or not.
2) Time spent on lectures, assignments, and quizzes: This shows how much time a student is spending on different learning activities. If a student is spending too little or too much time, it could be a sign of stress or difficulty.
3) Performance metrics (scores, completion rates): These are the student's marks in quizzes, assignments, and tests, as well as whether they're finishing their work on time. A drop in performance or missing deadlines could be a warning sign.
4) Self-reported stress levels (optional): This is when students are asked how stressed they feel, through a simple form or questionnaire. If they report high stress often, it helps us understand their emotional state better.
5) Facial expression data (from webcam input): This uses the webcam to detect facial expressions like sadness, frustration, or tiredness. It gives us clues about how the student is feeling during their study sessions [5],[6].

B. Pre-processing

The logs were cleaned, normalized, and labelled into three burnout levels: Low, Moderate, High. Noise such as missing entries or short inactivity was removed [8].

C. Feature Engineering

To train the machine learning model, we used some important features (data points) that could help in identifying students at risk of burnout. Here's what each feature means:

1) Study time consistency: This checks if a student is studying regularly. If their study hours suddenly change a lot from day to day, it could be a sign that something is wrong or they are losing focus.
2) Drop in performance over time: This looks at the student's marks and progress. If their scores are going down week after week, it might mean they are stressed, unmotivated, or struggling to keep up [6].
3) Frequency of late submissions: This tracks how often a student submits assignments or quizzes after the deadline. Frequent delays may be a sign of academic pressure or burnout.
4) Emotional expressions (sadness, frustration): If the system can detect negative emotions like sadness or frustration through facial expressions while the student is studying, it could indicate emotional stress [9].

Session gaps and irregular patterns: This looks at how regularly the student is logging in and studying. If there are long breaks or very random login times, it may show a lack of interest or mental fatigue.

D. ML Model

To predict academic burnout, we tested a few different machine learning models. Each model works in a slightly different way to find patterns in student behaviour and decide if a student is at risk. Here's a basic explanation of each:

1) Logistic Regression: This is one of the simplest models. It looks at the data and tries to draw a clear line (or decision boundary) between students who are at risk of burnout and those who are not. It's fast and easy to use for binary (yes/no) problems [11].
2) Random Forest: This model works like a team of decision trees. Each tree gives its own prediction, and then the final decision is made by voting. It's very good at handling different types of data and gives more accurate results than a single tree.
3) Support Vector Machine (SVM): SVM tries to find the best possible boundary (margin) that separates two groups in this case, students at risk and not at risk. It works well when the data is spread out in a way that's not too simple.
4) XG Boost: This is a powerful and smart model that builds many small decision trees one after another, learning from previous mistakes each time. It usually gives high accuracy and is often used in real-world machine learning competitions.

E. Evaluation Metrics

To check how well our machine learning models worked, we used a few important evaluation measures. These help us understand how accurate and reliable the model is in predicting academic burnout.

The models were evaluated using:

1) Accuracy: Accuracy tells us how many predictions were correct out of all the predictions made. For example, if the model correctly identifies most students who are burned out or not, it has high accuracy. But accuracy alone is not always enough.

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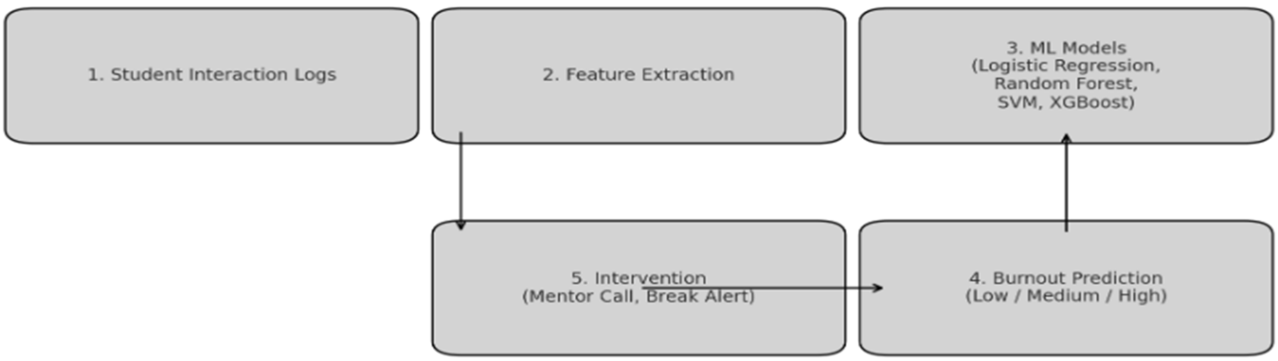
2) Precision & Recall: Precision shows how many of the students that the model *predicted as burned out* were actually burned out. A high precision means fewer false alarms. Recall tells us how many of the *actual burned-out students* the model was able to correctly find. A high recall means we didn't miss many students who needed help.
3) F1-Score: This is a combination of precision and recall. It gives a balanced score, especially useful when we care about both false positives (wrong alarms) and false negatives (missing someone who needs help).
4) ROC-AUC: This measures how well the model can separate students at risk from those who are not. A higher ROC-AUC (closer to 1) means the model is doing a great job at distinguishing between the two.

IV. SYSTEM ARCHITECTURE



The proposed system is designed to detect early signs of academic burnout using machine learning and student interaction data. The overall architecture includes the following key components:

1) Student Interaction Logs: The process begins with collecting data from the student's activity on an online learning platform. This includes login/logout times, time spent on different learning tasks, quiz scores, assignment submissions, and optional emotion data from webcam input.
2) Feature Extraction: From the raw logs, important features are extracted that can help identify burnout patterns. These include study time consistency, changes in performance, emotional indicators (like frustration), and irregular behaviour (such as frequent late submissions or long gaps between sessions).
3) Machine Learning Models: The extracted features are passed into machine learning models such as Logistic Regression, Random Forest, SVM, and XG Boost. These models are trained to analyze the behaviour and predict the risk level of academic burnout (low, moderate, or high).
4) Burnout Prediction: Based on the model's output, each student is classified into a burnout category. This helps identify which students may need support or guidance.
5) Intervention Module: Once a high-risk student is identified, the system can trigger helpful actions such as sending an alert to a mentor, suggesting a study break, or offering motivational support. This timely response can help reduce stress and improve the student's learning experience.

This architecture ensures that burnout risks are detected early and addressed in a personalized and non-intrusive way, leading to better academic and emotional outcomes for students.

V. RESULT AND DISCUSSION

The findings clearly showed that student activity logs can reveal early signs of academic burnout. Certain behaviour patterns stood out in students who were at higher risk:

1) They spent long hours logged into the platform but didn't complete much work, showing low productivity. frequent switching between tasks
2) They often jumped from one task to another without finishing them, which indicated a lack of focus[12].
3) Their facial expressions (when available through webcam) showed tiredness, frustration, or emotional strain[13].
4) There was a noticeable drop in their quiz marks and the overall quality of their assignment submissions

The system was able to identify such patterns early. As a result, timely actions like mentor check-ins, encouraging messages, or break suggestions could be provided. These early steps helped students perform better and gave them a more positive learning experience.

VI. APPLICATIONS

1) University Portals: Integration with LMS like Moodle or Google Classroom
2) Counseling Systems: Automatic alert generation for student mental health teams
3) Parental Feedback: Monthly burnout reports for parents
4) Mobile App: Notifications for students to take breaks or seek help

VII. CONCLUSSION

This study shows that machine learning can be a powerful tool to detect early signs of academic burnout by analyzing students' behaviour on online platforms like how often they log in, how long they study, or how their performance changes over time. By noticing these early warning signs, the system can alert teachers or mentors before the student's condition gets worse.

Early detection means students can get help such as counselling, study support, or simple motivation at the right time. This not only helps students feel better mentally and emotionally but also improves their academic performance and confidence.

Such systems are especially useful in today's digital learning environment, where teachers may not always notice when a student is struggling. By using technology in a smart and thoughtful way, we can create a learning space that doesn't just focus on marks but also takes care of students' mental well-being.

In the future, combining this system with real-time emotion tracking, wearable devices, or mobile apps could make it even more effective and accessible to students everywhere.

VIII. FEATURE AND WORKS

1) Real-time emotion detection using webcam + audio cues
2) Integration with wearable devices for physiological stress tracking
3) More diverse datasets across institutions for model generalization

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