Academic Burnout Prediction: A Machine Learning-Based System Using Random Forest Algorithm

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Chapter 1

Introduction

1.1 The problem and its background

In today's fast-changing educational landscape, students face growing academic pressure, the shift to digital learning, and a broad range of personal responsibilities. As learning environments evolve, so too do the challenges students encounter—one of the most prominent being academic burnout. While technology has improved educational access and efficiency, it has also contributed to an "always-on" culture that can increase emotional strain. Based on the article by Salmela-Aro and Upadyaya (2020), modern students are frequently caught in an imbalanced cycle of high academic demands and limited personal resources, which often leads to disengagement and emotional exhaustion.

Several studies have highlighted the increasing levels of psychological stress among students. The COVID-19 pandemic, for instance, has worsened these issues by combining health fears with increased academic workloads. According to Portoghese et al. (2020), this has significantly amplified symptoms of burnout, often resulting in mental health deterioration and academic decline. Traditionally, burnout detection relied on interviews and surveys, which are subjective and often too slow to flag early symptoms. As Aslan, Ochnik, and Çınar (2020) pointed out, traditional tools may miss the subtle behavioral signs that signal a student is nearing burnout.

Emerging technologies, particularly machine learning (ML), offer promising new approaches. Shatte, Hutchinson, and Teague (2021) noted that ML is capable of identifying early signs of mental health risks through pattern recognition rather than waiting for students to report issues. Random Forest algorithms are especially effective due to their interpretability and accuracy (Lin & Wang, 2021). This is further supported by Santos, Cardoso, and de Souza (2021), who found that Random Forest could reliably predict academic risks, enabling timely educational interventions.

Several studies reinforce these findings. AlFayez, Alshahrani, and Zolkipli (2024) successfully used supervised machine learning algorithms to predict student stress. Akuratiya and Karunananda (2024) demonstrated that Random Forest could detect college mental stress accurately. Similarly, Ziadé et al. (2023) used predictive models to assess depression, anxiety, and stress in university students. Ibrahim and Kamal (2023) emphasized that the early detection of stress using Random Forest supports proactive academic guidance.

This study focuses on the education sector, specifically within colleges and universities. These institutions serve not only as academic hubs but also as organizations responsible for student well-being. Their primary output is educated individuals, while the services they render include academic instruction, performance tracking, and student advising. However, many still rely on outdated, manual systems for detecting academic distress.

To bridge this gap, this study proposes a machine learning-based system that uses the Random Forest algorithm to predict academic burnout. For students, the system provides early alerts, allowing for timely interventions like counseling or academic adjustments. For instructors, it offers a deeper understanding of student performance trends, helping tailor instruction. Academic counselors can prioritize at-risk students more effectively. This system ensures that mental health concerns are addressed before they escalate.

Technology, particularly machine learning, is essential for modern educational support. Its predictive and scalable nature allows for proactive care, surpassing the limits of traditional methods. This research is driven by the need to integrate mental wellness with academic performance, enabling healthier, more supportive educational environments.

1.2 Review of Related Literature

In this section, the researchers main topic is those related studies of research questions and reviewing that previous existed literature, uncovering the research gaps or research reports and evaluating the research evidence related to that research question.

Random Forests in Educational Data Mining

According to Bakri, et. Al.(2024), the effectiveness of Random Forest algorithms in data mining instruction by employing unbalanced data techniques to maximize graduation on-time (GOT) forecasts. Random under-sampling (RUS), random over-sampling (ROS), hybrids of RUS and ROS, synthetic minority over-sampling techniques for nominal classes (SMOTE-NC), and hybrids of SMOTE-NC and RUS are some of the strategies used to deal with unbalanced data. Based on AUC values, the SMOTENC and RUS hybrid approaches performed best on testing data, whereas the RUS-ROS hybrid performed best when compared to other approaches.

Predicting Academic Performance Using Motivation Factors

(Orji F., et. Al. 2022) Based on motivational characteristics such as intrinsic and extrinsic motivation, RF was used in a study to forecast students' academic performance and study techniques. The RF model outperformed other models, such as Decision Trees and Support Vector Machines, with a high prediction accuracy of 94.9%.The models used in this work can be used to forecast how well students will do and how they will study, allowing for the implementation of suitable interventions to enhance learning outcomes. Therefore, designing online educational systems with tactics that might enhance a variety of student learning traits may make it more likely that students will stick with their learning assignments as needed. Furthermore, the findings indicate that the qualities could be combined and utilized to modify and customize the educational process.

Early Detection of Academic Underperformance

(Balabied, S.A.A, et. Al.(2023) In order to identify students who are at danger of academic failure, RF has been used to evaluate behavioral data from online learning settings. The approach supports early intervention techniques by spotting trends in student interactions. This study's specific goal was to develop a model that can recognize at-risk pupils and enable prompt interventions to support their academic success. accomplishment. The model of the random forest classifier has been employed to analyze Open University Learning Analytics provides anonymized huge datasets. (OULAD) to find trends and connections between different elements that influence the success or failure of students.According to the study's conclusions, this algorithm's accuracy was 90%. in determining which pupils might be in danger and giving them the required assistance to achieve success.Among Open Learning Environments' (OLEs) main advantages is their ability to scale. OLEs offer a wide range of people flexible and easily accessible learning possibilities. number of pupils, frequently on a worldwide basis. Because of its scalability, the creation of OLEs that encompass a variety of topics and fields, from engineering and computer science to the social sciences and humanities. But the OLE scalability also has drawbacks, such as the fact that it can be too challenging to offer individualized assistance and criticism to people. Early student projection performance can enhance students' educational experiences by offering early assistance and interventions.

Stress and Mental Health Prediction

(Zhang, L., et. Al.2024) said that This survey included 2088 college students from five different universities. A training group (80%) and a validation group (20%) were randomly assigned to the participants. This work used and trained a variety of machine learning models, such as logistic regression (LR), support vector machine (SVM), k-nearest neighbor (KNN), random forest (RF), decision tree (DT), logistic gradient boosting machine (eXGBM), and others. Eleven indicators were used to assess the model's performance, and the model with the highest score was chosen. Furthermore, 751 participants from three universities underwent external evaluation. After that, the AI tool was made available online as an AI application.With an area under the curve (AUC) of

0.932 (95% CI: 0.911–0.949), the eXGBM model outperformed the other models. RF came in second with an AUC of 0.927 (95% CI: 0.905–0.943). In terms of accuracy (0.850), precision (0.824), recall (0.890), specificity (0.810), F1 score (0.856), Brier score (0.103), log loss (0.326), and discrimination slope (0.598), the eXGBM model performed better than the others. According to the evaluation rating system, RF scored 49, while the eXGBM model obtained the highest score of 60. LR, DT, and SVM only received scores of 19, 32, and 36, respectively. The remarkable AUC value of 0.918 was obtained through external validation.When it comes to identifying college students who are at risk of experiencing significant mental anguish, the AI technology shows encouraging predictive performance. It may help direct intervention tactics and encourage early detection and prophylactic actions.

Predicting Student Stress Levels Using Machine Learning

(Arya, S., et. al. 2024) stated that everyone agrees that stress exists somewhere. Many of us encounter circumstances that add to our everyday problems, impacting professionals like parents, teachers, physicians, lawyers, and journalists. Students at universities are facing comparable difficulties. Finding the causes of stress among Tribhuvan University Dharan students in Nepal is the goal of this study. By examining these stressors, we are able to anticipate and stop stress in its tracks.The idea of stress is widely accepted these days. Professionals like teachers, doctors, lawyers, journalists, and parents are among the many among us who deal with situations that add to our everyday troubles. Similar difficulties are also being faced by university students. The purpose of this study is to determine the causes of stress among Tribhuvan University Dharan students in Nepal. By examining these stressors, we can anticipate and stop stress before it starts.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) are some of the machine learning and deep learning models that are proposed in this paper. SVM had the lowest test accuracy at 85.45%, while the Naive Bayes model reached 90%. Hyperparameter adjustment increased these models' accuracy. Compared to other circumstances, the "academic period" is the most stressful time for students, according to the study's main finding.

Handling Imbalanced Data in Burnout Prediction

(Feher, G., et, al.2024), People in a variety of professions, including doctors, nurses, and teachers, might experience burnout, which is typically described as a condition of emotional, physical, and mental tiredness. Reduced motivation, decreased productivity, and a general decline in wellbeing are the results of burnout.A total of 1,576 high school teachers (522 males) made up the final sample. They answered a variety of sociodemographic, health, and psychological questionnaires. In particular, the most significant factors examined in this study were depression, sleeplessness, internet behaviors (such as when and why one uses the internet), and problematic internet usage.A total of 19.7% of the teachers in the final sample had burnout. Random forest with class weights produced the best predicting performance on the holdout test sample (AUC =

0.811; balanced accuracy = 0.745, sensitivity = 0.765; specificity = 0.726). Subscales of the Problematic Internet Use Questionnaire, Athen's Insomnia Scale, Beck's Depression Inventory, and self-reported current health state were the best indicators of burnout. Although the algorithms' performances were similar to those of earlier research, it is crucial to remember that we tested our models on holdout data that had never been seen before, indicating greater generalizability. Another noteworthy discovery is that, in addition to depression and sleeplessness, other factors including problematic internet use and online time were also found to be significant predictors of burnout.

Sentiment Analysis for Anxiety Detection

(Saifullah, S., et. al. 2021) A 2021 study used sentiment analysis and machine learning to identify worry in social media data. Using TF-IDF feature extraction and count-vectorization, Random Forest obtained the greatest accuracy of 84.99%.The COVID-19 pandemic had an effect on all demographics. Anxiety is brought on by this circumstance, which is detrimental to everyone. Through its job program, the government plays a significant role in resolving these issues. It also has many pros and cons that cause public anxiety.To do that, anxiety must be identified in order to enhance government initiatives that raise public expectations. In order to identify worry in social media comments about government initiatives to combat this pandemic, this study uses machine learning.This idea would use sentiment analysis to identify anxiety based on both positive and negative remarks made by online users. K-NN, Bernoulli, Decision Tree Classifier, Support Vector Classifier, Random Forest, and XG-boost are among the machine learning techniques used.YouTube comments were crawled to create the data sample. A total of 4862 comments were used, 3211 of which were positive and 1651 of which were negative. Positive data indicates hope (not fear), but negative data indicates anxiety. TF-IDF and count-vectorization feature extraction are the foundations of machine learning processing. The results demonstrated that the random forest with feature extraction of vectorization count and TF-IDF of 84.99% and 82.63%, respectively, had the highest accuracy in training, while the sentiment data in testing totaled 3889 and 973. K-NN is the best test for precision, whereas XG-Boost is the best test for recall. Therefore, using data from social media, Random Forest is the most accurate method for determining someone's level of anxiety.

Physician Burnout Prediction Using Activity Logs

(Liu, H., et. al. 2022) HiPAL, a deep learning system for detecting physician burnout using activity logs from electronic health records, was first presented in a 2022 study. The study demonstrates the potential of machine learning in burnout prediction without the use of Random Forest.Burnout affects about half of the healthcare workforce, making it a serious public health risk. The first comprehensive deep learning framework for forecasting physician burnout is presented in this study. It is based on electronic health record (EHR) activity logs, which are digital records of doctor job activities that can be found in any EHR system.Unlike previous methods that only used surveys to quantify exhaustion, our system predicts burnout by explicitly learning deep representations of physician actions using extensive clinician activity logs.With a hierarchical predictive model and a pre-trained time-dependent activity embedding mechanism specifically designed for activity logs, we present the Hierarchical Burnout Prediction based on Activity Logs (HiPAL), which mimics the naturally occurring hierarchical structure of clinician activity logs and captures the changing burnout risk of doctors over the short and long term. We present a semi-supervised system that learns to transmit knowledge collected from unlabeled clinician activities to the HiPAL-based prediction model in order to leverage the vast number of unlabeled activity logs. A big academic medical center's trial with more than 15 million clinician activity records gathered from the EHR shows how our suggested framework outperforms state-of-the-art methods in terms of training efficiency and physician burnout prediction.

Burnout Prediction Among Nursing Staff

(Zyl-Cillie, M.M.V., et. al. 2024) A study conducted in 2024 used Random Forest models to forecast emotional tiredness and burnout among South African nurses. With a 76.8% accuracy rate, the model found that organizational factors were a stronger predictor than demographic variables.Globally, there is an increasing need for high-quality healthcare, and South African nurses are under pressure to deliver treatment with few resources. Nurses experience burnout and fatigue as a result of this rigorous work environment. To effectively help nurses and educate policymakers, it is essential to comprehend the precise causes of these problems. The specific causes linked to burnout and emotional weariness among South African nurses are currently little understood. Furthermore, it's questionable if demographic data alone can predict these elements.Machine learning models for categorization were created using the PyCaret 3.3 package using 1165 survey responses from nurses working in medical-surgical units throughout South Africa. The models were assessed based on their confusion matrix performance, accuracy score, and Area Under the Curve (AUC) score. Furthermore, the accuracy score of models that solely used demographic data was contrasted with that of models that used complete survey data.From full survey data, the gradient booster classifier (GBC) model predicted self-reported experiences of burnout (75.8%) and emotional weariness (76.8%) with the greatest accuracy score. The accuracy scores for predicting self-reported experiences of burnout and emotional weariness were 60.4% and 68.5%, respectively, using demographic data alone.Supervised machine learning models can accurately predict self-reported feelings of burnout or emotional exhaustion among nurses in South Africa from full survey data but not from demographic data alone. The models identified fatigue rating, confidence in management and management who listens to employees as the most important factors to address to prevent these issues among nurses in South Africa.

Predicting Burnout in EFL Teachers

(Baniadamdizaj, S., et. al. 2022) Several machine learning methods were used in the study to forecast the burnout levels of Iranian EFL teachers. The study discovered that support vector classifiers and linear discriminant analysis were the most accurate in predicting emotional weariness, even though Random Forest was one of the models utilized. Constantly experiencing mental, bodily, and emotional stress leads to burnout. It usually has to do with one's work and involves a loss of personal identity and a sense of diminished accomplishment. Teachers are typically high achievers who enjoy working hard because of the stress that comes with accountability requirements, workload, and hours. They face formidable obstacles. They have to handle changing educational regulations, adjust curricula to accommodate a variety of learning styles, care for pupils with special needs, and balance administrative tasks. Furthermore, compensation is still minimal when compared to other graduate positions.As a result, many teachers suffer from teacher burnout following extended exposure to poorly managed emotional and interpersonal job stress, which leads to staff turnover and numerous socioeconomic issues. In this sense, precise forecasting offers crucial advantages for research and decision-making. A sample of 1433 Iranian EFL teachers was given the Maslach Burnout Inventory in order to achieve this goal. Additionally, using the Python programming language, nine distinct machine learning methods were applied to the data set in order to forecast burnout levels. The accuracy of the algorithms was also used to examine their performance. To sum up, this study's findings show how to predict instructors' burnout levels in order to stop the problem's negative effects.

1.3 Significance of the Study

This study offers a practical and innovative contribution to the field of education by introducing a machine learning-based system capable of predicting academic burnout using the Random Forest algorithm. Implementing the machine learning-based system enables schools to provide timely support and intervention, thereby improving academic outcomes, increasing retention rates, and promoting student well-being.

Students benefit significantly from the system's ability to provide feedback and early alerts regarding burnout risks. Given the global issue of academic pressure, the system helps students become self-aware, manage workloads, and seek help when needed. It promotes healthier study habits and fosters emotional resilience, essential for sustaining academic success and well-being in competitive educational settings.

The study helps reduce the stigma around seeking support by acknowledging and proactively addressing mental health within educational systems. By proactively acknowledging and addressing mental health, educational systems help reduce the stigma around seeking support. This, in turn, helps minimize institutional expenses linked to student dropout and mental health-related issues. Early detection of burnout allows schools to allocate support services more effectively, which in turn improves graduation rates and cultivates a more competent and emotionally resilient student body. By fostering emotional resilience and academic success, the system helps form well-prepared, productive individuals, ultimately contributing to a knowledge-driven economy.

1.4 Statement of the Problem

In today's academic environment, students face increasing pressure from academic demands, digital learning, and personal responsibilities. Family-related issues are a major source of emotional exhaustion, often worsening when combined with school-related stress, leading to academic burnout—characterized by emotional fatigue, detachment, and decreased performance. Traditional methods like surveys and interviews often fail to detect struggling students early. While schools have access to valuable academic data, they lack efficient tools for early detection. This study aims to address this gap by developing a machine learning-based system using the Random Forest algorithm to predict academic burnout and enable timely intervention.

This study specifically focus on the problem of the research are:

1. How can academic institutions identify students at risk of a burnout using available academic performance and activity data?
2. How can Random Forest-based prediction models be developed to analyze students data and detect early signs of burnout?
3. How can the proposed system help teachers, counselors, colleges, and administrators to provide support to students before burnout affects their performance?
4. How can the system present burnout prediction in an interpretable way to support informed decision-making within the school?

1.5 Scope and Limitation

The researcher's goal is to use machine learning-based Random Forest algorithm, to help detect academic burnout among students based on academic data. As researchers, the focus is on building, functional system that demonstrates the concept of burnout prediction. The intention is to show how early signs of academic distress can be flagged through predictive analysis, with the goal of helping schools intervene before burnout worsens.

The study covers the development of a basic machine learning–based system that uses selected student data (e.g., grades, attendance, and activity patterns) to predict possible signs of academic burnout. Furthermore, the study aims to provide a basic user interface for educators or counselors to upload data and receive clear prediction results. Its purpose is in the hope of showing how even a basic machine learning tool can support student well-being, especially when traditional detection methods fall short.

The system will include the following features:

- A simple interface to manually input or upload data related to student performance.
- Burnout Prediction using Random Forest algorithm that processes the input data to predict whether a student is at risk.
- A results display output showing the stats whether the student is at risk or not, with a simple interpretation of the result.
- A minimal, beginner-friendly front end user interface intended for use even by non-technical people.

The study will be conducted within an academic setting, and will rely on datasets and data may be limited due to privacy and access limitations.

Due to design constraints and the researchers' limited background, this study does not cover:

- Real-time integration with external systems or live student databases.
- Automated data collection from learning platforms (e.g., logs).

- Advanced machine learning techniques beyond Random Forest.
- Psychological profiling, diagnostics, or professional mental health intervention features.
- Data security or privacy compliance protocols beyond data handling for research purposes.

Chapter 2

Methodology

This study adopts a quantitative-experimental research design utilizing machine learning methodologies to predict academic burnout among students. The researchers designed a predictive system using the Random Forest algorithm, a supervised machine learning model known for its high accuracy and robustness, especially in classification tasks. The design focuses on data collection, preprocessing, model training, system implementation, and evaluation.

The research involved gathering data from student respondents using a burnout assessment survey instrument. After preprocessing the collected data, the data was fed into a Random Forest classifier. The model was trained and tested using appropriate performance metrics such as accuracy, precision, recall, and F1-score. The end product is a prototype system capable of predicting burnout risk levels (e.g., Low, Moderate, High).

2.1 Conceptual Framework

The conceptual framework of this study integrates educational psychology and machine learning. It centers on the hypothesis that academic burnout can be predicted using patterns in student behavior and academic performance data.

The framework involves three core stages:

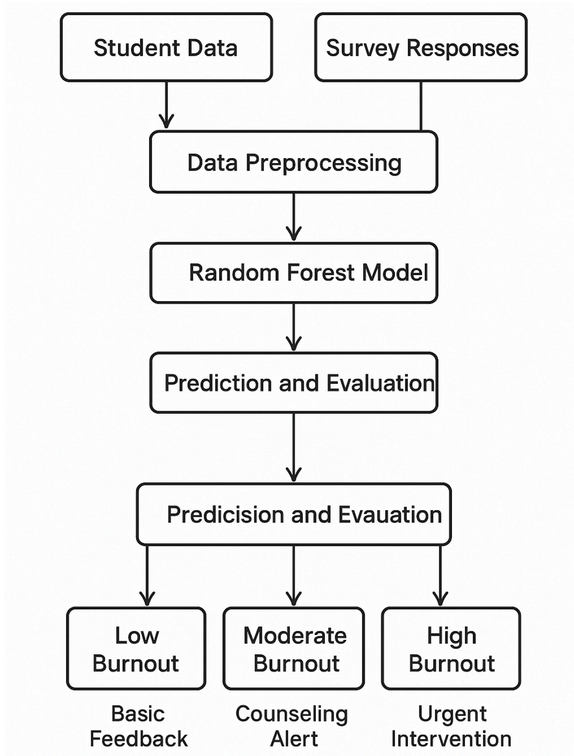

Figure 2.1 System Concept

1. Input Stage
    - Student academic data (e.g., grades, attendance, course load)
    - Psychological survey responses (burnout indicators like exhaustion, cynicism, and academic efficacy)
2. Process Stage
    - Data preprocessing
    - Feature selection and engineering
    - Model training using Random Forest Algorithm
    - Validation using testing dataset
3. Output Stage
    - Burnout prediction (Low / Moderate / High)

- User feedback system
- Insights for academic intervention or guidance counseling

Random Forest Algorithm

In line with the study's aim to create a burnout prediction system, machine learning provides the foundation for detecting patterns in student responses that signify mental and emotional strain. Among the many algorithms available, Random Forest stands out for its high accuracy, robustness to noise, and ease of interpretation. This chapter details the process from data collection to model testing, built upon a synthetic dataset simulating real student responses to the Maslach Burnout Inventory – Human Services Survey (MBI-HSS).

Dataset

The data used for predicting academic burnout among students consisted of 150 rows and 22 columns designed to assess the burnout levels. The Maslach Burnout Inventory – Human Services Survey (MBI-HSS) is a validated instrument used to assess burnout, especially among professionals and students in human services.

It measures three key dimensions of burnout:

- Emotional Exhaustion (EE)
- Depersonalization (DP)
- Personal Accomplishment (PA)

The instrument used was based on the Maslach Burnout Inventory – Human Services Survey (MBI-HSS), a well-established psychological assessment tool originally developed to measure burnout in professions involving caregiving or service to others, and now widely adapted to academic settings, including students. The MBI-HSS was selected due to its high reliability, interpretability, and its ability to capture the multidimensional nature of burnout.

Each questions in the MBI-HSS is rated on a 7-point Likert scale, where respondents indicate how frequently they experience each symptom:

0 = Never

1 = A few time a year

2 = Once a month or less

3 = A few time a month

4 = Once a week

5 = A few times a week

6 = Everyday

The results from the survey are compiled into a dataset where each respondent's answers are translated into numerical values, with separate columns for each item and a computed burnout level (High, Moderate, or Low), which serves as the label for machine learning classification.

Maslach Burnout Inventory – Human Services Survey (MBI-HSS)

The MBI-HSS categorizes burnout into three key dimensions, which are Emotional Exhaustion (EE), Depersonalization (DP), and Personal Accomplishment (PA). Each of these dimensions reflects a specific aspect of burnout. Emotional Exhaustion measures the emotional fatigue and depletion a student experiences due to academic demands. Depersonalization captures the degree of detachment or cynicism students develop toward their academic responsibilities or peers. Personal Accomplishment evaluates the sense of success and competence students feel in relation to their academic performance and progress. The full questionnaire contains 22 items distributed across these three dimensions.

1. Emotional Exhaustion

This dimension consists of 9 items that assess the feeling of being emotionally overextended and exhausted by academic work.

Item No.	Question
EE1	I feel emotionally drained from my studies.
EE2	I feel used up at the end of a day at school.
EE3	I feel fatigued when I get up in the morning and have to face another day at school.
EE4	I feel frustrated by my academic workload.
EE5	I feel I’m working too hard on my academic tasks.
EE6	Studying all day is really a strain for me.

EE7	I feel burned out from my schoolwork.
EE8	I feel like I’m at the end of my rope academically.
EE9	I feel emotionally drained when I deal with school-related matters.

Table 2.1: Emotional Exhaustion Questions

Based on Table 2.1 high scores in this category are associated with extreme fatigue, exhaustion, or the inability to continue functioning effectively in academic life. This is often the first and most visible sign of burnout in students.

2. Depersonalization

This dimension includes 5 items that measure an unfeeling and impersonal response toward peers or academic activities.

Item No.	Question
DP1	I feel I treat some classmates or instructors as if they were impersonal objects.
DP2	I’ve become more callous toward people since I started school.
DP3	I worry that my academic efforts make me uncaring.
DP4	I’ve become less sensitive to people since I started this course.
DP5	I doubt the significance of what I’m learning.

Table 2.2: Depersonalization Questions

Depersonalization reflects a psychological detachment from one's academic environment. It is characterized by emotional distance, apathy, and cynicism. Students with high DP scores may no longer feel emotionally connected to their coursework or peers.

3. Personal Accomplishment

This dimension consists of 8 items that evaluate feelings of competence, success, and productivity in one's academic life.

Item No.	Question
PA1	I can easily understand how my studies are helping others.
PA2	I deal effectively with the problems of my academic life.
PA3	I feel I'm positively influencing the people around me through what I learn.
PA4	I feel very energetic in my studies.
PA5	I have accomplished many worthwhile things in my education.
PA6	I feel exhilarated after completing a challenging academic task.
PA7	I have learned valuable things in school that I can apply practically.
PA8	I feel confident in my academic abilities.

Table 2.2: Personal Accomplishment Questions

Unlike EE and DP, **lower** scores in the PA category indicate higher levels of burnout. A student who feels ineffective, underachieving, or unmotivated is at risk. High PA scores, on the other hand, indicate resilience and satisfaction.

Random Forest Classifier

To classify individuals into distinct levels of burnout—Low, Moderate, and High—based on psychometric questionnaire responses, we employed a supervised machine learning approach. Specifically, we selected the Random Forest Classifier, a tree-based ensemble algorithm, due to its high predictive accuracy, resistance to overfitting, and its capacity to estimate feature importance, which is valuable for interpretability in psychological or health-related domains.

a. **Data Preprocessing:** The dataset comprises 150 samples, each annotated with a target label representing burnout severity:

   Dataset: 150 samples (50 Low, 50 Moderate, 50 High) with 22 features (Q1-Q22).

   - 50 Low
   - 50 Moderate
   - 50 High

   Train-Test Split: To ensure the generalizability of our model, we split the dataset into: 80% training (120 samples), 20% testing (30 samples) using stratified sampling to maintain class balance.

   - Training Set: 80% (120 samples)
   - Testing Set: 20% (30 samples)

b. **Hyperparameter Tuning:** A grid search was performed to optimize model performance and the optimal parameters.

   n_estimators=100 (number of decision trees)

   max_depth=10 (prevents overfitting)

   min_samples_split=2 (minimum samples to split a node)

   min_samples_leaf=1 (minimum samples per leaf node)

   n_estimators: More trees improve performance and reduce variance

max_depth: Limits tree depth to prevent overfitting

min_samples_split: Ensures sufficient data for node splits

min_samples_leaf: Allows leaf nodes to contain a single instance

c. **Training of the Model:** The model was trained with the following parameters:

```
final_model = RandomForestClassifier(
    n_estimators=100,
    max_depth=10,
    min_samples_split=2,
    min_samples_leaf=1,
    random_state=42
)
model.fit(X_train, y_train)
```

d. **Classification Metrics**

In classification tasks, especially in multi-class problems like predicting burnout levels (Low, Moderate, High), evaluation metrics are crucial to assess how well a model distinguishes between different classes. Below are the three key metrics used in the study:

Precision (Positive Predictive Value): Precision refers to the proportion of instances that the model predicted as positive (for a particular class) which were actually correct. It evaluates the model's accuracy in its positive predictions and is especially important when false positives are costly.

$$Precision = \frac{True\ Positive}{True\ Positive - False\ Positive}$$

If the model predicts an individual has a High burnout level, precision tells us how often that prediction is correct. A high precision for the “High” class means that when the model says “High,” it is usually correct and does not mislabel individuals with lower burnout.

Recall (Sensitivity): Recall measures the proportion of actual positives that were correctly identified. It reflects the model’s ability to detect all relevant instances of a specific class. It is particularly important when false negatives are costly or dangerous (e.g., missing people with high burnout).

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

A high recall for the “Moderate” class indicates that most individuals who actually have moderate burnout are correctly identified by the model, minimizing missed detections.

F1-Score (Harmonic Mean): The F1-Score is the harmonic mean of precision and recall. It provides a balanced evaluation when you need to consider both false positives and false negatives. It is useful in cases of class imbalance or when both types of errors are important.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

The F1-score gives a single metric that balances the need to correctly identify people with a specific burnout level (recall) and the need to avoid incorrectly labeling others (precision). This is especially helpful when evaluating the overall performance of each class.

Software Engineering Paradigm

This study follows the Agile Methodology to guide the implementation of the Academic Burnout Prediction System, Agile Methodology emphasizes development, early delivery, and continuous feedback making it highly suitable for projects evolving user needs, such educational tools with predictive machine learning components. Since the project involves both predictive modeling and user-facing web interface, Agile allows the developers test and refine the system in short manageable cycles called sprints.

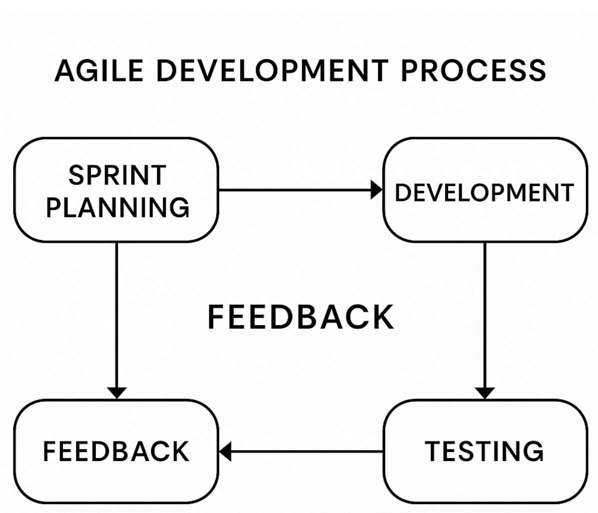

Figure 2.2: Agile Development Process Diagram

Step 1: Sprint Planning

The initial phase focused on identifying and prioritizing core functionalities necessary for the system's first working version. This included defining modules for inputting students' academic data, implementing the Random Forest-based burnout prediction engine, and designing a user-friendly interface to display the prediction outcomes. These features were broken down into sprint tasks and scheduled based on development feasibility and importance to system objectives.

Step 2: Iterative Development (Sprints)

Development was conducted in iterative cycles or "sprints," typically spanning one to two weeks. Each sprint concentrated on building and delivering specific system features. For example, an early sprint involved training and validating the machine learning model using preprocessed academic datasets, while subsequent sprints addressed the creation of the front-end web interface, backend integration, and user interaction mechanisms.

Step 3: Continuous Integration and Testing

At the conclusion of each sprint, the newly developed components were integrated into the existing system and subjected to rigorous testing. This included both unit testing of individual modules (e.g., model accuracy, UI responsiveness) and system testing to ensure end-to-end functionality. Continuous integration ensured that errors were identified and resolved promptly, maintaining system stability throughout development

Step 4: Stakeholder Feedback and Refinement

After each iteration, the functional build was reviewed by academic stakeholders such as faculty members and student counselors. Their feedback—covering usability, prediction clarity, and interface accessibility—was documented and analyzed to refine system features. This process supported iterative improvements and ensured the system aligned with real-world user needs and expectations.

Step 5: Deployment and Ongoing Maintenance

Upon the successful implementation and validation of all core features, the system was prepared for deployment in a controlled academic setting. Although full-scale deployment was beyond the thesis scope, considerations for future scalability, security, and usability were documented. Post-deployment, the system can undergo continued refinement through additional sprints, allowing for feature enhancements such as advanced risk visualizations, batch data processing, or institutional dashboard tools.