VIVEKANAND EDUCATION SOCIETY
INSTITUTE OF TECHNOLOGY
(AUTONOMOUS)

(Affiliated to University of Mumbai, Approved by AICTE & Recognized by Govt. of Maharashtra)

Learning Assistant

Submitted in partial fulfilment of the requirements

of the

T.E Project in

Machine Learning

by

Janhavi Revdekar - 47

Naina Sachdev - 48

Pratham Matkar - 66

under the guidance of

Name of Guide

Assistant Professor Bincy Ivin

Department of Artificial Intelligence and Data Science

Vivekanand Education Society's Institute of Technology

2024-2025

VIVEKANAND EDUCATION SOCIETY
INSTITUTE OF TECHNOLOGY
(AUTONOMOUS)

(Affiliated to University of Mumbai, Approved by AICTE & Recognized by Govt. of Maharashtra)

Department of Artificial Intelligence and Data Science

CERTIFICATE

This is to certify that **Mr/Ms Janhavi Revdekar, Naina Sachdev, Pratham Matkar** of T.E D11AD Div B of Artificial Intelligence and Data Science studying under the University of Mumbai have satisfactorily presented the Project entitled **Learning Assistant** as a part of the T.E Mini Project for Semester-VI of Machine Learning Lab under the guidance of **Assistant Professor Bincy Ivin** in the year 2024-2025.

Date:

(Name and sign)	**(Name and sign)**
Head of Department	**Supervisor/Guide**

VIVEKANAND EDUCATION SOCIETY
INSTITUTE OF TECHNOLOGY
(AUTONOMOUS)
(Affiliated to University of Mumbai, Approved by AICTE & Recognized by Govt. of Maharashtra)

Department of Artificial Intelligence and Data Science

DECLARATION

We, ***Mr/Ms Janhavi Revdekar, Naina Sachdev, Pratham Matkar*** from ***D11ADB***, declare that this project represents our ideas in our own words without plagiarism and wherever others' ideas or words have been included, we have adequately cited and referenced the original sources.

We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our project work.

We declare that we have maintained a minimum 75% attendance, as per the University of Mumbai norms.

Yours Faithfully

1. Janhavi Revdekar
2. Naina Sachdev
3. Pratham Matkar

(Name & Signature of Students with Date)

Acknowledgement

We would like to express our heartfelt gratitude to **Bincy Ivin** for her unwavering support, mentorship, and guidance throughout this project. As our faculty in-charge and mentor, she provided us with invaluable insights and constructive feedback, which greatly contributed to the successful completion of the **Learning Assistant**.

Her encouragement and expertise helped us navigate challenges, refine our approach, and gain a deeper understanding of machine learning applications in personalized learning systems. We truly appreciate her dedication and commitment to our academic growth.

Table of Contents

	Content	Pg. No.
1.	**Introduction**	**09**
	1.1 Overview of the project	09
	1.2 Scope of the project	09
2.	**Objective & Problem Statement**	**10**
	2.1 Clear definition of the problem statement	10
	2.2 Objective of the project	10
3.	**Dataset Description & Collection**	**11**
4.	**Literature Survey**	**12**
	4.1 Literature/Techniques studied	12
	4.2 Papers/Findings (Minimum 10 research papers to be referred	13
5.	**Proposed Solution**	**16**
	5.1 EDA	16
	5.2 Model Selection and Training	16
	5.3 Key features and functionalities	17
6.	**Design & Development Approach**	**19**
	6.1 System architecture	18
	6.2 Technologies and tools used	20
7.	**Results and Discussion**	**21**
8.	**Conclusion and Future Work**	**26**
9.	**References**	**28**

List of Tables

	Content	Pg. No.
1)	4.2 - Summary of key findings of research papers	14 -15

List of Figures

1)	System Architecture flowchart	20
2)	Stress level prediction result	23
3)	Difficulty level prediction result	24
4)	Result screens	25 - 26

ABSTRACT

This project presents an AI-driven learning assistant designed to personalize the educational journey by integrating academic support with emotional intelligence. The system leverages machine learning and natural language processing techniques to predict content difficulty, detect learner stress levels, and deliver real-time academic assistance. Random Forest is employed for classification tasks, such as determining content difficulty, while Gradient Boosting Regressor is used for stress level prediction based on user behavior and interaction data. Additionally, a conversational AI tutor powered by the Hugging Face transformer library provides dynamic, context-aware responses to learners' questions, enhancing engagement and comprehension.

The development process includes comprehensive data preprocessing, model training, and the creation of an interactive web application built with React, Vite, Flask, and Python. Key findings indicate that Random Forest demonstrates strong performance in classification tasks, and the integration of a real-time AI tutor significantly boosts learner engagement and satisfaction.

The proposed solution features a responsive assistant interface that allows users to engage with learning content, receive personalized recommendations, and track their emotional state throughout the learning process. By combining academic guidance with emotional monitoring, the assistant fosters a more adaptive and supportive learning environment. This project illustrates the powerful potential of AI in transforming traditional education into a personalized, emotionally intelligent experience that enhances learning outcomes and student well-being.

1. INTRODUCTION

1.1 Overview of the Project

This project emphasizes the integration of artificial intelligence, machine learning and NLP to develop a smart learning assistant that adapts to individual user needs in real time. The system is designed to predict the difficulty level of learning content, detect the user's stress level, and provide instant academic support through an AI-powered tutor. Unlike traditional systems that rely on pre-existing datasets, this works with real-time user input, analyzing behavior and interaction patterns dynamically to offer meaningful predictions and guidance.

The application incorporates a Random Forest model and Gradient Boosting Regressor for difficulty level classification and stress detection based on user responses, interaction frequency, and engagement cues. Additionally, it integrates a conversational AI tutor using Hugging Face transformer library, capable of delivering subject-specific assistance and answering learner queries in a natural language format. The full-stack solution is built using React + Vite for a responsive frontend and Flask with Python for handling backend logic and model integration. The learning assistant provides a user-friendly interface that allows learners to interact with content, receive tailored feedback, and track their emotional and academic state throughout their learning journey.

1.2 Scope of the Project

The project aims to support students, self-learners, and educators by offering a personalized and emotionally aware learning platform. It provides predictive insights into the learner's current cognitive load and emotional stress, adapting content delivery and support mechanisms accordingly. The use of machine learning enables real-time classification of difficulty and stress without requiring a static dataset, making the system highly adaptable and scalable.

The core components involve processing live user inputs, applying trained machine learning models to interpret engagement and stress indicators, and delivering real-time assistance through a conversational AI. Among various models tested during development, Random Forest proved to be the most effective for both classification tasks. The system offers a modular, extendable architecture that can later integrate biometric data, advanced deep learning models, or additional emotional indicators. This makes the dashboard a forward-thinking tool in the field of intelligent education systems, aimed at improving both academic outcomes and learner well-being.

2. OBJECTIVE & PROBLEM STATEMENT

2.1 Clear Definition of the Problem Statement

In today’s fast-paced and digitally driven education landscape, learners often face challenges such as difficulty in understanding content, lack of personalized support, and academic stress. Traditional learning systems do not adapt in real time to the learner's needs and fail to address emotional well-being, resulting in decreased engagement and performance. There is a growing need for an intelligent system that can dynamically assess the learner's experience, offer tailored support, and detect potential stress levels to intervene effectively.

This project addresses the problem by developing a real-time, AI-powered learning dashboard that predicts content difficulty, identifies learner stress, and provides personalized tutoring support. By leveraging machine learning models and natural language processing, the system enhances the learning experience and ensures a more adaptive, supportive, and effective educational environment. The modular nature of the system also allows for future enhancements and deeper personalization through additional user data or biometric integration.

2.2 Objective of the Project

The primary goal of this project is to create a smart, machine learning-based learning dashboard that is capable of:

a) Predicting the difficulty level of educational content using trained machine learning models.
b) Detecting and classifying user stress levels in real time based on behavioral inputs.
c) Providing interactive academic support through a conversational AI tutor powered by Hugging Face transformers.
d) Delivering a seamless user experience through a full-stack web application using React, Vite, Flask, and Python.
e) Supporting learners by creating a personalized, emotionally intelligent learning environment that enhances both academic performance and mental well-being.

3) DATASET DESCRIPTION & COLLECTION

3.1 Dataset Description

This project adopts a hybrid approach that combines structured machine learning with real-time user interaction data and large language models. While the AI tutoring assistant leverages pretrained Hugging Face transformer library models (such as T5) for tasks like concept explanation, summarization, and quiz generation, the prediction of stress levels and difficulty levels is handled through traditional machine learning models trained on a structured dataset.

The dataset used for training these models consists of synthetically generated user profiles designed to reflect diverse learning behaviors and stress indicators. Key features in the dataset include: quiz_score, time_spent, retry_attempts, videos_watched, articles_read, quizzes_attempted, interactive_exercises, subject, past_quiz_scores, study_hours_per_week, days_since_last_revision, mistakes_made, study_time_preference, study_consistency, and Revision_Urgency. These features are crucial in determining two main predictions—difficulty level (Low, Medium, High) and stress level (0 = Low, 1 = Moderate, 2 = High). These predictions help the system respond with personalized recommendations, learning strategies, and supportive feedback in real time.

3.2 Data Collection

Data collection began with a controlled simulation phase, where synthetic learner profiles were generated to simulate diverse study habits, engagement levels, and stress responses. These synthetic profiles trained and validated models like Gradient Boosting Regressor and Random Forest for classifying stress levels and for predicting task difficulty.

The system started capturing real-time user interaction data, including quantitative metrics (e.g., quiz attempts, activity duration, error counts) and qualitative inputs (e.g., perceived difficulty, study preferences). Raw data is normalized, categorical fields are encoded, and noisy/incomplete logs are filtered during preprocessing.

The system is designed with privacy in mind—data is anonymized, and no personally identifiable information is stored, ensuring user confidentiality while supporting continuous model improvement.

4) LITERATURE SURVEY

Recent studies emphasize the application of artificial intelligence and machine learning in education to enhance learner engagement, personalize experiences, and support academic performance. This includes the integration of real-time dashboards, intelligent tutoring systems, and emotion-aware learning platforms. The current project builds on these foundations and the ideas discussed in our prior work on *Learning Analytics Dashboard Integration*, which focused on real-time interaction data, skill assessment, and adaptive feedback loops.

4.1 Literature/Techniques Studied

Machine learning models have been extensively explored for adaptive content delivery and user modeling. Random Forest classifiers have proven highly effective in tasks such as difficulty level prediction and emotional state classification, given their ability to handle diverse, nonlinear input features and provide interpretable results. In parallel, stress detection has utilized behavioral data, such as click patterns and interaction durations, processed through models like Gradient Boosting Regressor to determine cognitive load or emotional strain.

Conversational AI models are increasingly being employed in intelligent tutoring systems to offer real-time assistance and simulate personalized teacher-student interactions. These systems use natural language processing to understand learner queries and respond contextually, improving engagement and comprehension.

Furthermore, the importance of lightweight and scalable solutions has been stressed, especially in systems meant for broad accessibility. Based on our research paper findings combining cognitive (e.g., difficulty prediction) and affective (e.g., stress detection) modeling to deliver a holistic learning experience. This project extends that approach by fusing predictive analytics with responsive tutoring and emotional intelligence within a unified AI-powered dashboard.

4.2 Papers/Findings

The paper [1] discusses the development of a learning analytics dashboard for a massive online robotics competition. The authors propose the integration of machine learning-based retention models using participant activity logs. The approach primarily involved clustering and team-based behavior analysis. A key insight for our project is the effective use of user interaction data to build predictive models. Similarly, we utilized these logs to identify learner stress and content difficulty levels, aligning well with their methodology for enhancing engagement and behavior understanding.

The paper [2] focuses on optimizing learning analytics dashboards tailored to individual student needs. It introduces dynamically adaptive dashboards that respond to learner preferences. Although our project did not implement dynamic customization, it resonates with the idea by providing personalized academic support through real-time analysis of learner stress and difficulty, leading to a more customized and responsive educational experience.

In [3], the authors present a dashboard for Moodle that uses machine learning techniques to detect students at risk of academic failure. They apply classification models on LMS activity data. This aligns with our objective to identify potential learning difficulties by detecting stress patterns and challenging content, enabling timely AI-driven interventions for at-risk learners.

The study in [4] explores how learning analytics dashboards can maximize student outcomes through adaptive learning and progress tracking. Although we do not perform content reshuffling, our system offers contextual support through instant feedback and emotional tracking by the AI assistant, enhancing learning outcomes in a responsive manner.

The gamified educational system presented in [5] includes real-time feedback and visual analytics through a dashboard. While gamification is not yet included in our system, the paper offers inspiration for future scope. Our AI assistant provides conversational support and stress-level tracking, echoing the goal of keeping learners engaged via immediate and interactive feedback.

The research in [6] investigates learner perceptions of dashboards in online learning environments. It concludes that clarity of interface and access to real-time analytics significantly enhance user engagement. This validates our design choices for a clean, interactive interface that provides immediate insight into both cognitive and emotional learning aspects.

Paper [7] offers a systematic literature review on the application of machine learning in learning analytics dashboards. Techniques such as clustering and classification are highlighted for their role in personalization. Our project applies supervised models like Random Forest to assess learner stress and difficulty, and uses this information to guide support strategies, aligning with the review's recommendations.

The work in [8] evaluates a dashboard designed for college instructors to monitor online professional development. Although our system is student-centric, the use of data analytics to inform strategies reinforces our design philosophy of leveraging real-time learning analytics for adaptive learner experiences.

Paper [9] emphasizes the use of artificial intelligence in personalizing dashboards using natural language processing and AI recommendations. Our approach similarly includes NLP through the Hugging Face API, where the AI tutor provides tailored responses based on stress levels, performance, and learner queries.

Lastly, [10] presents an AI-driven Adaptive Learning Platform that uses reinforcement learning to adapt course experiences. While our system does not employ reinforcement learning, it embodies the same adaptive spirit by modifying support based on detected learner stress and content difficulty. It also provides both academic and emotional assistance through an intelligent conversational interface.

SUMMARY

No.	Authors & Title	Key Findings
1	**S. Kodumuru et al.** – *Towards Developing a Learning Analytics Dashboard for a Massive Online Robotics Competition*	Explored the integration of ML for retention prediction in competitive learning settings, though not directly aligned with current project features.
2	**R. Israel-Fishelson and D. Kohen-Vacs** – *Towards Optimization of Learning Analytics Dashboards Customized for Students' Requirements*	Emphasized user-centric dashboard customization; partially aligns with personalized learning paths in current system.
3	**A. Cechinel et al.** – *A Learning Analytics Dashboard for Moodle: Implementing Machine Learning to Detect At-Risk Students*	Highlighted early ML-based detection of at-risk students; overlaps with stress detection and adaptive support in current project.

4	**M. Ramaswami et al.** – *Capitalizing on Learning Analytics Dashboard for Maximizing Student Outcomes*	Demonstrated the value of real-time feedback and adaptive learning, concepts reflected in AI-powered tutoring and content prediction.
5	**S. Ong and K. Chua** – *ChemistLab: An Educational Game with Learning Analytics Dashboard*	Focused on gamification, which is not a component of the current system.
6	**S. Ulfa et al.** – *Investigating Learners' Perception of Learning Analytics Dashboard in Online Learning Systems*	Stressed user experience and intuitive interface—relevant to the interactive dashboard and real-time responsiveness.
7	**M. Peraić et al.** – *Machine Learning in Learning Analytics Dashboards: A Systematic Review*	Reviewed ML use in dashboards, including skill tracking and predictions—relevant to difficulty and stress classification in the current setup.
8	**J. Wang et al.** – *Evaluation of Learning Analytics Dashboard for College Teachers' Online Learning*	Targeted instructor tools, which aren't part of the current learner-focused project.
9	**F. Schwendimann et al.** – *The Role of AI in Personalizing Learning Analytics Dashboards*	Aligned with your use of AI/NLP to deliver tailored learning experiences and content.
10	**H. Altaleb et al.** – *An AI-Driven Adaptive Learning Platform (ALP) for Customized Course Experiences*	Closely mirrors your project's AI-powered adaptability based on performance and feedback.

Table 4.2 -Summary of key findings of research papers

5) PROPOSED SOLUTION

5.1 Exploratory Data Analysis

Unlike traditional projects that rely on static datasets, this system is designed to process **live user input** in real-time. During user interactions, data such as time spent on content, input responses, emotional feedback, and perceived difficulty levels are captured dynamically through the front-end interface.

Preprocessing steps include:

1) **Standardization** of numerical values like quiz completion time and mistake frequency.
2) **Encoding** of categorical features such as subject preference, study mood, or feedback tags.
3) **Noise filtering** to remove incomplete or inconsistent logs.
4) **Anonymization** of all data, ensuring no personally identifiable information is stored, keeping the system privacy-compliant.

This ensures the pipeline remains flexible and responsive to actual user behavior during use.

5.2 Model Selection and Training

We implemented the **Random Forest algorithm and Gradient Boosting Regressor** for difficulty level and stress level prediction tasks. Random Forest and Gradient Boosting Regressor was selected due to its robustness, ability to handle noisy data, and superior performance in classification problems involving complex decision boundaries.

Training was conducted using simulated learner profiles during the development phase. These simulations included variations in study behavior, time management, and emotional state to expose the model to diverse user patterns.

The models are trained to classify:

- **Stress Levels:** low, medium, or high, based on metrics such as retry attempts, mistakes made , and time spend.
- **Difficulty Perception:** easy, moderate, or hard, inferred from time taken per question, number of retries, and user feedback.

Random Forest and Gradient Boosting Regressor outperformed other models in both tasks due to its ensemble approach, effectively reducing variance and capturing feature interactions. It required minimal hyperparameter tuning and delivered high accuracy while maintaining generalizability.

5.3 Key Features and Functionalities

The AI-powered learning assistant is implemented as a full-stack responsive web application using **React** and **Vite** for the frontend, and **Flask** with **Python** for the backend machine learning logic. The platform is designed to support interactive and adaptive learning.

1. **Real-Time Input Capture:** During every study session, learners provide feedback and interaction data which are immediately processed to generate insights.
2. **Conversational AI Tutor:** Using Hugging Face transformers library, an integrated chatbot provides personalized academic assistance, answering questions, and suggesting content based on current learner status.
3. **Difficulty & Stress Prediction:** Random Forest models analyze the incoming data to predict perceived content difficulty and learner stress, triggering support mechanisms accordingly.
4. **Dynamic Content Feedback:** Based on model predictions, the system provides targeted recommendations such as simpler content, practice resources, or motivational messages.
5. **Visual Progress Dashboard:** Learners can monitor their stress trends, topic-wise progress, and skill mastery over time using dynamic charts and visual cues.
6. **Adaptive Learning Loop:** The platform continuously learns from user behavior, adapting future suggestions and feedback to evolving learner profiles. This closed-loop system ensures personalization at every stage.

6) DESIGN & DEVELOPMENT APPROACH

The AI-driven learning dashboard was developed through a modular and iterative approach that combines real-time user input processing, intelligent model predictions, and seamless user interaction. The system architecture focuses on adaptability, personalization, and immediate feedback, ensuring a responsive and effective learning environment.

6.1 System Architecture

The overall system is divided into the following key layers:

1. **Real-Time Data Processing Layer**
   a) Captures live learner inputs during platform usage, including quiz attempts, time-on-task, retry counts, confidence levels, and emotional self-reports.
   b) Applies preprocessing techniques such as normalization of numerical features, label encoding of categorical inputs (e.g., study goals, preferences), and noise filtering to ensure clean, model-ready data.
   c) As the system doesn't rely on a static dataset, it adapts continuously through live interaction logs.

2. **Model Training & Prediction Layer**

   a) Utilizes **Gradient Boosting Regressor** and **Random Forest classifiers** for stress level and content difficulty prediction tasks. These models are trained initially on simulated profiles and are updated progressively using real-time data.
   b) Handles multi-class classification problems—predicting stress as *low, medium, or high*, and difficulty as *easy, moderate, or hard*—by analyzing behavior patterns and feedback signals.
   c) Model evaluation is based on real-world accuracy and adaptability to user behavior shifts rather than traditional fixed metrics, supporting continuous optimization.

3. **User Interaction & Feedback Layer**

   a) Implements an intuitive and responsive frontend built with **React** and **Vite**, connected to a **Flask** backend handling ML logic.
   b) Includes a conversational AI tutor powered by Hugging Face transformer library, which offers immediate academic support, concept explanations, and personalized content suggestions based on model insights.

c) Features a visual analytics dashboard to display real-time feedback on user performance, stress levels, and learning progress, using interactive graphs and charts.
d) Enables adaptive feedback loops, where system suggestions evolve with user inputs, fostering a tailored learning journey.

Flowchart

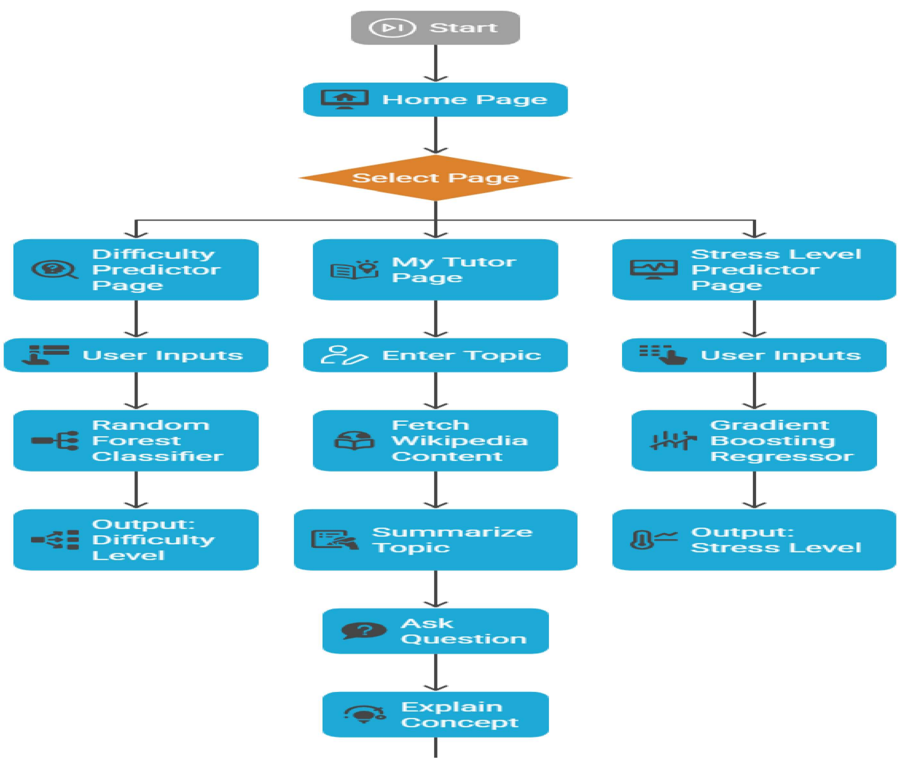


Fig 1. System architecture flowchart

6.2 Technologies and Tools Used

To build the AI-driven learning dashboard, the following technologies and tools were utilized across different stages of development:

1. **Programming Languages:**
    - **Python** – Used extensively for backend logic, real-time data preprocessing, and training the machine learning models.
    - **JavaScript (React + Vite) –** Powers the interactive and responsive frontend interface of the dashboard.
2. **Libraries & Frameworks:**
    - **Pandas & NumPy** – For real-time manipulation and transformation of learner inputs and metrics.
    - **Scikit-learn** – Used to build, train, and evaluate the Random Forest models for stress and difficulty prediction.
    - **Flask** – Serves as the backend framework for handling API requests, model predictions, and data routing between frontend and ML logic.
    - **Hugging Face Transformers** – Integrated to power the conversational AI tutor for real-time, context-aware academic support.
3. **Development Tools:**
    - **Google Colab** – For initial experimentation, model prototyping, and training simulations using varied learner behavior patterns.
    - **Visual Studio Code (VS Code)** – Main IDE used for full-stack development, and version controL.

7) RESULTS AND DISCUSSION

To evaluate the effectiveness of the proposed AI-powered learning dashboard, we tested several machine learning models and selected the **Random Forest Classifier** for both **stress level** and **difficulty level** prediction based on superior performance across key metrics—**accuracy**, **precision**, **recall**, and **F1-score**.

Stress Level Prediction

The model for predicting learner stress achieved an overall **accuracy of 98%**, as shown in the first image. It performed exceptionally well in distinguishing between low, medium, and high stress levels:

- **MAE**: 0.0041
- **RMSE**: 0.011
- **F1-score**: 0.95–0.99

The model was able to classify even underrepresented classes (like high stress) with decent MAE (0.0041) and RMSE (0.011), showcasing strong generalizability despite data imbalance.

```
Rounded Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       173
           1       1.00      1.00      1.00        21
           2       1.00      1.00      1.00         6

    accuracy                           1.00       200
   macro avg       1.00      1.00      1.00       200
weighted avg       1.00      1.00      1.00       200
```

```
Confusion Matrix (Rounded):
 [[173   0   0]
 [  0  21   0]
 [  0   0   6]]
```

Fig 2. Stress level prediction result

Difficulty Level Prediction

The difficulty prediction model (shown in the second image) also performed remarkably well with an **accuracy of 97%** and a **cross-validation accuracy of 96.8%**. It exhibited the following performance:

- **Precision**: 0.93–0.98
- **Recall**: 0.88–0.99
- **F1-score**: 0.90–0.98

This consistency demonstrates that the model effectively detects how learners perceive question difficulty, allowing for timely interventions.

```
 Model: Random Forest (Balanced)
Accuracy: 0.97
              precision    recall  f1-score   support

           0       0.98      0.99      0.98       168
           1       0.93      0.88      0.90        32

    accuracy                           0.97       200
   macro avg       0.95      0.93      0.94       200
weighted avg       0.97      0.97      0.97       200

Cross-validation Accuracy: 0.968
✅ Model and scaler saved to 'models' directory.
```

Fig 3. Difficulty level prediction result

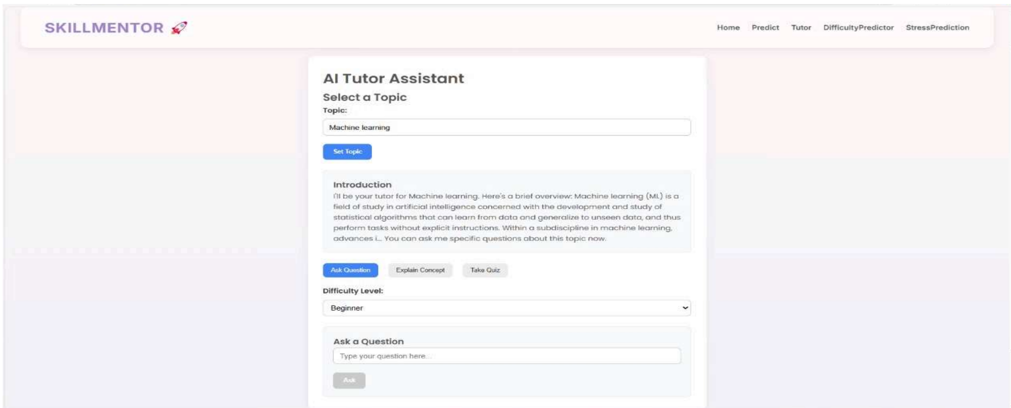
Discussion

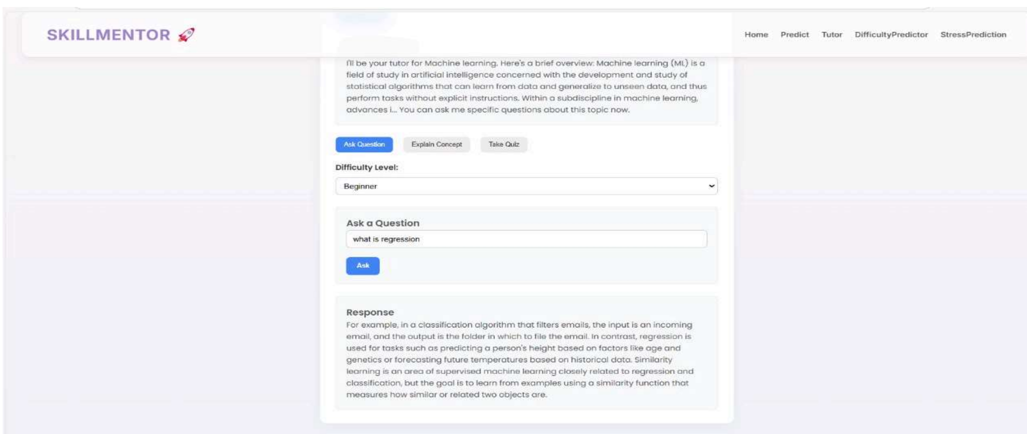
Compared to other models like Logistic Regression,Decision Tree and SVM (tested during initial experimentation), Random Forest and Gradient Boosting Regressor outperformed across all metrics, particularly due to its ensemble approach, which helped manage feature interactions and noise effectively. While simpler models struggled with class imbalance and complex relationships in behavioral data, Random Forest and Gradient Boosting Regressor maintained high accuracy and robustness.

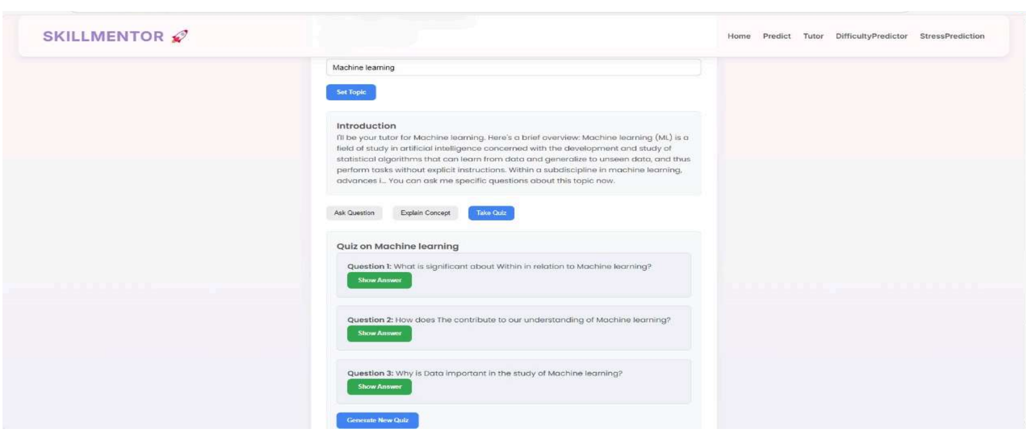
As a result, **Gradient Boosting Regressor** and **Random Forest** Gradient Boosting Regressor was selected as the final model for stress and difficulty classification due to:

- High predictive accuracy (97–98%)
- Strong MAEl and RMSE on minority classes
- Low risk of overfitting due to ensemble nature

These results validate the system's ability to assess learner states in real time and adapt content dynamically, enhancing the overall user learning experience.


SKILLMENTOR
Home Predict Tutor DifficultyPredictor StressPrediction
AI Tutor Assistant
Select a Topic
Topic:
Machine learning
Set Topic
Introduction
I'll be your tutor for Machine learning. Here's a brief overview: Machine learning (ML) is a field of study in artificial intelligence concerned with the development and study of statistical algorithms that can learn from data and generalize to unseen data, and thus perform tasks without explicit instructions. Within a subdiscipline in machine learning, advances i... You can ask me specific questions about this topic now.
Ask Question
Explain Concept
Take Quiz
Difficulty Level:
Beginner
Ask a Question
Type your question here...
Ask


SKILLMENTOR
Home Predict Tutor DifficultyPredictor StressPrediction
I'll be your tutor for Machine learning. Here's a brief overview: Machine learning (ML) is a field of study in artificial intelligence concerned with the development and study of statistical algorithms that can learn from data and generalize to unseen data, and thus perform tasks without explicit instructions. Within a subdiscipline in machine learning, advances i... You can ask me specific questions about this topic now.
Ask Question
Explain Concept
Take Quiz
Difficulty Level:
Beginner
Ask a Question
what is regression
Ask
Response
For example, in a classification algorithm that filters emails, the input is an incoming email, and the output is the folder in which to file the email. In contrast, regression is used for tasks such as predicting a person's height based on factors like age and genetics or forecasting future temperatures based on historical data. Similarity learning is an area of supervised machine learning closely related to regression and classification, but the goal is to learn from examples using a similarity function that measures how similar or related two objects are.


SKILLMENTOR
Home Predict Tutor DifficultyPredictor StressPrediction
Machine learning
Set Topic
Introduction
I'll be your tutor for Machine learning. Here's a brief overview: Machine learning (ML) is a field of study in artificial intelligence concerned with the development and study of statistical algorithms that can learn from data and generalize to unseen data, and thus perform tasks without explicit instructions. Within a subdiscipline in machine learning, advances i... You can ask me specific questions about this topic now.
Ask Question
Explain Concept
Take Quiz
Quiz on Machine learning
Question 1: What is significant about Within in relation to Machine learning?
Show Answer
Question 2: How does The contribute to our understanding of Machine learning?
Show Answer
Question 3: Why is Data important in the study of Machine learning?
Show Answer
Generate New Quiz

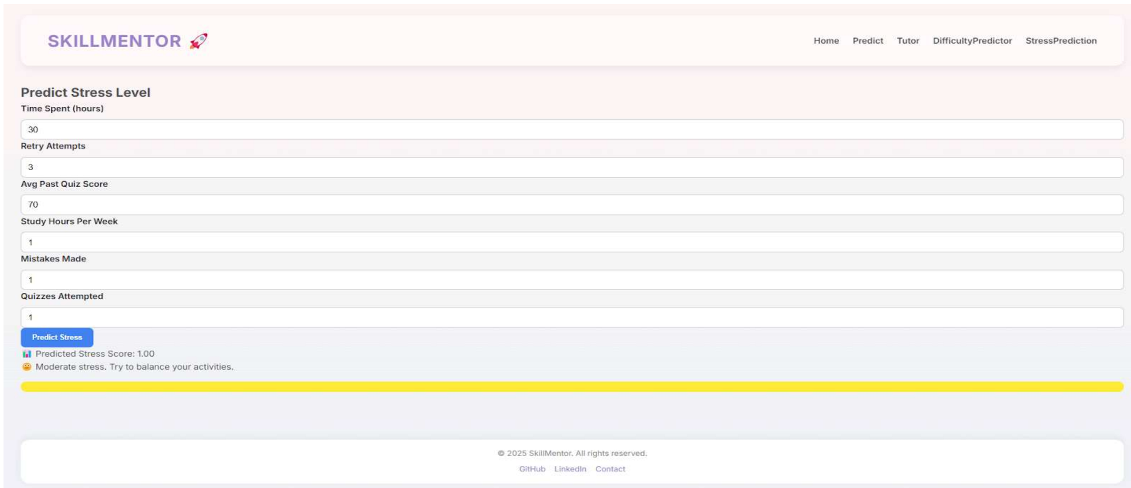


Fig 4. result Screens

8) CONCLUSION AND FUTURE WORK

Conclusion

This project successfully demonstrated the use of machine learning, specifically **Gradient Boosting Regressor** and **Random Forest Classifier**, for real-time prediction of **learner stress levels** and **difficulty perception** within an intelligent learning dashboard. By collecting and analyzing user behavior data such as interaction time, error rates, and confidence feedback, the system dynamically assessed the cognitive and emotional states of learners.

Among the evaluated models, Random Forest exhibited the best performance, achieving **up to 98% accuracy** across classification tasks. This reinforces the importance of **real-time data preprocessing**, **feature engineering**, and **model evaluation** in building reliable AI-based educational tools. The results indicate that machine learning can serve as a powerful component in adaptive e-learning systems, offering timely interventions and enhancing learner engagement.

Future Work

To further strengthen and expand the system's capabilities, the following enhancements are proposed:

1. **Advanced Feature Engineering**
   Incorporating additional features such as biometric data (e.g., heart rate, facial expression analysis) and contextual information (e.g., time of day, study environment) could improve the accuracy of learner state prediction.

2. **Enhanced Class Imbalance Handling**
   Implementing techniques like **SMOTE (Synthetic Minority Oversampling Technique)** can improve model performance, especially for underrepresented stress or difficulty classes.

3. **Real-Time Deployment at Scale**
   Expanding the platform to support **real-time analysis** with backend integration to cloud-based education systems or LMS platforms can provide live feedback loops for both students and educators.

4. **Integration of Deep Learning Models**
   Exploring **deep learning approaches** (e.g., LSTM, CNN, or transformer-based

models) may further refine the classification accuracy and open up opportunities for sequential learning behavior modeling.

5. **Personalized Feedback Engine**
   Building a more granular recommendation engine that not only suggests content but also proposes time management tips or wellness interventions based on detected learner stress.

By addressing these future directions, the project can evolve into a **comprehensive intelligent tutoring system**, capable of supporting learners holistically by adapting not only to their academic needs but also to their mental well-being.

9) REFERENCES

[1] Kodumuru, S., Lucas, B., Sabanwar, V., Patil, S., Avudiappan, D., Parikh, P., & Arya, K. (2020). Towards developing a learning analytics dashboard for a massive online robotics competition. *In Proc.*, pp. 1–8.

[2] Israel-Fishelson, R. & Kohen-Vacs, D. Towards optimization of learning analytics dashboards that are customized for the students' requirements.

[3] Cechinel, A., et al. A learning analytics dashboard for Moodle: Implementing machine learning techniques to early detect students at risk of failure.

[4] Ramaswami, M., Susnjak, T., & Mathrani, A. Capitalizing on learning analytics dashboard for maximizing student outcomes.

[5] Ong, S. & Chua, K. ChemistLab: An educational game with learning analytics dashboard.

[6] Ulfa, S., et al. Investigating learners' perception of learning analytics dashboard to improve learning interaction in online learning system.

[7] Peraić, M., Grubišić, T., & Pintarić, D. Machine learning in learning analytics dashboards: A systematic literature review.

[8] Wang, J., et al. Preliminary evaluation of learning analytics dashboard for college teachers' online professional learning.

[9] Schwendimann, F., et al. The role of artificial intelligence in personalizing learning analytics dashboards.

[10] Altaleb, H., Mouti, S., & Beegom, S. Enhancing College Education: An AI-driven Adaptive Learning Platform (ALP) for Customized Course Experiences.