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Student Learning Assistant Based on Adaptive LLM

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***Abstract*—Most learners are not in a position to grasp academic concepts because the current learning platforms do not offer customized learning. The majority of existing systems provide all students with the same learning content without making themselves fit to their respective level of understanding. This drawback does not allow learners to determine their weak areas and work on them intelligibly successfully.**

In response to this dilemma, this paper provides a proposal of an Adaptive Large Language Model (LLM)-based student learning assistant that will offer individualized educational assistance. The system is deployed as a web-based platform that will have the role based access to the administrators, professors, and students. The completion of syllabus progress is updated by professors and quizzes are automatically created and updated as per the topics completed. Student responses are examined with an aim of detecting the weak areas and level of understanding. Based on this analysis, the system produces individual explanations and suggestions.

The suggested platform includes real-time feedback, automatic quiz creation, performance analytics as well as adaptive tutoring support. The system will seek to integrate LLM with adaptive learning mechanisms with an aim of achieving the following: promote intellectual knowledge, better student interaction, and help teachers to better track student performance.

***Index Terms*—Large Language Models, Adaptive Learning, Personalized Education, Automated Quiz Generation, Student Performance Analysis, Intelligent Tutoring System**

I. Introduction

The recent changes in Artificial Intelligence, specifically Large Language Models (LLMs), have changed several fields, such as healthcare, finance, and education. LLMs are able to understand and write human language through text learning on large volumes of text.

One of the areas of application of these capabilities can be education. Conventional approaches to learning usually depend on the delivery of the content which is not dynamic. Students are given the same material irrespective of their learning rate or level of understanding.

In this study, we are suggesting the Adaptive LLM-Based Student Learning Assistant which combines smart tutoring, automatic quiz creation, and education analytics in an integrated system. An intelligent tutoring system refers to software that is capable of replicating a human tutor's role within a computer program.

II. Related Work

The artificial intelligence has been extensively investigated in the educational technology via intelligent tutoring system, adaptive learning system and learning analytics.

The introduction of adaptive learning platforms, like ALEKS and DreamBox, provided individualized learning opportunities by assessing the performance of its students and modifying question difficulty levels.

Recent studies are interested in the application of Large Language Models to the field of education systems. LLMs help in dynamic generation of content, automated tutoring and real-time explanations.

RAG is a combination of information retrieval and Augmentation Generation creating language models, where machines are able to come up with correct answers depending on the sources of knowledge.

III. Methodology

A. System Overview

The suggested adaptive learning assistant is based on the modular architecture that combines large language models, retrieval, as well as learning analytics.

The professor dashboard feeds progress of syllabus updates which automatically generates quizzes depending on the completed topics. Quizzes generated are attempted by the students using the student dashboard. The answers are also graded automatically, and performance analytics used to determine areas that they are weak in. According to this

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analysis, the AI tutor produces descriptions and individual learning suggestions.

B. Knowledge Base Construction

The system has an organized body of knowledge which is built on syllabus textbook material and documents. With the help of the MiniLM transformer model, educational materials are transformed into semantic vectors representations. Sentence-Transformers framework.

MiniLM synthesizes contextual representations of syllabus topics and textbook content. The semantic meaning is encoded in the embeddings and can be stored in form of a vector database, in which they enable efficient semantic search, both in the generation of quizzes and in explanation.

C. Retrieval-Augmented Generation

The system uses Retrieval-Augmented Generation (RAG) which is used to retrieve contextual information which is syllabus aligned and then responses are generated. When a query or when a quiz generation request is made, the system finds out the most relevant content from the vector database.

The similarity of semantics between syllabus is measured with the Cosine Similarity embeddings and content vectors stored. This method of similarity calculation is used to locate the most applicable training content needed to create context-sensitive responses.

D. Automated Quiz Generation

When syllabus completion status is updated by the professors, automated generation of quizzes is accomplished. The RAG is used to retrieve the relevant syllabus content in the system turns the retrieved context into the Large Language Model.

Approximate Nearest Neighbour (ANN) search is an appropriate method of identifying the semantically related embeddings in the retrieval process. This enables the system to be able to choose learning content in relation and create syllabus-based quiz within a short period of time questions.

E. Analysis of Student Performance

Once the students have tried the quizzes, the system measures the answers and computes performance scores. The scoring of quizzes is done according to the percentage of correctness responses in comparison to the number of questions asked.

The performance of students on various topics that are being studied is analysed to draw patterns of knowledge and education emptiness. There are subjects that have low performance over time are outlined as weak points that need further explanations.

F. Personalized Feedback

According to the analysis of performance, the system creates individual explanations adjusted to the level of understanding of the student. The AI tutor accesses pertinent content of syllabus and creates simplistic explanations of complicated things.

FAISS vector indexing algorithms are the efficient stores and retrieval algorithms inserting vectors of knowledge base. This is an indexing system that facilitates fast semantic search and provides real time generation of individualized learning explanations.

IV. System Architecture

The suggested Adaptive LLM-Based Student Learning Assistant will adhere to a layered architecture that incorporates user dashboards, intelligent processing modules, and data storage components. The structure is made to accommodate automated generating quizzes, measuring performance in students, and tailored learning programs.

Fig. 1 shows the general architecture of the system. The system is structured into four large layers: Client Layer, LLM Processing Layer, Application Logic Layer and Data Storage Layer.

A. Client Layer

The Client Layer is what gives the user interface by which the administrators, professors, and students may communicate with the system. Each user role is equipped with a special dashboard with multiple functionalities.

Professor dashboard enables the instructors to revise syllabus completion students monitor performance and status. The student dashboard allows the students to take quizzes, check score, and consult the AI tutor to explain the concept. The administrator dashboard is in charge of configuration of the system and user access.

B. Application Logic Layer

Application Logic Layer undertakes core system business on a case-by-case basis such as quiz weak topic detection, learning analytics and evaluation.

In the case when students are trying to do quizzes, their answers are automatically taken into consideration to compute performance scores. These scores are analysed by the system to determine subjects and topic patterns of understanding. Based on this analysis, the weak topics are identified and learning advice generated to aid student improvement.

C. Data Storage Layer

The Data Storage Layer deals with structured and semantic information that is needed by the system. There are two databases that support the activities of the system.

MongoDB is used in storing the user profiles, quiz attempt, student performance data. This database supports the performance analysis and learning analytics. Syllabus embeddings created as a result of course are stored in a vector database materials. These embeddings allow semantic retrieval when there is a search during the RAG process to generate quiz and AI tutor explanation.

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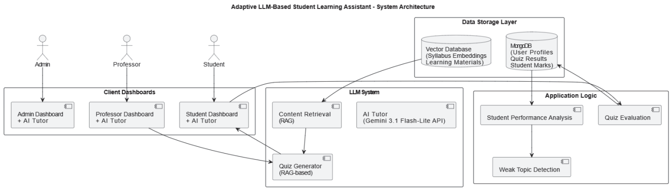

Fig. 1. Adaptive Student Learning Assistant Architecture

TABLE I
SYSTEM INPUTS

Input Category	Input Fields	Purpose
User Registration	Name, Email ID, Password	Allows the user to access the learning system
User Login	Email / Password	Authenticate Authorized users
Syllabus Update	Subject, Unit Topic	Trigger quiz generation for completed unit
Quiz Attempt	Student Answers, Quiz ID	Submit response to be assessed
AI Tutor Query	Student Question or Topic	Ask questions concerning concepts
Performance Data	Student ID, Quiz Records	Retrieve performance data to analyse

V. System Inputs and Outputs

System Inputs: The suggested student-focused and Adaptive LLM-Based Student Learning Assistant needs to have structured student and professor input to facilitate personalization learning and automatic quiz generation. First of all, students will give an account register and suggest with the account of name, email ID, and password. After students will be able to log-in with their credentials, which are approved by the administrator. Professors revise syllabus progress at the end of a specific unit. Based on these updates, the system automatically makes quizzes based on the Large Language Model. These quizzes are tried by the students by providing an answer, and they can also engage in the AI tutor chat in order to ask course-related questions topics.

System Outputs: The system generates a number of outputs to facilitate adaptive learning. The Large Language Model automatically creates quizzes that correspond to the unit completed when the professors change the information in the syllabuses. After students take quizzes, the system marked questions and had an output with results in the shape of grades and comments. Analytics in learning spot poor subjects and come up with recommendations on how to get better. There is also the AI tutor chat which offers discussions each time students raise questions.

VI. Experiments and Evaluation

The suggested Adaptive LLM-Based Student Learning Assistant was tested to dissect its performance in creating quizzes, assessing student achievement, and offer adaptive learning assistance. The assessment is based on automated quiz generation, quiz score analysis, poor topic identification, and AI tutor interaction.

TABLE II
SYSTEM OUTPUTS

Output Category	Output Type	Description
Activation of Account	Approval Message	Students are allowed to use the system
Quiz Generation	Generated Quiz	LLM is used to create quiz out of syllabus update
Quiz Result	Score Report	Shows the performance of quizzes
Performance Analysis	Weak topic detection	Detection of weak areas and learning gaps
AI Tutor Response	Generated Explanation	Gives responses to student queries
Student Progress	Learning Dashboard	Displays student progress and mastery

A. Automated Quiz Generation

In the case of professors updating the syllabus progress of a given unit, the Large Language Model will automatically generate quizzes that are consistent with the updated topics. All tests include various questions that are aimed at testing conceptual knowledge about the particular topic. Quizzes generated were analyzed on the basis of relevance of topic and coverage of syllabus content.

B. Quiz Score Analysis

Students tried the quizzes that were created by the system. The answers submitted by the students were automatically judged to generate quiz scores. The quiz score of every student can be calculated with the help of the following formula:

$$\text{QuizScore} = \frac{\text{Number of Correct Answers}}{\text{Total Questions}} \times 100$$

This score is the percentage of accurate responses to questions in a particular quiz.

In order to examine the performance of the classes, the average score of the quiz of all students was calculated as:

$$\text{AverageScore} = \frac{\sum_{i=1}^{n} \text{Score}_i}{n}$$

Score_i indicates the score of the i-th student and n represents the total number of students.

C. Performance Analysis on Topic Basis

The system compares the responses of the students in the quizzes to establish the weak areas. The topic performance is computed based on the precision of the responses to the topic. The ones with low average scores are indicated as weak areas. The system then comes up with customized explanations to assist students to enhance their comprehension of those topics.

D. AI Tutor Interaction

The students also have the option of communicating with the AI tutor chat and asking questions regarding the course concepts. The tutor comes up with explanations through the Large Language Model and contextual knowledge extracted in the syllabus database. This enables students to clear up on questions immediately and enhances their conceptual knowledge.

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TABLE III
SYSTEM EVALUATION METRICS

Evaluation Metric	Observation
Quiz Generation Relevance	Higher correspondence to the syllabus topics
Mean Quiz Score	According to the number of questions
Weak Topic Detection	Effective topic identification of hard topics
AI Tutor Response Quality	Contextual responses
Student Interaction	Improved quiz participation

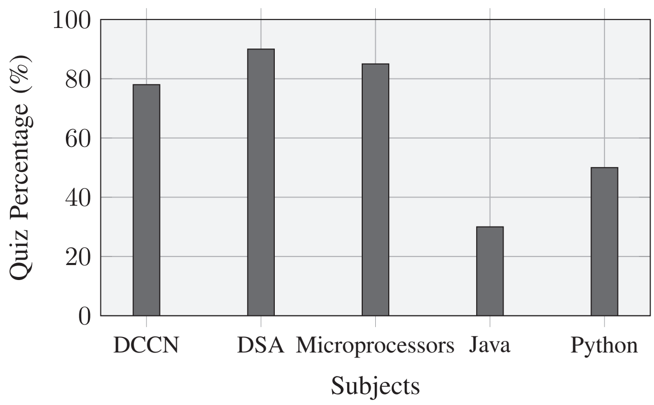

Fig. 2. Percentage Obtained by a Student Across Different Subjects

E. Evaluation Metrics

The proposed system was evaluated with the help of the multiple evaluation measures such as quiz generation relevance, student engagement and weak topic detection.

F. Student Quiz Analysis Percentage

The quiz results of a to determine the performance of the adaptive learning system students in various courses were examined. The graph shows the percentage achieved by the student upon the completion of quizzes in some of the different subjects. The subjects are plotted in the X-axis, and the percentage is plotted in the Y-axis achieved by the student.

VII. RESULTS AND DISCUSSION

The research test shows the efficiency of the suggested Student Learning Assistant based on adaptive LLM in enhancing student learning outcomes. Quizzes were generated according to syllabus in order to test the system updates and interpreting the student feedback on the topic of several courses.

The student performance in various subjects has been represented in the percentage analysis in Fig. 2. As it can be seen, the student scored greater percentage marks in Data Structures and Algorithms (DSA) and Microprocessors. Strong conceptual knowledge in those areas. Conversely, the performance in such subjects as was lower in comparison Java programming, which implies the existence of learning gaps.

The suggested system automatically helps to detect such weak areas with the help of the performance analysis and offers personalized explanations with the help of the AI tutor module. The system can suggest the specific learning material that could help the students understand more by examining the results of quizzes and patterns of responses of difficult topics.

Moreover, the automated quiz generation system is to make sure that examinations are kept on par with the syllabus progress. Faculty is able to revise syllabus students, and then the system generates quizzes dynamically to assess students comprehension. This process saves manual work among the educators and ensures a constant monitoring of the student learning.

The learning process is also increased by the AI tutor chat through enabling them to ask questions and get instant clarifications. This interactive support assists students to explain their uncertainties right after making the attempt quizzes, thus, strengthening their conceptual knowledge.

On the whole, the outcomes of the experiment suggest that the suggested adaptive learning system can be used to facilitate individual education efficiently by integrating automated generation of quizzes, performance analytics and intelligent tutoring. The system allows students and instructors to check the progress in learning and fix gaps in knowledge are more effectively known.

VIII. FUTURE IMPROVEMENTS

Despite the fact that the offered Adaptive LLM-Based Student Learning Assistant proves to be able to achieve encouraging outcomes when it comes to personalized learning and automated assessment, there are a range of improvements that can be investigated in the course of future research.

The system is now in place to cover one academic department. When expanding the platform to other institutions, it can be increased to accommodate various departments and other interdisciplinary topics in the future. This would enable the system to deal with a wider range of knowledge base and offer personalized support in learning in various areas.

The other possible enhancement is the incorporation of the platform with the institutional Learning Management Systems (LMS) to facilitate a smooth adoption within universities. It is such integration that would enable automatic synchronization of course material, student records and assessment data.

Multimedia learning materials like can also be used in future research video lectures, diagrams and interactive simulations in order to increase student interaction. Besides this, sophisticated learning analytics methods may be used forecast performance patterns of students and prescribe adjustive study plans.

These additions would also increase the scalability, usability, and efficiency of the suggested adaptive learning platform.

IX. CONCLUSION

In this paper, an Adaptive LLM-Based Student Learning Assistant was introduced aimed to enhance individual learning by means of intelligent tutoring and automatically generated assessments. The suggested system is a combination of Large Language Models that are generated dynamically and based

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on syllabus with learning analytics models summarizes and compares the performance of students in various subjects.

The system will allow professors to update their syllabus advancements, and the system will automatically build quizzes based on topics that have been covered. Students can attempt these exams and give student feedback on performance in percentages, so as to permit the system to detect weak areas and offer specific clarifications. The integration an AI tutor chat also improves the learning process because it gives students the opportunity to demystify and gain concept explanations immediately.

The experimental assessment proved that the suggested system is effective provides adaptive learning through student quiz analysis and identification subject-wise learning gaps. The performance analysis which is in percentage assists not only the students but also the instructors know the trends of learning and enhance academic outcomes. It combines automatic quiz creation and performance analysis and acts as AI-powered tutoring providing a personalized learning experience on a large scale.

On the whole, the Adaptive LLM-Based Student Learning Assistant has a positive impact on learning the creation of smart learning systems that can promote student activity, better conceptual learning, and data-driven learning strategies.

REFERENCES

[1] ALEKS Corporation: ALEKS (Assessment and Learning in Knowledge Spaces) (2005)
[2] DreamBox Learning: Adaptive learning technology in DreamBox (2014)
[3] Lewis, P., Perez, E., Piktus, A., et al.: Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks. arXiv preprint arXiv:2005.11401 (2020)
[4] Qin, H.: Transforming Education with Large Language Models: Opportunities, Challenges, and Ethical Considerations. Preprint, DOI: 10.13140/RG.2.2.16976.52488 (2024)
[5] Brown, T.B., Mann, B., Ryder, N., et al.: Language models are few-shot learners. arXiv preprint arXiv:2005.14165 (2020)
[6] Reimers, N., Gurevych, I.: Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks. arXiv preprint arXiv:1908.10084 (2019)
[7] Johnson, J., Douze, M., Jegou, H.: Billion-scale similarity search with GPUs. IEEE Transactions on Big Data (2019)