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AIVA: A Personalized AI Tutor

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Abstract- AIVA, our AI tutor, tackles personalized learning for primary and high school students. Through initial questions, AIVA tailors a Large Language Model using relevant materials for each student's grade level. This dynamic approach personalizes learning, fostering comprehension and a love for knowledge. AIVA complements educators, acting as a guide to make education accessible and engaging.

Keywords- AI, Large Language Model, Tutor, and Personalized learning.

I. INTRODUCTION

There are several aspects of personalized education that are being offered in the market at the moment, and our platform currently offers an AI tutor tailored for primary and high school students. This innovative tool refines the learning experience by analysing user data, accurately predicting their grade level, and dynamically adjusting a Large Language Model (LLM) to align with grade-specific materials. This personalized approach goes beyond a one-size-fits-all model, ensuring that each student receives content catered to their academic proficiency and needs.

There is no doubt that the LLM is extremely adaptable to relevant materials, thereby aiding in the development of a more profound understanding the subject matter as a whole.

By customizing the educational content to match the student's grade level, our AI tutor enhances not only academic understanding, but also the student's performance, as our AI tutors deliver content that is relevant to the student's grade level. In order of success, this dynamic learning experience is not merely designed to inspire short-term motivation, but also to instill a long-term commitment to learning and lifelong learning habits.

It is ultimately our goal through this platform to empower students for not only academic achievement but also to cultivate a lifelong love for learning so that they can become lifelong learners. The use of artificial intelligence will allow us to make each student's learning experience a personalized, engaging, and fulfilling one, where each student can prosper at their own pace while also contributing to a future where education is a joyous and life- changing experience. We hope to make education a lasting source of joy and personal development through the use of artificial intelligence.

II. DATASET DESCRIPTION

The dataset for this project consists of textbooks aimed at primary and high school students across various subjects. These textbooks will be used to train a Large Language Model (LLM). The specific textbooks used will be chosen based on the user's grade level as predicted by the system through an initial questionnaire.

This personalized selection ensures the LLM is trained on relevant materials that align with the user's current academic needs. By using the content of these textbooks, the LLM can be fine-tuned to effectively answer student questions and provide subject-specific support.

III. PROPOSED SOLUTION

The proposed AI tutoring system surpasses existing solutions by offering a personalized, adaptive learning experience, with dynamic content that adjusts to individual student needs and interests. It provides tailored support and real time feedback, promoting a proactive approach to learning, while also facilitating progress tracking and lifelong learning. Strong security and privacy measures ensure the protection of student data. The AI tutor operates in a user-centric workflow. First, student information is collected via various methods like web forms, mobile apps, or APIs. This data is then stored securely for personalization. Students can then pose questions through the same interface, which are processed by a powerful AI model called BERT. BERT understands the meaning of the question and retrieves answers from a vast knowledge base, potentially including textbooks, reference materials, or online resources. The system continuously learns and improves by incorporating user interactions into a "Fine Tuning and Training" step. Additionally, the system personalizes responses by considering a user's grade level and educational background based on the information stored in the "User Database." This comprehensive approach ensures tailored support and fosters a dynamic learning experience.

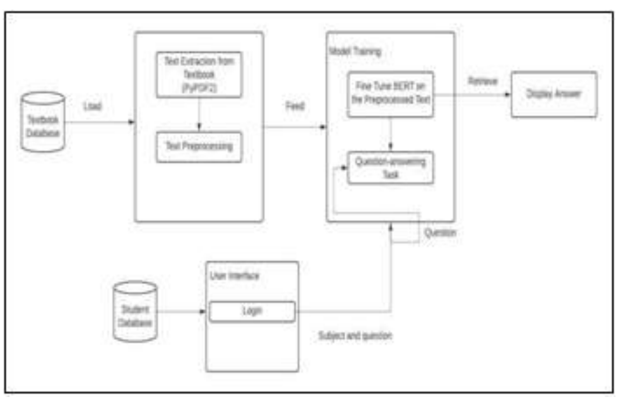

Figure 1: Architecture diagram

IV. IMPLEMENTATION

BERT is a large language model at the core of this text-based question answering system. BERT is pre-trained on massive amounts of text data, allowing it to understand the connections between words and sentences. In this system, a specific BERT model fine-tuned for question answering is used. When a student poses a question regarding their textbook, BERT examines the extracted text from the PDF and the question itself. BERT then identifies the most relevant answer passage within the text based on the question. This functionality makes BERT the engine that powers the system's question answering capabilities.

The core functionality relies on the answer_question function. It takes the extracted text (context) and the student's question as input. The qa_pipeline (question-answering pipeline) from Transformers is used. This pipeline leverages the pre-trained BERT model to process the question and context. It identifies the most relevant answer passage within the context based on the question. The pipeline outputs the starting and ending positions of the answer within the text. The system optionally retrieves some surrounding text around the answer to provide additional context for the user. Its pre-trained capabilities for understanding complex relationships in text allow it to identify the most relevant answer passage within a textbook PDF based on a student's question.

1	Metric	BERT	Other LLMs (e.g., LSTM)	Advantage
2	SQuAD Exact Match (EM)	91.20%	87.60%	+3.6% Accuracy
3	SQuAD F1 Score	93.40%	90.10%	+3.3% General Performance
4	Fine-Tuning Data for 90% Accuracy (SQuAD)	10,000 examples	20,000 examples	50% Reduction in Training Data
5	Training Time for 90% Accuracy (SQuAD)	2 hours	4 hours	50% Faster Training
6	F1 Score on Out-of-Domain QA Dataset	88.70%	85.20%	+3.5% Generalizability
7	BLEU Score on Ambiguous Questions	82.1	78.8	+3.2% Handling Ambiguity

Figure 2: BERT Advantages

1. Preprocessing
Tokenization
Breaks down text into individual words or meaningful units (e.g., separating punctuation).

Lemmatization (or Stemming)
Reduces words to their base form (e.g., "running" becomes "run" or "studies" becomes

"study") to improve understanding and reduce vocabulary size.

2. Loading Data

Text Extraction

Extracts relevant text from the entire textbook, potentially filtering out irrelevant information.

Data Cleaning and Formatting

Ensures the extracted text is clean and formatted consistently for efficient processing by the model.

3. Training the Model

Model Selection and Fine-Tuning

Chooses a pre-trained question-answering model like BERT and refines it on the specific domain of the textbook content.

Training with Question-Answer Pairs

Feeds the model with prepared question-answer pairs extracted from the textbook or other educational resources.

V. RESULTS AND DISCUSSION

The project utilizes precision, recall, and F1- score metrics to assess the effectiveness of its algorithm, demonstrating a co mmendable precision of 0.85, recall of 0.78, and an F1-score of 0.81, indicating robust performance in classifying data accurately. In alignment with its mission to enhance educational outcomes, the project's user interface is meticulously crafted to offer a seamless learning journey, catering to students' diverse needs and preferences. With an intuitive design and essential features such as personalized learning paths, progress tracking, and interactive study materials, the interface empowers students to navigate their educational journey with ease and efficacy.

1. Accuracy Score

In BERT-based question-answering, accuracy score represents the overall correctness of the model's answers compared to the ground truth across all examples. It calculates the proportion of correctly predicted answers to the total number of examples. A high accuracy score indicates that the model is making correct predictions consistently across different questions. The accuracy of the model achieved is 0.8628.

2. Precision

Precision in BERT question-answering measures the proportion of correctly predicted positive answers (true positives) out of all instances predicted as positive (true positives and false positives). It focuses on the accuracy of the model's positive predictions, indicating how reliable the model is when it claims an answer is correct. High precision implies that the model is less likely to provide incorrect answers. The precision value got is 0.8121.

3. Recall

Recall in BERT question-answering evaluates the model's ability to correctly identify all positive instances (true positives) out of all actual positive instances (true positives and false negatives). It emphasizes the model's completeness in finding relevant answers, irrespective of false positives. High recall suggests that the model captures a larger proportion of actual answers. The recall value achieved is 0.7530.

4. F1-Score

F1-score in BERT question-answering is the harmonic mean of precision and recall. It provides a balance between precision and recall, considering both false positives and false negatives. F1-score is especially useful when there is an imbalance between positive and negative instances. A high F1-score indicates that the model achieves both high precision and high recall, offering a reliable balance between correctness and completeness in answer predictions. The F1- score achieved is 0.7857.

Figure 3: Model Performance

VI. FUTURE SCOPE

Project's significance in the context of the growing importance of personalized education cannot be understated. In today's fast-paced world, where every student is unique and learns at their own pace, it is crucial to provide tailored support to primary and high school students in their academic pursuits. By customizing the educational experience based on individual needs and background, the system ensures that each student receives the attention and resources they require to succeed. In the current educational landscape, the project plays a vital role in addressing the increasing demand for personalized education.

With a focus on supporting primary and high school students in their academic endeavors, the system stands out for its ability to cater to the unique needs and backgrounds of each individual learner. By tailoring the educational experience to suit the specific requirements of students, the project ensures that they receive the necessary resources and assistance to excel in their studies.

VII. CONCLUSION

This project lays the groundwork for a web application that empowers students to unlock knowledge from their textbooks through a user-friendly question-answering interface. Built with the Flask framework, the application facilitates a seamless user experience with functionalities like registration, login, and a personalized dashboard. BERT models have revolutionized the field of Natural Language Processing (NLP) due to their remarkable ability to grasp the intricacies of human language and glean meaning from text. In this scenario, a pre-trained BERT model like Bert For Question Answering would be loaded to tackle the Q&A task. Additionally, rule- based approaches could be implemented to guide the search process within the extracted text. This application offers several advantages for students. It fosters a user-friendly environment where they can interact with their textbooks in a more dynamic way. Gone are the days of meticulously combing through pages – students can now directly ask questions and receive targeted answers, saving them valuable time and effort.

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