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Online Personalized learning remediation/tutoring tool

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***Abstract*—With the given project, we set out to explore the use of Generative AI coupled with the Retrieval-Augmented Generation system-end methodologies for optimizing teaching pedagogy. Using the system, it ingests educational data with embeddings created by Sentence Transformers, indexed, and queried through Pinecone to obtain relevant or pedagogical insights. Integrating the Groq API ensures that teaching strategies are tailored concerning context such as students' average marks and feedback. One of the issues discussed is embedding-based retrieval systems and vector similarity, as well as the role of generative models in producing usable teaching suggestions.**

This is a major step in the direction of AI-driven personalized education. The Pedagogy Suggestion System is touted as an AI-powered teaching assistant that helps educators become better teachers. It takes in structured datasets that contain information on courses, teaching techniques, student feedback, and performance metrics. Based on its analysis of the datasets, it detects the most appropriate teaching methods to recommend for a given course. In contrast, the Andragogy Suggestion System is geared toward adult learners, who commonly seek to advance their career, learn some new skills, or work toward personal development. The system generates tailored learning plans that fit an individual's unique learning style, strengths, and weaknesses, along with their goals.

Keywords: Generative AI (Gen AI), Retrieval-Augmented Generation (RAG), Sentence Transformers, Pinecone, Embedding-based Retrieval, Education, Vector Databases, Data-Driven Teaching Strategies.

I. INTRODUCTION

The ultimate aim of this project is to enhance the quality and efficacy of education by leveraging the potential of artificial intelligence and data. This system will facilitate both conventional teachers and adult learners by creating data-driven suggestions that are contextually specific, goal-oriented, and user-specific in their approach.

One of the major objectives is to increase educational results by using intelligent insights. By examining past educational data, including curriculum content, instructional techniques, student comments, and academic achievement, the system finds patterns and generates useful insights. These insights assist in enabling informed decisions by the instructors regarding how to better teach, how to change instruction to meet the needs of the students, and how to achieve improved learning results.

One of the primary emphases is to tailor the learning experiences of adult students. Adults come to education with specific intentions—improving new skills, career progress, or personal interests, for example. This project develops a system of AI that considers the preferences, aptitudes, weaknesses, and goals of every adult learner and then provides the best approach, resources, and milestones to keep the learning pertinent and stimulating..

II. PROBLEM STATEMENT AND CHALLENGES

In conventional education systems, uniform teaching strategies tend to ignore individual learning needs, paces, and styles. Students with difficulty in comprehending complex concepts may not be provided with timely or tailored guidance, resulting in knowledge gaps and lower academic performance. With the growing need for scalable, adaptive, and learner-focused tools, there is an urgent need for intelligent tutoring systems that can tailor instruction, offer immediate feedback, and dynamically adapt content. This study seeks to create a tutorial tool *powered by GenAI utilizing large language models to provide effective, interactive, and personalized learning support that's specific to individual students' differing needs.*

a) Personalization Accuracy

Ensuring the GenAI model has accurate understanding and flexibility to suit varied learner profiles, such as learning speed, past performance, and content format preference.

b) Content Relevance and Contextual Understanding

Producing explanations and tutorials that are contextually relevant and curriculum-compliant.

c) User Engagement and Interaction

Creating intuitive and interactive interfaces that motivate students to actively employ the tutorial tool without becoming excessively reliant on it.

d) Evaluation and Feedback Loop

Evaluating the quality of suggestions and allowing students to give feedback in order to better future interactions

III) LITERATURE SURVEY

Retrieval-Augmented Generation (RAG) mixes language models and external knowledge retrieval to enhance text generation accuracy and relevance. Compared to conventional models, RAG accesses information real-time from outside sources such as vector databases and thus is most effective in application areas such as education, medicine, and customer support (Lewis et al., 2020).

Vector Embeddings transform text into vectors of high dimensions maintaining semantic meaning. Methods such as Word2Vec, GloVe, and transformer-based models (e.g., BERT, GPT) support tasks like semantic search, recommendations, and clustering by retaining contextual meaning (Mikolov et al., 2013).

Pinecone is a highly specialized vector database tuned for quick and scalable similarity search. Pinecone enables real-time AI usage through effective processing of large embeddings in terms of space using techniques such as HNSW, hence being suited for RAG-using systems (Subramanian et al., *2021).*

IV METHODOLOGY

The approach for this project combines AI-based personalization with core educational theories—Pedagogy (child-centered learning) and Andragogy (adult-centered learning)—to create an adaptive tutorial tool. The system is developed based on the following multi-stage approach:

3.1 Data Collection and Preprocessing

Organized datasets such as course material, learner details, and past performance records are gathered. This information is cleaned through complete-case analysis to manage the missing data and standardized for consistency. Corresponding fields are combined into a single textual format to create a rich context for embedding.

3.2 Embedding and Vectorization

The processed text data is infused into high-dimensional vector representations through transformer-based models like BERT or Sentence-BERT. The embeddings are retained in a vector database like Pinecone for similarity searching.

3.3 Personalized Learning through RAG Framework

Utilizing Retrieval-Augmented Generation (RAG), the system fetches contextually related content from the vector database in real-time and provides responses based on a Large Language Model (for example, Mistral or GPT). This allows the system to tailor tutorial content to personal learner requirements according to their question, past performance, and inclinations.

3.4 Integration of Andragogy vs Pedagogy

For Pedagogical learners (normally younger learners), the system provides guided, structured learning through step-by-step explanation.

For Andragogical learners (adults), the system facilitates self-directed learning through offering choices, context-based exploration, and real-world application-based content.

Learner profiles and age groups facilitate dynamically adapting the delivery mode accordingly.

3.5 Feedback Loop and Adaptation

User interactions, feedback, and quiz results are logged and analyzed continuously to improve the system's recommendations and content presentation. This provides an adaptive learning environment that adapts with the learner's progress.

3.6 User Interface and Experience Design

A simple, responsive, and accessible web interface is developed to ensure ease of use across different devices and user groups.

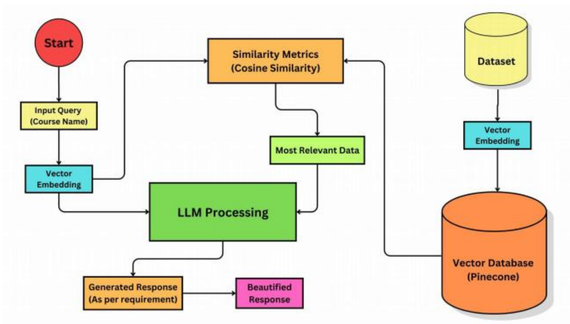

Fig 1. Architecture of RAG System

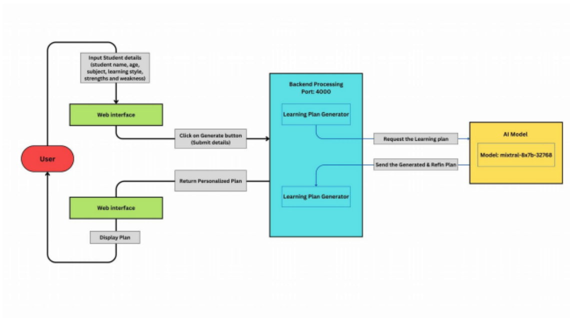

Fig 2. Architecture of Andragogy System

Pedagogy Workflow (Teacher-Focused Learning)
1) Course Input Entry
Instructors or system administrators enter organized course information, such as topic, goals, and conventional teaching approaches.

2) Embedding Generation
The application creates vector embeddings of course material based on a pre-trained model for semantic comprehension.

3) Retrieval of Best Practices
The system looks into a vector database (e.g., Pinecone) to find efficient pedagogical practices based on analogous previous courses.

4) AI-Driven Suggestion
GenAI models recommend appropriate pedagogy approaches, taking into account course level, student proficiency, and set learning outcomes.

5) Output to Instructor
Proposed approaches are presented to the instructor, who modifies or implements them in designing lessons

Andragogy Workflow (Learner-Centered Adult Learning)
1)Learner Profile Analysis
The system gathers user-specific information such as previous performance, learning style, and feedback history.

2)Personalized Input Parsing
Learner-submitted questions or learning objectives are embedded and contextualized with GenAI.

3)Relevant Strategy Retrieval
With semantic search, the tool retrieves adult learning strategies (e.g., self-directed learning, experiential content).

4)Context-Aware Suggestion Generation
The system produces and ranks suggestions according to user autonomy, experience, and motivation — fundamental andragogical principles.

5)Adaptive Output Delivery
The learner is given tailor-made content and methods that reinforce goal-oriented, adaptable learning.

V COMPARATIVE ANALYSIS

Embedding Models transform text content into high-dimensional numerical vectors without losing semantic relationships. Such models, including Word2Vec, GloVe, BERT, and GPT, enable machines to understand and process human language meaningfully. In this tutorial tool, transformer-based models (e.g., MiniLM, BERT, or OpenAI embeddings) are employed to embed course content, learner questions, and feedback to ensure contextual understanding and response generation.

Vector databases such as Pinecone, Weaviate, or FAISS keep and handle such embeddings efficiently for similarity-based retrieval. They facilitate Retrieval-Augmented Generation (RAG) by rapidly retrieving semantically coherent data points in real-time. In this project, the vector database keeps embedded representations of course content and learner interactions, which are then queried to return personalized, contextually relevant responses.

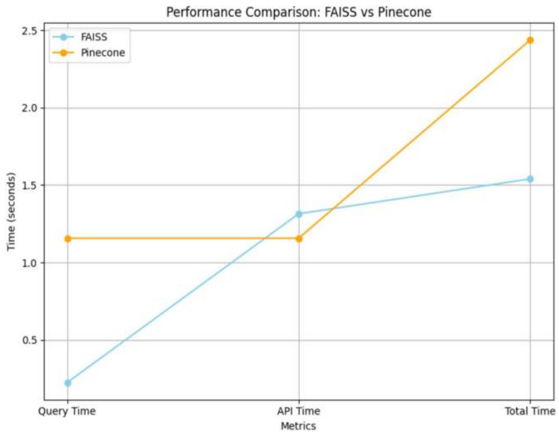

Fig 3. using all mpnet-base-v2

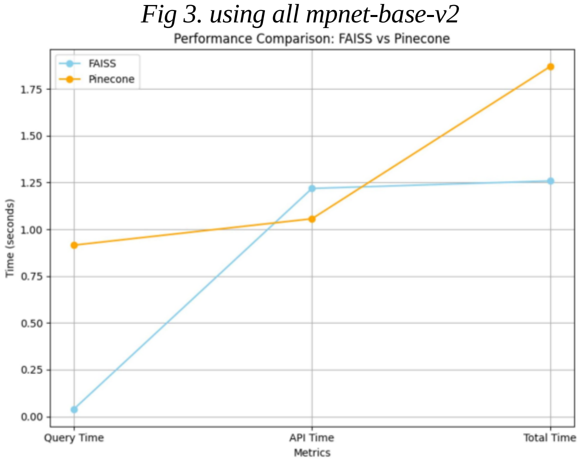

Fig 4. Using all miniLM-L6-v2

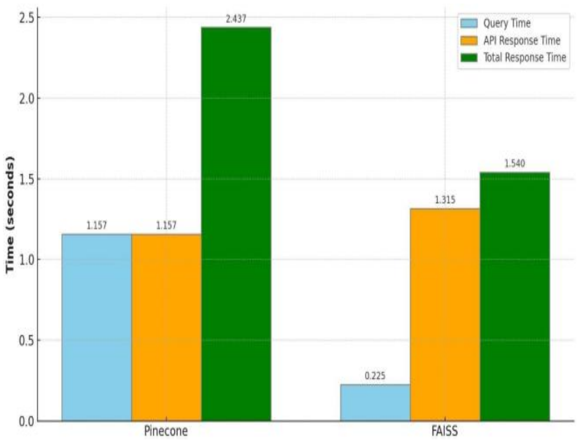

Fig 5. Comparing using all mpnet-base-v2

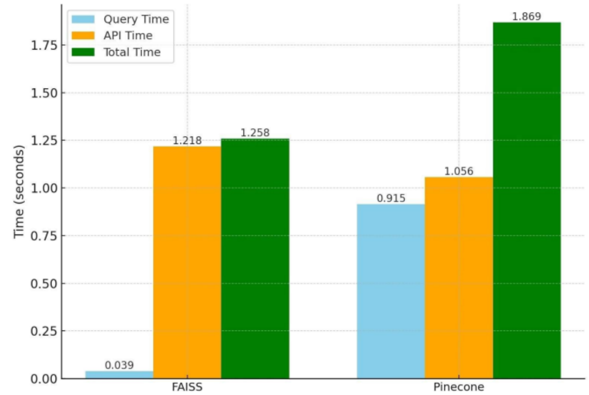

Fig 6. Comparing using all miniLM-L6-v2

VI) CONCLUSION

The incorporation of Generative AI in education, specifically through a tailored tutorial tool, represents a revolutionary change in the design, delivery, and customization of learning experiences. This study illustrates the effective integration of pedagogical and andragogical models in an AI-driven setting, enabling the system to cater to varied learner profiles—ranging from formal K-12 students to autonomous adult learners. By integrating powerful Large Language Models (LLMs) with vector embedding methods and high-performance vector databases such as Pinecone, the system provides contextually correct, real-time answers that boost knowledge retention, relevance, and learner independence.

The use of andragogy assists adult students with self-timed modules, problem-based design, and pragmatic applicability. At the same time, pedagogical methodologies provide foundational curriculum-based training to younger or inexperience learners. This two-model strategy guarantees that the tool stays inclusive, expandable, and extremely adaptive. The Retrieval-Augmented Generation (RAG) framework even further enhances the platform by having dynamic external sources of knowledge fused into it, which makes responses richer, recent, and concordant to learner queries.

In general, the tutorial tool provides a robust, learner-oriented learning solution that solves major problems in conventional systems—like one-size-fits-all instruction, absence of personalization, and fixed content. It sets the stage for more innovations in AI-powered learning and contributes significantly towards the worldwide goal of learning democratization through intelligent, personalized, and accessible platforms.

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