

Affective Learning Companion Using Transformer – Based Emotion Understanding

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ABSTRACT

Intelligent Tutoring Systems (ITS) have improved personalized learning, but many existing systems still focus mainly on cognitive performance while overlooking the learner’s emotional state. Since emotions such as confusion, frustration, and engagement directly influence learning effectiveness, incorporating affective awareness can improve tutoring quality and learner interaction. This paper presents EchoConnect, a real-time emotion-aware intelligent tutoring system that dynamically adapts instructional responses based on detected learner emotions. The system uses a DistilRoBERTa-based transformer model for text-based emotion classification and integrates a large language model through the Groq API to generate adaptive tutoring responses with low latency. Learner emotions are mapped into four educational categories: ENGAGED, CONFUSED, FRUSTRATED, and NEUTRAL, which guide pedagogical strategies such as step-by-step explanations, encouragement, or advanced problem-solving. EchoConnect also maintains session-level context to support multi-turn personalized learning interactions. The proposed architecture combines a React frontend, FastAPI backend, and MongoDB persistence layer to enable scalable and responsive real-time tutoring. Experimental evaluation achieved approximately 84% emotion classification accuracy with stable adaptive response quality and consistent multi-turn interaction performance. The results demonstrate the feasibility of integrating affective computing and real-time adaptive tutoring within modern AI-driven educational systems.

Keywords: Affective Computing, Intelligent Tutoring Systems, Transformer Models, Emotion Detection, Adaptive Learning, Real-Time Processing.

INTRODUCTION

Intelligent Tutoring Systems (ITS) have become increasingly important in digital education by providing personalized learning and automated instructional support. However, many existing tutoring systems mainly focus on academic performance while overlooking the learner’s emotional state during interaction.

Emotions such as confusion, frustration, and engagement significantly influence learning effectiveness. Human tutors naturally adapt their teaching strategies based on these emotional cues, but most AI-based tutoring systems still lack this capability.

Recent advancements in Natural Language Processing (NLP), transformer-based models, and large language models (LLMs) have enabled more effective real-time emotion detection and adaptive educational interaction. This paper presents EchoConnect, a real-time emotion-aware intelligent tutoring system that dynamically adapts tutoring responses according to detected learner emotions.

The proposed system uses a DistilRoBERTa-based model for emotion classification and integrates a large language model through the Groq API for adaptive response generation. EchoConnect categorizes learner emotions into ENGAGED, CONFUSED, FRUSTRATED, and NEUTRAL states to support personalized and context-aware tutoring interaction.

LITERATURE REVIEW

Sr. No.	Paper Title & Year	Methodology Used	Key Contribution	Limitations
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1	“Knowledge Tracing: Modeling the Acquisition of Procedural Knowledge” (1994)	Knowledge Tracing	Tracks learner understanding over time	Does not consider learner emotions
2	“Affective Computing” (1997)	Emotion-Aware Computing	Introduced emotion recognition in intelligent systems	Not focused on educational tutoring
3	“Attention Is All You Need” (2017)	Transformer Architecture	Improved contextual language understanding	High computational requirements
4	“DistilBERT: Smaller, Faster, Cheaper and Lighter” (2020)	Distilled Transformer Model	Enables fast and lightweight NLP inference	Slight reduction in accuracy
5	“Towards an Affect-Sensitive AutoTutor” (2007)	Emotion-Aware Tutoring	Demonstrated adaptive tutoring using learner emotion	Limited scalability and older techniques
6	“ChatGPT for Good? On Opportunities and Challenges of LLMs for Education” (2023)	Large Language Models	Highlighted educational applications of LLMs	Limited emotional personalization

METHODOLOGY

The proposed EchoConnect framework follows a real-time emotion-aware adaptive tutoring approach designed to support personalized educational interaction. The system consists of a React frontend, FastAPI backend, MongoDB database, and AI-based emotion detection and tutoring modules.

First, the learner interacts with the tutoring interface by submitting textual queries. The input text is processed using a DistilRoBERTa-based transformer model to detect the learner’s emotional state. The detected emotions are categorized into ENGAGED, CONFUSED, FRUSTRATED, and NEUTRAL.

Based on the detected emotion, the system dynamically adjusts the tutoring strategy. Confused learners receive step-by-step explanations, frustrated learners receive supportive guidance, engaged learners receive advanced explanations, and neutral learners receive balanced instructional responses. The tutoring responses are generated using a large language model through the Groq API. Session history and learner interactions are stored in MongoDB to maintain contextual continuity across multiple interactions. The complete workflow includes user input, emotion detection, adaptive response generation, session storage, and real-time response delivery. The system is designed to provide low-latency interaction suitable for intelligent tutoring applications.

RESULTS AND DISCUSSIO



Fig. 1. Echo Connect Dashboard Interface

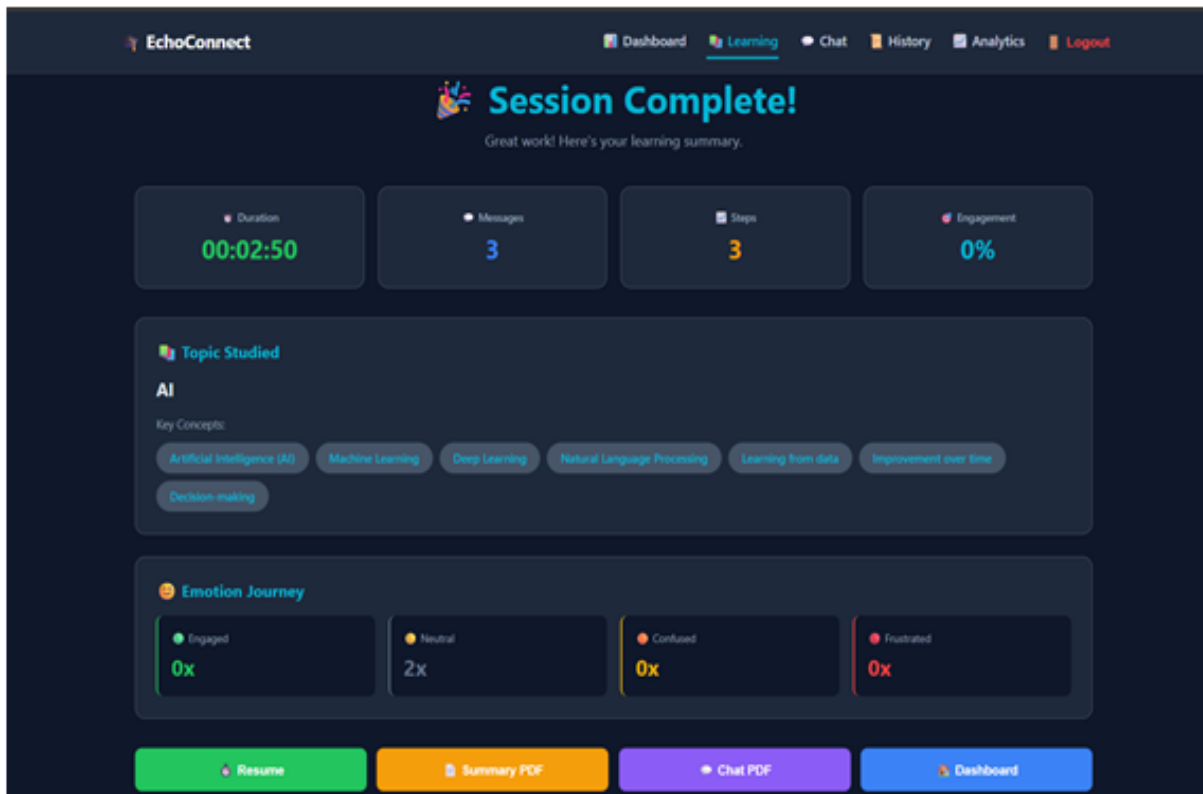


Fig. 2. Real-Time Adaptive Tutoring Interaction

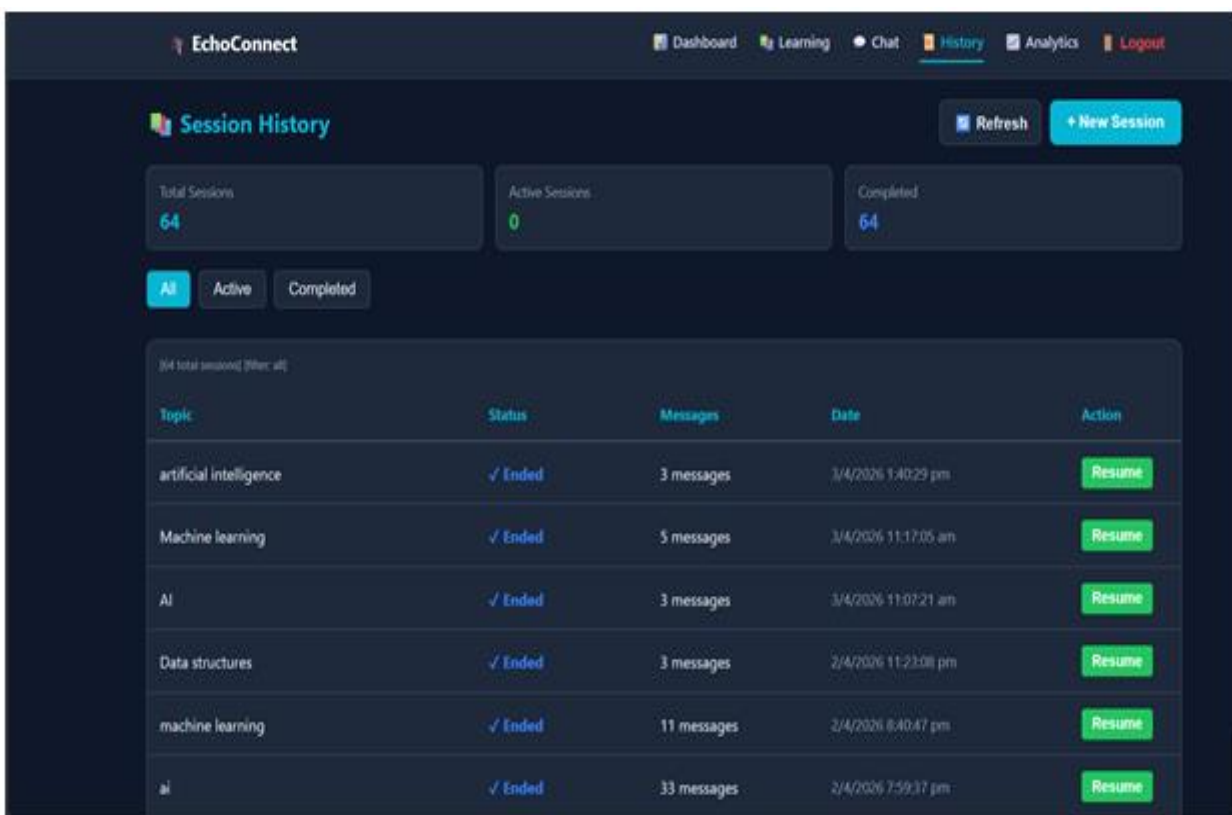


Fig. 3. Session Summary and Emotion Analytics

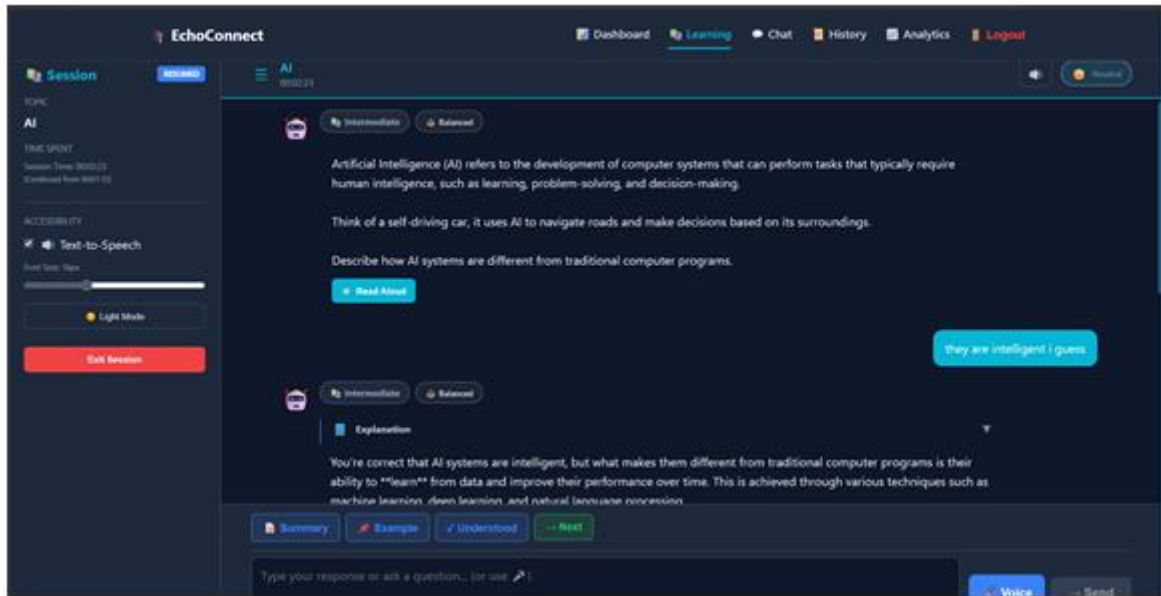


Fig. 4. Session history

CONCLUSION

In conclusion, EchoConnect presents a practical approach for integrating affective computing with intelligent tutoring systems. Instead of providing uniform responses, the system dynamically adapts instructional behavior according to learner emotions, creating a more personalized learning experience.

The integration of transformer-based emotion detection, adaptive tutoring strategies, and large language model response generation enables real-time emotionally aware interaction. The experimental results demonstrated the feasibility of integrating affective computing, transformer-based emotion detection, and large language model tutoring within a unified adaptive educational framework.

Although the current implementation has limitations such as limited emotion categories and dependency on external APIs, the project demonstrates the potential of emotion-aware tutoring systems in modern education. Future improvements may include multimodal emotion recognition, multilingual support, and enhanced learner modeling for more advanced personalization.

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