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# Adaptive chatbot for Neo-Learn Using Deep Learning

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**Abstract—**In the evolving landscape of digital education, the need for personalized, scalable, and always-available student support has led to the integration of intelligent virtual assistants. This research presents the design and development of an AI-powered adaptive chatbot for e-learning platforms, utilizing deep learning and natural language processing techniques. The chatbot employs a feedforward neural network built with PyTorch, trained on categorized intents in JSON format to understand and respond to user queries. By leveraging tokenization, stemming, and bag-of-words vectorization, the system achieves effective intent classification and real-time response generation. The chatbot addresses common student inquiries, delivers educational resources, and provides navigation support, enhancing learner engagement while reducing instructor workload. The modular and lightweight architecture ensures ease of customization and scalability, making it a valuable tool for modern e-learning environments.

**Keywords—Deep Learning, Natural Language Processing (NLP)Intent Classification, Feedforward Neural Network, PyTorch**

## I. INTRODUCTION

` The rapid transformation of education through digital platforms has sparked a growing demand for intelligent and interactive learning tools. Among these innovations, chatbots stand out as pivotal in improving user engagement, accessibility, and responsiveness in e-learning systems. Chatbots, powered by artificial intelligence and natural language processing (NLP), can simulate human-like conversations and provide immediate, personalized support to learners. By offering real-time assistance with queries related to course content, navigation, or schedules, these virtual agents enhance the overall learning experience and help bridge the gap in learner-instructor communication.

Despite the growing adoption of online education platforms, one critical challenge remains: the absence of instant and tailored support. Traditional learning management systems often fall short in addressing students' unique questions in real time, especially outside of standard academic hours. Learners frequently encounter delays when waiting for human responses to simple or recurring queries, which can hinder their progress and engagement. This problem becomes even more prominent for students in different time zones or with irregular schedules. To overcome these limitations, there is a growing need for automated, intelligent assistants capable of understanding natural language and delivering appropriate, context-aware responses.

This research proposes the development of an

adaptive AI-powered chatbot integrated with the Neo-Learn e-learning platform, utilizing deep learning for intent classification and natural language understanding. The system is designed using a feedforward neural network (FFNN) implemented with PyTorch and trained on a structured JSON dataset containing categorized intents and example user queries. The chatbot uses core NLP techniques such as tokenization, stemming, and bag-of-words vectorization to preprocess user input. With its ability to learn from examples and improve over time, the chatbot provides scalable and efficient support to both students and educators by automating routine interactions.

The chatbot's modular design ensures easy integration with web platforms, efficient training, and the ability to update its knowledge base as new educational content is introduced. It also supports evaluation through key performance metrics such as accuracy, BLEU score, and cosine similarity, ensuring that the model is not only functional but effective in real-world usage. Ultimately, the system aims to empower students with 24/7 guidance, reduce the repetitive workload on educators, and foster an inclusive, adaptive e-learning environment that responds intelligently to diverse learner needs.

## II Related Work

In recent years, numerous studies have explored the application of chatbots in e-learning environments, aiming to enhance educational experiences through intelligent interaction.

**Salma El Janati et al. (2021)** proposed an adaptive e-learning chatbot using multimedia indexing, where natural language processing (NLP) and machine learning were used to deliver personalized content and guidance to students. Their system was designed to adapt based on learner behavior and content engagement, contributing significantly to the field of intelligent tutoring systems by focusing on adaptive learning.

Another notable work by **Saqib Hussain et al. (2021)** presented a chatbot architecture that processes student queries through an NLP pipeline, incorporating tokenization, stemming, and intent recognition. Their system, while effective for handling FAQs and administrative questions, operated largely on static responses and lacked advanced learning capabilities. The emphasis was on ease of integration into web and mobile platforms, highlighting the feasibility of using lightweight AI solutions in educational tools.

**Nikola Straková and Jan Válek (2021)** studied the broader implications of integrating AI chatbots into formal and informal educational settings. Their work evaluated the use of chatbots in improving learner engagement, motivation, and teacher efficiency. While their results supported the use of chatbots in promoting self-directed learning, the authors emphasized the importance of balancing AI assistance with human interaction to preserve empathy and nuanced understanding in education.

Most recently, a study by **Deepak Verma et al. (2024)** compared various machine learning models for classification tasks and discussed their applicability in chatbot frameworks. While this research was originally aimed at healthcare predictions, its findings on algorithm performance—especially the effectiveness of Random Forests and Support Vector Machines—provide insights into potential alternatives for intent classification in educational chatbots. Collectively, these studies form the foundation upon which this project builds, with the key advancement being the integration of a deep learning-based chatbot with adaptive and scalable architecture tailored specifically for e-learning platforms like Neo-Learn.

## III Existing System

The existing e-learning platforms often lack real-time and personalized support for learners. These systems are typically static, offering limited interaction capabilities and relying on pre-set content or scheduled instructor responses. When students face questions regarding course content, deadlines, or platform navigation, they usually experience delays while waiting for instructor replies. This inefficiency becomes more pronounced during non-working hours or for students in different time zones. Moreover, educators spend a significant portion of their time addressing repetitive queries, which detracts from content development and personalized mentorship. Traditional chatbot solutions used in education tend to rely on keyword matching or rule-based logic, which results in shallow understanding of user intent, inability to generalize from data, and limited adaptability.

## IV Proposed System

The proposed system introduces an AI-powered adaptive chatbot integrated with the Neo-Learn e-learning platform. This chatbot leverages **deep learning**, specifically a **Feedforward Neural Network (FFNN)** built using PyTorch, to perform **intent classification** based on user input. It incorporates **natural language processing (NLP)** techniques such as tokenization, stemming, and bag-of-words to preprocess inputs and convert them into numerical features for the neural model. The system is designed to provide **real-time, context-aware, and automated responses** to student queries around the clock. Its lightweight and modular architecture enables quick inference, easy training, and seamless scalability. Additionally, it supports continuous learning and system updates, allowing administrators to add new intents or responses simply by updating the intents dataset (JSON file) and retraining the model. This approach aims to reduce educator workload, enhance student engagement, and provide personalized assistance efficiently and accurately.

## V. Methodology

The development of the adaptive chatbot for Neo-Learn follows a modular and structured methodology, integrating machine learning and natural language processing for intent recognition and response generation. The system architecture diagram illustrates the complete flow—from user input via a web interface to the chatbot's output—showing the interaction between frontend, Flask-based backend, NLP preprocessing, and the feedforward neural network (FFNN) model. The **UML use case diagram** highlights the roles of users and administrators, showcasing functionalities like chatting, training the model, and retrieving responses. The **class diagram** defines the system's object-oriented structure, detailing relationships between key components such as the chatbot, user, message, intent, and model. The **activity diagram** captures the sequential processing of user input, while the **sequence diagram** provides a timeline of message flow between the frontend, backend, NLP module, model, and response generator. Together, these diagrams support the implementation methodology by providing a visual blueprint for system design, interaction flow, and functional integration, ensuring a scalable, maintainable, and efficient AI chatbot solution.

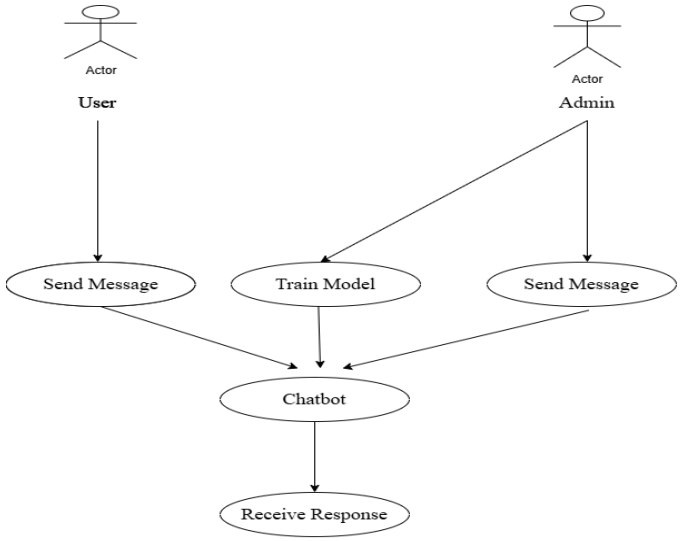



Fig 1 Use Case Diagram

This use case diagram illustrates the interactions between **Users**, **Admins**, and the **Chatbot system**. Users and Admins can **send messages** to the chatbot, initiating a conversational flow. Admins additionally have the ability to **train the model**, updating the chatbot's understanding and response capabilities.

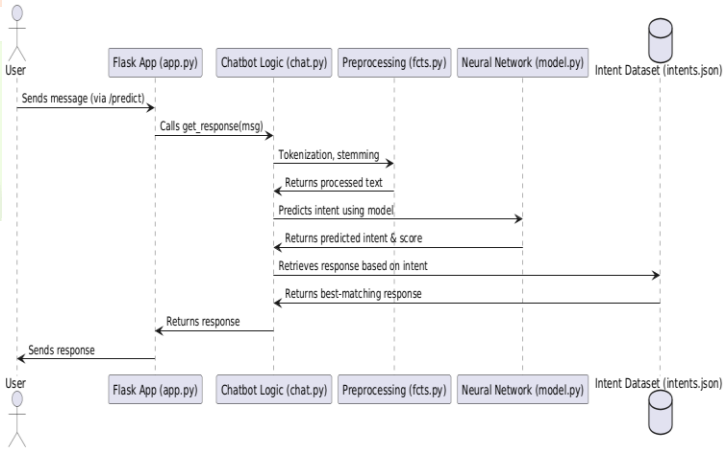



Fig 2 sequence Diagram

When a user sends a message, it is received by the Flask application through the /predict route. The app then calls the get_response function from the chatbot logic module to process the message. This message is first cleaned and tokenized by a preprocessing module to prepare it for analysis. The processed text is then passed to a neural network model which predicts the user's intent and gives a confidence score. Based on the predicted intent, the chatbot retrieves the most appropriate response from a predefined dataset of intents. Finally, this response is sent back to the user through the Flask application.

## VI RESULTS & ANALYSIS

Fig 3 Web hosting

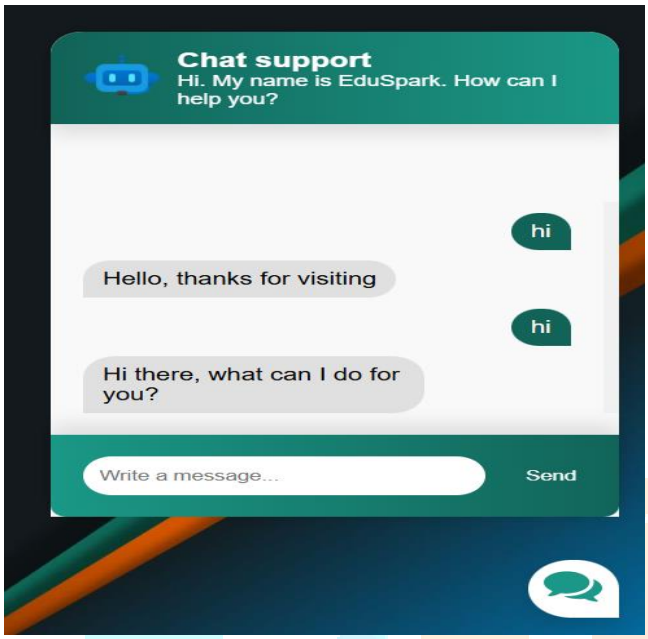


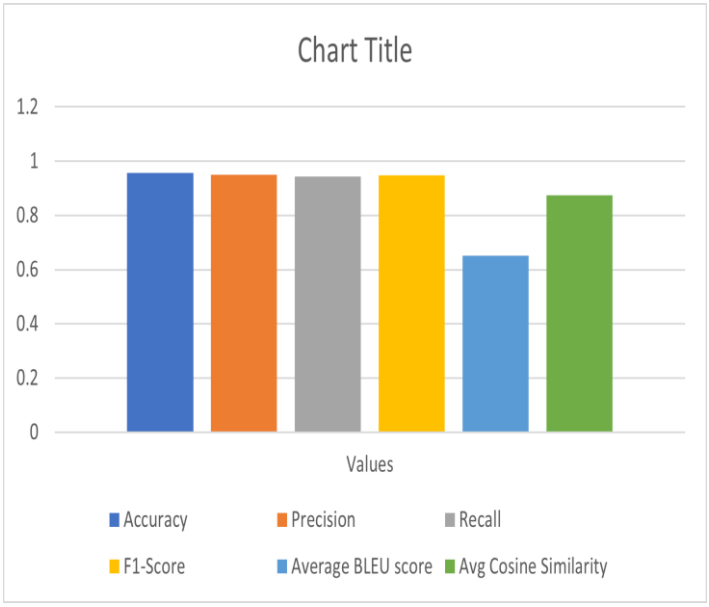

Fig 4 Chatbot Interface

Table 1 Evaluation Metrics

| Intent | Average BLEU Score |
|---|---|
| greeting | 0.7123 |
| literature | 0.6894 |
| scientific | 0.672 |
| goodbye | 0.6415 |
| thanks | 0.63 |

Table 2 Average BLEU Score

| Metrics | Values |
|---|---|
| Accuracy | 0.9562 |
| Precision | 0.9503 |
| Recall | 0.9438 |
| F1-Score | 0.9469 |
| Average BLEU score | 0.6521 |
| Average Cosine Similarity | 0.8734 |



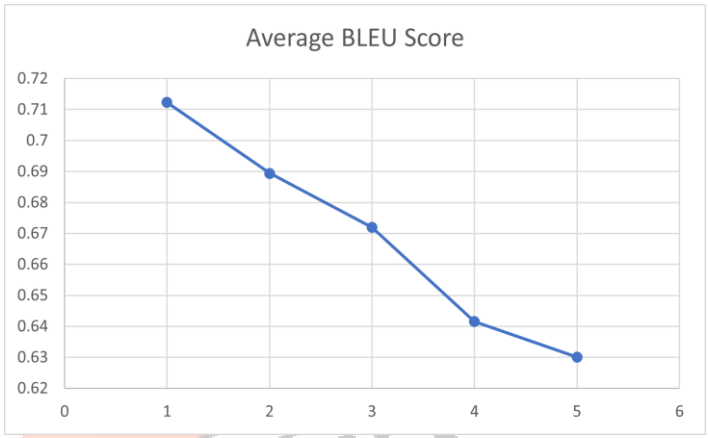




Fig 5 Evaluation Metrics

This bar chart compares various performance metrics of a model, including Accuracy, Precision, Recall, F1-Score, Average BLEU score, and Average Cosine Similarity. Most metrics are close to or above 0.85, except for Recall, which is noticeably lower at around 0.65.

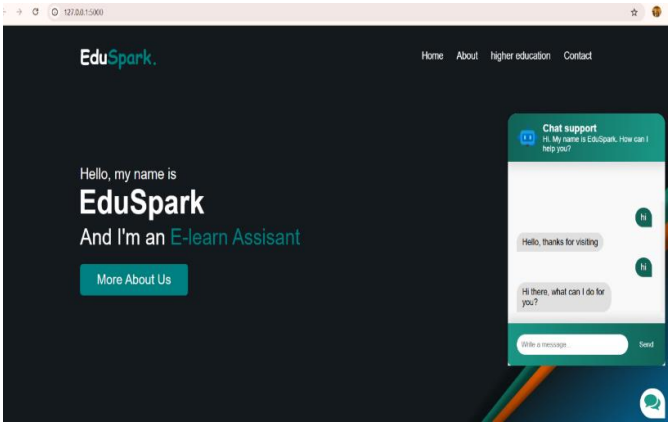



Fig 6 Average BLEU Score

This line chart shows the trend of the Average BLEU Score over five different evaluation points. The BLEU score steadily declines from around 0.71 to 0.63, indicating a drop in the model's translation or response quality. The downward trend suggests the model's performance is degrading over time or across conditions. This insight may call for retraining or tuning to maintain quality.

## VII Conclusion

The research project primarily aims to explore the influence of artificial intelligence (AI) in modern business environments, particularly focusing on small and medium enterprises (SMEs). In recent years, AI technologies have rapidly evolved, enabling businesses to streamline operations, enhance customer experiences, and make data-driven decisions. This study examines how SMEs are adopting AI tools and the challenges they encounter during implementation. It also highlights the significant role AI plays in improving operational efficiency and reducing human error. Despite these benefits, SMEs often face barriers such as limited financial resources, lack of technical expertise, and resistance to change. The research emphasizes the importance of strategic planning and staff training in overcoming these obstacles. Additionally, the integration of AI is analyzed from a competitive advantage perspective, where businesses can outperform rivals by leveraging automation and predictive analytics. The research methodology involves a combination of qualitative and quantitative data collection, including surveys and interviews with SME owners and employees. Findings suggest that while the adoption rate of AI in SMEs is still in its early stages, there is growing awareness of its potential. Several case studies are presented to demonstrate successful implementation strategies. Moreover, ethical concerns, including data privacy and algorithmic bias, are addressed. The study recommends a phased approach to AI adoption, encouraging SMEs to start small and scale gradually. Government support and industry collaboration are also recognized as key enablers. The research contributes to the understanding of digital transformation in the SME sector and outlines practical recommendations for stakeholders. In conclusion, AI represents a transformative opportunity for SMEs, but realizing its full potential requires deliberate planning, investment, and continuous learning.

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