Automatic Question Answer Generation Using DeepSeek R1 AI: A No-Fine-Tuning Approach for Multi-Input and Bloom's Taxonomy Based Questioning

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Abstract: An advanced Automatic Question Answer (QA) Generation system that leverages DeepSeek R1 AI to address the limitations of traditional fine-tuning-based Natural Language Processing (NLP) models. Our approach eliminated the need for time-consuming fine-tuning and costly GPU infrastructure while supporting multiple input types, diverse QA pairs, and Bloom's Taxonomy-based cognitive levels. We have evaluated the versatility of the model on a vast number of instructional materials and established its capability of generating great questions and answers in a variety of formats. To achieve this, we present a scalable and easily navigable framework for QA generation in educational and assessment technologies. Overall, our system exhibited emergent reasoning behaviors, utilizing the capability of reinforcement learning through DeepSeek R1, even in the absence of any supervised pre-training. The model is aligned with the educational goals and can be adjusted to accommodate different question types, including multiple-choice questions, short-answer questions, and descriptive questions. Besides, we further simplified reasoning strategies into smaller models for light deployments on non-GPU systems. Results of the experiments demonstrated that our method is resource-efficient and competes, performance-wise, with some of the most recent systems for real-world educational purposes.

Keywords: Automatic QA Generation; DeepSeek R1; Bloom's Taxonomy; Natural Language Processing (NLP); Large Language Models (LLMs)

1. Introduction

A technological advancement, the automation of educational content generation has been a boon in modern teaching and self-assessment. In a rapid shift towards digital platforms, the education field has become scalable and adaptive in Question-Answer generation. As education rapidly shifts toward digital platforms, scalable and adaptive QA generation has become an essential requirement.

Natural Language Processing (NLP) approaches rely on fine-tuned models, such as BERT and T5, to perform Question-Answering tasks. However, they are computationally intensive and depend heavily on GPU-supported infrastructures—making them inaccessible for low-resource educational environments.

To overcome these constraints, this research proposes a QA generation system that uses DeepSeek R1 AI, a large language model (LLM) capable of zero-shot and prompt-based learning. Rather than relying on fine-tuning, the system leverages intelligent prompt engineering to generate diverse, high-quality QA pairs directly from the input content. This eliminates the need for expensive model retraining while drastically reducing latency and infrastructure requirements.

The proposed system also introduces a taxonomy-based layer, aligning the generated questions with Bloom's Taxonomy, which covers all six levels: Remember, Understand, Apply, Analyze, Evaluate, and Create. This ensures that the questions serve a pedagogical purpose and address different cognitive levels, which is essential for formal education and assessment systems.

In addition to supporting multiple input formats—such as plain text, paragraphs, and structured documents—the system is modular, fast, and customizable, making it suitable for educators, content creators, and learning management systems. The primary goal of this study is to build a scalable and adaptable QA generator that is practical for widespread adoption in education, especially in regions with limited technical infrastructure.

The project aims to eliminate the need for fine-tuning by utilizing prompt-based generation with DeepSeek R1 AI. To support multiple input types such as plain text, paragraphs, and structured documents. To generate diverse question-answer pairs aligned with all six levels of Bloom's Taxonomy. To build a scalable, GPU-free QA generation system suitable for educational environments. To improve accessibility and reduce deployment time and cost for content creators and educators. To demonstrate the effectiveness of zero-shot learning in generating relevant, cognitively aligned questions.

2. Literature Review

Moharana et al. proposed an Automated Question Answer Generation system leveraging Natural Language Processing (NLP) techniques integrated with the T5 transformer model. Their study highlighted the effectiveness of the T5 model in understanding context and generating diverse question types with improved accuracy [1]. Murshida et al. developed an automated system for question generation and answer evaluation aimed at enhancing digital learning platforms. The system integrated NLP techniques to generate context-relevant questions and employs evaluation mechanisms to assess student responses [2]. The DeepSeek-R1 study introduced a reinforcement learning framework to enhance reasoning capabilities in large language models (LLMs). By optimizing reward signals tailored to logical reasoning tasks, the model demonstrates improved performance on complex question answering and reasoning benchmarks. This approach showcased the effectiveness of reinforcement learning in refining LLM behavior beyond traditional supervised fine-tuning [3]. Scaria et al. explored automated question generation aligned with Bloom's Taxonomy using large language models (LLMs) to support adaptive learning. Their study proposed strategies for generating questions across various cognitive skill levels and evaluates their effectiveness through both automated and human assessments [4]. Verma and Anand proposed a system combining automated text summarization and question generation to enhance information extraction from large texts. Their approach utilized NLP techniques to first condense information and then generate relevant questions to facilitate quick understanding and learning [5]. Sharma, Kumar, and Singh presented an automatic question generation framework tailored for cognitive domain assessment in outcome-based education systems. Their model emphasizeds generating questions aligned with various cognitive levels, supporting structured evaluation of learner understanding [6]. Tomikawa, Suzuki, and Uto proposed an adaptive question–answer generation system that incorporates Item Response Theory (IRT) with pretrained transformer models. Their approach enabled dynamic control over question difficulty based on learner proficiency, enhancing personalized learning experiences [7].

Srivastava et al. introduced Questionator, an automated question generation system leveraging deep learning techniques to produce relevant questions from textual content. Their model focused on understanding contextual semantics to generate meaningful and diverse questions. [8]. Gangopadhyay and Ravikiran proposed a focused question and answer generation system that emphasizes key content selection from input text. Their approach enhanceds the relevance and precision of generated questions by identifying and prioritizing essential information. The study demonstrated an improved performance in educational and information retrieval contexts through targeted content extraction [9].

Arbaaeen and Shah conducted a comprehensive survey on NLP-based question answering techniques, covering traditional rule-based methods to advanced deep learning models. Their work categorized QA systems based on architecture, data processing approaches, and application domains. Their review highlighted current challenges and future directions for improving accuracy, context understanding, and scalability in QA systems [10].

3. Methodology

This proposed work follows a system design and evaluation approach to develop an automatic QA generation tool using DeepSeek R1 AI. The system operates without any model fine-tuning, relying entirely on zero-shot prompt engineering for generating relevant and cognitively aligned questions. The proposed system architecture is demonstrated in Figure 1.

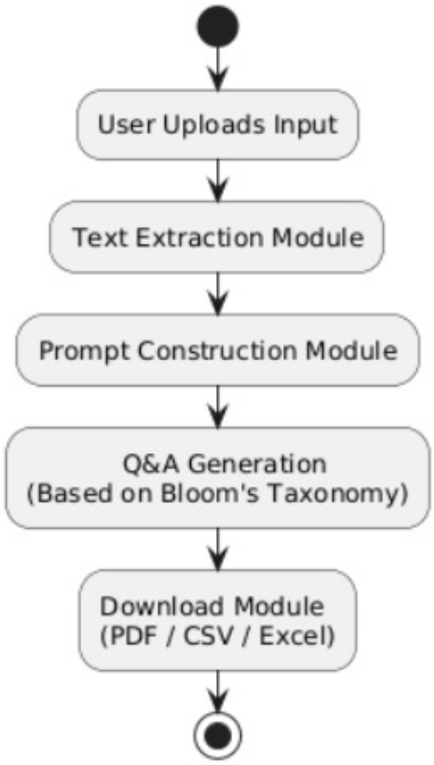

Figure 1: The Proposed System Architecture

3.1 System Architecture

The system consists of the following core components:

- **Input Layer**: This layer accepts various input forms.
- **Prompt Processor**: Converts input content into structured prompts designed to guide DeepSeek R1 in generating question-answer pairs.
- **DeepSeek R1 API Layer**: Connects to the DeepSeek R1 model for generating QA pairs in real time using a zero-shot method.
- **Frontend Interface**: A user interface for input submission and viewing generated outputs.

The system was developed using Python for backend orchestration, with DeepSeek R1 integrated via API. Testing was performed on standard hardware without GPU acceleration, demonstrating the model's effectiveness in low-resource settings.

4. Results and Discussion

The Proposed Question-Answer generation system was tested against various academic content inputs and executed on standard non-GPU hardware to validate its efficiency in low-resource environments. The evaluation focused on four key parameters like Relevance of generated questions to the input content, Cognitive diversity aligned with Bloom's Taxonomy, Accuracy of answers, System responsiveness under varying input lengths, and question counts. The system reliably delivered results within seconds, generating multi-format questions tailored to both topic content and selected Bloom levels. Unlike traditional fine-tuned models, this system requires no retraining or high-performance infrastructure, making it ideal for educational institutions with limited resources.

Sample Output:

A demonstration was conducted using a file titled **"java brief notes.pdf"**, where the system extracted content such as:

"What is Java? Java is a programming language and a platform..."

User-selected configuration:

- **Bloom Levels:** All six (Remembering to Creation)
- **Question Types:** Single Answer, Fill-in-the-Blank, Multiple Choice, Yes/No, Full Sentence
- **No. of Questions:** 30

Table 1 demonstrates the Sample Output.

Table 1: Sample Output

Bloom Level	Question Type	Generated Question
Remembering	Single Answer	What is Java?
Understanding	Full Sentence	Explain Java as a platform with an example.
Application	Fill-in-the-Blank	Java is a _______ language and a _______.
Analysis	Multiple Choice	Which of these best describes Java's architecture?
Evaluation	Yes/No	Is Java considered a fully object-oriented language?
Creation	Full Sentence	Create a sample problem where Java can be applied.

This flexibility allows educators to generate rich, cognitive-level-aligned question sets instantly, tailored to subject matter and target learners. The QA generation system achieved strong results across key educational parameters. By leveraging DeepSeek R1 in a zero-shot manner, the model efficiently generated contextually relevant questions and cognitively diverse outputs—without relying on fine-tuning or GPUs. The system supports multiple input types and empowers users to customize difficulty levels and output formats. This makes it highly suitable for deployment in online learning platforms, digital classrooms, and self-study apps. Minor limitations were observed when overly vague or abstract inputs were provided, but these can be mitigated by refining the prompts or preprocessing the text.

5. CONCLUSION

This proposed work presents an innovative, fine-tuning-free automatic question-answer generation system that leverages DeepSeek R1 AI. By utilizing prompt engineering and zero-shot capabilities, the system overcomes key limitations, including high computational cost, dependency on GPU infrastructure, and limited adaptability. The system supports multiple input formats, various question types, and aligns with all six levels of Bloom's Taxonomy, enabling cognitively rich assessments. Evaluation results demonstrated high relevance, rapid response times, and broad educational applicability—all achieved without fine-tuning or model retraining. This work presents a scalable and cost-effective tool for educators, content developers, and e-learning platforms, enabling the generation of personalized and efficient question-answer pairs across various domains. The proposed system offers a practical, deployable solution that bridges modern AI capabilities with real-world educational needs.

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