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Automatic Question and Answer Generating System

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ABSTRACT: The rising demand for automated educational tools has spurred the creation of systems capable of generating both questions and answers from text. This study presents a novel approach leveraging transformer-based models, specifically BERT and T5 model, for automatic question and answer generation. By incorporating Bloom's Taxonomy, the system categorizes generated questions into distinct cognitive levels, enhancing their pedagogical value. The T5 model questions, while BERT is extracts precise answers from the input text. Additionally, a machine learning classifier is integrated to classify the questions into Bloom's levels, ranging from simple recall to advanced analysis and evaluation. The proposed system ensures that the generated questions align with different cognitive objectives, making it a versatile tool for educational purposes. Performance evaluation is conducted using metrics such as BLEU and F1 scores, which highlight the system's effectiveness in generating meaningful and contextually accurate question-answer pairs. The integrating of deep learning techniques with Bloom's Taxonomy demonstrates the potential for scalable, adaptive educational technologies. This system contributes to the advancement of automated learning tools by offering a structured and efficient approach to generating questions and answers that align with diverse cognitive requirements.

KEYWORDS: Automatic Question Generation, Question Answering, Natural Language Processing, BERT, T5 Model, Bloom's Taxonomy, Machine Learning, Educational Technology.

I. INTRODUCTION

The rapid advancement of Natural Language Processing (NLP) and machine learning technologies has led to the development of sophisticated automatic question-answer (Q&A) generation systems. These systems play a crucial role in educational platforms, customer service, and information retrieval, offering efficient ways to generate questions and provide accurate answers from a given body of text.[1],[3],[6]. This paper focuses on the design and implementation of an automatic question-answer generation system using advanced NLP techniques, specifically leveraging transformer-based models like BERT, T5 Model, and Bloom's Taxonomy for question generation.[2],[5]

The need for automatic Q&A systems has grown in response to the increasing demand for intelligent, automated solutions across various sectors, including education, healthcare, and corporate training. These systems enable efficient content curation, interactive learning experiences, and personalized assessments, minimizing the time and effort required for manual question creation and answer retrieval. By utilizing state-of-the-art NLP techniques, the system aims to generate questions that align with Bloom's Taxonomy, categorizing questions into different cognitive levels such as remembering, understanding, and applying. [3],[4]. This enhances the educational value of the system by ensuring that the questions serve varied learning objectives.[7]

II. RELATED WORK

2.1 Rule-Based Systems

Rule-based systems generate questions by applying predefined syntactic rules to transform declarative sentences into interrogatives. For instance, Heilman et al. used patterns to form factual questions. These systems are fast and efficient for simple text but struggle with complex sentence structures.

2.2 Template-Based

SystemTemplate-based systems use predefined question templates filled with extracted information from text. Lovenia et al. demonstrated how templates and named entities can generate questions. However, this approach lacks flexibility for complex or abstract content.

2.3 Neural Network-Based Approaches

With advances in neural networks, sequence-to- sequence models, and transformers like BERT, question generation has improved significantly. These models, like the one proposed by Du et al., learn context and generate more complex questions than rule-based systems. Lee et al. further enhanced diversity with variational autoencoders.

2.4 Question and Answer Validation

To ensure accuracy, generated questions are validated by comparing the initial answer from the Answer Extraction model with the answer generated after the Question Generation and Answering steps. If they match, the question-answer pair is considered valid, ensuring coherence.

Automatic question generation (AQG) has been an area of growing interest in natural language processing (NLP) due to its applications in educational technology, assessments, and conversational AI. Early rule-based systems focused on syntactic and semantic parsing of sentences to generate questions by identifying key components such as verbs and subjects (Heilman & Smith, 2010). However, these methods were limited by their reliance on handcrafted rules, making them inflexible and unable to generalize across different contexts.

With the rise of deep learning and transformer models, automatic question generation has greatly advanced. BERT (Devlin et al., 2019) has succeeded in NLP tasks by leveraging deep bidirectional text context, though it focuses more on understanding than generation. This led to models like T5 (Raffel et al., 2020), which treats all tasks as sequence-to-sequence problems, offering greater flexibility for generating grammatically correct, contextually relevant questions.

Recent studies have also explored integrating pedagogical frameworks like Bloom's Taxonomy into question generation systems. For instance, Chinkina et al. (2017) applied Bloom's levels of cognitive complexity to generate questions aimed at assessing different learning outcomes, from simple factual recall to higher-order thinking skills. This integration is crucial for educational settings, where a variety of question types are needed to assess learners' understanding comprehensively

In addition to model-based approaches, answer generation systems have also evolved. Early systems used template-based approaches (Rus et al., 2012), which required manually crafted templates for generating answers. While these systems were precise, they lacked scalability and adaptability to diverse text inputs. Modern approaches utilize pre-trained language models, such as GPT-3 and T5, for generating and extracting answersbased on the input text, allowing for more natural and varied answer generation.

III. PROPOSE SYSTEM

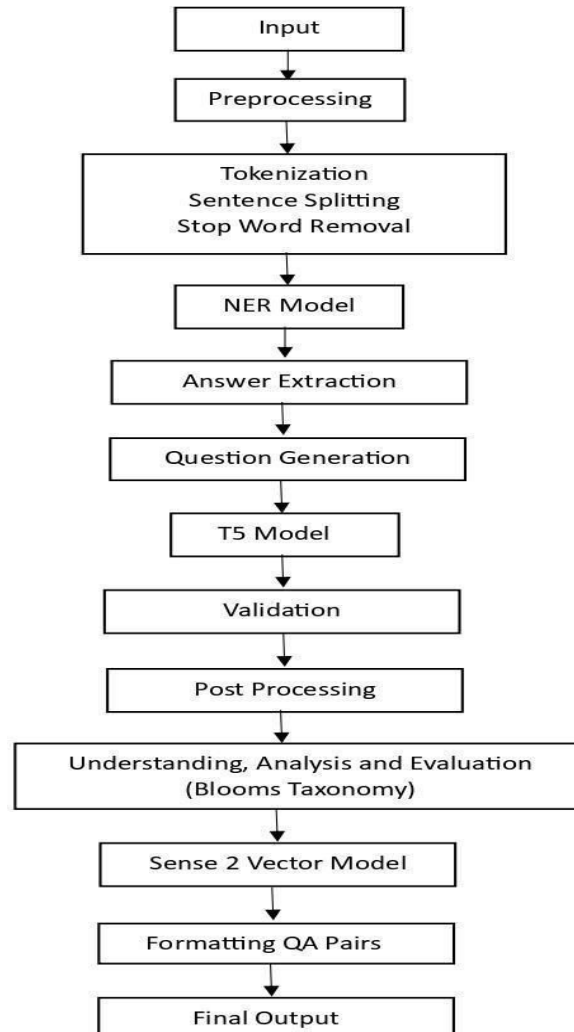


Fig3.1 System Architecture of Automatic question and answer generating system.

The automatic question and answer generation is designed to process input text through several stages to produce high-quality question-answer pairs as shown in the fig3.1. The system begins with the input module, where text data is provided by the user. It then passes through the preprocessing stage, which includes tokenization, sentence splitting, and stop word removal to prepare the text for analysis. Named Entity Recognition (NER) is applied to identify key entities within the text. Following preprocessing, the system employs a T5 model for question generation and an answer extraction module to retrieve relevant answers from the text. After generating initial question-answer pairs, the system performs **post- processing** to ensure accuracy. It further incorporates **Bloom's Taxonomy** to classify the questions according to different cognitive levels, such as understanding, analysis, and evaluation. The system also utilizes a **Sense2Vector model** to enhance the quality and relevance of the generated pairs. Finally, the **output** consists of well-formatted question-answer pairs ready for evaluation or use.

The proposed system is designed to generate various types of questions and answers from an input text using advanced natural language processing (NLP) techniques. The system comprises multiple modules that work together to achieve this goal.

3.2 MCQ-Based Question Answer Generation

This module is responsible for generating multiple-choice questions (MCQs) from a given text.

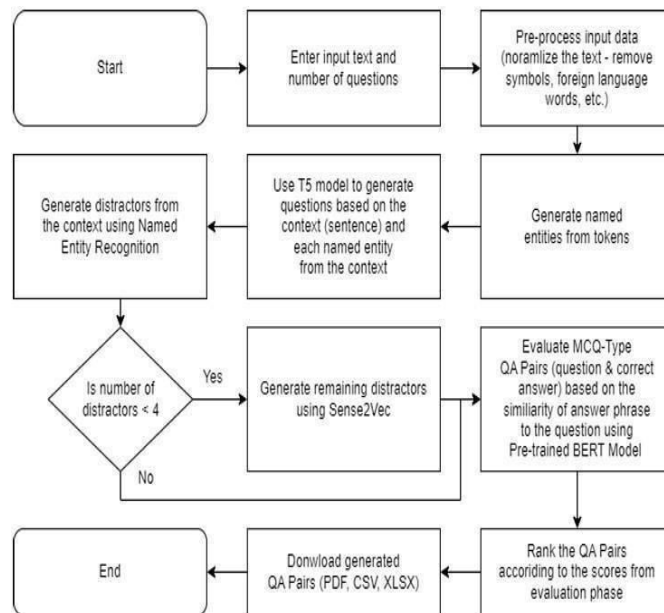


Fig 3.2 MCQ-Based Question Answer Generation Model It identifies key points in the passage and creates corresponding questions, providing several answer choices, including distractors to challenge the learner.

3.3 Wh -Type Question Answer Generation

In this module, the system generates "Wh"-type questions (e.g., who, what, where, when, why, and how) by analyzing the input text and focusing on extracting the most relevant facts.

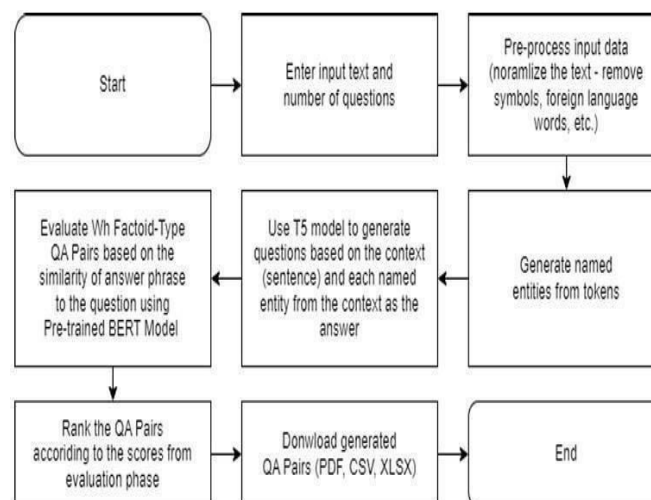


Fig 3.3 Wh -Type Question Answer Generating Model.

From followed fig3.3 This type of question helps assess a learner's ability to recall specific information from the text

3.4 Full Sentence Question Answer Generation

This module focuses on generating complete sentence questions that demand more comprehensive answers.

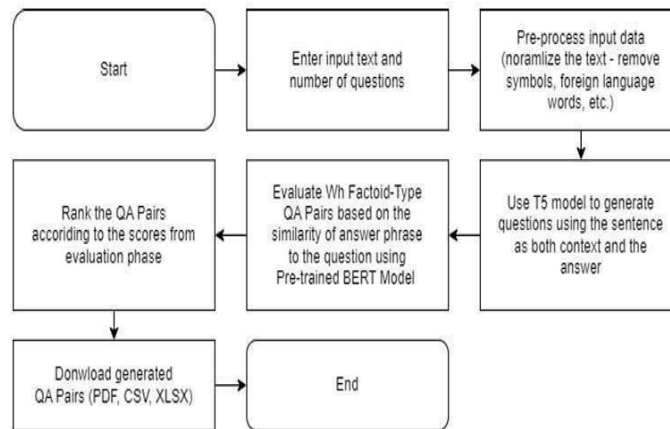


Fig 3.4 Full Sentence Question Answer Generation Model.

It ensures that the questions require a higher level of engagement and understanding of the text, promoting deeper comprehension.

3.5 Blooms taxonomy- Mapping of Questions Blooms Taxonomy

To accommodate different learning levels, the system incorporates Bloom's Taxonomy to categorize the generated questions into varying difficulty levels.

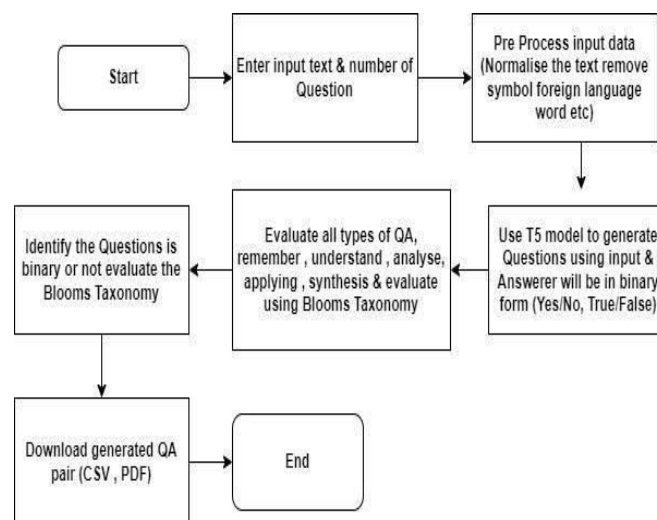


Fig 3.5 Mapping of Questions Blooms Taxonomy Model

Questions can be generated targeting simple recall (lower levels), or more complex analysis and evaluation (higher levels), ensuring that the system can support diverse educational needs.

IV. METHODOLOGY**4.1. Data Preprocessing and Text Representation**

The system begins by collecting input text data from educational materials such as articles, textbooks, or lectures. This text undergoes preprocessing, which involves removing stop words, punctuation, and irrelevant content. Tokenization is performed to split the text into smaller units (words and sentences). Subsequently, the text is vectorized into numerical representations using techniques such as Word2Vec or making it suitable for processing by machine learning models.

4.2 Question Generation

For the question generation phase, the system utilizes pre-trained models such as **T5** or **BERT** that are fine-tuned for question generation tasks. These models are able to understand the context and generate meaningful questions based on the input text. The question generation process is formulated as follows:

Q= Question Generator(C)

Where:

- Q is the generated question,
- C represents the input context (the provided text).

The model identifies key concepts in the text and formulates a question that aligns with the information provided. The generated question is designed to be semantically rich and relevant to the content, allowing for a focused query of the text.

4.3 Answer Extraction

After generating a question, the system moves on to answer extraction. This is achieved through an extractive question-answering model (e.g., T5 or BERT), which identifies the most relevant part of the input text to serve as the answer. The answer generation process is mathematically described as:

A=Answer Generator(Q, C) Where:

A is the generated answer,

Q is the previously generated question, C is the context (the input text).

The system extracts a snippet from the context that best answers the generated question, utilizing the semantic understanding provided by the pre-trained models

4.4 Evaluation of Answer Quality

To evaluate the quality and relevance of the generated answers, the system employs two key metrics: Cosine Similarity, BLEU score, and Recall.

1. Cosine Similarity: This metric measures the similarity between the generated answer and a reference answer. It is defined as:

$$\text{Cosine Similarity (A, B)} = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \cdot \|\mathbf{B}\|}$$

Cosine Similarity

Where:

- A and B are the vector representations of the generated and reference answers, respectively. A higher cosine similarity indicates a closer match between the generated answer and the reference answer.

2. BLEU Score: The **BLEU** score is used to evaluate the n-gram overlap between the generated answer and a reference answer. The formula for BLEU is

$$BLEU(r,h)=\exp(\min(1-|h||r|,0))\cdot\prod_{n=1}^N p_n$$

Here is the BLEU formula:

Where:

- r is the reference answer,
- h is the generated answer,
- p_n is the precision for n -grams, and N is the maximum n -gram length (typically up to 4- grams).
- **Recall:** Recall evaluates how much of the relevant content from the reference answer is covered by the generated answer. It is defined as:

3. Recall: Recall evaluates how much of the relevant content from the reference answer is covered by the generated answer. It is defined as:

4.

$$\text{Recall} = \frac{\text{Number of Relevant Items Retrived}}{\text{Total Number of Relevant Items in Reference Answer}}$$

4.5 Question Classification using Bloom's Taxonomy To classify the generated questions based on their cognitive complexity, the system incorporates Bloom's Taxonomy. A machine learning model, trained on labeled data, lassifies each generated question into one of the cognitive levels (e.g., Knowledge, Comprehension, Application, etc.). The classification function is given by: $CT = \text{Bloom Classifier}(Q)$

4.6 Final Output and Review

The generated questions, their corresponding answers, and the associated cognitive levels are compiled into a structured output. The system presents the results in a format that is easy for educators to review. Teachers can assess the quality of the generated questions and answers, provide feedback, and make any necessary adjustments. The system's ability to minimize human error and save time makes it an efficient solution for large-scale question and answer generation in educational settings.

V. ALGORITHM

Text Analysis and Question-Answer Generation Using NLP

1. Input: Accept a text passage as input.
2. Text Preprocessing : Tokenize the text into words or sentences.
3. Apply NLP Techniques : Named Entity Recognition (NER): Extract named entities (e.g., people, places, dates).
4. Generate Questions : Focus on entities, key terms, and main ideas from the text.
5. Generate Answers: Retrieve answers from the text passage using techniques such as Sentence matching.
6. Display Questions and Answers: Present the generated questions and their corresponding answers in a user-friendly format.
7. End Process.

VI. FUTURE SCOPE

1. Integrating advanced models like GPT or BERT for better accuracy.
2. Expanding to support multiple languages.
3. Tailoring questions based on user preferences or learning styles.
4. Handling more advanced and abstract questions.
5. May struggle with complex or ambiguous texts, leading to inaccuracies.
6. The quality of generated questions depends on the effectiveness of NLP techniques.
7. Poor or unclear input text affects output quality.
8. Current models may miss nuances or handle sarcasm poorly.

VII. CONCLUSIONS

The system shows that using the T5 model for making questions automatically is possible. It uses NLP tools like Named Entity Recognition and Sense2Vec to avoid duplicate answers. This method is useful for education, research, and business. It can help make tests automatically and improve how computers work with natural language. Although the results are good, there are still problems with making the questions answers accurate, making the system work with a lot of data, and finding better ways to measure how good the questions are. In the future the system will be improved and used with educational tools.

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