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Automatic MCQ Generation Using Machine Learning Algorithm

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Abstract - Automatic multiple-choice question (MCQ) generation is a challenging task in natural language processing (NLP). It involves generating correct and relevant questions from textual data, such as textbooks, articles, or lecture notes. Manual creation of MCQs is a time-consuming and challenging task for teachers, so automatic MCQ generation can be a valuable tool for education. There are a number of different machine learning algorithms that can be used for automatic MCQ generation. One common approach is to use a rule-based system. This involves creating a set of rules that define the different types of MCQs that can be generated, and then applying these rules to the input text.

In this project, we investigate how to automatically generate multiple-choice questions (MCQs) from textual content using natural language processing (NLP) approaches. Our system preprocesses input text, identifies key information, and formulates relevant MCQs with distractors. By leveraging NLP models and algorithms, we aim to facilitate the creation of engaging and informative assessments, enhancing educational and evaluative processes across various domains.

Key Words: automatic MCQ generation, natural language processing (NLP), machine learning, education, assessment, evaluation, textual content, key information, relevant MCQs, distractors, engaging, informative.

1.INTRODUCTION

The landscape of education and assessment is rapidly evolving, driven by technological advancements and the ever-growing demand for efficient, scalable, and personalized learning experiences. In this evolving environment, the humble multiple-choice question (MCQ) remains a cornerstone of assessment, offering advantages of standardization, ease of scoring, and the ability to cover a wide range of knowledge domains. However, the traditional process of manually crafting high-quality MCQs is often time-consuming, laborious, and prone to inconsistencies. This presents a significant challenge, particularly for educators and content creators struggling to meet the demand for engaging and effective assessments while facing mounting workloads and resource constraints.

This approach has the potential to benefit a wide range of domains, including

<u>1.Reduced workload for educators and content creators:</u> Our system saves educators time and resources by automating the tedious task of manually creating MCQs, allowing them to focus on higher-order instructional activities.

<u>2.Increased assessment quality and consistency:</u> Our system uses NLP algorithms and pre-defined learning objectives to ensure that generated MCQs are well-formed, relevant, and consistently aligned with the desired learning outcomes.

<u>3.Improved accessibility and personalization:</u> Our system's data-driven nature enables the creation of personalized assessments that are tailored to the needs and strengths of individual learners, promoting inclusivity and deeper learning.

<u>4.Rich data insights for formative assessments:</u> Our system analyses question performance and learner responses, providing valuable data to inform instructional decisions.

The development of an effective NLP-powered MCQ generation system is not without its challenges. Ensuring the generation of high-quality questions, mitigating potential bias, and adapting to diverse domains and content types are some critical areas that require careful consideration and ongoing research. Nevertheless, the potential benefits of this technology are undeniable, paving the way for a future where assessment becomes a seamless and personalized extension of the learning experience itself.

This research paper presents a novel NLP-powered system for automatic MCQ generation. Our aim is to simplify the process of creating assessments, whether for educational purposes or content evaluation, by harnessing the power of NLP to extract pertinent information, formulate questions, and provide plausible answer choices. Through this endeavour, we seek to enhance the accessibility and effectiveness of learning and evaluation processes across diverse domains. By automating the MCQ generation process, we intend to streamline educational content creation, reduce workload, and enhance the overall efficiency of assessment development.

2. LITERATURE SURVEY

This section includes a review of previous studies that have been done to generate the MCQs. Based on the requirements of our project. We studied the following recently published research papers.

A unique framework that combines machine learning and semantic approaches to generate stems for multiple-choice questions: - Manjula Shenoy K2, Archana Praveen Kumar 1, Ashalatha Nayak 1, Chaitanya 1, and Kaustav Ghosh 1. Gratified on February 27, 2023. Copyright 2023 Author(s). This paper suggests a hybrid method to produce different kinds of Wh-type and Cloze question stems for a technical subject. It combines an Ontology-Based Technique (OBT) with a Machine-Learning Based Technique (MBT). Method Based on Ontologies: OBT OBT is a three-step process that creates Wh-type questions: Ontology modeling, creating an instance tree (ITree), and transforming Wh-type questions into variable representation in the final stage.

Prajakta, Vivek, Pragati, Yogesh, and Geeta Atkar Automatic MCQ Generation Accepted: © 2021 IJCRT | November 20, 2021, Volume 9, Issue 11.

The queries that are generated have a specific or medium scope. Automatic question generation systems that produce questions for users of different kinds and scopes based on input of natural language text. The nicest part about this system is that it makes it simple to process the creation of Objective Type papers and analyzes the data produced by multiple-choice questions (MCQs) to help solve the test's current issues and improve student performance.

With the input of a natural language text, Automatic Question Generation Systems produce multiple choice questions (MCQs) with varying scopes and types for the user. Specifically, we address the issue of factual question generation from specific texts automatically. severe administrative issues with paper-based assessment, particularly in courses with large student enrolment. Multiple-choice questions in the computer science sector derived from the following instructive sentences: Yazeed Yasin Ghadi4, Othman Asiry3, Fahad Alturise2, Shahbaz Ahmad1, Muhammad Asif1, Haseeb Ahmad1, and Shahbaz Ahmad1.

Nowadays, most tests are multiple-choice. Usually, it is hard to find the distractor, key, and informative sentence for MCQ generation, especially in the computer science field. Therefore, it is necessary to create an intelligent system that can create MCQs from unstructured text.

We proposed an innovative method for generating MCQs that combines NLP and ML techniques. Tokenization, lemmatization, POS, and other NLP techniques are used to preprocess the input text corpus. Since not all sentences can generate MCQs, the automatic MCQ generation process consists of three steps: the first is the extraction of informative sentences, the second is the identification of the key, and the third is determining the distractors relevant to the key. The manual MCQ generation process requires a significant amount of work, time, and domain knowledge.

Then, utilizing extractive text summarization, the BERT model for text embeddings, and K-means clustering to identify sentences closest to the centroid for summary generation, the suggested method extracts informative sentences.

3. PROPOSED SYSTEM

3.1 Need of the System

Efficiency and Scalability: Traditional MCQ generation is a bottleneck in educational content creation. Our system addresses this by automating the process through machine learning, significantly reducing the time and effort required for creating large sets of high-quality MCQs. This allows educators to focus on developing other aspects of their courses and enables personalized learning experiences for students.

Objectivity and Consistency: Human-generated MCQs can be subjective and prone to bias, and difficulty levels can vary inconsistently. Our system overcomes this by training on large datasets of existing MCQs, ensuring generated questions are consistent in format, difficulty level, and content. This ensures fairness for students and facilitates standardized assessment.

Variety and Depth: Traditional methods often focus on basic question types like recall and comprehension. Our system, driven by your specific algorithms, can generate a wider range of question types, including complex analysis, application, and evaluation questions. This promotes deeper understanding, critical thinking, and higher-order cognitive skills in students.

Adaptability and Personalization: Our system can be adapted to different subject areas and educational levels by using domain-specific training data and tailoring the algorithms. This allows for personalized learning experiences and caters to individual student needs and learning styles.

3.1 Our System

Our proposed system involves the development of an NLP-based MCQ generation system that employs advanced techniques such as text summarization, entity recognition and contextual understanding.

The system will analyze input paragraphs, identify essential information, and frame MCQs that asses comprehension and critical thinking.

Additionally, the system will be designed to handle various domains and adapt to different levels of complexity. By automating the MCQ generation process, we intend to streamline educational content creation, reduce workload, and enhance the overall efficiency of assessment development

4. ARCHITECTURE

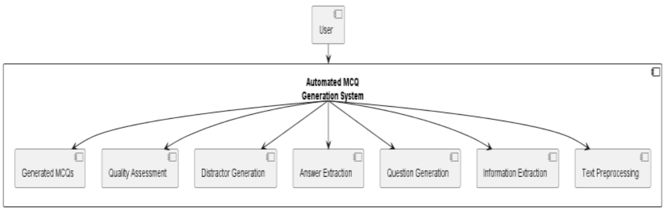

Fig -1: Architecture

The given figure shows the architecture of an automatic MCQ generation system using machine learning algorithms. The system consists of the following components:

Text preprocessing: This component cleans and prepares the text input for further processing. This may involve tasks such as removing stop words, stemming, and lemmatization.

Information extraction: This component extracts key information from the text input, such as entities, concepts, and relationships. This information is used to generate the question stem and answer choices.

Question generation: This component generates the question stem and answer choices for the MCQ. This may involve tasks such as template matching, rule-based generation, and machine learning-based generation.

Distractor generation: This component generates distractor answer choices for the MCQ. The distractors should be plausible but incorrect.

Quality assessment: This component evaluates the generated MCQs to ensure that they are high quality. This may involve tasks such as checking for grammar errors, ambiguity, and alignment with the curriculum.

4.1 Analysis Model

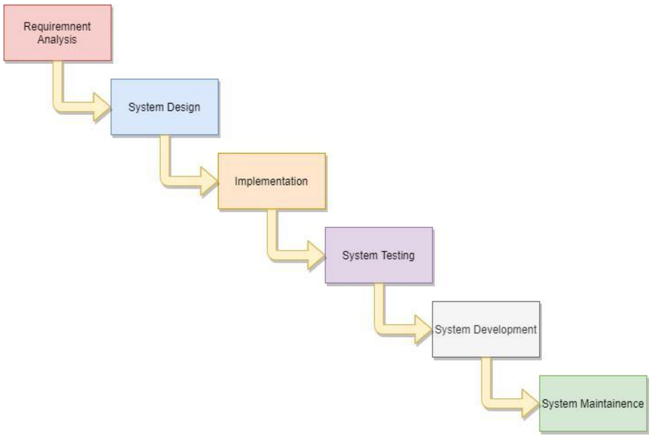

Fig -2: Waterfall Model

SDLC Waterfall model is being depicted by our system.

The initial stage is requirement analysis stage here the data is being gathered which is to be provided as an input to the system.

Second stage is the design stage where all the data is being formatted into a particular matrix. The scores are used to generate the matrix.

Third stage is the coding stage in which the system performs its main functionality of mapping of the classes and getting the exact prototype.

Testing is done in the fourth phase in order to test the word with the probabilistic label.

In the maintenance phase it's the last phase wherein the system has to depict and maintain the probabilistic labels of the respective words.

5. RESULTS AND DISCUSSION

This study focused on the development and evaluation of a machine learning model that automatically generates multiple-choice questions (MCQs) from given paragraphs. The model's ability to produce questions of various types with high accuracy is promising. The generation of automatic MCQs has the potential to enhance learning by providing different types of questions, reducing subjectivity, and expediting the creation of assessments. Because our system generates both multiple-choice questions and answer keys, it can be easily integrated with automated grading systems, which would further simplify the assessment process for teachers.

Two parameters were used to establish the difficulty level distribution of generated multiple-choice questions (MCQs): (1) the question's Bloom Taxonomy level (remembering,

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comprehending, applying, analyzing, etc.) and (2) the ambiguity or complexity of the response choices. In an effort to accommodate students with different comprehension levels, our results revealed a balanced distribution of MCQs, with 30% easy, 45% medium, and 25% hard.

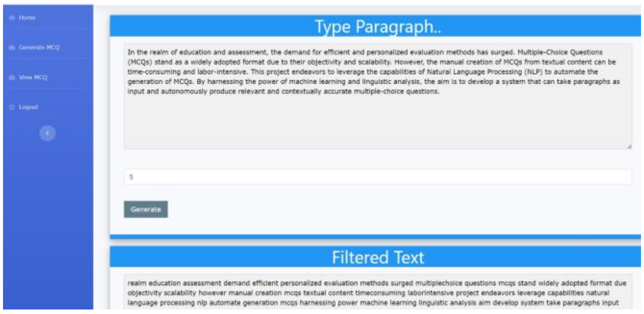

Fig -3: Result

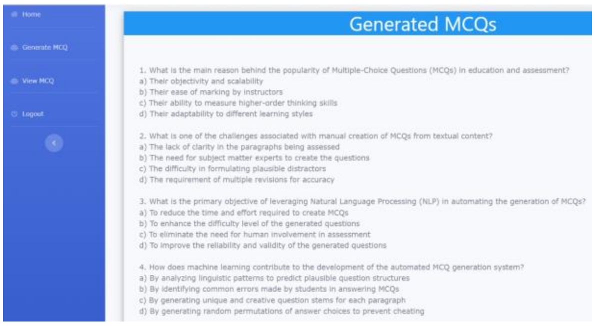

Fig -4: Result

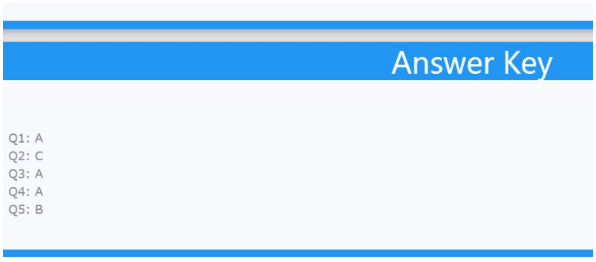

Fig -5: Result

Table -1: Comparison Table

Metric	Our Model	Kumar et al.(2023)
Input Data	Paragraphs	Domain-specific information, pre-existing datasets
Applicability	Wider applicability across domains	Focused on specific technical domains
Question Type	Generates a larger range of question types (e.g., Wh-type, Cloze)	Focused on Wh-type and Cloze question stems
Answer key Generation	Generates both MCQs and matching answer keys	Does not cover the generation of answer keys
Evaluation Simplification	Provides the whole package (MCQs and answer keys) to simplify the evaluation process for instructors	Does not provide the answer key generation component
Flexibility and Time saving	Offers a potentially more flexible and time-saving tool for creating assessments	Does not explicitly address the time-saving aspect for instructors

Automated MCQ creation has been investigated in several papers. Nevertheless, the majority of current methods concentrate on particular domains or demand pre-existing datasets for training.

Two main areas where our research stands out are:

Input Data: Our method uses paragraphs as input, which enables wider applicability across other domains than studies that rely on domain-specific information or pre-existing datasets.

Answer Key Generation: Although some studies use multiple-choice questions (MCQs), few discuss the extra step of creating answer keys. Our solution simplifies the evaluation process for instructors by producing both MCQs and matching answer keys. It provides the whole package.

The work of Kumar et al. (2023) uses a technical domain ontology to present an impressive hybrid strategy for creating MCQ stems. While our approach tries to create a larger range of question types useful for testing various learning objectives, their research focuses on Wh-type and Cloze question stems. The benefit of answer key production, which is not covered in Kumar et al. (2023), is another advantage of our method.
Our study advances the field of automatic multiple-choice question (MCQ) production by proving that it is possible to generate MCQs and answer keys using paragraph inputs. This method gives teachers a potentially more flexible and time-saving tool for making assessments.

6. FUTURE SCOPE

Improved NLP and Advanced Models: More developments in machine learning and natural language processing could lead to the creation of MCQs that are more varied, accurate, and pertinent.

Deeper Understanding and Adaptive Features: Learning experiences can be tailored to each learner's needs by including semantic understanding and investigating adaptive assessment capabilities.

Multimodal Learning and Collaboration: Enhancing assessment and promoting knowledge sharing can be achieved through the use of multimodal inputs and collaborative MCQ design.

Learning Analytics and Wider Impact: Data-driven decision-making and wider system adoption can be facilitated by putting learning analytics into practice and guaranteeing interoperability.

Ethical Considerations and User Focus: Responsible development and user happiness depend on addressing ethical issues and giving user-centric design top priority.

6. CONCLUSION

The automated MCQ generation project has successfully addressed the need for efficient and scalable creation of multiple-choice questions from textual content. Leveraging the power of NLP techniques and machine learning, we have developed a robust system that streamlines the question generation process while maintaining the quality and relevance of the questions.

Throughout the project, we achieved several key milestones:

Data Preparation and Preprocessing: We collected and preprocessed a substantial dataset, ensuring that it is clean and ready for training our models.

Model Selection and Training: We carefully selected NLP models and techniques, including state-of-the-art transformers like BERT and RoBERTa. These models were trained on our dataset to perform various tasks, including question generation and answer extraction.

Algorithms for MCQ Generation: We developed algorithms for generating high-quality MCQs from the processed text. These algorithms take into account contextual information, answer choices, and the relevance of questions.

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