www.ijbar.org
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

AI-Powered Question Generation and Learning Support

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***Abstract*-- The system has advanced capabilities such that it bears the capacity to generate different types of questions from analyzed textual content and even allows for the uploading of documents and prompts, hence rendering the question generation system comprehensive. With advanced NLP, the system extracts major concepts and creates questions in a specified format, hence, typical limitations commonly found in conventional question paper generation do not feature in this elicitation system. The existence of a chatbot for realtime support makes user interaction and support during question generation a more effective affair. It is programmed to manage individualized question banks through an SQL database, with each bank tied to a unique identifier for easy retrieval and organization. There are three user types that can use the systemadministrator, trainer, and student-allowing customized access and functionalities tailored to these user groups. The administrator operates the back end of the system, a trainer can generate and analyze student performance, and students can take assessments based on these generated question banks. This abstract encapsulates the innovative features of the system along with the advantages and possible application in educational settings, hence it becomes vital in improving the quality and effectiveness of educational assessments.**

Keywords--NLP, AI, NLTK, POS Tagging.

I . INTRODUCTION

The advancement of the education sector has enabled the need for effective and efficient means of evaluation, which is further heightened in demand. The traditionally known methods of producing question papers are very timeconsuming and prone to human error, leading to inconsistency in the quality of evaluation. To overcome these problems, we propose here the Automated Question Paper Generator employing Natural Language Processing (NLP), machine learning, and artificial intelligence to make the process of producing diverse and high-quality assessment material more optimal. Moreover, with the increasing volume of educational content in the new era, the challenges of the conventional approach to question paper preparation become more complex. The advent of electronic learning material has flooded the educators with large quantities of information to draw upon for the creation of tests. This overflow of content can lead to problems related to: spotlighting the most relevant concepts, formulating questions that would be suitably challenging, relevant to the population under test, and creating efficient but inaccurate tests within a scant time. Hence, there is a desperate need for new approaches capable of optimizing the efficiency of the question generation process without compromising on quality and relevance of tests.

To overcome these difficulties, we propose the development of an Automated Question Paper Generator using Natural Language Processing (NLP), machine learning, and artificial intelligence.The system will revolutionize the way assessment is developed by automating the question generation process-a process that can serve the dual purposes of easing the burden of instructors and enhancing the quality of assessments. Enabling the system with NLP techniques, it would understand course content, identify important concepts, and generate a number of questions in standards with learning outcomes defined. The process of completing machine learning, NLP, and artificial intelligence will enable the automated generation of questions.

II. LITERATURE REIVEW

Al-Besher[1] proposed about recent improvements in Conversational Search Systems (CSS) focus on understanding what users mean, using the context of past conversations to answer questions even when users provide minimal in-formation. Using Bidirectional Encoder Representations from Transformers (BERT), these systems calculate highly precise semantic similarity between current and past queries, thus providing substantially accurate answers without multi-turn interactions. Contextual data inference integration improves Closed-Domain-based CSS by reducing dependence on several aspects of user context and this integration increases response efficiency. This approach allows many quick, context-aware answers. Some user queries lack detail.

Barlybayev[2] proposed several automated multiple-choice question generation systems are under development to streamline the assessment process; this development guarantees quick scoring, consistent grading and shorter exam periods. Sequence-to-sequence learning improvements now directly translate several sentences from text passages into many questions and this provides a more efficient method than older, manually-ruled approaches. This method improves question generation by minimizing human error. The effectiveness of transformer models in question generation across many fields stems from improvements in neural machine translation, generalization and image captioning.

Das[3] proposed online learning's easy access to educational resources points out the need for well-executed assessment methods. Automatic Question Generation (AQG) overcomes shortcomings in manual question creation. This is achieved through NLP and ML techniques. Large recent improvements considerably improve the relevance of questions and these improvements also automate assessments using textual and pictorial data. This survey reviews several key current best practices in AQG, along with automated evaluation.

Deena[4] introduced automatic Question Generation (AQG) increases assessment efficiency by creating many objective-type questions from wide-ranging study materials. Many schools and universities are increasingly using AQG to develop superior tests with advanced NLP, thereby requiring less external assistance. Important studies highlight rule-based approaches, particularly dependency parsing, as especially effective for creating True/False, 'Wh' and fill-in-the-blank questions.Com- pelling experimental results demonstrably show AQG's meaningful effectiveness in generating an important number of high-quality, meaningful assessment questions, thereby substantially supporting ICT as well as Clever Tutoring Systems within the educational landscape.

Fawzi[5] introduced automating the creation of educational questions will be important for expanding online education, letting learners worldwide personalize their learning and easily check their understanding. This strict study compares how well large and small language models generate educational questions. Our Small language models, through pre-training and fine-tuning, produce educational questions of comparable quality, creating lightweight models convenient for training, storage and deployment.

Koshy[6] introduces complexity obstructs access for some knowledge workers. Automated Question Generation (AQG) can close this gap and it uses several structured methods to extract some understandings. Research extensively explores advanced deep learning-based entity recognition and it also explores advanced question formulation to create highly factual, precisely relevant questions from complex relational datasets. Studies indicate that AQG exceeds many AI systems in accuracy. AQG also maintains fluency. Future work will focus on improving several AQG pipelines to better handle a wider variety of datasets.

Maity[7] proposed a model that generates remarkably diverse, contextually relevant questions and they use advanced prompting techniques such as zero-shot and chainof-thought prompting. Task-specific question generation considerably benefits from large fine-tuning. Prompt-tuning is also analytically important for this process. Wide-ranging research points out LLMs' large capacity for response evaluation, perceptive feedback and considerably streamlined assessment. Although promising, quality, cost efficiency, as well as pedagogical alignment remain difficult to guarantee.

Mulla[8] introduced an advanced chatbots, advanced automated assessments and complex conversational AI systems. Modern QG systems use text, images and videos to create questions that improve user engagement. Research categorizes many QG use cases into three types—standalone, visual and conversational—with each type supported by several datasets. This review explores progress, applications and challenges in automatic question generation.

Nguyen[9] proposed advances in natural language processing and question generation now automatically create questions from educational materials. This research explores several pipelines using text-to-text transformers (T5) and specific concept extraction models to generate and evaluate questions. Studies evaluate question quality using several information scores and automated GPT-3 ratings and they also conduct manual review; the results are promising. This review examines the strengths and limitations of NLP-based question generation in education. Future improvements for this technology are also discussed.

Wang[10] research indicates that many AQG methods use specific prompt patterns and thorough collective knowledge bases to improve question quality. Research indicates that applying these techniques to Large Language Models generates questions similar to those educators develop. AI's important potential to substantially assist teachers is supported by strong practical applications and thorough evaluations, clearly showing that both AI and teachers can effectively collaborate to improve question generation and assessment.

III. METHODOLOGY

Developing an AI-powered question generation and learning support system involves a strategic approach that begins with understanding the needs of the target users—primarily students and educators. Identifying the types of questions required, such as multiple-choice, open-ended, or fill-in-theblank, ensures the system meets various educational goals.

After defining these needs, suitable AI technologies are selected, often based on powerful natural language processing models like GPT or BERT. These models can be fine-tuned using educational datasets to enhance their ability to generate relevant, accurate, and curriculum-aligned questions.The next phase focuses on designing the system architecture, which outlines how the AI model, content database, and user interface interact. Educational materials are gathered and preprocessed to train or fine-tune the AI model effectively.

A. SYSTEM ARCHITECTURE

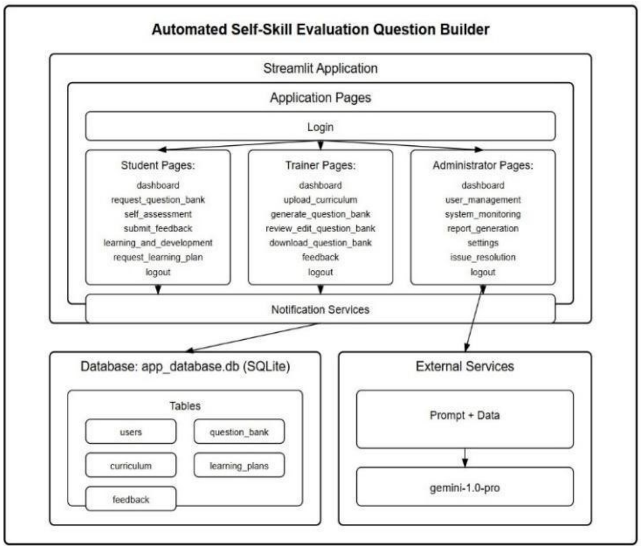

Fig1.Architecture of Diagram of AI-powered Question Generation and Learning support.

The "AI-powered Question Generation and Learning support" is certainly a Streamlit was skillfully employed for the front end, and Python was thoroughly implemented for the important backend logic. There is the Google Gemini API, in addition to the frontend and SQLite for data storage. The system follows a structure. Each method always incorporates user authentication. Each question generation is targeted, every performance tracking is continuous, with each personalization being individual recommendations.

i.User Authentication and Role-Based Access

The system uses Streamlit built-in authentication to man- age user sessions securely. Every user is redirected when logging in thereby guaranteeing, depending on the assigned role, such as Admin Trainer, or Student.

ii. Question Generation Using Google Gemini API

The Trainer system is implemented to effectively create multiple-choice questions (MCQs) through two approaches: pulling a topic from an uploaded PDF or inputting a topic manually. Once the topic is input, the Google Gemini API works on the input to produce well-organized MCQs that cover questions, multiple answer options, and the correct solutions. Trainers can check and edit the generated questions prior to saving them in the database to ensure that the content is correct, pertinent, and aligned with learning objectives. This efficient process integrates automation with human intervention to improve the quality and effectiveness of the generated questions.

iii.Syllabus Upload and Question Management

Trainers have the ability to upload every syllabus in either Excel format or as a PDF, along with many questions can be generated from reference materials. The uploaded files Trainers can organize many questions, and all of the questions are stored for later use. Banks, which are sorted by topic wise as well as difficulty levels.

iv. Exam Module for Students

Stored MCQs are available for students to access, and exams can be taken on their selected topics. The system carefully tracks student responses. It also evaluates to what extent something is working along with how it is happening. If students meet the needed criteria they can download the certifiactes automatically. Multiple certificates are produced upon completion of the program as proof certificates.

v. Personalized Question Recommendations

The system examines student performance and is dynamic. The difficulty of every question (Easy, Moderate, Hard) can be adjusted in stored SQLite data. If a student struggles a lot with some topics, the easier questions are suggested by the system. Students who are performing well, the system also increases difficulty train them appropriately.

vi. Query Resolution System

Students and also Trainers, both have the ability to raise queries to the Admin. Trainers and admins both have the ability to field many questions from all of the students. The Admin can give trainers clarifications if they ask. The full control guarantees smooth query resolutions and smooth communication from Admin.

vii. Database Management and Performance Tracking

Every login, every user interaction, all question banks, and each of the exam results, SQLite stores activities. This enables efficient retrieval and also analysis of trends in question difficulty and student progress and trainer contributions.

viii. Streamlit Based UI Design

Streamlit is used for construction of the system interface, giving each intuitive and interactive experience. Users navigate through Particular functionalities are grounded in their respective roles, thus guaranteeing an effortless operation. Admins, Trainers, and Students will have seamless experience.

B. IMPLEMENTATION

Developing an AI-powered question generation and learning support system involves several key steps.

a. Identify users and types of questions.
b. Choose appropriate AI/NLP models.
c. Design architecture (UI, backend, database).
d. Collect and prepare educational content.
e. Train AI models.
f. Backend handles requests; frontend manages user experience.
g. Conduct testing and debugging.
h. Deploy and maintain.

IV. RESULTS AND ANALYSIS

The results of the project primarily yield performance insights regarding users, assessment trends, and areas that need improvement. This included reports on employee performance, tracking of individual progress, and feedback analysis. Such insights could be made to have a holistic view of user engagement, learning patterns, and what areas, if any, need intervention for improved performances overall.

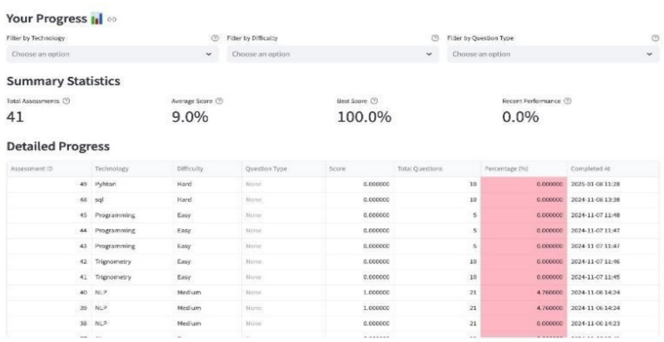

Fig1.Summary Statistics of a user

Fig1 summarizes the user assessment. The summarized statistics show a total of 41 assessments, an average score of 9.0%, a maximum score of 100%, and a recent performance of 0%. In the detailed progress section, individual assessments are listed, tagged with technology used, difficulty, and completion status. A few assessments, mostly Python, SQL, and NLP, show repeated 0s. The percentage column shows in red zones where performance has been persistently poor, suggesting that they may need to revise content delivery or enhance learning support strategies.

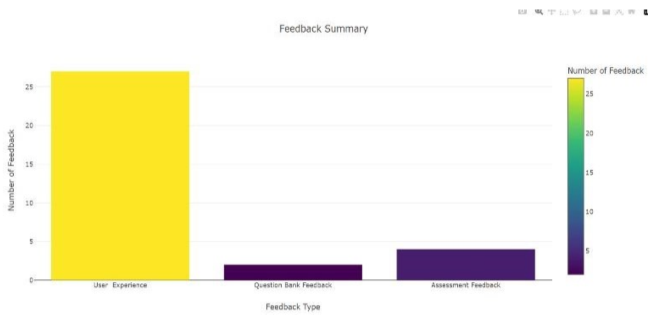

Fig2.Feedback Summary Analysis

Fig2 shows a summary of the feedback collected in several categories. Three different types of feedback are presented in this graph: User Experience, Question Bank Feedback, and Assessment Feedback. User Experience notes the most feedback, with over 25 comments, indicating a very high level of user interest when it comes to improving interaction and usability in the system. On the other hand, feedback on Question Banks and Assessments counted much less, showing somewhat reduced concern and involvement. The colour gradient scale is given on the right; yellow shows many comments, and dark purple shows a low number of comments. Prioritizing User Experience improvements, while addressing some concerns on question content and additional design aspects for assessments, is thus considered the idea.

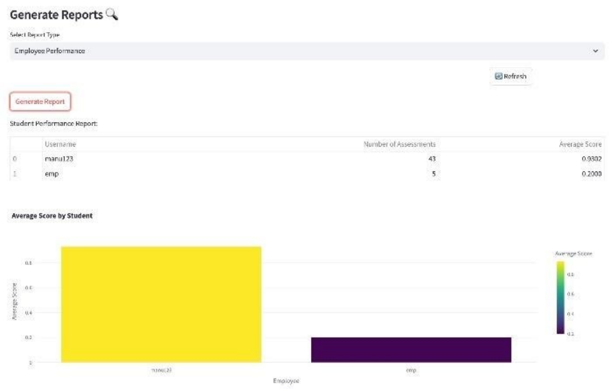

Fig3.Summary of Employees Performance

Fig3 shows further contrast in performance between users is evidenced by the Employee Performance Report. Particularly the user, "manu123," completed 43 assessments, recording a Marvelous mark of 0.9302 in average score, whereas "emp" took part in merely 5 assessments and attained an average of 0.2000. The gap between these two scores is astonishing; it indicates that "manu123," by and large, displays better understanding and engagement with the assessments. The visual bar chart reinforces this, showing quite graphically the difference in scores that exist. Such stunning insights can help to identify top achievers, while laying bare others who may need the extra bit of help.

V. CONCLUSION

The AI-Powered Question generation and Learning Support revolutionizes and transforms skill assessment using Generative AI to automatically generate personalized multiple-choice questions derived from topics or offered syllabus. This removes the manual question construction, which enables trainers to concentrate more in personalized content and feedback delivery. With Streamlit as the graphical user interface, the system provides a seamless opportunity to students, faculty, and school administrators, for the facilitation of role management, inquiry modification, and performance evaluation tracking. The system also contains difficulty-based questions generation to accommodate students' learning levels, improving engagement participation, and learning outcomes. The future outlook for this system is good, especially. The use of advanced artificial intelligence models makes adaptive learning algorithms and multimedia-based questions. These improvements can enable the system to offer even more individualized learning experiences that enable student progress on their own pace. As the system keeps on evolving, it can expand to cover the needs of various industries, i.e., corporate training and certification testing. The Automated Self-Skill Evaluation Question Builder provides an active, effective, and adaptive response to revise competency assessments, providing students with customized learning and improving the overall learning process. Skill Evaluation Question Builder provides an active, effective, and adaptive response to revise competency assessments, providing students with customized learning and improving overall learning process.

VI. FUTURE SCOPE

The future of this system will depend on whether it can evolve with improvements in AI and machine learning. First, by using more advanced AI models could improve the relevance and worth of the questions to the subject. Comprising more than multiple-choice questions (MCQs), the system can have other types of questions, like brief ones answer, fill- in-the-blank, or even essay-type questions, let asking for more rigorous assessments. Another potential improvement entails the addition of an adaptive learning method, which modifies the level of difficulty as you play based on the student's performance and his learning, be outside of the established Easy, Moderate, and Hard categories. The system can also be upgraded by adding multimedia. content, through which trainers can generate images or videos, it will assist in establishing various types of questions for assessment. Also, shifting to a larger database such as PostgreSQL may respond to performance issues as the user base grows.

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