SURVEY ON NEXT GEN AI QUESTION GENERATOR USING NLP

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ABSTRACT

This project introduces an AI-driven Question Generator Web Application built using the Flask web framework, aimed at automating the generation of educational questions from user-provided text inputs. Designed for educators, students, and instructional designers, the application streamlines the process of creating topic-specific questions, which are essential in academic assessments, quizzes, and self-evaluation tools. The system features a modular backend composed of multiple components: a Question Generator, Difficulty Classifier, NLP (Natural Language Processing) Processor, and a Question Output module. When a user submits a topic, the NLP Processor analyses the text for linguistic structure and content semantics. The Difficulty Classifier then determines the appropriate level—basic, intermediate, or advanced—based on selected preferences. The Question Generator uses this data to produce a specified number of well-formed, relevant questions. Finally, the Question Output module formats these questions for clear presentation on the user interface. The application employs Flask for its backend logic and routing, integrates CORS for cross-origin API calls, and supports RESTful communication for dynamic interactions. On the front end, the system uses HTML, CSS, and JavaScript to render a responsive interface, including a login system for user authentication and access control. Key features include real-time question generation, difficulty-level customization, and a user-friendly design. This allows users to quickly generate educational content without needing deep technical or pedagogical expertise. The use of AI not only accelerates the content creation process but also introduces a scalable, efficient approach to personalized learning tools. In essence, this project demonstrates the potential of combining AI and web technologies to enhance modern education. It stands as a proof of concept for integrating intelligent systems into practical web applications, with future potential for extension into multilingual support, adaptive learning systems, and integration with learning management Systems (LMS).

Keyword: - *AI, question generation, natural language processing, difficulty classification, Flask, web application, user authentication.*

1. INTRODUCTION

The digital transformation of education has brought forth innovative tools that enhance learning Efficiency, reduce manual tasks, and personalize the learning experience. Among these innovations, Artificial Intelligence (AI) and Natural Language Processing (NLP) play a significant role in Automating academic processes, especially in the area of question generation. Traditionally, educators Spend a significant amount of time designing and validating question papers. However, with the rise of AI-powered educational tools, this process can now be automated, more adaptive, and consistent. The proposed project, titled "Next-Generation AI Question Generator Framework using NLP", aims to address the challenges in existing systems by introducing an intelligent, adaptive, and user-friendly Framework for generating context-sensitive questions. This section outlines the project's background, its objectives, purpose, scope, and the specific problem it addresses.

2. MILESTONES

This literature survey provides a comprehensive review of knowledge-enhanced text generation, a growing research area in Natural Language Processing (NLP) that integrates external or internal knowledge into text generation models. The survey categorizes knowledge sources into internal (e.g., topics, keywords, linguistic features) and external (e.g., knowledge bases, graphs, and unstructured text), and explores how these can be incorporated into encoder-decoder architectures, learning objectives, and inference strategies. By analysing more than 80 papers, the survey highlights recent methods and applications such as dialogue systems, summarization, and question answering. It also discusses the challenges, benchmarking tools, and future directions in building more intelligent, informative, and coherent natural language generation systems.

This literature survey presents a computational model developed to automate the generation of sentence completion questions for the TOEFL exam. The system utilizes Natural Language Processing (NLP), K-Nearest Neighbor (KNN) algorithm, and heuristic techniques to process news articles and identify appropriate blank positions for questions. Key stages of the system include data preprocessing, POS tagging, feature extraction, classification of blank positions using KNN, and distractor selection based on expert-designed heuristics. The study achieved an average question quality score of 81.93%, demonstrating strong grammatical correctness, answer consistency, and distractor quality. This approach offers a scalable and efficient solution for creating high-quality language test questions in educational settings.

This literature survey provides a comprehensive review of knowledge-enhanced text generation, a growing research area in Natural Language Processing (NLP) that integrates external or internal knowledge into text generation models. The survey categorizes knowledge sources into internal (e.g., topics, keywords, linguistic features) and external (e.g., knowledge bases, graphs, and unstructured text), and explores how these can be incorporated into encoder-decoder architectures, learning objectives, and inference strategies. By analysing more than 80 papers, the survey highlights recent methods and applications such as dialogue systems, summarization, and question answering. It also discusses the challenges, benchmarking tools, and future directions in building more intelligent, informative, and coherent natural language generation systems.

The article presents an Automated Question Generator System using Natural Language Processing (NLP) libraries. It emphasizes the importance of automating question creation from text for educational and self-assessment purposes. The system utilizes popular NLP libraries like Spacy and NLTK for tasks such as tokenization, stemming, lemmatization, and POS tagging. The input text is broken into tokens and syntactically and semantically analysed to generate relevant questions. The methodology includes chunking and identifying semantic roles like subject and object. Named Entity Recognition (NER) is also applied to enhance question relevance. The system focuses mainly on generating 'wh'-type questions. It is designed for use in schools, colleges, universities, and coaching institutions. The authors also discuss the use of Bloom's taxonomy for generating questions of varying difficulty levels. Accuracy, precision, and recall metrics are used to evaluate the system's performance. Results show an average accuracy of about 70.46%. Future enhancements include better accuracy and storing generated questions for reuse.

The article “Computational Intelligence Framework for Automatic Quiz Question Generation” explores how computational intelligence and NLP techniques can be applied to automate quiz and exam question creation. It presents a framework capable of generating four main types of questions: true/false, multiple choice, fill-in-the-blank, and “Wh”-type (e.g., Who, What, When) questions. The system uses a combination of rule-based approaches and machine learning models, particularly Long Short-Term Memory (LSTM) networks, for analysing and processing text. Techniques like named-entity recognition (NER) and super-sense tagging (SST) help classify sentence components for appropriate question generation. The framework allows instructors to rank the quality and relevance of generated questions, helping improve the model’s performance over time. It also includes methods for generating distractor options in multiple choice questions using synonyms, antonyms, and domain-specific terms. Challenges such as handling technical jargon, paraphrasing, and pronoun relevance are discussed. The system was tested in real educational settings, and surveys indicated that students often could not distinguish between human- and machine-generated questions, suggesting the framework’s effectiveness.

The article titled "A comprehensive survey on answer generation methods using NLP” presents a detailed review of Question Answering (QA) systems and their advancements. It emphasizes how QA systems differ from traditional search engines by delivering direct, concise answers to user queries in natural language. The paper outlines the foundational structure of QA systems, which includes question analysis, document retrieval, and answer extraction. It discusses key challenges such as understanding question intent, handling contextual data, and enabling real-time responses. The authors categorize QA systems into four types: opinion-based, extraction-based, retrieval-based, and generative, each with unique features and limitations. Moreover, the survey explores three different methodological approaches: linguistic, statistical, and pattern matching. Various datasets and evaluation metrics like BLEU, ROUGE, and F1 scores are also described. The paper includes comparisons among multiple QA models across diverse applications, including healthcare, e-commerce, and multilingual platforms. It highlights the increasing role of deep learning and pre-trained models like BERT in enhancing QA performance. The article concludes with discussions on future directions to address current limitations and improve QA accuracy, contextual understanding, and scalability.

The article "A Survey of Natural Language Generation” provides a comprehensive overview of the field of Natural Language Generation (NLG). It begins by explaining NLG as the process of generating human-like text from structured or unstructured data. The paper discusses the significant evolution of NLG due to deep learning, especially neural encoder-decoder models and Transformers. It categorizes NLG tasks into data-to-text and text-to-text generation, covering sub-tasks like text summarization, question generation, and style transfer. The survey details general methods such as RNNs, Transformers, attention mechanisms, GANs, and pre-trained models like GPT and BART. It also explores challenges in evaluating NLG outputs, emphasizing the need for better metrics. The paper highlights datasets and benchmarks for each task and identifies future directions, including multimodal integration with vision and creativity. Overall, this survey serves as a valuable resource for understanding both foundational and cutting-edge NLG research.

The article titled “Automated Question Generator using NLP” presents a system designed to automate the generation of academic questions from textual content. It aims to reduce the time and effort educators spend creating question papers manually. The system uses Natural Language Processing (NLP) techniques like tokenization, POS tagging, and lemmatization to analyse and process input text. It focuses on generating WH-type questions (e.g., what, when, who) that align with Bloom’s taxonomy of learning. The methodology includes steps such as input pre-processing, sentence selection, and question formation. Tools like NLTK, WordNet Lemmatizer, and SpaCy are used to handle linguistic data. The proposed system addresses limitations of manual methods like inefficiency and potential data leakage. Evaluation metrics include accuracy, relevance, fluency, and diversity of questions. In testing, the system generated 654 questions from 60 input paragraphs, achieving 81.65% accuracy. Overall, the study shows that automated question generation can enhance learning assessments while saving time and resources.

The article "Automatic Question Generator Using Natural Language Processing" introduces a system that creates questions from text using NLP techniques. It helps educators save time by automating the creation of assessments like multiple-choice, fill-in-the-blank, and yes/no questions. The system uses tools like SpaCy, NLTK, and Sense2vec for processing text and generating relevant questions. Educators can input text, and the system extracts key information to form questions with correct answers and distractors. Students can use the platform to practice and assess their understanding of a topic. The system includes secure login for both teachers and students, and all generated questions are stored in a database. It supports easy access to questions by topic and type. The article also reviews related research on rule-based and machine learning approaches in NLP. The system is especially useful for exam preparation and online learning. Future improvements could include generating descriptive questions and adding automated answer-checking features.

The article titled "MCQ Generation using NLP Techniques" focuses on the development of an automated system for generating multiple-choice questions (MCQs) from video lectures using Natural Language Processing (NLP). The proposed system involves two main phases: video summarization and MCQ generation. Video content is first converted into text using speech recognition tools, and then NLP techniques such as BERT, RAKE, and T5 are applied for summarization and keyword extraction. The summarized content is used to form questions, correct answers, and distractors (incorrect options). This model significantly reduces the time and effort involved in manual question creation and is beneficial for e-assessments and competitive exam preparation. The system aims to overcome limitations of existing summarization models such as low accuracy and domain dependency. The paper also highlights how the model is trained to adapt and improve based on patterns in input data. Technologies like LSTM, CNN, and RNN are utilized to enhance semantic understanding. The automated approach not only supports educators but also helps students in quick revision and concept testing. It ultimately proposes a scalable solution to modern educational needs through intelligent automation.

The paper "The Future of Learning in the Age of Generative AI: Automated Question Generation and Assessment with Large Language Models" by Subhankar Maity and Aniket Deroy (2024) explores how generative AI, particularly large language models (LLMs), is reshaping the landscape of education. It emphasizes the automation of question generation and assessment processes, highlighting their potential to reduce the workload of educators while enhancing personalized learning. The authors delve into prompt engineering techniques like zero-shot, few-shot, and chain-of-thought prompting to optimize question quality and contextual relevance. The study evaluates the role of fine-tuning and prompt-tuning in adapting LLMs for educational purposes. It also presents use cases in automated test creation, formative assessment, and intelligent tutoring systems. The paper discusses evaluation metrics for generated questions, such as diversity, relevance, and cognitive complexity. It stresses the importance of human oversight to ensure pedagogical soundness and prevent biases in automated systems. Furthermore, the authors explore how LLMs can provide adaptive feedback and grading for student responses. They address ethical considerations, such as data privacy and academic integrity in AI-powered education. Ultimately, the paper concludes that with proper design and governance, LLMs can significantly augment educational systems, making learning more scalable, inclusive, and engaging.

The article titled "Automated MCQ Generator using Natural Language Processing" discusses the development of a system that automates the creation of Multiple-Choice Questions (MCQs) using advanced NLP techniques. The process begins by summarizing the input text using the BERTSUM model, which identifies the most important sentences suitable for question generation. Keywords are then extracted from the summarized text using the RAKE (Rapid Automatic Keyword Extraction) algorithm, and these keywords become the correct answers in the MCQs. Each keyword is mapped to its respective sentence to form a question. To make the MCQs more challenging and effective, the system generates distractors (incorrect but plausible options) using WordNet, a lexical database that helps in identifying related words through linguistic relations such as hypernyms and hyponyms. Word sense disambiguation ensures that the distractors are relevant to the context. The BERTSUM + Transformer model was chosen due to its high accuracy and efficiency in text summarization tasks. This approach reduces the manual workload for educators and is especially helpful in online and competitive exam settings. The system produces well-structured questions with meaningful distractors, improving the assessment process. The paper concludes that this automated approach is not only time-saving and cost-effective but also has the potential for further enhancement with advancements in NLP technology.

The article titled "Automated Question Generator System: A Review" explores the development and potential of systems that automatically generate questions from given text using natural language processing (NLP) techniques. It highlights the importance of question generation in educational assessments and conversational systems, particularly in the context of AI-powered assistants. The authors describe the evolution from rule-based methods to more advanced neural network-based models, emphasizing the effectiveness of Stanford POS tagging and Bloom's Taxonomy for question categorization. The proposed system allows users to input grammatically correct English paragraphs, from which relevant sentences are identified and transformed into questions. A self-attention encoder is used to address challenges in processing longer texts. The literature review outlines various machine learning and rule-based methods that have been applied to classify questions according to Bloom's levels, such as remembering, understanding, and applying. Prior research has used classifiers like SVM, KNN, and neural networks with different features and preprocessing techniques. The paper concludes that combining syntactic and semantic methods improves classification accuracy. It also suggests the adoption of hybrid approaches for better performance. Overall, the study finds significant scope for improving educational tools using automated question generation.

The article "Automatic Question Generation and Evaluation" discusses the development of a system that generates questions automatically using Natural Language Processing (NLP) techniques. The system can create two types of questions: Fill-in-the-blank (FIB) questions through machine learning methods and Wh-type questions using a rule-based approach. To prepare the input for question generation, the text undergoes preprocessing steps like tokenization, part-of-speech tagging, and named entity recognition (NER). FIB questions are formed by identifying key answer phrases within the text and generating distractor options using word embeddings and cosine similarity. Wh questions are generated based on different sentence structures, applying specific transformation rules depending on the presence of named entities or discourse markers. The system also includes an evaluation module where users can rate the generated questions based on grammar, answerability, difficulty, and contextual relevance. Additionally, Wh questions are evaluated automatically using BLEU scores by comparing them with human-crafted references. Human evaluators were involved in assessing both FIB and Wh questions to determine their effectiveness. The experimental results indicated that the system performs better with simple, assertive sentences, achieving a 59% accuracy for FIB and 49% for Wh questions. The authors conclude that although the model works well for basic sentence structures, it can be improved further through domain-specific training and the use of advanced neural network architectures

The article Introduces ArikiTurri, an automatic question generator designed to aid Basque language learning by using real corpora and NLP (Natural Language Processing) techniques. ArikiTurri can generate four types of questions: fill-in-the-blank, word formation, multiple choice, and error correction. The system operates independently from the assessment platform but integrates with tools like Makulu, which allows teachers to use, review, or edit generated questions. It relies on XML mark-up language for both input and output, ensuring flexibility and compatibility. The quality of generated questions depends heavily on the robustness of NLP tools and the richness of the source corpus. The evaluation involved expert teachers using a high-level language corpus, which showed that over 80% of the questions were well-formed and useful. The system also features modules for selecting candidate sentences, identifying answer focuses, generating distractors, and rejecting ill-formed questions. Although primarily tested with multiple choice and error correction questions, the results demonstrate that ArikiTurri significantly reduces the workload for teachers. Future plans include refining distractor generation and exploring additional question types like transformation and question answering.

The article titled "Automatic Question Generation: A Systematic Review" presents a comprehensive overview of techniques used to generate questions automatically using Natural Language Processing (NLP). It highlights the growing need for efficient assessment tools in education, especially to reduce the time and effort teachers spend on manual question creation. The authors define Automatic Question Generation (AQG) as a method of producing syntactically and semantically valid questions from various sources such as text or knowledge bases. The paper discusses multiple applications of AQG, including MOOCs, chatbots, healthcare, and customer service. Traditional methods like template and syntax-based approaches are compared with modern deep learning models such as sequence-to-sequence frameworks. The literature review categorizes AQG strategies into syntax-based, semantic-based, and template-based techniques, each with their strengths and limitations. The article also reviews significant systems and algorithms like Word2Vec, Paragraph Vector, and DrQA, and introduces reinforcement learning-based models for improved question generation. A comparative study using Bloom's taxonomy is provided to show how different methods align with educational objectives. The conclusion emphasizes the potential of AQG in educational technology and the need for ongoing improvements. Overall, the article serves as a valuable resource for understanding the development and future direction of automatic question generation systems.

The article "Exploring NLP and Information Extraction to Jointly Address Question Generation and Answering" discusses the integration of Question Generation (QG) and Question Answering (QA) using Natural Language Processing techniques. The authors developed a tool that can generate factual questions from text and answer them independently. They used Part-of-Speech (POS) tagging and Named Entity Recognition (NER) for analysing sentence structure and identifying questionable facts. Their QA component uses Information Retrieval and Open Information Extraction to locate and rank possible answers. They aimed to create a bidirectional feedback loop where QA helps validate the clarity of generated questions, and QG assists in testing the robustness of QA. The system was tested using Wikipedia-based datasets, and its outputs were evaluated by teachers on criteria like objectivity, grammar, and clarity. Results showed promising accuracy, particularly in identifying correct answers and matching relevant sentence contexts. Some ambiguity issues were noted, especially in sentences with multiple entities. Overall, the study highlights how combining QG and QA can contribute to education and automated knowledge assessment.

The article discusses the development of an Automated Essay Scoring (AES) system that integrates ontology and Natural Language Processing (NLP) to improve the evaluation of student essays. The study aims to create a more reliable and accurate scoring system by incorporating machine learning algorithms, such as linear regression, ridge regression, LASSO, and gradient boosting regression. Features like grammar, spelling, word count, and domain-specific concepts are used to enhance prediction accuracy. A key component is the use of Bloom's Taxonomy for automatically generating and classifying essay questions based on cognitive levels. The research utilizes datasets including the Kaggle ASAP dataset and actual student essays from Human-Computer Interaction courses. Results showed that gradient boosting regression had the highest accuracy and reliability, with a Cohen's Weighted Kappa score of 0.659, indicating strong agreement with human graders. Ontology engineering plays a central role in identifying domain concepts within essays to support scoring. Furthermore, the system's usability was evaluated by faculty members, who found it satisfactory. This study contributes to reducing subjectivity in grading and saving educators' time. Overall, the research highlights how machine learning and NLP can enhance the educational assessment process effectively.

The article presents a comprehensive literature review of Automatic Question Generation (AQG) systems, emphasizing the integration of Natural Language Processing (NLP) techniques to automate the generation of exam questions. It highlights the manual effort required by educators to create questions and suggests AQG as a time-saving alternative. Various systems and methodologies are discussed, including Cloze Question Generation, discourse-based question formation, and Bloom's taxonomy-based templates. NLP tools like Named Entity Recognition (NER) and Semantic Role Labeling (SRL) play a key role in identifying question types and generating relevant content. The review explores different formats such as multiple-choice questions (MCQs), WH-questions, and gap-fill questions, applied across domains and even languages like Punjabi. Some systems incorporate semantic analysis, artificial immune systems, and domain-specific ontologies for more accurate question generation. Evaluations are performed using metrics like precision, recall, and Cohen's Kappa to assess linguistic and semantic quality. The research also explores multimedia-based question generation using video and images for educational enhancement. In conclusion, the paper acknowledges the promising progress of AQG systems but notes the need for further research to improve accuracy and expand to new question formats.

The article explores the use of Natural Language Processing (NLP) and Machine Learning (ML) to semi-automatically generate programming exercises, aiming to assist educators and enhance student learning. It emphasizes the difficulty many students face in introductory programming courses and the burden on teachers to create diverse exercises. By leveraging AI models such as GPT-3, GPT-2, CodeT5, and Key-to-Text, the study analyses different approaches to generating both problem statements and source code snippets. Case studies show that while advanced models like GPT-3 offer high-quality output, they also bring challenges related to cost, infrastructure, and accessibility. In contrast, simpler models used in modular pipelines (e.g., generating the problem statement with Key-to-Text and code with CodeT5) can produce coherent results with fewer resources. The paper also categorizes different exercise types and their structural components, ensuring generated content aligns with common educational formats. Ultimately, the research supports the development of an AI-powered tool that can help both students and teachers by generating personalized and scalable programming challenges. Future work includes expanding the system with templates, a domain-specific language, and a user-friendly interface to improve accessibility and usability.

The article presents a comprehensive framework for an automatic English question generation system designed to assist in educational and dialogue-based applications. It begins by discussing the significance of question generation (QG) in learning environments and outlines the challenges in automating this task. The proposed system uses a rule-based approach driven by templates, leveraging the OpenNLP statistical parser to analyse sentence structures and generate syntactically accurate questions. It categorizes questions into types such as factoid, list, and other semantic-based forms and distinguishes between simple and complex questions. The system is structured into three main modules: training, question generation, and exam creation. During the training phase, sentences from rich text documents are tagged and processed to create templates stored in a database. These templates are later matched to generate questions from new input. The system supports both WH-questions and complete sentence transformations based on predefined remarks like time, location, or person. It allows educators to review, modify, and classify the difficulty of generated questions. Designed with scalability and usability in mind, the system facilitates efficient student evaluation while reducing the manual workload on instructors. Experimental results demonstrate the system's adaptability, speed, and potential for broader application through continuous learning and rule expansion.

The article titled "State-of-the-Art Approach to e-Learning with Cutting Edge NLP Transformers" explores the development of an interactive e-learning platform enhanced by natural language processing (NLP) techniques. With the rise of online learning during the pandemic, students face challenges in accessing and understanding vast amounts of information. The paper addresses this by proposing a system that provides automatic text summarization, question generation (including MCQs, fill-in-the-blanks, and one-word questions), and question answering. It leverages advanced transformer models like T5, BERT, and Distil BART for these tasks due to their superior performance over traditional models like LSTM. The system architecture includes frontend development in React.js and backend services with Node.js and MongoDB, incorporating Python scripts for core NLP functionalities. Evaluation results showed that the system achieved over 79% accuracy in question generation and over 81% in distractor generation. The use of Sense2Vec, ConceptNet, and WordNet supports effective distractor creation. The project fills the gap in existing educational tools by integrating summarization and assessment into a single platform. It offers roles for both students and authors, allowing content uploads, summaries, and editable assessments. Future enhancements include score tracking, integration with platforms like Moodle, and improved interactivity for learners.

The article introduces QAssist, an AI-based Question Answering (QA) system designed to help analyze natural-language software requirements. Traditional requirements, written in natural language, are often ambiguous, incomplete, or inconsistent, making manual analysis time-consuming and error prone. QAssist uses state-of-the-art Natural Language Processing (NLP) to assist stakeholders by providing quick and accurate answers to questions about these requirements. It draws answers not only from the Software Requirements Specification (SRS) but also from domain-specific knowledge sources, which it can construct automatically when necessary. The authors also created a dataset named REQuestA, which contains 387 question-answer pairs from six industrial SRSs across three domains. QAssist applies a two-stage process combining information retrieval and machine reading comprehension using models like BERT and ALBERT. The system demonstrated high accuracy, with a recall of 90.1% and 96.5% in retrieving relevant passages from the SRS and external resources, respectively. It pinpointed correct answers with an average accuracy of 84.2%. Compared to general-purpose search engines, QAssist provides more domain-relevant and precise results. The tool and dataset are publicly available and open up new possibilities for automating quality assurance in requirements engineering.

The article "AI-Powered Text Generation for Harmonious Human-Machine Interaction: Current State and Future Directions" provides a comprehensive overview of recent developments in text generation using deep learning. It begins by tracing the evolution of text generation from template-based systems to modern neural models like RNNs, Seq2Seq, GANs, and reinforcement learning. The authors emphasize the shift from simply producing coherent sentences to generating personalized, context-aware, and emotionally intelligent content. Key applications are explored, including dialogue systems, text summarization, review generation, and image captioning. The paper discusses how dialogue systems have moved from task-based tools like Siri to more sophisticated chatbots that adapt to user personalities. In summarization and review generation, both retrieval-based and generative models are examined, with growing focus on capturing context and personalization. The article also delves into image-to-text technologies such as captioning and visual question answering, which combine computer vision and NLP. The importance of personalized text generation is highlighted as a future research direction, aiming to tailor content to individual user traits. Evaluation metrics such as BLEU, ROUGE, and word vector similarity methods are reviewed. The paper concludes by identifying challenges including data scarcity, handling ultra-long context, incorporating co-textual information, and establishing unified evaluation standards.

The article titled "Deep Learning for Source Code Modeling and Generation: Models, Applications and Challenges" provides an in-depth survey on how deep learning (DL) techniques are applied to source code analysis and generation. It begins by highlighting the success of DL in natural language processing (NLP) and discusses the similarity between natural language and programming code, which allows NLP models to be adapted for source code. The authors categorize traditional modeling techniques, such as domain-specific languages, probabilistic grammars, and n-gram models, pointing out their limitations like inflexibility and inability to capture long-term dependencies. They then introduce the encoder-decoder framework, which is central to many DL applications, and detail various deep models including RNNs, CNNs, and Transformers. The paper emphasizes the advantages of DL in automatically learning features and generalizing across tasks, as well as recent advances in attention mechanisms and memory-augmented networks. It discusses how these models are applied to tasks such as code summarization, bug detection, code completion, and program synthesis. The authors also compile key datasets used in this research area and highlight challenges such as handling out-of-vocabulary tokens and modeling code structure. Ultimately, the paper serves as a comprehensive guide for researchers and practitioners interested in applying DL to software engineering tasks.

3.CONCLUSIONS

The Next Generation AI Question Generator Framework using NLP improves how questions are Created using artificial intelligence. It uses advanced language processing techniques to generate Accurate, relevant, and diverse questions. This framework can be useful in education, exams, chatbots, And content creation. It helps save time and ensures high-quality questions. Overall, this technology Makes question generation faster, smarter, and more efficient. The proposed AI-based Question generator Framework successfully automates the creation of meaningful and contextually relevant Questions from text using NLP techniques. By integrating deep learning models, semantic analysis, and syntactic parsing, the system ensures coherence, adaptability, and scalability across various Domains

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