International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 12 Issue: 02 | Feb 2025 www.irjet.net p-ISSN: 2395-0072

AI Content Generation Technology – Survey Paper

Vaibhav Gawas, Omkar Gore, Kaustubh Indulkar, Siddhesh Jagtap, Prof. Yogita Fatangare

Department of IT Engineering, P.E.S. Modern College of Engineering, Maharashtra, Pune

---

Abstract - *This survey explores the evolving role of generative artificial intelligence (GenAI) in content creation, software development, and educational applications, synthesizing insights from current research and real-world implementations. The review emphasizes advancements in program code generation through GenAI, evaluating aspects such as accuracy, efficiency, and maintainability in comparison to human-generated code. Additionally, frameworks like GAIDE demonstrate GenAI's transformative potential in education, where it significantly reduces workload and enhances content quality for instructional design. The implications of GenAI extend across various fields including academic content development, professional writing, and SEO highlighting its dual impact as a productivity catalyst and a source of challenges related to academic integrity, ethical considerations, and quality assurance. This paper underscores the importance of strategic GenAI integration to maximize benefits while addressing potential limitations..*

Keywords: Generative AI, Content Generation, Program Code Evaluation, GAIDE, GPT models, SEO.

1.INTRODUCTION

The rapid advancement of generative artificial intelligence (GenAI) has transformed various domains, including software development and content generation. Emerging tools based on large language models (LLMs), such as OpenAI's GPT series, Codex, and specialized educational frameworks, have showcased the potential of AI to automate and enhance tasks traditionally requiring human expertise. This has led to a huge shift in how content is produced, from academic materials and instructional design to program code generation.

The impact of GenAI extends beyond simple automation; it redefines the efficiency, accessibility, and adaptability of creating complex results. Research has demonstrated that while GenAI models can produce high-quality, human-like content, their outputs vary in terms of correctness, maintainability, and computational efficiency. For example, studies comparing AI-generated code from different models reveal notable performance disparities based on the complexity of problems and the programming languages used.

In the educational sector, the demand for innovative teaching methods and tools has encouraged the integration of GenAI into course content development. Frameworks such as GAIDE (Generative AI for Instructional Development and Education) emphasize structured methodologies that leverage GenAI's capabilities for educators, addressing the need for scalable and engaging content. However, these tools come with challenges related to academic integrity and reliance on AI-generated materials.

This survey paper studies current research and findings related to GenAI applications in content and code generation. It reviews evaluations of generative models, discusses practical frameworks, and highlights the dual impact of GenAI—acting as both an enabler of innovation and a potential disruptor of established norms. The paper aims to provide a comprehensive overview of how GenAI can be effectively integrated into various fields while emphasizing strategies to mitigate associated limitations.

In the end, this AI-powered content generator aims to democratize content creation by providing users with a powerful, flexible tool that automates much of the process. Whether users are looking to generate social media posts, blog articles, or even code snippets, this application will streamline the workflow and enable users to produce high-quality content at scale. The project bridges the gap between AI capabilities and everyday content creation, offering a versatile solution for a wide range of industries and individuals.

2. LITERATURE SURVEY

1. The study by Sangita Pokhrel, Shiv Raj Banjade [1] explores a content generation tool leveraging GPT-3 for producing high-quality outputs for blogs, social media posts, and other text content. The tool's use of an RNN architecture enhances predictive accuracy compared to traditional rule-based systems. While the tool improves content creation efficiency, challenges remain regarding ethical implications and maintaining audience relevance.

2. Ethan Dickey , Andres Bejarano [2] explain how GAIDE framework introduces a structured method for educators to integrate GenAI, such as ChatGPT 3.5 and 4.0, into curriculum design. It helps streamline content development, reducing workload and improving material quality. While early results show promise in terms of efficiency and student engagement, the study acknowledges potential issues, such as dependency on AI and occasional inaccuracies.

3. This survey YIHAN CAO, SIYU LI, YIXIN LIU, ZHILING YAN, YUTONG DAI, PHILIP S. YU, LICHAO SUN [3] traces the evolution of AI-generated content, from early GANs to

advanced multimodal models like ChatGPT and DALL-E. It covers foundational generative techniques across text and image modalities, along with challenges such as content authenticity and ethical concerns. The survey underscores the significant impact of transformer-based models and RLHF in advancing multimodal content generation.

4. This paper Baskhad Idrisov ,Tim Schlippe [4] compares AI-generated code with human-produced code, evaluating their correctness, efficiency, and maintainability. Using models like GPT-based Codex, ChatGPT, and CodeWhisperer, the study reveals that while GitHub Copilot achieved the highest problem-solving rate, performance varied significantly among models. It highlights that even partially correct AI outputs often require minimal adjustments for correctness, showcasing both the potential and current limitations of GenAI in coding(Research Paper 4).

5. This study GUELAILIA Redouane, BOUZIANE Mohamed [5] examines AI's impact on Search Engine Optimization (SEO), using machine learning (ML) and natural language processing (NLP) to improve ranking factors like content quality and user experience. The authors address AI's role in refining SEO strategies while also considering challenges like data privacy. AI-enhanced SEO is shown to boost search visibility and user engagement, thus supporting brand development.

6. This paper Daeseung Park , Gi-taek An , Chayapol Kamyod , Cheong Ghil Kim [6] investigates prompt engineering to enhance content generation in Korean LLMs. By introducing a Query Transformation Module (QTM) that rephrases input prompts, the authors achieved an 11.46% improvement in the naturalness and specificity of responses. Their results highlight prompt engineering's potential for improving LLM performance in conversational AI without extensive fine-tuning.

3. METHODOLOGY

3.1. Research Scope and Model Selection

This survey examines generative AI models across text, image, audio, and code domains, focusing on state-of-the-art architectures like Transformer-based models (e.g., GPT-3, GPT-4) for text, GANs for image generation, and multimodal models such as CLIP and DALL-E. These models were selected based on their relevance and proven capabilities in generating diverse types of AI-driven content [1],[3].

3.2. Data Collection and Preprocessing

Data for model training and evaluation was sourced from publicly available datasets widely used in AI content generation. For text generation, datasets such as CommonCrawl, Books, and general web datasets were used. Image generation models were trained on datasets like ImageNet and COCO, which are standard in computer vision research. Code generation relied on open-source GitHub repositories and competitive coding datasets, such as HumanEval, to provide diverse coding examples. To improve model performance and output quality, data preprocessing included filtering out noise, normalizing image data, and ensuring code data met syntax and logic standards [4], [3].

3.3. Model Training and Fine-Tuning

The selected models were initially trained on large, generalized datasets to build foundational knowledge, followed by task-specific fine-tuning to adapt to nuanced content generation needs. Fine-tuning included Reinforcement Learning from Human Feedback (RLHF) to improve coherence and relevance in text models, making adjustments based on user feedback. Additionally, reward models and task-specific adjustments were employed, especially for instructional content models, to refine responses based on desired outcomes. These fine-tuning methods helped tailor models for specific tasks, enhancing accuracy and reliability in content generation [1], [3].

3.4. Evaluation Metrics

To assess model performance across various types of generated content, we applied distinct, domain-specific metrics. Text generation was evaluated based on fluency, coherence, and relevance using metrics like BLEU, ROUGE, and human preference ratings. Image generation quality was assessed using Fréchet Inception Distance (FID) for realism and diversity, as well as prompt alignment. Audio generation quality was evaluated through spectral analysis and human assessments focused on clarity, naturalness, and similarity to human-produced audio. For code generation, metrics included correctness, maintainability (measured by cyclomatic complexity), and efficiency. These metrics allowed for a thorough evaluation of each model's quality and applicability in real-world scenarios [4], [3].

3.5. Comparative Analysis

Models were compared across both unimodal and multimodal tasks to evaluate their effectiveness, adaptability, and scalability in different content generation contexts. Consistent benchmark datasets were used to ensure fair comparisons, enabling insights into each model's strengths and limitations across various content types [3].

3.6. Limitations and Assumptions

This survey acknowledges inherent biases in training datasets and human evaluations, which can impact model output quality. Mitigation efforts included diverse dataset selection and preprocessing, although computational constraints limited testing on newer datasets. Despite these precautions, subjective biases in qualitative evaluations remain a consideration [1],[4].

4. PROPOSED SYSTEM

Proposed system is built on a microservice-based architecture, which integrates several key components.. The system consists of the following primary modules:

1.User Authentication:

We implement authentication using Clerk, a serverless authentication service that provides OAuth login options, including Google, Microsoft, and email. This ensures secure and scalable access control for users.

Upon login/signup, users are authenticated and allowed access to the core functionality of the content generation platform.

2.User Interface (UI):

The front end is structured with clear sections for navigation, including:

Home: The starting page where users can initiate content requests.

History: A log of previous user interactions, showing the content generated.

Billing: For users to manage their payment plans.

Settings: Customizable preferences for each user.

The UI sends requests to the server, where users input the content they want to generate (via user entries or pretext).

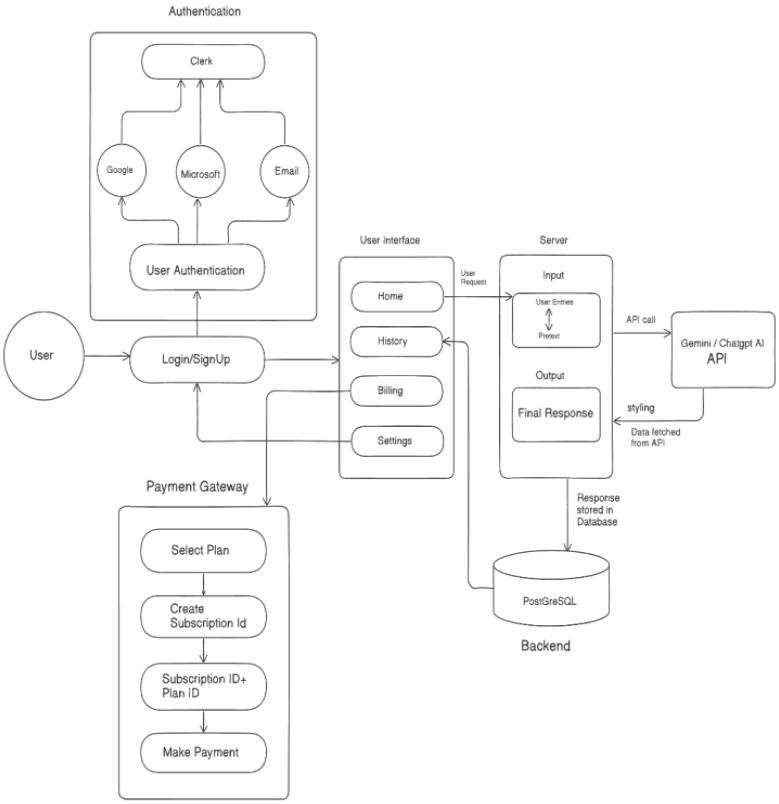

Fig -1: System Architecture

3.Server-Side Processing:

The core of our AI content generation lies in the server, where user input is preprocessed and sent to AI models via an API.We use APIs such as Gemini or ChatGPT AI to generate content based on user inputs. The response from these APIs is then formatted and styled according to predefined rules.

PostgreSQL is used to store user interaction history and responses for easy retrieval on the UI.

4.Payment Gateway:

To monetize the service, we have integrated a subscription-based payment system. The workflow is as follows:

Users select a plan.

A Subscription ID and Plan ID are created.

The user is directed to the payment gateway to complete the transaction.

Upon successful payment, the user is granted access to premium features.

5.Data Collection and Preprocessing

The content generated by the AI models is based on dynamic user inputs. We utilize various APIs like ChatGPT or Gemini

AI to process and generate human-like content. The data flow involves:

User Inputs: The user provides pretext or specific keywords, which are sent via an API call to the selected AI model.

Preprocessing: User inputs are sanitized to remove any unwanted characters or injections. This preprocessing ensures clean and accurate inputs are sent to the AI models.

API Responses: The API returns a structured response which is then styled and formatted as per the application's requirements.

6. Algorithms Implemented

The AI model used behind the scenes is based on state-of-the-art NLP models like GPT (Generative Pre-trained Transformer) from OpenAI or other equivalent large language models (LLMs). These models are pre-trained on massive corpora of text, enabling them to generate coherent and contextually relevant content.

The algorithms handle text generation tasks by:

Parsing user input.

Utilizing transformer architectures to predict the next word sequence based on context.

Generating content with fluency and relevance to the user's request.

4. CONCLUSIONS

This survey underscores the transformative potential of generative AI (GenAI) in fields like content creation, software development, and education. By automating complex tasks, GenAI enhances efficiency and accessibility, as seen in tools for code generation and frameworks like GAIDE for academic content development. However, GenAI's widespread use also presents challenges, including quality assurance and ethical considerations. As GenAI technologies advance, addressing these limitations through strategic safeguards will be essential for responsible application, allowing GenAI to maximize its impact as a valuable, trustworthy tool across diverse domains.

REFERENCES

[1] Pokhrel, Sangita & Banjade, Shiv. (2023). AI Content Generation Technology based on Open AI Language Model. Journal of Artificial Intelligence and Capsule Networks. 5. 10.36548/jaicn.2023.4.006..

[2] Dickey, E., & Bejarano, A. (2023). GAIDE: A Framework for Using Generative AI to Assist in Course Content Development. ArXiv. https://arxiv.org/abs/2308.12276Lee, Mina, Megha Srivastava, Amelia Hardy, John Thickstun, Esin Durmus, Ashwin Paranjape, Ines Gerard-Ursin et al. "Evaluating human-language model interaction." arXiv preprint arXiv:2212.09746 (2022).

[3] Cao, Y., Li, S., Liu, Y., Yan, Z., Dai, Y., Yu, P. S., & Sun, L. (2023). A Comprehensive Survey of AI-Generated Content (AIGC): A History of Generative AI from GAN to ChatGPT. ArXiv. https://arxiv.org/abs/2303.04226

[4] Idrisov, B.; Schlippe, T.Program Code Generation with Generative AIs. Algorithms 2024, 17,62. https://doi.org/10.3390/a17020062.

[5] Redouane, G. U. E. L. A. I. L. I. A., & Mohamed, B. O. U. Z. I. A. N. E. Enhancing Search Engine Optimization through Artificial Intelligence.

[6] D. Park, G. -t. An, C. Kamyod and C. G. Kim, "A Study on Performance Improvement of Prompt Engineering for Generative AI with a Large Language Model," in Journal of Web Engineering, vol. 22, no. 8, pp. 1187-1206, November 2023, doi: 10.13052/jwe1540-9589.2285.