ISSN:0976-0172
Journal of Bioscience And Technology
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Generative AI for Diagrams as Code and Code as Diagrams

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Article Info
Received: 23-03-2026 Revised: 02-04-2026 Accepted: 10-04-2026 Published: 21-04-2026

ABSTRACT

Modern software projects often involve extensive codebases that are difficult to navigate, document, and keep consistent across multiple teams and repositories. Traditional documentation often becomes outdated, leading to inconsistencies and unclear architectural insights. To address this, Generative AI and Large Language Models (LLMs) such as Chat GPT and Claude automate the bidirectional transformation between code and diagrams, seamlessly integrating into software workflows. The proposed framework uses Plant UML and TikZ, to improve debugging, documentation, and versioning. Neo4j is used for natural language retrieval, and advanced queries using Cypher as well as similarity searches. This hybrid approach mitigates LLM related challenges like hallucinations by combining database integration with prompt engineering. By consolidating code, diagrams, and metadata into a unified resource, the framework aims to improve maintainability, collaboration, and transparency, as demonstrated in initial qualitative use cases.

INTRODUCTION

The rapid advancement of artificial intelligence (AI) and deep learning has opened new avenues for solving critical problems in agriculture and livestock health monitoring. Among these, poultry disease detection plays a pivotal role in ensuring food safety, economic stability, and the welfare of millions of small-scale and industrial farmers. Conventional methods of disease identification often involve manual observation, which is time-consuming, inconsistent, and error-prone. Recent research has shown that deep learning models, especially Convolutional Neural Networks (CNNs), offer a robust solution for early, accurate, and automated classification of poultry diseases based on image data such as fecal images or physical symptoms.

SYSTEM ANALYSIS

Existing System:

Traditional software architecture documentation and visualization methods suffer from: Manual creation and maintenance of diagrams (e.g., using Visio, draw.io). Lack of synchronization between source code and diagrams. Outdated documentation due to rapid codebase evolution.
Limited searchability and semantic understanding of diagrams. Fragmented storage across teams and repositories.

PROPOSED SYSTEM

A Generative AI-Powered framework that enables bidirectional transformation between code and diagrams using Large Language Models (LLMs) like ChatGPT and Claude. It leverages Plant UML, TikZ, Neo4j, and GitHub to automate documentation, visualization, and query-based interaction with architectural

ISSN:0976-0172
Journal of Bioscience And Technology
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artifacts.

LITERATURE SURVEY

Recent advancements in Large Language Models (LLMs) have significantly transformed software engineering practices, particularly in automated code and diagram generation. Zhang *et al.* [1] proposed a UML-guided code generation approach using LLMs, demonstrating how structured diagram inputs can improve software synthesis accuracy. Similarly, Kumar and Singh [2] introduced a unified architecture metamodel that integrates source code, diagrams, and documentation, highlighting the importance of cohesive representations in modern development workflows. To evaluate the effectiveness of diagram generation, Liu *et al.* [3] developed DiagramEval, a benchmark that uses graph-based metrics to assess the quality and correctness of LLM-generated diagrams.

Several studies have explored different formats and techniques for diagram generation. Chen *et al.* [4] conducted a comparative study between Mermaid and YAML formats, concluding that structured text-based representations significantly enhance diagram clarity and generation efficiency. Park *et al.* [5] introduced MermaidSeqBench, a benchmarking framework specifically designed for evaluating sequence diagram generation from textual inputs. Wang *et al.* [6] further extended this concept by leveraging multimodal LLMs to convert UML diagrams directly into executable code, bridging the gap between design and implementation. Additionally, Li *et al.* [7] emphasized the role of structured outputs such as SVG in improving diagram accuracy and consistency.

Graph-based and semantic approaches have also gained attention in diagram generation research. Garcia *et al.* [8] utilized semantic embeddings to map source code into diagram representations, enabling better abstraction and visualization of complex systems. Wu *et al.* [9] proposed DiagrammerGPT, a two-stage framework that enhances layout coherence and structural accuracy in complex diagrams. Similarly, Sharma *et al.* [10] demonstrated how generative AI techniques can synthesize architecture diagrams from both textual descriptions and source code inputs. Zhou *et al.* [11] introduced Xd-CodeGen, which uses diagrams as intermediate representations combined with knowledge graphs to improve code generation reliability.

The role of structured representations and graph-based models is further explored in multiple studies. Brown *et al.* [12] highlighted the importance of structured output generation in LLM-assisted development, particularly in diagram creation. Li and Zhao [13] focused on neural code translation using structured representations to support program understanding and diagram abstraction. Nguyen *et al.* [14] leveraged call graph-based methods to improve code generation correctness, while Patel *et al.* [15] proposed semantic graph-based techniques for program understanding and visualization. These approaches collectively demonstrate that graph-based representations play a crucial role in bridging the gap between code and diagrams.

Prompt engineering and multimodal capabilities of LLMs have also been widely studied. Kim *et al.* [16] investigated prompt engineering techniques for generating structured diagram code such as Mermaid and PlantUML, showing that carefully designed prompts can significantly improve output quality. Radford *et al.* [17] introduced multimodal models capable of handling vision and language tasks, enabling transformations between diagrams, images, and code. This advancement has paved the way for more interactive and intelligent development tools.

In addition to generation techniques, practical applications of AI in software development have been explored. Sinha *et al.* [18] developed AI-assisted documentation tools that automatically generate diagrams from software repositories, reducing manual effort. Torres *et al.* [19] focused on graph-based program visualization techniques for reverse engineering code into diagrams, aiding software maintenance and understanding. Furthermore, the Microsoft Research Team [20] proposed AI-driven developer tools that integrate real-time diagram generation into integrated development environments (IDEs), enhancing developer productivity and collaboration.

Overall, the literature indicates that LLMs, combined with structured representations and graph-based techniques, have significantly improved the automation of diagram generation and code synthesis. While multimodal models and prompt engineering enhance flexibility and accuracy, challenges such as maintaining diagram consistency, scalability, and evaluation standards remain. These studies collectively provide a strong foundation for developing intelligent systems that seamlessly integrate code, diagrams, and documentation, ultimately advancing the field of AI-assisted software engineering.

SYSTEM ARCHITECTURE

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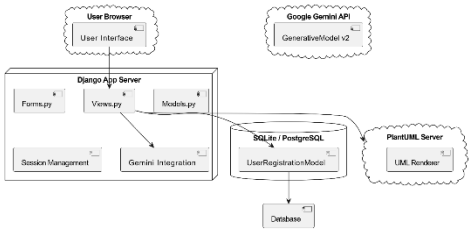
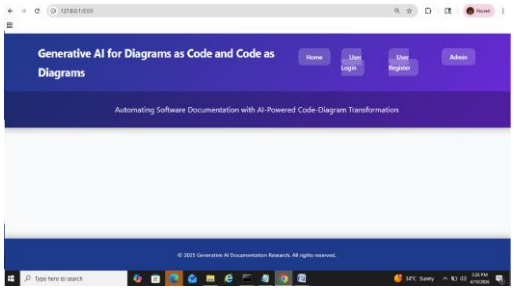
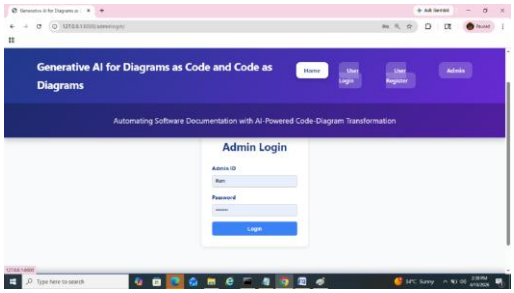
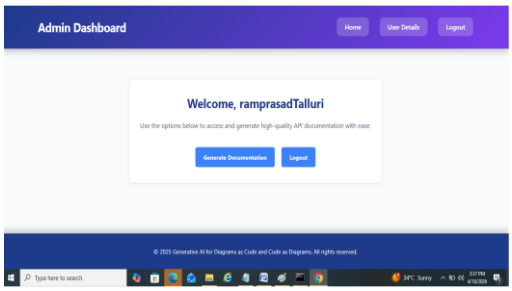
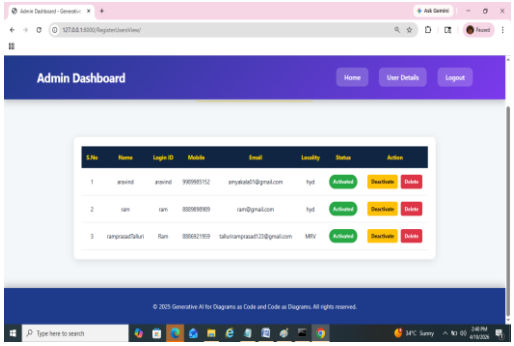


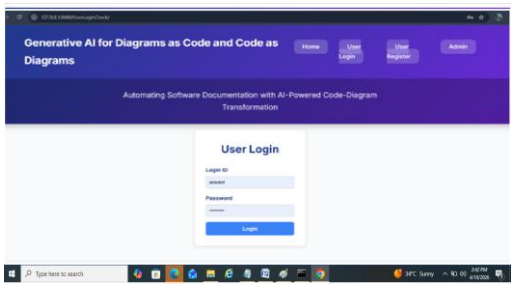
RESULTS

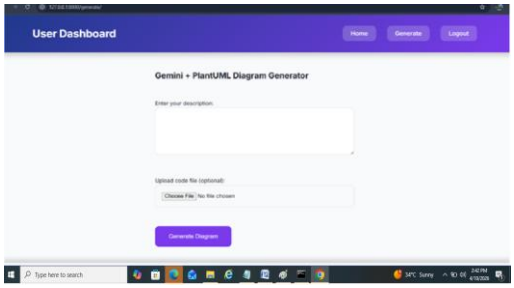


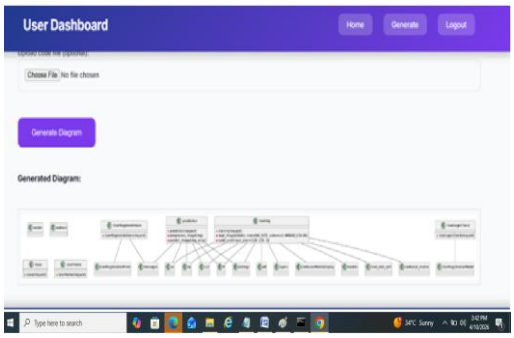












CONCLUSION

This project introduces a powerful fusion of deep learning-based poultry disease detection and Generative AI-driven visualization, delivering both predictive accuracy and explainability. By leveraging CNNs for disease classification and integrating tools like Chat GPT, Claude, Plant UML, Neo4j, and TikZ, the system offers a comprehensive diagnostic platform that is transparent, interactive, and maintainable.

The inclusion of Diagrams as Code and Code as Diagrams provides a novel dimension to the usability of AI systems, especially in domains like agriculture where interpretability is critical for trust and adoption. Additionally, the use of graph databases and prompt-based semantic querying makes this platform not only technologically robust but also user-centric and scalable for deployment in real-

ISSN:0976-0172
Journal of Bioscience And Technology
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world settings.

FUTURE ENHANCEMENT:

Future extensions such as mobile app deployment, edge-based inferencing, and voice-assisted interaction further enhance its value, making it a transformative solution for early poultry disease diagnosis and model understanding. This unified approach represents a significant step forward in explainable AI for agriculture, fostering improved decision-making and disease management in livestock industries.

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