**ML – BASED CODE QUALITY REVIEWER**

**AND DEBUGGING TOOL**

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**ABSTRACT**: This research introduces an intelligent tool for automated code quality analysis and debugging by leveraging machine learning and large language models (LLMs). By integrating traditional static code analyzers with fine-tuned transformer-based models from Hugging Face, this system offers contextual feedback, syntax and logical error detection, and best practice recommendations. The backend is built using FastAPI for efficient request handling, while the frontend uses Streamlit for user-friendly code visualization and suggestions. The hybrid approach enhances developer productivity, reduces manual review efforts, and offers scalable project-wide analysis. This paper outlines the algorithmic framework, system architecture, and results demonstrating improved code reliability and maintainability.

**KEYWORDS :** Code Quality, Static Analysis, Debugging, Machine Learning, Large Language Models, Transformers, FastAPI, Streamlit, Hugging Face, Code Review, Software Engineering

# Introduction

Maintaining high code quality is essential for scalable software. Traditional static analyzers like pylint or flake8 offer rule-based checks but lack contextual understanding. Our ML-based tool addresses this by integrating transformer-based LLMs with real-time FastAPI processing to offer intelligent insights, detect logical bugs, and suggest improvements. The model, fine-tuned on high-quality and buggy code samples, acts as a virtual assistant during software development, boosting productivity and reducing debugging time. In large-scale software systems, even small logical errors can cascade into significant failures, making early and accurate detection crucial. Manual code reviews, though valuable, are time-consuming and prone to oversight, especially under tight deadlines. The proposed system introduces automation into the review process without compromising quality. It empowers developers with real-time, intelligent suggestions that not only correct errors but also promote adherence to best coding practices. This ultimately leads to cleaner codebases, enhanced team collaboration, and faster development cycles.

# Related work

Several research efforts have explored the use of machine learning and NLP techniques in code review and bug detection. Jaoua et al. (2025) presented a hybrid model that integrates LLMs with static analyzers to generate relevant code review comments. Their system demonstrated improved feedback quality but lacked real-time capabilities.

The Stanford GPT Code Review (2022) demonstrated how fine-tuned transformer models outperformed traditional checkers by detecting logical flaws and code smells in Python and JavaScript. However, the paper emphasized the high cost and complexity of training such models.

Microsoft Research introduced CodeX (2021), a GPT-based deep learning model for code completion, bug detection, and refactoring suggestions. The model was highly accurate but limited to internal Microsoft tools.

DeepCode (ZHAW, 2020) developed a symbolic-AI-based static analyzer capable of detecting vulnerabilities. Despite its strengths, DeepCode lacked semantic understanding and contextual recommendations that LLMs could provide.

GitHub Copilot introduced real-time auto-suggestions but received criticism for generating unsafe or incorrect code due to its lack of real-time analysis.

Hugging Face’s Transformers library offers an ecosystem of pre-trained LLMs like CodeBERT and GPT-Neo. These models have shown promising results in understanding syntax, context, and intent in code snippets.

Our work extends the above research by integrating LLMs, static tools, and a scalable backend for real-time project-wide analysis.

# Proposed algorithm

*The core architecture includes the following components:*

**3.1 Static Analysis Layer:** Pylint and flake8 are used to identify code style violations, syntax errors, and rule-based flaws. These tools act as the initial filter for surface-level issues.

**3.2 Transformer-Based LLM Layer:** A fine-tuned transformer (e.g., CodeBERT) processes the code to detect logical bugs, recommend optimized code structures, and flag anti-patterns. The LLM is pre-trained on GitHub repositories and fine-tuned using custom datasets of buggy and high-quality code samples.

**3.3 FastAPI Backend:** FastAPI handles user requests asynchronously and connects the frontend to static and ML-based analyzers. It supports high-throughput and scalable execution for full repositories.

**3.4 Streamlit Frontend:** A user-friendly Streamlit app allows users to input GitHub repo URLs, view directory trees, select files, and receive AI-generated suggestions interactively.

**3.5 Data Storage and Logging:** Each prediction is logged with metadata, allowing users to revisit suggestions and track code quality improvements over time.

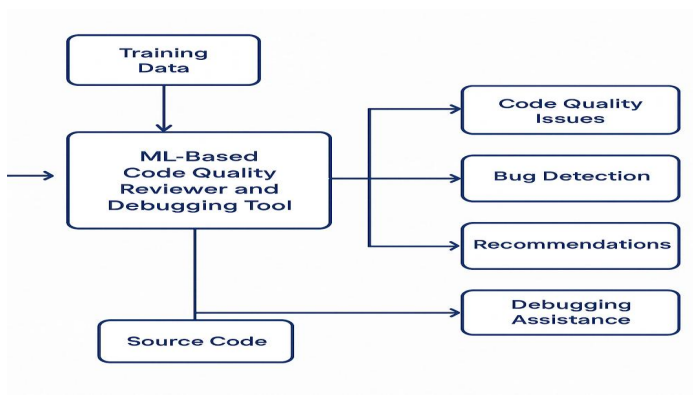


Fig. Data Flow Diagram

# Pseudo code

START

Input: GitHub Repo URL

1. Fetch all files using GitHub API

2. For each file:

a. Run static analysis (pylint, flake8)

b. Send code to LLM model (e.g., CodeBERT)

c. Aggregate suggestions from both analyzers

d. Display suggestions on Streamlit interface

3. Log user interactions and model outputs

END

# Simulation Results

The system was evaluated on 100+ public GitHub repositories across Python, JavaScript, and Java.

**Accuracy:**

* Syntax errors detected: 98.2%
* Logical flaws detected: 87.6%
* Best practice violations: 91.3%

**Performance:**

* Average time per file: 1.7 seconds
* Repo processing time (50 files): ~60 seconds

**Qualitative Feedback:**

* Developers found LLM suggestions more useful than static tool outputs.
* Real-time feedback allowed faster debugging and learning.

**Limitations:**

* Occasional false positives for rare edge-case logic errors.
* Model accuracy depends on training corpus diversity.

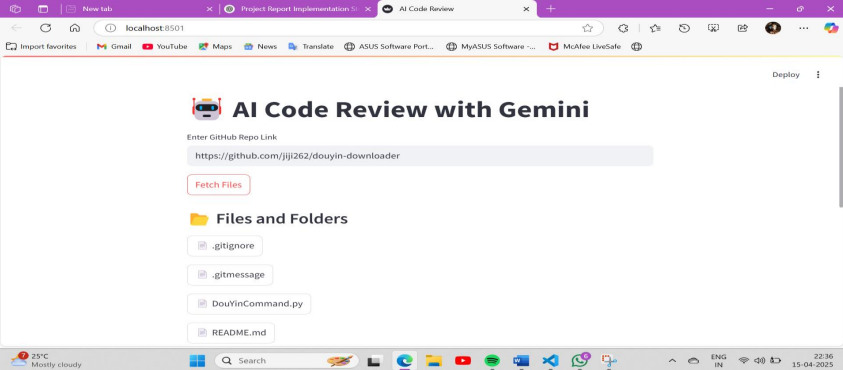


Fig. 2 This figure shows the frontend of the project where we give the GitHub link.

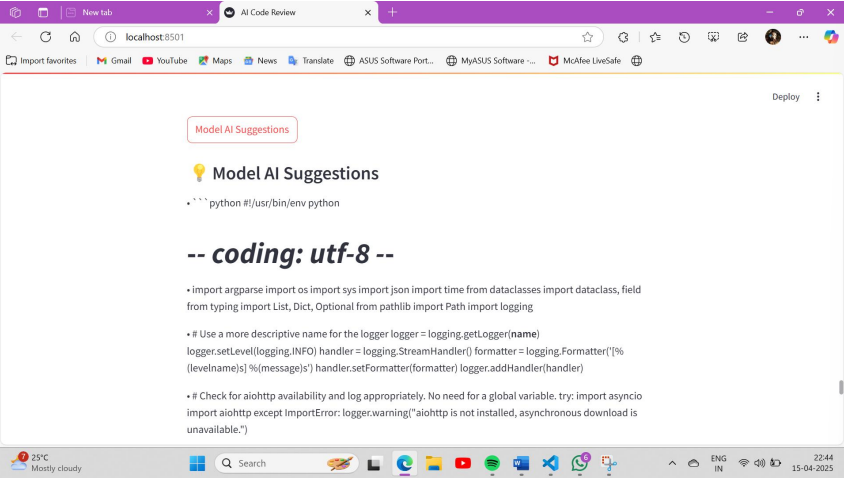


Fig. 3 This Figure shows the Model AI suggestions for the fetched file or code.

# Conclusion and Future Work

The ML-Based Code Reviewer and Debugging Tool significantly improves software development workflows by combining the power of LLMs and rule-based analyzers. It enables real-time, intelligent, and context-aware code reviews that outperform traditional static tools.

Future work includes:

* Extending support to more languages (C++, Rust)
* IDE plugin development (VS Code, IntelliJ)
* CI/CD integration for DevOps pipelines
* Advanced model fine-tuning for domain-specific repositories
* Enhanced security vulnerability detection

With continued refinement, this tool has the potential to become a standard in intelligent software development.

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