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Report on

AI DRIVEN CODE REVIEW TOOL FOR SMOOTH PULL REQUEST MERGING

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Candidate's Declaration

We hereby declare that the work presented in this project report, submitted in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology** in the Department of Computer Engineering, Aligarh Muslim University, titled **"AI Driven Code Review Tool for Smooth Pull Request Merging"**, is a record of our authentic work carried out during the **VII Semester** (August 2024 to December 2024) and **VIII Semester** (January 2025 to May 2025) under the guidance of **Prof. Mohammad Sarosh Umar**, Department of Computer Engineering, AMU.

We affirm that the matter presented in this report has not been submitted for the award of any other degree or diploma of this or any other Institute/University.

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This is to certify that the above declaration made by the candidates is true to the best of my knowledge and belief.

Prof. Mohammad Sarosh Umar
Supervisor, Department of Computer Engineering
Date: April 30, 2025

Acknowledgement

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Abstract

The AI-Driven Code Review Tool for Smooth Pull Request Merging aims to revolutionize the software development process by automating and enhancing code reviews. Leveraging a fine-tuned Llama-2-7b-chatf language model, the tool analyzes JavaScript code snippets from GitHub pull requests, identifies issues such as syntax errors, performance bottlenecks, and style inconsistencies, and provides actionable feedback to developers. Integrated with GitHub via webhooks and APIs, it listens for pull request events, extracts code changes, and posts AI-generated review comments in real-time, facilitating seamless collaboration and reducing merge conflicts.

The model is trained on a carefully curated dataset compiled from diverse programming resources, focusing on prevalent JavaScript errors to ensure robust and relevant suggestions. Evaluated on a dedicated test set, the system demonstrates strong performance with evaluation metrics (BERTScore: 0.9375, ROUGE-1: 0.8412, ROUGE-L: 0.8319). By streamlining code reviews, improving code quality, and minimizing technical debt, this tool empowers developers, reviewers, and project managers to accelerate development cycles and maintain high software standards.

Keywords

Pull Requests, Code Reviews, Github Webhooks, BERTSCore, Git Diffs, LoRA, Quantization

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Chapter 1

Introduction

Introduction

1.1 Overview

In the fast-paced world of software development, the code review process stands as a critical gatekeeper for ensuring high-quality, maintainable, and efficient code. However, traditional manual code reviews often present significant challenges, including time delays, inconsistent feedback, and the potential for merge conflicts that can stall project timelines and accumulate technical debt. As development teams grow and the volume of pull requests increases, these inefficiencies become more pronounced, underscoring the need for innovative solutions to streamline and enhance the code review process. The AI-Driven Code Review Tool for Smooth Pull Request Merging addresses this pressing need by harnessing the power of artificial intelligence to automate and optimize code reviews, delivering precise, context-aware feedback in real-time.
This major project introduces a sophisticated tool designed to revolutionize how developers, reviewers, and project managers collaborate on GitHub pull requests. At its core, the tool leverages a fine-tuned Llama-2-7b language model, meticulously trained on a curated dataset derived from diverse programming resources, with a focus on prevalent JavaScript errors. By analyzing JavaScript code snippets, the system identifies critical issues such as syntax errors, performance bottlenecks, and style inconsistencies, providing actionable suggestions that empower developers to refine their code efficiently. Seamlessly integrated with GitHub through webhooks and APIs, the tool listens for pull request events, extracts code changes, and posts AI-generated review comments, fostering seamless collaboration and minimizing merge conflicts.

1.2 Problem Statement

Manual code reviews in software development are slow, inconsistent, and resource-intensive, causing delays in pull request merging and increasing merge conflicts. Identifying JavaScript errors, performance issues, and style violations demands expertise, yet human reviewers often miss subtle problems or lack scalability for high pull request volumes. These shortcomings lead to technical debt, reduced productivity, and lower code quality. An automated, AI-driven solution is needed to integrate with GitHub, detect coding issues in real-time, and deliver consistent, actionable feedback to streamline collaboration and enhance software quality.

1.3 Motivation

The escalating complexity and scale of modern software projects demand efficient, high-quality code review processes to sustain rapid development and robust deliverables. Yet, the reliance on manual reviews often results in bottlenecks, inconsistent evaluations, and overlooked errors, particularly in JavaScript-heavy codebases where subtle bugs can have significant consequences. These challenges frustrate developers, overburden reviewers, and delay project timelines, ultimately impacting team morale and product reliability.

The vision for the AI-Driven Code Review Tool stems from the need to empower development teams with an intelligent, automated assistant that enhances productivity and precision. By integrating seamlessly with GitHub and leveraging advanced AI to provide instant, accurate feedback on code issues, this project seeks to alleviate the burdens of manual reviews, foster stronger collaboration, and elevate software quality. The potential to transform code review into a streamlined, consistent, and scalable process drives this initiative, aiming to support developers in delivering exceptional software with confidence and efficiency.

1.4 Objectives

Following are the objectives for the project:

- To develop an AI-powered code review system utilizing a fine-tuned Llama-2-7b-chatf model to automatically analyze JavaScript code snippets, detecting common errors, performance bottlenecks, and style inconsistencies with high accuracy.
- To generate precise, context-aware review comments that provide developers with clear and actionable suggestions to enhance code quality and maintainability.
- To integrate seamlessly with GitHub using webhooks and APIs to detect pull request events, extract code changes, and post AI-generated feedback in real-time, minimizing delays in the review process.
- To foster effective collaboration among developers, reviewers, and project managers by reducing merge conflicts and ensuring consistent, high-quality feedback across pull requests.
- To streamline the code review process to decrease technical debt, accelerate development cycles, and uphold high software standards for scalable, maintainable codebases.

By addressing these objectives, the project aims to transform the code review process through automation, improving efficiency, consistency, and code quality in software development. Additionally, it seeks to empower development teams with a scalable, AI-driven tool that enhances collaboration, reduces technical debt, and supports the delivery of robust software in fast-paced development environments.

Chapter 2

Background and Literature Survey

Background and Literature Survey

2.1 Background

In contemporary software engineering practices, code review stands as a cornerstone activity for ensuring high-quality, maintainable, and robust software. It typically involves manual inspection of code changes by peers or senior developers to identify defects, enhance code readability, enforce coding standards, and facilitate knowledge transfer within teams. As software projects grow in complexity and scale, the volume and intricacy of code changes subject to review increase proportionally, making manual code reviews resource-intensive, time-consuming, and occasionally inconsistent [1, 3].

The traditional model of code review, although effective, struggles to meet the demands of modern agile and continuous delivery pipelines. Developers often face review bottlenecks, delayed feature integration, and reviewer fatigue. Consequently, there is an urgent need to optimize code review practices without sacrificing quality [2].

The growing capabilities of Artificial Intelligence (AI), particularly through the advent of Large Language Models (LLMs), have introduced new possibilities. These models, trained on vast corpora of code and natural language, demonstrate impressive performance in tasks such as code generation, bug fixing, documentation, and now, code review support [4, 5]. AI-assisted code reviews offer the potential to automate the identification of coding issues, suggest improvements, ensure stylistic consistency, and even generate human-readable feedback.

Moreover, AI-based code review systems are not meant to replace human reviewers entirely but rather to augment human capabilities, enhance review consistency, reduce the cognitive load on developers, and facilitate faster and more informed decision-making during code integration processes [2, 4].

Despite these promising developments, several challenges persist. These include ensuring contextual understanding of code changes, preventing biased or incorrect suggestions, managing computational resource demands, and integrating seamlessly into existing software development workflows [5].

2.2 Literature Review

2.2.1 Traditional Code Review Practices

Manual code review has long been recognized as an effective quality assurance practice. Early studies demonstrated that peer reviews significantly reduced defect rates and improved software maintainability [1]. Typically performed post-implementation, manual reviews involve critical inspection of code artifacts for logical errors, security vulnerabilities, performance issues, and stylistic deviations.

However, as projects scale and timelines shrink, reliance solely on manual efforts becomes impractical. Research has shown that reviewer fatigue, human error, and inconsistencies in review quality can emerge, especially under tight deadlines or high PR volumes [3].

2.2.2 Early Efforts in Code Review Automation

The earliest attempts at automating code review involved the use of static analysis tools and rule-based engines. Tools such as FindBugs and PMD were designed to automatically flag potential issues based on predefined coding rules [4]. While helpful, these tools were limited to surface-level issues and lacked the ability to understand broader design patterns or contextual code intentions.
Subsequent efforts incorporated machine learning classifiers trained on labeled datasets to predict code defects. Neural Machine Translation (NMT)-based models were later explored to generate code review comments automatically, demonstrating better adaptability but suffering from limited data availability and generalization challenges [3].

2.2.3 Leveraging Large Language Models (LLMs)

The introduction of large-scale pre-trained models, such as GPT-3.5 and CodeT5, marks a paradigm shift in code review automation. These models possess substantial capabilities in understanding both syntactic structures and semantic nuances of source code [2].
Two dominant strategies emerged for utilizing LLMs in code review tasks:

- **Fine-Tuning:** LLMs are further trained on domain-specific datasets (e.g., annotated code review comments) to tailor their outputs to specific programming languages, coding standards, or organizational guidelines [2].
- **Prompt Engineering:** Carefully crafting input prompts allows the models to perform tasks in a zero-shot or few-shot manner without retraining, providing flexibility and reducing computational costs [2, 3].

Empirical studies have demonstrated that fine-tuning leads to higher performance when sufficient data is available, but prompt engineering remains a valuable approach in cold-start scenarios or when rapid prototyping is necessary [2].

2.2.4 Recent AI Tools and Architectures

Recent advancements have yielded practical AI-based code review assistants:

- **AICodeReview Plugin:** Developed as an IntelliJ IDEA extension, AICodeReview utilizes GPT-3.5 to automatically detect syntax and semantic errors, propose code improvements, and generate review explanations. It supports multiple languages and integrates seamlessly into the developer workflow [4].
- **PRHAN Model:** The PRHAN model leverages Hybrid Attention Networks (HAN) combined with Byte Pair Encoding (BPE) to automatically generate high-quality pull request (PR) descriptions [5]. It addresses the limitations of RNN-based methods, improving both efficiency and quality by using attention-only architectures.
- **AI-driven PR Merging Assistants:** Systems employing fine-tuned LLMs assist in reviewer assignment, code quality checking, and PR merging decisions, effectively reducing the time-to-merge without compromising code integrity [1].

2.2.5 Challenges and Limitations

Despite promising advancements, the deployment of AI in code review automation faces several key challenges:

- **Data Noise and Bias:** Training datasets may contain inconsistent, outdated, or biased examples, potentially leading to flawed or unfair suggestions [3, 5].
- **Contextual Understanding Limitations:** Current LLMs, while powerful, sometimes fail to grasp complex project-specific contexts or subtle architectural patterns [4].
- **Resource Constraints:** Fine-tuning and operating large models require significant computational resources, posing a barrier for smaller organizations [2].
- **Evaluation Metrics Limitations:** Traditional metrics like ROUGE and BLEU may inadequately capture the true effectiveness and relevance of generated code review comments, necessitating more nuanced evaluation frameworks [5].

Thus, ongoing research is needed to refine AI models, enhance their interpretability, ensure fairness, and develop better evaluation standards for AI-assisted code review systems.

Chapter 3

Proposed Design & Architecture

Proposed Design & Architecture

3.1 Prerequisites

This section explores four fundamental components that underpin the AI-Driven Code Review Tool: pull requests, GitHub webhooks, large language models, and code diffs. Together, these technologies enable the automation and enhancement of the code review process, fostering efficient collaboration, higher code quality, and more dynamic software development workflows.

3.1.1 Pull Requests

Pull requests (PRs) are a cornerstone of collaborative software development. They provide a structured mechanism for proposing, discussing, and integrating changes into a shared codebase. Originating from distributed version control systems like Git, PRs are widely used on platforms such as GitHub, GitLab, and Bitbucket.

Purpose and Workflow

The primary objective of a pull request is to facilitate a collaborative review process before changes are merged into the main branch. The typical workflow includes:

- A developer creates a feature branch and implements changes.
- A pull request is opened against a target branch, usually `main` or `develop`.
- Team members review the proposed changes, offering feedback, suggesting improvements, or requesting modifications.
- Upon approval, the changes are merged into the target branch.

Benefits

- **Quality Assurance**: Enforces code reviews to catch bugs early.
- **Knowledge Sharing**: Distributes knowledge across the team.
- **Audit Trail**: Provides historical records of code evolution.
- **Discussion and Collaboration**: Encourages peer discussion on implementation strategies.

However, manual pull request reviews can be time-consuming and are prone to human error, motivating the integration of automation tools.

3.1.2 GitHub Webhooks

Webhooks are user-defined HTTP callbacks triggered by specific events. GitHub webhooks allow repositories to communicate with external systems in real time.

Mechanism

When a configured event (e.g., a pull request creation) occurs in a repository, GitHub sends an HTTP POST payload to the specified server endpoint. This payload contains structured data describing the event.

Configuration

Setting up a webhook typically involves:

- Specifying the endpoint URL to receive webhook payloads.
- Selecting the events that trigger the webhook, such as `push`, `pull_request`, or `issues`.
- Optionally securing the webhook using a secret token to validate payloads.

Applications

- **Continuous Integration/Deployment (CI/CD)**: Trigger builds and deployments.
- **Automation**: Launch automated code review, testing, or analysis.
- **Monitoring**: Track repository activities for reporting or alerting.

Webhooks are vital for creating responsive and automated workflows, enabling instant actions based on repository activities.

3.1.3 Large Language Models

Large Language Models (LLMs) are advanced AI systems capable of understanding and generating human-like text. Trained on massive corpora of text data, they are adept at a wide range of tasks, including natural language understanding, translation, summarization, and code analysis.

Characteristics

- **Scale**: LLMs have billions of parameters, enabling them to capture complex linguistic patterns.
- **Training Data**: Sourced from books, articles, websites, and code repositories.
- **Capabilities**: Text generation, sentiment analysis, code completion, question answering, and more.

Role in Code Review

In the context of this project, an LLM — specifically the Llama-2-7b-chatf model developed by Meta AI — is fine-tuned to:

- Analyze code snippets for errors and vulnerabilities.
- Suggest improvements and optimizations.
- Provide contextual feedback tailored to JavaScript projects.

Llama-2-7b-chatf Model

The Llama-2-7b-chatf model comprises 7 billion parameters, offering a balance between computational efficiency and performance. It has been adapted to excel in code-related tasks, making it suitable for real-time code review applications.

3.1.4 Code Diffs

Code diffs represent the differences between two versions of a file or a codebase. They are essential for understanding changes introduced in pull requests and form a crucial input for automated code review systems.

Structure

A typical code diff highlights:

- **Additions**: Lines added to the codebase, often marked with a `+` symbol.
- **Deletions**: Lines removed from the codebase, often marked with a `-` symbol.
- **Context**: Surrounding unchanged lines to provide situational awareness.

Generation

Version control systems like Git automatically generate diffs using commands such as `git diff`. These diffs can be visualized in plain text, color-coded formats, or graphical interfaces.

Importance in Automation

For an AI-Driven Code Review Tool, code diffs:

- Serve as input data for LLMs to analyze.
- Enable targeted feedback focused only on new or changed lines.
- Reduce the complexity of analyzing entire files by narrowing the scope.

By interpreting diffs, the AI system can provide more efficient and contextually relevant review comments.

3.1.5 Summary

Pull requests, GitHub webhooks, large language models, and code diffs are integral components of a modern, automated code review pipeline. Their synergy facilitates more efficient, scalable, and accurate code reviews, contributing significantly to the advancement of collaborative software engineering practices.

3.2 Software Requirements Specification (SRS)

3.2.1 Introduction

Purpose

The purpose of this document is to define the requirements for the AI-Powered Pull Request (PR) Reviewer system. It will automate code review processes by analyzing pull request diffs, identifying potential issues using machine learning models, and providing intelligent feedback to developers.

Scope

The system will integrate with Git-based repositories (e.g., GitHub) to automatically review PRs using pre-trained language models (e.g., Llama). It will parse code diffs, classify code quality, and generate inline suggestions or summary feedback through GitHub API.

Definitions, Acronyms, and Abbreviations

- PR: Pull Request
- NLP: Natural Language Processing
- API: Application Programming Interface
- UI: User Interface
- ML: Machine Learning
- LLM: Large Language Model
- CI/CD: Continuous Integration / Continuous Deployment

References

- GitHub API Docs
- IEEE SRS Standard 830

Overview

This SRS describes the functional, non-functional, and interface requirements of the system along with design constraints.

3.2.2 Overall Description

Product Perspective

- This system will function as an automated reviewer bot integrated with GitHub, similar to existing CI tools, but with AI-based reasoning.

Product Functions

- Fetch PR diff via webhook
- Parse and tokenize code changes
- Run classification model
- Generate feedback comments
- Post feedback to GitHub

User Classes and Characteristics

- Developer: opens PRs, receives feedback
- Maintainer: oversees reviews, configures the bot
- Admin: deploys and monitors the model backend

Operating Environment

- Backend: Spring Boot, Ngrok
- AI Model: GPT, Llama
- GitHub Integration: via REST API and webhooks

Design and Implementation Constraints

- GitHub API rate limits
- Token limits for model input
- Real-time latency requirements

User Documentation

- Developer Guide (README)
- Admin Deployment Manual
- API Reference (OpenAPI/Swagger)

Assumption and Dependencies

- Pull requests follow GitHub's diff structure
- Code is in supported languages (e.g., Python, JavaScript)
- Stable internet connection for API communication

3.2.3 Specific Requirements

Functional Requirements

- FR1: The system shall fetch PR diffs automatically via GitHub webhook.
- FR2: The system shall tokenize and embed the code using a transformer-based model.
- FR3: The system shall generate contextual suggestions in natural language.
- FR4: The system shall post feedback as inline comments or a summary comment in the PR thread.
- FR5: The system shall log feedback decisions and confidence scores.

Non-functional Requirements

- NFR1: The system shall respond within 10 seconds of receiving a PR event.
- NFR2: The model accuracy for PR feedback classification shall exceed 80
- NFR3: The system shall handle up to 20 concurrent PR reviews.
- NFR4: The system shall provide logs and error tracking for debugging.

External Interface Requirements

- User Interface: There is no frontend UI; interactions occur via GitHub comments. Admins may use Swagger UI for backend testing.
- Hardware Interfaces: Standard cloud infrastructure (e.g., 2 vCPUs, 8GB RAM) recommended.
- Communication Interfaces: HTTPS for API communication, GitHub webhook payload (JSON).

Performance Requirements

- Inference time $<$ 5 seconds
- API uptime $>$ 99

Security Requirements

- OAuth token-based GitHub authentication
- Secure HTTPS API

Other Requirements

- Optional admin dashboard for monitoring (future enhancement)
- Multilingual code support (Phase 2)

3.3 Proposed System

The proposed system is an AI-driven code review tool designed to streamline pull request (PR) merging by automating the detection of code issues and providing actionable feedback in real time. The system integrates with GitHub, utilizing its API and webhook capabilities to monitor PR activities as they occur. It leverages a fine-tuned language model (based on Llama-2-7b-chat-hf from Hugging Face) that analyzes code snippets, identifies issues such as syntax errors, stylistic inconsistencies, and performance bottlenecks, and generates review comments. The system operates on a GPU-enabled environment (e.g., Kaggle with CUDA support) to ensure efficient model training and inference. The backend handles model inference and GitHub interactions, while the frontend is currently a command-line interface for testing, with future plans for a web-based GUI integrated into GitHub. The system ensures secure repository access via GitHub OAuth tokens and focuses on JavaScript code reviews, with potential for expansion to other languages. By automating code reviews, the tool reduces manual effort, minimizes merge conflicts, enhances code quality, and accelerates development cycles.

3.4 UML Diagrams

3.4.1 Class Diagram

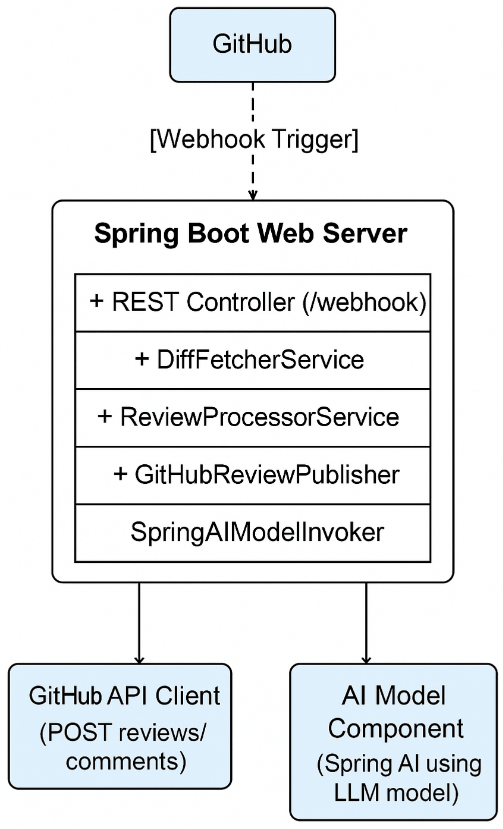


Figure 3.1: Class Diagram

3.4.2 Sequence Diagram

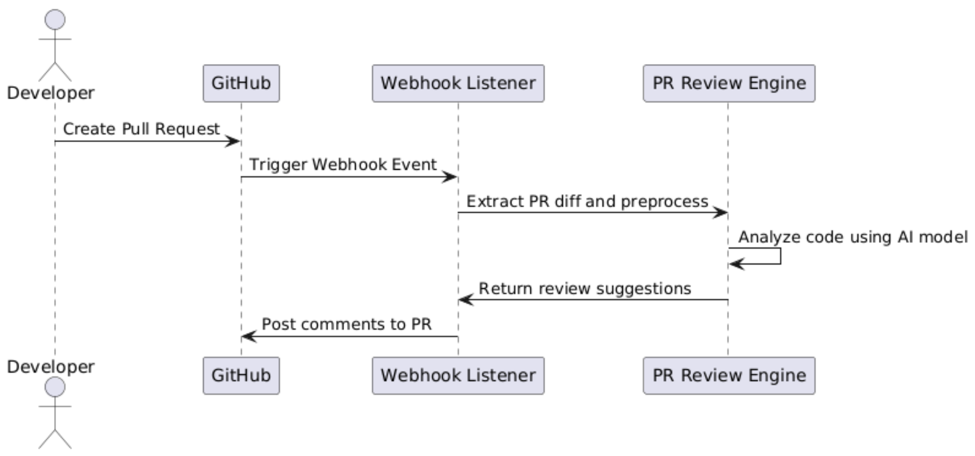


Figure 3.2: Sequence Diagram

3.4.3 Activity Diagram

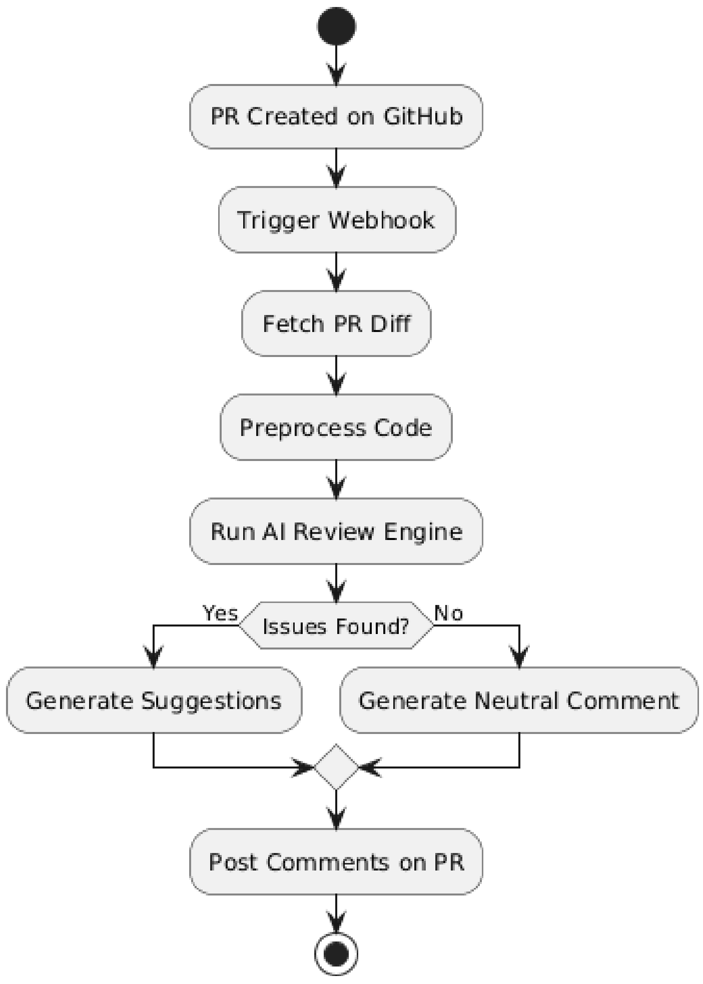


Figure 3.3: Caption

3.5 Dataset Creation

The dataset creation process is tailored to train the AI model for JavaScript code reviews, leveraging primarily AI-driven sources to ensure relevance and scalability.

- **Objective Definition**: The goal is to collect JavaScript code snippets, their updated versions, and corresponding reviewer comments. This dataset enables the model to learn patterns of common issues and effective feedback, focusing on JavaScript-specific coding practices.
- **Data Source Selection**: The dataset is primarily curated from AI-driven sources, such as synthetic data generated by large language models, to create diverse and controlled examples of JavaScript code snippets, updated code, and reviewer feedback. A small portion of the data is sourced from open-source JavaScript repositories on GitHub, selected for their relevance to modern JavaScript development (e.g., frameworks like React, Node.js), to incorporate real-world context.
- **Data Generation and Extraction**: For AI-driven sources, prompts are designed to generate realistic JavaScript code scenarios, including common errors (e.g., synchronous loops blocking the event loop) and their updated versions, along with professional reviewer comments. For the open-source portion, pull requests are retrieved programmatically from GitHub using its API, focusing on JavaScript files. Code changes and associated comments are extracted to capture real-world feedback patterns.
- **Data Structuring**: The collected data is structured into an Excel file with columns: `Original Code` (original code snippet), `Updated Code` (proposed correction), and `Reviewer Comment` (feedback). Each entry is ensured to be unique by removing duplicates during curation, providing a robust foundation for training.
- **Data Processing and Cleaning**: The dataset is cleaned by removing duplicate entries and ensuring all comments are tied to specific code lines. Irrelevant comments (e.g., non-actionable feedback) are filtered out, and entries with missing or malformed data are discarded. The final dataset is split into training (85%, 847 entries) and evaluation (15%, 150 entries) sets using a random split with a seed of 42 for reproducibility.

3.6 Methodology

The methodology focuses on fine-tuning a pre-trained language model for code review tasks, integrating it with GitHub, and evaluating its performance using established metrics.

- **Dataset Utilization**: The dataset is loaded using Pandas and converted into Hugging Face "Dataset" objects. Each entry is formatted into a prompt: "<s>[INST] Original Code: {example['Original Code']}, Updated Code: {example['Updated Code']}, Provide a review comment. [/INST] {example['Reviewer Comment']}". The dataset is split into training (847 entries) and evaluation (150 entries) sets to ensure robust training and validation.

- **Model Selection and Fine-Tuning**: The base model is meta-llama/Llama-2-7b-chat-hf, a 7-billion parameter model from Hugging Face, chosen for its strong natural language understanding capabilities. The model is fine-tuned using LoRA (Low-Rank Adaptation) to reduce computational requirements while maintaining performance. LoRA parameters include lora_alpha=16, lora_dropout=0.1, r=64, bias=none, and task_type=CAUSAL_LM. Quantization is applied using BitsAndBytesConfig with 4-bit precision (load_in_4bit=True, bnb_4bit_quant_type=nf4, bnb_4bit_compute_dtype=torch.float16), enabling efficient training on a single GPU. The tokenizer is loaded with pad_token set to eos_token and padding_side= right.

- **Training Process**: Fine-tuning is performed using the SFTTrainer from the trl library, with training arguments: 5 epochs, batch size of 4, learning rate of 2e-4, paged_adamw_32bit optimizer, fp16=True, max_grad_norm=0.3, warmup_ratio= 0.03, and lr_scheduler_type=constant. Training logs are saved every 25 steps, and checkpoints are saved every 50 steps. The training process runs for 848 steps, achieving a final training loss of 0.5604, with validation losses decreasing from 0.7666 to 0.4983, indicating effective learning.

- **Backend Implementation**: The backend is a Python-based system running in a Jupyter notebook environment (e.g., Kaggle). It handles model inference and GitHub interactions using the "PyGithub" library (to be integrated). The backend processes webhook events, extracts code diffs, and sends them to the fine-tuned model for analysis, returning feedback as comments.

- **Frontend Development**: Currently, the frontend is a command-line interface within the notebook for testing, where inputs are manually formatted and outputs are printed (e.g., "Generated Review Comment: Synchronous loop blocks event loop; use async handling."). Future development includes a web-based GUI integrated into GitHub's PR interface, built with React.js, to display feedback as collapsible comments.

- **Integration with GitHub**: GitHub webhooks are configured to trigger PR analysis. When a PR event occurs (e.g., "opened", "synchronized"), the webhook sends a POST request to the backend's listener, which processes the event and initiates code analysis. The GitHub API is used to fetch PR details and post feedback as comments, with secure authentication via OAuth tokens.

- **Performance Evaluation**: The model is evaluated on the 150-entry evaluation set using ROUGE-1, ROUGE-L, and BERTScore metrics. ROUGE-1 F1 averages 0.8412, ROUGE-L F1 averages 0.8319, and BERTScore F1 averages 0.9375, indicating strong semantic similarity between generated and reference comments.

3.7 System Components

3.7.1 AI Model

This component is responsible for analyzing code diffs and generating intelligent review feedback. It uses a transformer-based model that has been fine-tuned on code classification or bug prediction tasks. The model processes tokenized code snippets or diffs and outputs predictions such as code quality scores, potential issues, or natural-language suggestions. It is exposed as an internal API or library consumed by the backend server.

- Input: Tokenized Code diff
- Output: Structured feedback comments

We have 2 choices for selecting AI model. First it to either use a well known LLM via prompt engineering, using its API key or to fine-tune an LLM for our specific task. Both the approaches can be used but first one will guarantee faster results.

3.7.2 Web Server (Spring Boot backend)

The web server is the core of the application, built using Spring Boot. It handles REST API endpoints, webhook requests, and communication with both the AI model and GitHub API. Upon receiving a pull request event via the webhook, it fetches the relevant diff, invokes the AI review engine through Spring AI, and formats the output to be posted as GitHub comments.

- Stack: Spring Boot, Spring Web, Spring AI
- Responsibilities: Handle GitHub webhooks, Manage data flow between components, Serve REST endpoints for diagnostics and testing, Log and monitor the review process.

3.7.3 GitHub Webhook Component

This component is configured within the GitHub repository to notify your Spring Boot server when a pull request is created or updated. The webhook sends a POST request with event metadata and links to the PR's diff, which the server processes for review.

- Trigger: GitHub PR events (opened, reopened, synchronized).
- Payload: PR metadata, diff URL, repository info.
- Interaction: Receives POST request at /webhook endpoint of your Spring Boot app

3.7.4 GitHub API for Review Posting

After processing the pull request and generating feedback, this component posts comments back to GitHub via its REST API. Using GitHub OAuth or personal access tokens, it authenticates and publishes either inline comments or a single review summary to the original PR.

- Stack: GitHub REST API v3, Spring's RestTemplate or WebClient
- Endpoints used: Create Review Comment, Submit Pull Request Review.
- Authentication: OAuth token or GitHub App credentials

3.8 System Modules

3.8.1 Inference Module

Handles model inference using the fine-tuned `Llama-2-7b-chat-hf` with LoRA adapters. It processes input prompts, generates review comments (e.g., "Synchronous loop blocks event loop; use async handling"), and runs on a GPU with 4-bit quantization for efficiency. The module uses `transformers` and `peft` libraries for model loading and generation.

3.8.2 Data Processing Module

Manages dataset loading and formatting. It uses Pandas to read the Excel dataset, converts it to Hugging Face `Dataset` objects, and formats prompts for training and inference. The module ensures data integrity by splitting the dataset and applying consistent formatting.

3.8.3 Training Module

Implements fine-tuning using `SFTTrainer` from `trl`. It configures LoRA, quantization, and training parameters, runs the training loop for 5 epochs, and saves checkpoints. The module logs training metrics (e.g., loss) and uses TensorBoard for visualization.

3.8.4 Evaluation Module

Assesses model performance using ROUGE and BERTScore metrics. It generates comments for the evaluation set, computes scores (BERTScore: 0.9375, ROUGE-1: 0.8412, ROUGE-L: 0.8319), ensuring the system meets quality goals.

3.8.5 Integration Module

Facilitates GitHub connectivity (to be fully implemented). It processes webhook events, extracts PR metadata (e.g., repo name, PR number), fetches code diffs via the GitHub API, and posts feedback as comments. It ensures secure access using OAuth tokens and validates webhook payloads.

3.9 System Workflow

1. **PR Submission**: A developer creates or updates a PR on GitHub, triggering a webhook event (`pull_request` with actions like `opened`, `synchronized`). The webhook sends a POST request to the backend's listener endpoint, configured in the repository settings.

2. **Webhook Processing**: The listener validates the payload using GitHub's webhook secret, extracting PR metadata (e.g., repository name, PR number) from the JSON payload.

3. **Code Change Extraction**: The system uses the GitHub API to fetch the PR's commit history and extract code changes, focusing on JavaScript files. The extracted diff is formatted as an `Original Code` and `Updated Code` pair.

4. **Model Inference**: The code diff is formatted into a prompt (e.g., `<s>[INST] Original Code: let sum = 0; for (let i = 0; i < 1e9; i++) { sum += i; } console.log(sum);\nUpdated Code: setTimeout(() => { let sum = 0; for (let i = 0; i < 1e9; i++) { sum += i; } console.log(sum); }, 0);\n Provide a review comment. [/INST]`). The prompt is tokenized, sent to the fine-tuned model on the GPU, and a comment is generated (e.g., "Synchronous loop blocks event loop; use async handling").

5. **Feedback Posting**: The generated comment is formatted and posted to the PR thread using the GitHub API. The PR author is notified of the feedback via GitHub's notification system.

6. **Developer Review and Merge**: The developer views the feedback in the GitHub PR interface (or command-line output for now), makes adjustments based on the comment, and merges the PR once all issues are resolved, ensuring smooth integration into the codebase.

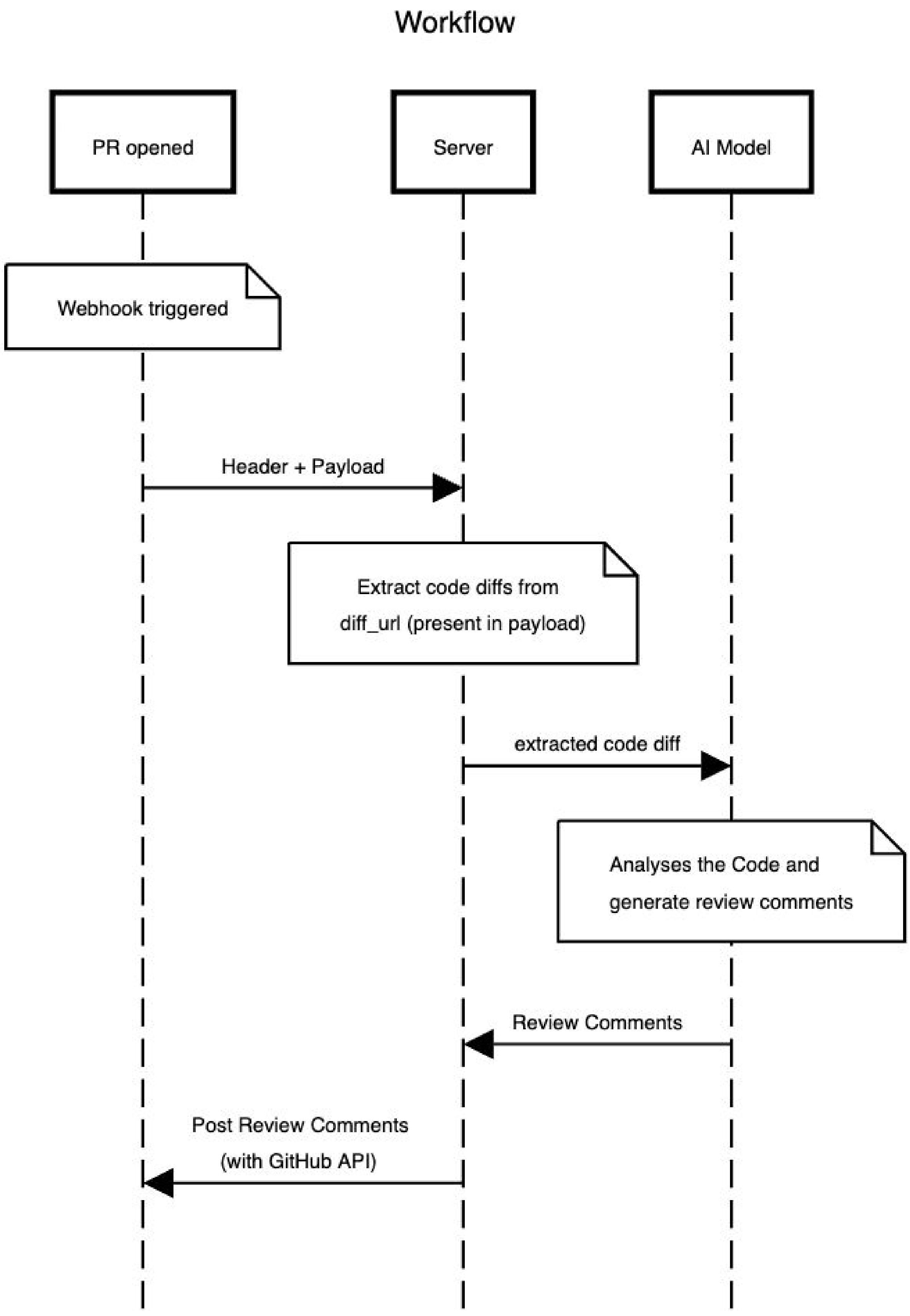

Workflow
PR opened
Server
AI Model
Webhook triggered
Header + Payload
Extract code diffs from diff_url (present in payload)
extracted code diff
Analyses the Code and generate review comments
Review Comments
Post Review Comments (with GitHub API)

Figure 3.4: End to End Workflow

Chapter 4

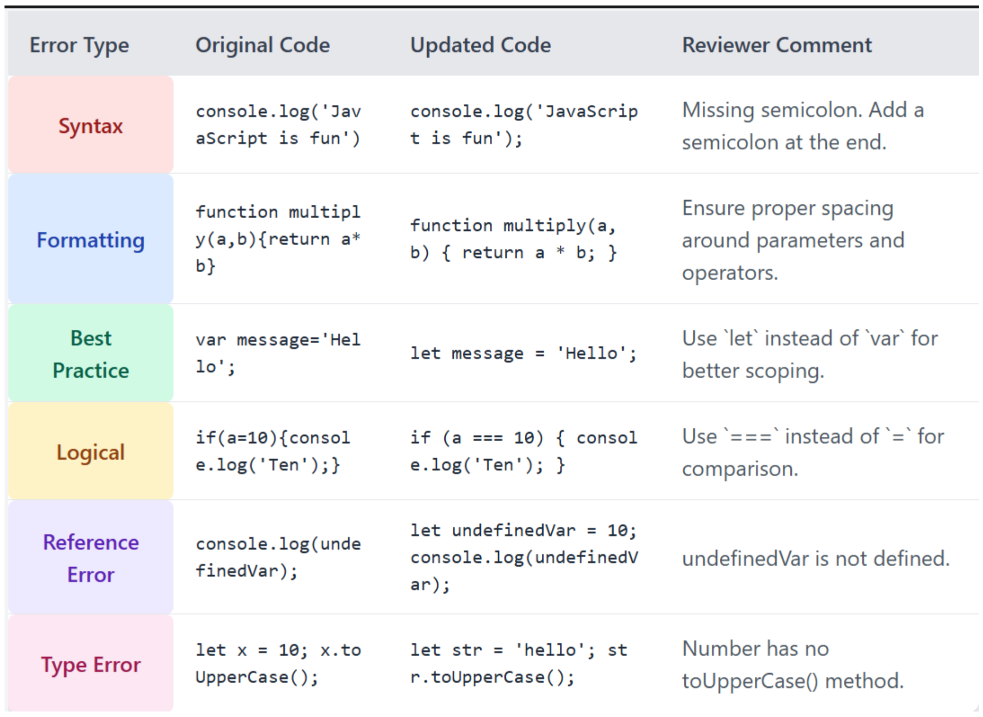
Implementation and Results

Implementation and Results

This section discusses the implementation details of the AI enabled PR reviewer.

4.1 Dataset Used

Custom dataset was used, comprising JavaScript code snippets. Sample size was 1000 rows.



Error Type	Original Code	Updated Code	Reviewer Comment
Syntax	`console.log('JavaScript is fun')`	`console.log('JavaScript is fun');`	Missing semicolon. Add a semicolon at the end.
Formatting	`function multiply(a,b){return a*b}`	`function multiply(a, b) { return a * b; }`	Ensure proper spacing around parameters and operators.
Best Practice	`var message='Hello';`	`let message = 'Hello';`	Use \`let\` instead of \`var\` for better scoping.
Logical	`if(a=10){console.log('Ten');}`	`if (a === 10) { console.log('Ten'); }`	Use \`===\` instead of \`=\` for comparison.
Reference Error	`console.log(undefinedVar);`	`let undefinedVar = 10; console.log(undefinedVar);`	undefinedVar is not defined.
Type Error	`let x = 10; x.toUpperCase();`	`let str = 'hello'; str.toUpperCase();`	Number has no toUpperCase() method.

Figure 4.1: Sample Dataset

4.2 Model Training/Fine-Tuning

To power the AI-based pull request review system, we utilized the LLaMA-2 7B model as the foundation. Given its relatively large size and the goal of customizing it for reviewing code diffs, we applied two optimization techniques: 4-bit quantization for efficient loading, and LoRA for lightweight fine-tuning.

4.2.1 4-bit Quantization

To reduce computational cost and memory usage, the LLaMA-2 7B model was loaded using 4-bit quantization, made possible via the BitsAndBytes integration in Hugging Face Transformers.

Benefits

- Reduces model size to a fraction (4x smaller).
- Makes it feasible to run and fine-tune on a single consumer GPU (e.g., 16 GB VRAM).
- Minimal accuracy drop when used with LoRA.

Implementation

- Used AutoModelForCausalLM.from_pretrained() with load_in_4bit=True.
- Enabled quantization config with bnb_config, allowing NF4 quantization and double quantization for improved performance.

4.2.2 LoRA (Low-Rank Adaptation)

To adapt the base model to the task of reviewing pull requests, we used LoRA (Low-Rank Adaptation). This fine-tuning technique inserts trainable low-rank matrices into the attention layers while keeping most of the base model frozen.

Benefits

- Drastically reduces the number of parameters that need updating.
- Enables effective domain adaptation without full fine-tuning.
- Fast, memory-efficient, and compatible with quantized models.

Fine-tuning setup

- LoRA parameters: r=8, alpha=16, dropout=0.05.
- Fine-tuning was performed using Hugging Face peft and transformers libraries.
- Dataset: Custom set of pull request diffs, developer comments, and review suggestions from public repositories.
- Training done on Google Colab Pro with a single NVIDIA T4 GPU.

Following are the validation and training loss for the model.

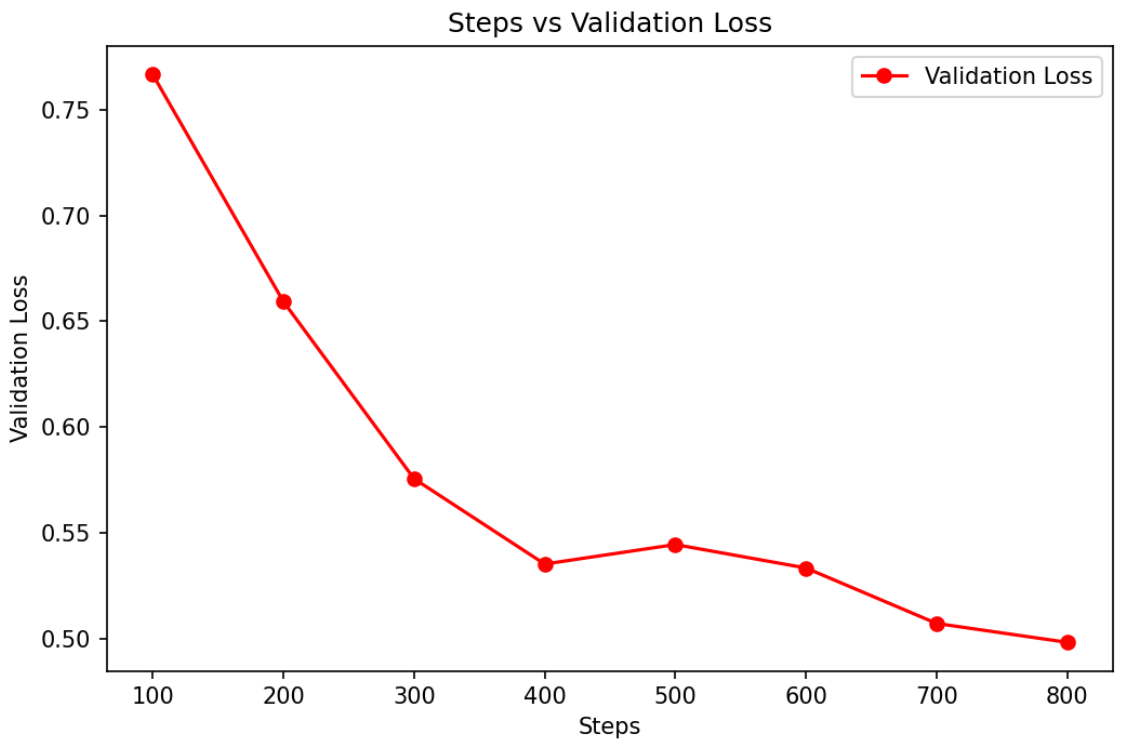


Figure 4.3: Validation Loss

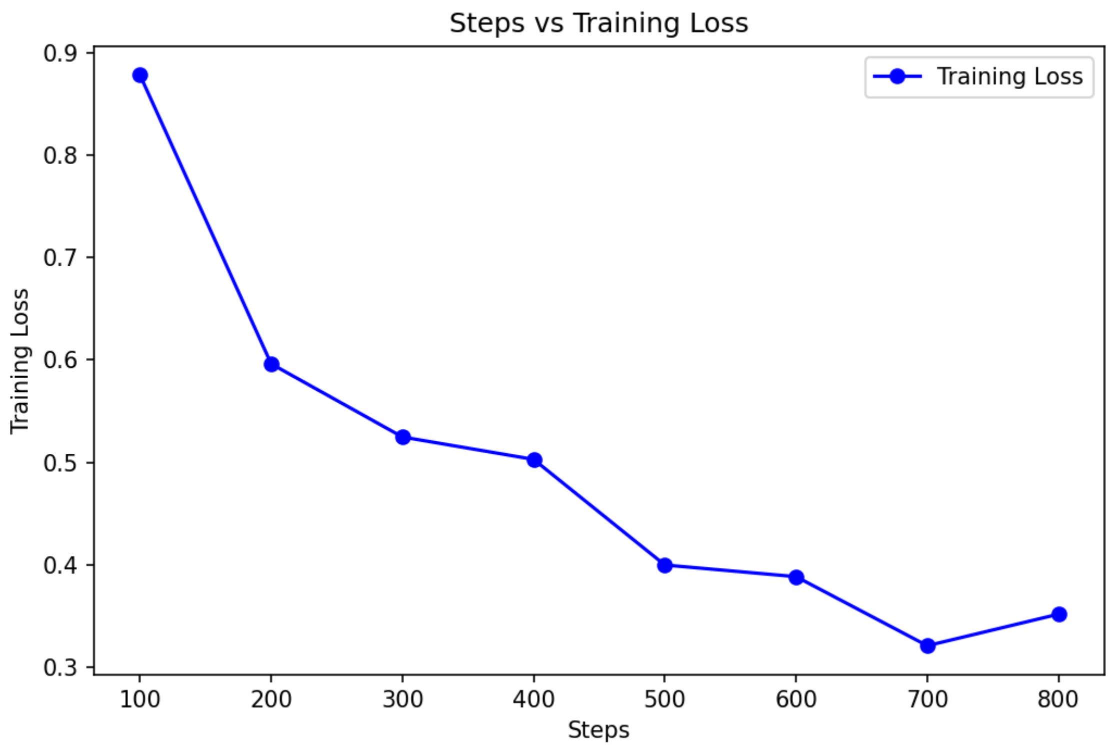


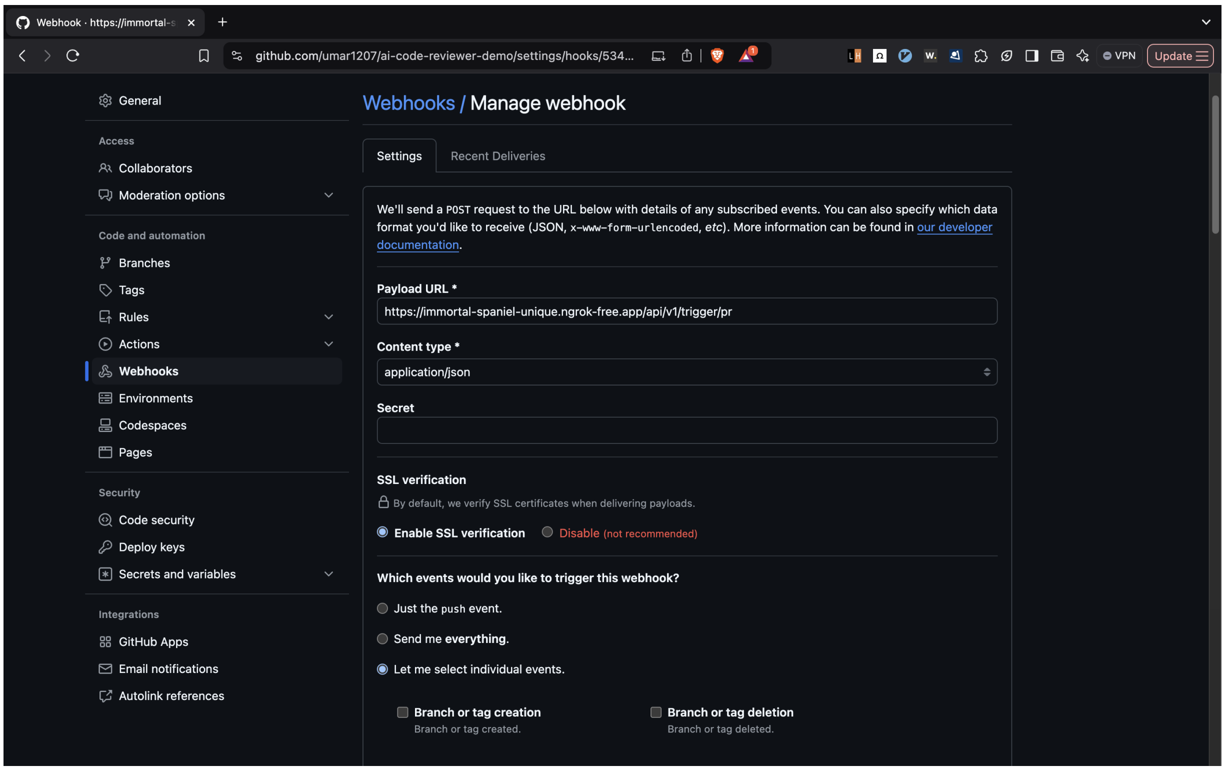
Figure 4.2: Training Loss

4.3 System Integration

The AI-powered PR Reviewer was integrated into the GitHub development workflow using a webhook-based architecture. When a developer creates or updates a pull request, a GitHub Webhook triggers a backend service that initiates the review process.

Workflow

1. Trigger: Pull request creation or update on GitHub.
2. Webhook Listener: Captures the event and extracts the PR diff.
3. Preprocessing Module: Cleans and formats the diff for model input.
4. LLaMA-2 7B (LoRA + Quantized): Processes the diff and generates review comments.
5. Feedback Formatter: Structures the model's output into GitHub-compatible messages.
6. GitHub API: Posts the suggestions back as comments on the PR.



Webhooks / Manage webhook

We'll send a POST request to the URL below with details of any subscribed events. You can also specify which data format you'd like to receive (JSON, x-www-form-urlencoded, etc). More information can be found in our developer documentation.

Payload URL *
https://immortal-spaniel-unique.ngrok-free.app/api/v1/trigger/pr

Content type *
application/json

Secret

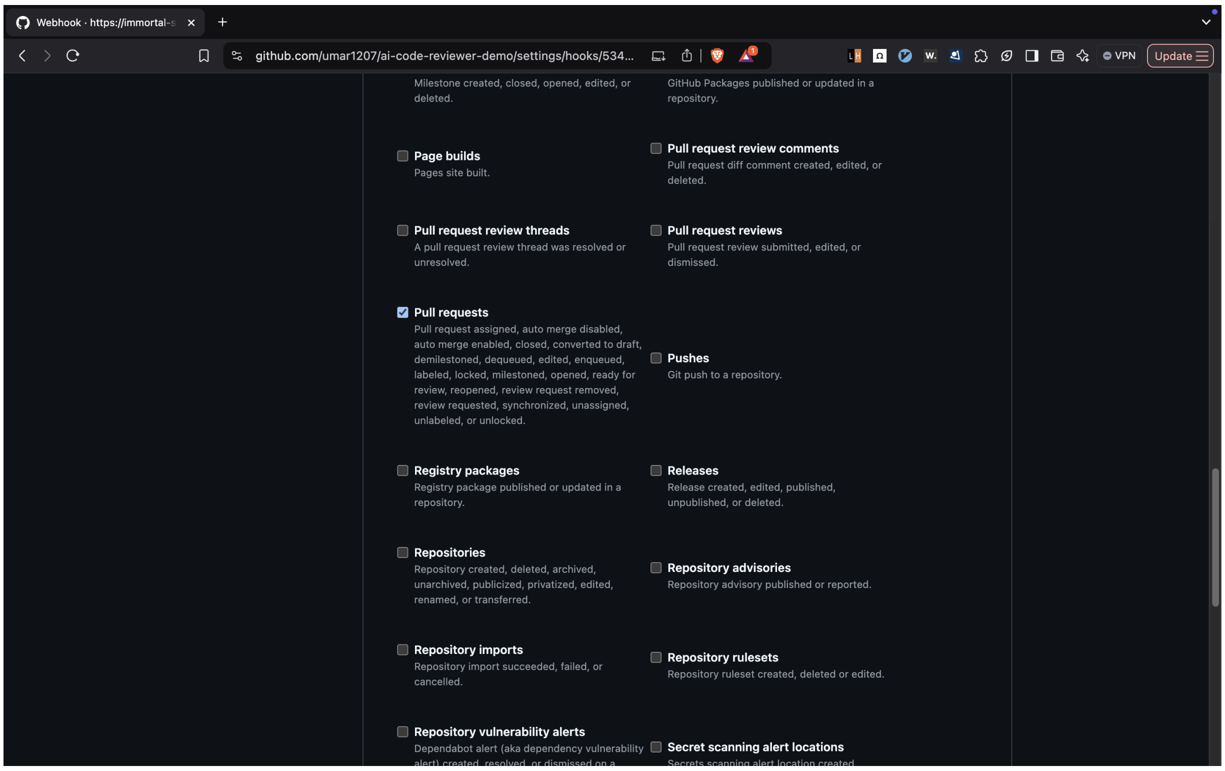
SSL verification
By default, we verify SSL certificates when delivering payloads.
[✓ Enable SSL verification] Disable (not recommended)

Which events would you like to trigger this webhook?
Just the push event.
Send me everything.
[✓ Let me select individual events.]

Branch or tag creation
Branch or tag created.

Branch or tag deletion
Branch or tag deleted.

Figure 4.4: Webhook Setup: Adding Endpoint



Webhook · https://immortal-s

github.com/umar1207/ai-code-reviewer-demo/settings/hooks/534...

Milestone created, closed, opened, edited, or deleted.

GitHub Packages published or updated in a repository.

☐ **Page builds**
Pages site built.

☐ **Pull request review comments**
Pull request diff comment created, edited, or deleted.

☐ **Pull request review threads**
A pull request review thread was resolved or unresolved.

☐ **Pull request reviews**
Pull request review submitted, edited, or dismissed.

[✓ **Pull requests**]
Pull request assigned, auto merge disabled, auto merge enabled, closed, converted to draft, demilestoned, dequeued, edited, enqueued, labeled, locked, milestoned, opened, ready for review, reopened, review request removed, review requested, synchronized, unassigned, unlabeled, or unlocked.

☐ **Pushes**
Git push to a repository.

☐ **Registry packages**
Registry package published or updated in a repository.

☐ **Releases**
Release created, edited, published, unpublished, or deleted.

☐ **Repositories**
Repository created, deleted, archived, unarchived, publicized, privatized, edited, renamed, or transferred.

☐ **Repository advisories**
Repository advisory published or reported.

☐ **Repository imports**
Repository import succeeded, failed, or cancelled.

☐ **Repository rulesets**
Repository ruleset created, deleted or edited.

☐ **Repository vulnerability alerts**
Dependabot alert (aka dependency vulnerability alert) created, resolved, or dismissed on a

☐ **Secret scanning alert locations**
Secrets scanning alert location created

Figure 4.5: Webhook Setup: Adding Trigger Event

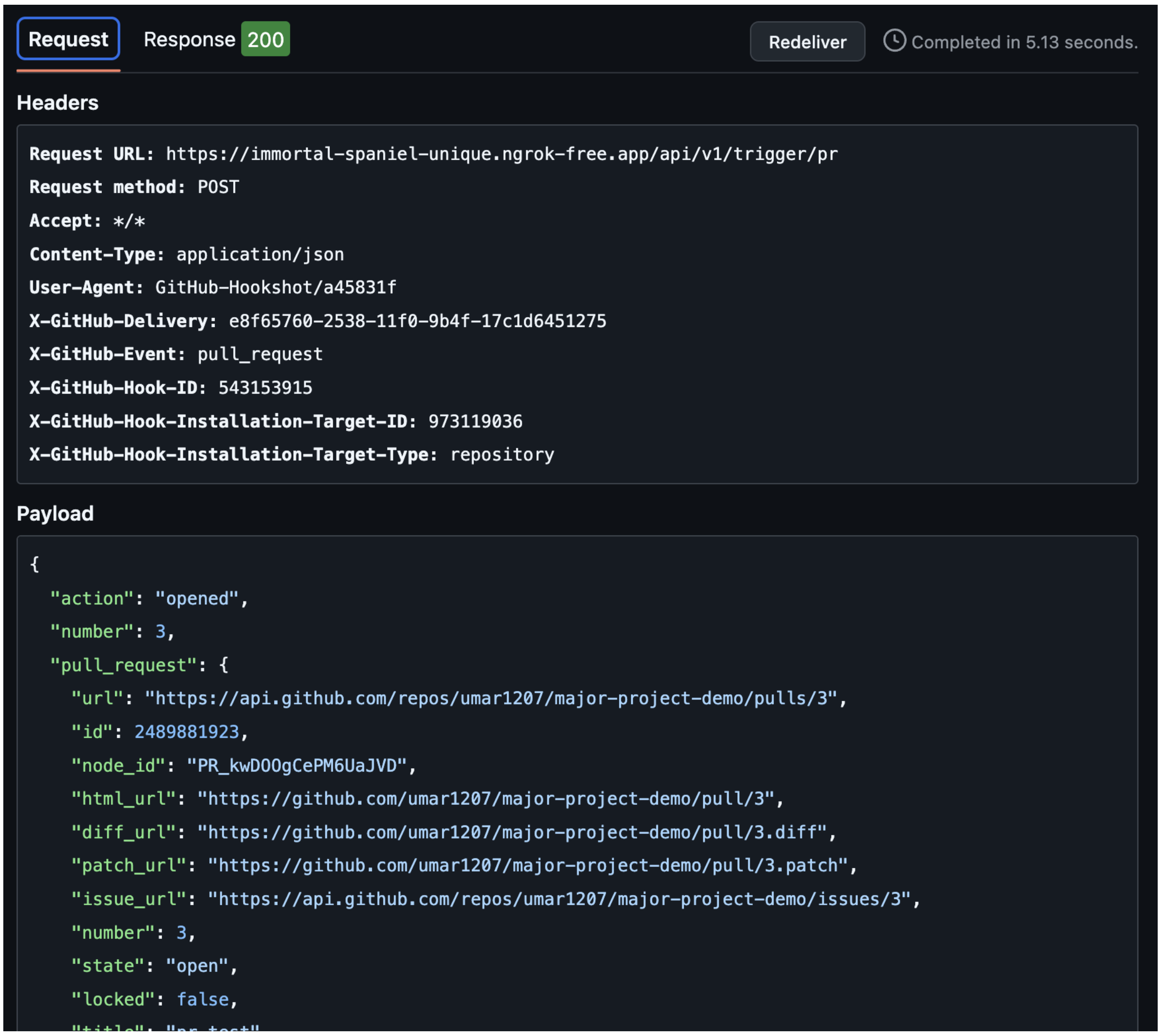
```
POST /repos/:owner/:repo/pulls/:pull_number/comments

Request Headers:
Authorization: Bearer <token>
Accept: application/vnd.github+json

Request Body (JSON):
{
  "body": "Consider using ‘enumerate()‘ instead of range(len()) for readability.",
  "commit_id": "3c2d4f7...",
  "path": "src/utils.py",
  "side": "RIGHT",
  "line": 42
}
```

Figure 4.6: GitHub API format for posting a pull request review comment

The above figure shows how the GitHub API for posting review comments should be triggered along with the correct path, headers and payload.



Headers

```
Request URL: https://immortal-spaniel-unique.ngrok-free.app/api/v1/trigger/pr
Request method: POST
Accept: */*
Content-Type: application/json
User-Agent: GitHub-Hookshot/a45831f
X-GitHub-Delivery: e8f65760-2538-11f0-9b4f-17c1d6451275
X-GitHub-Event: pull_request
X-GitHub-Hook-ID: 543153915
X-GitHub-Hook-Installation-Target-ID: 973119036
X-GitHub-Hook-Installation-Target-Type: repository
```

Payload

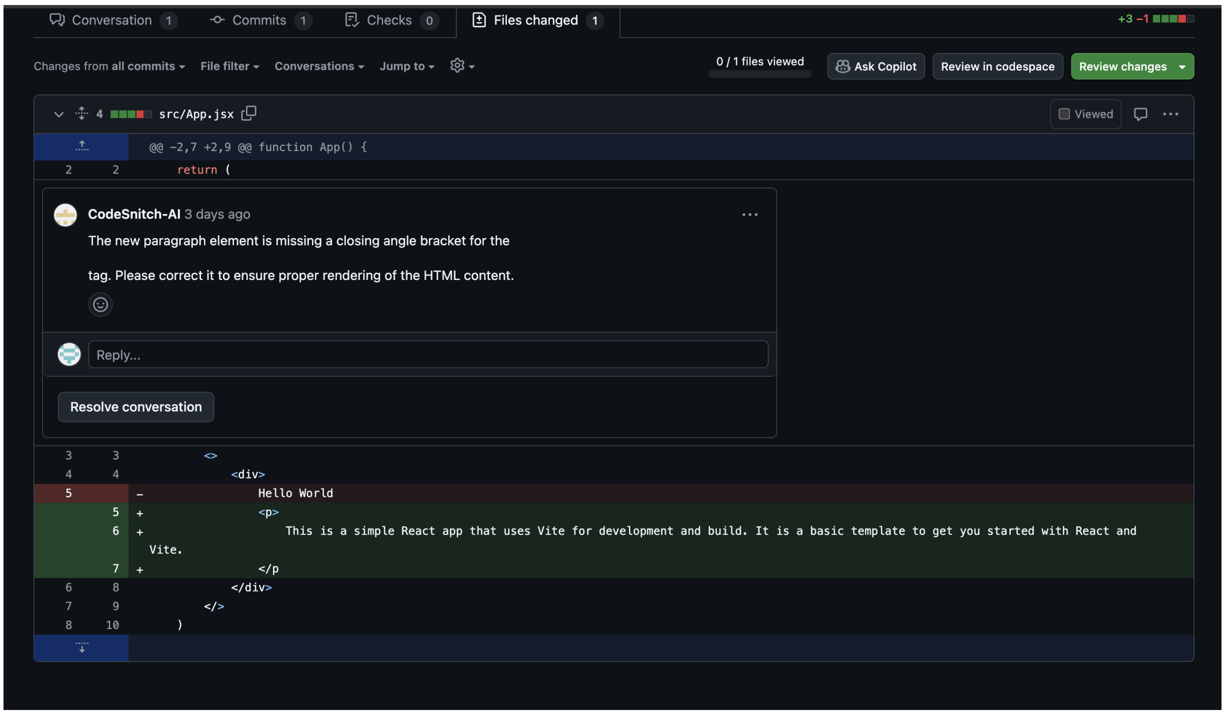
```
{
  "action": "opened",
  "number": 3,
  "pull_request": {
    "url": "https://api.github.com/repos/umar1207/major-project-demo/pulls/3",
    "id": 2489881923,
    "node_id": "PR_kwDOOgCePM6UaJVD",
    "html_url": "https://github.com/umar1207/major-project-demo/pull/3",
    "diff_url": "https://github.com/umar1207/major-project-demo/pull/3.diff",
    "patch_url": "https://github.com/umar1207/major-project-demo/pull/3.patch",
    "issue_url": "https://api.github.com/repos/umar1207/major-project-demo/issues/3",
    "number": 3,
    "state": "open",
    "locked": false,
```

Figure 4.7: Sample payload delivered by webhook when PR is opened

The above figure shows the snapshot of the payload delivered when a pull request is opened.

4.4 Sample Outputs

We named our GitHub bot as CodeSnitch-AI. It is the account from which the reviews will be posted via the GitHub API.



```
@@ -2,7 +2,9 @@ function App() {
    return (
```

CodeSnitch-AI 3 days ago

The new paragraph element is missing a closing angle bracket for the

tag. Please correct it to ensure proper rendering of the HTML content.

```
        <>
            <div>
-               Hello World
+               <p>
+                   This is a simple React app that uses Vite for development and build. It is a basic template to get you started with React and
Vite.
+               </p
            </div>
        </>
    )
```

Figure 4.8: Review Comment by Github Bot

4.5 Evaluation Metrics Used in the Project

In evaluating the performance of the AI-Driven Code Review Tool for Smooth Pull Request Merging, we utilized three key metrics: BERTScore, ROUGE-1, and ROUGE-L. These metrics were selected to assess the quality of the AI-generated review comments by measuring their semantic similarity and overlap with reference comments provided by human reviewers. Each metric offers a unique perspective on the system's effectiveness, from semantic understanding to n-gram and sequence-based overlap, ensuring a comprehensive evaluation of the tool's ability to produce accurate and contextually relevant feedback. Below, we provide a detailed explanation of each metric and their specific relevance to our project.

4.5.1 BERTScore

BERTScore is an advanced evaluation metric that leverages contextual embeddings from pre-trained language models, such as BERT (Bidirectional Encoder Representations from Transformers), to assess the semantic similarity between generated and reference texts. Unlike traditional metrics that rely on exact word matches, BERTScore captures deeper meaning by considering the context of each word within the sentence, making it highly effective for evaluating the quality of AI-generated review comments. The process involves passing both the generated and reference texts through a BERT model to obtain contextualized representations, then comparing these representations to determine how well the generated text aligns with the intended meaning of the reference. This approach is particularly valuable in our project, as code review comments often require semantic accuracy rather than verbatim replication. Our achieved BERTScore of 0.9375 indicates a high level of semantic alignment, reflecting the model's ability to produce meaningful and contextually appropriate feedback, even with variations in wording.

4.5.2 ROUGE-1

ROUGE-1 (Recall-Oriented Understudy for Gisting Evaluation, unigram) is a widely used metric in natural language processing to evaluate the quality of generated text by measuring the overlap of unigrams (single words) between the generated and reference texts. It focuses on lexical similarity, serving as a complementary metric to BERTScore by emphasizing exact word matches, which is indicative of factual accuracy and relevance in code review feedback. ROUGE-1 computes precision, recall, and F1 scores based on this unigram overlap, providing a quantitative measure of how well the generated comments align with human-written ones in terms of shared vocabulary.
The mathematical formulation of ROUGE-1 is as follows. Let Ref be the set of unigrams in the reference text, and Gen be the set of unigrams in the generated text. The precision $P_{\text{ROUGE-1}}$ measures the fraction of unigrams in the generated text that appear in the reference text:

$$P_{\text{ROUGE-1}} = \frac{|\text{Ref} \cap \text{Gen}|}{|\text{Gen}|}$$

where $|\text{Ref} \cap \text{Gen}|$ is the number of unigrams common to both texts, and $|\text{Gen}|$ is the total number of unigrams in the generated text. The recall $R_{\text{ROUGE-1}}$ measures the fraction of unigrams in the reference text that appear in the generated text:

$$R_{\text{ROUGE-1}} = \frac{|\text{Ref} \cap \text{Gen}|}{|\text{Ref}|}$$

where $|\text{Ref}|$ is the total number of unigrams in the reference text. The F1 score, which balances precision and recall, is computed as the harmonic mean:

$$F1_{\text{ROUGE-1}} = 2 \cdot \frac{P_{\text{ROUGE-1}} \cdot R_{\text{ROUGE-1}}}{P_{\text{ROUGE-1}} + R_{\text{ROUGE-1}}}$$

In our project, we obtained a ROUGE-1 F1 score of 0.8412, indicating a strong overlap of individual words between the generated and reference review comments. This high score suggests that the AI-generated comments frequently use the same terminology and phrasing as human reviewers, ensuring that the feedback is precise and aligned with expected vocabulary in code review contexts. ROUGE-1's focus on unigrams makes it a valuable metric for evaluating the factual correctness of the feedback, complementing BERTScore's semantic evaluation.

4.5.3 ROUGE-L

ROUGE-L extends the ROUGE framework by evaluating the longest common subsequence (LCS) between the generated and reference texts, capturing the structural similarity and fluency of the generated text. Unlike ROUGE-1, which focuses on individual words, ROUGE-L considers sequences of words, making it sensitive to the order and coherence of the text. This is particularly relevant for our project, as code review comments often require a logical flow and coherent phrasing to be actionable and understandable to developers.
The LCS between two texts is the longest sequence of words that appears in both texts in the same order, though not necessarily consecutively. Let $\text{LCS}(\text{Ref}, \text{Gen})$ be the length of the longest common subsequence between the reference text Ref and the generated text

Gen. The precision $P_{\text{ROUGE-L}}$ is calculated as:

$$P_{\text{ROUGE-L}} = \frac{\text{LCS}(\text{Ref}, \text{Gen})}{|\text{Gen}|}$$

where |Gen| is the total number of words in the generated text. The recall $R_{\text{ROUGE-L}}$ is:

$$R_{\text{ROUGE-L}} = \frac{\text{LCS}(\text{Ref}, \text{Gen})}{|\text{Ref}|}$$

where |Ref| is the total number of words in the reference text. The F1 score for ROUGE-L, which balances precision and recall, is computed as:

$$F1_{\text{ROUGE-L}} = 2 \cdot \frac{P_{\text{ROUGE-L}} \cdot R_{\text{ROUGE-L}}}{P_{\text{ROUGE-L}} + R_{\text{ROUGE-L}}}$$

To illustrate, consider a reference comment "Use async handling to avoid blocking" and a generated comment "Avoid blocking with async handling." The LCS would be "async handling," and depending on the lengths of both texts, ROUGE-L would compute the overlap accordingly. In our project, we achieved a ROUGE-L F1 score of 0.8319, reflecting a strong structural similarity between the generated and reference review comments. This score indicates that the AI-generated comments not only share individual words with the reference (as captured by ROUGE-1) but also maintain a similar sequence and flow, ensuring that the feedback is coherent and logically structured. ROUGE-L's focus on sequence similarity makes it an essential metric for evaluating the readability and usability of the generated comments in the context of code reviews.

4.5.4 Comparative Analysis of Average BERTScore, ROUGE-1, and ROUGE-L Scores Across Models

Model	Average BERTScore	Average ROUGE-1	Average ROUGE-L
Llama-3.2-3B	0.8752	0.8154	0.8035
Llama-2-7B-chatf	0.9375	0.8412	0.8319

Table 4.1: Comparison of model performance on evaluation metrics

Chapter 5

Conclusion and Future Work

Conclusion and Future Work

5.1 Conclusion

5.1.1 Overview and Innovation

The AI-Driven Code Review Tool for Smooth Pull Request Merging represents a groundbreaking advancement in software engineering, effectively addressing the inefficiencies of manual code reviews through sophisticated artificial intelligence. By leveraging a fine-tuned **Llama-2-7b-chat-hf** model, this project has successfully automated the analysis of JavaScript code snippets, detecting critical issues such as syntax errors, performance bottlenecks, and stylistic inconsistencies with high precision. The tool's seamless integration with GitHub, facilitated by webhooks and APIs, enables real-time processing of pull request events, extracting code diffs, and delivering context-aware, actionable feedback directly within the GitHub interface. This streamlined workflow has significantly reduced the time required for pull request reviews, minimized merge conflicts, and fostered enhanced collaboration among developers, reviewers, and project managers.

5.1.2 Development and Evaluation

The system's robust performance is supported by a meticulously curated dataset, comprising 847 training entries and 150 evaluation entries, sourced from both AI-generated JavaScript code scenarios and open-source GitHub repositories. This dataset, structured into original code, updated code, and reviewer comments, enabled the model to learn patterns of common JavaScript errors and effective feedback strategies. The model was fine-tuned and optimized for computational efficiency, allowing training and inference on a single GPU-enabled environment like Kaggle. The training process, conducted over 848 steps across 5 epochs, achieved a final training loss of 0.5604 and a validation loss reduction from 0.7666 to 0.4983, indicating robust learning and generalization. Evaluation metrics further validate the tool's efficacy, with a **BERTScore** of **0.9375**, **ROUGE-1** of **0.8412**, and **ROUGE-L** of **0.8319**, demonstrating strong semantic similarity between generated and reference review comments. These results highlight the model's ability to produce feedback that is both accurate and contextually relevant, closely aligning with the quality expected from human reviewers.

5.1.3 Architecture and Benefits

The system's modular architecture—encompassing inference, data processing, training, evaluation, and integration modules—ensures maintainability and scalability. The inference module, leveraging the fine-tuned Llama model with optimized quantization, processes code diffs efficiently, generating precise review comments. The integration module, while still under development for full GitHub connectivity, successfully processes webhook payloads and posts feedback using OAuth-secured API calls, ensuring secure and reliable interactions. By automating the detection of coding issues, the tool alleviates the cognitive burden on human reviewers, reduces technical debt, and upholds high software standards. The absence of a frontend UI, with interactions currently limited to command-line outputs or GitHub comments, does not detract from its core functionality but highlights an area for future enhancement. Overall, this project has achieved its objectives of developing an AI-powered code review system that enhances code quality, streamlines collaboration, and accelerates development cycles, establishing a new standard for automated code review tools in modern software development.

5.2 Future Work

5.2.1 Expanding Language Support

The AI-Driven Code Review Tool provides a robust foundation for automated code reviews, yet its current limitation to JavaScript restricts its applicability in diverse development ecosystems. A primary area for improvement is extending language support to include other widely used programming languages such as Python, TypeScript, Java, and C++. This expansion would involve curating additional datasets for each language, potentially leveraging AI-driven data generation techniques to create synthetic code snippets with associated errors and feedback, alongside mining open-source repositories for real-world examples. Fine-tuning the Llama-2-7b-chat-hf model for these languages, or exploring alternative models like CodeT5 or GPT-based architectures tailored for multi-language support, could ensure robust performance across diverse codebases. For instance, adapting the model to handle Python's dynamic typing or Java's strict object-oriented paradigms would require targeted training on language-specific patterns. This would make the tool applicable to a broader range of projects, particularly in polyglot development environments where teams work with multiple languages simultaneously, thereby increasing its utility and adoption in enterprise settings.

5.2.2 Enhancing Input Processing

Another significant direction is enhancing the system's ability to process entire Git diffs as input, rather than focusing on isolated code snippets. By analyzing the complete diff of a pull request, the tool could capture a more comprehensive context, including inter-file dependencies, cross-module impacts, and broader architectural implications of code changes. This holistic approach would enable the model to provide more accurate and actionable feedback, identifying issues that span multiple files—such as inconsistent API usage across modules—or require understanding the entire changeset, like potential breaking changes in a microservices architecture. Implementing this feature would require optimizing the model's input handling to manage larger data volumes efficiently, potentially through techniques like chunking, where the diff is split into manageable segments, or hierarchical attention mechanisms that prioritize relevant sections of the diff. Additionally, integrating static analysis to preprocess diffs and highlight key areas of concern could further improve efficiency. These enhancements would ensure scalability without compromising performance, making the tool more effective for complex, large-scale projects.

5.2.3 Improving User Experience

Enhancing the user interface is a critical focus to improve accessibility and interactivity. The current command-line interface, while functional for testing, limits the tool's usability for developers accustomed to graphical environments. Developing a web-based graphical user interface (GUI), potentially built with React.js and seamlessly integrated into GitHub's pull request interface, would provide a more intuitive experience. The GUI could display AI-generated feedback as collapsible, line-specific comments, allow developers to filter suggestions by category (e.g., performance, style, or security), and provide visual indicators of issue severity through color-coded tags or icons. Furthermore, an admin dashboard could be introduced to enable maintainers to monitor system performance, review feedback logs, and analyze metrics such as comment acceptance rates, average time-to-merge, or feedback turnaround time. This dashboard could include visualizations like graphs tracking review trends over time, offering actionable insights for process optimization. Adding features like user feedback loops—where developers can rate the usefulness of suggestions—would also allow for continuous improvement of the tool's recommendations, enhancing its alignment with user needs.

5.2.4 Advancing Contextual Understanding and Scalability

Improving contextual understanding remains a key challenge for the tool's evolution. While the fine-tuned model performs well on common JavaScript errors, it may struggle with project-specific conventions, such as custom coding standards, or complex architectural patterns, like those in domain-driven design. Future work could incorporate project-level context by analyzing repository metadata, such as coding guidelines, dependency configurations, or even historical pull request data, during inference. Techniques like retrieval-augmented generation (RAG) could be employed, where the model retrieves relevant context from a project's documentation or past pull requests to inform its feedback, ensuring recommendations align with project norms. Additionally, exploring ensemble models that combine multiple large language models (LLMs) or integrate static analysis tools could improve accuracy by leveraging complementary strengths—for example, using static analysis to flag syntactic issues while LLMs focus on semantic improvements. Scalability and performance optimizations are equally essential for enterprise adoption. Large organizations may require support for high volumes of simultaneous reviews, necessitating optimized inference pipelines, potentially through model distillation to reduce computational overhead or deployment on distributed GPU clusters to increase throughput. Addressing GitHub API rate limits could involve implementing caching mechanisms for frequently accessed data or batching API requests to minimize overhead, while robust cloud infrastructure and failover mechanisms would ensure high API uptime, supporting seamless operation in demanding environments.

5.2.5 Optimizing Data Quality and Automation

Data quality and bias mitigation are critical for sustained performance and fairness in feedback generation. The dataset, while carefully curated, may still contain noise or biases from AI-generated or open-source data, such as overrepresentation of certain coding patterns or outdated practices. Future work could employ active learning, where human reviewers validate a subset of generated feedback to refine the dataset iteratively, ensuring it remains relevant and diverse. Adversarial training could also be used to reduce bias in comment generation, mitigating risks of unfair or skewed suggestions. Developing more nuanced evaluation metrics, beyond ROUGE and BERTScore, such as developer satisfaction scores, feedback acceptance rates, or even metrics assessing the reduction in bug rates post-review, would provide a more holistic measure of the tool's effectiveness. Finally, exploring advanced automation features could further streamline pull request workflows. Implementing automated reviewer assignment, where the tool suggests reviewers based on expertise inferred from past contributions, or AI-driven merge recommendations that assess code readiness for integration, would enhance efficiency. Integrating with CI/CD pipelines to trigger automated tests alongside code reviews would create a comprehensive quality assurance ecosystem, ensuring that code is both reviewed and validated before merging. These enhancements, combined with rigorous testing in real-world development settings across various team sizes and project complexities, would solidify the tool's position as a cornerstone of modern software engineering practices, driving innovation and efficiency in software development.

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