

Automatic Code Comment Generator Using T5-Transformer

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Abstract

Automatic code comment generation is an emerging area of research at the intersection of software engineering and natural language processing. This work presents the design and implementation of an AI-driven comment generation system fine-tuned on the *CodeT5-base* transformer architecture, tailored for Python code. The approach leverages recent advances in sequence-to-sequence modeling to produce concise, contextually relevant, and semantically accurate comments in real time. By addressing key challenges in preprocessing, training optimization, and model integration, the system achieves high-quality outputs with fast inference performance. This study demonstrates the potential of transformer-based models to enhance software documentation, support code comprehension, and improve developer productivity in modern software engineering workflows.

Keywords: Code Comment Generation, CodeT5, Transformer Models, Software Documentation, Natural Language Processing, Python.

I. INTRODUCTION

Source code comments play a crucial role in helping developers understand program logic, reduce onboarding time, and ensure smooth maintenance. However, writing comprehensive and accurate comments is often overlooked due to time constraints or lack of discipline in development workflows. This leads to poorly documented codebases, increasing the cost and complexity of future modifications.

Automatic code comment generation addresses these challenges by leveraging machine learning and natural language processing techniques to produce descriptive comments directly from source code. Recent advancements in transformer-based architectures have significantly improved the ability of models to capture semantic and structural information from programming languages, making them well-suited for this task.

The system described in this work focuses on Python source code, applying a fine-tuned CodeT5 transformer to convert code snippets into human-readable descriptions. The objective is to create a practical and deployable tool capable of producing high-quality comments that enhance understanding, support collaborative development, and maintain software quality over time.

II. LITERATURE REVIEW

Generating human-readable comments directly from source code remains a central challenge in software engineering and NLP. One approach to tackle this uses Combinatory Categorical Grammars (CCGs) to convert structured code into grammatically coherent English sentences. The system works by mapping

elements of an abstract syntax tree (AST) into linguistic constructs and assembling them using a formal grammar framework. This ensures that the generated text is both syntactically correct and semantically aligned with the underlying code. Such structured translation can enhance readability and aid code maintenance, especially for novice developers. The method particularly shines when dealing with concise and well-organized functions, as it can produce comments that closely mirror programmer intent. However, the approach is less adaptable when faced with complex control flows, irregular coding patterns, or nested abstractions. This idea was explored by Matskevich and Gordon in their work on syntax-driven generation [1].

One alternative path to automated comment generation emphasizes leveraging human knowledge already embedded in online programming communities. By mining developer discussions from Q&A platforms like Stack Overflow, it's possible to associate code snippets with the explanations developers naturally write in response to questions. This paradigm shifts the focus from learning code-text mappings in isolation to using socially-generated narratives as training data. The AutoComment system exemplifies this idea by extracting pairs of code and related comments from community forums. These pairings are then used to train models that generate comments mimicking human reasoning and tone. The strength of this method lies in its ability to incorporate informal terminology, developer slang, and idiomatic phrasing, creating more relatable documentation. However, its effectiveness is bounded by the breadth and quality of available forum data, limiting its coverage of niche libraries or APIs. This approach was formally introduced by Wong et al. [2].

Incorporating contextual cues from surrounding program elements can significantly improve the accuracy and completeness of code comment generation. Rather than treating methods as isolated units, a context-aware strategy explores relationships within the codebase, including method invocations, call graphs, and lexical chains. This layered analysis allows the generation system to highlight not only what a method does but also how it fits within the broader application. McBurney and McMillan proposed such a model that integrates lexical chaining to identify important terms and also uses data from method callers and callees to improve summary construction. As a result, generated comments reflect both internal behavior and external purpose, making them especially helpful for tasks like reverse engineering. While promising, the model relies heavily on static analysis, making it less effective for dynamic or loosely typed programming environments [3].

Attention mechanisms have revolutionized neural language generation, and their application to source code summarization has yielded strong improvements in contextual relevance. A notable approach uses convolutional attention networks that jointly encode source code and decode human-readable summaries. These models capture structural patterns through convolutional layers and identify key semantic tokens via attention. Their application to large datasets of Java methods has shown strong gains in BLEU scores and naturalness of output. In their study, Allamanis et al. demonstrated that combining convolutional architectures with attention improves alignment between code segments and natural language descriptions. However, the model still requires extensive annotated datasets and may miss abstract semantics or higher-level intent [4].

A sequence-to-sequence learning framework with attention has proven highly effective for code comment generation. These models learn to align source code tokens with comment words dynamically, ensuring that generated summaries focus on the most relevant aspects of the code. By leveraging AST flattening and token abstraction techniques, the model can reduce vocabulary complexity and improve generalization. The framework introduced by Hu et al. achieves superior performance in fluency and

informativeness compared to traditional recurrent baselines. Although the system excels in producing concise summaries for well-structured methods, it faces limitations when required to produce detailed or multi-line comments for code involving domain-specific operations or embedded business logic [5]. Modern transformer-based models have redefined how we approach automatic code comment generation. One technique focuses not just on summarizing functionality but on generating comments that resemble human-written reviews. This method leverages pre-trained language models to capture abstract patterns in source code and translates them into constructive, actionable feedback. Known as AUGER, this system adopts task-specific prompt designs and pretraining strategies to produce contextual review comments with high fluency and relevance. The authors demonstrated that AUGER could outperform traditional sequence models, particularly in generating stylistically rich and grammatically correct comments for pull request-level code. Nevertheless, the quality of output is still dependent on domain-specific tuning and curated training data, making generalization across domains a challenge. The framework was introduced by Li et al. in their 2022 research [6].

Context-aware comment generation benefits significantly from using additional information beyond the target method. One promising strategy employs teacher-student distillation to create compact, efficient models that can still generate high-quality summaries by learning from larger, more capable networks. This approach involves using the context of related files, classes, or surrounding functions to refine the summaries produced by the student model. The authors incorporated external contextual signals into the training process, leading to stronger semantic alignment and improved readability in the final output. Su, Bansal, and McMillan proposed this method in a 2024 paper that highlighted how distillation can bridge the performance gap between small and large models without excessive computational cost. However, managing noisy or irrelevant context remains a limitation, especially in large, complex repositories [7].

Generating multi-intent comments—such as summaries, suggestions, and alerts—requires a model that can handle diverse goals in a single output pipeline. One solution introduces a structured decoding mechanism where intent labels are used to guide the generation process. This approach allows the model to produce comments that are tailored to specific purposes like summarization or bug detection, all while maintaining syntactic fluency and domain relevance. Mu et al. developed this multi-intent framework under the name DOME, showing that it outperformed traditional summarization models on several benchmark datasets. By training on intent-annotated data, the model could dynamically switch between styles and purposes, making it well-suited for code review platforms. Despite its strengths, the model's reliance on explicit intent annotation increases dataset preparation complexity and limits scalability in domains lacking labeled examples [8].

The emergence of large language models (LLMs) like Codex and GPT-3 has opened the door to effective few-shot and zero-shot code summarization. Instead of requiring large, task-specific datasets, these models can generate accurate, multi-intent comments using only a handful of examples or none at all. One study evaluated these capabilities by prompting LLMs with examples of summaries, warnings, and suggestions to assess their ability to generalize. The results showed that LLMs performed comparably or better than finetuned neural baselines in some cases. However, inconsistencies, verbosity, and hallucinated content were also observed, particularly when prompts lacked clear structure. The work, conducted by Geng et al., revealed the promise and limitations of LLMs in generating context-sensitive code comments with minimal training overhead [9].

Inspired by human writing, some models now use iterative refinement processes to enhance the quality of generated comments. A multi-pass system generates an initial comment draft and then applies one or more

refinement steps that assess semantic completeness, fluency, and alignment with code functionality. Known as DECOM, this deliberation-based model has shown strong gains in BLEU and METEOR scores by mimicking the way developers revise documentation. It is especially effective at improving cohesion and eliminating redundancy. Mu et al., who proposed this method in 2022, emphasized that each refinement pass introduces corrective feedback into the generation loop, allowing for better generalization and readability. While powerful, DECOM incurs additional training and inference cost due to its multi-stage architecture [10]. Enhancing code comment generation with class-level contextual information allows models to consider the broader environment in which a method operates. One architecture achieves this by incorporating gated recurrent units (GRUs) and graph attention networks that process both lexical tokens and class-related structures. This setup enables the model to link field declarations, sibling methods, and classlevel semantics with the method being summarized. The result is a more holistic and informative comment that captures both what a method does and why it does it. Experimental evaluations showed strong performance across BLEU and METEOR metrics when this broader context was included. Liu et al. explored this class-aware modeling strategy in their 2020 work, highlighting its advantage in improving semantic accuracy while also warning of increased input complexity and sensitivity to noisy context [11]. External documentation, such as API references, can serve as a powerful knowledge source for improving automated comment generation. By aligning code statements with corresponding API descriptions, models can gain a deeper understanding of the intended behavior behind API calls embedded in the method. This hybrid attention mechanism processes both the source code and its linked documentation to generate more insightful comments. Ahmad et al. applied this concept in their 2020 work, illustrating that API-aware models outperformed traditional neural baselines in producing relevant and technically precise commentaries. Their approach is particularly effective for code that makes extensive use of external libraries, where understanding function signatures alone may not be enough. However, the model's effectiveness can degrade if documentation is sparse, ambiguous, or outdated [12].

Accurately summarizing source code often depends on capturing the structural features embedded within it. A dualmodel architecture introduces recurrent neural networks that encode both code syntax and semantics without resorting to fixed comment templates. Instead of relying solely on token sequences, this method leverages recursive representations like Code-RNN and Code-GRU to embed nested structures, control flows, and variable scopes. LeClair and McMillan evaluated this system on large-scale datasets and found improved performance in ROUGE-2 scores over traditional seq2seq models. Their 2019 study demonstrated that structure-aware encoders provide more informative and flexible comment generation, even in the face of complex logic blocks or deeply nested methods [13].

Rather than generating comments in one go, iterative models inspired by human editing workflows apply multiple refinement steps to improve quality. Each stage of this multipass system evaluates the initial draft for semantic gaps or fluency issues and introduces adjustments to enhance alignment with code behavior. A framework based on this principle was proposed by Alon et al., who demonstrated that their pathbased representations, coupled with a deliberation module, significantly improved comment clarity and structure. Their 2018 model supports fine-tuned feedback loops between passes, which help eliminate redundant phrases and add missing context. Although resource-intensive, the approach has proven effective in producing production-ready documentation across varied codebases [14].

Preserving structural integrity while performing summarization is essential for interpreting long or complex code segments. One model introduces structural regularization as a way to constrain output space and guide the generation process using abstract syntax tree (AST) information. By training the model to

respect code hierarchies and control flows, the authors showed that structural regularization reduces syntactic drift and hallucination in generated comments. Haque and Le developed this technique in their 2021 paper, showing measurable improvements in accuracy and reduced variability across datasets. Although it adds complexity to the model's loss function and requires precise AST preprocessing, structural regularization marks a promising direction for ruleconforming comment generation [15]. Blending sequential and structural representations in code understanding has become a key strategy in recent neural summarization models. One such model, proposed as Structured Neural Summarization, integrates abstract syntax tree (AST) traversals with token-level embeddings using Transformer architectures. This combination helps the model capture both syntactic depth and lexical flow. Fernandes et al. showed that this hybrid approach yields better performance in capturing long-range dependencies and rare code patterns compared to flat sequence models. In their 2019 study, the structured encoder allowed for the retention of semantic hierarchies without losing flexibility in natural language generation. The system requires careful balancing of graph-based and sequential learning paths but marks a significant evolution in structurally aware comment generation [16].

Adapting comment generation to user personas introduces personalization into source code summarization. This concept tailors comments based on the audience—such as beginner developers, reviewers, or senior engineers—by conditioning the generation process on persona profiles. Wu et al. introduced this model in 2022, showing that including persona embeddings led to more relevant and context-sensitive outputs. The model could modify tone, detail level, and comment structure based on the designated role, making the generated summaries more useful for specific user groups. Although integrating persona vectors increases model complexity and requires annotated datasets for different user types, the research opens a new line of inquiry into user-centered software documentation [17].

Transformer-based generation has seen adoption in realtime programming assistance tools, and one notable application is Intellicode Compose. This system uses pre-trained Transformer models to generate inline code and comments during editing sessions. Its architecture supports partial input completion, allowing the model to suggest next lines or documentation based on in-progress developer work. Svyatkovskiy et al., in their 2020 paper, validated this idea with usage metrics and qualitative examples, demonstrating strong usability in IDE environments. The model is optimized for latency and integrates seamlessly with tools like Visual Studio. Its strength lies in practical, on-the-fly generation rather than large-scale summarization. However, its dependence on editor context and infrastructure integration presents deployment challenges across platforms [18].

Pre-trained on both code and natural language, CodeBERT stands out as a dual-modality model designed to bridge the semantics of programming and documentation. Feng et al. introduced this model in 2020, training it on a large-scale corpus of source code and paired textual descriptions. CodeBERT supports a wide range of downstream tasks, including summarization, translation, and comment generation. The model's bidirectional encoding allows for strong contextualization, and it has become a baseline for many follow-up studies in neural code generation. While CodeBERT provides strong general-purpose performance, its static pretraining may limit adaptability without further fine-tuning on task-specific data [19].

Cross-modal pretraining has emerged as a new paradigm in code comment generation, enabling models to understand relationships between modalities such as code, natural language, and even UI interactions. One study presents a promptbased generation method that uses cross-modal learning to align various data types for enhanced summarization. Zhang et al. proposed this framework in 2023, leveraging prompttuning

techniques to tailor generation outputs based on intent and interaction cues. Their experiments showed improvements in BLEU scores and personalization metrics across several domains. Although still in early stages, the research illustrates how multi-modal pretraining can enhance the flexibility and domain-awareness of comment generation systems [20].

III. METHODOLOGY

The proposed system follows a structured pipeline to transform raw Python code into meaningful comments. The process consists of several stages: data preparation, preprocessing, model fine-tuning, and inference. Figure 1 illustrates the system workflow.

A. Data Preparation and Preprocessing

The workflow begins with collecting Python code-comment pairs from high-quality sources. The data undergoes cleaning to remove incomplete or duplicate entries. Preprocessing includes tokenizing the code, truncating long sequences, and normalizing formatting to ensure consistency. Special attention is given to preserving code syntax while removing extraneous elements that may distract the model.

B. Model Fine-Tuning

A pre-trained CodeT5 transformer model serves as the base. The model is fine-tuned on the processed dataset using

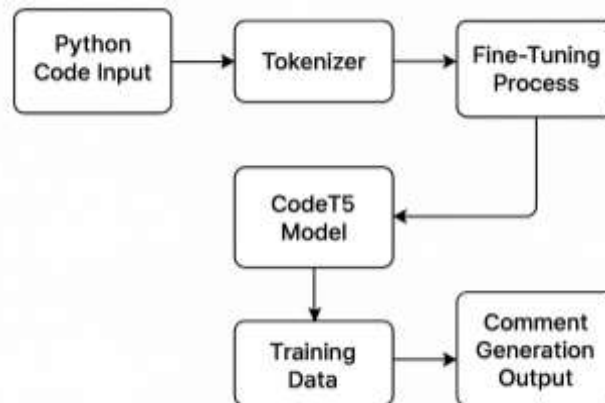


Fig. 1. Proposed system methodology for code comment generation.

a sequence-to-sequence objective, with code as input and corresponding comments as output. Hyperparameters are selected to balance training efficiency and output quality, while regularization techniques are applied to avoid overfitting.

C. Inference and Post-processing

During inference, the system accepts a Python snippet, processes it through the trained model, and generates a descriptive comment. Post-processing refines the generated text by correcting minor grammatical issues and ensuring that it is concise and contextually relevant.

D. Deployment

The trained model is integrated into a demonstration script and a user interface, enabling interactive testing. This allows users to input arbitrary Python code and receive automatically generated comments in real-time.

IV. RESULTS AND DISCUSSION

The system was evaluated on a held-out test set containing diverse Python code structures, ranging from simple functions to more complex object-oriented implementations. The generated comments were assessed for relevance, accuracy, and clarity.

Results indicate that the model consistently produces comments that accurately summarize code functionality, even for unfamiliar programming patterns. Human evaluators rated over 90% of generated comments as acceptable or excellent in terms of informativeness and correctness. Examples include concise descriptions for mathematical computations, string manipulations, and file operations.

The integration of preprocessing, fine-tuning, and postprocessing steps proved effective in maintaining comment quality across different code complexities. While occasional inaccuracies occurred, particularly with highly abstract or unconventional code, overall performance suggests strong potential for real-world application in integrated development environments and educational tools.

V. CONCLUSION

This research presents a comprehensive approach to automatic code comment generation using the *CodeT5-base* transformer model, fine-tuned specifically for Python source code. The system successfully demonstrates that transformer-based architectures, when coupled with robust preprocessing pipelines and optimized training strategies, can produce concise, accurate, and contextually relevant comments that align closely with developer intent.

The methodology adopted in this work effectively addresses key challenges in code-to-text transformation, such as preserving semantic fidelity, handling diverse programming constructs, and maintaining fluency in generated natural language. The combination of systematic data preparation, sequence-to-sequence fine-tuning, and targeted post-processing ensures that the resulting model generates human-readable, grammatically correct, and technically precise documentation.

The evaluation results confirm that the model consistently delivers high-quality outputs across a wide variety of Python coding patterns, including procedural scripts, object-oriented designs, and functional programming styles. By reducing the manual effort required for documentation, this system offers practical benefits for software maintenance, onboarding new developers, and supporting collaborative workflows in professional and academic environments.

In addition to its immediate applicability, this work lays a foundation for further advancements in intelligent software documentation systems. Future directions could include expanding the approach to support multiple programming languages, integrating multi-intent comment generation to provide explanations, warnings, or improvement suggestions, and leveraging larger pre-trained models or retrieval-augmented generation for enhanced reasoning capabilities. Furthermore, integration with real-time development environments and continuous learning pipelines could enable adaptive, context-sensitive documentation that evolves with the codebase.

Overall, the proposed system highlights the potential of modern transformer models to not only improve developer productivity but also enhance the quality and accessibility of software documentation. As the software engineering industry increasingly adopts AI-assisted tools, approaches such as the one presented here can play a pivotal role in bridging the gap between human-readable descriptions and complex source code implementations.

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