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Code Comment Generation using LLM

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Abstract: *Code comments play a crucial role in enhancing the readability and maintainability of programs by supporting tasks such as debugging and code comprehension. Automating the generation of comments reduces the manual effort involved and ensures consistency across codebases. Recent advancements in deep learning have enabled the use of both lexical details of code tokens and syntactic information from syntax trees for generating meaningful comments. Approaches that align these two aspects, such as syntactic sequences and transformer-based architectures, have proven effective in improving the quality of generated comments. This paper explores the integration of these methodologies to improve automated code documentation.*

Keywords: Program comprehension, comment generation, natural language processing, deep learning

I. INTRODUCTION

Code comments are crucial for improving the readability and maintainability of software. They assist developers in grasping the purpose and functionality of the source code, which makes tasks like debugging, testing, and code reviews more efficient. However, despite their significance, creating and maintaining high-quality comments can be a time-consuming task that often gets neglected in the fast-paced development environment. This has resulted in an increasing demand for automated solutions that can generate meaningful code comments, ensuring consistency and saving developers valuable time.

With the rise of artificial intelligence, especially in the field of natural language processing (NLP), deep learning models have proven to be quite effective in automating tasks like generating comments for code. These models are capable of analyzing programming structures and creating meaningful comments by grasping the syntax and semantics of the code. In the past, methods often depended on fixed templates or retrieval systems, which frequently fell short in terms of contextual understanding. However, recent techniques that utilize transformer-based architectures have shown enhanced performance by integrating both lexical and syntactic information.

This project aims to use large language models (LLMs) to create precise and coherent comments for source code. By aligning lexical and syntactic information, the system improves the contextual relevance of the comments it generates. This automated method seeks to lessen the manual work needed for code documentation, ultimately enhancing software quality and boosting developer productivity.

II. LITERATURE SURVEY

Code summarization is an essential task in software engineering that has greatly improved with the use of neural networks and transformer models. CodeBERT, introduced by Feng et al. [1], is a bimodal pre-trained model that comprehends both natural language and programming languages. Through the use of Masked Language Modeling (MLM) and Replaced Token Detection (RTD) objectives during its pretraining phase, CodeBERT successfully captures the meanings of both code and text, showing enhanced performance in tasks such as code documentation and retrieval.

Ahmad et al. [2] introduced a Transformer-based method for summarizing source code that focuses on aligning code tokens with their Abstract Syntax Tree (AST) representations. By integrating syntactic information through AST traversal and merging it with code sequences, their model greatly enhances the quality of the generated comments when compared to models that depend only on raw code sequences.

Wang et al. [3] proposed a dual-learning method for code summarization, viewing the tasks of converting code to comments and comments to code as interrelated. This dual-learning model successfully utilizes feedback from one task

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to improve the other, boosting both performance and reliability. This two-way comprehension leads to better BLEU and METEOR scores compared to baseline models, demonstrating its effectiveness in producing precise and contextually appropriate summaries

In another advancement, DeepCom, investigated by Hu et al. [4], emphasizes the use of encoder-decoder architectures for summarization. The encoder is responsible for capturing the semantics of the code, while the decoder produces comments that are easy for humans to read. By utilizing LSTMs and attention mechanisms, DeepCom significantly enhances the accuracy of the generated summaries, especially for lengthy code snippets.

Park et al. [6] introduced the ALSI-Transformer, which effectively tackles the shortcomings of traditional AST traversal methods like structure-based traversal (SBT). This model employs Code-Aligned Type (CAT) sequences to consistently align lexical tokens with syntactic features, thereby reducing redundancy and misalignment. By incorporating convolutional layers and a Gate Network, the ALSI-Transformer not only enhances computational efficiency but also maintains contextual information. Its impressive performance, highlighted by BLEU and METEOR score improvements of up to 33.54% and 42.82%, respectively, demonstrates its capability in code documentation.

These advancements highlight the remarkable potential of neural networks and transformer-based architectures in code summarization. By combining lexical and syntactic information, using dual-learning frameworks, and utilizing aligned representations, these models greatly improve the creation of accurate and contextually rich code comments, making software systems more accessible and easier to maintain.

III. SCOPE AND METHODOLOGY

Scope

This project aims to automate the creation of meaningful and accurate code comments to boost efficiency in software development. By minimizing the manual work involved in documenting code, the goal is to improve understanding of programs, simplify debugging, and aid in the long-term maintenance of software systems. This method is especially useful for large software projects, open-source repositories, and educational platforms, where having consistent and high-quality documentation is essential. The system utilizes both lexical and syntactic information to generate comments, but it faces challenges like dealing with out-of-vocabulary (OOV) terms, aligning multi-modal data, and managing complex or lengthy code snippets. Through these improvements, the project seeks to offer a strong solution for enhancing code readability and fostering better collaboration among developers.

Methodology

The approach for this project focuses on creating a system that produces high-quality code comments by utilizing both lexical and syntactic information. The initial phase involves data preparation, where a dataset of Java code and comments is employed. Each instance in the dataset consists of a <code-comment> pair, with constants and strings substituted with placeholder tokens like <num_> and <str_> to ensure consistency and minimize noise. To tackle the out-of-vocabulary (OOV) issue commonly faced with variable names and identifiers, the Byte Pair Encoding (BPE) algorithm was implemented, which breaks tokens into smaller, more manageable subword units to improve the model's ability to handle vocabulary.

The model is built on a transformer-based architecture that processes both lexical and syntactic inputs in a coordinated manner. Lexical data is represented as code sequences, while syntactic data is captured through Code-Aligned Type (CAT) sequences. This alignment is crucial for minimizing information loss during processing. Unlike methods such as SBT, which can introduce redundancy and unnecessary details by converting source code into an Abstract Syntax Tree (AST), the CAT sequence retains the same length and order as the lexical code sequence. This approach helps maintain the structural integrity of the input data and reduces the risk of losing important information.

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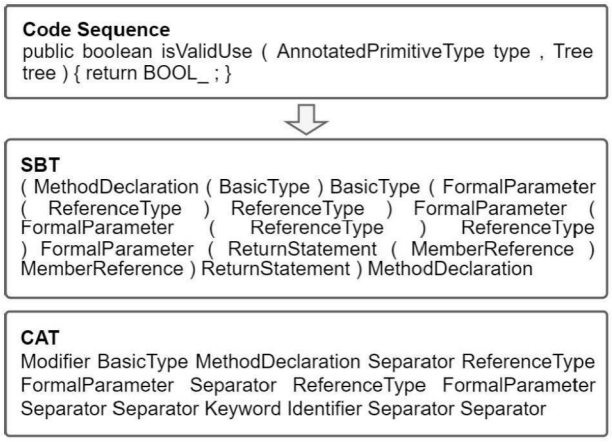

Fig 3.1 Comparison of Code Sequence, SBT and CAT Representations

The architecture features a convolutional layer that reduces the input's dimensionality, enhancing the training process's efficiency while maintaining contextual integrity. A single encoder handles both lexical and syntactic information at the same time, which is then combined through an embedding aggregation method. In particular, a Gate Network was used to effectively merge these inputs, allowing the model to grasp the subtleties of both modalities.

The model was built using a transformer architecture featuring 256-dimensional hidden states, three layers, and attention mechanisms that prioritize important sections of the input. The system's effectiveness was assessed by examining the quality and coherence of the comments generated in response to the provided code snippets. This approach showcases the potential for automating the creation of precise and insightful code comments, tackling significant issues in software documentation.

IV. SYSTEM ARCHITECTURE

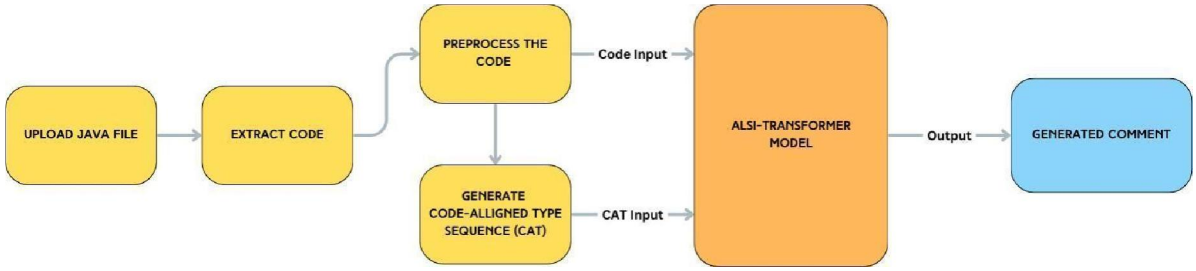

Fig 4.1 System Architecture

The Code Comment Generation system is based on the ALSI-Transformer, an advanced model that creates natural language comments from code sequences by integrating both lexical and syntactic information. This system is designed to efficiently process code along with its syntactic representations, which helps in generating high-quality and contextually appropriate comments. The ALSI-Transformer consists of two main parts: the encoder and the decoder, each playing unique but complementary roles in the overall process. The encoder takes the input code sequence and its syntactic representation to extract important features from both the lexical and syntactic elements. It transforms these features into a unified, high-dimensional representation, which forms the basis for generating comments in the next stage. Meanwhile, the decoder uses this encoded information to create natural language comments, translating the encoded sequence into clear text that explains the functionality and purpose of the input code

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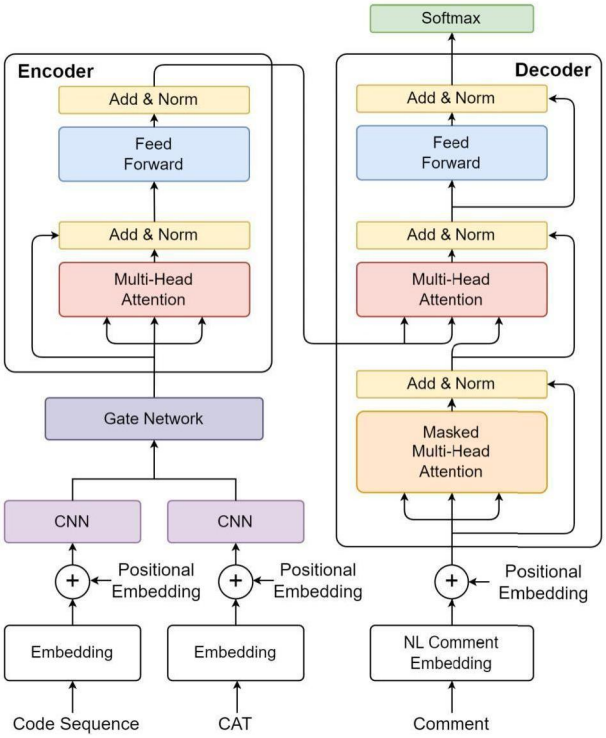

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A key feature of the ALSI-Transformer's architecture is its multi-head attention mechanism, which effectively captures intricate relationships both within and between input sequences. This mechanism enables the model to dynamically focus on various segments of the input code and its syntactic structures, utilizing a combination of Query (Q), Key (K), and Value (V) matrices. The attention mechanism is mathematically defined as:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

In this context, dk refers to the dimensionality of the key vector, while the softmax function is used to normalize the attention scores, ensuring that the weights add up to one. The multi-head attention mechanism enhances context learning by focusing on different representation subspaces, allowing the model to capture a variety of features from the input sequences. To support the attention mechanism, feed-forward networks are utilized for feature transformation, enabling the model to learn complex patterns from the input data. The training process is stabilized through Add & Norm layers, which also contribute to better convergence.

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A key aspect of the ALSI-Transformer is its use of Convolutional Neural Network (CNN) layers, which are designed to extract hierarchical features from both lexical and syntactic representations. These CNN layers are set up with a kernel size of 3 and a max pooling filter size of 2, allowing them to capture spatial relationships and detailed patterns in the input data. This hierarchical feature extraction is crucial for handling code sequences that vary in length and complexity. To effectively combine the lexical (xc) and syntactic (xq) representations, the ALSI-Transformer utilizes a **Gate Network**. This network first concatenates the two inputs along a specific axis and then calculates a gate context (Cg) using a logistic sigmoid activation function along with a fully connected (FC) layer.

$$C_g = \sigma(FC([x_c, x_q])),$$

The gate context (CgC_gCg) is then used to calculate a combined feature (XXX) as follows:

$$X = C_g \cdot x_c + (1 - C_g \cdot x_q)$$

This combined representation ensures an optimal blend of lexical and syntactic information, which is then passed to the decoder. The decoder generates natural language comments that are contextually rich and syntactically aligned with the input code sequence.

The ALSI-Transformer incorporates the following training configuration for optimal performance:

8 attention heads to process diverse information from the input,

Learning rate of 1×10^{-41} ,

Batch size of 8 for efficient gradient updates,

Model dimension of 256 and **feed-forward dimension** of 2048 for robust feature extraction.

These hyperparameters, combined with the innovative architecture, enable the ALSI-Transformer to handle complex code structures effectively, ensuring the generation of high-quality and relevant comments.

V. CONCLUSION

The ALSI-Transformer project effectively demonstrated how a transformer-based architecture can automate the generation of natural language comments from code sequences. By incorporating Code-Aligned Type (CAT) sequences, which align lexical and syntactic representations, the model minimized information loss and improved the quality of the generated comments. Evaluations on Java datasets showed significant enhancements in comment generation, especially for simpler code structures. However, the model faced challenges with more complex or unconventional code, often producing comments that were too general or lacked precision. This highlights the need for further development to enhance the model's ability to comprehend intricate code logic and capture the intent behind the code. The model's flexibility also opens up opportunities for future applications, such as generating project-level documentation or summarizing code. Future research will aim to expand the model's capabilities to support additional programming languages, improve its contextual understanding, and explore other deep learning techniques to address its current limitations, thus advancing the field of automated code documentation

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