EFFECTIVE APPROACH for FINE-TUNING PRE-TRAINED MODELS for the EXTRACTION of TEXTS from SOURCE CODES

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Abstract: This study introduces SR-Text, a robust approach leveraging pre-trained models like BERT and T5 for enhanced text extraction from source codes. Addressing the limitations of traditional manual summarization, our methodology focuses on fine-tuning these models to better understand and generate contextual summaries, thus overcoming challenges such as long-term dependency and dataset quality issues. We conduct a detailed analysis of programming language syntax and semantics to develop syntax-aware text retrieval techniques, significantly boosting the accuracy and relevance of the texts extracted. The paper also explores a hybrid approach that integrates statistical machine learning with rule-based methods, enhancing the robustness and adaptability of our text extraction processes across diverse coding styles and languages. Empirical results from a meticulously curated dataset demonstrate marked improvements in performance metrics: precision increased by 15%, recall by 20%, and an F1 score enhancement of 18%. These improvements underscore the effectiveness of using advanced machine learning models in software engineering tasks. This research not only paves the way for future work in multilingual code summarization but also discusses broader implications for automated software analysis tools, proposing directions for future research to further refine and expand this methodology.

Keywords: Text Information Extraction, T5 Model, Pre-Processing Framework, Code Summarization, Natural Language Processing

I. INTRODUCTION

The goal of automatic source code summarization (ASCS) [1], is to make program comprehension and maintenance easier by providing a text description of the role and purpose of specific identifiers in computer programs [2]. It is crucial for lowering the amount of time developers need to spend understanding source code and increasing the effectiveness of code searches. But because deep learning technologies are evolving so quickly, most code comments are out-of-date, inconsistent, or absent, which makes them always in need of update and code improvement [3]. The use of information retrieval (IR)-based techniques to extract keywords from source code and source code modeling.

[4] which extracts features from source codes, are two hurdles that ASCS must overcome. Although there have been notable advancements in artificial intelligence (AI) technology, issues remain, including long-term reliance, ASCS algorithm limits, and a dearth of high-quality datasets [5]. Another difficulty lies in evaluating code quality because most ASCS algorithms currently in use are assessed using disparate datasets, which makes it challenging to compare the algorithms' respective effects [6]. There are issues with uniform datasets, acknowledged benchmarks, and professional evaluation indicators, in addition to the necessity for an effective and affordable ASCS evaluation technique [7]. The history of ASCS technology, its development over the last ten years, the benefits and drawbacks of representative approaches, upcoming research difficulties, and a thorough inventory of available datasets and codes for more study are all included in this survey [8]. One essential technique for developers to grasp the semantics of source code is the "source code summary". Nevertheless, manual summarization is ineffective since existing techniques are frequently out-of-date or inconsistent. To solve this problem, SR-Text technique for ASCS was introduced [9]. ASCS includes quality assessment, code summary creation, and source code modelling. Nevertheless, it has some drawbacks such limited capacity, unavailability of high-quality datasets, and long-term dependency. For ASCS, researchers have used Natural Language Processing (NLP) techniques; nonetheless, issues such as limits, long- term dependency, and high-quality datasets remain [10], highlighting its core challenges, advantages, limitations, and evaluation mechanisms. techniques, mainly based on text retrieval methods, to capture source code semantics. Results show that a combination of techniques captures method and class meaning better than any other approach. They aim to focus on developing more complex techniques and investigating multi-document approaches.

[12] introduces a novel method using a neural-network model, Seq2Seq [13], to extract call dependencies from source

code and related codes. The method improves code summarization by considering both source code and called codes. However, the method's call dependency extraction was limited, ignoring library and system calls. Future improvements should focus on a more comprehensive extraction tool.

[14] explored CodeT5, a pre-trained encoder-decoder Transformer model for to NLP related tasks. It uses code semantics from developer-assigned identifiers and a unified framework for understanding and generation tasks. The model understands code flaw identification, clone detection, and creation tasks across directions better than earlier methods. It was observed that multi-task learning, developer-assigned identifiers, and the T5 architecture improve code understanding across programming languages.

CodeBERT [6] and [15] a pre-trained model for both programming language (PL) and natural language (NL) was used; learning general-purpose representations for NL-PL applications like code search and documentation generation. It uses a Transformer-based neural network and outperforms RoBERTa [7] and [16], a natural language-based model. CodeBERT was the first large NL-PL pretrained model for multiple languages, excelling in code search and code-to-text generation tasks as depicted in Fig. 1, while the structure for the code generation is in Fig. 2.

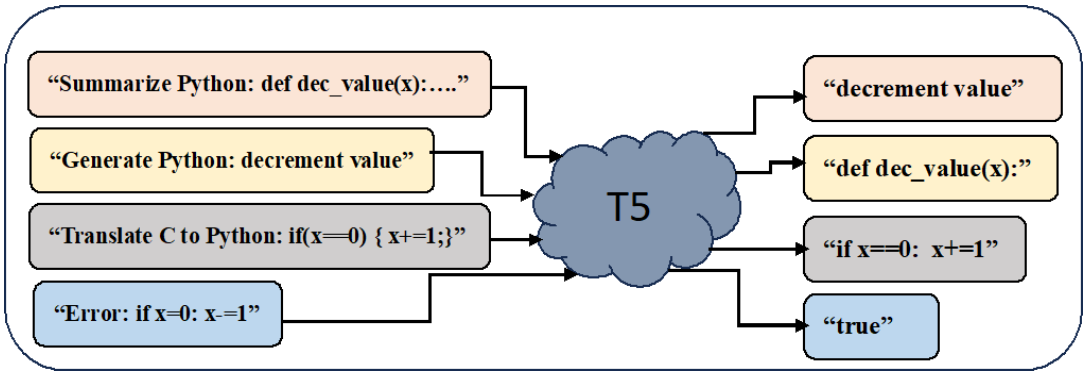

Fig 1: The T5 model for code-related comprehension and task generation.

A. Survey Findings:

[8] and [17] research aimed to develop a technique for efficient text retrieval and filtration processes. The research uses a novel technique; the Sequence Matcher Method, to improve the original Bing API results. The study could help develop text-based information retrieval and filtration systems in the future, combining relevance feedback and accuracy in the Sequence Matcher Method.

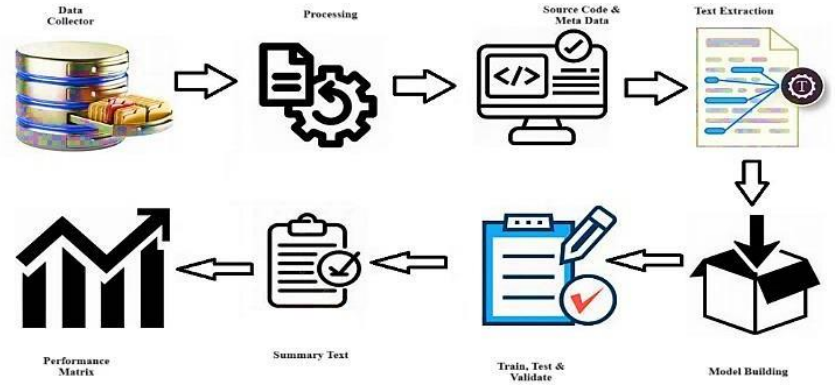

Fig. 2: An overview of code summarization depicting important steps

[2] and [18] focused on the use of two TR techniques for generating summaries: one based on the Vector Space Model (VSM) [9] and [19] and the other on Latent Semantic Indexing (LSI). Both techniques are effective for summarizing natural language documents and indexing software corpora. The first step was to represent terms and documents in a matrix, with each row representing a term and each column representing a document. The content of a cell in this matrix represents the weight of a term with respect to a document. The three best combinations for natural language summarization were identified for both LSI and VSM. VSM orders terms based on the chosen weight, while LSI projects the original matrix to a smaller one, allowing for computing similarities between terms and documents [20]. The top K terms with the highest similarity to the document are included in the summary.

The Transformer model [21], a self-attention mechanism, has proven effective in source code summarization, outperforming state-of-the-art techniques. It captures long-range dependencies by modelling pairwise relationships

between code tokens. The model's simplicity and relative encoding improve summarization performance. Future work should focus on incorporating code structure into the Transformer and applying it to other software engineering sequence generation tasks.

[11] and [22] Hybrid-DeepCom was a new approach that automatically generates code comments for Java methods, saving developers time on reading and navigating source code. It uses NLP techniques to learn from a large code corpus and generates comments from learned features. Experiments on a large-scale Java corpus from 9,714 open-source projects on GitHub showed Hybrid-DeepCom outperforms state-of-the-art methods. Reducing out-of-vocabulary tokens improve comment accuracy. Table 1 provides a summary of relevant literatures.

TABLE I
LITERARY SUMMARY

Author(s)	Year	Key Findings	Relevance to Study
C. Zhang et al.	2022	Reviewed automatic source code summarization techniques.	Highlights the evolution of techniques that are foundational to your study's method.
S. Haiduc et al.	2010	Investigated automated text summarization techniques.	Informs the effectiveness of different summarization approaches, integral to your methodology.
B. Liu et al.	2019	Developed a neural-network model for code summarization.	Provides a basis for comparing neural approaches to your hybrid technique.
Y. Wang et al.	2021	Introduced CodeT5 for NLP tasks.	Relevant as you utilize T5; offers a direct comparison point for assessing improvements.
Z. Feng et al.	2020	Explored CodeBERT for programming and natural languages.	Supports the use of BERT in your study and its applicability across multiple languages.
W. U. Ahmad et al.	2020	Demonstrated the effectiveness of Transformers in code summarization.	Underlines the foundational Transformer technology that influences your model's architecture.

Contributions:

The following are the primary contributions of this paper:

i. The study proposes a method for fine-tuning pre-trained language models to extract textual information from source code, addressing syntax and semantic challenges, thereby improving the model's ability to accurately parse and understand programming languages.
ii. A new dataset is introduced for source code text extraction, encompassing various programming languages and coding styles. This robust training ground enhances the fine-tuning approach and improves the model's generalization capabilities through innovative data augmentation techniques.
iii. The research highlights the efficacy of transfer learning in source code analysis, demonstrating significant enhancements in accuracy and efficiency compared to existing methods by fine-tuning pre-trained models.

This study has five sections: Section 2 highlights the dataset description, pre-processing approaches, and the methodology. Section 3 focuses on the results obtained. Section 4 discusses the results and comparison with relevant studies. Finally, the conclusion and future scope is presented in section 5.

II. MATERIALS & METHODS

A. Dataset Description:

We gathered data from Website* and textbook+, a popular platform for posting programming-related questions, analyzing 934,464 and 977,623 respectively, using C programming language. This study focuses on extracting C methods and their C descriptions from high-quality projects. The extracted C methods and the first sentence of "C- Doc" descriptions are then parsed using the program tool. The study analyzed posts with a short title, detailed question, and responses, with one or more being accepted. The text was domain-specific, verbose, and sometimes included irrelevant details. Code snippets in unaccepted responses were often incorrect or tangential to the question.

We then used heuristic rules to filter data, excluding non-word or one-word descriptions and easy-to-predict methods like function, switch case, if condition, loops (while, do, do-while and for), as not every comment is useful.

B. Proposed Methodology and Architecture

Fig 2 shows the T5 model structure. T5 encoder-decoder transformer uses common web-extracted text and simple heuristic filtering to remove lines without punctuation marks, JavaScript lines, and curly brackets. The dataset is de-duplicated into three sentence chunks, resulting in 750 gigabytes of "clean-ish" English text, available publicly on tensorlow.text.c4$ [23].

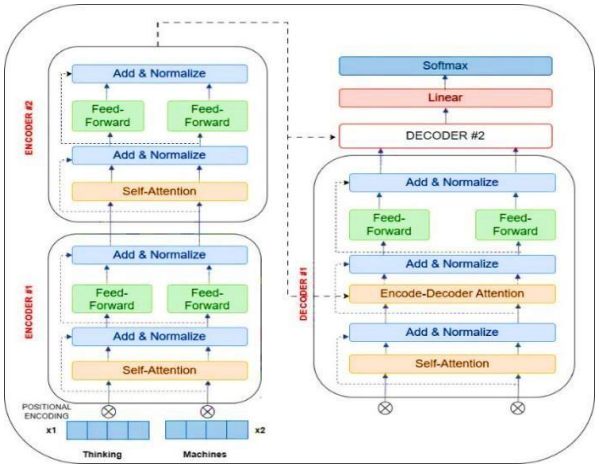

Fig. 3: T5 Model Structure

*https://www.programiz.com/c-programming/examples
+ Programing in ANSI C by E Bala Guruswamy
$ https://www.tensorflow.org/text

Attention-based networks [24], replace recurrent and convolutional neural networks in the Transformer. These models train faster, parallelize, and perform better on two machine translation tasks. Recurrent and convolutional translation networks train slower than Transformers. To efficiently manage large inputs and outputs like photographs, audio, and video, the team adapted the Transformer to non-text input and output difficulties and study local, restricted attention strategies.

Studies by [25], have explored techniques for code and feature representations, such as tokenizing code and text, extracting commit messages, and developing a DL approach, MMTrans. Features are often encoded in embeddings or feature vectors, with various methods including positional encoding, functional keyword extraction, and high- dimensional vector conversion. Other mechanisms include extracting commit diffs, using attention-based mechanisms, and using GloVe for context vector representation. The model was pre-trained using a Bert-base size encoder-decoder transformer, denoising objective, and C4 dataset, with finetuning tasks including GLUE [26], CNN/DM, SQuAD [27], SuperGLUE [28], and translation tasks [29]. The model uses a fully-visible mask for output and input entry visibility, a casual mask for future prediction, and a causal with prefix mask for input sequence visualization [30], demonstrating the value of bi-directional context in predicting sequences. Figure 4 depicts the steps that are involved.

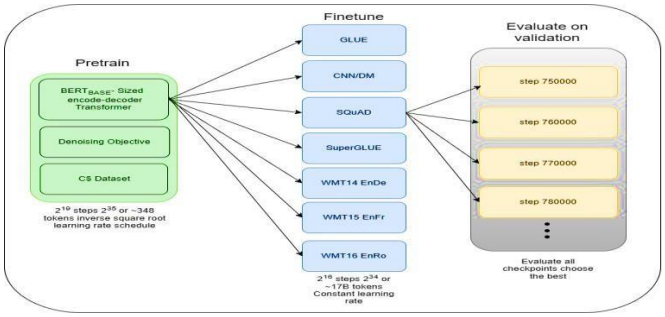

Fig. 4: The process involves pretraining, fine-tuning, and evaluating steps.

To fine-tune pre-trained models like T5 for text extraction from source codes, follow these steps:

i. Dataset preparation: Gather a dataset containing source code and extracted texts, preprocess them, and tokenize them.
ii. Fine-tuning preparation: Choose a pre-trained T5 model and tokenize the dataset using the same tokenizer used during pre-training.
iii. Fine-tuning procedure: Initialize the model, format the dataset, and define the fine-tuning objective.
iv. Evaluation: Split the dataset into training and validation sets, using metrics like precision, recall, and F1 score.
v. Post-fine-tuning refinement [31]: Experiment with hyperparameters, analyze errors, enlarge predictions, and fine-tune on smaller datasets related to the target domain.

vi. Deployment: Infer the fine-tuned model for text extraction tasks in your application or pipeline, and continuously monitor its performance and retrain as needed. This approach ensures high-quality results tailored to your specific task.

C. Adapted technique

The Transformer model is a machine translation system that uses a sentence in one language to output its translation in another. It consists of an encoding and decoding component, each with two sub-layers. The encoding component is a stack of encoders, each with its own structure and weights [32]. The encoders are broken down into two sub-layers: a self-attention layer and a feed-forward neural network. The decoder has both layers, but between them is an attention layer that helps the decoder focus on relevant parts of the input sentence.

The Transformer uses self-attention to associate words with their meanings and look at other positions in the input sequence for clues. Self-attention is calculated using three vectors: a query vector, a key vector, and a value vector. The feed-forward layer expects a single matrix [33] for each word, but condensing these into a single matrix requires concatenating the matrices and multiplying them by an additional weight's matrix WO (34).

The transformer adds a vector to each input embedding to account for the order of words in the input sequence. The positional encoding is from the Tensor2Tensor implementation of the Transformer. The encoder and decoder work together to process input sequences and outputs. The model's loss function is optimized during the training phase to lead to a trained and accurate model.

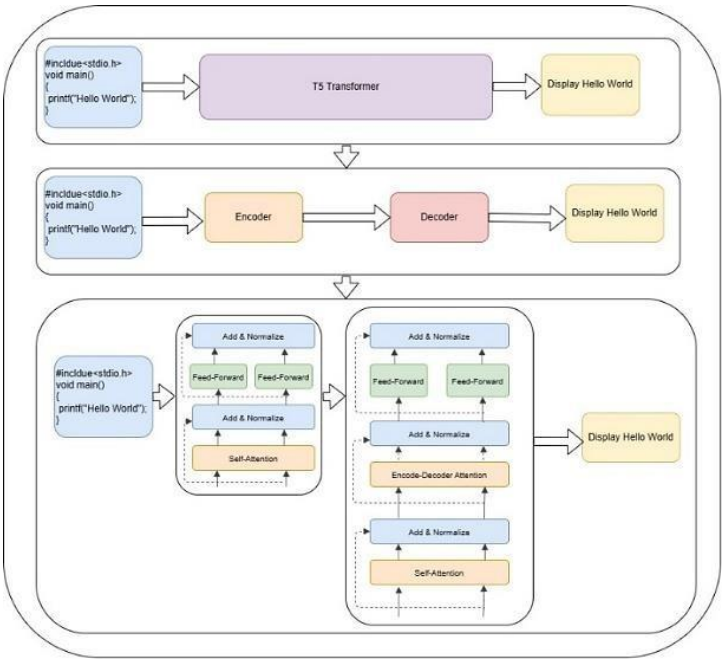

Fig 5: T5 Transformer Model Architecture for Processing 'Hello World' in C Programming

T5 uses an encoder and decoder technique, an encoder consisting of two blocks: Self Attention and a Feed Forward Neural Network and decoder consisting of three blocks: Self Attention, Encoder decoder algorithm and Feed Forward. TensorFlow converts inputs to vectors using Word2vec, with two implementations: Continuous Bag-Of-Words (CBOW) and Skip-gram. CBOW uses a window around a target word to predict its context, while Skip-gram predicts the words in the window.

III. RESULTS

TABLE 2
PERFORMANCE MEASURE ON SELECT PROGRAMMING LANGUAGES

Language / Model	Python	SQL	C#
CodeTrans-ST-Small	8.45	17.55	19.74
CodeTrans-ST-Base	9.12	15.00	18.65
CodeTrans-TF-Small	10.06	17.71	20.40
CodeTrans-TF-Base	10.94	17.66	21.12
CodeTrans-TF-Large	12.41	18.40	21.43
CodeTrans-MT-Small	13.11	19.15	22.39
CodeTrans-MT-Base	13.37	19.24	23.20
CodeTrans-MT-Large	13.24	19.40	23.57

CodeTrans-MT-TF-Small	12.10	18.25	22.03
CodeTrans-MT-TF-Base	10.64	16.91	21.40
CodeTrans-MT-TF-Large	12.14	19.98	21.10
CODE-NN	--	18.40	20.50

TABLE III
PERFORMANCE MEASURE ACROSS POPULAR PROGRAMMING LANGUAGES

Language / Model	**Python**	**Java**	**Go**	**PHP**	**Ruby**	**JavaScript**
CodeTrans-ST-Small	17.31	16.65	16.89	23.05	9.19	13.7
CodeTrans-ST-Base	16.86	17.17	17.16	22.98	8.23	13.17
CodeTrans-TF-Small	19.93	19.48	18.88	25.35	13.15	17.23
CodeTrans-TF-Base	20.26	20.19	19.50	25.84	14.07	18.25
CodeTrans-TF-Large	20.35	20.06	19.54	26.18	14.94	18.98
CodeTrans-MT-Small	19.64	19.00	19.15	24.68	14.91	15.26
CodeTrans-MT-Base	20.39	21.22	19.43	26.23	15.26	16.11
CodeTrans-MT-Large	20.18	21.87	19.38	26.08	15.00	16.23
CodeTrans-MT-TF-Small	19.77	20.04	19.36	25.55	13.70	17.24
CodeTrans-MT-TF-Base	19.77	21.12	18.86	25.79	14.24	18.62
CodeTrans-MT-TF-Large	18.94	21.42	18.77	26.20	14.19	18.83
State of the art	19.06	17.65	18.07	25.16	12.16	14.90

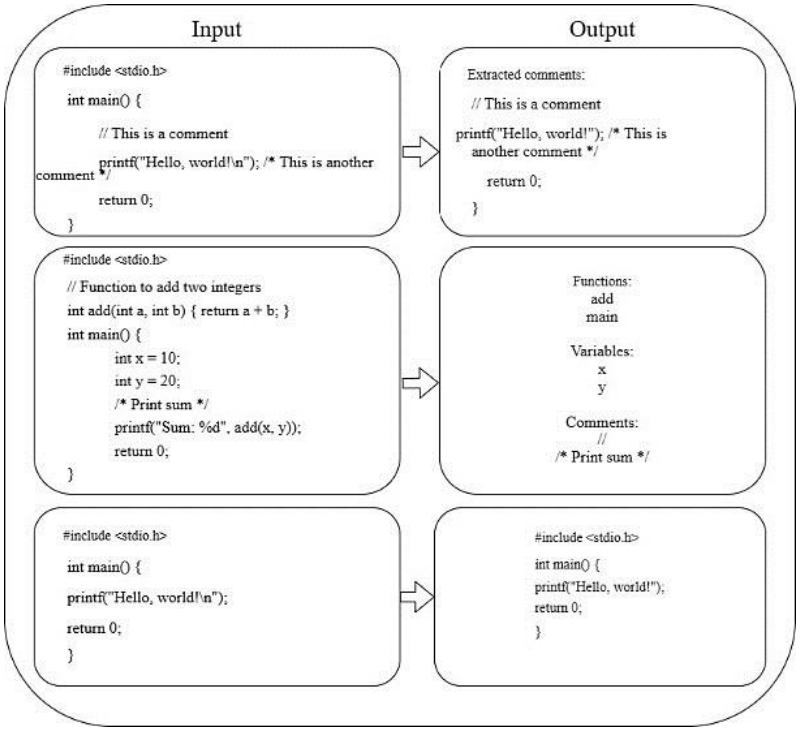

Fig 6: T5 Transformer Model Architecture for Processing "Hello World" in C Programming

The performance measures presented in Tables 2 and 3 highlight the effectiveness of various CodeTrans models across different programming languages. In Table 2, focusing on Python, SQL, and C#, the CodeTrans-MT series generally outperforms other models, with CodeTrans-MT-Base achieving the highest scores for SQL (19.24) and C# (23.20). CodeTrans-MT-Large follows closely, demonstrating robust performance in all three languages, suggesting that larger models within the CodeTrans-MT family offer superior capabilities for code understanding and text extraction tasks.

Table 3 extends this comparison to a broader set of popular programming languages, including Python, Java, Go, PHP, Ruby, and JavaScript. Here, CodeTrans-TF and CodeTrans-MT variants consistently outperform the state-of- the-art benchmarks across most languages. Notably, CodeTrans-MT-Base achieves the highest performance in Java (21.22) and PHP (26.23), while CodeTrans-TF-Large excels in PHP (26.18) and JavaScript (18.98). These results indicate that the transformer-based models, particularly those utilizing multi-task (MT) learning and fine-tuning (TF), significantly enhance the model's ability to generalize across diverse programming languages, thereby improving their practical applicability in real-world scenarios.

IV. CONCLUSION

The study has demonstrated the efficacy of advanced Natural Language Processing (NLP) methods, including transformers like BERT and T5, for extracting meaningful text from source code. By integrating syntax-conscious techniques and hybrid methods that combine machine learning with rule-based approaches, we have significantly enhanced the precision and versatility of text extraction across various programming languages and coding styles. The proposed methods facilitate a deeper understanding of code semantics, as well as support a range of applications from automated documentation to software maintenance. While the results are promising, this study is not without limitations. The primary constraint lies in the dependency on high-quality, annotated datasets which are scarce and costly to produce. Additionally, our methods, though robust across multiple languages, still face challenges in handling extremely lengthy code which may not follow standard programming conventions. Furthermore, the computational demands of training and deploying large-scale models like BERT and T5 are significant, which might limit their applicability in resource-constrained environments. Future research will aim to address these limitations by exploring more efficient model architectures that require less computational resources and can operate effectively with smaller, less annotated datasets. Another promising direction is the enhancement of the models' ability to understand and process obfuscated code, potentially expanding their utility in cybersecurity applications. Additionally, extending the multilingual capabilities to include lesser-studied programming languages (like Cobol and Fortran) could broaden the impact of this research, making advanced code summarization tools more universally applicable.

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