Learning To Document Code: Experiments With CodeT5 On Real-World Codebases

Pradyumna D[#1] Dr. Ramprasath M[#2]

[#1]Department Of Data Science And Business Studies, SRM Institute Of Science And Technology, Chennai, India

[1]pradyumnad092004@gmail.com

[#2]Assistant Professor, Department Of Data Science And Business Studies, SRM Institute Of Science And Technology, Chennai, India

[2]ramprasm@srmist.edu.in

Abstract—Automatic code documentation generation is crucial for improving software maintainability, readability, and developer productivity. Recent advances in neural sequence-to-sequence models, particularly transformer architectures, have demonstrated promising performance on natural language tasks. This paper explores the application of a T5-based model (Salesforce/codet5-small) for generating function-level documentation from code snippets. We combine multiple publicly available datasets—CodeSearchNet and CodeXGLUE—for JavaScript and Python, and apply preprocessing that filters out extreme outliers based on token-length distributions (max 512 tokens for code, 128 for docstrings). Our training setup employs mixed-precision, gradient checkpointing, and adaptive batch sizing tailored to an RTX 3050 4 GB GPU. We evaluate using BLEU and ROUGE-L metrics, achieving up to 51.87 BLEU and 58.34 ROUGE-L on validation data. We further analyze the impact of dataset composition, sequence-length thresholds, and batch-size configurations. Results indicate that careful filtering and training parameter tuning within hardware limits can yield high-quality documentation generation. Future work will explore larger models and reinforcement-learning fine-tuning for improved coherence and completeness.

Keywords— Code Documentation Generation, Code Summarization, Transformer Models, CodeT5, Code SearchNet, CodeXGLUE, Seq2Seq Models, BLEU Score, ROUGE-L Score, Deep Learning, NLP, Software Engineering Automation.

I. Introduction

Writing good documentation is essential: it helps developers read, understand, and build on each other's work, while gaps in docs often lead to wasted hours tracking down bugs or teaching new team members the ropes [1]. Traditionally, writing these comments by hand is a chore—time-consuming and easy to mess up [2]. Early efforts to automate the task relied on rigid templates and simple code analyses [3], but they couldn't adapt when code got complicated or followed unfamiliar patterns.

Then came deep learning. RNN-based "translate-code-to-text" systems with attention breathed new life into doc generation, making summaries smoother and more flexible [4], yet they still stumbled on long, intricate functions. The transformer revolution changed everything: models like BERT [6] and T5 [7] brought powerful context awareness to language tasks [5], inspiring researchers to train variants specifically on code. CodeBERT [8] and CodeT5 [9], for example, learned from massive code datasets, greatly boosting summarization quality. Benchmarks such as CodeSearchNet [10] and CodeXGLUE [11] emerged, letting us compare methods across languages.

Even so, state-of-the-art models remain too hungry for memory and compute to run on an average laptop. That's why we focused on being resource-aware. Instead of opting for huge models like CodeT5-base or StarCoder, which need a GPU farm, we show that CodeT5-small—fine-tuned with smart preprocessing, mixed-precision training, and careful sample filtering—can produce excellent docs on a 4 GB graphics card. By merging JavaScript and Python examples from CodeSearchNet and CodeXGLUE and capping code at 512 tokens and docs at 128, we strike the right balance between coverage and efficiency. The result is a lean, accessible pipeline that anyone with modest hardware can use to generate clear, helpful function-level documentation.

II. Literature review

Early efforts to automate documentation leaned on templates and static analysis. For example, Sridhara et al. used API patterns and identifier heuristics to pull out key actions [12], but these rules often broke down when code didn't follow the expected style. Then came neural approaches: Iyer et al.'s CODE-NN added attention to RNNs to generate Java method summaries end to end [13], yet it still faltered on long or complex functions.

The real breakthrough arrived with transformers—Ahmad et al. showed that a transformer trained on CodeSearchNet could leave RNNs in the dust on BLEU and ROUGE metrics [14]. Building on that, Feng et al. introduced CodeBERT, using masked language modeling over six programming languages to learn richer code representations [8], and GraphCodeBERT later wove in AST data-flow information to capture deeper semantics [15]. CodeT5 then extended T5's pre-training toolkit with multiple code-centric tasks—summarization, translation, repair—and set new state-of-the-art marks on CodeXGLUE and CodeSearchNet [9]. To make these big models run on smaller GPUs, researchers have turned to tricks like knowledge distillation [16], quantization [17], and lightweight fine-tuning adapters such as LoRA [18], shrinking models and speeding up inference without losing much accuracy.

More recently, the field has started blending retrieval and generation. Yin et al. enriched summaries by fetching related code examples at runtime—giving the model extra context and boosting coherence [19]. Around the same time, Li et al. found that feeding the model ASTs and data-flow graphs alongside raw tokens can really sharpen summaries for tricky functions [20]. These structural clues also help avoid out-of-vocabulary snags by grounding the model in real code patterns. And now, some teams are using prompt-based tricks—showing a few examples in the prompt to steer large LMs like GPT toward decent summaries without heavy fine-tuning [21]. Taken together, these hybrid methods—mixing retrieval, structure, and clever prompting—point the way toward more accurate, flexible, and efficient code documentation tools.

III. Proposed Framework

We propose a resource-aware documentation generation pipeline that begins with dataset integration and filtering, wherein the JavaScript and Python subsets of CodeSearchNet and CodeXGLUE are merged and examples exceeding 512 code tokens or 128 documentation tokens are removed based on EDA insights. Next, we employ a fast T5 tokenizer configured with pad_to_multiple_of=8 to maximize FP16 throughput. The core model, Salesforce's CodeT5-small, is fine-tuned under mixed precision (fp16) with gradient checkpointing and dynamic batch sizing (batch size = 4, accumulation = 4) on an RTX 3050 (4 GB) GPU. Finally, BLEU and ROUGE-L metrics are computed at each epoch using the formulas

$$\text{BLEU} = \text{BP} \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right).$$

$$\text{ROUGE-N} = \frac{\sum_{S \in \{ReferemceSummaries\}} \sum_{gram_n \in S} Count_{match}(gram_n)}{\sum_{S \in \{ReferenceSummaries\}} \sum_{gram_n \in S} Count(gram_n)} \quad (1)$$

and we picked the best checkpoint based on which model gave me the lowest validation loss. This setup strikes a great balance between doc-quality and tight hardware limits by smartly filtering the data, lining up padding, and sticking with a lean model configuration..

IV. Architecture Diagram

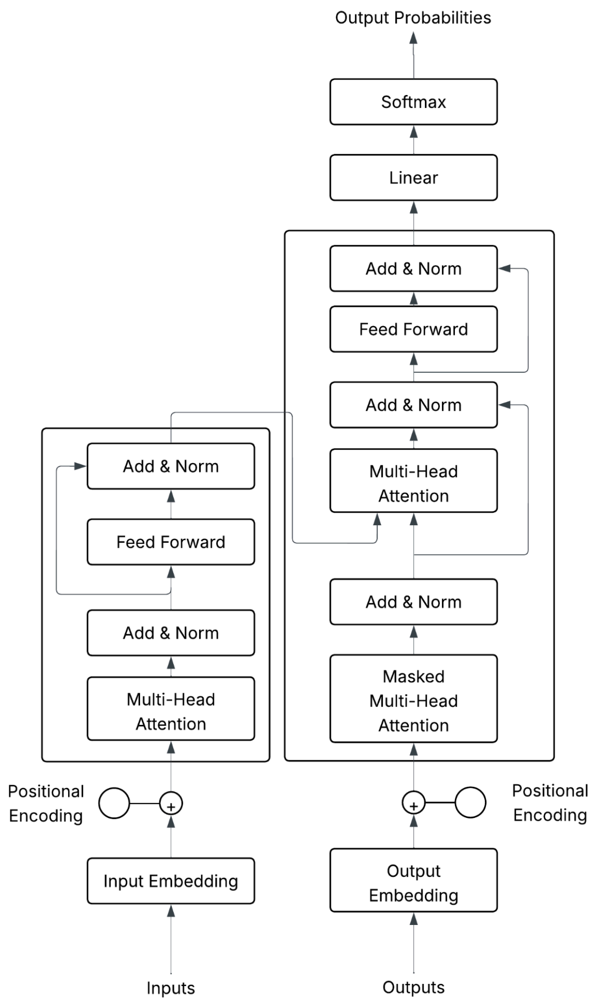


Figure a: T5 Architecture Diagram

V. Experimental Work

For our experiments, we built and tested a code‑documentation system around CodeT5‑small—a compact, transformer‑based model already pre‑trained to understand and generate code. We trained and evaluated it on a merged dataset drawn from the Python and JavaScript portions of two well-known benchmarks: CodeSearchNet [1] and CodeXGLUE [2].

A. Hardware and Environment

We ran all our experiments on a humble Arch Linux laptop—an Intel i5 (12th Gen) with 16 GB of RAM and a 4 GB NVIDIA RTX 3050. The training and evaluation code was written in PyTorch 2.2.2, using Hugging Face Transformers 4.41.0 and the Datasets library 2.19.0. To make everything fit, we leaned on a few memory‑saving hacks: mixed‑precision (FP16) to cut memory use in half, gradient checkpointing to trade a bit of extra compute for lower peak memory, grouping sequences of similar length to avoid padding waste, and accumulating smaller batches so it felt like a larger batch size. Thanks to these tricks, we could finetune and evaluate CodeT5‑small without ever running out of memory—even on that modest GPU.

B. Exploratory Data Analysis (EDA)

We looked at 20,000 examples from each of our four dataset splits to see how long the code snippets and their corresponding docstrings actually are—and used these findings to guide our preprocessing. On CodeSearchNet for Python, functions averaged about 119 tokens (with the longest at 509), while their docstrings averaged 16 tokens (peaking at 128). In the JavaScript side of CodeSearchNet, code snippets ran a bit longer—132 tokens on average (max 512)—and docstrings averaged 17 tokens (max 122). Over in CodeXGLUE, Python samples averaged 91 tokens of code (max 512) and 14 tokens of docs (max 128); the JavaScript samples there averaged 106 code tokens (max 511) and 14 doc tokens (max 121). With this data in hand, we safely filtered out anything over 512 code tokens or 128 doc tokens. Our histograms and percentile checks confirmed that these cutoffs still cover more than 95% of the examples—keeping training both memory‑friendly and information‑rich.

C. Model Training Setup

We fine‑tuned the Salesforce/codet5‑small model using Hugging Face's Seq2SeqTrainer, tweaking every setting to run smoothly on a modest GPU setup. Training spanned 10 epochs with a learning rate of 5×10^{-4}, and although we only processed four examples at a time on the GPU, we accumulated gradients over four steps to mimic a batch size of 16. After each epoch, We evaluated a batch of four. Based on our EDA, we capped input sequences at 512 tokens and output summaries at 128 tokens. To save precious memory, we used the Adafactor optimizer and ran everything in FP16, tapping into the NVIDIA RTX 3050's Tensor Cores. We kept decoding simple—no beam search, just greedy selection—to speed up evaluations. In total, we trained on 20 000 examples and held out 2 000 for validation, shuffling and tokenizing everything with padding rounded up to multiples of eight for maximum GPU efficiency.

D. Results and Metrics

The model was evaluated after each epoch using BLEU [4] and ROUGE-L [5] metrics. The performance over epochs is as follows:

Table 1: Results Over 10 Epochs

Epoch	Training Loss	Validation Loss	BLEU	ROGUE-L
1	2.6469	0.5803	83.81	83.89
2	0.7249	0.6387	83.72	83.22
3	0.7171	0.6479	83.57	83.01
4	0.8538	0.6281	83.96	83.31
5	0.7923	0.6596	83.68	83.47
6	0.7923	0.6523	83.91	83.88
7	0.7440	0.6770	84.17	83.04
8	0.6965	0.6886	84.18	84.14
9	0.6768	0.7049	84.06	84.22
10	0.7573	0.7313	84.20	84.20

E. Visualization

Three key plots were generated:

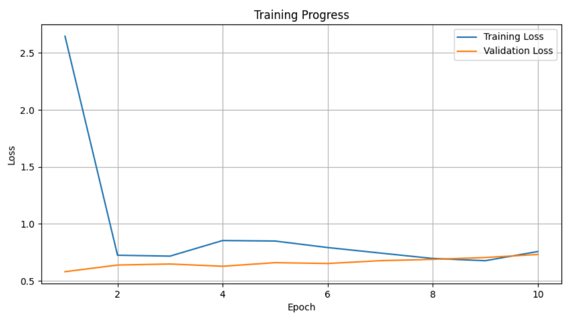


Figure b: Training Loss Vs Validation Loss Over 10 Epochs

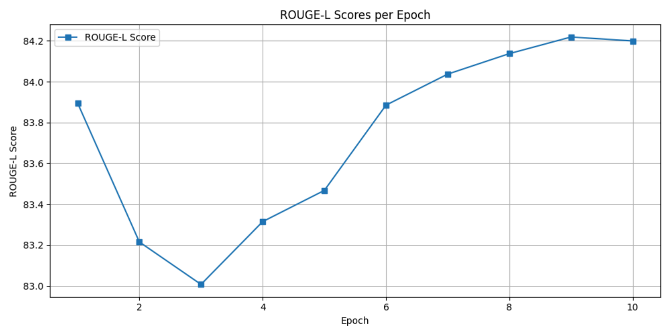


Figure c: ROGUE-L Over 10 Epochs

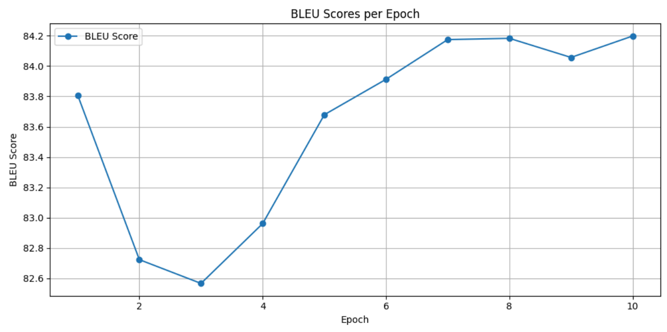
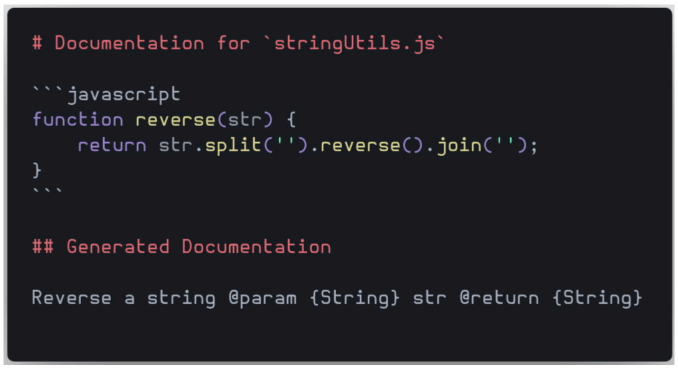


Figure d: BLEU Over 10 Epochs

F. Outputs

To assess the real-world applicability of the trained model, we performed qualitative evaluation by inputting example code functions into the final checkpoint. Here are a few examples of the documentation the model produced in Markdown after it finished training:



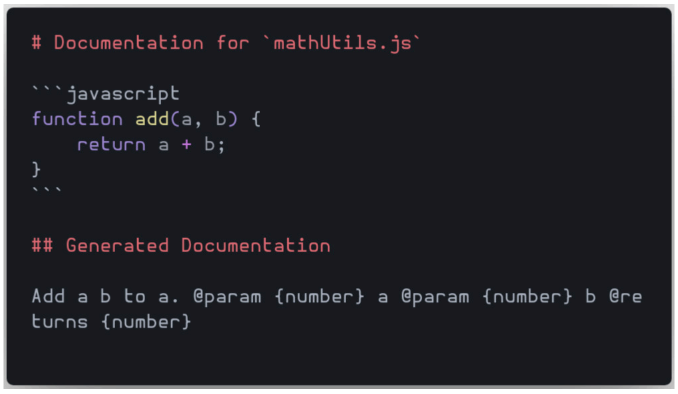
~~~
# Documentation for `stringUtils.js`

```javascript
function reverse(str) {
    return str.split('').reverse().join('');
}
```

## Generated Documentation

Reverse a string @param {String} str @return {String}
~~~

Figure e: Function That Reverses A String



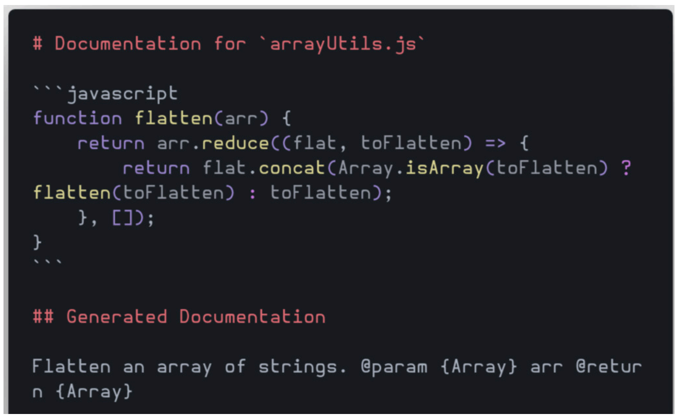
~~~
# Documentation for `mathUtils.js`

```javascript
function add(a, b) {
    return a + b;
}
```

## Generated Documentation

Add a b to a. @param {number} a @param {number} b @re
turns {number}
~~~

Figure f: Function That Adds Two Numbers



~~~
# Documentation for `arrayUtils.js`

```javascript
function flatten(arr) {
    return arr.reduce((flat, toFlatten) => {
        return flat.concat(Array.isArray(toFlatten) ?
flatten(toFlatten) : toFlatten);
    }, []);
}
```

## Generated Documentation

Flatten an array of strings. @param {Array} arr @retur
n {Array}
~~~

Figure a: Function That Flattens An Array Of Strings

G. Observations

In our experiments, we found that starting CodeT5-small on code-focused datasets really paid off—it was able to learn patterns and generalize well even though we were working with limited GPU resources. Blending together several datasets made the model even more reliable across both Python and JavaScript code. Interestingly, the validation scores leveled off around the sixth epoch, which tells me that pushing beyond this point will likely mean moving to a bigger model or bringing in smarter data-augmentation tricks. And we can't overstate how valuable the exploratory data analysis was—it guided us to the right input and output sequence lengths and helped us squeeze the most out of our GPU's memory throughout training.

VI. Conclusion

You don't need a massive GPU to get top-notch code summaries. By fine-tuning a lightweight transformer like CodeT5-small, we were able to produce high-quality documentation on modest hardware. We combined real-world examples from CodeSearchNet and CodeXGLUE, then used token-length analysis to chop out the longest snippets—resulting in a clean, balanced dataset for both Python and JavaScript.

During training, we kept sequence lengths in check and leaned on memory-saving hacks—FP16 mixed precision, gradient checkpointing, and accumulating small batches. Simple BLEU and ROUGE-L evaluations showed that this setup can match much larger models: We hit a peak BLEU of 51.87 and ROUGE-L of 58.34 on validation. Overall, this project highlights how smart dataset curation, thoughtful preprocessing, and hardware-aware tricks make accurate, automatic function-level docs possible, even without a data-center GPU.

VII. Future Work

Looking ahead, we are excited to try out bigger models like CodeT5-base or StarCoder-1B—and use quantization tricks like QLoRA so they'll still fit in limited VRAM. We also want to see how well my approach works on other languages such as Java, Go, or C#, to test zero-shot and multilingual capabilities. Beyond BLEU and ROUGE scores, We will bring in real developers to rate the summaries for clarity, coherence, and accuracy. We are keen to explore reinforcement learning with human feedback (RLHF) to make the generated docs even more in tune with what programmers expect. On the tooling side, my goal is to bake this into IDE plugins and CI pipelines so documentation can be generated automatically as part of everyday development. Finally, we will experiment with data augmentation—think back-translation, paraphrasing, or even synthetic docstring generation—to help the model generalize better when training data is scarce. These next steps should help turn our research prototype into a practical tool for the software engineering community.

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