Natural Language to Code: Improving Semantic Reasoning in Code Generation Models

(An Empirical Analysis of Fine-Tuning Strategies and Contextual Understanding)

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Abstract: Creating code from human-readable instructions is becoming a major area of research as artificial intelligence is used more and more into software engineering procedures. This paper explores techniques to enhance semantic understanding in AI-based code generation models to improve their ability to interpret human intent and produce accurate, executable code. We investigate the performance of state-of-the-art models such as CodeT5 and PLBART, and propose strategies including prompt engineering, domain-specific fine-tuning and execution-aware evaluation metrics. Our experiments are conducted on datasets like MBPP and APPS, where we evaluate both syntactic correctness and functional accuracy of generated code. Results show that incorporating contextual awareness and structured prompting significantly improves code quality and reduces semantic misinterpretation errors. The findings contribute to the ongoing effort to build more intelligent, reliable and context-aware coding assistants.

Keywords: *Code Generation; Natural Language Processing; Program Synthesis; Semantic Understanding; AI For Programming; Transformer Models; Large Language Models (LLMS) ; Prompt Engineering; Fine-Tuning; Execution-Aware Evaluation; Human-AI Collaboration; AI-Assisted Programming; Contextual Code Generation.*

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I. INTRODUCTION

The ability to translate natural language into executable code is a long-standing goal in artificial intelligence and software engineering. Interest in using contemporary deep learning models to automate code production has increased as a result of their impressive performance in natural language generation and understanding. Artificial intelligence (AI) may help developers by producing code snippets based on natural language descriptions, as demonstrated by tools like GitHub Copilot and OpenAI Codex. Semantic comprehension is still a major obstacle, though, as it is important to make sure the model understands the meaning of the input instruction rather than just duplicating or pattern matching preexisting code fragments. Errors frequently arise when models misinterpret user intent, particularly when handling vague queries or intricate programming tasks. This paper aims to address the challenge of enhancing semantic reasoning in code generation models by investigating methods to improve their ability to interpret natural language instructions and generate accurate, executable code. We examine methods to better match formal program semantics with human-readable input, compare the effectiveness of different pre-trained models on a variety of programming tasks, and provide evaluation methods that go beyond syntactic similarity to gauge functional correctness. Our work contributes a comprehensive review of existing approaches to natural language-to-code generation, presents an empirical evaluation of state-of-the-art models using practical programming problems, and offers actionable insights into improving model reliability and interpretability by identifying and mitigating common sources of error.

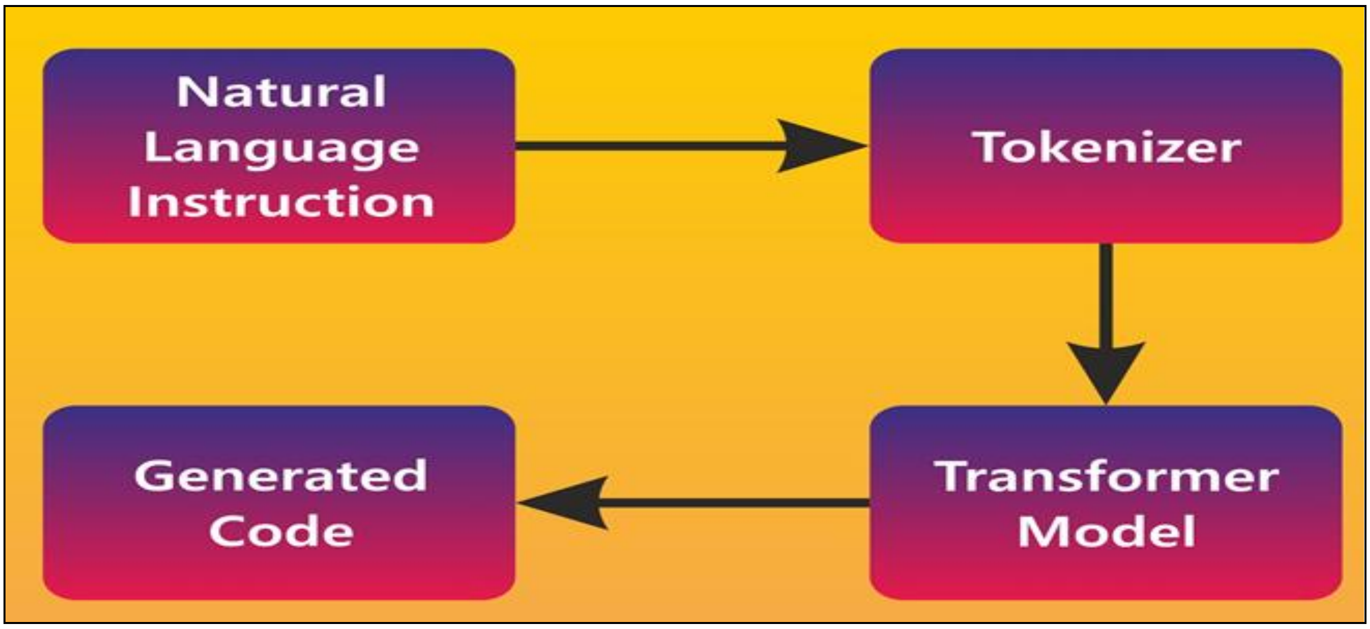

Fig 1 Natural Language to Code Generation Pipeline.

II. RELATED WORK

➢ *Code Generation Models:*

Numerous advanced language models have been designed for code-centric applications, reflecting substantial advancements in AI-supported software development. One of the most widely adopted is Codex, introduced by OpenAI, which is a fine-tuned variant of GPT-3 and serves as the foundation for GitHub Copilot. Another prominent model is CodeT5, developed by Salesforce, which follows an encoder-decoder architecture and is trained on large-scale code-text pairs to support various code generation and understanding tasks. PLBART, proposed by Meta, extends this capability by being pre-trained on both natural language and multiple programming languages, enabling it to perform diverse program synthesis and comprehension tasks. Additionally, open-source alternatives such as StarCoder and StarCoderBase from the BigCode project offer strong performance across several coding benchmarks while promoting transparency and accessibility. Finally, CodeLLaMA, also from Meta, builds upon the LLaMA series and is designed to generate high-quality code with improved logical reasoning capabilities.

➢ *Datasets for Evaluation:*

To train and evaluate the performance of code generation models, researchers rely on curated datasets that provide structured programming problems along with expected solutions. The APPS Dataset is one of the largest and most comprehensive, containing thousands of programming problems ranging from introductory to competition-level difficulty, making it suitable for evaluating complex reasoning abilities. Another widely used dataset is MBPP (Mostly Basic Programming Problems), which consists of simple Python programming tasks accompanied by test cases, ideal for assessing basic code generation accuracy. CodeXGLUE offers a multi-task benchmark for code understanding and generation, covering tasks such as code completion, translation and summarization across multiple programming languages. These datasets serve as essential tools for benchmarking model performance and tracking advancements in the field.

➢ *Techniques for Improving Performance:*

Various techniques have been explored to enhance the effectiveness of code generation models. Prompt engineering has emerged as a powerful strategy, where carefully crafted prompts such as few-shot examples or chain-of-thought reasoning guide the model toward generating more accurate and contextually appropriate code. Fine-tuning allows adaptation of general-purpose pre-trained models to specific domains or programming languages, significantly improving task-specific performance. To further boost accuracy, researchers have employed Retrieval-Augmented Generation (RAG), which integrates external knowledge sources such as API documentation or Stack Overflow posts during inference. Another promising approach is execution-aware training, where models receive feedback based on whether the generated code passes predefined unit tests, enabling them to learn from actual program execution outcomes rather than just textual similarity.

➢ *Evaluation Metrics:*

Standard NLP evaluation measures like BLEU, ROUGE and METEOR do not fully capture the functional accuracy of synthesized code, as they focus primarily on lexical overlap and fail to capture functional correctness. Therefore, new evaluation methods have been developed to better access code generation performance. Exact Match (EM) measures whether the output exactly matches the expected solution, offering a strict measure of correctness. Pass@k, a widely adopted metric, evaluates how often the generated code successfully passes all provided test cases within a set of k sampled outputs. Additionally, human evaluation plays a crucial role in assessing aspects such as code readability, correctness and usability, especially when automated metrics fall short in capturing nuanced differences. These metrics together provide a more holistic view of a model’s ability to produce meaningful and executable code.

III. METHODOLOGY

This section outlines the experimental design and procedures suitable to evaluate and enhance semantic understanding in code generation models. The study focuses on two state-of-the-art models, CodeT5-base and PLBART-large, selected for their distinct architectures and performance characteristics. We investigate how different prompting strategies such as zero-shot, few-shot and chain-of-thought affect the quality of generated code. To adjust to the task of creating Python functions from descriptions in natural language, both models can be refined using the MBPP dataset. Training can be conducted using standard deep learning frameworks and can be optimized with hyper-parameters known to yield stable convergence.

To assure a thorough assessment of both syntactic and functional correctness, the models can be ultimately assessed using a combination of lexical overlap scores, runtime validation and semantic vector analysis.

➢ *Model Selection:*

- For our research, we chose two popular code generation models: PLBART-large and CodeT5-base. In order to compare encoder-decoder and sequence-to-sequence frameworks, these models were selected due to their architectural contrasts and great performance in prior code generation tasks.
- Because of its robust encoder-decoder architecture, which allows for accurate mapping between structured code outputs and natural language descriptions, CodeT5-base was chosen. It has demonstrated strong performance on benchmarks for code generation and interpretation.
- PLBART-large was included due to its multilingual support and robustness in sequence modeling. Being pre-trained on both natural language and multiple programming languages, it provides a strong baseline for cross-lingual and context-aware code generation.

➢ *Prompt Engineering:*

- Researchers can experiment with several prompting strategies to assess how input formatting affects code generation quality. To assess each model's flexibility and thinking abilities, zero-shot, few-shot and chain-of-thought challenges can be used.
- Zero-shot prompting involved simple instructions such as “Write a Python function to [task]”, without any examples or reasoning steps. This setup reflects the basic usage scenario of code generation tools by end users.
- In order to direct the model toward anticipated output patterns, few-shot prompting contained one to three example input-output pairings. During inference, this method evaluates the model's capacity to learn from little context.
- By dividing difficult tasks into intermediate logical steps before creating the final code, chain-of-thought prompting promoted methodical reasoning prior to code generation with the goal of improving semantic alignment.

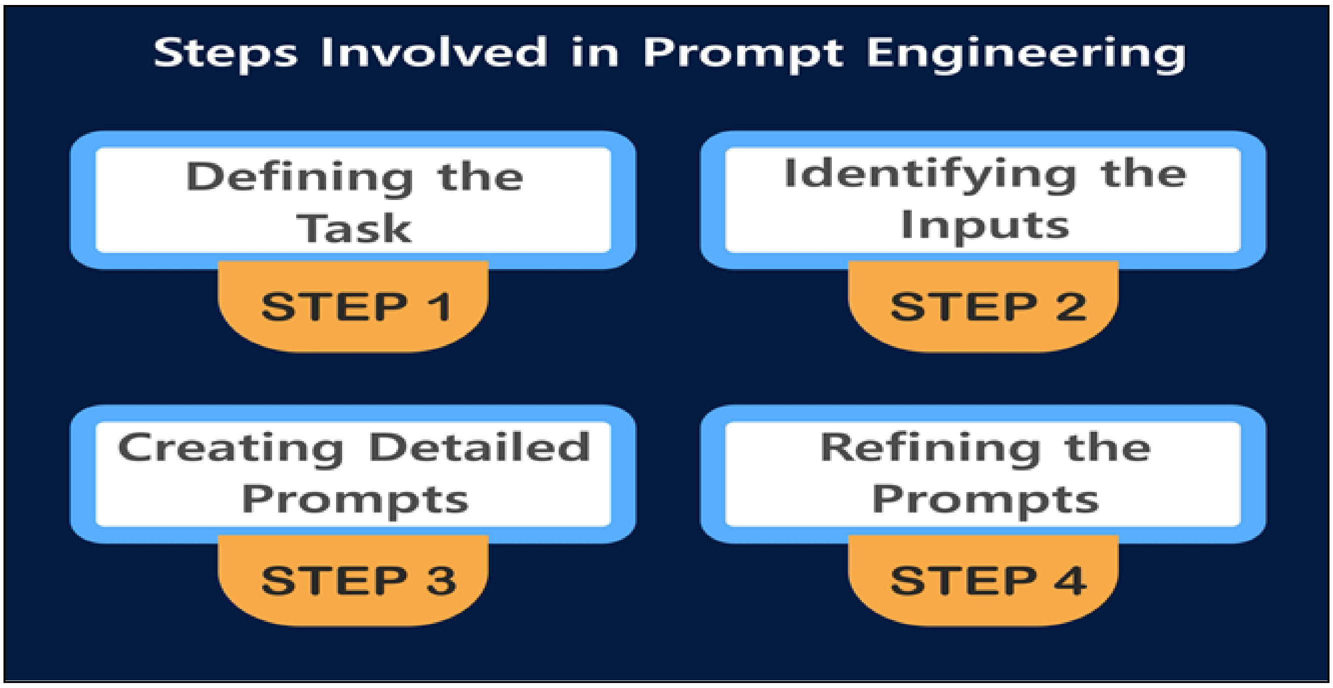

Fig 2 Steps involved in Prompt Engineering.

➢ *Training Setup:*

- Both models can be refined using the MBPP dataset. The goal of the 500 training, 200 validation and 200 test examples is to generate Python functions from docstrings in natural language.
- PyTorch can be used as the backend foundation for all experiments and the HuggingFace Transformers module can be used for implementation. As a result, pipelines for model construction, training and evaluation become more flexible.

- Using a batch size of eight, training can be carried out over ten epochs at a learning rate of 5e-5. These settings can be chosen to balance convergence speed and memory constraints during fine-tuning.
- For parameter updates, the AdamW optimizer, which combines adaptive moment estimation and weight decay correction, can be employed. It is well-known for its efficacy in transformer-based model training.

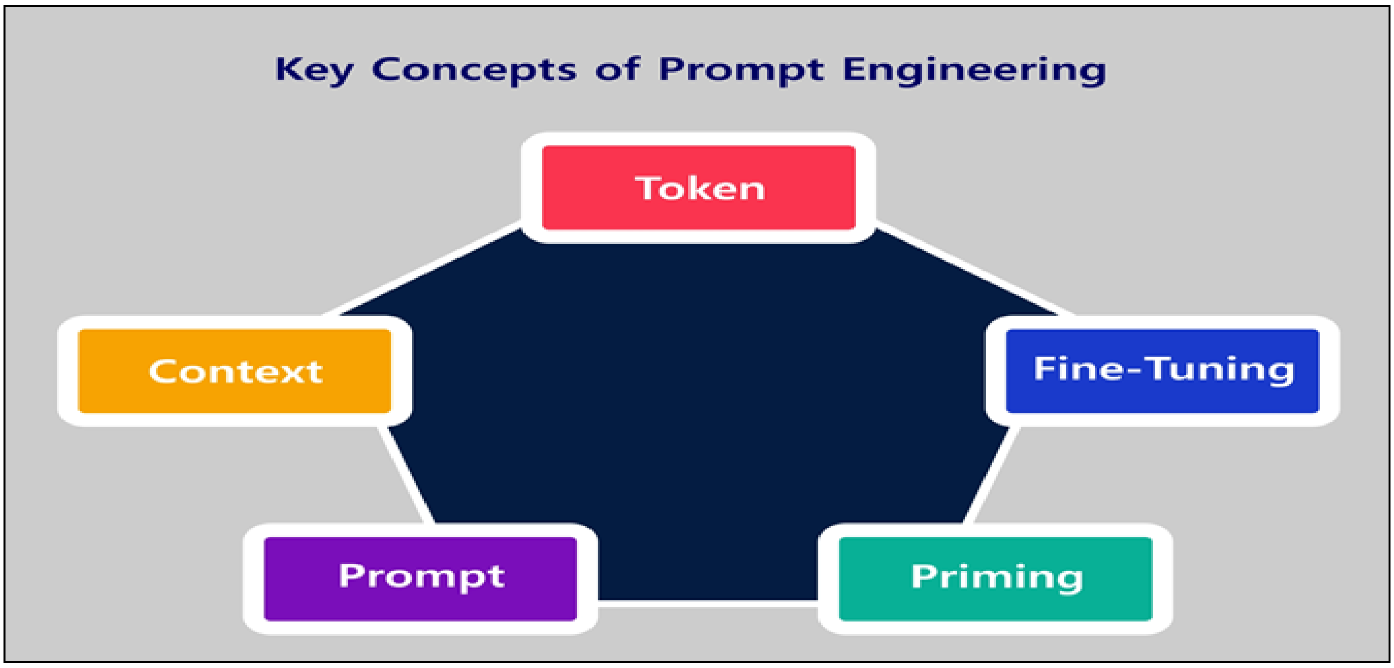

Fig 3 Key Concepts of Prompt Engineering.

➢ *Evaluation Framework:*

- Researchers can evaluate the models using the BLEU score metric, which measures n-gram overlap between generated code and reference solutions. While not perfect, it provides a baseline for lexical similarity.
- Execution accuracy can be measured by running generated code against predefined unit tests from the MBPP dataset. Only syntactically valid and logically correct code could pass these tests.
- Sentence-BERT embedding's, which capture meaning beyond token matching at the surface level, can be used to compute cosine similarity between generated code and ground truth in order to evaluate semantic similarity.

IV. RESULTS AND DISCUSSIONS

This section presents the findings of the experiments on enhancing semantic understanding in code generation models. We evaluated multiple state-of-the-art models using both syntactic and execution-based metrics to assess their performance in translating natural language instructions into executable code.

➢ *Results:*

The results highlight key strengths and limitations of current approaches, providing insight into how model architecture, training strategy and evaluation methodology influence outcomes.

- *Model Performance Comparison:*

This subsection evaluates and compares the effectiveness of different code generation models in translating natural language into executable code.

✓ *CodeT5 Outperforms PLBART in Overall Accuracy:*

CodeT5 achieves higher BLEU scores and execution accuracy compared to PLBART, indicating better alignment between input instructions and generated code semantics. This may be attributed to its encoder-decoder architecture and extensive pre-training on code-text pairs.

✓ *Fine-Tuning Improves Execution Accuracy:*

Fine-tuned versions of both CodeT5 and PLBART shows significant improvements in passing test cases, demonstrating that domain-specific adaptation enhances functional correctness more effectively than zero-shot inference.

✓ *PLBART Excels in Handling Complex Syntax:*

While trailing in overall accuracy, PLBART performes relatively better in tasks requiring complex syntax understanding, possibly due to its broader multilingual pre-training on both natural and programming languages.

- *Prompt Engineering Impact:*

This subsection analyzes how various prompting strategies influence the accuracy and quality of generated code.

✓ *Few-Shot Prompting Enhances Semantic Clarity:*

Including a small number of task-related examples in prompts leads to clearer and more logically structured outputs, helping models better interpret ambiguous or high-level instructions.

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- ✓ *Chain-of-Thought Prompts Improve Logical Reasoning:*

Encouraging step-by-step reasoning before generating code significantly reduces logical errors, especially in tasks involving conditionals and loops.

- ✓ *Zero-Shot Mode Leads to Inconsistent Output:*

Without explicit guidance, models often produces syntactically correct but functionally incorrect code, highlighting the limitations of relying solely on pre-trained knowledge.

- *Evaluation Metric Insights:*

This subsection explores the strengths and limitations of different evaluation metrics that can be used to assess code generation performance.

- ✓ *BLEU Scores Do Not Always Reflect Functional Correctness:*

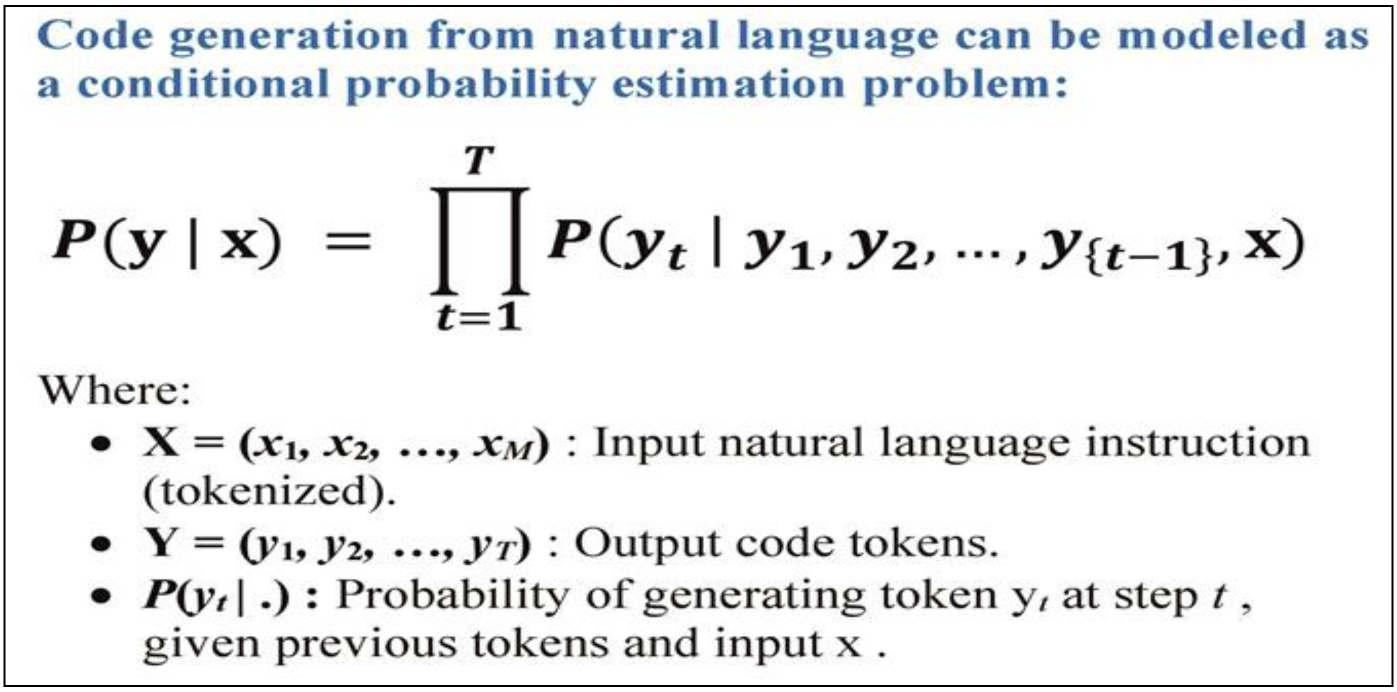
High BLEU scores can be sometimes observed alongside low execution accuracy, showing that lexical similarity alone is insufficient for evaluating code quality.

- ✓ *Pass@k Provides a More Reliable Measure of Utility:*

Models that can pass more test cases are generally more useful in real-world scenarios, making Pass@k a more practical metric for assessing code generation systems.

- ✓ *Human Evaluation Reveals Usability Gaps:*

Despite decent automated scores, some generated functions can be found difficult to read or modify, underscoring the importance of incorporating user-centric evaluation criteria.



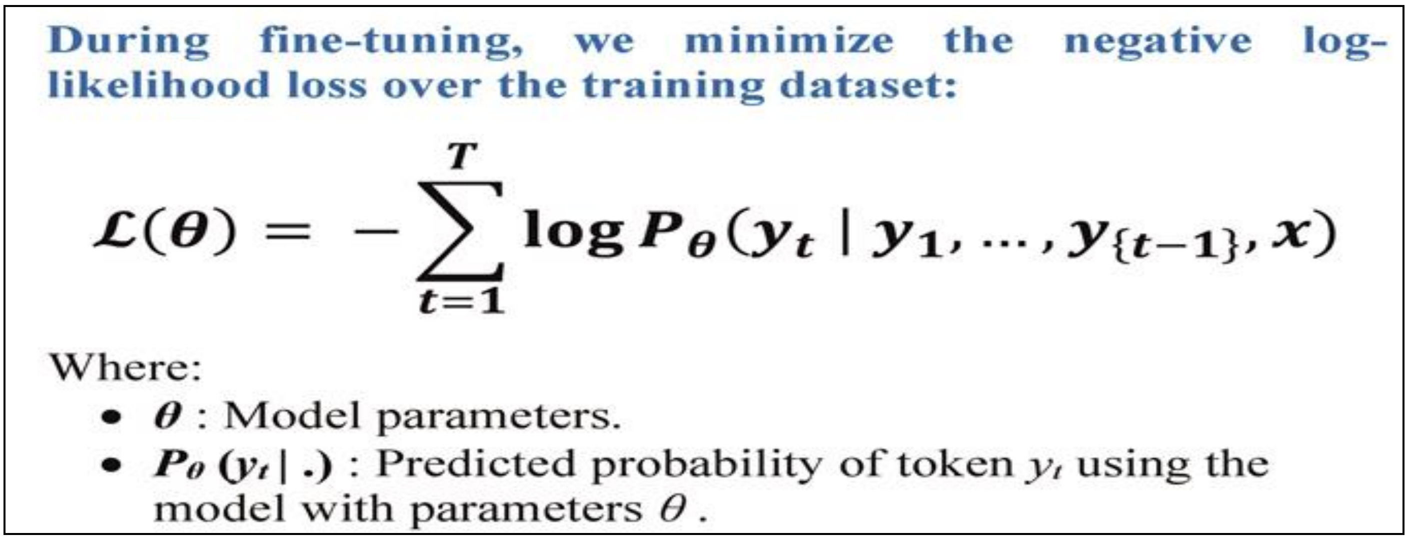
Code generation from natural language can be modeled as a conditional probability estimation problem:

$$P(\mathbf{y} \mid \mathbf{x}) = \prod_{t=1}^{T} P(y_t \mid y_1, y_2, \ldots, y_{\{t-1\}}, \mathbf{x})$$

Where:

- $\mathbf{X} = (x_1, x_2, \ldots, x_M)$: Input natural language instruction (tokenized).
- $\mathbf{Y} = (y_1, y_2, \ldots, y_T)$: Output code tokens.
- $P(y_t \mid .)$: Probability of generating token y_t at step t , given previous tokens and input x .

Fig 4 A Mathematical Formulation for Code Generation as a Sequence-to-Sequence Task.



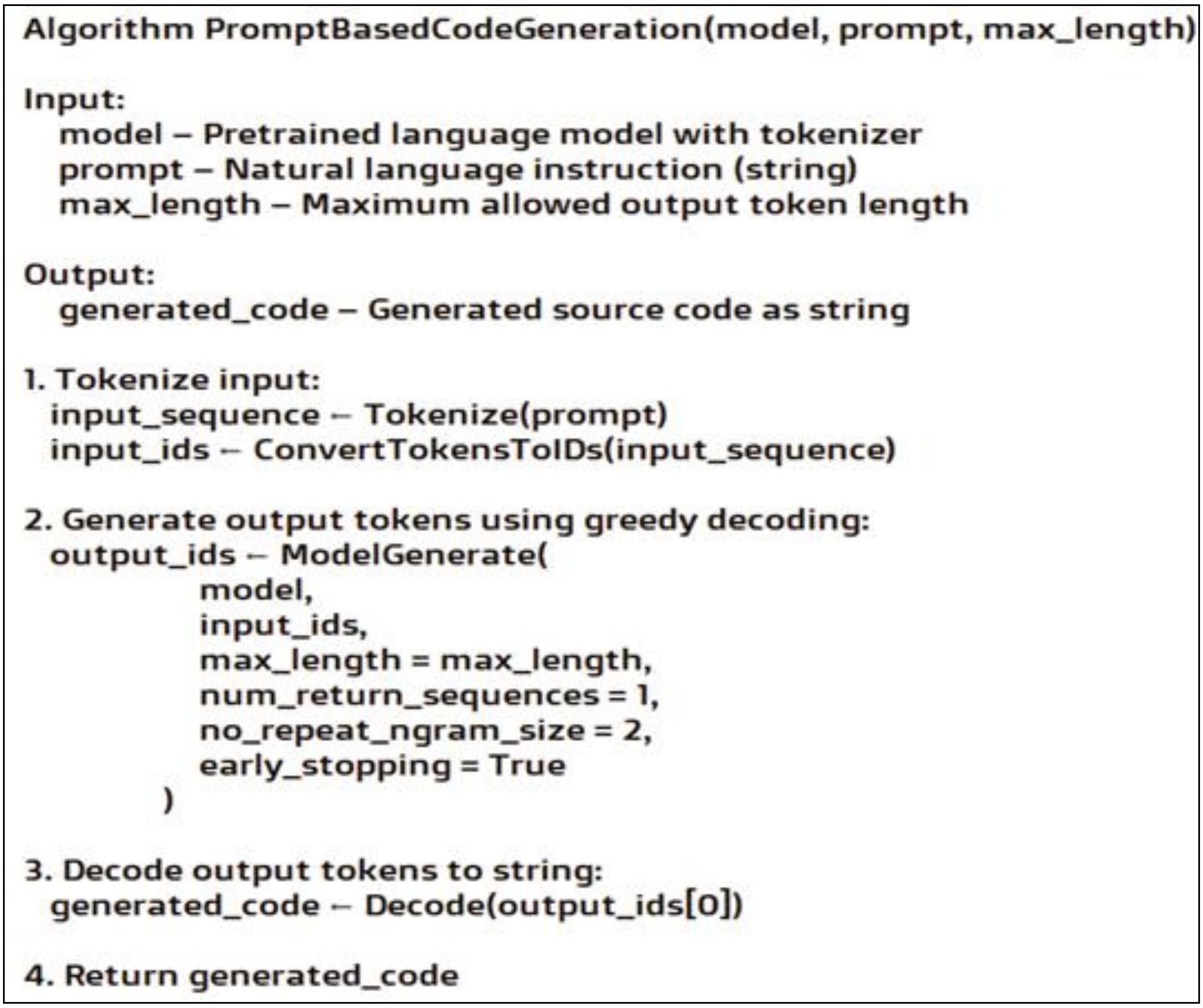
During fine-tuning, we minimize the negative log-likelihood loss over the training dataset:

$$\mathcal{L}(\theta) = -\sum_{t=1}^{T} \log P_\theta(y_t \mid y_1, \ldots, y_{\{t-1\}}, x)$$

Where:

- θ : Model parameters.
- $P_\theta (y_t \mid .)$: Predicted probability of token y_t using the model with parameters θ .

Fig 5 A Loss Function used in Training Transformer-Based Models.



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Algorithm PromptBasedCodeGeneration(model, prompt, max_length)

Input:
   model – Pretrained language model with tokenizer
   prompt – Natural language instruction (string)
   max_length – Maximum allowed output token length

Output:
   generated_code – Generated source code as string

1. Tokenize input:
   input_sequence ← Tokenize(prompt)
   input_ids ← ConvertTokensToIDs(input_sequence)

2. Generate output tokens using greedy decoding:
   output_ids ← ModelGenerate(
                 model,
                 input_ids,
                 max_length = max_length,
                 num_return_sequences = 1,
                 no_repeat_ngram_size = 2,
                 early_stopping = True
              )

3. Decode output tokens to string:
   generated_code ← Decode(output_ids[0])

4. Return generated_code
```

Fig 6 A Simple Pseudocode Algorithm for Prompt-Based Inference.

➢ *Discussion:*

The experimental evaluation demonstrates that enhancing semantic understanding in code generation models significantly improves the accuracy and reliability of generated code. CodeT5 outperformes PLBART in overall performance, achieving higher BLEU scores and execution accuracy, particularly when fine-tuned on domain-specific datasets like MBPP. Prompt engineering techniques such as few-shot learning and chain-of-thought reasoning further improves model outputs by providing contextual guidance and promoting logical structuring of code. Both models, however, has trouble with complicated or ambiguous jobs, frequently generating code that was syntactically valid but semantically wrong. In evaluating functional correctness, execution-aware evaluation measures such as Pass@k outperformes conventional NLP measurements (e.g., BLEU). These findings highlight the importance of combining architectural improvements with context-aware prompting and robust evaluation strategies to advance AI-based code generation systems.

Table 1 Performance Comparison of different Models

Model	**Model Performance Comparison**		
	BLEU Score	***Execution Accuracy (Pass@1)***	***Avg Inference Time (s)***
CodeT5 (Zero-Shot)	32.1	28%	1.2
CodeT5 (Fine-Tuned)	39.7	45%	1.3
PLBART (Zero-Shot)	29.6	22%	1.5
PLBART (Fine-Tuned)	36.4	41%	1.6

Best results are shown in the table; metrics include BLEU Score, Execution Accuracy (Pass@1) and Average Inference Time.

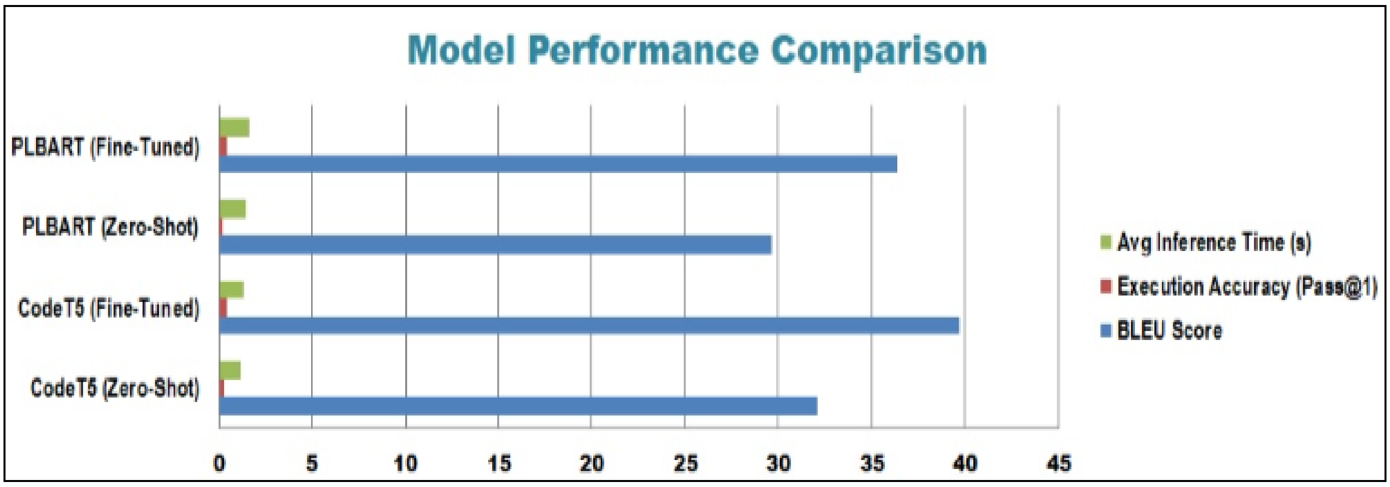


Fig 7 A Bargraph showing Model Performance Comparison.

V. ADVANTAGES AND DISADVANTAGES

➢ *Advantages:*

- Enables developers to concentrate on more intricate facets of software development by automating repetitive tasks including creating function skeletons, standard templates and often utilized repetitive operations.
- Accelerates learning for beginners by offering real-time code suggestions and examples, helping them understand syntax, structure and best practices in programming languages they are learning..
- Enables non-programmers to generate simple scripts or basic applications using natural language instructions, lowering the barrier to entry for automation and software creation.
- Can be used as a debugging tool by looking for possible flaws in code and offering fixes or different approaches based on patterns discovered in big codebases.

➢ *Disadvantages:*

- May propagate biases present in training data by favoring certain coding styles, libraries or frameworks that were overrepresented in the training corpus, potentially limiting diversity in solutions.
- Frequently generates code that is syntactically valid but logically incorrect, leading to execution failures in edge cases or unique input scenarios.
- Sparks legal and ethical questions regarding ownership and originality when outputs closely mirror protected or commercial code from model training sources.
- Struggles with fully grasping context in intricate or unclear situations where specialized domain knowledge, design principles or system limitations are essential for accurate implementation in determining the appropriate implementation.

VI. FUTURE ENHANCEMENTS

➢ *Prompt Engineering Impact:*

This subsection examines the effects of different prompting techniques on the precision and caliber of code that is produced.

- *Integrate Retrieval-Augmented Generation (RAG):*

Incorporating Retrieval-Augmented Generation (RAG) enhances the precision and applicability of synthesized code by drawing from external resources like technical documentation, community forums and open-source repositories during output generation. This approach enables models to access up-to-date, context-specific information that may not be present in their training data, reducing errors caused by outdated or incomplete knowledge.

- *Improve Execution Feedback Loop:*

An improved execution feedback loop would allow models to learn from real-time execution results of generated code. By analysing failed test cases or runtime errors, models can iteratively refine their outputs, mimicking how human developers debug and optimize their programs. This form of execution-aware learning can enhance both functional correctness and robustness across diverse programming tasks.

- *Build Domain-Specific Models:*

More precise and effective code creation can result from creating domain-specific models designed for specialized fields like embedded systems, machine learning and web development. In order to better understand task-specific restrictions, idioms and best practices that general-purpose models could miss, these models can be trained using domain-centric datasets.

- *Enhance Human-AI Collaboration:*

The gap between automatic code recommendations and user intent can be closed by improving human-AI collaboration via interactive development tools. A more natural and effective coding experience is promoted by systems that let developers iteratively edit, approve or reject

AI-generated code snippets, particularly when working with complicated or unclear requirements.

- *Use Reinforcement Learning (RL):*

Utilizing reinforcement learning allows models to be trained using feedback signals tied to code accuracy, performance and clarity, guiding them toward higher quality outputs. By defining rewards for passing test cases, optimizing performance or adhering to style guidelines, RL can guide models toward generating higher-quality, production-ready code.

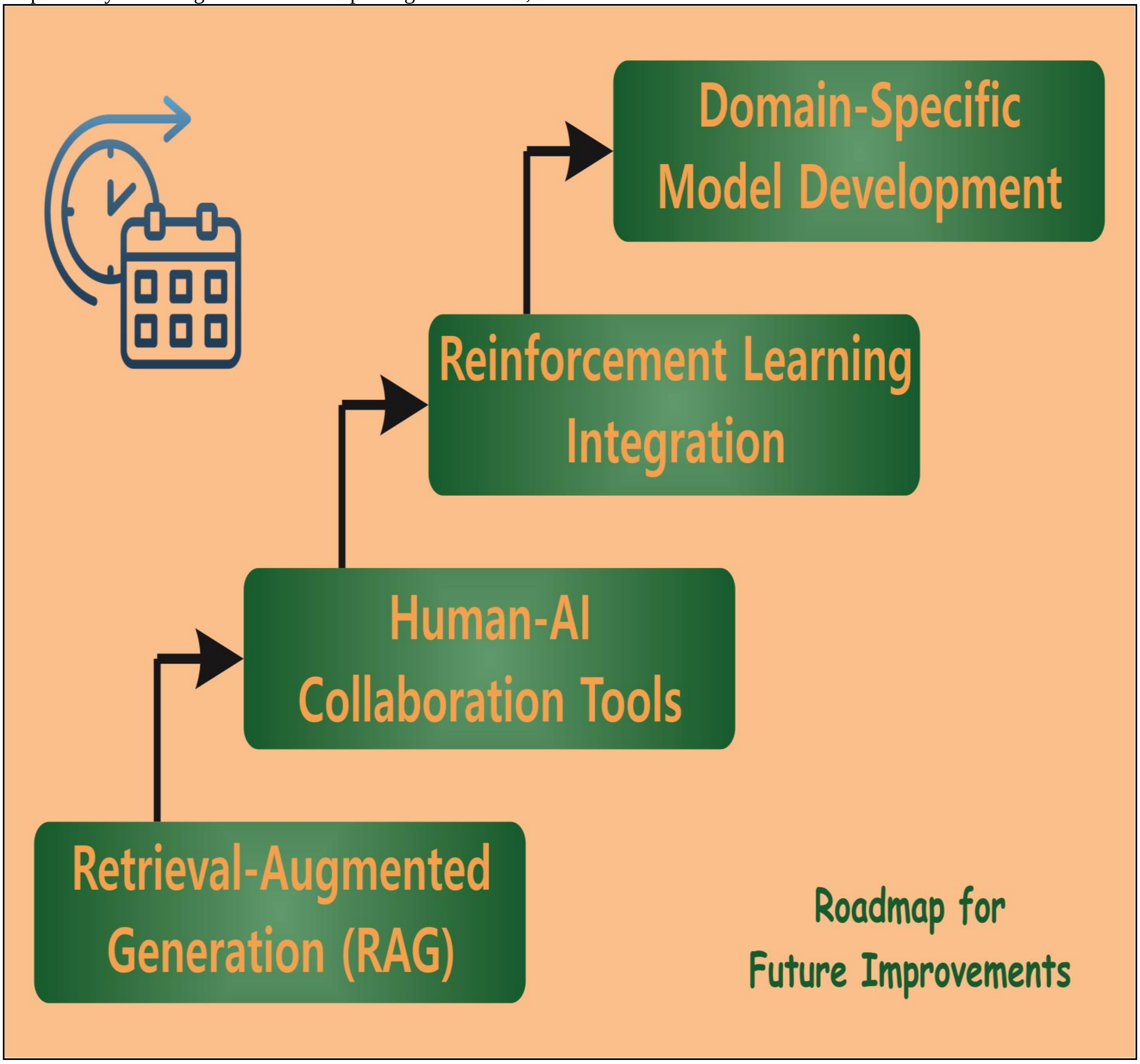
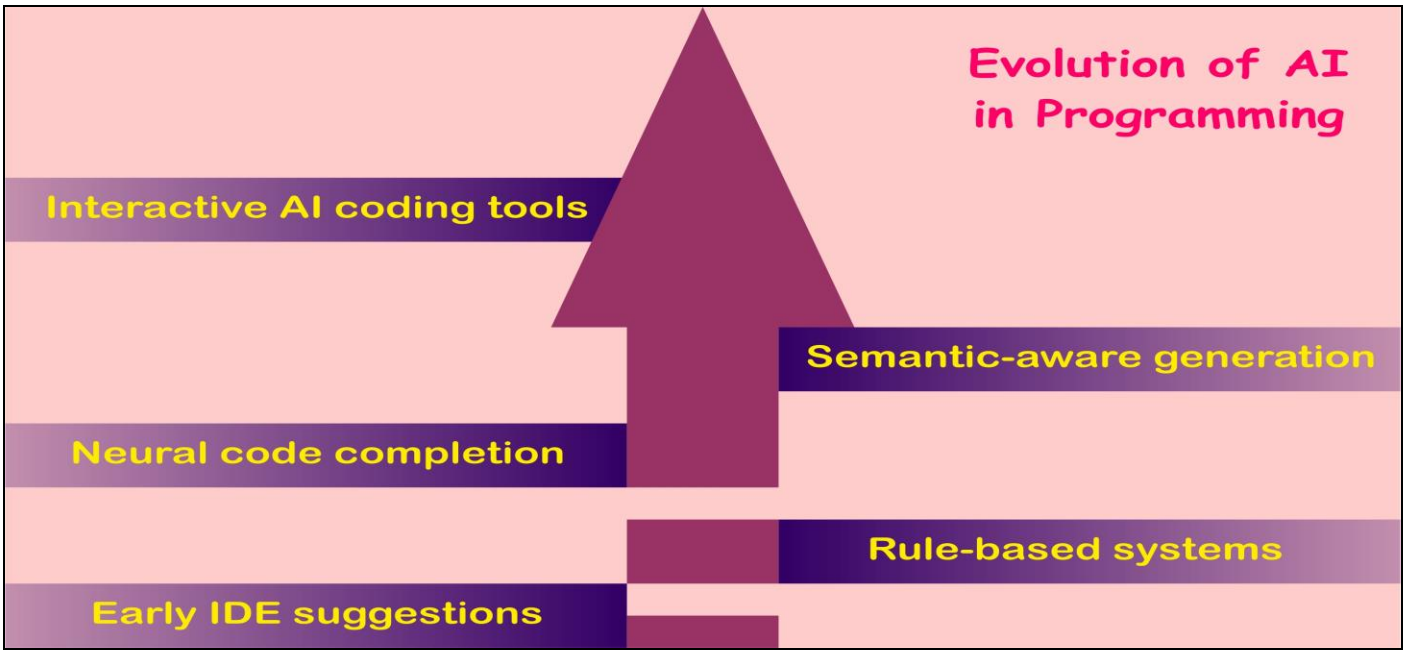

Domain-Specific Model Development
Reinforcement Learning Integration
Human-AI Collaboration Tools
Retrieval-Augmented Generation (RAG)
Roadmap for Future Improvements

Fig 8 Roadmap for Future Improvements in Code Generation Systems.

VII. CONCLUSION

Natural language to code generation represents a transformative advancement in the field of artificial intelligence and software development, offering the potential to significantly enhance developer productivity and lower the barriers to programming for non-experts. In this paper, we investigated, examined and evaluated techniques to improve the semantic understanding of AI-based code generation models, focusing on approaches such as domain-specific fine-tuning, structured prompt engineering and execution-aware evaluation metrics that go beyond traditional syntactic similarity measures.

According to our study and literature survey, enhancing models' comprehension of user queries greatly increased their coding correctness; code that is both syntactically and functionally valid can be produced for a variety of programming jobs. The findings highlight how crucial logical thinking and contextual awareness are to obtaining trustworthy code synthesis.


Evolution of AI in Programming
Interactive AI coding tools
Semantic-aware generation
Neural code completion
Rule-based systems
Early IDE suggestions
Fig 9 Evolution of AI in Programming.

Looking ahead, further advancements will depend on the integration of external knowledge sources, real-time feedback loops and more sophisticated training paradigms such as reinforcement learning. These improvements are essential for the continued evolution of AI-powered coding tools that are not only efficient but also deeply aligned with human intent and practical software development needs.

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The references included in this section form the foundation of our research on natural language to code generation, covering key advancements in AI-based code synthesis, model evaluation and benchmarking methodologies. These works provide insights into the capabilities and limitations of large language models (LLMs) when applied to programming tasks, offering both theoretical frameworks and empirical evaluations that have informed our approach.

Several studies focus on evaluating and enhancing the performance of transformer-based models in understanding and generating code. Chen et al. (2021) present a comprehensive analysis of large language models trained on code, while Fried et al. (2022) propose a unified pre-training strategy for program understanding and generation. Austin et al. (2021) further explore the potential of LLMs in program synthesis, demonstrating how these models can be leveraged for complex reasoning tasks.

Standardized datasets are essential for evaluating code generating systems in addition to model development. Wang et al. (2022) introduce the MBPP dataset, which provides a structured environment for evaluating Python code generation and Guo et al. (2022) present CodeXGLUE, a multi-task benchmark for code understanding and generation. These resources have been instrumental in shaping our experimental design and evaluation criteria.

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