Large Language Models Are Effective Code Watermarkers

Anonymous ACL submission

Abstract

The widespread use of large language models (LLMs) and open-source code has raised ethical and security concerns regarding the distribution and attribution of source code, including unauthorized redistribution, license violations, and misuse of code for malicious purposes. Watermarking has emerged as a promising solution for source attribution, but existing techniques rely heavily on hand-crafted transformation rules, abstract syntax tree (AST) manipulation, or task-specific training, limiting their scalability and generality across languages. Moreover, their robustness against attacks remains limited. To address these limitations, we propose **CodeMark-LLM**, an LLM-driven watermarking framework that embeds watermark into source code without compromising its semantics or readability. CodeMark-LLM consists of two core components: (i) *Semantically Consistent Embedding* module that applies functionality-preserving transformations to encode watermark bits, and (ii) *Differential Comparison Extraction* module that identifies the applied transformations by comparing the original and watermarked code. Leveraging the cross-lingual generalization ability of LLM, CodeMark-LLM avoids language-specific engineering and training pipelines. Extensive experiments across diverse programming languages and attack scenarios demonstrate its robustness, effectiveness, and scalability.

1 Introduction

With the rapid development of open-source ecosystem and the significant improvement of large language models' (LLMs) ability, LLMs have shown strong performance in tasks such as source code generation, refactoring and understanding (Shrivastava et al., 2023; Deng et al., 2023; Wei et al., 2023; Pei et al., 2023). However, the unauthorized use of source code has long posed a security risk—one that is becoming increasingly critical with the growth of developer communities and the rapid advancement of LLMs (Khoury et al., 2023; Liu et al., 2023). For instance, plagiarists may replicate open-source code with slight modifications and redistribute it under a different license to illegitimately claim ownership. In addition, LLMs may inadvertently reproduce copyright-protected code from their training data (Sun et al., 2022) or generate plausible but insecure code without clear attribution. These risks not only threaten the integrity of the software ecosystem but also underscore the urgent need for mechanisms that support code traceability and ownership verification. Therefore, designing an efficient and practical mechanism for source code traceability and ownership verification has become an urgent research challenge.

Currently, traceability and copyright protection technologies, mainly using digital watermarking schemes (Singh and Chadha, 2013), are widely used for images (Baluja, 2017; Hayes and Danezis, 2017), audio (Boney et al., 1996; Liu et al., 2024b) and text (Chang and Clark, 2014; Yang et al., 2022). The success of digital watermarking techniques in the multimedia domain is attributed to the inherent tolerance of human perception to minor alterations. However, such methods are not applicable to the source code domain, as even minor alterations can break syntactic correctness or change program behavior. Unlike multimedia data, source code is subject to strict syntactic rules and precisely defined semantics, and structural integrity must be maintained to ensure functional equivalence and compilability (Wan et al., 2022). In addition, the diversity of programming languages and differences in coding styles further limit the direct applicability of traditional watermarking methods in the software domain.

Recent approaches have made certain progress in addressing these challenges but still exhibit notable limitations. As shown in Table 1, these methods often suffer from several limitations: (i) high de-

Method	Training-Free	Automatic	Parser-Independent	Language-Agnostic	Robustness
CodeMark (Li et al., 2023)	✗	✗	✗	✗	✗
SrcMarker (Yang et al., 2024)	✗	✗	✗	✗	✓
ACW (Li et al., 2024)	✓	✗	✗	✗	✗
CodeIP (Guan et al., 2024)	✗	✗	✓	✓	✓
RoSeMary (Zhang et al., 2025)	✗	✗	✓	✓	✓
CodeMark-LLM	✓	✓	✓	✓	✓

Table 1: Qualitative comparison of code watermarking methods across five criteria: **Training-Free** (does not require model training), **Automatic** (requires no handcrafted rules), **Parser-Independent** (does not rely on AST or syntax tools), **Language-Agnostic** (supports multiple languages without language-specific design), and **Robustness** (resilient to code modifications). ✓: Supported; ✗: Not supported.

sign complexity: these methods (Li et al., 2023; Yang et al., 2024; Li et al., 2024; Guan et al., 2024; Zhang et al., 2025) require handcrafted transformation rules, AST-based code rewriting, or additional model training, which reduces scalability and deployment flexibility. (ii) lack language generality: their designs rely heavily on language-specific features and cannot be directly applied across multiple programming languages. (iii) limited robustness: CodeMark (Li et al., 2023) and ACW (Li et al., 2024) are vulnerable to common attacks.

To address the above limitations, we propose CodeMark-LLM, an LLM-based source code watermarking framework that opens up a new paradigm in code watermarking research, which comprises two main components: Semantically Consistent Embedding and Differential Comparison Extraction. *In the watermark embedding phase*, Semantically Consistent Embedding leverages prompt-driven LLM to automatically generate and apply semantic-preserving code transformations, eliminating reliance on training, handcrafted rules, or AST parsing. These transformations are adaptively selected to support diverse programming styles, enabling broad language generality. *In the watermark extraction phase*, Differential Comparison Extraction performs multi-granularity comparisons between candidate and watermarked code to identify applied transformations and decode the watermark. This differential analysis, grounded in LLM's code reasoning capabilities, ensures robust watermark recovery even under common obfuscation or reformatting attacks.

To substantiate the efficacy of our proposed method, we conducted comprehensive experiments across datasets encompassing multiple programming languages, including C, C++, Java, and JavaScript. The results show that, compared with other methods, the proposed approach achieves strong stealthiness and efficiency while maintaining high embedding capacity and the watermarked code can pass the syntax check and unit test with nearly 100% ratio. These findings highlight the great potential of LLMs to provide efficient, scalable, and robust solutions for code watermarking. The main contributions of this work are as follows:

- We propose **CodeMark-LLM**, a training-free code watermarking framework that eliminates reliance on handcrafted rules, AST tools, or model fine-tuning, addressing key design bottlenecks in prior work.
- We introduce a modular design comprising *Semantically Consistent Embedding* and *Differential Comparison Extraction*, enabling automatic transformation and resilient recovery without language-specific customization.
- We conduct extensive experiments across multiple programming languages and attack scenarios, demonstrating that CodeMark-LLM achieves superior fidelity, robustness, and language generality compared to prior approaches.

2 Related Work

Software watermarking aims to embed watermarks into software as a proof of ownership (Dey et al., 2019). It can be further divided into static and dynamic watermarking. *Static watermarking* embeds watermarks by directly modifying code structures or binaries (Balachandran et al., 2014; Chen et al., 2018; Collberg and Sahoo, 2005). For example, Kang et al. (Kang et al., 2021) modified binary function order to encode watermarks, while Monden et al. (Monden et al., 2000) added virtual methods to Java code for embedding bit strings. However, these methods focus on compiled binaries or intermediate representations, limiting their applicability to raw source code.

Dynamic watermarking encodes watermarks into the runtime behavior of programs, typically by modifying control flow or inserting special runtime states (Chen et al., 2017; Ma et al., 2019; Tian et al., 2015; Wang et al., 2018). Although dynamic watermarking can be robust in certain settings, it requires the actual execution of software, making it

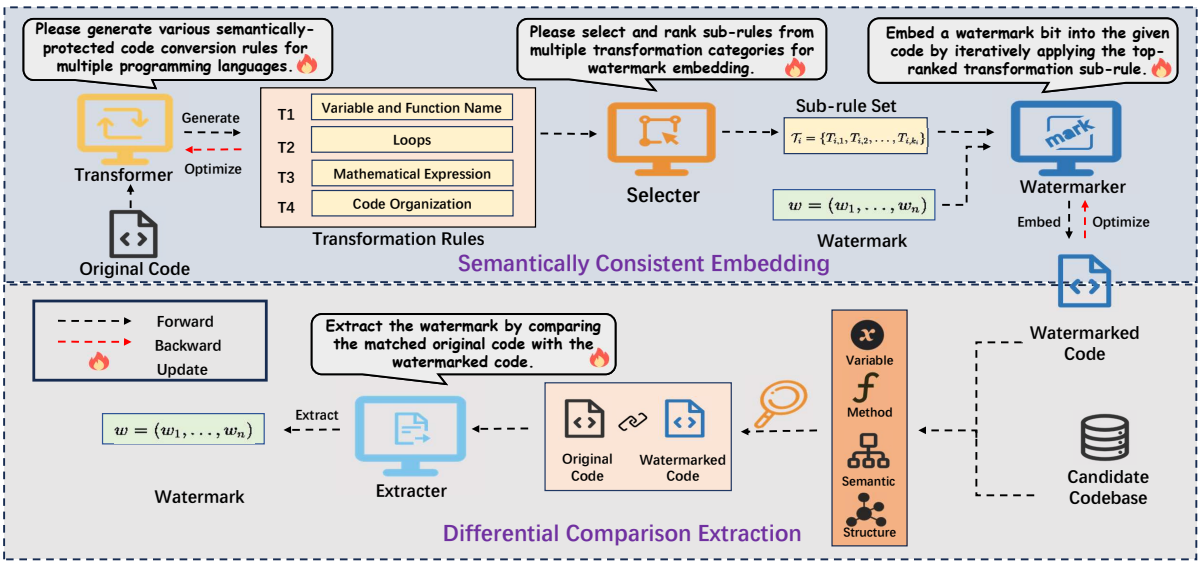


Figure 1: The overall framework of CodeMark-LLM.

impractical for source code snippets or lightweight development environments. Moreover, both static and dynamic schemes are rule-based and manually constructed, limiting scalability and cross-language generalization.

Semantic-preserving watermarking techniques have emerged as a solution to the limitations of traditional approaches by enabling flexible watermark embedding while maintaining program functionality (Quiring et al., 2019; Yang et al., 2022; Zhang et al., 2020). RopGen (Li et al., 2022) designed 23 handcrafted transformation rules tailored for C, C++, and Java. NatGen (Chakraborty et al., 2022) further leveraged these rules to pretrain LLMs for semantic understanding. CodeMark (Li et al., 2023) employed a GNN-based variable renaming strategy to preserve readability, yet it suffers from limited capacity and vulnerability to renaming attacks. SrcMarker (Yang et al., 2024) combines rule-based transformations with neural models, but heavily depends on handcrafted rules, AST parsing, and expensive training, risking syntax errors and requiring dedicated decoders. ACW (Li et al., 2024) uses fixed, manually defined code transformations to embed watermarks, which limits its adaptability across programming languages and reduces robustness in diverse code contexts.

The emergence of LLMs such as GPT (OpenAI, 2022) and DeepSeek (Liu et al., 2024a) has enabled new possibilities in code generation and transformation tasks (Jiang et al., 2024). Leveraging prompt engineering, LLMs have been successfully applied to areas such as code completion (Zhang et al., 2024), translation (Jana et al., 2024), data augmentation (Ding et al., 2024) and text steganography (Wu et al., 2024). Inspired by the above, we propose CodeMark-LLM, a novel code watermarking framework that utilizes LLM to dynamically select semantic-preserving transformations. It enables broader transformations and better cross-language scalability.

3 Method

This section presents the design of the CodeMark-LLM framework, which consists of two core modules: Semantically Consistent Embedding and the Differential Comparison Extraction. Each module leverages LLM for language-agnostic, semantics-preserving watermarking. The overall workflow is illustrated in Figure 1.

3.1 Preliminaries and Problem Formulation

Task Overview. We study the problem of embedding watermark into source code while preserving its functionality, syntax validity, and readability. This facilitates ownership verification and source tracing in open-source ecosystems. We leverage LLM to automatically generate, apply, and reason over semantic-preserving code transformations. This LLM-centric formulation allows CodeMark-LLM to operate across programming languages with minimal human intervention.

Notation. Let $\mathcal{C}_0$ be the set of valid, compilable source code, and $\mathcal{C}_1$ the set of watermarked code. A code snippet is denoted by $\boldsymbol{c}_0 \in \mathcal{C}_0$ (original code) or $\boldsymbol{c}_1 \in \mathcal{C}_1$ (watermarked code). The watermark is a binary sequence $w = (w_1, \ldots, w_n) \in \mathcal{W}$, where $\mathcal{W}$ is the set of all possible n-bit sequences. We define $\mathrm{Sem}(\cdot)$ as the input-output behavior of a code snippet. In CodeMark-LLM, two code snippets are semantically equivalent if they exhibit the same be-

Category	Sub-Rule Type	Example (Original → Transformed)
Variable / Function Name	CamelCase to snake_case	`testStream()` → `test_stream()`
	snake_case to CamelCase	`my_var` → `myVar`
	To PascalCase	`remove()` → `Remove()`
	To UPPERCASE	`value` → `VALUE`
	To lowercase	`Value` → `value`
	Add suffix	`data` → `dataVal`
Loops	for to while	`for(...)` → `while(...){...}`
	while to for	`while(...)` → `for(...)`
	Flatten nested loop	`for(i){...for(j)...}` → `for(k)...`
	while to do-while	`while(c){...}` → `do{...} while(c);`
	Step increment	`i++` → `i+=2`
	Reverse loop	`for(i=0;...)` → `for(i=n-1;...)`
Math Expression	Group ops	`x + y + z` → `x + (y + z)`
	Mul to add	`2 * x` → `x + x`
	Factorization	`a*b + a*c` → `a*(b + c)`
	Identity transform	`x*x - y*y` → `(x - y)*(x + y)`
	Div to reciprocal	`a / b` → `a * (1 / b)`
	Pow to mul	`x*x` → `x * x`
	Expand distributive	`a*(b + c)` → `a*b + a*c`
Code Organization	Optimize cond.	`if(x>0) return;` → `if(!(x>0)) return;`
	Reorder decl.	`int a; str b;` → `str b; int a;`
	Swap params	`f(a, b)` → `f(b, a)`
	Format spacing	`int x=5;` → `int x = 5;`
	Add braces	`if(a) return;` → `if(a){ return; }`
	Reorder cond.	`if(a && b)` → `if(b && a)`
	Insert blank line	`x=1; y=2;` → `x=1; \\y=2;`
	Adjust op space	`x=y+z;` → `x = y + z;`
	Inline temp var	`int t=x+y; return t;` → `return x+y;`
	Split decl.	`int x=0,y=1;` → `int x=0; int y=1;`

Table 2: CodeMark-LLM's set of transformation rules (partial list).

havior under all inputs, which is verified via LLM. The embedding process is then modeled as:

$$\boldsymbol{c}_1 = \text{Embed}(\boldsymbol{c}_0, w), \tag{1}$$

where $\text{Sem}(\boldsymbol{c}_0) = \text{Sem}(\boldsymbol{c}_1)$. Based on the settings adopted in prior work, we assume that the original dataset is available. Let $\mathcal{D} \subseteq \mathcal{C}_0$ denote a candidate codebase that may contain the original, unmarked code. The closest match $\hat{\boldsymbol{c}} \in \mathcal{D}$ is identified, and the watermark is recovered via:

$$\hat{w} = \text{Extract}(\boldsymbol{c}_1, \hat{\boldsymbol{c}}), \tag{2}$$

where $\hat{w}$ is the final watermark.

3.2 Semantically Consistent Embedding

Transformation Rule Set Design. The transformation rule set $\mathcal{T}$ encodes watermark information into semantic-preserving code transformations, forming the core of watermark embedding. To address the limitations of static, language-specific transformation methods, CodeMark-LLM employs LLM to construct a diverse, cross-language rule set $\mathcal{T}$:

$$\mathcal{T} = \bigcup_{i=1}^{m} \mathcal{T}_i, \quad \mathcal{T}_i = \{T_{i,1},\ T_{i,2},\ \ldots,\ T_{i,k_i}\} \tag{3}$$

where $m = 4$ is the total number of transformation classes, and k_i is the number of sub-rules in the i-th class $\mathcal{T}_i$, with each $T_{i,j}$ representing a specific semantic-preserving transformation. All transformations preserve the semantics of the original code. As a result, we curate a verified set of sub-rules spanning four transformation classes, as summarized in Table 2. This expressive and diverse rule set forms the foundation for flexible and resilient bit-wise watermark encoding in source code.

Contextual Rule Selection with LLM Assistance. To support bit-wise watermark embedding under syntactic and semantic constraints, CodeMark-LLM employs a two-stage transformation strategy guided by LLMs. Given $\boldsymbol{c}_0$ and $w = (w_1, \ldots, w_n)$, the LLM first analyzes the code structure and determines applicable transformation types. For each selected type, LLM ranks candidate rules by suitability to the input code, producing a prioritized sequence of sub-rules represented as $\mathcal{L}_k(\boldsymbol{c}_0) = [T_{k,1}, T_{k,2}, \ldots]$ for each transformation class $\mathcal{T}_k$. To further enhance stealthiness and reduce the risk of pattern leakage, we apply a category balancing strategy that evenly distributes transformation types across the watermark bits, thereby improving robustness against statistical detection.

Watermark Embedding Execution. Given $\boldsymbol{c}_0$, $w = (w_1, w_2, \ldots, w_n)$, and the sub-rule ranking lists $\mathcal{L}_k(\boldsymbol{c}_0) = [T_{k,1}, T_{k,2}, \ldots] \subseteq \mathcal{T}_k$ for each bit position k, the watermark embedding process proceeds iteratively as follows:

$$\boldsymbol{c}^{(k)} = \begin{cases} T_k^*(\boldsymbol{c}^{(k-1)}), & \text{if } w_k = 1 \\ \boldsymbol{c}^{(k-1)}, & \text{if } w_k = 0 \end{cases}, \tag{4}$$

$$\boldsymbol{c}^{(0)} = \boldsymbol{c}_0, \quad \boldsymbol{c}_1 = \boldsymbol{c}^{(n)}$$

Dataset	Method	BitAcc (%)	MsgAcc (%)	BPF
CSN-Java	AWT_{code}	93.91	78.41	4
	SrcMarker	97.26	92.74	4
	CodeMark-LLM	**98.05**	**95.79**	4
CSN-JS	AWT_{code}	89.33	63.97	4
	SrcMarker	96.34	89.84	4
	CodeMark-LLM	**98.08**	**95.62**	4
GH-C	AWT_{code}	95.10	81.70	4
	$\text{CALS}_{\text{code}}$	96.07	92.81	1.22
	SrcMarker	93.36	79.52	4
	CodeMark-LLM	**97.49**	**92.81**	4
GH-Java	AWT_{code}	95.05	82.40	4
	$\text{CALS}_{\text{code}}$	94.43	91.83	1.40
	SrcMarker	90.93	75.14	4
	CodeMark-LLM	**97.05**	**92.74**	4

Table 3: The success rate of watermark extraction for different watermarking methods and the embedding capacity (BPF).

where T_k^* is the highest-ranked sub-rule selected from $\mathcal{L}_k(\boldsymbol{c}_0)$ for embedding the k-th bit w_k.

To ensure valid watermark embedding and semantic consistency, each transformation T_k^* is verified to preserve semantics: $\text{Sem}(T_k^*(\boldsymbol{c}^{(k-1)})) = \text{Sem}(\boldsymbol{c}^{(k-1)})$. If this check fails, LLM reanalyze the context and select the next best transformation from the ranked list $\mathcal{L}_k(\boldsymbol{c}_0)$ to generate $\boldsymbol{c}^{(k)}$. This retry mechanism leverages LLM's contextual reasoning to maintain watermark accuracy and stealth.

3.3 Differential Comparison Extraction

Multi-Feature Matching Retrieval. Given $\boldsymbol{c}_1$ and $\mathcal{D}$, CodeMark-LLM retrieves the most probable original code $\hat{\boldsymbol{c}}$ via a joint similarity function:

$$\hat{\boldsymbol{c}} = \arg\max_{\boldsymbol{c}_i \in \mathcal{D}} \Big[\alpha\, \text{Sim}_m(\boldsymbol{c}_i, \boldsymbol{c}_1) + \beta\, \text{Sim}_v(\boldsymbol{c}_i, \boldsymbol{c}_1) + \gamma\, \text{Sim}_s(\boldsymbol{c}_i, \boldsymbol{c}_1) + \delta\, \text{Sim}_{\text{sem}}(\boldsymbol{c}_i, \boldsymbol{c}_1)\Big], \tag{5}$$

$$\text{Sim}_m(\boldsymbol{c}_i, \boldsymbol{c}_1) = 1 - \frac{\text{LevDist}(\text{name}(\boldsymbol{c}_i), \text{name}(\boldsymbol{c}_1))}{\max\big(|\text{name}(\boldsymbol{c}_i)|, |\text{name}(\boldsymbol{c}_1)|\big)}, \tag{6}$$

$$\text{Sim}_v(\boldsymbol{c}_i, \boldsymbol{c}_1) = \frac{|V(\boldsymbol{c}_i) \cap V(\boldsymbol{c}_1)|}{|V(\boldsymbol{c}_i) \cup V(\boldsymbol{c}_1)|}, \tag{7}$$

$$\text{Sim}_s(\boldsymbol{c}_i, \boldsymbol{c}_1) = \cos\Big(\vec{f}_s(\boldsymbol{c}_i), \vec{f}_s(\boldsymbol{c}_1)\Big), \tag{8}$$

$$\text{Sim}_{\text{sem}}(\boldsymbol{c}_i, \boldsymbol{c}_1) = 1 - \frac{\text{LevDist}(\text{norm}(\boldsymbol{c}_i), \text{norm}(\boldsymbol{c}_1))}{\max\big(|\text{norm}(\boldsymbol{c}_i)|, |\text{norm}(\boldsymbol{c}_1)|\big)}, \tag{9}$$

where Sim_m, Sim_v, Sim_s, and Sim_{sem} denote similarity scores on method signatures, variable usage, structural, and semantic features, respectively. The $\text{name}(\cdot)$ denotes the function name, $V(\cdot)$ is the set of variable identifiers, $\vec{f}_s(\cdot)$ is a vector of structural token counts, and $\text{norm}(\cdot)$ is the normalized function string after whitespace removal. We tune the weights $\alpha, \beta, \gamma, \delta$ via grid search for robustness against code transformations.

Rule Inference and Watermark Recovery. For each watermark bit w_k, LLM plays a pivotal role by reconstructing the guided sub-rule list $\mathcal{L}_k(\hat{\boldsymbol{c}}) = [T_{k,1}, T_{k,2}, \dots] \subseteq \mathcal{T}_k$ from the matched original code $\hat{\boldsymbol{c}}$, adapting the process from Section 3.2 using contextual understanding. The LLM selects the top-ranked sub-rule $T_k^* = \mathcal{L}_k(\hat{\boldsymbol{c}})[0]$ based on its analysis of syntactic and semantic features. We recover the bit using:

$$\hat{w}_k = \begin{cases} 1, & \text{if } T_k^*(\hat{\boldsymbol{c}}) \approx \boldsymbol{c}_1 \\ 0, & \text{otherwise} \end{cases}, \tag{10}$$

where $\approx$ denotes structural and semantic similarity, assessed via cosine similarity and $\text{Sem}(\cdot)$. If the initial match is unclear, the LLM iteratively optimizes sub-rule selection to improve accuracy and ensure robustness. The final watermark is $\hat{w} = [\hat{w}_1, \dots, \hat{w}_n]$.

4 Evaluation

In this section, we empirically evaluate CodeMark-LLM. We first describe the general experimental setup in Section 4.1. For CodeMark-LLM, depending on our design goals, we evaluate its watermark accuracy (Section 4.2), transparency (Section 4.3), efficiency and economic cost (Section 4.4) and robustness (Section 4.5).

4.1 Experiment Setup

Datasets and Preprocessing. To evaluate CodeMark-LLM across languages, we use three dataset types covering C, C++, Java, JavaScript, and Python. For CSN-Java and CSN-JS (Husain et al., 2019), functions are paired with natural

Method	Metric	Syntax		Execution			
		CSN-Java	CSN-JS	MBCPP	MBJP	MBJSP	MBPP
AWT_{code}	BitAcc(%)	93.91	89.33	97.12	93.88	83.97	/
	Pass(%)	0.18	0.51	0.00	0.00	0.00	/
$CALS_{code}$	BitAcc(%)	-	-	92.89	93.31	93.50	/
	Pass(%)	-	-	68.19	68.65	76.77	/
SrcMarker	BitAcc(%)	97.26	96.34	96.04	99.44	96.94	/
	Pass(%)	93.09	**100**	97.64	97.86	97.99	/
CodeMark-LLM	BitAcc(%)	**98.05**	**98.08**	**99.64**	**99.72**	**99.47**	**97.85**
	Pass(%)	**99.85**	99.11	**99.35**	**99.31**	**99.87**	**99.69**

Table 4: Operational semantic results based on performed operations. For CSN, we use syntax checking; for MBXP, we use execution-based checking. "**-**" indicates that the method was not evaluated on the dataset due to prohibitive computational cost. "**/**" indicates that the method cannot be applied to the Python language.

language descriptions from open-source projects. GitHub-C and GitHub-Java are used for C/C++ and Java in smaller-scale evaluation due to baseline constraints. For execution-based validation, we adopt MBXP (Athiwaratkun et al., 2022) datasets, which include C++, Java, JavaScript, and Python (MBCPP, MBJP, MBJSP, MBPP). Each function is embedded with a 4-bit watermark. Detailed settings are provided in Appendix B.1.

Baselines and LLM. We choose Srcmarker, AWT_{code} and $CALS_{code}$ proposed in Srcmarker as the baselines. AWT_{code} and $CALS_{code}$ are obtained by modifying AWT (Abdelnabi and Fritz, 2021) and CALS (Yang et al., 2022), both of which are natural language watermarking tools. AWT_{code} shares a similar architecture with AWT but uses source code datasets for training. $CALS_{code}$ replaces the original BERT (Devlin et al., 2019) with CodeBERT (Feng et al., 2020) to better accommodate source code data. For LLM-based code watermarking, we utilize the GPT-4o API to automate the embedding and extraction process, due to GPT-4o's strong reasoning abilities and wide usage. We also evaluate other representative LLMs, including DeepSeek-V3 and Gemini 1.5 Pro, with results shown in Appendix B.

4.2 Watermark Accuracy

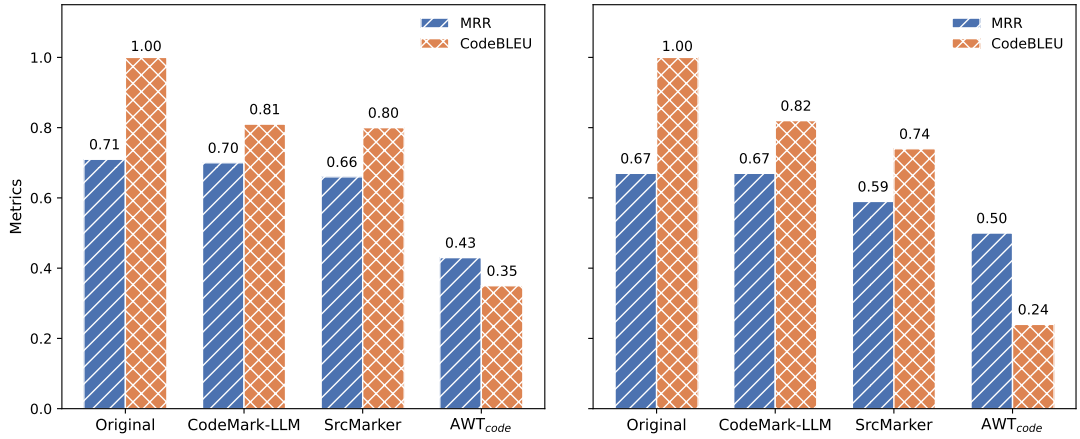
Metrics. We compare CodeMark-LLM with the baselines on two types of datasets for accuracy and capacity. Accuracy is measured by Bit Accuracy (BitAcc) and Message Accuracy (MsgAcc). BitAcc denotes the percentage of correctly extracted bits, while MsgAcc represents the percentage of entire messages that are correctly recovered. Capacity is measured in terms of the average number of bits in the embedding function (BPF).

Results. Table 3 shows that CodeMark-LLM consistently outperforms all baselines across datasets. Compared to SrcMarker, AWT_{code}, and $CALS_{code}$, CodeMark-LLM achieves a significant breakthrough in deployment efficiency by eliminating the need for any training, while still maintaining a high embedding capacity (BPF = 4). $CALS_{code}$ faces severe efficiency bottlenecks, preventing deployment on CSN-JS (3.5k) and CSN-Java (10k) datasets. To further assess cross-model robustness, we additionally conduct experiments where the watermarker and extractor are instantiated with different LLMs, and report the results in Appendix B.5.

4.3 Transparency

Metrics. We evaluate operational semantics using syntax checking and execution-based tests to verify functional correctness of watermarked code. As functions in the CSN dataset are not compilable independently, we use `tree-sitter` to identify AST errors. For MBXP, we employ the pass rate—the fraction of watermarked code passing all unit tests. Natural semantics assessment uses CodeBLEU (Ren et al., 2020) and MRR. CodeBLEU evaluates similarity through syntax, data flow, and n-gram matching, measuring differences following CodeXGLUE (Lu et al., 2021). MRR evaluates watermarking's effect on code naturalness by measuring the retrieval rank of watermarked code for a natural language query, with a higher score indicating better semantic retention. The computation uses a fine-tuned CodeBERT (Feng et al., 2020).

Operational semantic results. The operational semantic results are displayed in Table 4. Training-based methods (AWT_{code}, $CALS_{code}$, SrcMarker) have limited adaptability: they cannot be applied to Python, while CodeMark-LLM naturally supports it and maintains strong performance. AWT_{code}, though trained on source code, performs poorly in execution-based evaluation, failing to preserve functionality. $CALS_{code}$, despite replacing BERT with CodeBERT, still fails over 25% of tests due to limited understanding of complex code rules.



(a) Natural semantic evaluation results on CSN-JS (b) Natural semantic evaluation results on CSN-JS

Figure 2: Natural semantics metrics for CodeMark-LLM, SrcMarker and AWT$_{\text{code}}$. "Original" refers to the unwatermarked code.

Method	Training Time (h)	Embedding Time (s)	Extraction Time (s)	Total Time (h)	Economic Cost ($)
AWT$_{\text{code}}$	61.5	0.1055	**0.0023**	61.5	0.0123
SrcMarker	13.32	**0.0741**	0.0034	13.32	0.0027
CodeMark-LLM	**0**	3.3333	1.3333	**5.85**	**0.0020**

Table 5: Comparison of runtime and per-sample economic cost across different watermarking methods.

SrcMarker approaches CodeMark-LLM but relies on handcrafted transformations and AST rewriting, causing inconsistent variable renaming and failures in syntax or unit tests. Failure cases for the other methods are provided in Appendix B.3. CodeMark-LLM achieves nearly 100% BitAcc and Pass across datasets, retaining the original code semantics without altering its structure. The typical transformation example is in Appendix B.2.

Natural semantic results. Figure 2 illustrates the results for natural semantics. Higher MRR and CodeBLEU values indicate better preservation of natural semantics. On the CSN-JS dataset, CodeMark-LLM achieves results close to the original text in MRR, with only a 0.01 drop in CSN-Java, and maintains CodeBLEU scores above 0.81, demonstrating effective naturalness preservation. In contrast, both SrcMarker and AWT$_{\text{code}}$ perform worse than CodeMark-LLM in preserving natural semantics. SrcMarker shows a larger decrease in MRR and CodeBLEU scores on both datasets, indicating limitations in naturalness preservation. AWT$_{\text{code}}$ performs even worse, with CodeBLEU sharply reduced by syntax errors despite retaining searchable tokens and identifiers.

4.4 Efficiency and Economic Cost

Metrics. We compare CodeMark-LLM with the baselines using Per-sample Cost, which includes both total time (embedding and extraction time) and economic cost. SrcMarker and AWT$_{\text{code}}$ require significant computational resources, so we estimate training costs using a common market rental price of $2/hour for GPU usage. Due to the extremely high runtime of CALS$_{\text{code}}$ (over 342 hours), we do not include it in the comparison.

Results. Table 5 shows that CodeMark-LLM achieves lower per-sample cost and shorter runtime compared with training-based methods. While methods such as SrcMarker and AWT$_{\text{code}}$ incur significant overhead from model training, their cross-language generalization is nearly zero because they require language-specific adapters for each target language. This severely limits their efficiency in large-scale multilingual deployment. By contrast, CodeMark-LLM requires no training, adapts naturally to different programming languages, and thus offers higher deployment flexibility and clear advantages in scalability.

4.5 Robustness

Random removal attack. We evaluate watermark robustness against a removal attack, where the adversary is aware of the use of code transformations for embedding but lacks knowledge of the exact transformation rules. Therefore, the most straightforward attempt to remove the watermark is to randomly perform either variable renaming or code transformations. To simulate this, we randomly rename 25%, 50%, 75%, and 100% of variables, and apply up to 1, 2, or 3 random code transformations per snippet. We measure post-attack water-

Attack	SrcMarker				CodeMark-LLM			
	GH-Java		GH-C		GH-Java		GH-C	
	BitAcc	CB	BitAcc	CB	BitAcc	CB	BitAcc	CB
No Atk.	90.93	-	93.36	-	**97.05**	-	**97.49**	-
T@1	78.81	45.34	89.49	42.89	**93.65**	**62.83**	**92.97**	**67.11**
T@2	73.46	45.12	81.59	42.81	**92.97**	**62.75**	**89.11**	**61.74**
T@3	69.83	44.53	79.08	42.75	**92.83**	**62.17**	**87.20**	**60.83**
V@25%	79.90	43.93	84.80	42.61	**96.42**	**66.24**	**96.13**	**69.32**
V@50%	78.58	43.78	82.24	42.48	**96.10**	**59.04**	**95.97**	**63.45**
V@75%	70.64	43.60	70.48	42.28	**95.28**	**51.91**	**95.70**	**56.36**
V@100%	59.80	43.42	62.69	41.98	**95.05**	**43.48**	**94.71**	**49.08**

Table 6: Performance under random removal attack. CB: CodeBLEU; T: random code transformation; V: random variable substitution.

Method	Metrics	MBJP	MBJSP	MBCPP	MBPP
SrcMarker	BitAcc (%)	50.12 (49.32↓)	50.72 (46.22↓)	49.18 (46.86↓)	/
	Pass (%)	98.46	99.25	99.74	/
	CodeBLEU (%)	**48.80**	**49.80**	**50.75**	/
CodeMark-LLM	BitAcc (%)	**76.93** (22.79↓)	**79.0**2 (20.45↓)	**83.48** (16.16↓)	**79.72**(18.13↓)
	Pass (%)	**99.17**	**99.87**	**99.74**	**99.38**
	CodeBLEU (%)	47.85	48.55	44.88	**41.19**

Table 7: Performance under adaptive de-watermarking. "Pass" is the percentage of de-watermarked code that passes the test case. Values in parentheses report the absolute decrease compared to the watermarked code before the attack."/" indicates that the method cannot be applied to the Python language.

mark recovery accuracy to assess robustness, and report CodeBLEU scores before and after the attack to quantify semantic preservation and perceptual cost. As shown in Table 6, CodeMark-LLM consistently achieves high BitAcc across all attack intensities, demonstrating strong resilience to both structural and identifier-level perturbations. In contrast, SrcMarker shows a sharp decline in BitAcc under increasing attack strength, particularly under full variable renaming (V@100%), where accuracy drops to 59.80% on GH-Java and 62.69% on GH-C. This indicates its limited capacity to trace watermarks once identifiers are obfuscated. CodeMark-LLM's superior robustness stems from its rule-aligned embedding, which binds each watermark bit to a semantic transformation context and employs a multi-feature matching mechanism that enables accurate recovery even after aggressive code modifications. The results of random removal attacks on the MBXP dataset are provided in Appendix B.7.

Adaptive de-watermarking. We further simulate a stronger adversary who is aware of the LLM-based embedding mechanism but lacks access to the specific embedding strategy. To remove potential watermarks, the attacker paraphrases the watermarked code using a general-purpose LLM, while preserving functional correctness. As shown in Table 7, the code retains a high execution success rate while exhibiting a clear drop in CodeBLEU, indicating effective code rewriting without altering functionality. Despite such high-level semantic changes, CodeMark-LLM consistently achieves high BitAcc, demonstrating strong resilience. CodeMark-LLM's watermarking is guided by semantically consistent transformation patterns, whose categories remain invariant even when low-level lexical variations occur. This allows reliable extraction by comparing the attacked code with the original and detecting transformation traces aligned with the predefined stylistic families.

5 Conclusion

We present CodeMark-LLM, a novel LLM-based framework that redefines the paradigm of source code watermarking. Unlike prior methods that rely on handcrafted rules, AST manipulations, or retraining, CodeMark-LLM uses prompt-driven semantic transformations to embed and extract watermarks without any model fine-tuning or language-specific engineering. This enables lightweight deployment and seamless adaptation to multiple programming languages. Extensive experiments demonstrate that CodeMark-LLM achieves strong robustness against common and adaptive attacks while maintaining high watermark fidelity and code functionality. These results highlight the potential of LLMs as a practical and generalizable foundation for secure and language-agnostic software ownership verification.

Limitations

While CodeMark-LLM demonstrates strong performance across multiple criteria, a few limitations remain. First, the use of LLMs introduces some non-determinism in generation, which may occasionally cause minor deviations such as formatting inconsistencies. These cases are rare and typically resolved via simple retry or prompt refinement. Second, although CodeMark-LLM is training-free, the reliance on commercial LLM APIs may introduce modest inference latency or cost in large-scale applications. Finally, our current implementation focuses on function-level watermarking; extending it to module-level or cross-file granularity remains a promising direction for future work.

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A Prompt of CodeMark-LLM

This section describes in detail the design of hints in CodeMark-LLM.

A.1 Prompt Design of Semantic Consistent Embedding

We provide the prompt template used by CodeMark-LLM to guide the LLM in performing semantically consistent watermark embedding. The prompt instructs the model to apply one transformation per bit based on the specified sub-rule list while preserving program semantics. The full structure is shown in Figure 3.

A.2 Prompt Design of Differential Comparison Extraction

To extract the watermark, CodeMark-LLM employs a comparison-based prompt that guides the LLM to identify applied transformations between original and watermarked code. This enables accurate bit recovery based on transformation traces. The prompt structure is shown in Figure 4.

B Additional Experimental Results

B.1 Dataset Preprocessing Steps

We processed the datasets following the data preprocessing methods outlined in the SrcMarker. Subsequently, the datasets were partitioned into training, validation, and test sets. For the GitHub-C and GitHub-Java datasets, we performed a random split with an 8:1:1 ratio. For the CSN dataset, we utilized its original train/valid/test split, while for the MBXP dataset, all samples were employed as the test set. The statistics of the datasets are shown in Table 8.

B.2 Transformation Examples for CodeMark-LLM

Fig. 5 shows the segments before and after code watermark embedding. The method name on line 1 has been changed from calc_sum to calcSum, which is a legal method name. The for loop on line 3 has been equivalently replaced by a while loop, introducing the additional variable i for control and adding i++ at the end of the loop. The expression in line 4 has been reordered and does not affect the functionality of the code. The return statement on line 6 is wrapped in a block of code. The transformation introduces no functional difference, demonstrating the effectiveness of CodeMark-LLM-based transformations.

Prompt Template for Watermark Embedding in CodeMark-LLM

Role: You are a skilled programmer capable of rewriting code while preserving its functionality and syntax correctness.
Description: Given a source code and a randomly generated watermark bitstring, apply semantic-preserving transformations to embed the watermark.
Rules:

- For each bit $w_k = 1$, apply exactly one transformation from the k-th selected sub-rule.
- If $w_k = 0$, leave the code unchanged.
- Follow transformation-specific constraints.
- No functionality changes or added comments are allowed.

Example: Input: $w = (1, 0, 0, 1)$ and sub-rules {CamelCase to snake_case, for to while, group ops , insert blank line}
Output: Transformed code applying rules 1 and 4, skipping 2 and 3.
Task: Given code, bitstring $w = (w_1, \ldots, w_n)$, and sub-rule list {T}, output the watermarked code.

Figure 3: Prompt template for watermark embedding in CodeMark-LLM.

Prompt Template for Watermark Extraction in CodeMark-LLM

Role: You are an expert in identifying subtle transformations between source code versions.
Description: Given an original and a watermarked code, determine which transformations occurred to recover the embedded watermark.
Rules:

- For each bit position k, compare original and transformed code using sub-rule T_k.
- Set $w_k = 1$ if the rule was applied, otherwise $w_k = 0$.
- Justify decisions based on code structure and semantic consistency.

Example: Input: Code pair {Original, Watermarked}, sub-rules {T}
Output: $w = (1, 0, 0, 1)$ with justification per bit.
Task: Recover $w = (w_1, \ldots, w_n)$ from comparison between `[ORIGINAL]` and `[TRANSFORMED]` based on sub-rule sequence.

Figure 4: Prompt template for watermark extraction in CodeMark-LLM.

Dataset	**GitHub**		**MBXP**				**CSN**	
	C	Java	C++	Java	JS	Python	Java	JS
#Functions	4,577	5,501	764	842	797	974	173,326	63,258

Table 8: Dataset Statistics.

```java
public static int calc_sum(int a, int b) {
    int result = 0;
    for (int i = 0; i < 3; i++) {
        result = result + a + b;
    }
    return result;
}
```

(a) Original Code

```java
// method name renaming
public static int calcSum(int a, int b) {
    int result = 0;
    int i = 0;
    // loop transformed
    while (i < 3) {
        // expression reordered
        result = b + a + result;
        i++;
    }
    // return wrapped in block
    { return result; }
}
```

(b) Watermarked Code

Figure 5: A code snippet watermarked by CodeMark-LLM.

B.3 Failure Cases of AWT_{code} , $\text{CALS}_{\text{code}}$, and SrcMarker

Three representative failure cases from **AWT_{code}**, **$\text{CALS}_{\text{code}}$**, and **SrcMarker** are shown in Figure 6, Figure 7, and Figure 8, respectively. In the case of AWT_{code}, the transformation introduces multiple syntax-breaking modifications. Specifically, it erroneously inserts spaces within function names and parameter lists, replaces valid constructor calls with malformed expressions, and introduces unmatched parentheses and invalid logical operators. For $\text{CALS}_{\text{code}}$, the transformation causes a typographical error in a variable name, changing `testTuple` to `testTuuple`. This syntactic mistake results in an undefined variable reference, which leads to a compilation failure. SrcMarker introduces both syntactic and semantic errors during watermark embedding. First, the original function parameter `onHotUpdateSuccess` is incorrectly replaced with `sizeMap`, while the internal logic still invokes `onHotUpdateSuccess()`, resulting in an undefined function call. Second, the error message string is corrupted by the removal of whitespace, significantly reducing its readability. Finally, the condition `typeof sizeMap = == 'function'` is invalid due to an incorrect equality check. These issues highlight SrcMarker's lack of context awareness and the absence of syntactic correctness verification in its transformation process.

B.4 Generalization Across LLMs

To further validate the generalization ability of CodeMark-LLM, we conducted supplementary experiments on different LLMs. In addition to GPT-4o, we selected **DeepSeek-V3** and **Gemini 1.5 Pro** for evaluation. Under the same experimental setup, we compared the performance of watermark embedding and extraction, reporting two metrics: BitAcc and Pass. As shown in Table 9, CodeMark-LLM consistently achieves high performance on both models, with BitAcc remaining above 97% and Pass approaching 100%. This indicates that CodeMark-LLM does not rely on a specific LLM. Moreover, no systematic degradation was observed due to model differences, which provides strong evidence of the cross-model generalization capability of CodeMark-LLM.

B.5 Cross-LLM Embedding and Extraction

To evaluate the stability of CodeMark-LLM across different LLMs, we conducted experiments where the watermarker and extractor were instantiated with different LLMs, including **GPT-4o**, **DeepSeek-V3**, and **Gemini 1.5 Pro**. As shown in Table 10, the BitAcc remains consistently above 95% across all combinations, with minimal performance degradation compared to same-model settings. These results demonstrate that our framework maintains stable embedding and extraction accuracy even when different LLMs are used in cross-model scenarios.

B.6 Evaluation of Inference Runtime Cost During Watermark Embedding

To evaluate the inference runtime cost during watermark embedding, we conducted experiments on the CSN-Java dataset. The code lengths were divided into three categories: Short (less than 10 lines), Medium (10-50 lines), and Long (more than 50 lines). Considering that training-based methods consume a significant amount of GPU resources (we used an NVIDIA RTX 4090 GPU for training in our experiments), we adopted a commonly used market rental price ($2/h) as the basis for estimating training costs. To facilitate comparison, we used the **Per-sample Cost** as the evaluation metric. The experimental results, as shown in Table 11, indicate that CodeMark-LLM achieves significantly lower per-sample costs across all code length categories. As the size of the codebase increases, this cost remains lower than that of

```
function createInstance(defaultConfig) {
  var context = new Axios(defaultConfig);
  var instance = bind(Axios.prototype.request, context);
  utils.extend(instance, Axios.prototype, context);
  utils.extend(instance, context);
  return instance;
}
```

(a) Original Code

```
// Function name and parameter name split with spaces
function create Instance (default Config ) {
    // Invalid constructor and variable declaration
    var context , Math Axios (default Config );
    // Incorrect method call with mismatched brackets
    var instance , bind (Blog )prototype )request , context );
    // Logical operator and comment confusion
    // Copy raised to instance utils .extend (instance , Math .prototype , context )&&
    // Copy context to instance utils .extend (instance , context )&&
    &return instance &&
}
```

(b) Watermarked Code

Figure 6: Fail case of AWT_{code}. "Original" refers to the unwatermarked code.

training-based methods. Moreover, training-based methods have almost no cross-language adaptability because they require specific adapters for each programming language, which significantly reduces the efficiency of traditional methods in large-scale cross-language deployment. In contrast, CodeMark-LLM does not rely on language adapters and naturally adapts to different programming languages, offering higher deployment flexibility. Therefore, CodeMark-LLM demonstrates greater advantages in large-scale cross-language deployment.

B.7 Robustness Evaluation on MBXP

In this section, we provide supplementary experimental results for the robustness evaluation on MBXP dataset. We use the same setup described in Section 4.5. The results are shown in Table 12, CodeMark-LLM demonstrates strong robustness against both structure-level and identifier-level random removal attacks on the MBXP dataset. It maintains high BitAcc and functionality across Java, JavaScript, and C++ subsets under varying attack intensities. While accuracy slightly degrades as the number of applied transformations or the extent of variable renaming increases, the system remains consistently reliable, even under full variable renaming or multiple code transformations.

```
vector<int> sumOfAlternates(vector<int> testTuple) {
  // ...
  sum[0] += testTuple[i];
}
```

(a) Original Code

```
vector<int> sumOfAlternates(vector<int> testTuple) {
  // ...
  // Incorrect variable name
  sum[0] += testTuuple[i];
}
```

(b) Watermarked Code

Figure 7: Fail case of $\text{CALS}_{\text{code}}$. "Original" refers to the unwatermarked code.

Method	Metric	MBJP (%)	MBJSP (%)	MBCPP (%)	MBPP (%)
AWT_{code}	BitAcc(%)	93.88	83.97	97.12	/
	Pass(%)	0	0	0	/
$\text{CALS}_{\text{code}}$	BitAcc(%)	93.31	93.50	92.89	/
	Pass(%)	68.65	76.77	68.19	/
SrcMarker	BitAcc(%)	99.44	96.94	96.04	/
	Pass(%)	97.86	97.99	97.64	/
$\text{CodeMark-LLM}_{\text{deepseek}}$	BitAcc(%)	98.69	**99.56**	**98.75**	**98.37**
	Pass(%)	97.25	99.75	98.50	99.75
$\text{CodeMark-LLM}_{\text{gemini}}$	BitAcc(%)	**98.70**	98.19	98.13	97.37
	Pass(%)	**99.40**	**100**	**99.75**	**100**

Table 9: Performance on cross-model generalization. "/" indicates that the method cannot be applied to the Python language.

Watermarker	Extractor	MBJP (%)	MBJSP (%)	MBCPP (%)	MBPP (%)
GPT-4o	GPT-4o	**99.72**	99.47	**99.64**	**97.85**
	DeepSeek-V3	99.30	**99.72**	98.85	95.51
	Gemini-1.5-pro	99.26	**99.72**	99.48	95.38
DeepSeek-V3	DeepSeek-V3	98.69	**99.56**	**98.75**	98.37
	GPT-4o	95.59	97.62	98.28	96.73
	Gemini-1.5-pro	**99.62**	95.67	98.28	**98.99**
Gemini-1.5-pro	Gemini-1.5-pro	98.70	98.19	98.13	**97.37**
	GPT-4o	98.79	98.43	98.54	96.38
	DeepSeek-V3	**99.34**	**99.75**	**98.98**	96.96

Table 10: Bit Accuracy (BitAcc) of Cross-LLM Watermarking and Extraction Across Datasets

```
1  async function tryApplyUpdates (onHotUpdateSuccess) {
2    if (!module.hot) {
3      console.error('HotModuleReplacementPlugin is not in Webpack configuration
         .')
4      //...
5    }
6    //...
7    function handleApplyUpdates (err, updatedModules) {
8      //...
9      if (typeof onHotUpdateSuccess === 'function') {
10       onHotUpdateSuccess()
11     }
12     //...
13   }
14   //...
15 }
```

(a) Original Code

```
1  async function tryApplyUpdates ( sizeMap ) {
2    if ( ! module.hot ) {
3      // Incorrect string literal due to missing spaces
4      console.error ( 'HotModuleReplacementPluginisnotinWebpackconfiguration.' ) ;
5      //...
6    }
7    //...
8    function handleApplyUpdates ( err , updatedModules ) {
9      //...
10     // Wrong condition and misplaced function call
11     if ( typeof sizeMap = == 'function')  onHotUpdateSuccess ( ) ;
12     }
13     //...
14   }
15   //...
16 }
```

(b) Watermarked Code

Figure 8: Fail case of SrcMarker. "Original" refers to the unwatermarked code.

Code Length	Method	Training Time (h)	Embedding Time (s)	Extraction Time (s)	Total Time (h)	Economic Cost ($)
Short	SrcMarker	13.32	**0.0952**	0.0037	13.32	0.0027
	AWT_{code}	61.50	0.1713	**0.0026**	61.50	0.0123
	$CodeMark\text{-}LLM_{deepseek}$	**0**	5.0200	3.6000	27.02	0.0018
	$CodeMark\text{-}LLM_{gemini}$	**0**	1.9000	1.1000	11.15	**0.0011**
	$CodeMark\text{-}LLM_{gpt\text{-}4o}$	**0**	1.4000	1.0000	**5.85**	0.0013
Medium	SrcMarker	13.32	0.0794	0.0032	13.32	0.0027
	AWT_{code}	61.50	**0.0346**	**0.0019**	61.50	0.0123
	$CodeMark\text{-}LLM_{deepseek}$	**0**	8.8000	5.1000	27.02	0.0021
	$CodeMark\text{-}LLM_{gemini}$	**0**	3.1000	1.5000	11.15	**0.0012**
	$CodeMark\text{-}LLM_{gpt\text{-}4o}$	**0**	2.4000	1.2000	**5.85**	0.0017
Long	SrcMarker	13.32	**0.0924**	0.0032	13.32	0.0027
	AWT_{code}	61.50	0.1107	**0.0023**	61.50	0.0123
	$CodeMark\text{-}LLM_{deepseek}$	**0**	24.0000	4.6800	27.02	0.0028
	$CodeMark\text{-}LLM_{gemini}$	**0**	6.6000	1.7000	11.15	**0.0017**
	$CodeMark\text{-}LLM_{gpt\text{-}4o}$	**0**	6.2000	1.8000	**5.85**	0.0029

Table 11: Comparison of Inference Runtime and Economic Cost.

Attack	MBJP		MBJSP		MBCPP	
	BitAcc(%)	Pass(%)	BitAcc(%)	Pass(%)	BitAcc	Pass(%)
No Atk.	99.72	99.31	99.47	99.87	99.64	99.35
T@1	88.84	93.92	93.10	98.37	92.64	95.16
T@2	86.84	86.74	88.08	98.12	91.36	92.15
T@3	84.46	82.32	88.05	96.99	89.20	91.23
V@25%	96.03	91.57	95.68	96.49	94.93	90.18
V@50%	95.75	88.81	93.62	93.60	92.67	88.48
V@75%	90.61	87.97	90.90	90.97	91.66	88.09
V@100%	82.29	87.29	87.86	89.34	90.35	86.91

Table 12: Performance under random removal attack