UNIVERSITY OF SALERNO

DEPARTMENT OF COMPUTER ENGINEERING, ELECTRICAL ENGINEERING AND APPLIED MATHEMATICS

Master's Degree Course in Computer Engineering

Natural Language Processing and
Large Language Models

Automatic Detection of LLM-Generated Source Code

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Chapter 1

Introduction

Generative Artificial Intelligence (AI) is a rapidly advancing branch of AI that, in recent years, has made tremendous progress, largely due to the widespread adoption of deep learning techniques. Generative models are now powerful deep learning architectures capable of producing highly realistic text, images, and even video content.

The famous Turing Test is frequently referenced in this context. In this test, a human judge had to determine whether they were communicating with another human or with a machine. This milestone was already surpassed in 2014, with early systems such as Eugene Goostman [1].

Today, it is widely accepted that much of the content generated by generative models is indistinguishable from human-produced material and indeed, for humans, **this distinction is increasingly difficult to make**.

The introduction of the Transformer architecture in 2017 [2] revolutionized the field and led to the development of Large Language Models (LLMs), which quickly became part of everyday life. This wave began with the public availability of GPT-3 [3] in June 2020 [3], followed by a growing ecosystem of LLMs including GPT-4 [4], PaLM [5], LLaMA [6], Claude [7], and Mistral [8].

Generative AI, however, is not limited to natural language processing. It has also enabled powerful models for image generation, such as Stable Diffusion [9], and more recently for video synthesis, with systems like Veo-3 [10].

Although the usefulness and extraordinary capabilities of these tools are undeniable, there are many scenarios in which it becomes necessary to have user-friendly tools to detect whether text, images, or videos were generated by an AI.

This thesis presents a more modest, yet equally important objective: **detecting artificially generated source code** produced by code generation models such as OpenAI Codex [11], GPT-4 [4], and Code LLaMA [12].

While natural language detectors are well-established and widely studied in scientific literature, the detection of AI-generated code remains a far less consolidated and more recent research area. The contribution of this work is to **analyze the most relevant scientific advancements** made in the past year, which are often fragmented and inconsistent due to the unique challenges involved in distinguishing machine-generated code, a task that is arguably more complex than natural text detection.

1.1 Historical Overview of Code Generation by LLMs

The history of code generation can be explored from several perspectives.

1.1.1 Natural Language Processing

One possible starting point possible perspective for analysing the evolution of code generation is to trace the development of Natural Language Processing (NLP), the field that studies how machines process and interact with human language. NLP comprises two major subdomains: Natural Language Understanding (NLU), which focuses on a machine's ability to interpret and "understand" human language, and Natural Language Generation (NLG), which concerns the generation of natural-sounding text.

This distinction is particularly relevant because the technologies currently used for code generation are essentially the same as those employed for natural language generation. In fact, Transformer-based models trained on source code data approach code generation in the same way they would handle natural text generation by predicting sequences of tokens in context using learned statistical patterns [2].

From this point of view we can start in the 1943 during World War II with the invention of Colossus, one of the first digital electronic computers, developed in order to analyse encrypted communications from the German military.

In parallel, the discipline of Natural Language Processing (NLP) began to take shape as early as the 1940s, culminating in the 1954 Georgetown experiment the first public demonstration of machine translation. Another milestone came in 1966 with the creation of ELIZA [13], considered the first chatbot in history, which simulated the behaviour of a psychotherapist using pattern-matching rules.

During the 1970s and 1980s, symbolic approaches to NLP became popular. These early attempts aimed to enable machines to "understand" language through manually encoded rules and logic-based systems. In the 1990s, the importance of statistical methods became evident, marking a shift from rule-based to probabilistic models for language processing.

In 2006 Google launched its now ubiquitous Google Translate service. The following decade saw the rise of voice-based assistants: Apple's Siri (2011), Microsoft's Cortana (2014), Amazon's Alexa (2014), and Google Assistant (2016).

A major breakthrough came with the introduction of distributed word representations, especially word2vec [14] and GloVe [15], published in 2013 and 2014 respectively. These methods enabled dense vector representations that captured semantic relationships between words in large corpora.

The most significant leap, however, occurred in 2017 with the publication of the now seminal paper "Attention is All You Need" [2], which introduced the Transformer architecture. This architecture remains the dominant framework in NLP and underpins nearly all modern LLMs. Transformers enabled major advances in tasks such as text generation, machine translation, question answering, text summarization and, more recently, code generation.

The first LLMs capable of code generation began to appear around 2019–2020, notably with the release of GPT-2 [16]. In 2021, OpenAI released Codex [11], a GPT-3

[3] derivative trained specifically for code generation and explanation, which was later integrated into GitHub Copilot.

Between 2022 and 2024, a wave of new LLMs for code generation was released, including CodeT5 [17], CodeGen [18], CodeGeeX [19], and Code LLaMA [12].

1.1.2 Code Generator

Another possible point of view is the one focused on code generation itself. This is not a completely new concept: it dates back to 1957 with Fortran. Fortran is both a programming language with an integrated compiler, developed by IBM. A compiler can be seen as a code generation tool, since it translates source code into machine code, the only "language" truly "understandable" by a computer [20].

Compilers have a long history and have been continuously improved over time, but they are not the only tools for code generation. Already in 1976, the concept of intelligent editors emerged with Emacs, thanks to its support for custom macros [21]. Later, in 1996, IntelliSense introduced symbolic completion, namely the ability of the IDE to suggest code based on the context and the symbols already present.

In 1999, with XSLT, one of the first standardized tools for automatic transformation between markup languages was introduced [22]. During the same years, the work of Zelle[23] and Mooney[24] (1996–1999) proposed methods based on Natural Language processing to generate database queries from natural language expressions.

At the same time, template-engine-based tools for server-side spread, such as Jinja2 (2005)[25] and Mako (2006)[26], which allowed the generation of dynamic code by combining data with predefined structures.

In 2017, with research on AST-guided code generation, LSTM models began to be used to generate code in a more structured way, guided by the syntax of the programming language [27].

Finally, in 2021, with GitHub Copilot, one of the most advanced code completion tools was introduced: so efficient that it is capable of generating entire code sections from simple textual prompts, thanks to the use of generative AI models based on Transformer architectures [11].

1.1.3 LLMs code oriented

Another possible starting point is from the publication of the paper *Attention Is All You Need* in 2017, which introduced the Transformer architecture [2] and, enabled the widespread development of Large Language Models (LLMs). We must remember that the first LLMs were typically designed to analyse and generate just natural language text, so not all LLMs were capable of generating code, or at least not of generating syntactically correct or functional code.

In 2018, two foundational models were introduced: BERT [28], an encoder-only architecture designed to generate dense semantic representations of natural language, and GPT-1 [29], a decoder-only model capable of generating coherent text. Those models were not yet able to generate code, but they have been an important baseline for future code-oriented models.

In fact in 2019, OpenAI released GPT-2 [16], a more powerful decoder-only model capable of producing much more convincing text compared to GPT-1. Although GPT-2 was not specifically trained to generate code, its training corpus included code snippets. In the same year, TabNine, a popular code completion extension for several IDEs, replaced its n-gram-based next-token prediction with a version of GPT-2 fine-tuned on source code [30].

Also in 2019, Microsoft Research and GitHub introduced the CodeSearchNet dataset [31], a multilingual code dataset and one of the first large-scale corpora usable to train Transformers for code generation tasks.

In 2020, Microsoft Research released CodeBERT [32] *(based on BERT)*, trained on both natural language and code using the CodeSearchNet dataset. CodeBERT is designed for tasks such as code search and code summarization. While it does not generate code, it is an encoder-only model capable of deeply understanding the structure and semantics of source code. Through CodeBERT is possible producing rich and dense representations suitable for downstream tasks like classification, or for use as input to decoders in generative pipelines.

In 2021, several LLMs capable of generating realistic and reliable code were introduced. OpenAI published Codex [11], a GPT-3 [3] derivative fine-tuned on source code from the GitHub Code dataset. In the same paper OpenAI introduced the HumanEval benchmark, designed to assess the performance of Codex [11] on programming problems *(and in future all LLMs code oriented)*. On HumanEval, Codex (12B) was able to solve 28.8% of the problems on the first attempt, significantly outperforming all previous models on code generation.

Codex [11] sparked widespread interest in the use of LLMs for code generation, indeed in the same year is released GitHub Copilot, powered by Codex [11].

In the same year, many additional datasets were published, including MBPP (Mostly Basic Python Problems) [33], the APPS dataset [34], and CodeXGLUE [35].

In December 2021, Salesforce AI Research released CodeT5 [17], an open-source encoder-decoder model that, unlike Codex [11], supports a wider variety of code-related tasks. Thanks to task-specific training strategies, CodeT5 proved to be highly versatile, supporting code summarization, generation, and translation.

In 2022, Google introduced AlphaCode [36], achieving a performance in the top 54.3 percentile on competitive programming tasks on Codeforces. In the same year, PolyCoder [37], a decoder-only model trained solely on 249 GB of source code, was also released as an open-source alternative.

In 2023, GPT-4 [4] (although not exclusively trained for code generation) achieved an 80% success rate on HumanEval. Claude 3 by Anthropic reportedly reached 85%, and Meta's open-source model Code LLaMA [12] scored 57%.

In 2024, Google introduced Gemini [38], which, when integrated into an inspired AlphaCode framework, reached performance within the top 15% of coding competition participants.

1.2 Motivations Behind LLM-Generated Code Detection

Although it may seem exaggerated to begin the historical overview of code generation Section 1.1.2 with compilers, this choice aims to emphasize that the present work does not seek to demonize the contribution or usefulness of code generation tools. It is undeniable that such tools are extremely valuable in both professional software development, accelerating simpler phases of implementation, and in educational contexts, where they can serve as useful assistants for learning how to write code.

Nevertheless, it is equally clear that is raising the need, in certain contexts and for specific reasons, to limit or discourage the use of highly advanced tools for code autocompletion or generation.

One important reason concerns **academic and professional integrity**: the undeclared use of LLMs in evaluation contexts makes the assessment process highly problematic. Students, for example, may complete assignments or even exams using LLMs without contributing meaningfully to the generated code, potentially impairing their learning of fundamental programming concepts (getting the most out with the least effort). Similarly, during a technical interview, a candidate might rely on a tool like AlphaCode 2 to generate solutions to proposed problems. This is the main topic of *"The Impact of Large Language Models on Programming Education..."* [39] in which is demonstrated that a widespread use of LLMs code generator has negatively affects over students' capability.

Figure 1.1 illustrates possible correlation between final grade and the use of LLM. We can observe that an increase in LLM usage tends to correlate with lower average student grades, although it is not a decisive factor in determining the final score.

Another critical issue lies in the way LLMs generate code. Since these models are trained on massive corpora, evaluating the security and efficiency of the generated code is nearly impossible. The output may be **vulnerable or inefficient** due to subtle flaws that are hard to detect, especially when the code appears well-formatted and logically structured. This happens to overreliance on commonly seen patterns in the training corpus rather than more appropriate niche solutions. The security issues are highlighted by the study *"Do Users Write More Insecure Code with AI Assistants?"* [40]. This study shows a decrease in code security simply by using an AI assistant instead of traditional programming.

Intellectual property is yet another motivation for detecting LLM-generated code, a general problem in generative AI. This is not limited to the origin of training data but also concerns the risk that an LLM may reproduce copyrighted code, posing significant legal risks to software companies that could unknowingly integrate such code into their products. This issue is not an exaggerated concern, it's a tangible risk [41].

The least important reason, which directly concerns the development of code-oriented LLMs themselves, is the need to distinguish machine-generated code in training

datasets. If a model is trained on LLMs' code we might run into a general LLM code oriented **Model Collapse**. Indeed, training LLM on LLMs' code serves to deteriorate the output diversity and adaptability to real-world scenarios. This feedback loop issue is addressed for example in *"The curse of recursion..."* [42]. If no method exists to detect such code, the datasets used for training future models would have to be limited to code written before the widespread availability of LLMs, in order to avoid contamination. This would result in code generation models being trained on increasingly outdated data.
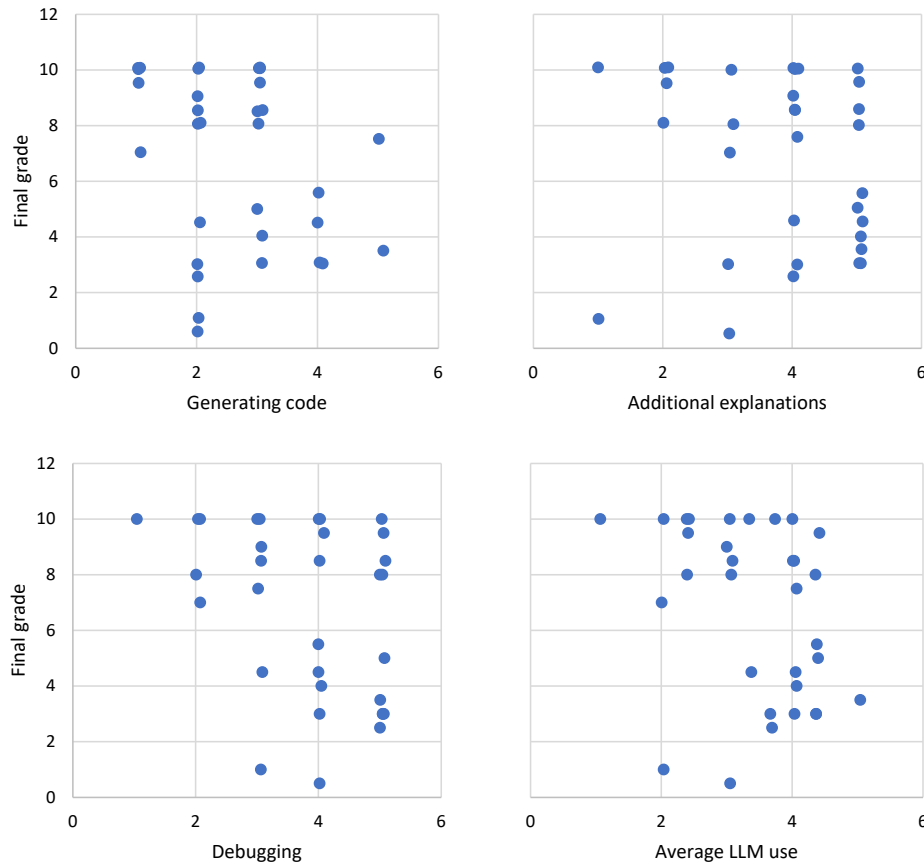

Figure 1.1: Scatter plot from the paper *The Impact of Large Language Models on Programming Education and Student Learning Outcomes*, illustrating the relationship between LLM usage and students' final performance.

1.3 Challenges in LLM-Generated Code Detection

The detection of short texts generated by LLMs remains a challenging task. While partial solutions have been proposed, the problem cannot yet be considered fully resolved. Nonetheless, it is widely acknowledged that detection tools achieve strong performance when applied to moderately sized texts (longer than just a few lines).

A well-known example is **DetectGPT** [43], a zero-shot method that does not require training a separate classifier but instead relies on an auxiliary LLM to assess whether a given passage is likely machine-generated. DetectGPT is often regarded as the state-of-the-art among open-source methods for AI-generated text detection.

In addition to open-source methods, commercial solutions such as **GPTZero** [44] have gained popularity. GPTZero can be accessed via a web interface and combines language-model-based heuristics with machine learning classifiers. While it is effective in many cases, it is not infallible. For example, GPTZero has been reported to mistakenly flag texts written by non-native speakers, whose lexical variety may be lower, as AI-generated.

Even the creators of GPTZero explicitly state that a positive detection should not be taken as conclusive proof, but rather as a probabilistic signal or indicator.

As stated in several papers analysed in this work, such as *Uncovering LLM-Generated Code: A Zero-Shot Synthetic Code Detector via Code Rewriting [45]*, **methods designed for detecting natural language text are largely ineffective when applied to code**. The causes of this limitation are primarily related to the structural and syntactic properties of programming languages.

Unlike natural language, where the same idea can be expressed using a vast variety of words and syntactic structures, source code is governed by strict and formal grammar rules. As a result, many tokens must appear in a specific and rigid order. Consequently, techniques based on lexical probability, such as those used by DetectGPT, tend to fail when applied to code, as they cannot meaningfully capture the constrained nature of programming syntax.

Moreover, many natural language detectors rely on input perturbation to assess sensitivity or likelihood distributions, a process that is significantly more difficult to perform on source code without introducing semantic or syntactic errors.

A further practical limitation is the lack of publicly available datasets specifically designed for training code-based LLM detectors. While large and well-established code corpora do exist, researchers who aim to train classification models for code detection often have to construct their own datasets, with all the associated challenges in terms of bias, coverage, and quality assurance.

These issues have contributed to a significant gap in the literature: unlike DetectGPT, which is widely recognized for natural language detection, there is no single, consolidated approach for LLM-generated code detection. Instead, the field is characterized by a proliferation of parallel methods, often employing fundamentally different techniques and evaluation protocols.

1.4   Thesis Objectives

This thesis aims to pursue a structured series of objectives, each forming a necessary foundation for the subsequent stage of the project.

The overarching goal is to **develop a software tool capable of reliably distinguishing source code written by humans from that generated by Large Language Models** (LLMs). Given the lack of standardization in the current literature, this project first seeks to **establish a fair and reproducible evaluation framework**.

The initial task involves **selecting** a sympathetic and representative **dataset** that can serve both for retraining detection models and for evaluating their performance consistently. A comparative analysis of current scientific literature datasets will be conducted, taking into account objective criteria such as class balance, diversity of programming languages, code length variability, and feature distribution. The selected dataset will play a central role in ensuring that all subsequent experiments are comparable and grounded on a common basis.

Once the dataset is established, the next phase consists in **collecting and systematically evaluating the various detection models suggested in recent literature**. These models will be executed on the selected dataset using consistent and comparable metrics in order to allow for a meaningful comparison. Special attention will be given to understanding the assumptions and limitations of each model. For instance, we will examine which datasets were originally used for training, which evaluation metrics are most informative in this context, the computational requirements of each method, and the specific scenarios in which they demonstrate optimal or suboptimal performance. In this phase, it will also be possible to identify the underlying reasons why certain models outperform others.

Following this benchmarking effort, the most promising method will be selected for further investigation. At this stage, will be proposed enhancements aimed at improving accuracy, robustness, or efficiency. These improvements must be tailored to the nature of the selected model.

The final phase of the project will focus on the development of a usable and **user-friendly software interface**, which allows end users to apply the selected detection model with minimal technical effort. The interface may include customizable parameters such as confidence thresholds or model options, depending on the characteristics of the adopted approach. Particular care will be taken to ensure that the tool is accessible and adaptable, so that it can be employed in diverse real-world scenarios, from academic integrity enforcement to software development auditing. Ultimately, this thesis intends to contribute both a rigorous comparative study and a practical, operational tool, filling a current gap in the literature and paving the way for future research and application in this emerging area

Chapter 2

Overview of current state of the art

Before analysing the individual contributions, it is necessary to understand the current state of the art. As discussed in Section 1.1.3, there are no widely established or consolidated approaches for detecting LLM-generated code. However, this does not imply a lack of research on the topic.

A subset of existing works focuses solely on providing datasets for training and evaluating detection models. The majority, instead, aim to propose detection techniques, including zero-shot approaches or methods requiring deep neural networks.

Since this area has only started to be actively explored around 2024, a significant portion of the literature has been published on platforms such as arXiv. Although arXiv is extremely useful for identifying cutting-edge research, it primarily hosts **preprints** (papers which have not yet undergone peer review by the scientific community).

This does not mean that arXiv publications should be disregarded, but the fact that most work in this area remains unpublished in peer-reviewed venues highlights the early and still-developing nature of this research topic.

Preprints

- **CoDet-M4** [46]: Presentation of a dataset obtained by using five different LLMs.

- **AIGCodeSet** [47]: Presentation of a python dataset obtained by using three different LLMs.

- **CodeMirage** [48]: !

- **How Far Are We?** [49]: Analysis of Natural Language Methods Applied to Code, the GPTSniffer Tool, and the Proposal of Alternative Detection Approaches.

- **DetectGPT4Code** [50]: Uncovering LLM-Generated Code: A Zero-Shot Synthetic Code Detector via Code Rewriting. In Proceedings of the AAAI Conference on Artificial Intelligence.

Peer-reviewed paper

- **Uncovering LLM-Generated Code** [51]: Proposal of a Detection Method Based on Code Rewriting and a Custom-Trained Similarity Model.

- **DetectCodeGPT** [52]: Analysis of Differences Between Human-Written Code and LLM-Generated Code, and Introduction of a Detector Based on Purely Stylistic Perturbations.

- **Detecting AI-Generated Code Assignments Using Perplexity** [53]: Proposal of a Detector Based on Perturbation.

- **ChatGPT Code Detection** [54]: Generation of a dataset for GPT-3.5 and development of a detection method.

Although developing an LLM for code generation is not the objective of this work, a brief digression on the LLMs considered state-of-the-art (SOA) for code generation is essential in order to better assess the performance of detection methods.

Chapter 3

Dataset Analysis

The goal of this chapter is to identify or construct a suitable dataset to evaluate the performance of the various detection methods proposed in the literature. It is worth noting that the literature does not only include works specifically aimed at creating benchmark datasets, but in several cases, datasets are generated solely for the purpose of validating or training the proposed detection methods or models.

3.1 Dataset Evaluation Criteria

All datasets made publicly available by the scientific community will be carefully analysed and compared. The goal is to identify the most suitable dataset—either directly or through integration, for the evaluation of code detection methods under consistent conditions. Each dataset will be assessed based on the following criteria:

1. **Total number of code samples available:** a larger number of samples generally improves statistical robustness during evaluation and model training.

2. **LLMs used to generate synthetic code:** datasets that include code generated by multiple LLMs are better suited for evaluating a method's generalization capability.

   (a) **Number of LLMs:** to avoid a method from focusing too much on stylistic features of a specific LLM, it is essential to have codes generated by different LLMs.

   (b) **Actual degree of use in contemporary times:** while it is desirable for detection methods to have long-term viability, it is undeniable that a detector effective on current LLMs (such as GPT-4 [4]) is more useful than one targeting outdated models (such as GPT-3 [3]).

   (c) **Actual types diversity among LLMs:** it is also necessary to analyse the diversity of the models themselves. For instance, it is more informative to include in the same dataset code produced by both an open-source LLM like CodeLlama[12] and a commercial one like GPT-3 [3], rather than, for example, code from GPT-3 [3] and Codex [11] (which is itself based on GPT-3).

3. **Code diversity:** ensuring diversity in the code is essential to understand how generalizable a method is to the overall code domain, or whether it is specialized in the stylistic patterns of specific LLMs *(a particularly relevant issue for methods relying on stylistic features of the code).*

   (a) **Different programming languages:** while Python is currently the most relevant language in the field of artificial code generation (indeed, many datasets primarily consist of Python code such as MBPP [33]), it is valuable to evaluate detection methods across as many programming languages as possible. At the very least, it is worth assessing different detection methods on different languages, possibly recommending specific approaches depending on the language being analysed.

   (b) **Different types of code:** although language differences are important, they are not sufficient. Python, for example, can be used both as an object-oriented and a procedural language. Understanding the type of code being analysed can aid both in training and in evaluating a detector.

   (c) **Code size:** code length is a key parameter, as the ease of identifying the origin of the code may vary depending on its size. It is worth noting that in certain contexts, such as homework assignments, short code snippets are extremely common.

   (d) **Code context:** it is useful to include examples of human-written code from both competitive settings (such as Leetcode dataset [55]) and open-source project environments (such as CodeSearchNet [31]), in order to evaluate detectors across different real-world contexts.

4. **Validity information:** this includes whether the dataset provides information on the validity of human-written code, the exact prompts used to generate LLM code, or whether code quality and correctness have been validated.

   (a) **Generation prompts:** it may be useful to evaluate the different prompts used to generate the code, as it is well known that varying the prompt can lead to significantly different outputs from an LLM.

   (b) **Source of human-written code:** many datasets are based on collections of human-written code that are later used to generate LLM outputs. Knowing the source of this human code ensures the reliability and correctness of the dataset.

   (c) **Code quality:** performing tests such as verifying whether both human and LLM-generated code actually works is essential. *There is little value in analysing whether non-functional code was produced by an LLM or not.*

   (d) **Paper reliability:** this point is important for preprinted paper, for which we can't rely on the scientific community.

Although all these are evaluation parameters, it is natural that some are more relevant than others: knowing the source of the human-written code remains more important than simply including a few additional LLMs in the code generation process.

3.2 Datasets Proposed in the Scientific Literature

The works whose main contribution is the creation of a dataset are mostly preprints, and thus require careful consideration. The papers primarily dedicated to dataset generation include: CoDet-M4 [46], AIGCodeSet [47], and CodeMirage [48].

3.2.1 CoDet-M4

The main contribution of this work is the construction of a dataset derived from existing human-written code datasets, by generating synthetic code using six different LLMs. The authors then train several models on this dataset to evaluate their performance, demonstrating that their dataset can significantly improve the effectiveness of various code detection models. The authors employ the following models as code generators:

- **GPT-4o**: A proprietary model developed by OpenAI, selected to represent the state-of-the-art among large-scale, closed-source LLMs.

- **CodeLlama (7B)**: An open-source model by Meta, specifically trained for code-related tasks. It is one of the most popular code-oriented language models.

- **Llama3.1 (8B)**: A more recent version of Meta's Llama family. Although it is a general-purpose model, it exhibits strong performance in code generation.

- **CodeQwen 1.5 (7B)**: An open-source model from Alibaba Cloud, also specialized in code, and part of the Qwen series.

- **Nxcode-orpo (7B)**: A fine-tuned variant of CodeQwen. The authors include it to evaluate the robustness of detectors against different fine-tuning strategies applied to the same base model (in this case, ORPO – Monolithic Preference Optimization).

Strengths

- The introduction of one of the most extensive and diverse datasets proposed for the task of LLM-generated code detection.

- Dataset cleaning is carefully performed, including the use of *Codeforces* as one of the tools to assess the correctness of human-written code (*Section 3.3: Quality Assurance*).

- The authors also construct an "out-of-domain" dataset, specifically designed to contain code with characteristics intentionally different from the main dataset (*Section 4.4:Out-of-Domain Experiment*).

- The dataset includes code in three different programming languages, unlike other works that focus solely on Python (*Section 3.1: Data Collection*).

Weaknesses

- Suspiciously high in-domain classification metrics, with F-scores exceeding 98% (*Table 2*).

- The prompts used to generate synthetic code vary depending on the source, potentially introducing an unintentional correlation between code types and the generation prompts (*Appendix F*).

- Most of the LLMs used for code generation are lightweight models, with GPT-4o being the only large-scale LLM involved (*Section 3.2: Code Generation*).

- Once the dataset is downloaded from the official portal on huggingface, several important intuitive reliability metrics are found to be missing:

  - The declared train/validation/test split described in the paper is not included; only the test set is provided. This makes **reproducing their results more difficult**.
  - Some significant **code-level features are missing**, such as whether the code sample is class-based or function-based.
  - The authors state in the paper that they plan to keep updating the dataset, which may explain small discrepancies in the number of code samples compared to what is reported. For example, there are fewer GitHub samples than those claimed in the original publication as shown in Figure 3.2 The strange think is that the number of code not only increased but also decreased.

- Focusing on the human code (*Section 3.1: Data Collection*):

  - **LeetCode corpora**: Pan et al. [56] (5,069) and others (2,800) so the total should be: 7,869 but according to the paper table we should have 13,528 codes Figure 3.2 *(we don't know the source of half of the codes)*.
  - **Code-Forces corpora**: the dataset has 103,792 codes but they are all solutions of only 2,523 problems from a publicly available Kaggle dataset [57].
  - **GitHub corpora**: 135,566 codes from CodeSearchNet [31] and GitHub API in 2019 *(code not up to date)*

- Even if the dataset as a whole may appear fully balanced, clear imbalances emerge when focusing solely on the human-written code:

  - There is an imbalance in the number of code samples generated by different LLMs (with relatively few generated by GPT models Figure 3.3)
  - LeetCode human-written code samples are significantly fewer Figure 3.4, meaning that many more generations were performed on LeetCode problems compared to other corpora.

Split	Language	Source	Target		Total
			Human	LLM	
Train	C++	LeetCode	2,242	46,888	**49,130**
		CodeForces	33,005	9,766	**42,771**
		GitHub	49,000	19,885	**68,885**
	Python	LeetCode	6,397	44,164	**50,561**
		CodeForces	25,569	9,646	**35,215**
		GitHub	12,442	8,434	**20,876**
	Java	LeetCode	2,283	46,988	**49,271**
		CodeForces	24,121	3,853	**27,974**
		GitHub	48,998	11,874	**60,872**
Validation	C++	LeetCode	282	4,962	**5,244**
		CodeForces	4,194	1,221	**5,415**
		GitHub	1,562	1,056	**2,618**
	Python	LeetCode	738	4,640	**5,378**
		CodeForces	3,285	482	**3,767**
		GitHub	5,500	2,488	**7,988**
	Java	LeetCode	287	4,929	**5,216**
		CodeForces	3,060	1,207	**4,267**
		GitHub	5,500	1,483	**6,983**
Test	C++	LeetCode	283	4,978	**5,261**
		CodeForces	4,203	1,221	**5,424**
		GitHub	1,564	1,056	**2,620**
	Python	LeetCode	728	4,722	**5,450**
		CodeForces	3,291	482	**3,773**
		GitHub	5,500	2,491	**7,991**
	Java	LeetCode	288	4,972	**5,260**
		CodeForces	3,064	1,206	**4,270**
		GitHub	5,500	1,487	**6,987**
Total			252,886	246,581	**499,467**

Figure 3.1: Table of dataset number of codes

(a) Paper source distribution

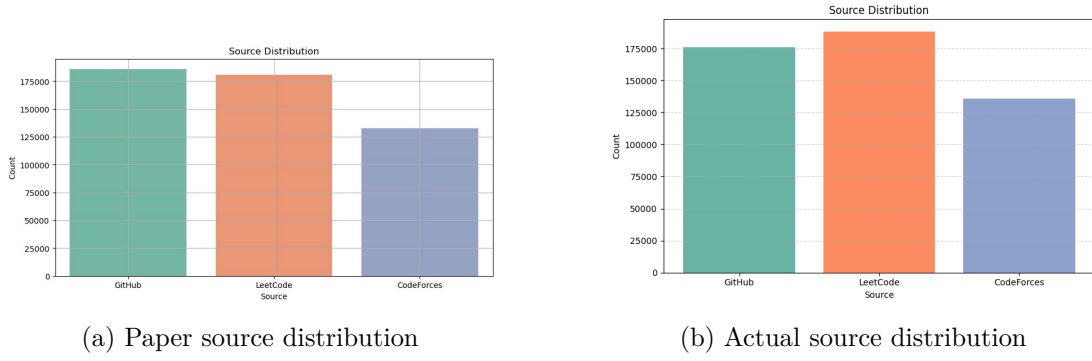
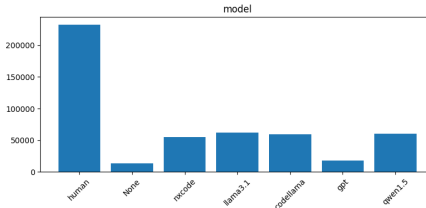(b) Actual source distribution

Figure 3.2: histogram differences
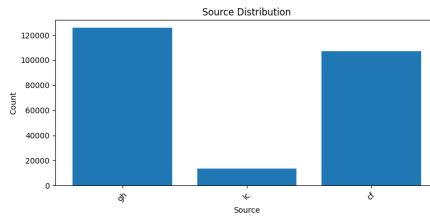

Figure 3.3: LLMs codes distribution

Figure 3.4: human-written code distribution

Final evaluation

Total number of code samples available	
(a) Total number of human code	246,221
(b) Total number of LLMs code	254,331

LLMs used to generate synthetic code	
(a) Number of LLMs	6 LLMs: *(GPT-4o, CodeLlama 7B, Llama3.1 8B, CodeQwen 1.5 7B, Nxcode-orpo 7B)*
(b) Diversity among LLMs	3 different source models: *(GPT-4o,CodeLlama,CodeQwen)*
(c) Actual degree of use in contemporary times	High

Code diversity	
(a) Different programming languages	Python, Java, C++
(b) Different types of code	Functional, Object-Oriented *(missing information in the dataset)*
(c) Code size	1st percentile: 42 characters, 3rd percentile: 68 characters
(d) Code context	Mixed (competitive and open-source)

Validity information	
(a) Generation prompts	Provided (different between LLMs)
(b) Source of human-written code	GitHub, Codeforces [57], Pan et al. [56]
(c) Code quality	Evaluated and filtered
(d) Paper reliability perception	Low, missing or inconsistent information

Table 3.1: Evaluation Summary: CoDetM4 Dataset

Despite being a very interesting dataset, especially due to the large amount of available code, it proves to be unreliable both because of the authors' lack of precision and due to some of its intrinsic characteristics, such as an unusual data imbalance. While it is not a dataset to be entirely discarded, its use must certainly be carefully evaluated.

3.2.2 AIGCodeSet

3.2.3 CodeMirage

3.3 Final Dataset

Chapter 4

Detection Methods

Let us recall that the ultimate goal is to build a binary classifier capable of determining whether a piece of source code was written by a human or generated by a Large Language Model (LLM). For binary classifiers, **accuracy** is typically the default evaluation metric, unless one classification outcome, such as true positives or false positives, is considered more critical than the other. Given that this classifier can be used in scenarios where a programmer could be 'accused' of not having authored the code themselves, it is essential that such claims be made with a high degree of confidence. While it is certainly desirable to allow end users to configure the decision threshold, the default setting should prioritize a **low FPR** (false positive rate) to prevent unjust accusations.

4.1 Evaluation Metrics

4.2 Evaluation of Existing Methods

4.3 Proposed Improvements

Chapter 5

User Interface

5.1 Requirements Analysis

5.2 Design Choices

5.3 Implementation and Features

Chapter 6

Conclusion

6.1 Final Evaluation and Perceived Quality

6.2 Future Work

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