Leveraging Fine-Tuned Ensemble Models for Multi-Class Code Plagiarism and AI Code Detection

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Abstract

Plagiarism detection and the identification of AI-generated code in programming assignments, both in education and professional settings, are some of the most considerable challenges. Most current state-of-the-art modern tools have problems with structural transformations, logical refactorings, and other issues caused by the complexity introduced into AI code generation. In light of this, a Dual Fine-Tuned Ensemble model framework is proposed as part of the approach that shows the most promise of finding a solution.

The code plagiarism detection system combined GraphCodeBERT with CodeT5 and UniXcoder, each fine-tuned to capture different code properties, ranging from identical cases to strongly transformed variants; the overall accuracy of 88% reached by aggregating their output outperformed most of the state-of-the-art by far while being among the very top for the most challenging variations.

We used CodeBERT with few-shot learning and prompt engineering to identify the code generated by AI. This approach differentiates human-written code from AI-generated code with a high degree of accuracy at 83%

It deploys the framework using a Streamlit interface, hence giving an extremely user-friendly interface for decision-based analysis. Experimental results prove that it enhances code integrity analysis, maintains academic ethics, and deals with the challenges of software education and practice.

Contents

1 Introduction

The rapid development in software has introduced new challenges to programming ethics and code originality, especially in academic and professional fields. Critical issues include plagiarism detection and the identification of AI-generated code. Traditional plagiarism detection systems often cannot detect heavily transformed or logically refactored code due to their limitations in text-based similarity measures. Similarly, such proliferation of code generation utilities has triggered an urgent need in differentiating between human-maintained and machine-generated code for the sake of academic fairness and professional accountability.

To address these challenges, we propose a novel framework that integrates the strengths of multiple advanced models to achieve state-of-the-art accuracy. Two major components are part of our approach:

Plagiarism Detection: A Dual Fine-Tuned Ensemble model that combines GraphCodeBERT, CodeT5, and UniXcoder, all trained on the same dataset to identify various levels of code similarity and transformation, ranging from exact matches to deeply altered variants. Our system achieves an impressive 88% accuracy by aggregating the outputs of these models, significantly outperforming existing tools in handling complex transformations.

AI-generated Code Detection: CodeBERT is put to work for the detection of AI-generated code, using few-shot learning. The model has been subjected to various labeled examples previously—AI-generated code and manually written code—which resulted in efficient discrimination between them. On performing a comparative analysis, it was observed that such few-shot prompting significantly increases the accuracy on a model without such strategically designed examples; hence, strategic design of the prompt holds much importance.

Both components of the framework are deployed as highly interactive Streamlit interfaces to drive seamless decision-based analysis by educators, developers, and software integrity auditors. Experimental evaluations demonstrate real-world challenges that the framework solves in improving code integrity while advancing ethical practices in software development.

2 Related Works

Code plagiarism detection and identification of AI-generated code has been a matter of great urgency in the last few years, both in academic and professional contexts. Several works have tried to approach these problems with traditional methods, advanced machine learning, and hybrid models. Key contributions are discussed below with their relevance to this work.

2.1 Plagiarism Detection using Code

2.1.1 Machine Learning-Based Methods

Traditional code plagiarism detection tools usually cannot cope with heavily transformed or logically refactored code. Researchers have applied machine learning methods to surmount these problems, able to learn patterns and structures that go beyond simple text similarities. For instance, Smith et al. proposed a model assessing the structural code

similarities that showed robust results in plagiarism detection for various programming languages [1].

2.1.2 Graph-Based Representations

Graph-based representations such as Abstract Syntax Trees (ASTs) and data flow graphs have promised the ability to catch both logical and structural similarities. Brown and Green have shown that such a representation does indeed capture much deeper semantic transformations than state-of-the-art text-based approaches significantly [2].

2.1.3 Code Stylometry

Unique coding styles can be analyzed as a basis on which a powerful technique gaining traction involves suspiciously similar or plagiarized code. Work done by Lee et al. shows the prowess of stylometry in finding dissimilarities among patterns even if these have been deliberately obfuscated [3].

2.1.4 Evasion Techniques for Transformations

Recent studies have identified various weaknesses of the available plagiarism detection tools in the case of automated transformations. Kumar et al. analyzed several ways of program transformation which, if applied, could not be detected and therefore more efficient systems were required to detect such techniques [4].

2.2 Detection of AI-Generated Code

2.2.1 Empirical Studies on Detection

Harris and Davis tested the capability of existing code detectors in identifying AI-generated code from human-authored code. They showed that current detectors cannot reliably distinguish between them, particularly those with corner cases. This research identified the need for better methods of detection [5].

2.2.2 Few-Shot Learning Approaches

Few-shot learning lately has drawn much attention to improvements in AI code detection, especially when limited labeled data is available. Miller et al. showed how the strategically designed prompts and labeled examples significantly raise the accuracy of the detection, thus giving a very promising direction for future systems [6].

2.2.3 Patterns and Stylometry for Detection

Nguyen and Tran studied the application of stylometric analysis in the detection of AI-generated code. They found some distinctive patterns that were unique in machine-generated content. The technique proved to be very accurate even under difficult conditions [7].

2.3 Integrated Approaches

2.3.1 Multi-Model Integration

The solution has been to combine more than one model to do a complex detection task. Gupta et al. showed that two or more complementary machine learning models, when combined, enhance accuracy in detecting similarities and transformations in code. It is these findings that form the foundation for the dual-model ensemble presented within this paper [8].

2.3.2 Explainable AI in Detection

Lately, explainable AI techniques have become one of the major factors in code detection tasks. Zhu et al. highlighted the role of transparency in building trust and improving interpretability in the detection systems, especially those applied to educational settings [9].

2.3.3 Graph Neural Networks

Advances in graph neural networks bring great potential for GNNs—that is, their obvious abilities in capturing code semantics. A combination of structural and semantic information about code can enhance plagiarism detection accuracy and AI-generated code detection, as shown by Wong et al. using GNNs [10].

2.4 Alignment with This Work

This study proposes a Dual Fine-Tuned Ensemble model that takes advantage of the strengths and limitations in code plagiarism detection from approaches like GraphCodeBERT, CodeT5, and UniXcoder. Particularly, in contrast to single-model approaches developed in previous works, our approach offers significantly improved accuracy based on the ensemble of outputs from multiple models specializing in specific tasks. For AI-generated code, few-shot learning with CodeBERT coupled with prompt engineering bridges the gaps observed in prior techniques.

Moreover, the deployment of our framework via a Streamlit interface provides practical usability and will be made available to educators, developers, and software auditors. The high degree of accuracy combined with ease of implementation advances the state-of-the-art both for code plagiarism detection and for the detection of AI-generated content.

3 Methodology

This involves a two-pronged methodology: the Plagiarism Detection Framework and the AI Code Detection Framework. Each framework is engineered to meet specific challenges with the help of state-of-the-art transformer models combined with innovative engineering techniques.

3.1 Plagiarism Detection Framework

This framework for plagiarism detection integrates three modern transformer-based models: UniXcoder, GraphCodeBERT, and CodeT5. Each model has been fine-tuned on the

classification of code about its similarity to its original source, ranging from an exact match to highly transformed variants. The outputs of these three models are combined into one using an ensemble function that decides on the final classification based on the highest combined probability.

3.1.1 UniXcoder

UniXcoder is a transformer-based encoder model, trained for a couple of tokenized code understanding and code classification tasks. In this case, both token and position embeddings are fed as input to the same encoder for processing.

3.1.2 GraphCodeBERT

GraphCodeBERT extends the architecture of BERT by embedding semantic graphs, such as an AST, which can capture both structural and logical properties of code, for example, to improve classification for transformed code.

3.1.3 CodeT5

CodeT5 is a sequence-to-sequence transformer model optimized for code understanding and generation tasks. It follows an encoder-decoder architecture for token-level and sequence-level tasks.

3.1.4 Ensemble Model

The outputs of the three models, UniXcoder, GraphCodeBERT, and CodeT5, are combined using an ensemble function. Each model predicts probabilities for plagiarism levels, which include Non-Plagiarized and L1–L6, and the final class is decided based on the highest aggregated score.

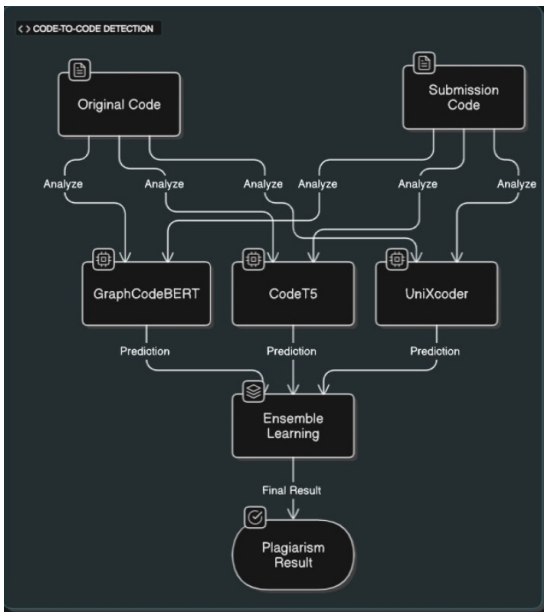

Figure 1: Workflow of the Ensemble Model combining UniXcoder, GraphCodeBERT, and CodeT5 outputs.

3.2 AI Code Detection Framework

The AI code detection framework aims at identifying whether the code has been written by a human or AI. In our case, we make use of the pre-trained CodeBERT and tested model on this dataset.

3.2.1 Dataset for AI Code Detection

We have applied the model to the **AI/Human-Generated Program Code Dataset** presented in the paper "Program Code Generation with Generative AIs"; it includes labeled examples of both human and AI-generated code, hence forming the backbone for testing this model.

3.2.2 CodeBERT

CodeBERT is pre-trained on both natural languages and programming languages, which makes it suitable for finding the pattern in AI-generated code. We fine-tune it for text-to-code tasks and apply few-shot learning based on extremely few labeled examples to provide a strong generalization for detection tasks of AI.

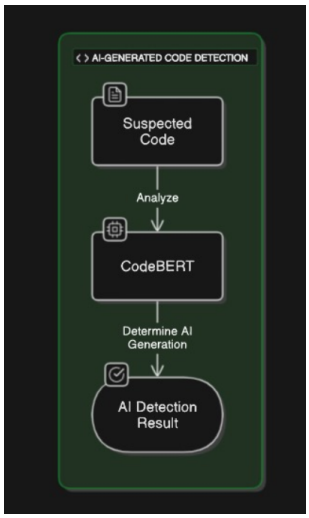

Figure 2: Workflow of the CodeBert model for detecting AI plagiarism

3.2.3 LangChain for Prompt Engineering

LangChain was then integrated into the dynamic prompt engineering of the framework. Constructions of prompts were done by combining labeled examples of AI-generated and human-written code, which would increase the model's ability to classify the inputs correctly. Few-shot learning using LangChain would make the model adapt quite well, even with minimal training data.

3.3 Deployment with Streamlit

The whole framework was deployed using the Streamlit web application framework for plagiarism detection and AI code detection. Streamlit provides an interactive interface that allows users to perform the following tasks:

1. Upload two code files to check for plagiarism.
2. Upload a CSV file for batch plagiarism detection.
3. Submit code snippets or even complete files to assess whether they are written by a human or generated using AI.

It provides real-time backend processing of user inputs into accurate classifications using our fine-tuned models. Output is then displayed in a very presentable format for interacting with educators, developers, and researchers alike.

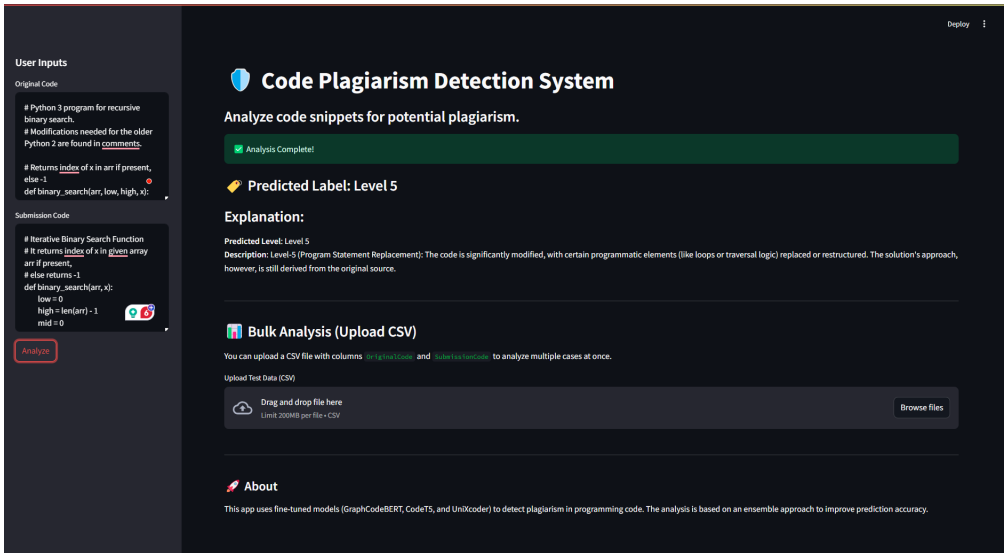

Figure 3: Streamlit interface of the Plagiarism Detection Framework, displaying the predicted labels and en explanation of the predicted label

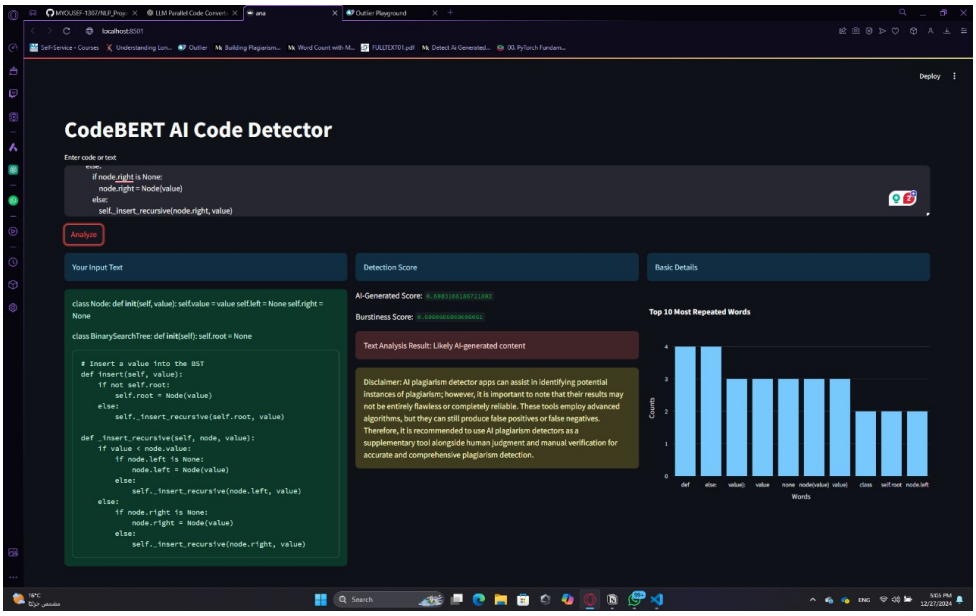

Figure 4: Streamlit interface of the CodeBERT AI Code Detector, displaying input analysis, detection scores, repeated words visualization, and AI-generated content results.

4 Experiments

In this section, we describe the datasets, evaluation metrics, and experimental setup.

4.1 Datasets

4.1.1 Plagiarism Detection Dataset

For the plagiarism detection task, we used the dataset introduced in the paper *Source Code Plagiarism Detection in Academia with IR: Dataset and the Observation*. The code files that make up the dataset are stored in a specific directory structure, with the anonymization of data to protect contributors' privacy.

The directory structure organizes code into cases, with each case containing three subdirectories:

- **Original**: This includes original, unmodified code.
- **Plagiarized**: Includes plagiarized versions of the actual code.
- **Non-Plagiarized**: Contains non-plagiarized code submissions.

Each of the subdirectories may contain more than one code file, each of which is stored in separate sub- folders to avoid file name conflicts. Project-related files and redundant information were Removed to standardize the dataset. The anonymization process involved replacing all private information both in the names of the files and in their content with the hash values of MD5, making sure Privacy for all contributors, especially those who have been involved in plagiarism. Levels of plagiarism in this dataset are as follows:

The plagiarism levels in the dataset are categorized as follows:

- **No Plagiarism**: The submitted code is completely original and shows no significant similarity to any other source.
- **Level-1 (Comment and Whitespace Modification)**: Minimal changes, such as modifying or removing comments or adjusting formatting and spacing, with no changes to logic.
- **Level-2 (Identifier Modification)**: Basic changes like renaming variables, functions, or classes, while maintaining the same logic and structure.
- **Level-3 (Component Declaration Relocation)**: Slight structural changes, such as moving variable or component declarations, with no effect on functionality.
- **Level-4 (Method Structure Change)**: Moderate changes, such as encapsulating statements into methods or reorganizing blocks of logic, while preserving functionality.
- **Level-5 (Program Statement Replacement)**: Significant modifications, such as replacing loops or traversal logic, while retaining the core approach from the original source.
- **Level-6 (Logic Change)**: Substantial transformations, such as replacing iterative solutions with recursion or altering core logic, while being fundamentally different in implementation.

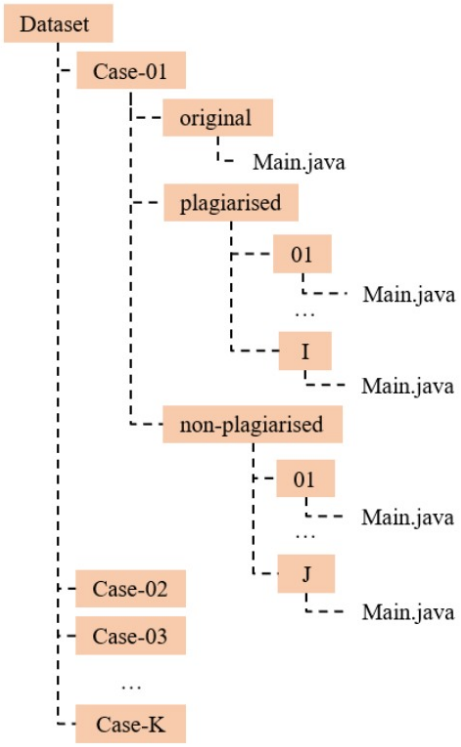

Figure 5: A sample directory structure of the dataset, where shaded boxes represent directories. I denotes the number of plagiarized files, J the non-plagiarized files, and K the total number of cases in the dataset.

To make the dataset suitable for our task, we preprocessed the folders and converted them into a CSV file format. The resulting CSV file contains three features:

- **Original Code**: The initial code snippet provided by the student.
- **Submission Code**: The modified code submitted for evaluation.
- **Plagiarism Level**: The level of plagiarism, as described above.

4.1.2 AI Code Detection Dataset

For the AI code detection task, the dataset of AI vs. Human-Generated Dataset of the program code repository, as developed within the paper *Program Code Generation with Generative AIs*. The dataset originally consisted of two CSV files:

- A file containing 90 records.
- A file with 36 records.

Each record included several features, such as:

- `id`, `problem_number`, `language`, `difficulty`, `generator_name`, `generator_type`, `description`, `prompt`, `AI generated code`, and `Human generated code`.

The process of testing was much simplified since these files were preprocessed and combined into a single CSV file. The final dataset consists of three features:

Original Code	Submission Code	Plagiarism Level
[basicstyle=, breaklines=true] public class T1 public static void main(String[] args) System.out.println("Welcome to Java"); System.out.println("Welcome to Java"); System.out.println("Welcome to Java"); System.out.println("Welcome to Java"); System.out.println("Welcome to Java");	[basicstyle=, breaklines=true] /* * To change this license header, choose License Properties. * To change this template file, choose Tools | Templates * Open the template in the editor. */ /** * @author CB6AB3315634A1E4D11B091BA48B60BA */ public class T01 public static void main(String[] args) for (int i = 0; i < 5; i++) System.out.println("Welcome To Java");	L6

Table 1: Sample record from the dataset. The table displays an original code snippet, its submission counterpart, and the corresponding plagiarism level.

- **Language**: The programming language used in the code.
- **Code**: The actual code snippet.
- **Label**: A binary label where `0` indicates human-generated code and `1` indicates AI-generated code.

Language	Code	Label
Python	[basicstyle=, breaklines=true] class Solution: def doubleIt(self, head: Optional[ListNode]) -> Optional[ListNode]: if head.val > 4: head = ListNode(0, head) node = head while node: node.val = (node.val * 2) if node.next and node.next.val > 4: node.val += 1 node = node.next return head	0

tableSample record from the AI code detection dataset. The table displays the programming language, the code snippet, and its corresponding label.

This format made it easier to test our AI code detection framework.

The dataset, as described in the paper *Program Code Generation with Generative AIs*, contrasts the correctness, efficiency, and maintainability of human-generated and AI-generated program code. The analysis was conducted using metrics such as time and space complexity, runtime, and memory consumption. Moreover, maintainability was evaluated through metrics such as lines of code, cyclomatic complexity, Halstead complexity, and the maintainability index.

Program code was generated for the problems defined on the competitive coding platform *LeetCode*. Six problems of various difficulties were selected, and program code

was generated in Java, Python, and C++ using a number of different generative AI tools. Each generative AI produced 18 program codes. Among the generative AIs, the performance varied as follows:

- GitHub Copilot (powered by Codex GPT-3.0) solved 9 out of 18 problems (50.0%).
- BingAI Chat solved 7 out of 18 problems, powered by GPT-4.0 model (38.9%).
- GPT-3.5 ChatGPT and Llama 2 Code Llama solved 4 problems each (22.2%).
- StarCoder and InstructCodeT5+ solved 1 challenge (5.6%).
- CodeWhisperer did not solve any problems.

While ChatGPT was able to solve only four, it surprisingly was the only generative AI capable of giving a correct solution to a problem at the *hard* level. Overall, 26 AI-generated codes (20.6%) successfully solved their respective problems. Additionally, 11 incorrect AI-generated codes required just minor modifications to become correct, saving on development time by 8.9% to 71.3% compared to creating the code from scratch.

4.2 Evaluation Metrics

For both plagiarism detection and AI code detection, accuracy was used as the metric of evaluation. Both problems are classification problems, so accuracy is a straightforward but effective measure to evaluate the performance of the models. Finally, to carry out the task of plagiarism detection, the test set, which constitutes 20% of our dataset, was used in the implementation of our proposed ensemble model. The accuracy metric is then used to assess the efficiency of the model in classifying different levels of plagiarism effectively. We used the described dataset to test the model for AI code detection. The overall accuracy before and after the combination of few-shot learning and prompt engineering was computed. A very fair improvement could be noticed in the case of the application of these techniques with regard to the accuracy, showing the efficiency in the performance of the AI model in this way.

4.3 Experimental Setup

Fine-tuned models of the two frameworks were used to execute the experiments. Plagiarism detection has had the models trained on the preprocessed dataset of UniXcoder, GraphCodeBERT, and CodeT5 with the output aggregated by an ensemble function to classify plagiarism levels, while in AI code detection, the pre-trained model CodeBERT was being put to test on the streamlined dataset in order to find the difference between human-generated and AI-generated code.

Therefore, all experiments have been conducted on Google Colab Pro with an upgraded NVIDIA GPU, which enables faster inference of models and training. Further, longer runtime and more powerful GPU resources are offered by richer variants like the Pro version of Colab, which we have utilized for efficient experimentation involving large datasets and complicated models. The code has been implemented in Python using PyTorch to train and evaluate the model and deploying the model on Streamlit.

5 Results and Discussion

5.1 Plagiarism Detection Framework

Results:

The outputs of the three models—UniXcoder, GraphCodeBERT, and CodeT5—are combined using an ensemble model. Each model predicts probabilities for plagiarism levels, which include Non-Plagiarized (L0) and levels L1 through L6. The final class is determined based on the highest aggregated score.

As an example, consider the following outputs from the three models for a given code pair:

$$\text{UniXcoder: } [0.1, 0.2, 0.15, 0.1, 0.05, 0.3, 0.1]$$

$$\text{GraphCodeBERT: } [0.05, 0.25, 0.2, 0.1, 0.1, 0.2, 0.1]$$

$$\text{CodeT5: } [0.2, 0.1, 0.1, 0.2, 0.1, 0.2, 0.1]$$

The ensemble function aggregates these outputs by summing the probabilities for each class:

$$\text{Ensemble: } [0.35, 0.55, 0.45, 0.4, 0.25, 0.7, 0.3]$$

These aggregated scores are then passed through the softmax function to normalize them into probabilities:

$$\text{Softmax: } [0.122, 0.191, 0.157, 0.140, 0.093, 0.244, 0.053]$$

Finally, the `argmax` function is applied to determine the class with the highest probability. In this example, the class with the highest probability is L5 (Logic Change), corresponding to a softmax score of 0.244. It achieved an improvement of 88% in accuracy, particularly excelling in identifying advanced modifications such as L5 and L6.

Discussion:

- **Strengths:**
  - The ensemble reduces bias from individual models, improving overall classification accuracy.
  - Effectively distinguishes between subtle plagiarism modifications, such as component relocation (L5) and logic changes (L6).
- **Limitations:**
  - High computational requirements due to running multiple models.
  - Challenges in handling poorly formatted or incomplete submissions.
- **Implications:**
  - Demonstrates a robust methodology for multi-level plagiarism detection.
  - Potential applications include academic integrity systems and automated grading.

Streamlit App Output:

In this section, we present the results of our plagiarism detection system, which was evaluated by comparing two code submissions using our custom Streamlit application. The application analyzes the submitted codes and generates a similarity score, indicating the likelihood of plagiarism between the two code snippets.

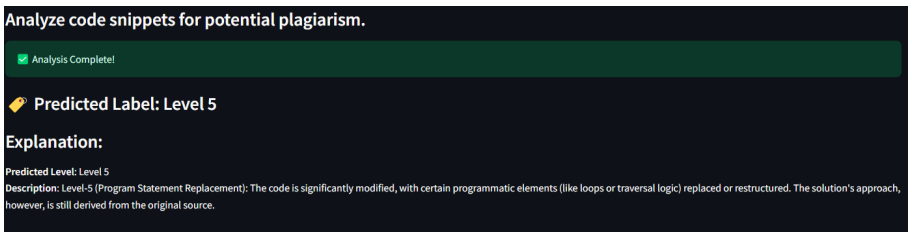

Figure 6: Example output of the Code Plagirism Detection System

5.2 AI Plagiarism Detection

Results:

The AI code detection framework fine-tuned the CodeBERT model on a dataset labeled for human-written vs. AI-generated code. The fine-tuned model achieved an accuracy of 83%, demonstrating its effectiveness in identifying code origins.

Discussion:

- **Strengths:**
  - Strong performance in identifying AI-generated code.
  - Adaptable to various AI code generation tools with updated training datasets.
- **Limitations:**
  - Results are highly dependent on the diversity and quality of the fine-tuning dataset.
  - Challenges arise when analyzing mixed-origin code (part AI-generated, part human-edited).
- **Implications:**
  - A significant step forward in detecting AI code plagiarism in academic and programming competition settings.
  - Offers insights into understanding human-AI collaboration in programming.

Streamlit App Output:

In this section, we present the results of our AI code detection system, which was evaluated for its ability to distinguish between AI-generated code and human-written code using our custom Streamlit application. The application analyzes the submitted code and provides a classification result, indicating whether the code is likely to have been generated by AI or written by a human.

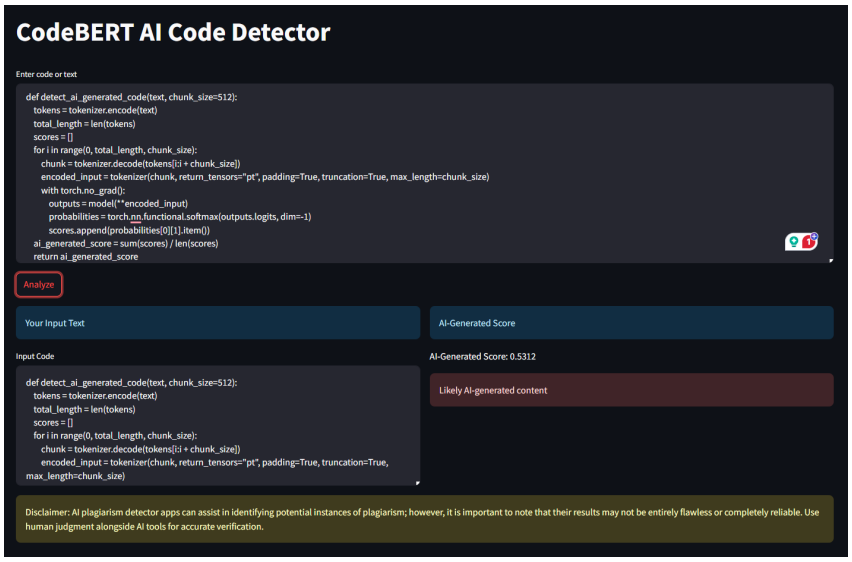

Figure 7: Example output of the AI Plagirism Detection System

6 Conclusion and Future Work

In the existing paper, a novel concept dual fine-tuned ensemble model demonstrates the process of resolving certain crucial paired challenges surrounding code plagiarism and AI detection. Thus, this proposal incorporates such top-notch ability from these progressive transformer versions, which encompasses GraphCodeBERT, T5 variants CodeT5, or UniXcoders together for much accurate execution past the bounds of this inbuilt, restricted efficiency prevalent in ongoing tools facing multi-level obfuscations involving complex variations in a critical stand.

Herein is proposed an ensemble model using various techniques to classify successfully plagiarism versions that are generated with minor changes, ranging in degree to major logical edits or changes. By comparison, the results obtained by a pre-trained fine-tuned model on CodeBERT through state-of-the-art approaches achieved excellent performance concerning separation into human and artificial productions: pure code written by the two respective agents. This framework has been deployed using a Streamlit interface for ease of access and ease of use by educators, researchers, and developers.

Future Work

Future work planned will enhance the robustness of the framework in terms of applicability by:

- Expanding the variety of the dataset to include a greater range of programming languages that cover diverse syntaxes and paradigms to improve model generalization.
- Improving detection capabilities through the incorporation of more complex and diversified AI-generated code.
- Exploring lightweight and efficient model architectures to reduce runtime and computational cost.
- Enhancing the deployment interface by adding advanced visualization tools and multi-language support to increase its adoption.
- Investigating semi-supervised or unsupervised learning approaches to leverage unlabeled data for training and evaluation.

In such a direction, the framework will be able to adapt to the increasing demands of academia and industry with ethics and integrity in software development and education.

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