SmellDetector: Multi-Label Code Smell Detection and Refactoring with Large Language Models

Anonymous ACL submission

Abstract

Large Language Models (LLMs) have demonstrated impressive capabilities in many tasks such as code generation and automated program repair. However, code LLMs have ignored another important task in programmers' daily development work, which is to improve the maintainability, readability, and scalability of the program. All of these characteristics are related to code smells and we study how to improve them by detecting and removing code smells. Most works on code smells still rely on using measures formulated by experts as features, but lack of use of the rich prior knowledge contained in code LLMs. In this paper, we propose SmellDetector, a comprehensive model for both code smell detection and refactoring opportunities detection in Java. We train the model with the designed prompt which contains both code smells of class-level and method-level in the same code snippet, including more than 20 types. We achieve state-of-the-art performance on the code smell detection task and change the basic paradigm of code smell detection from binary classification problem to multi-label classification. Finally, it has been verified through experiments that good code smell detection helps to detect refactoring opportunities.

Detection Prompt

Input:

```
Please read the following Java class code and analyze the
code smell of class level and method level separately,
pointing out the reasons:

public class AlphaClass {
  //...class variables
  public methodA(Entity a) {
    // statement 1
    // statement 2
  }
  ...
}
```

Output:

```
We analyze the code smells at the class level and method
level separately as follows:

In Class level of AlphaClass:
0:There is no class level's code smell and it's clean.

In Method level of methodA:
1:Long Statement because ...//reason 1

The following is my reference standard for determining
whether the smell of the above code exists:

clean: ... // Clean smell definition
Long Statement: ... // Long statement definition
```

Figure 1: Example of Code Smell Detection Dataset.We added the definition and description of predicted code smells as output supervision, with the purpose of enhancing the model's understanding of code smells.

1 Introduction

Recently, Large Language Models (LLMs) have achieved impressive performance in code generation (Roziere et al., 2023), especially in the scene of algorithm competitions, and there are many commercial code models available on the market. When it comes to daily development of software engineers, it is an important but often overlooked issue that how to keep system maintainability (Löwe and Panas, 2005), or reduce the code smell. Code smells usually appear in object-oriented programming scenarios that use a large number of class structures and long codes, bring technical dept to a software system (Foster et al., 2012) and harming its maintainability and evolution (Sjøberg et al., 2012). In other words, code smell does not currently affect the running of the program and output correct results, but it hinders its further development and iteration.introduction [1] As early as the millennium, many researchers paid attention to the problem of code smell (Fowler and Beck, 1997).

[1]We present a example dataset for code smell detection and refactoring in anonymous github: https://anonymous.4open.science/r/paper_example_dataset-8293, and due to the space limit we only present 200 examples.

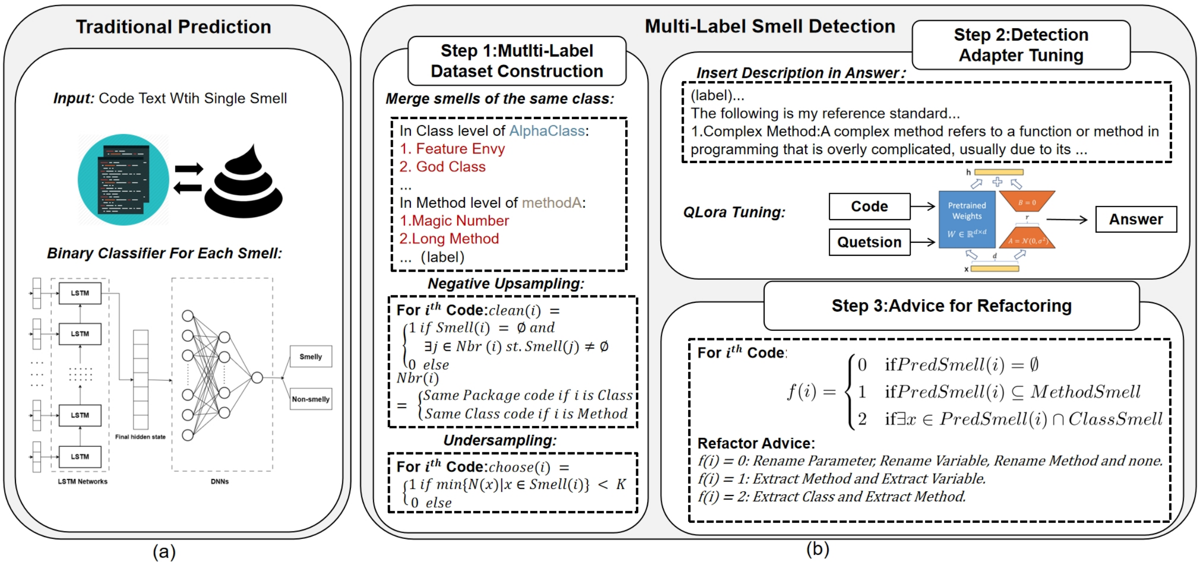

Figure 2: Flowchart of code smell detection work.(a) shows the SOTA method(Ho et al., 2023) of traditional code smell detection while (b) shows the main process of our work.

The traditional method is to calculate various indicators of the code, such as LCOM (lack of method cohesion) and NMD (number of declared methods), and judge whether the code has a certain code smell based on the threshold. When deep learning algorithms became popular, many researchers used indicators of code smell as features, or input code text features into the model for training to avoid the instability caused by directly selecting thresholds (Jha et al., 2019; Sharma et al., 2021). In addition, in the study of code refactoring, an important research direction is to find refactoring opportunities and simplify the refactoring task to predict whether a specific refactoring method should be used, which is similar to smell detection in terms of method (Aniche et al., 2020).

However, some of the above methods have shortcomings: the information they use to identify code smells usually comes from indicators and labels designed by experts, and they do not consider using LLM to generate additional smell knowledge and utilize the human-like reasoning ability of LLM. Most methods treat it as a binary classification problem, and N models need to be trained for N types of code smells, which increases the time cost. In addition, although code refactoring opportunity detection and code smell detection are essentially information-complementary tasks, previous methods often lack the ability to explore the connection between them and make them mutually reinforcing.

We hope to introduce the text generation ability of LLM to generate description knowledge for different code smells, and combine it with code text by reasoning during fine-tuning, thereby skipping the process of designing feature engineering for each smell separately and making code smell detection more unified.

In this paper, we present SmellDetector, a comprehensive code smell detection and elimination model, aiming to provide adapters based on LLM for detecting code smells' types and find refactoring opportunities.

We summarize our contributions below:

- We propose the first model based on code LLM fine-tuning for code smell detection and refactoring opportunities detection. Our training dataset and method is general and can be easily applied to other LLMs with greater capabilities. The model has achieved the state-of-arts in code smell detection task.

- We collected and organized the first hierarchical code smell dataset from previous datasets, which actually helps to complete the coarse localization of code smell detection. It contains multiple code smells in the same code snippet, including 212,612 code smells and 20 types.

- We have experimentally proven that effective code smell detection is helpful in detecting code refactoring opportunities, and provides researchers with research ideas that the two tasks should be reasonably combined.

2 Related Work

2.1 Code Smell Detection

Code Smell is considered as inadequate implementation and design in code (Fowler and Beck, 1997), bringing various hazards, such as damaging code readability and maintainability. Beck et al. provide a detailed definition of 22 code smells through natural language. In order to automate the detection of code smell in batches, Moha et al. proposed a method of calculating program metrics and determining whether they have reached a preset threshold. Additionally, Palomba et al. use history information to detect the code smells and inspire the ideas of many researchers.

Traditional metric based methods may not be as accurate in distinguishing some fuzzy and complex code smells because of threshold. Therefore, some researchers (Fernandes et al., 2016) use machine learning methods to solve this problem, such as Bayesian (Khomh et al., 2011), SVM (Maiga et al., 2012) and Random Forest (Hall et al., 2011). Although ML algorithms perform well in smell detection, experts are still needed to perform feature extraction. On the contrary, deep learning algorithms can autonomously learn advanced features. Some researcher (Guo et al., 2019) use LSTM and CNN to extract text and metric information separately while White use RtNN and RvNN to capture features in source code and abstract syntax tree (White et al., 2016). DeepSmell (Ho et al., 2023) has reached the state-of-art performance before, but it still has a serious flaw: it needs to train a separate model for each type of code smell, which increases training and deployment costs.

2.2 Code Refactoring

When Beck et al. purposed the definitions of 22 code smells, corresponding refactoring methods have been proposed at the same time, such as Extract (method, variable...), Rename(method, variable...), Move method and so on, which are still the most commonly used (Al Dallal and Abdin, 2017). Refactoring methods and code smells have some semantic connections and they are not one-to-one correspondences and one refactoring can mitigate multiple code smells, such as Extracting Class is useful for duplicate code/clones, god classes and data blocks (Lacerda et al., 2020).

Since the usable code refactoring methods remain largely unchanged, finding an opportunity for refactoring means completing one refactoring. Many researchers use metric to search code snippets suitable for a certain type of refactoring, like the cohesion metric (Al Dallal and Briand, 2012), in-class semantic similarities metric (Bavota et al., 2014) and between-class cohesion metric (Bavota et al., 2010). Other researchers proved the effectiveness of using machine learning algorithms (Aniche et al., 2020) and neural networks (Alenezi et al., 2020) to find refactoring opportunities. When more and more reliable refactoring datasets are being proposed by integration of manual annotation and detection tools (Tsantalis et al., 2020; Moghadam et al., 2021), LLM may be a new method to help break through code refactoring.

2.3 Code Large Language Models

Recently, Large Language Models (LLMs) have achieved excellent performance in code generation tasks, such as codellama (Roziere et al., 2023), Alphacode (Li et al., 2022), InCoder (Fried et al., 2022) and GPT-3 (Brown et al., 2020). Thanks to the large model's massive training data and generation capabilities brought by huge parameters, the large code model has the ability to generate code that meets the needs of the problem under the input of natural language prompts. In addition, it can also correct erroneous codes (Silva et al., 2023) According to review of code smell (Malhotra et al., 2023), the use of LLM for code smell detection is still a blank area currently.

3 Methodology

3.1 Overview

We provide an overview of the SmellDetector pipeline in Figure 2. The SmellDetector consists of two parts: two fine-tuned adapters can be plug-and-played with LLM to complete code smell detection and refactoring. In the following subsections, we will show how the it works through dataset construction, adapter training and conversations round.

3.2 Dataset Construction

We built a detection dataset consists of 97,316 files and 212,612 code smells including 20 types in class level and method level. For refactoring, we built a dataset consists of 16,000 refactoring program fragments pairs.

Detetion. Through literature research, we have selected two publicly available code smell datasets as the first step: QScore (Sharma and Kessentini, 2021) and MLCQ (Madeyski and Lewowski, 2020).

Class smell	Number	Method Smell	Number
Feature Envy	8,337	Magic Number	32,157
Insufficient Modularization	575	Long Parameter List	8,296
Deficient Encapsulation	19,943	Complex Method	16,900
Unnecessary Abstraction	8,662	Empty catch clause	7,953
Rebellious Hierarchy	1,173	Long Method	6,366
Multifaceted Abstraction	2,325	Long Statement	34,240
Broken Modularization	8,524	Long Identifier	8,313
Cyclic Hierarchy	2,060	Complex Conditional	9,919
Missing Hierarchy	2,320	Missing default	8,348
Blob	293	/	/
Data Class	356	/	/
Class clean	14,631	Method Clean	12,261

Table 1: The specific number of various code smells' categories in our detection dataset

These datasets have been verified for their reliability by automatic detection and expert certification, but they usually retain the relationship between a code snippet and a code smell. We clone the source code from Github and check for different code smells that share the same code snippets. When a class has multiple member methods, we will mark its class smell and method smell respectively based on the collected data. Since different code repositories may reference the same third-party code, when splitting the training and testing data, we need pairwise matching to filter out repeated identical fragments.

Considering the lack of negative examples in the dataset, we upsample the negative examples by traversing other methods and classes in the directory where the positive examples are located and use them as negative examples (clean).

For i^{th} Code, $clean(i)$ indicates whether to treat it as a clean smell sample:

$$clean(i) = \begin{cases} 1 \text{ if } Smell(i) = \emptyset \text{ and} \\ \quad \exists j \in Nbr(i) st.Smell(j) \neq \emptyset \\ 0 \text{ else} \end{cases}$$

while $Smell(i)$ represents the set of code smells that exist in code i.

$$Nbr(i) = \begin{cases} Package(i)'s\ classes \text{ if } i \in Class \\ \quad Class(i)'s\ methods \text{ if } i \in Method \end{cases}$$

In addition, there is an obvious class imbalance in the dataset. We use undersampling to solve this problem: choose(i) indicates whether to add the i^{th} code to our dataset.

$$choose(i) = \begin{cases} 1 \text{ if } minN(x)|x \in Smell(i) < K \\ 0 \text{ else} \end{cases}$$

Based on the mean of the less frequent categories, we set K to 10000. The specific number of code smells can be found in Table 1. **Refactoring**. Through literature research, we choose (Aniche et al., 2020) as source data, which consists of Apache,F-Droid, and GitHub's repositories. If it is a refactoring of the class, then we extract the class code pairs as training data, or use string matching to detect member methods whose content has changed while it is a refactoring of the method. Considering the lack of negative labeling in Aniche's open dataset, we firstly collect manually labeled negative examples from Refactoring Miner2 (Tsantalis et al., 2020). Since the number of collected negative examples is still relatively small, we use some successfully refactored program fragments as negative examples, which means this type of refactoring is no longer needed.

3.3 Adapter Training

3.3.1 Base Model Selection

We hope that in addition to having the ability to finish traditional code smell work (classification of a single smell or classification of a single level such as method or variable), the SmellDetector also has strongr generalization, which means perform better in few-shot scenarios. Therefore, we prefer to choose a base model that has both context understanding and code generation capabilities. We first selected LLMs that have performed well recently as the first step, like CodeLLama-7B (Roziere et al., 2023), Baichuan-7B (Baichuan, 2023) and Qwen-7B (Bai et al., 2023). Then, we use Chain-of-Thought(COT) to test the performance of the model on code smell detection when it is not trained. Specifically, we provide the definition of a certain code smell, positive examples, and negative examples as prompts, let the model

Model Name	Feature Envy	Data Class	Long Method	
	F_1	F_1	F_1	AvgF_1
CodeLLama-7B	12.50	**34.99**	**15.94**	**21.14**
Baichuan2-7B	15.45	33.77	12.20	20.47
Qwen-7B	15.16	33.61	9.16	19.31

Table 2: Results of few-shot tests of three base models on the MLCQ partitioned data set

imitate and generate predictions and reasons for code smells, and evaluate its generation quality by calculating f1 metric. The experimental result is in Table 2 and we choose CodeLLama as our base model.

3.3.2 Prompt Design

Since our application scenario is different from the pre-training scenario of general code models: the input is code and the output is natural language, including the classification and explanation of code smells, we conducted some preliminary experiments using different prompts to verify the training effect, and finally selected the following prompts, and specific examples can be seen in Figure 1.

In code smell detection, the input and output prompt format is that:

Detection Input:[Analyze Instruction] + [Java code]

Detection Output: [$Class$ Name] + [$Class$ Smell 1,2,...n] + [$Method_1$ Name] + [$Method_1$ Smell 1,2...m_1] + [$Method_2$ Name] + [$Method_2$ Smell 1,2...m_2] + ... + [Definition of $Smell_1$, $Smell_2$..$Smell_k$].

The design of output prompt helps the model to have the ability to output multiple smells of multiple fragments of code under a class-method structure after fine-tuning. Since there are too many types of code smells, it is not feasible to put the description of code smells as knowledge in the input prompt like the traditional COT idea, which will exceed the pre-training length limit of the most model. Therefore, we extract the code smells involved in each sample's description and put them into the output term as supervision.

In code smell refactoring, the input and output prompt format is that:

Refactoring Input:[Refactor Instruction] + [Java code]

Refactoring Output:[Refactoring Name] + [Refactoring code]

The output prompt is designed to make the model have the ability to identify application refactoring opportunities and specific refactoring at the same time.

Based on the conjecture that correct code smell information helps the refactoring model predict refactoring opportunities, we use the smell detection model trained previously to perform smell detection on the samples in the training set of the refactoring model, and add the smell information to the refactoring model.The input prompt is adjusted to:

Refactoring Adjusted Input:[Refactor Instruction] + [Name of $Smell_1$, $Smell_2$..$Smell_k$] + [Java code]

3.4 Advice for Refactoring

In addition to directly adding smell names to fine-tune the refactoring opportunity detection model, we also considered another way to utilize code smell detection. Specifically, we use a code smell detection model to detect the code of each refactored example and classify it into three levels:

$f(i)$ represents the smell level of code i:

$$f(i) = \begin{cases} 0 & \text{if} PredSmell(i) = \emptyset \\ 1 & \text{if} PredSmell(i) \subseteq MethodSmell \\ 2 & \text{if} PredSmell(i) \cap ClassSmell \neq \emptyset \end{cases}$$

For each predicted refactoring method, we obtain the code smell level it can solve through its definition. We tested the performance of the refactoring opportunity detection model on 6 methods in total. The classification suggestions for refactoring methods based on the three code smell levels are:

0: Rename Parameter, Rename Variable, Rename Method and none.

1: Extract Method and Extract Variable.

2: Extract Class and Extract Method.

We only consider examples for which the actual prediction matches the opinion on the refactor, i.e., we ignore examples for which the actual predicted

CodeSmellType	Model	Detect Metric		
		Precision	Recall	F_1
Complex Method	DeepSmell	0.731	0.779	0.754
	AE-Dense	0.483	0.630	0.547
	SmellDetector(not tuned)	0.934	0.366	0.526
	SmellDetector(tuned)	0.995	0.925	**0.956**
Complex Conditional	DeepSmell	0.575	0.604	0.589
	AE-Dense	0.170	0.387	0.237
	SmellDetector(not tuned)	0.999	0.519	0.683
	SmellDetector(tuned)	0.998	0.989	**0.994**
Multifaceted Abstraction	DeepSmell	0.287	0.272	0.279
	AE-Dense	0.031	0.747	0.060
	SmellDetector(not tuned)	0.167	0.005	0.009
	SmellDetector(tuned)	0.995	0.710	**0.831**
Feature Envy	DeepSmell	0.341	0.258	0.294
	AE-Dense	0.170	0.387	0.237
	SmellDetector(not tuned)	0.959	0.079	0.146
	SmellDetector(tuned)	0.988	0.899	**0.936**

Table 3: Comparison of our approach with other 2 baseline code smell detection methods (DeepSmell, AE-Dense) under 4 kinds of code smells. The precision, recall and f1 score of the baseline are from their paper because they trained binary-classification model for each type when we conduct experiment with a multi-classification model.

reconstruction method is not in the refactoring set corresponding to the code smell levels.

3.4.1 Model Training

We use QLora-tuning (Dettmers et al., 2023) to train SmellDetector, which means inserting several new parameters, called adapters, to the base of the original model. During training, the parameters of the original model are frozen and only the parameters of the adapter are updated. Instead of fine-tuning the LLM, lora-based method can achieve good performance on relatively small datasets.

4 Experiment

We conducted the following experiments, including two different topics and corresponding data sets: code smell detection and refactoring opportunity detection. The purpose of the experiment is to explore the following questions: (1) How well does the adapter fine-tuned from a large code model perform in code smell detection and code refactoring opportunity detection when combined with the designed hints. (2) How does this compare to traditional code smell research work? (3) Does appropriate smell detection help refactoring opportunity detection?

4.1 Experiment Setup

Dataset. In addition to testing on the dataset we created, we conduct code smell detection experiment on the benchmark created by (Sharma et al., 2021). Considering that the original benchmark had four types of code smells, with significant distribution imbalance and excessive negative examples, we set the maximum number of positive and negative examples for each type of code smell to 10000 and after shuffling the order, divide it into 25% as the test set. In terms of refactoring opportunity detection, we conduct experiment on the benchmark created by (Aniche et al., 2020). Considering that our current method mainly processes a single file, we selected 6 types of refactoring operations that basically complete the refactoring operation within a single file for detection.

Baseline.For the code smell detection task, we have chosen DeepSmells (Ho et al., 2023) and AE-Dense (Sharma et al., 2021) as the baseline. At the same time, we evaluate the performance of SmellDetector without secondary fine-tuning (only fine-tuned on the dataset we created) and after secondary fine-tuning (also fine-tuned on the benchmark training set). For the refactoring opportunity detection task, we have chosen (Aniche et al., 2020) as the baseline.

Metric. The two tasks of code smell detection and refactoring opportunities are actually classification problems. The SOTA work mentioned in the baseline all handles it as a binary classification problem, which means training a separate classifier for each code smell. On the contrary, we handle it as a multi-classification problem, because this is more in line with people's usage habits and can significantly reduce training and deployment costs. For each type, we report and compare the mean precision, recall

Class Smell	Detect Metric		
	Precision	Recall	F_1
Feature Envy	0.864	0.845	0.855
Insufficient Modularization	0.659	0.346	0.454
Deficient Encapsulation	0.990	0.995	0.992
Unnecessary Abstraction	0.995	0.985	0.990
Rebellious Hierarchy	0.905	0.830	0.866
Multifaceted Abstraction	0.910	0.619	0.737
Broken Modularization	0.996	0.990	0.993
Cyclic Hierarchy	0.868	0.800	0.833
Missing Hierarchy	0.922	0.858	0.889
Blob	0.833	0.897	0.864
Data Class	0.913	0.824	0.866
clean	0.916	0.953	0.934
Method Smell	**Detect Metric**		
	Precision	Recall	F_1
Magic Number	0.944	0.868	0.904
Long Parameter List	0.951	0.918	0.934
Complex Method	0.946	0.909	0.927
Empty catch clause	0.947	0.945	0.946
Long Method	0.922	0.855	0.888
Long Statement	0.892	0.826	0.858
Long Identifier	0.970	0.762	0.853
Complex Conditional	0.945	0.895	0.919
Missing default	0.957	0.926	0.941
clean	0.634	0.789	0.703

Table 4: The results of testing the code smell detection task on the dataset we organized. We treat it as a multi-label classification problem.

and F1 score. We use classification report tools to calculate the metric in multi-label classification scene (Pedregosa et al., 2011).

Training/Inference Settings.For SmellDetector training, we set max sequence length to 6000 to handle situations where the code is particularly long, and use 2 epoch and a learning rate with 1e-4 to train the adapter. For the training parameters of qlora, we set lora rank to 64, lora alpha to 16 and lora dropout to 0.05. For SmellDetector inference, we set top p to 0.9, temperature to 0.35 and repetition penalty to 1.0.

4.2 Result of Code Smell Detection

Comparison with baselines. The result of comparison with other baselines is in Table 3. AE-dense (Sharma et al., 2021) propose the benchmark what we use for testing and DeepSmell (Ho et al., 2023), which consists of fusion of deep convolutional and LSTM recurrent neural networks, is a state-of-the-art method on the benchmark. Due to performance limitations, the code smell detection task is treated as multiple binary classification problems, and multiple binary classification models are trained to exchange space and cost for higher classification accuracy.

From experimental data, we can see that our SmellDetector achieved better results, and we essentially tested a multi-class model on a binary dataset. The three code smell types except Multifaceted Abstraction are actually relatively common in our data set, so SmellDetector without secondary fine-tuning also achieved good precision in this benchmark, The reason why recall performs poorly is that SmellDetector(not tuned) is a classifier with more than 20 categories and treats other categories that do not belong to this benchmark as negative examples, so the recall rate is significantly lower than the accuracy rate. This experiment can show that SmellDetector which is based on LLM has made great progress on the task of code smell detection.

Testing in our dataset including 20 types. The result of testing in our dataset is in Table 4. Considering the paradigm of the data set we organized, a code snippet may have multiple code smells, which is a multi-label classification problem. For the sake of convenience, we do not consider the correctness judgment of the predicted cause of code smell for the time being. We only consider whether the code smell itself occurs or not, and extract the predicted classification items through string matching. In addition, a sample may contain predictions for a class and multiple member methods at the same time, so we match the predictions with the class names and method names in the real labels, and use the matching code snippets as a more fine-grained calculation metric. the basic unit. Finally, we use the scikit-learn tool library to calculate the precision, recall and f1-score of multi-label classification. From experimental data, we find that classification performance is basically positively related to the amount of data and some categories with relatively clear and concise definitions are exceptions, such as blob and data class.

4.3 Result of Refactoring Opportunities Detection

Comparison with baselines. The result of comparison with other baseline is in Table 5. Aniche has proposed the benchmark consisting of Class-level, Method-level and Variable-level refactoring and Random Forest achieved the best performance in this benchmark (Aniche et al., 2020). When we fine-tune a binary-classification model for each class of refactoring method like the baseline, we

Refactor Method	Random Forest			Binary Classification(Ours)		
	P	R	F_1	P	R	F_1
Rename Parameter	0.99	0.99	**0.99**	0.98	0.99	0.98
Rename Variable	1.00	0.99	**0.99**	0.98	0.98	0.97
Rename Method	0.79	0.85	0.81	0.98	0.99	**0.98**
Extract Variable	0.90	0.83	0.87	0.98	0.87	**0.92**
Extract Method	0.80	0.92	0.84	0.99	0.95	**0.97**
Extract Class	0.85	0.93	0.89	0.89	0.93	**0.91**
Avg	0.89	0.92	0.90	0.97	0.95	**0.96**

Table 5: The results of testing the refactoring opportunities detection task on the benchmark created by the previous SOTA method , when Random Forest is the previous SOTA method, and Binary Classification is the method that finetuning a binary-classification model for each class, just like Random Forest.

Refactor Method	Base			+trained with smell			+advice		
	P	R	F_1	P	R	F_1	P	R	F_1
Rename Parameter	0.56	0.48	0.51	0.50	0.59	**0.54**	0.53	0.53	0.53
Rename Variable	0.36	0.39	**0.37**	0.37	0.31	0.34	0.34	0.37	0.36
Rename Method	0.74	0.38	0.50	0.54	0.44	0.49	0.73	0.47	**0.57**
Extract Variable	0.63	0.52	**0.57**	0.70	0.43	0.53	0.63	0.47	0.53
Extract Method	0.45	0.26	0.33	0.44	0.18	0.26	0.43	0.42	**0.43**
Extract Class	0.73	0.41	**0.53**	0.76	0.30	0.43	0.76	0.41	**0.53**
none	0.37	0.93	0.52	0.35	0.91	0.51	0.46	0.93	**0.62**
Avg	0.54	0.48	0.48	0.52	0.46	0.45	0.56	0.52	**0.51**

Table 6: The results of testing the refactoring opportunities detection task on the dataset we organized, when Base is the lora-tuning method in Chapter 3.3.2, +trained with smell is the lora-tuning method with code smell name as additional input information, and +advice is selecting examples that comply with advice in the Base method.

achieve the state-of-the-art performance.

Testing about our refactoring methods. The result of testing about our refactoring methods is in Table 6. When we treat refactoring opportunities detection as a multi-class classification problem and output the refactor code at the same time, the classification performance is much lower than the data in Table 5. We try to treat code smell name as additional input information and the test result shows that it fails. In our inference, the reason why it can not make sense is that the given information of code smell is too little and LLM lacks enough prior knowledge of individual code smells to judge at present. Therefore, we added analysis based on expert prior knowledge and changed the method of directly using code smell names as additional input to recommended refactoring methods based on detected code smells. For details, please refer to Chapter 3.4 .The experimental data shows its effectiveness. How to reasonably combine the two tasks of code smell detection and refactoring opportunity detection is worth further research.

5 Conclusion

In this paper, we proposed SmellDetector, a comprehensive code smell detection and elimination model. We collect and organize the first hierarchical code smell dataset from previous datasets, which contains multiple code smells in the same code snippet, including 212,612 code smells and 20 types of class level and method level. By testing on the benchmark built by previous SOTA method, our model has achieved the state-of-art in code smell detection and we can detect four times the number of smell types than before, changing the basic paradigm of code smell detection from binary classification problem to multi-label classification. We have experimentally demonstrated that effective code smell detection helps detect opportunities for code refactoring and provide researchers with ideas for a reasonable combination of two tasks.

Limitations

In this paper, we followed the previous research paradigm on code smell, which focused on the two tasks of code smell detection and refactoring opportunity detection. However, we lack further attempts at specific reconstruction to eliminate smells. Although we have fine-tuned the refactoring model to output refactored code, we lack powerful tools to judge whether the refactored code is effective. Simply applying natural language generated metrics, such as calculating the BLEU or ROUGE of labeling refactoring code and predicting reconstructed code, is of little significance. In the future, we should solve this problem by establishing benchmarks or proposing new metrics, so as to establish a more direct research paradigm for code smell refactoring.

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