Detecting Crowdsourced Test Report Consistency for Mobile Apps with Deep Image Understanding and Text Analysis

Shengcheng Yu, Chunrong Fang*, Yexiao Yun, Zhenfei Cao, Kai Mei, Zhihao Cao, Zhenyu Chen
State Key Laboratory for Novel Software Technology, Nanjing University, Nanjing, China
Corresponding author: fangchunrong@nju.edu.cn

ABSTRACT
Crowdsourced testing, as a distinct testing paradigm, has attracted much attention in software testing, especially in mobile application (app) testing field. Compared with in-house testing, crowdsourced testing outperforms because it utilizes the diverse testing environments of different crowdworkers faced with the mobile testing fragmentation problem. However, crowdsourced testing also brings some problem. The crowdworkers involved are with different expertise, and they are not professional testers. Therefore, the reports they may submit are numerous and with uneven quality. App developers have to distinguish high-quality reports from low-quality ones to help the bug revealing and fixing. Some crowdworkers would submit inconsistent test reports, which means the textual descriptions are not focusing on the attached bug occurring screenshots. Such reports cause the waste on both time and human resources of app developing and testing.

To solve such a problem, we propose ReCoDe in this paper, which is designed to detect the consistency of crowdsourced test reports via deep image-and-text fusion understanding. First, according to a pre-conducted survey, ReCoDe classifies the crowdsourced test reports into 10 categories, which covers the vast majority of reported problems in the test reports. Then, for each category of bugs, we have distinct processing models. The models have a deep fusion understanding on both image and textual descriptions. We also have conducted an experiment to evaluate ReCoDe, and the results show the effectiveness of ReCoDe to detect consistency crowdsourced test reports.

CCS CONCEPTS
• Software and its engineering → Software testing and debugging.

KEYWORDS
Crowdsourced Testing, Image-and-Text Fusion Understanding, Consistency Detection

ACM Reference Format:
Shengcheng Yu, Chunrong Fang*, Yexiao Yun, Zhenfei Cao, Kai Mei, Zhihao Cao, Zhenyu Chen. 2021. Detecting Crowdsourced Test Report Consistency for Mobile Apps with Deep Image Understanding and Text Analysis. In Conference 2021. ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/nmnnnn.nmnnnn

1 INTRODUCTION
Crowdsourced testing has become one of the mainstream testing paradigms, and it is famous for its openness. The openness of crowdsourced testing has brought many advantages and disadvantages. On one hand, crowdsourced testing makes it possible for the apps under test (AUT) to run on different testing environments, i.e., device model, manufacturer, operating system, screen resolution, etc. Therefore, both functionality and compatibility can be well tested. On the other hand, the openness also brings extra workload and risks. In crowdsourced testing, the expertise of crowdworkers is widely ranged, and the quality of the reports they submitted cannot be controlled. Faced with such a situation, app developers have to distinguish the low quality test reports from the high quality ones, which is a great burden for app developers.

In the crowdsourced testing scenario, crowdworkers are required to submit a test report consisting a screenshot when the bug occurs and the textual descriptions for the bug. Some other information, like testing environment, is automatically captured and attached. Therefore, one of the most important criteria is that the screenshot and the textual description within a report are consistent. Otherwise, app developers will be confused while exploring and reproducing the bugs based on the test reports. One thing to notice is that the consistency of app screenshots and textual descriptions will not necessarily lead to a high quality report, while eliminating inconsistent reports can save the app developers’ time to understand the inconsistent contents.

However, it is challenging to identify the inconsistent test reports automatically. Bugs of several different types can be revealed from the GUI screenshots, e.g., functional error, app crash, etc. Different bug types have different visual and textual features, so it is hardly possible to use a unified model to identify inconsistency of different bug types. Moreover, in software testing field, some words have specific meanings, different from common scenarios, and some different words refer to the same operations or objects, like click and press. Therefore, such ambiguous words require additional processing to detect the consistent test reports.

In this paper, we propose a two-stage approach, ReCoDe, for crowdsourced test report consistency detection via deep image-and-text fusion understanding. ReCoDe consists of 2 stages, the Classifying Stage and the Detecting Stage. Some one-stage approaches [15] [17] [23] adopts the encoder-decoder structure, and takes the app screenshots and textual descriptions as input. However, the available dataset is limited, and the parts with bugs of the...
screenshots are delicate. Therefore, it is hard to train an effective one-stage model to detect the crowdsourced test report consistency.

During the **Classifying Stage**, **ReCoDe** first constructs a taxonomy for the bugs that can be revealed in the crowdsourced test reports. The taxonomy contains 10 types of different bugs (full list in Table 1), including functional error, app crash, display problem, etc. The taxonomy targets at the textual descriptions in the test reports. To construct the taxonomy, we adopt the state-of-the-art deep learning (DL) model for natural language processing (NLP) tasks, BERT [9]. BERT has several pre-trained models obtained on the basis of general-purpose datasets, and to make it more suitable for the crowdsourced testing, we fine-tune the models with a self-constructed large-scale crowdsourced test report dataset (referred as **ReCoDe-BERT**). However, the most challenging problem is that the crowdsourced test report dataset is collected from the real-world industry crowdsourced testing platform, so the data distribution is significantly unbalanced. Therefore, we introduce an **Augmentor**, which is used to augment the textual descriptions of crowdsourced test reports. To improve the augmenting effect, we design different strategies for textual descriptions of different types of bugs. With the help of the Augmentor, more data can be generated, and can be used to fine-tune the ReCoDe-BERT model for textual description classification.

With the augmented dataset from Augmentor, we build the **Classifier** based on the ReCoDe-BERT model. As a bug description classifier, we have to pre-define the types. Different from in-house testing, crowdsourced testing is black-box, and most crowdworkers are of different expertise. Crowdsourced testing is conducted from the perspective of app end users, so some bugs cannot be revealed in crowdsourced testing. Therefore, we conduct a survey to investigate what types of bugs can be revealed in the crowdsourced testing, and their frequency. According to the survey results, we conclude 10 types of different bugs, including Functional Defect, Crash, Layout Problem, Display Problem, Network Error, Null Screen, Performance Problem, Error Prompt, Garbled Error, Transition Problem. These types covers about 90% of all test reports. The rest are about user experience, the textual descriptions actually describe the problems in the screenshots, while we do not take them as the “bugs” in this paper. Therefore, we hold that the coverage of the constructed taxonomy is wide.

After the bugs classified by the Classifier, **Decomposer** is introduced to analyze the app screenshots and textual descriptions. For the app screenshots, Decomposer combines the traditional computer vision (CV) technologies and deep learning models, and identify the widgets on the app screenshots. Moreover, Decomposer will also have more understanding on the widgets, including text extraction and matching, widget type detection. Decomposer also conducts the layout characterization based on the extracted widgets, and the layout characterization present the relative relationship among all the widgets. For textual descriptions, Decomposer first conducts the text segmentation, and Decomposer also analyzed the dependency parsing of the textual descriptions, which extract the significant words that help locate the bug and the corresponding widget in the app screenshots. Such words we define as locating features, and locating features include color words (C), position words (P), text words (X) and type words (Y) (details in Section 4.2). With the combination of locating features from textual descriptions and the widgets from app screenshots, **Detector** can detect the crowdsourced test report consistency.

Bugs revealed from the crowdsourced test reports are of different types, and different types of bugs are with different features. For example, the Null Screen problem is always attached with an app screenshot of almost all-black or all-white, the app screenshot of Network Error always contains the texts about network error codes (e.g., Error 404), etc. Therefore, different strategies are applied for different types of bugs. The strategies of **ReCoDe** is divided into 2 categories, the General Strategy and the Specific Strategy. For Functional Defect, Layout Problem, Display Problem, Transition Problem, the General Strategy is used, because the screenshot have similar features, and the key is to match the widgets and the text fragments. For Crash, Network Error, Null Screen, Performance Problem, Error Prompt, Garbled Error, each type has very distinct features. Therefore, one Specific Strategy is designed for each type of bugs. With the designed strategies, Detector can detect the consistencies or inconsistencies of the mobile app crowdsourced test reports.

To verify the effectiveness of the proposed **ReCoDe**, we implement the tool and conduct an empirical experiment with a large-scale crowdsourced test report dataset. The test reports in the dataset are collected from a real-world crowdsourced testing platform, and contains 22,720 test reports. The experiments results show that **ReCoDe** can effectively detect consistency in crowdsourced test reports.

In this paper, we declare the following novel contributions.

- We propose a novel approach, **ReCoDe**, to detect the crowdsourced test report consistency via deep image-and-text fusion understanding.
- We construct a large-scale crowdsourced test report dataset containing 22,720 test reports. Also, we propose a data augmentation approach targeted at textual descriptions of crowdsourced test reports.
- We construct a bug taxonomy for crowdsourced test reports. The taxonomy covers the majority of the bugs that can be revealed from crowdsourced testing.
- We implement the tool based on **ReCoDe**, and design an experiment to verify the proposed **ReCoDe**. The results show that **ReCoDe** can effectively detect the consistency of crowdsourced test reports.

More information is available on the online package: https://sites.google.com/view/recode2022.

2 BACKGROUND & MOTIVATION

This section illustrates the background and motivation of this paper. We first present the severe problem of crowdsourced test report inconsistency, and then analyze the incapability of one-stage models.

2.1 Inconsistency in Test Reports

In mobile app crowdsourced testing, quality control of test reports has always been a pain point for improving crowdsourced testing efficiency. Due to the openness of crowdsourced testing, the involved crowdworkers are with different levels of expertise. Therefore, many low quality test reports are mixed with the high quality
test reports, and lead to a huge burden for app developers to review the test reports. One of the most significant features of low quality reports is that the app screenshots and textual descriptions are inconsistent, making the reports completely unusable.

![Report #47](image1) ![Report #285](image2) ![Report #1591](image3)

Figure 1: Inconsistent Crowdsourced Test Report Examples

1. Report #47: After turning off the “auto refresh” button, I cannot manually refresh the contents.
2. Report #285: Randomly click on some widgets in the menu, and return to the “world” page, then the app crashes.
3. Report #1591: Click on the “telephone” button at top-right corner and confirm, the telephone function is not invoked.

We give three vivid examples from our large-scale crowdsourced test report dataset (Figure 1). In the first example (Report #47), the crowdworker reports a *Functional Defect*, and in the textual description, the crowdworker mentions an “auto refresh” button, while there is no such a button (no such widget) on this page as shown in the app screenshot. In the second example (Report #285), the crowdworker is reporting a *Crash*, while the attached app screenshot does not show any crash, so the *app screenshot does not contain the bug in the textual description*. In the third example (Report #1591), the app shows that “the app has stopped running”, which indicates a *Crash*, while the textual descriptions are describing irrelevant matter. Therefore, the *textual description does not contain the bug in the app screenshot*.

In the above three examples shows three typical kinds of inconsistent crowdsourced test reports, while there are still many kinds, e.g., meaningless descriptions like “1111111...”, complains about the GUI design, like “I don’t like the color of the button”.

Such inconsistent crowdsourced test reports account for a large proportion of all test reports. We review all the reports in the large-scale crowdsourced test report dataset, and among the all 22,720 test reports, only 4,105 reports are consistent, which accounts for only 18.07% of the dataset (details about survey in Section 4.2). Without an effective filtering, app developers have to review all the reports. Therefore, we hope to propose an automated tool to help app developers filter out the inconsistent crowdsourced test reports and help them reduce the time and resources.

2.2 Incapability of One-Stage Approach

There exist many one-stage deep learning models that are capable of processing image and text data simultaneously [15] [17] [23]. However, such models cannot fit into the crowdsourced test report consistency detection task. We conclude two major reasons.

First, although we have constructed a large-scale dataset, the models still require a much larger scale dataset to reach a relatively good effect. Without a considerable size of dataset, the model may not be capable of extracting and learning useful features from the training data. Moreover, to the best of our knowledge, the dataset we contribute in this paper is the largest crowdsourced test report dataset with labeled information both in academic community and industry. While with such a dataset, the model still cannot effectively detect the inconsistency of crowdsourced test reports according to our practice.

Second, for the most of the crowdsourced test reports, the bugs shown on app screenshots will not occupy a large proportion of the whole page. For example, if a *Crash* appears, the prompt will only show on the center of the page; a *Functional Defect* will only link to a single *Button* or *TextView*. Therefore, during the encoding or embedding of the app screenshots, such areas indicating the bugs will probably be ignored, and the corresponding features will not be extracted and learned.

Due to the aforementioned incapability of one-stage approaches, we come up with a two-stage approach, which first classify the bugs, and detect crowdsourced test report consistency with different strategies, which can be more effective.

3 APPROACH

This section presents the design details of **ReCoDe**, which is used for mobile app crowdsourced test report consistency detection by deep image-and-text fusion understanding. **ReCoDe** is composed of *Classifying Stage* and *Detecting Stage*. The *Classifying Stage* include an *Augmentor* and a *Classifier*, and the *Detecting Stage* include a *Decomposer* and a *Detector* (Figure 2). For a given crowdsourced test report, **ReCoDe** first classify the report into a specific bug type with the *Classifier* according to the textual descriptions, and then utilize the *Decomposer* to extract the locating features. Finally the *Detector* detects the consistency of crowdsourced test reports based on the strategies.

3.1 ReCoDe Augmentor

To train the *Classifier* of **ReCoDe**, we label the consistency or inconsistency of the crowdsourced test reports (labeling details in Section 4.1.2). According to the label results, we find that only 4,105 test reports are consistent, and the data distribution of different type of bugs is uneven. Therefore, the data of some types can be inadequate to train the deep learning model based *Classifier*, so the data of some types should be augmented to reach an even distribution.

To reach the even distribution, we propose an *Augmentor*, which is used to augment the textual descriptions. According to our review to the crowdsourced test reports, we have augmenting rules for different types of bugs. The resourced for *Augmentor* is

number before augmentation

number after augmentation, actually used in taxonomy construction
from Github issues, app reviews from app stores, test reports from industry, and test reports (consistent ones and inconsistent ones) from crowdsourced testing.

For **Functional Defect** textual descriptions, the number is much larger than other types of bugs, so we do not augment the Functional Defect textual descriptions. During the **Classifier** construction, we randomly select approximately the same number of Functional Defect textual descriptions as other types of bugs.

For **Crash** textual descriptions, we search for the keywords, like “abnormal exit”, “app crash”, from the **Augmentor** resources to complete the augmentation.

For **Layout Problem** and **Display Problem** textual descriptions, we extract the keywords, such as “display”, “show”, “present”, to pick textual descriptions from **Augmentor** resources to augment the **Layout Problem** and **Display Problem** textual descriptions.

For **Network Error** textual descriptions, we focus on the keywords like “network”, and the HTTP error code like “404 not found”, “502 bad gateway”. Such keywords can help us find more textual descriptions from the **Augmentor** resources to augment the **Network Error** type textual descriptions.

For **Null Screen** textual descriptions, the keywords include “white screen”, “null screen”, “black screen” are used for collecting the textual descriptions of **Null Screen** from **Augmentor** resources.

For **Performance Problem** textual descriptions, we search for the textual descriptions of **Augmentor** resources with the keywords like “stuck system”, “long time”, “slow” and so on.

For **Error Prompt** textual descriptions, they usually appear with a pop-up window telling the error information. The crowdworkers tent to report what is showing in the pop-up window. Therefore, we collect **Augmentor** resources to augment the dataset with keywords like “prompt”, “show”, “pop-up” etc.

For **Garbled Error** textual descriptions, we first find textual descriptions containing the “garbled texts”, and then translate the original textual descriptions to another language and translate back with machine learning to have different descriptions.

For **Transition Problem** textual descriptions, we search with keywords “transit”, “back”, “exit”, in the **Augmentor** resources and augment the dataset.

With the above augmenting strategies, we build the **Augmentor** of **ReCoDe**, and augment the textual descriptions of each type of bug to a relatively equal number. The number of each type of bug is shown in Table 1.

### 3.2 ReCoDe Classifier

To construct the **Classifier**, it is necessary to first build a taxonomy. We investigate the crowdsourced test report dataset with 22,720 reports, and we conclude in total 10 types of bugs that will be revealed in crowdsourced testing from the perspective of crowdworkers as end users.

- **Functional Defect** is closely related to the business functions of the apps, and the apps behaves different from the
expectations of the users. Some are the business logic errors, and the app runs normally. Some are programing bugs, and the apps may throw exceptions.

- **Crash** has a significantly negative effect on user experience, and is one of the most severe type of bugs. Many reasons, including memory leak, hardware compatibility problem, will lead to the app crash.
- **Layout Problem** will happen due to the hardware incompatibility. Some widgets will not show as expected. For example, the text overlap, widget occlusion, blurred screen [16].
- **Display Problem** refers to the problem of missing widgets contents, like images, or even missing widgets. Such problems will make users not to able to go on with using the apps.
- **Network Error** is related to the network condition. Typical examples include the HTTP errors. Some are due to the client have weak network link, and others are because the servers have errors and cannot provide service.
- **Null Screen** is an obvious type of bugs. A large proportion of the app activity is all-black or all-white.
- **Performance Problem** means that the requests from app users will not receive responses in time. The apps keeps loading the resources or have the users wait for a long time.
- **Error Prompt** always comes with pop-up windows, and the messages about the bugs will be presented to app users.
- **Garbled Error** is caused by the the encoding and decoding of different character set. Such bugs make app users cannot understand the textual information from the apps.
- **Transition Problem** means the transitions among different app activities are not meeting the expected destination activity, and such problems will greatly confuse the app users.

With the pre-defined taxonomy, we build the **Classifier** on the basis of BERT model [9]. BERT is a pre-trained model, and we fine-tune the model with the augmented data, and rename the model as **ReCoDe-BERT**. The detailed model structure of the **Classifier** is shown in Figure 3. For the textual descriptions, we first conduct the word embedding, including Token Embedding, Segment Embedding, and Position Embedding, and represent the descriptions with vectors. Token Embedding transfers each words in the textual descriptions into fixed-length vectors (768 in **ReCoDe-BERT**). Segment Embedding process the sentence pairs to determine weather they are supposed to be classified into the same category. Position Embedding gives vectors representing the position of each word in the sentence, and helps the model obtain information from the context. Then the encoded vectors are feed into the Transformer [27] encoders connected in sequence. The encoders adopt the attention mechanism [18]. During the model training, we follow the common practice, and divide the data at the ratio of 6:2:2 for training set, validation set and test set. We set the batch size is 32, and the learning rate is $5 \times 10^{-5}$. The total training epoch is 30.

For a crowdsourced test report, the reported bug may be classified into different types. For example, in some app design, the Crash bug will be accompanied by the Error Prompt, saying “the app crashes” in a pop-up window. Therefore, it is not sound to simply classify the test report into one report. We collect the top-3 results with highest confidence to eliminate the negative effect from the ambiguity of crowdsourced test reports.

### 3.3 ReCoDe Decomposer

** Decomposer ** is designed for extracting the key semantic information from both app screenshots and textual descriptions. App screenshots can be seen as a set of widgets from the perspective of app users. Therefore, the first processing step on app screenshots is to extract the widgets. In **ReCoDe**, we construct a widget extracting model utilizing the advantages of traditional computer vision (CV) technologies and deep learning models. Widgets on app screenshots are divided into text widgets and non-text widgets. Text widgets are extracted by OCR algorithms and are linked to the non-text widgets. For example, the “submit” on the button. Text widgets are significant to directly conduct matching with the textual descriptions from crowdsourced test reports. However, some widgets are not accompanied with texts. We feed such widgets into a DL model proposed by Yu et al. [38], which can identify the type of the widgets. Further, in textual description, crowworkers will use the position relationship of other widgets to describe the problem widget. Therefore, we characterize the app screenshot layout based on the extracted widgets.

Textual descriptions contains the locating features that help app developers locate the position of the problem widgets in the app screenshots. ** Decomposer ** is used to extract such locating features from the textual descriptions. Locating features include color words (C), which describe the widget colors; position words (P), which describe the widget positions on the app screenshots; text words (X), which describe the texts on the target widgets; and type words (Y), which describe the widget types, i.e., Button, TextField.

Targeted at the locating features, we build the datasets respectively. We refer to different data sources, including Github issues,
app reviews from app stores, test reports from industry, and test reports from crowdsourced testing. Besides, we build the semantic identifying dataset, which stores negative words and double-negative words, and the prompt word dataset, containing words that indicate the existing texts on app screenshots will appear in the textual descriptions. Prompt words can help link app screenshots with textual descriptions.

With the dataset of locating features, negative words, and prompt words, we analyze the basic sentence relationships of the textual descriptions. We adopt the open-sourced dependency parsing analysis tool, DDParse, from Baidu. Dependency parsing analysis aims at analyzing the dependency relationship of the words to determine the sentence structure. For textual descriptions of crowdsourced test reports, the widely used sentence structures include: **SBV** (Subject-Verb structure), **VOB** (Verb-Object structure), **ADV** (Adverbial structure), **CMP** (Complement structure), **ATT** (Attributive structure), and **F** (Position-Word structure).

By dependency parsing analysis, each word is labeled with the sentence composition. Afterwords, we extract the keywords from the textual descriptions, and identify the prompt words, locating features and negative words according to the constructed dataset. If the sentence contains prompt words, we identify the prompt texts from the textual descriptions with the sentence structure; if the sentence does not contain prompt words, we observe that crowdworkers tend to describe the widgets with bugs, and we extract the key nouns and the corresponding qualifiers.

Then, with the extracted words from textual descriptions, we identify the emotional tendency of the textual descriptions based on the negative words and double-negative words.

**Decomposer** decomposes the app screenshots and textual descriptions into widgets and keywords respectively. Of the keywords from textual descriptions, we extract prompt words, which indicates the existing texts on app screenshots, locating features, which describe the features of the mentioned widgets on app screenshots, and (double-)negative words, which show the emotional tendencies of the textual descriptions. Acquiring such information can lay a solid foundation for the **Detector** to detect the crowdsourced test report consistency.

### 3.4 ReCoDe Detector

Different types of bugs have significantly different app screenshot features. Therefore, **ReCoDe** is designed to adopt a two-stage approach. **Detector** works on the basis of results from **Classifier** and **Decomposer**. Different detecting strategies are designed to detect the mobile app crowdsourced test report consistency. Such strategies are divided into 2 categories, the **General Strategy** and the **Specific Strategy**. The **General Strategy** is designed for **Functional Defect**, **Layout Problem**, **Display Problem**, and **Transition Problem**. The four types of bugs do not have distinct features on app screenshots. For the rest types of bugs, each type have distinct features revealed from app screenshots, so we design the **Specific Strategies** for each type in **Detector**. With the estimation of the strategies, a score, denoted as \( S_{dt} \), is assigned to each test report.

The **General Strategy** is designed for **Functional Defect**, **Layout Problem**, **Display Problem**, and **Transition Problem**. Texts are most widely used to conduct the match, while not all widgets can be identified by existing texts, and some widgets are not attached with texts, or more than one widget share the same texts. Therefore, we introduce the locating features, which contains more features to identify the widgets. Locating features include color words, position words, type words and text words. Color words indicate the colors of the target widgets; position words describe the approximate positions, like top-left corner of the screenshot; and type word means the widget type, i.e., Button or TextView. The locating features can be combined to identify the widgets. For example, "the widget on the left of the green ‘confirm’ button...", the textual description contains position words, color words, text words and type words in turn. For each widget extracted from textual descriptions by **Decomposer**, **Detector** identifies whether the four locating features exist, if so, widgets from app screenshots are matched by each locating features. Each locating feature are assigned to a weight, \( \omega_c \), \( \omega_p \), \( \omega_X \), and \( \omega_Y \), and if any locating feature is matched, the corresponding weight is counted, otherwise truncated. The sum of four locating feature weights is the widget score, and the \( S_{dt} \) is assigned to the average of all the widgets extracted from textual descriptions.

For the rest types of bugs, we design **Specific Strategies** for each type based on the bug features revealed in app screenshots.

For **Crash**, app developers always design a pop-up window that indicates the app crashes. The pop-up contains texts like “no response”, “stop running”, etc. Therefore, we first extract the pop-up windows from the app screenshots. Then, OCR technologies are adopted to extract the texts from the pop-up windows. If such texts contain the corresponding words related to crashes, **Detector** assigns the \( S_{dt} \) to 1, otherwise 0.

For **Network Error**, situations are divided into 2 categories. First, the embedded H5 pages may encounter the **Network Error**, and the app screenshots contain the error HTTP response status codes, like 404, 502 etc. We extract texts from app screenshots and locate the error HTTP response status codes to determine whether the app screenshots reflect a **Network Error**. Second, for native app activities, **Network Error** is shown by pop-up windows. We also use OCR technologies and match with keywords like “server error”, “unable to link” etc. Such words indicate the **Network Error** existence. If the keywords extracted from app screenshots contains texts from textual descriptions, **Detector** assigns the \( S_{dt} \) to 1.

For **Null Screen**, the feature is obvious. The whole app activity are all-white or all-black. According to this feature, we binarize the app screenshots into black-and-white ones. The white pixels refers to the widget borders and the black pixels refers to the backgrounds. Then, we detect the continues areas without widget borders. If there exist one or more areas that is accounts for over a certain ratio of the whole app screenshot in size, the \( S_{dt} \) is assigned the value 1, otherwise 0. The certain ratio is represented by \( \theta \), and we set it as 0.75 in our **ReCoDe** implementation.

For **Performance Problem**, app clients cannot receive expected responses from the servers, and the contents are waiting to be loaded. Therefore, the loading icons or texts are the distinct features of **Performance Problem**. Loading icons are of similar shape features, so we collect different loading icon styles from different
we build the locating feature dataset, including color words, position words, and double-negative words. With the keyword dataset and the extracted information from app screenshots and textual descriptions, the \( S_{di} \) is assigned the value 1, otherwise 0.

The Garbled Error are always triggered by the wrong character encoding and decoding with different source and target set. Therefore, we first extract all the texts from the app screenshots, and identify the each character whether it belongs to the Chinese characters or English letters. If there exist any character that does not belong to the preset character sets, the \( S_{di} \) is assigned the value 1, otherwise 0.

As illustrated in Section 3.2, we obtain 3 possible types from Classifier with top-3 confidence. However, due to the differences in confidence, we assign different weights for different results, \( \delta_i \) for \( top - i \) result. In our implementation of ReCoDe, we assign \( \delta_1, \delta_2, \delta_3 \) to 1, 0.9, 0.8, respectively, which shows the best performance according to practical experience and preliminary evaluation. As shown in Formula 1, the \( S_{top-3} \) is the maximum value among the three production of \( \delta_i \) and \( S_{dt}(top - i) \), and if \( S_{top-3} \) is greater than the preset threshold \( \lambda \), Detector will confirm the consistency of the crowdsourced test report (Formula 2). The \( \lambda \) is set 0.5 based on the experience from the industry.

\[
S_{top-i} = \max(\delta_i * S_{dt}(top - i)), i = 1, 2, 3
\]

\[
res = \begin{cases} 
1 & S_{top-3} > \lambda \\
0 & \text{otherwise}
\end{cases}
\]  

Detector designs the General Strategy and the Specific Strategies to deal with different types of bugs. To fulfill these strategies, we build the locating feature dataset, including color words, position words, text words, and type words. Also, semantic identifying dataset are used to assist the Detector, including negative words and double-negative words. With the keyword dataset and the extracted information from app screenshots and textual descriptions with Decomposer, Detector is capable of detecting the mobile app crowdsourced test report consistency.

4 EVALUATION

4.1 Experimental Setup

4.1.1 Research Question. We propose three research questions (RQ) to evaluate the effectiveness of ReCoDe.

\*ReCoDe currently processes bilingual apps (Chinese and English).

- RQ1 (Empirical Survey): How common are the inconsistent test reports in crowdsourced testing and how crowd-workers submit the crowdsourced test reports?
- RQ2 (Classifier Effectiveness): How effective can ReCoDe classify the bugs in crowdsourced test reports?
- RQ3 (Detector Effectiveness): How effective can ReCoDe detect the crowdsourced test report consistency?

4.1.2 Data Collection and Preprocessing. In this paper, we collect 22,720 mobile app crowdsourced test reports from one of the most popular crowdsourced testing platform (anonymous for double-blind principle). The test reports are of over 50 different mobile apps, and over 1,100 crowdworkers participate in the crowdsourced testing tasks. Five of the authors, as participants, which are graduate students or senior testing engineers with over 3 years of experience in mobile app testing, spend 10 months in total to manually label and cross-validate the data.

First, the participants are required to label the consistency or inconsistency of the test reports, and the results should be the consensus of all 5 participants after discussion. Second, 2 of the participants label the bug type of each test report separately. If their results are the same, the bug type is confirmed, and if the results are different, the other 3 participants will vote for the final results. Third, the participants will label the locating features in the textual descriptions. Each test report can be labeled with one or more locating features. Besides, the participants label the existence of negative words, double-negative words, and prompt words.

4.2 RQ1: Empirical Survey

For the detecting strategies of Detector, the premise is that the bugs can be revealed from app screenshots, and the textual descriptions can be analyzed to locate the bugs and corresponding buggy widgets. Therefore, we conduct an empirical survey on the mobile app crowdsourced test reports.

We first investigate the consistent situation of all crowdsourced test reports, which is the basis of this work’s motivation. Of the 22,720 crowdsourced test reports, only 4,105 reports are consistent. In other words, the textual descriptions of the reports actually describe the bugs revealed in the app screenshots submitted by crowdworkers. Only 18.07% consistent reports reflects the severe quality problem in crowdsourced testing. The large percentage of inconsistent test reports can lead to a waste of time of app developers in reviewing the test reports.

Also, we conclude some common inconsistent types. First, crowd-workers submit meaningless test reports, which have nothing to do with the bugs, because some tasks reward them only according to the report number they submit. Second, the crowdworkers report issues about GUI designs, which may affect user experience, while for app developers such issues are not considered as bugs. Third, some crowdworkers cannot precisely describe the problems in the app screenshots due to lack of experience or expertise, making the submitted reports hard to understand for app developers.

The second target of the empirical survey is to investigate the bug types revealed in crowdsourced testing. According to the results (Figure 4), the most common bug type in crowdsourced testing is Functional Defect, which accounts for 63.36%. The following bug type is Display Problem, accounting for 9.84%, and Performance
Problem, accounting for 63.36%. The least common bug type is Garbled Error, which only make up about 0.37% of the test reports. Crowdworkers always report Functional Defect, which relate to the app business logic, much more frequently, because Functional Defect most directly affects their using experience. Besides, Crash, Layout Problem, Display Problem, Performance Problem and Error Prompt also have significant negative effects to end users, while such problems often happens due to the compatibility problems introduced by the well-known “fragmentation problem” [32] [38] on mobile platforms, so only part of crowdworkers would report such problems.

However, some problems cannot be revealed in crowdsourced testing. For example, the NullPointerException, which only make up about 0.37% of the test reports.

Another problem we focus on is how crowdworkers locate the target widgets with bugs in textual descriptions. This also determines how we build the locating feature dataset in the Detector.

According to the manually labeling results, we find that most crowdworkers use four different categories of locating features, the color words (C), the position words (P), the text words (X) and the type words (Y). Text words are most intuitive and thus most widely used by crowdworkers, and 84.31% of the crowdsourced test reports use or partly use text words as locating features. 2.59%, 22.21% and 21.31% of the test reports use or partly use color words, position words and type words, respectively. Moreover, the three locating features are used together with text words to help locate the buggy widgets more accurately.

As to the locating feature number in the test reports, we find that most crowdworkers locate the buggy widgets with one locating feature, which accounts for 73.68% of all crowdsourced test reports. Crowdworkers are unprofessional end users of mobile apps, therefore, it is reasonable that the use single locating features to describe the widgets with bugs. However, there are still 0.17% test reports use four locating features, which indicates some crowdworkers are with rich experience and high expertise. Interestingly, all reports containing four locating features in textual descriptions are consistent. Besides, 22.21% and 3.94% test reports contains two and three locating features in textual descriptions respectively. Such data shows that using one or two locating features (mostly with text words) is within the majority crowdworkers’ capability, and some experienced crowdworkers can provide valuable consistent test reports with detailed textual descriptions.

![Figure 4: Bug Distribution among Mobile App Crowdsourced Test Reports](image)

**Figure 4: Bug Distribution among Mobile App Crowdsourced Test Reports**

4.3 RQ2: Classifier Effectiveness

In this research question, we research on the Classifier capability. Classifier is one important basis for the whole ReCoDe, and the classifying results determines the strategies applied on the test reports for consistency detection.

The Classifier solves a multiclass classification problem. As commonly defined, a true positive prediction (TP) is correctly predicting a positive sample, and a false positive prediction (FP) is incorrectly predicting a positive sample. A true negative prediction (TN) is correctly predicting a negative sample, and a false negative prediction (FN) is incorrectly predicting a negative sample. We use the accuracy, precision, recall and F1 score values to evaluate the effectiveness of Classifier.

$$\text{accuracy} = \frac{TP + TN}{TP + NP + TN + FN}$$  \hspace{1cm} (3)

$$\text{precision} = \frac{1}{n} \sum_{i=1}^{n} \frac{TP_i}{TP_i + FP_i}$$  \hspace{1cm} (4)

$$\text{recall} = \frac{1}{n} \sum_{i=1}^{n} \frac{TP_i}{TP_i + FN_i}$$  \hspace{1cm} (5)

$$F1\text{ score} = \frac{1}{n} \sum_{i=1}^{n} \frac{2P_iR_i}{P_i + R_i}$$  \hspace{1cm} (6)

The results of RQ2 is shown in Table 2 and Table 3. The Classifier is trained on the augmented consistent test report dataset (Section 3.1). The dataset contains 3,740 crowdsourced test reports, and is divided into training set, validation set and test set at the ratio of 6:2:2, which is the common practice of text classification tasks. We set the batch size as 32, and train the model for 30 epochs.

\footnote{The number of letter indicates of the types of used locating features. C - color words; P - position words; X - text words; Y - type words.}
Table 2: Test Report Classification Result (Test Set)

| Metric | top-1  | top-2  | top-3  |
|--------|--------|--------|--------|
| accuracy | 80.78% | 94.22% | 96.91% |
| precision | 81.22% | 95.23% | 97.10% |
| recall | 82.74% | 94.70% | 97.23% |
| F1 score | 81.97% | 94.97% | 97.17% |

Table 3: Test Report Classification Result (All Reports)

| Metric | top-1  | top-2  | top-3  |
|--------|--------|--------|--------|
| accuracy | 90.98% | 96.95% | 98.76% |
| precision | 92.03% | 95.27% | 95.92% |
| recall | 93.66% | 96.50% | 97.67% |
| F1 score | 92.84% | 95.88% | 96.79% |

Table 4: ReCoDe Effectiveness

| Metric | ReCoDe | ViLBERT |
|--------|--------|---------|
| accuracy | 64.40% | 70.80% |
| precision | 95.75% | 95.52% |
| recall | 50.07% | 60.04% |
| F1 score | 65.76% | 73.73% |

Table 2 shows the final results on the test set during the model training. For the top-3 results, the accuracy reaches 96.91%, the precision reaches 97.10%, the recall reaches 97.23%, and the F1 score reaches 97.17%. Besides, the values of top-1 results are all over 80%, and the values of the top-2 results reach approximate 95%. The results show that ReCoDe performs quite well in classifying the crowdsourced test reports into corresponding bug types.

However, results on consistent reports cannot completely show the ReCoDe’s effectiveness. Therefore, we have experiment on extra data. Table 3 shows the generalization capability of the Classifier. The data under experiment include all test reports of consistent and inconsistent ones, with the meaningless reports being eliminated. One thing to notice is that even though textual descriptions in inconsistent reports may not match the app screenshots, they are still expressing the bugs, so we evaluate the Classifier on such reports. For the extended data, the top-3 accuracy reaches 98.76%, the precision reaches 95.92%, the recall reaches 97.67%, and the F1 score reaches 96.79%. The values of top-1 results are over 90%, and the values of top-2 results are over 95%.

A seemingly counterintuitive phenomenon is that Classifier performs even better on extended data than on test set. We investigate the data distribution, and we find that the data in test set distribute equally in 10 bug types due to our control on purpose. However, the data distribution of the extended dataset is different, because the data are all collected from industry, and some types of bugs may appear more frequently, e.g., Crash, Null Screen. Such problems may have more apparent features for the Classifier. Therefore, the overall results are better than the results on test set.

The data indicates that Classifier of ReCoDe has good generalization capability, and can accurately classify the test reports to the corresponding bug type according to the textual descriptions.

4.4 RQ3: Detector Effectiveness

The Detector can be seen as a binary classification problem, the consistent reports are labeled 1 and the inconsistent ones are labeled 0, so we use the accuracy, precision, recall and F1 score values to evaluate the the ReCoDe. The calculation is as follows.

precision = \frac{TP}{TP + FP} \quad (7)

\[ \text{recall} = \frac{TP}{TP + FN} \quad (8) \]

\[ F1 \text{ score} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad (9) \]

To illustrate the ReCoDe effectiveness more intuitively, we set a baseline tool, ViLBERT [17], which is originally used for general scene image and text consistency detection. ViLBERT is one of the state-of-the-art one-stage approaches. During the retraining with test report dataset, we keep the original settings and hyperparameters, and construct the training set as the original dataset. The model is trained for 50 epochs.

Table 4 show the results of both ViLBERT and ReCoDe. For the accuracy value, ReCoDe (top-3) reaches 70.80%, outperforming ViLBERT (42.10%) by 68.18%. As for the precision value, ReCoDe (top-3) reaches 95.52%, outperforming ViLBERT (42.10%) by 126.9%. F1 score is the harmonic mean of precision value and recall value. ReCoDe (top-3) reaches 73.73%, outperforming ViLBERT (59.25%) by 24.44%. Experiment results of recall value of ViLBERT is strange, and reaches 100%. We look insight the detailed data, and find that ViLBERT predicts all crowdsourced test reports as consistent. Therefore, we hold that such models have no practical application value. Also, we infer that the reasons are that the data volume is far from enough for the model to extract features, and the widgets with bugs are non-salient, which lead to obstacles for the models to extract features.

4.5 Threats to Validity

4.5.1 Internal Threats. The internal threats to validity are the ReCoDe implementation and the model adaptation. To migrate such threats, we invite a third-party group to review our implementation and the retraining of the original deep learning models. Therefore, the negative effects of code implementation is minimized.

4.5.2 External Threats. One main external threat to validity is the representativeness of the apps under crowdsourced testing on the platform. To migrate the external threat, we use apps of different categories, including system, internet, tool, music, phone & SMS, finance, development, sports, shopping, and map. The wide ranges of app category can eliminate the external threat, and show the generalization capability of the ReCoDe.

4.5.3 Construct Threats. The ground truth is manually labeled which may bring the construct threats. However, we have tried our best to eliminate errors. First, the labeled results are double-checked and are consensus after discussion. Second, the labeling participants are senior software engineers or experienced graduate
students. As presented in [22], senior students are eligible developer proxies in the controlled experiments.

5 RELATED WORK

5.1 Crowdsourced Testing Quality Control

Crowdsourced testing has been more and more popular. Different from traditional testing paradigms, crowdsourced testing distribute testing tasks to a large group of crowdworkers, who are more like common end users instead of testing professionals. Crowdsourced testing utilize the dispersion of crowdworkers’ locations, devices, operating systems and testing ideas.

However, every coin has two sides, the openness of crowdsourced testing cause the severe quality control problem. Many pieces of research has been done to solve such a problem. Some starts from filtering the crowdworkers [34] [8] [7] [31], the papers proposes different strategies for selecting crowdworkers based on crowdworker features and task features, in order to control crowdsourced testing quality from the perspective of participants. However, participant is only one of the important factors that affect the crowdsourced testing quality, and even professional or highly matched crowdworkers may fail to submit effective reports due to economic reasons (platforms may reward workers according to the quantity of tasks they complete).

More work would focus on test report processing, i.e., report classification, duplication detection and report prioritization. Jiang et al. proposed TEFUR [14], using NLP algorithms to analyze and cluster test reports. Sun et al. [24] build a novel information retrieval model for detecting duplicate bug reports. Sureka et al. [25] introduced a model using character n-gram for duplicate detection. Nguyen et al. introduced DBTM [20], combining IR-based and topic-based features, to detect bug report duplication. DRONE, proposed by Tian et al. [26], is a machine learning-based approach to predict the test report priority by extracting and comparing different report features. Banerjee et al. [2] proposed a multi-label classifier to find the "primary" report of a cluster of reports. Alipour et al. [1] had a more comprehensive analysis of the test report context and improved the duplication detection accuracy. Wang et al. [28] consider the features of crowdworkers as a feature of test reports, and then complete the cluster task. They further et al. propose the LOAF [30], which is the first to separate operation steps and result descriptions for feature extraction. Hindle [13] makes improvements by combining contextual quality attributes, architecture terms, and system-development topics to improve deduplicate detection. Feng et al. proposed a series of approaches, DiVRisk [11] and BDDiv [12], to prioritize the test reports, and they first utilize the test reports screenshots. Yu proposed CroReG [36], which can analyze the app screenshots and generate the corresponding textual descriptions for feature extraction. The purpose of this paper is to eliminate the inconsistent crowdsourced test reports, so as to get rid of the negative effects introduced by such reports, especially the waste of time.

Additionally, ReCoDe is currently implemented to process crowdsourced test reports in Chinese and English, as well as the texts on app GUIs. However, other languages are usable by replacing the corpus and corresponding NLP algorithms.

6 DISCUSSION

Consistency is the lowest line for crowdsourced test reports to have positive effects of app developing and testing. We do not mean that the consistent test reports of ReCoDe can necessarily assist bug finding. The purpose of this paper is to eliminate the inconsistent crowdsourced test reports, so as to get rid of the negative effects introduced by such reports, especially the waste of time.

7 CONCLUSION

Crowdsourced testing has been facing severe quality control problem for a long time. Crowdsourced test reports consisting of textual descriptions and app screenshots are submitted by crowdworkers...
of different expertise, and are of a wide range of quality. Reviewing such reports is a great waste of time for app developers. Therefore, this paper introduces a novel approach, ReCoDe, to detect mobile app crowdsourced test report consistency via deep image-and-text fusion understanding. ReCoDe adopts traditional CV algorithms and advanced DL models for image understanding and neural language processing. Crowdsourced test reports are first classified into different bug types and adopt different strategies to detect the consistency. Experiment results show that ReCoDe has an excellent performance on classifying test reports and detecting consistency.

REFERENCES

[1] Anahita Alipour, Abram Hindle, and Elena Stroblia. 2013. A contextual approach towards more accurate duplicate bug report detection. In 2013 10th Working Conference on Mining Software Repositories (MSR), IEEE, 183–192.

[2] Sean Banerjee, Zahad Syed, Jordan Helmick, and Bojan Cukic. 2013. A fusion approach for classifying duplicate problem reports. In 2013 IEEE 24th International Symposium on Software Reliability Engineering (ISSRE). IEEE, 208–217.

[3] Chunyang Chen, Ting Su, Guozhu Meng, Zhenchang Xing, and Yang Liu. 2018. From ui design to gui skeleton: a neural machine translator to bootstrap multiple gui implementation. In Proceedings of the 40th International Conference on Software Engineering. ACM, 665–676.

[4] Jieshan Chen, Chunyang Chen, Zhenchang Xing, Xiwei Xu, Liming Zhai, Guoqiang Li, and Junshu Wang. 2020. Unblind your apps: Predicting natural-language labels for mobile gui components by deep learning. In 2020 IEEE/ACM 42nd International Conference on Software Engineering (ICSE). IEEE, 322–334.

[5] Jieshan Chen, Mulong Xie, Zhenchang Xing, Chunyang Chen, Xiwei Xu, Liming Zhu, and Guoqiang Li. 2020. Object detection for graphical user interface: old-fashioned vs deep learning or a combination?. In Proceedings of the 28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering. IEEE, 1202–1214.

[6] Nathan Cooper, Carlos Bernal-Cáceres, Oscar Chaparro, Kevin Moran, and Denys Poshyvanyk. 2021. It takes two to tango: Combining visual and textual information for detecting duplicate video-based bug reports. In 2021 IEEE/ACM 43rd International Conference on Software Engineering (ICSE). IEEE, 957–969.

[7] Qiang Cui, Junjie Wang, Guowei Yang, Miao Xie, Qing Wang, and Mingshu Li. 2018. Machine learning-based prototyping of graphical user interfaces for mobile apps. In 2018 IEEE/ACM 40th International Conference on Software Engineering (ICSE), Vol. 1. IEEE, 75–84.

[8] Qiang Cui, Song Wang, Junjie Wang, Yuanzhe Hu, Qing Wang, and Mingshu Li. 2017. Multi-Objective Crowd Worker Selection in Crowdsourced Testing. In IEEE, Vol. 17. 218–223.

[9] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. arXiv preprint arXiv:1810.04805 (2018).

[10] Timothy Doozat and Christopher D Manning. 2016. Deep biaffine attention for neural dependency parsing. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 34. 11336–11344.

[11] Zhe Liu, Chunyang Chen, Junjie Wang, Yuikai Huang, Jun Hu, and Qing Wang. 2020. OwlEyes: Spotting UI Display Issues via Visual Understanding. In 2020 50th IEEE/ACM International Conference on Software Engineering (ICSE). IEEE, 398–409.

[12] Jason Liu, Dhiruv Batra, Devi Parikh, and Stefan Lee. 2019. Vilbert: Pre-training task-agnostic visiolinguistic representations for vision-and-language tasks. arXiv preprint arXiv:1908.02265 (2019).

[13] Volodymyr Mnih, Nicolas Heess, Alex Graves, et al. 2014. Recurrent models of visual attention. In Advances in neural information processing systems. 2204–2212.

[14] Kevin Moran, Carlos Bernal-Cárdenas, Michael Curcic, Richard Bonett, and Denys Poshyvanyk. 2018. Machine learning-based prototyping of graphical user interfaces for mobile apps. IEEE Transactions on Software Engineering, 46, 2 (2018), 196–221.

[15] Yuan Tian, David Lo, and Chengnian Sun. 2013. Drone: Predicting priority of reported bugs by multi-factor analysis. In 2013 IEEE International Conference on Software Maintenance. IEEE, 295–304.

[16] Ashish Sureka and Pankaj Jalote. 2010. Detecting duplicate bug report using character-gram-based features. In 2010 Asia Pacific Software Engineering Conference. IEEE, 366–374.

[17] Yuan Tian, David Lo, and Chengnian Sun. 2013. Drone: Predicting priority of reported bugs by multi-factor analysis. In 2013 IEEE International Conference on Software Maintenance. IEEE, 295–304.

[18] Yuan Tian, David Lo, and Chengnian Sun. 2013. Drone: Predicting priority of reported bugs by multi-factor analysis. In 2013 IEEE International Conference on Software Maintenance. IEEE, 295–304.