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TLEL: A two-layer ensemble learning approach for just-in-time defect prediction

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ABSTRACT

Context: Defect prediction is a very meaningful topic, particularly at change-level. Change-level defect prediction, which is also referred as just-in-time defect prediction, could not only ensure software quality in the development process, but also make the developers check and fix the defects in time [1].
Objective: Ensemble learning becomes a hot topic in recent years. There have been several studies about applying ensemble learning to defect prediction [2–5]. Traditional ensemble learning approaches only have one layer, i.e., they use ensemble learning once. There are few studies that leverages ensemble learning twice or more. To bridge this research gap, we try to hybridize various ensemble learning methods to see if it will improve the performance of just-in-time defect prediction. In particular, we focus on one way to do this by hybridizing bagging and stacking together and leave other possibly hybridization strategies for future work.
Method: In this paper, we propose a two-layer ensemble learning approach *TLEL* which leverages decision tree and ensemble learning to improve the performance of just-in-time defect prediction. In the inner layer, we combine decision tree and bagging to build a Random Forest model. In the outer layer, we use random under-sampling to train many different Random Forest models and use stacking to ensemble them once more.
Results: To evaluate the performance of *TLEL*, we use two metrics, i.e., cost effectiveness and F1-score. We perform experiments on the datasets from six large open source projects, i.e., Bugzilla, Columba, JDT, Platform, Mozilla, and PostgreSQL, containing a total of 137,417 changes. Also, we compare our approach with three baselines, i.e., *Deeper*, the approach proposed by us [6], *DNC*, the approach proposed by Wang et al. [2], and *MKEL*, the approach proposed by Wang et al. [3]. The experimental results show that on average across the six datasets, *TLEL* could discover over 70% of the bugs by reviewing only 20% of the lines of code, as compared with about 50% for the baselines. In addition, the F1-scores *TLEL* can achieve are substantially and statistically significantly higher than those of three baselines across the six datasets.
Conclusion: TLEL can achieve a substantial and statistically significant improvement over the state-of-the-art methods, i.e., *Deeper, DNC* and *MKEL*. Moreover, *TLEL* could discover over 70% of the bugs by reviewing only 20% of the lines of code.

1. Introduction

To produce high-quality software, much effort needs to be invested to the process of testing and debugging. Unfortunately, developers often have limited resource and tight schedule, and are thus constrained to perform rigorous and comprehensive testing and debugging efforts on all parts of a code base. Defect prediction techniques are proposed to help prioritize software testing and debugging efforts; they can recommend software components that are likely to be defective to developers. Much research has been done on defect prediction; these techniques construct predictive classification models built on features such as lines of code, code complexity and number of modified files [7–9].

Many past defect prediction studies predict defects at coarse granularity level, such as file, package, or module [9–11]. In recent years, several research studies propose *just-in-time defect prediction techniques* that are able to predict defective changes (i.e., commits to a version control system) [1,12]. Just-in-time defect prediction is more practical because it can not only ensure software quality in the development process, but also make the developers check and

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fix the defects just at the time they are introduced. The advantage of just-in-time defect prediction includes: (1) it leads to smaller amount of code to be reviewed because only individual changes (rather than entire files or packages) need to be reviewed [13]; (2) it leads to an easier assignments of developers to fix bugs because we can easily identify the authors of the changes that introduce defects. In a recent work, Kamei et al. perform a large-scale empirical study on just-in-time defect prediction [1].

Ensemble learning becomes a hot topic in recent years. Many research studies have shown that ensemble learning can achieve much better classification performance than a single classifier [14,15]. There have been several studies about applying ensemble learning to defect prediction [2–5]. However, most ensemble learning approaches only use ensemble learning once. There are rare studies that leverages ensemble learning twice or more [16]. We notice that different ensemble learning methods are good for different datasets. Therefore, we assume that hybrid ensemble learning will improve the performance of just-in-time defect prediction much more. In particular, we focus on one way to do this by hybridizing bagging and stacking together. We leave other possibly hybridization strategies for future work.

We propose a novel approach *TLEL*. The approach can be seen as a two-layer ensemble learning technique. In the inner layer, we use bagging based on decision tree to build a Random Forest model. In the outer layer, we use stacking to ensemble many different Random Forest models.

To evaluate *TLEL*, we use two widely-used evaluation metrics: cost effectiveness [17–20], and F1-score [12,17,21,22]. Cost effectiveness evaluates prediction performance considering a given cost threshold, e.g., a certain percentage of code to inspect. For example, when a team has limited resources to inspect potentially buggy lines of code, it is crucial that by manually inspecting the top percentages of lines that are likely to be buggy, developers can discover as many bugs as possible. We measure cost effectiveness as the percentage of bugs that can be discovered by inspecting the top 20% LOC based on the confidence levels that a change classification technique outputs (PofB20) [1,8]. In addition, we also evaluate our method using the F1-score [12,17,21,22], which is a summary measure that combines both precision and recall. F1-score is a good evaluation metric when there is enough resource to inspect all predicted buggy changes. A higher F1-score usually means a better method for just-in-time defect prediction.

We perform experiments on six large-scale software projects from different communities, i.e., Bugzilla, Columba, JDT, Mozilla, Platform, and PostgreSQL, containing a total of 137,417 changes. We compare our approach with three baselines, i.e., *Deeper*, the approach proposed by us [6], *DNC*, the approach proposed by Wang et al. [2], and *MKEL*, the approach proposed by Wang et al. [3]. The experimental results show that on average across the six projects, *TLEL* could discover over 70% of the bugs by reviewing only 20% of the lines of code, as compared with about 50% for the baselines. Also, *TLEL* can achieve F1-scores of 0.25-0.67, which are substantially and statistically significantly higher than those of the baselines.

The main contributions of this paper are:

1. We propose a novel approach *TLEL*, which can be seen as a two-layer ensemble learning technique, to achieve a better performance for just-in-time defect prediction problem.
2. We compare *TLEL* with three baselines, i.e., *Deeper, DNC* and *MKEL*, on six large software projects. The experiment results show that our approach can achieve a better performance than all of them.

The rest of our paper is organized as follows. Section 2 introduces the background of our work. Section 3 presents the overall framework of our approach and elaborates the techniques that we use in our approach. Section 4 describes our experiments and the results. Section 5 presents some discussions about our work. Section 6 discusses the related work. Conclusion and future work are presented in the last section.

2. Preliminaries and motivation

In this section, we first introduce the general method of just-in-time defect prediction in Section 2.1. Next, we introduce ensemble learning in Section 2.2. Technical motivation will be presented at last.

2.1. Just-in-time defect prediction

Just-in-time defect prediction aims to predict if a particular file involved in a commit (i.e., a change) is buggy or not. Traditional just-in-time defect prediction techniques typically follow the following steps:

1. **Training Data Extraction.** For each change, label it as buggy or clean by mining a project's revision history and issue tracking system. Buggy change means the change contains bugs (one or more), while clean change means the change has no bug.
2. **Feature Extraction.** Extract the values of various features from each change. Many different features have been used in past change classification studies. The features include change diffusion (which represents the number of files a change involves), change size (which represents the number of lines of code churned in a change), change purpose (which represents whether a change is a defect fix) and so on [1].
3. **Model Learning.** Build a model by using a classification algorithm based on the labeled changes and their corresponding features.
4. **Model Application.** For a new change, extract the values of various features. Input these values to the learned model to predict whether the change is buggy or clean.

2.2. Ensemble learning

Ensemble learning becomes more and more popular in recent years. Generally, different classifiers have many different characteristics, such as the intrinsic principle and the sensitivity to different training data. It is likely that different classifiers make different predictions for the same data. Ensemble learning can improve the classification performance by combining the predictions of multiple different classifiers into a single robust prediction [14,15]. The two key parts of ensemble learning are base learners and ensemble methods. There are many classification techniques that can be used as base learners such as support vector machine, decision tree [23]. Also, there are mainly three ensemble methods, i.e., bagging, boosting and stacking [24].

In this paper, for the ensemble methods, we use both bagging and stacking to create a two-layer ensemble learning approach. Bagging, also referred to as bootstrapped aggregation, can reduce the variance of the prediction [24]. In bagging, data are sampled uniformly from the original training data set with replacement, so that different sets of sampled data lead to different models even if the algorithms of the models are the same. Eventually, the class of the majority vote from the different models becomes the final prediction label. Stacking is a very general ensemble learning approach, in which two levels of classification are used [24]. In the first level, several different classifiers are trained based on the training dataset. In the second level, a final classifier is trained based on the output of the first-level classifiers.

For the base learner, almost all the classification techniques can be used. However, different techniques have different theoretical

basis so that suitable to different problems. Here we introduce five of the popular classification techniques mentioned above. We select one with best performance as base classifier from them.

1. **Naive Bayes.** Naive Bayes is a probabilistic model based on Bayes theorem for conditional probabilities [23]. Naive Bayes assumes the feature variables are independent of one another. The simplification can quantify the relationship between the feature variables and the target labels as a conditional probability much easier.
2. **Support Vector Machine.** Support Vector Machine (SVM) is developed from traditional linear models [23]. As with all traditional linear models, it use a separating hyperplane as the decision boundary to differentiate two classes. However, traditional linear models only consider empirical error, while SVM considers structural error which includes both empirical error and confidence error. Therefore, the separating hyperplane achieved by SVM has maximum margin between two classes, which makes SVM one of the best classifiers.
3. **Decision Tree.** Decision Tree is modeled with the use of a set of hierarchical decisions on the feature variables, arranged in a tree-like structure [23]. In the tree-constructing process, Decision Tree can rapidly find the feature variables that differentiate different classes the most. In addition, it can generate explicit rules for different classes, while many other classifiers can not.
4. **Linear Discriminant Analysis.** Linear Discriminant Analysis (LDA) is similar to Principle Component Analysis (PCA) in that they both look for a linear combination of feature variables that best explains the data [23]. However, PCA doesn't consider differences between classes, while LDA attempts to model the difference and uses a perpendicular hyperplane to the most discriminating direction as a binary class separator.
5. **Nearest Neighbor Classifier.** Nearest Neighbor Classifier is an instance-based classifier [23]. The principle of it is very simple: Similar instances have similar class labels. For an unlabeled instance, we can check k most similar neighbors of it, and determine its label by the label the majority of the k neighbors belong to. There are many criteria to measure the similarity, such as Euclidean distance and Manhattan distance. In our paper, we use Euclidean distance.

2.3. Technical motivation

The effectiveness of our approach relies on two observations:

Observation 1. Decision tree is a good classifier for just-in-time defect prediction.

Observation 2. Ensemble classifier can achieve better performance than that of a single classifier.

To demonstrate the first observation, we make a rough investigation to look for the technique that performs the best for just-in-time defect prediction. We perform experiments on six datasets, i.e., Bugzilla, Columba, Eclipse JDT, Eclipse Platform, Mozilla and PostgreSQL using ten-fold cross validation[1]). We choose five popular classification techniques which are introduced briefly in the above Section, i.e., Naive Bayes (NB), Support Vector Machine (SVM), Decision Tree (DT), Linear Discriminant Analysis (LDA) and Nearest Neighbours (NN), as the candidates. We train the different classifiers using the same features[2] and we use PofB20 and F1-Score[3] to make comparison of their performances.

Tables 1 and 2 present PofB20 and F1-score of five classification techniques for just-in-time defect prediction. Note that SVM has F1-score of *NAN* in three datasets (i.e., JDT, Mozilla and Platform), which results from the severe imbalance problem of the three datasets (in which the minority class occupies only less than 15% of the whole dataset). The severely imbalanced training data leads to the construction of a poor SVM model and thus the SVM model predicts all the testing data as the majority class. Also because of the same reason, the values of PofB20 generated by SVM in the three datasets are very small (less than 20%). From the table, we can see that Decision Tree, whose average PofB20 is 53% and F1-score is 40%, performs the best for just-in-time defect prediction. Specifically, in terms of PofB20, decision tree can beat the other four classification techniques for all datasets except for one situation, where SVM has a little higher PofB20 than decision tree for the dataset Columba. In terms of F1-score, Decision Tree can beat the other four classification techniques for all datasets except for two situations, where Naive Bayes has a little higher F1-Score than Decision Tree for the datasets JDT and Platform. Therefore, we can conclude that Decision Tree is the best classifier among the five for just-in-time defect prediction and we will use it as base classifier in our proposed approach.

Table 1
PofB20 of five classification techniques for just-in-time defect prediction.

Project	NB(%)	SVM(%)	DT(%)	LDA(%)	NN(%)
Bugzilla	36.91	37.21	52.65	38.27	32.72
Columba	42.40	48.71	46.07	43.28	30.20
JDT	46.22	10.55	52.60	47.49	34.15
Mozilla	49.45	19.11	55.54	52.22	34.06
Platform	56.73	18.91	57.07	52.23	38.16
PostgreSQL	48.33	54.56	56.18	52.51	40.71
Average	46.67	31.51	53.35	47.67	35.00

Table 2
F1-score of five classification techniques for just-in-time defect prediction.

Project	NB	SVM	DT	LDA	NN
Bugzilla	0.5456	0.4593	0.5816	0.4682	0.5322
Columba	0.3780	0.2400	0.4838	0.4166	0.4796
JDT	0.3262	NAN	0.3075	0.1038	0.2702
Mozilla	0.1324	NAN	0.2138	0.1467	0.1817
Platform	0.3476	NAN	0.3316	0.0983	0.3135
PostgreSQL	0.4048	0.3358	0.4803	0.3895	0.4400
Average	0.3558	NAN	0.3998	0.2705	0.3695

The second observation has been demonstrated by many past studies [14,15]. There are two main components in the error of a classifier, i.e., bias and variance. Bias is the difference between the decision boundary of a classifier and the true decision boundary. Variance is caused by different training data. Ensemble classifier can often be used to reduce bias or/and variance [24]. Therefore, ensemble classifier can achieve better performance than that of a single classifier.

The above two observations motivate us to build an ensemble classifier based on decision tree. There have been several studies that leverage bagging [5,25,26] and stacking [25,26] in defect prediction. Unfortunately, whether their combination can improve the performance of defect prediction has not been studied yet. Interestingly, we find that bagging and stacking performs better for *different datasets*; thus, motivating our choice to combine them to allow the strengths of one to cover for the weaknesses of the other. Tables 3 and 4 present PofB20 and F1-score of bagging and stacking techniques (based on decision trees) for just-in-time defect prediction using the dataset that we have described earlier in this section. From the table, we can see that stacking is better than bagging on some datasets (i.e., JDT, Mozilla, Platform C in terms of PofB20), while bagging is the better than stacking on

[1] Detail information of the experiment setup is presented in Section 4.1.
[2] Detail information of the features we use are presented in Section 3.1.
[3] Detail information of the two evaluation metrics are presented in Section 4.2.

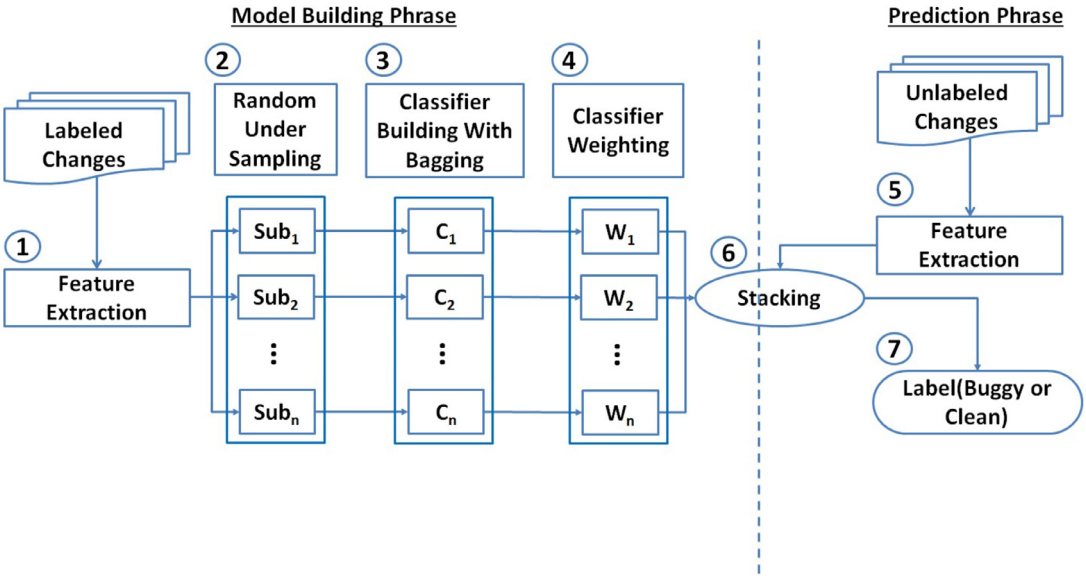


Fig. 1. The Overall Framework of *TLEL*. Sub_i represents a subset of the training datasets by using Random Under-Sampling. C_i represents a base classifier learned based on the corresponding subset. w_i represents a weight of the corresponding base classifier.

Table 3
PofB20 of bagging and stacking techniques for just-in-time defect prediction.

Project	Bagging(%)	Stacking(%)
Bugzilla	45.70	43.57
Columba	42.84	42.03
JDT	49.09	51.05
Mozilla	61.90	70.65
Platform	56.47	58.46
PostgreSQL	53.74	53.25

Table 4
F1-score of bagging and stacking techniques for just-in-time defect prediction.

Project	Bagging	Stacking
Bugzilla	0.6155	0.6789
Columba	0.5231	0.5897
JDT	0.2658	0.4094
Mozilla	0.1659	0.2560
Platform	0.3196	0.4299
PostgreSQL	0.5129	0.5853

some other datasets (e.g., Bugzilla, Columba and PostgreSQL C in terms of PofB20). Therefore, we propose to combine bagging and stacking to build a two-layer ensemble learning model.

3. Our proposed approach

In this section, we present the details of our proposed approach *TLEL*. We first present the overall framework, and then we describe in detail the individual steps in the overall framework.

3.1. Overall framework

Fig. 1 presents the overall framework of our proposed approach *TLEL*. The framework contains two phases: the model building phase and the prediction phase. In the model building phase, our goal is to build an ensemble classifier, by leveraging ensemble learning and decision tree, from historical changes with known labels (i.e., buggy or clean). In the prediction phase, this ensemble classifier would be used to predict if an unknown change would be buggy or clean.

Table 5
Fourteen basic change measures.

Name	Description
NS	The number of modified subsystems [27]
ND	The number of modified directories [27]
NF	The number of modified files [28]
Entropy	Distribution of modified code across each file [29]
LA	Lines of code added [30]
LD	Lines of code deleted [30]
LT	Lines of code in a file before the change [31]
FIX	Whether or not the change is a defect fix [32,33]
NDEV	The number of developers that changed the modified files [33]
AGE	The average time interval between the last and the current change [34]
NUC	The number of unique changes to the modified files [29]
EXP	Developer experience [27]
REXP	Recent developer experience [27]
SEXP	Developer experience on a subsystem [27]

Our framework first extracts a number of features from a set of training changes (i.e., changes with known labels) (Step 1). Features are various quantifiable characteristics of changes that could potentially distinguish changes that are buggy from those that are clean. In this paper, we use the 14 basic features proposed by Kamei et al. [1] as shown in Table 5. In addition, all the features are normalized using z-score method[4] so that the values of all features are in the same order of magnitude.

Next, we construct the base learners based on decision tree (Step 2–4). For each base learner, we firstly perform random under-sampling[5] [35] to handle the class imbalance problem [36] (Step 2). Then, the sampled data is used to train a classifier using Random Forest[6], which is an advanced version of bagging of decision trees (Step 3). After the classifier is trained, we can assign it with a weight (Step 4). The trained classifier together with its weight can be seen as a single unit of the ensemble learner (i.e. base learner). Note that random under-sampling will generate different sampled

[4] Detail information of this technique is presented in Section 3.2.
[5] Detail information of this technique is presented in Section 3.3.
[6] Detail information of this technique is presented in Section 3.4.

data every time so that we can learn many different Random Forest classifiers and corresponding weights when we repeat these steps.

After we have several trained Random Forest classifiers, we construct an ensemble classifier based on them and their corresponding weights using stacking. Note that our training process uses bagging and stacking in turn based on decision tree. Therefore, our approach can be seen as a two-layer ensemble learning technique.

In the prediction phase, the ensemble classifier is then used to predict whether a change with an unknown label is buggy or clean. For each of such changes, our framework first extracts the same set of features and normalize the values of the features using the same method as the model building phrase (Step 5). Next, these features are input into all the trained Random Forest classifiers (Step 6). With these classifiers, different prediction results would be generated. In the end, with the weights of these classifiers, we ensemble the different prediction results to produce a final prediction result, which is one of the following labels: buggy or clean (Step 7).[7]

3.2. Z-score method

Considering that the values of the 14 basic change features are not in the same order of magnitude, we perform data normalization on these features. In this paper, we use the z-score method to do the normalization [23]. It transforms all values to make their average value be 0 and their variance be 1. Given a feature f, we denote the mean and variance of the initial values in f as $mean(f)$ and $std(f)$ respectively. For each value f_i of the feature f, the normalized value z_i is computed as:

$$z_i = \frac{f_i - mean(f)}{std(f)}$$

3.3. Random under-sampling

Random under-sampling [36] is one of the effective approaches to deal with class imbalance problem. It randomly deletes data belonging to the majority class until the amount of data in the majority class is approximately equal to the minority. Random under-sampling can help the learned classifier not to be biased to the majority class, thus in most case it can improve the performance of the classifier [35,37]. In just-in-time defect prediction, the number of clean changes is much more than the buggy changes, which will lead to a bad classifier or even training failure. Therefore, random under-sampling is essential and important for just-in-time defect prediction to make the number of buggy (majority class) and clean (majority class) changes equal.

3.4. Inner layer ensemble: bagging

In the inner layer, we combine decision tree and bagging to build a Random Forest model. Random Forest is an advanced bagging technique based on decision tree [24]. Bagging works best when the base learners are independent and identically distributed. However, traditional decision trees constructed using bagging can't meet this condition. Random Forest solve the problem by introducing randomness into the model building process of each decision tree. In the construction of traditional decision trees, the split of each node are performed by considering the whole set of features, while in random forest, the split in each tree are performed by considering only a random subset of all features. The randomized decision trees have less correlation so that bagging them performs better.

[7] Detail information of this step is presented in Section 3.5.

3.5. Outer layer ensemble: stacking

Due to random under-sampling, we can learn different Random Forest classifiers trained by different subsets of training data. Therefore, we use stacking to ensemble them once more in the outer layer. We simply assign all the classifiers equal weights since all the training data should be treated equally.

For an unlabeled change x, we first input its normalized features into all the trained Random Forest classifiers to obtain different prediction results p. Each p generated by a Random Forest classifier is either 1 (buggy) or -1 (clean). Specifically, assume in a Random Forest classifier, there are nb decision trees that classify x as buggy while nc decision trees that classify x as clean. If $nb > nc$, then the final prediction result p generated by the specific Random Forest classifier will be 1, and otherwise -1. Since we have many Random Forest classifiers, each of which can generate a prediction result, we simply add all the prediction results due to equal weights of all the classifiers to generate $Ensemble(x)$, as follows:

$$Ensemble(x) = \sum_i p_{x,i}$$

According to the above formula, $Ensemble(x)$ can be positive or negative or even 0, depending on the number of prediction results p that are 1 or -1. From the ensemble score, we compute the output score $Out(x)$ as:

$$Out(x) = \frac{Ensemble(x)}{LOC(x)}$$

In the above equation, $LOC(x)$ refer to the number of total lines of code in x. If $Out(x) \geq 0$, we predict the change as buggy; else we predict it as clean.

The output score of a change considers both the likelihood of the change to be buggy and the effort to review the change. Therefore, the output score is a better indicator for sorting changes to be reviewed than the ensemble score. There are prior studies that also take into consideration review cost by dividing with LOC [38–40]. Mende et al. describe a model that takes the module size measured in lines of code into account [38,39]. Kamei et al. revisit bug prediction by making use of effort-aware models [40]. These studies conclude that models perform better when taking review cost into account.

Note that our two-layer ensemble learning approach is not mathematically equivalent to a single-layer random forest with the same number of trees. Below we elaborate it with an example where there are totally 100 decision trees. For a single-layer random forest, its prediction result p (1 or -1) depends on nb and nc (here $nb + nc$ equals to 100). On the contrary, for our two-layer ensemble learning approach, it contains 10 random forests, each of which has 10 decision trees and generates a prediction result p (1 or -1) depends on nb and nc (here $nb + nc$ equals to 10). The output of the 10 random forests are then added together to generate a final result. Due to random under-sampling, the result of a single random forest is not reliable enough while our approach considers the results of 10 random forests. Therefore, our two-layer ensemble learning approach can have more robust and better performance than that of a single-layer random forest.

4. Experiments and results

In this section, we evaluate the effectiveness of *TLEL*. The experimental environment is an Intel(R) Core(TM) T6570 2.00 GHz CPU, 8 GB RAM desktop running Windows 7. We first present our experiment setup and evaluation metrics in Sections 4.1 and 4.2 respectively. We then present six research questions and our experiment results that answer these research questions in Section 4.3.

Table 6
Statistics of the datasets used in our study.

Project	Time	# Instances	% Buggy
Bugzilla	1998.08–2006.12	4620	36%
Columba	2002.11–2006.07	4455	31%
JDT	2001.05–2007.12	35,386	14%
Mozilla	2000.01–2006.12	98,275	5%
Platform	2001.05–2007.12	64,250	14%
PostgreSQL	1996.07–2010.05	20,431	25%

Table 7
Confusion Matrix.

	Predicted buggy	Predicted clean
True Buggy	TP	FN
True Clean	FP	TN

4.1. Experiment setup

We evaluate *TLEL* on six datasets from six well-known open source projects, which are Bugzilla, Columba, Eclipse JDT, Eclipse Platform, Mozilla and PostgreSQL. These datasets are also used by Kamei et al. [1]. Table 6 summarizes the statistics of each dataset, containing the period of each dataset, the total number of instances (i.e., changes), and the proportions of the defective changes. Note that all the datasets are imbalanced. The most imbalanced dataset, Mozilla, contains only 5% defects, while the most balanced dataset, Bugzilla, contains 36% defects.

We use ten-fold cross validation [23] to evaluate the performance of *TLEL*. In 10-fold cross validation, we randomly divide each of the datasets into 10 folds, in which 9 folds are used as training dataset, and the remaining one fold is used as testing dataset. Also, cross validation means each fold is used as testing dataset once. Furthermore, we ensure that each fold has the same class proportion as the original dataset. To make the experiment results more convincing, we run ten-fold cross validation 100 times and record the average performance. Cross validation is a standard evaluation setting, which is widely used in software engineering studies [41,42].

4.2. Evaluation metrics

We use two evaluation metrics to evaluate the performance of our approach *TLEL*. One is cost effectiveness and the other is F1-score.

4.2.1. Cost effectiveness

Cost effectiveness is often used to evaluate defect prediction approaches [18–20,43,44]. Cost effectiveness is measured by computing the percentage of buggy changes found when reviewing a specific percentage of the lines of code. To compute cost-effectiveness, given a number of changes, we firstly sort them according to their output scores. We then simulate to review the changes one-by-one from the highest ranked change to the lowest ranked change and record buggy changes found. Using this process we can obtain the percentage of buggy changes found when reviewing different percentages of lines of code (1%–100%).

4.2.2. F1-score

The F1-score is a commonly-used measure to evaluate classification performance [21,23]. It combines Precision and Recall and can be derived from a confusion matrix, as shown in Table 7. The confusion matrix lists all four possible prediction results. If an instance is correctly classified as "buggy", it is a true positive (TP); if an instance is misclassified as "buggy", it is a false positive (FP). Similarly, there are false negatives (FN) and true negatives (TN). Based on the four numbers, Precision, Recall and F1-score are calculated. Precision is the ratio of correctly predicted "buggy" instances to all instances predicted as "buggy" ($Precision = \frac{TP}{TP+FP}$). Recall is the ratio of the number of correctly predicted "buggy" instances to the actual number of "buggy" instances ($Recall = \frac{TP}{TP+FN}$). Finally, F1-score is a harmonic mean of Precision and Recall: $F1\text{-}score = \frac{2*Recall*Precision}{Recall+Precision}$. F1-score is often used as a summary measure to evaluate if an increase in precision outweighs a reduction in recall (and vice versa).

4.3. Research questions

To evaluate the performance of *TLEL*, we compare it against three baselines. The first baseline is a deep learning approach proposed by us earlier [6]. The approach firstly uses deep belief network to generate a more expressive feature set, and then uses Random Under-Sampling and Logistic Regression. It is referred to as *Deeper* in the following text. The other two baselines are state-of-the-art approaches for defect prediction. One is a dynamic AdaBoost.NC approach proposed by Wang et al. [2]. The approach is based on AdaBoost and decision tree, but it can adjust the parameter in the training process dynamically. It is referred to as *DNC* in the following text. The other is a multiple kernel ensemble learning approach proposed by Wang et al. [3]. The approach is a boosting of multiple SVMs each with different kernel functions. It is referred to as *MKEL* in the following text. We examine our approach in terms of its effectiveness, stability and efficiency in the first four research questions.

TLEL has two tunable parameters, i.e., *NLearner* and *NTree*. *NLearner* is used to specify the number of base ensemble learners (Random Forest Classifiers) constructed. *NTree* is used to specify the number of decision trees in each Random Forest. In our experiments, we assign *NLearner* as 10 and *NTree* as 10 by default. For the fifth research question, we investigate the influence of different values of these parameters.

RQ1 How effective is TLEL?

Motivation. To validate the effectiveness of *TLEL*, we compare it with the three baselines mentioned above.

Approach. We use the two evaluation metrics mentioned above, i.e., cost effectiveness and F1-score, to make comparisons. They are commonly-used measures to evaluate the performance of a defect prediction approach. To make our results more convincing, we perform 10-fold cross validation 100 times and report the average results. In addition, to make fair comparisons, all the ensemble approaches have the same number of base learners. Specifically, there are 100 decision trees in *TLEL* and *DNC*, and there are 100 SVMs in *MKEL*.

For cost effectiveness, we record the percentage of buggy instances found when adding every one percentage of lines of code reviewed. So we will have 100 average values corresponding to the percentage of buggy instances found when reviewing 1%–100% lines of code. We specifically focus on the percentage of buggy instances found when reviewing 20% lines of code, which is referred to as PofB20 [8]. For F1-score, we calculate the average of the 100 F1-score values that we obtain after performing 100 times 10-fold cross validation. We use this average value to compare with the baselines.

In addition, we also calculate p-value and cliff delta to better investigate whether or not TLEL improve the baselines significantly and substantially.

Results. Tables 8–11 present the PofB20, Precision, Recall and F1-score values of *TLEL* as compared with those of the three baselines. From these tables, we can conclude several points.

Table 8
PofB20 values of TLEL and the three baselines.

Project	Deeper (%)	DNC(%)	TLEL(%)	MKEL(%)
Bugzilla	43.52	43.47	61.67	33.02
Columba	41.33	42.39	58.85	30.05
JDT	48.81	54.20	72.55	26.00
Mozilla	68.30	72.52	82.40	50.98
Platform	57.25	62.82	77.08	48.94
PostgreSQL	54.11	56.63	70.64	33.33
Average	**52.22**	**55.34**	**70.53**	**37.05**

Table 9
Precision of TLEL and the three baselines.

Project	Deeper (%)	DNC(%)	TLEL(%)	MKEL(%)
Bugzilla	57.28	57.15	62.39	36.71
Columba	48.01	45.75	51.22	30.55
JDT	26.02	27.37	29.34	14.20
Mozilla	13.23	20.11	15.79	5.19
Platform	26.31	28.66	31.42	14.66
PostgreSQL	46.93	43.58	49.86	25.00
Average	**36.30**	**37.10**	**40.00**	**21.05**

Table 10
Recall of TLEL and the three baselines.

Project	Deeper (%)	DNC(%)	TLEL(%)	MKEL(%)
Bugzilla	69.83	74.90	75.92	1
Columba	67.37	76.52	74.33	1
JDT	69.06	72.32	73.48	1
Mozilla	68.00	61.01	77.75	1
Platform	69.84	76.49	77.48	1
PostgreSQL	66.71	81.41	76.97	1
Average	**68.47**	**73.77**	**75.99**	**1**

Table 11
F1-score of TLEL and the three baselines.

Project	Deeper	DNC	TLEL	MKEL
Bugzilla	0.6292	0.6472	0.6850	0.5371
Columba	0.5606	0.5721	0.6065	0.4680
JDT	0.3779	0.3971	0.4194	0.2488
Mozilla	0.2215	0.3023	0.2625	0.0987
Platform	0.3822	0.4169	0.4471	0.2558
PostgreSQL	0.5509	0.5675	0.6052	0.4000
Average	**0.4537**	**0.4839**	**0.5043**	**0.3352**

First, from Table 8, we can see that the PofB20 values of *TLEL* range from 59% to 82%, which exceed those of the baselines substantially for all the datasets. On average, over 70% of the buggy instances can be found by reviewing only 20% of the lines of code, which is a substantial improvement as compared to the results achieved by the baselines. In addition, the result is also competitive with results reported by many recent studies about defect prediction [38,45]. For example, Ostrand et al. found on average 83% of the defects in 20% of the files [45]. However, note that their 20% of the files actually contains over 50% of the lines of code. And Mende et al. evaluate a model named LoC-MOM on two datasets KC1 and PC5, and find that when considering 20% of the files, LoC-MOM is able to identify around 55% of the defects in KC1 and over 90% in PC5 [38].

Second, from Tables 9 to 11, we can find that in terms of precision, *TLEL* is the best performer by achieving an average precision of 60%. And in terms of recall, *TLEL* is better than *Deeper* and *DNC*. Although *MKEL* has higher Recall than *TLEL*, the Precision of *MKEL* is rather low. Also, in terms of F1-score, which is the summary of the above two indicators, *TLEL* is the best predictor by achieving an average F1-score of 49%.

Table 12
Mappings of Cliff's delta values to effectiveness levels [46].

Cliff's delta (δ)	Effectiveness level
$-1 <= \delta < 0.147$	Negligible
$0.146 <= \delta < 0.33$	Small
$0.33 <= \delta < 0.474$	Medium
$0.474 <= \delta <= 1$	Large

Table 13
Adjusted P-values (after Bonferroni correction) of TLEL compared with the two baselines in terms of F1-Score.

Project	With deeper	With DNC
Bugzilla	< 1.32e−15	< 1.32e−15
Columba	< 1.32e−15	< 1.32e−15
JDT	< 1.32e−15	< 1.32e−15
Mozilla	< 1.32e−15	< 1.32e−15
Platform	< 1.32e−15	< 1.32e−15
PostgreSQL	< 1.32e−15	< 1.32e−15

Third, in the experiment, we find that the approach *MKEL* is the worst in terms of both PofB20 and F1-score in all of the datasets. The direct reason could be that the base learner of *MKEL* is SVM, which has been demonstrated (in Section 2.3) to have worse performance than decision tree for just-in-time defect prediction. In addition, there are actually two big weaknesses of *MKEL*. First, it needs two very huge three-dimension kernel matrixes, one for training data and the other for testing data, which leads to a high space complexity. Second, in *MKEL* the weight update strategy suffers from an algorithmic issue. In the strategy, the weights of defective samples will always increase and not decrease at all, while the weights of non-defective samples will always decrease and not increase at all. Although it seems that the strategy can be a solution to the class imbalance problem, it will lead to infinite loop when sampling using the weights in a later round, say, the 90th round of boosting. This is the case because each time the sampled data must contain two classes, but the tiny weights of non-defective samples in the later round won't allow it. Due to the reason, we set the number of boosting rounds as 50, which we have empirically tried and found to be a suitable number that will avoid the infinite loop issue.

In summary, *TLEL* is more effective than those baselines.

To better demonstrate the superiority of our approach, we perform the Wilcoxon signed-rank statistical test with Bonferroni correction to compute the p-value. We also compute the Cliff's delta. Wilcoxon statistical test is often used to check if the difference in two means is statistically significant (which corresponds to a p-value of less than 0.05). We include the Bonferroni correction to counteract the impact of multiple hypothesis tests. Cliff's delta is often used to check if the difference in two means are substantial. The range of Cliff's delta is in $[-1, 1]$, where -1 or 1 means all values in one group are smaller or larger than those of the other group, and 0 means the data in the two groups is similar. The mappings between Cliff's delta scores and effectiveness levels are shown in Table 12. Note that since *MKEL* suffers from performance and algorithmic issues, we won't compare our approach with it in the remainder of this section. By computing the p-value and Cliff's delta, the extent of which our approach improves over the two baselines can be more rigorously assessed.

Tables 13 and 14 present p-values and Cliff's deltas of *TLEL* compared with the two baselines for each of the six datasets. From the two tables, we can see the effectiveness of our approach more clearly. In terms of cost effectiveness, *TLEL* improves the performance of the baselines statistically significantly and substantially

Table 14
Cliff's delta of TLEL compared with the two baselines in terms of F1-ccore.

Project	With deeper	With DNC
Bugzilla	1(large)	1(large)
Columba	1(large)	1(large)
JDT	1(large)	1(large)
Mozilla	1(large)	−1(negligible)
Platform	1(large)	1(large)
PostgreSQL	1(large)	1(large)

in all datasets. In terms of F1-score, *TLEL* improves the performance of the baselines statistically significantly and substantially in five out of the six datasets.

TLEL is more effective than the two baselines for just-in-time defect prediction. On average, by reviewing only 20% lines of code, over 70% of the buggy changes can be found with it.

RQ2 How effective is TLEL *when different percentages of LOC are inspected?*
Motivation. We have validated the effectiveness of *TLEL* in terms of cost effectiveness and F1-score in the first research question. We have demonstrated that *TLEL* outperforms the baselines in terms of cost effectiveness statistically significantly and substantially. We want to go further by showing the percentage of buggy instances found when reviewing different amount of lines of code using *TLEL*. Given the same amount of lines of code reviewed, the more buggy instances found, the more useful an approach is.

Approach. We record the percentage of buggy instances found when adding every one percentage of lines of code reviewed. So we will have 100 average values corresponding to the percentage of buggy instances found when reviewing 1%–100% lines of code. We can generate a figure whose x-axis represents the percentage of code reviewed and y-axis represents the percentage of defects found for each dataset. In each chart there are three lines, representing *TLEL, Deeper* and *DNC* correspondingly.

Results. Fig. 2 shows six charts comparing the cost effectiveness of our approach *TLEL* with two baselines, *Deeper* and *DNC*, for different percentages of LOC inspected. The black solid curve corresponds to *TLEL*, the blue dashed curve corresponds to *Deeper* and the red dashed curve corresponds to *DNC*. From the charts, we can see that the red solid curves are always more convex than the blue dashed curves, which means that our approach can always detect more buggy changes than the two baselines in the whole range of percentages of LOC inspected. Therefore, the performance of our approach *TLEL* is much better than *DNC* and *Deeper* in terms of the cost effectiveness.

TLEL can identify more buggy changes than Deeper and DNC for a wide range of lines of code inspected.

RQ3 What is the benefit of using two ensemble layers in TLEL?
Motivation. We have validated the effectiveness of *TLEL* through the above two research questions. *TLEL* clearly outperforms the two state-of-the-art baselines. In this RQ, we want to go further by investigating the individual contribution of the two ensemble layers of *TLEL*.

Approach. To measure the individual contribution of the two ensemble layers to the overall performance of *TLEL*, we create two incomplete versions of *TLEL* – referred to as *Sub-1* and *Sub-2* respectively. For *Sub-1*, we use the inner layer ensemble bagging method to create a single random forest. The detail is the same as Section 3.4 but we do not use stacking. For *Sub-2*, we only use the outer layer ensemble stacking method to create another kind of ensemble of decision trees. The detail is the same as Section 3.5 except that we replace random forest with decision tree. Note that both *TLEL* and *Sub-2* use undersampling, so we also apply undersampling to *Sub-1*. That is, in *Sub-1* we first use undersampling to balance the training data and then build a single random forest. In addition, all the approaches take review cost into consideration by dividing with *LOC*. We can then observe the individual contribution of the two ensemble layers by comparing the performance of *Sub-1, Sub-2* and *TLEL*. Also note that the total number of base learners used by all the approaches are the same (i.e., 100) for a fair comparison.

Table 15
Individual contribution of each ensemble layer in terms of PofB20.

Project	Sub-1(%)	Sub-2(%)	TLEL(%)
Bugzilla	61.08	60.73	61.67
Columba	58.05	57.35	58.85
JDT	71.80	71.52	72.55
Mozilla	81.26	81.37	82.40
Platform	75.55	75.66	77.08
PostgreSQL	69.23	68.96	70.64
Average	**69.50**	**69.27**	**70.53**

Table 16
Individual contribution of each ensemble layer in terms of F1-score.

Project	Sub-1	Sub-2	TLEL
Bugzilla	0.6503	0.6789	0.6850
Columba	0.5783	0.5897	0.6065
JDT	0.3871	0.4094	0.4194
Mozilla	0.2300	0.2560	0.2625
Platform	0.4080	0.4299	0.4471
PostgreSQL	0.5647	0.5853	0.6052
Average	**0.4697**	**0.4915**	**0.5043**

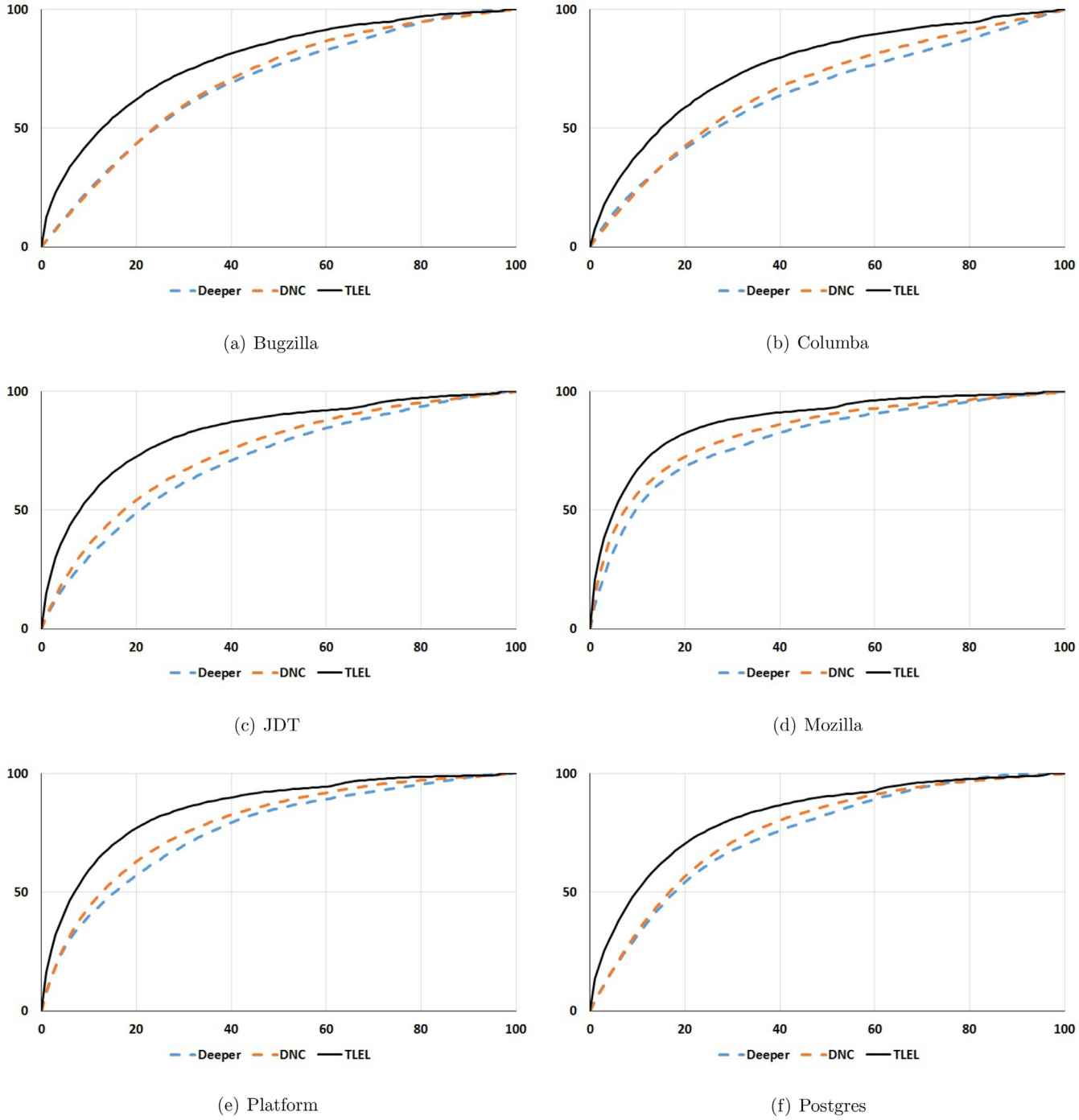
Table 17
Adjusted P-values (after Bonferroni correction) of TLEL compared with Sub-1 and Sub-2 in terms of PofB20.

Project	With Sub-1	With Sub-2
Bugzilla	< 1.32e−15	< 1.32e−15
Columba	< 1.32e−15	< 1.32e−15
JDT	< 1.32e−15	< 1.32e−15
Mozilla	< 1.32e−15	< 1.32e−15
Platform	< 1.32e−15	< 1.32e−15
PostgreSQL	< 1.32e−15	< 1.32e−15

Table 18
Cliff's deltas of TLEL compared with Sub-1 and Sub-2 in terms of PofB20.

Project	With Sub-1	With Sub-2
Bugzilla	1(large)	1(large)
Columba	1(large)	1(large)
JDT	1(large)	1(large)
Mozilla	1(large)	1(large)
Platform	1(large)	1(large)
PostgreSQL	1(large)	1(large)

Results. Tables 15 and 16 show the performance of *Sub-1, Sub-2* and *TLEL*. From the tables, we can note that *TLEL* outperforms *Sub-1* and *Sub-2* in all the datasets in terms of both PofB20 and F1-score. To better demonstrate the superiority of our approach to *Sub-1* and *Sub-2*, we compute p-values (with Bonferroni correction) and Cliff's delta as we do in RQ1.



(a) Bugzilla (b) Columba

(c) JDT (d) Mozilla

(e) Platform (f) Postgres

Fig. 2. Cost effectiveness trends for the six datasets.

Tables 17 and 18 present p-values and Cliff's deltas of *TLEL* compared with *Sub-1* and *Sub-2* for each of the six datasets. From the two tables, we can see the effectiveness of our approach more clearly. Through Wilcoxon signed-rank statistical test and Cliff's delta we find that the improvement achieved by our approach is statistically significant and substantial to both *Sub-1* and *Sub-2* in terms of both cost effectiveness and F1-score. It indicates that both of the two ensemble layers contribute to the overall performance of *TLEL*, and removing any one of them degrades the overall performance.

Both of the two ensemble layers contribute to the good performance of TLEL.

RQ4 What is the effect of varying the amount of training data on the effectiveness of TLEL?

Motivation. For some projects, the amount of training data (i.e., changes known to be buggy or non-buggy) can be limited. Thus, in this research question, we want to investigate the stability of *TLEL* by varying the amount of training data.

Approach. In the above research questions, we perform 10-fold cross validations which means that 90% of the data are used for training and 10% of data are used for testing. In this RQ, we perform 2-fold to 10-fold cross validations on the datasets. To make the results more convincing, we also perform each kind of cross validation 10 times. For each dataset, we plot two curves on one

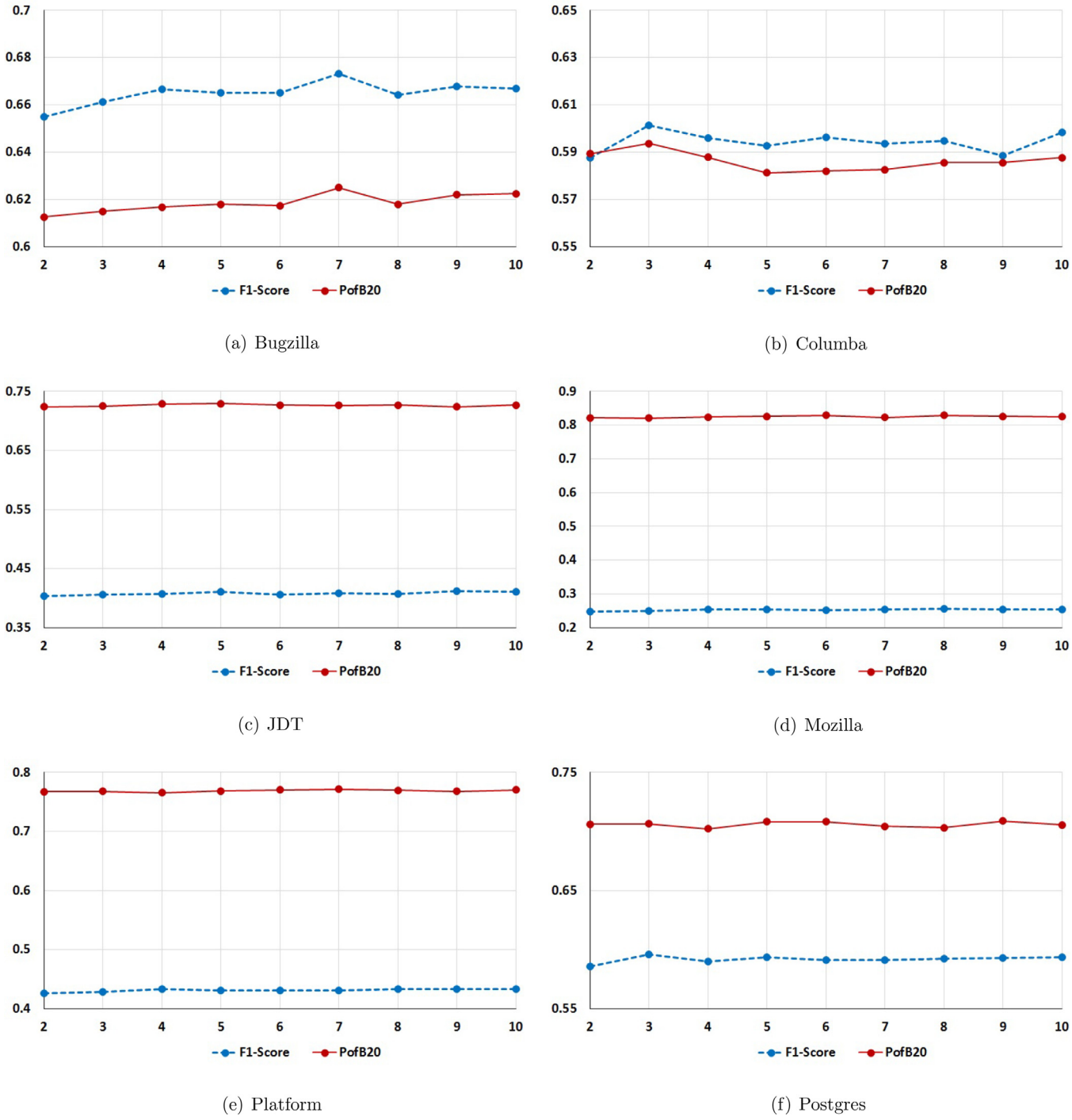


Fig. 3. Two-to-ten fold validation results on six datasets.

chart showing the PofB20 values and F1-scores for 2-folds to 10-folds cross validations.

Results. Fig. 3 presents the PofB20 values (red solid line) and F1-scores (blue dashed line) for different cross validations. In the figure, the curves are very stable. In terms of PofB20, the biggest fluctuation is less than 2%. In terms of F1-score, the biggest fluctuation is less than 3%. Therefore, we can conclude that *TLEL* has good stability and can work with different amount of training data very well.

TLEL is stable and able to work well for reduced amount of training data.

RQ5 How much time does it take for TLEL to run?

Motivation. Now that we have examined the effectiveness and the stability (with reduced training data) of our approach *TLEL*, we shall test the efficiency of *TLEL*. The efficiency of an approach is also an important indicator to evaluate whether or not the approach is good enough.

Approach. In order to answer the question, we measure the training and testing time of *TLEL*. The training time includes the time

Table 19
Training time of TLEL and the two baselines (in seconds).

Project	Deeper	DNC	TLEL
Bugzilla	4.56	5.88	1.65
Columba	3.77	7.08	1.55
JDT	9.40	101.75	4.14
Mozilla	13.31	723.65	4.73
Platform	23.91	439.38	7.95
PostgreSQL	11.74	40.48	3.81
Average	**11.12**	**219.70**	**3.97**

Table 20
Testing time of TLEL and the two baselines (in seconds).

Project	Deeper	DNC	TLEL
Bugzilla	0.002	0.02	0.06
Columba	0.004	0.02	0.07
JDT	0.005	0.20	0.09
Mozilla	0.021	0.60	0.16
Platform	0.011	0.52	0.14
PostgreSQL	0.006	0.10	0.07
Average	**0.008**	**0.24**	**0.10**

taken for all the rounds of random under-sampling and base learner training. The testing time is the time taken to produce all the prediction results for the whole testing dataset.

Results. Tables 19 and 20 present the training time and testing time of *TLEL* and the baselines on the six datasets. From Table 19, it takes only less than 4 s on average for *TLEL* to finish training a statistical model, while *Deeper* needs more than 10 s and *DNC* needs more than 200 s. From Table 20, the testing time of all approaches are very small, less than 1 s, which is quite acceptable.

> *On average, TLEL needs less than 4 s to build a statistical model and about 0.1 s to do the prediction, which we believe to be reasonably good.*

RQ6 What is the effect of varying the two parameters settings?
Motivation. We have shown the superiority of our approach *TLEL* in terms of its effectiveness, stability and efficiency. Note that in *TLEL*, there are two parameters (i.e., *NTree* and *NLearner*) that can be tuned. Therefore, we want to examine the effect of varying these parameters.

Approach. In order to answer the question, we perform two sets of experiments. In each set, we only change one parameter and fix the other parameter to see its individual influence to *TLEL*. For example, to examine the effect of parameter *NTree*, we only vary the value of *NTree* and fix *NLearner* to its default value (i.e., 10). We vary *NTree* from 1 to 20 when fixing *NLearner*, and vary *NLearner* from 1 to 20 when fixing *NTree*. Therefore, the total number of decision trees varies from 10 to 200. For each dataset, we plot two curves on one chart showing the PofB20 values and F1-scores for varying the two parameters settings.

Results. Figs. 4 and 5 present the effect of varying the values of the two parameters *NTree* and *NLearner* on the performance of *TLEL* on six datasets. From these figures, we can conclude several points.

First, for *NTree*, we can see that varying their values has little influence on the performance in terms of both PofB20 and F1-score. In all the datasets, the values of the two metrics change little when the values of *NTree* change. The biggest fluctuation is less than 0.05.

Second, for *NLearner*, we can find that varying its value has some influence on the performance in terms of both PofB20 and F1-score. Specifically, for PofB20 there is some improvement when *NLearner* varies from 1 to 10. However, the performances are similar when *NLearner* varies from 10 to 20. This indicates that the performance of *TLEL* improves with the increase of the number of base learners in the beginning, but remain stable when the number of base learners increases to a proper number.

Table 21
A clear comparison of two parameter settings in terms of PofB20.

Project	NTree=5 & NLearner=10 (%)	NTree=10 & NLearner=5 (%)
Bugzilla	61.67	61.97
Columba	59.37	57.83
JDT	73.06	72.04
Mozilla	82.58	81.26
Platform	77.19	76.24
PostgreSQL	70.52	70.05
Average	**70.73**	**69.90**

Table 22
A clear comparison of two parameter settings in terms of F1-score.

Project	NTree=5 & NLearner=10	NTree=10 & NLearner=5
Bugzilla	0.6838	0.6642
Columba	0.6202	0.5957
JDT	0.4284	0.4066
Mozilla	0.2719	0.2503
Platform	0.4526	0.4289
PostgreSQL	0.6108	0.5947
Average	**0.5113**	**0.4901**

Third, when considering *NTree* and *NLearner* together, we can find that the same number of base learners (decision trees) does not necessarily lead to the same performance. For example, the performance generated when *NTree* is 5 and *NLearner* is 10 is better than the performance generated when *NTree* is 10 and *NLearner* is 5. Tables 21 and 22 present a clear comparison of the two parameter settings in terms of PofB20 and F1-score. We can clearly see that the performance of the first parameter setting is better than that of the second parameter setting in terms of both PofB20 and F1-score. It indicates implicitly that the two ensemble layers have different contributions to *TLEL*.

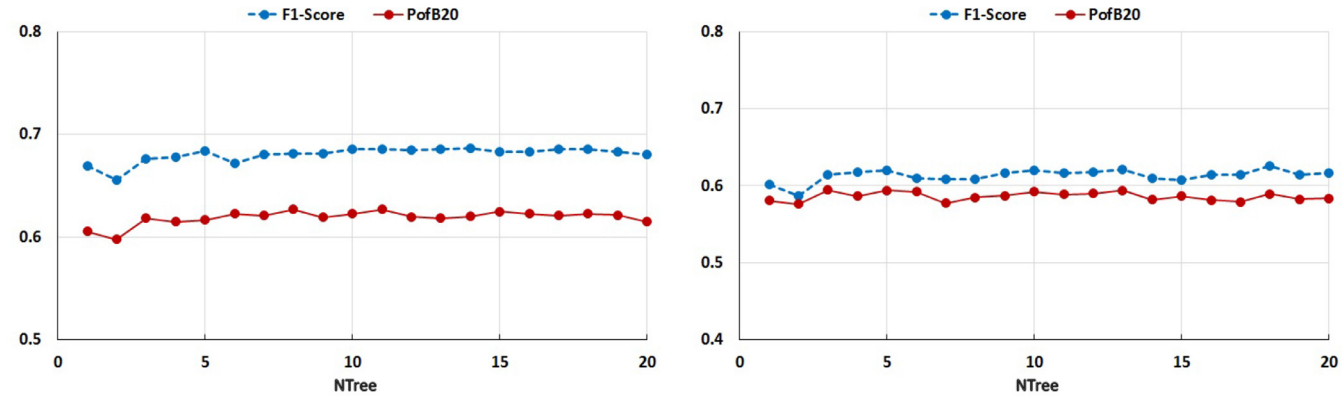
> *TLEL performance remains more or less the same when NTree is increased. On the other hand, its performance improves when NLearner is increased but the performance gain tapers off after NLearner reaches a certain number (i.e., 10).*

5. Discussion

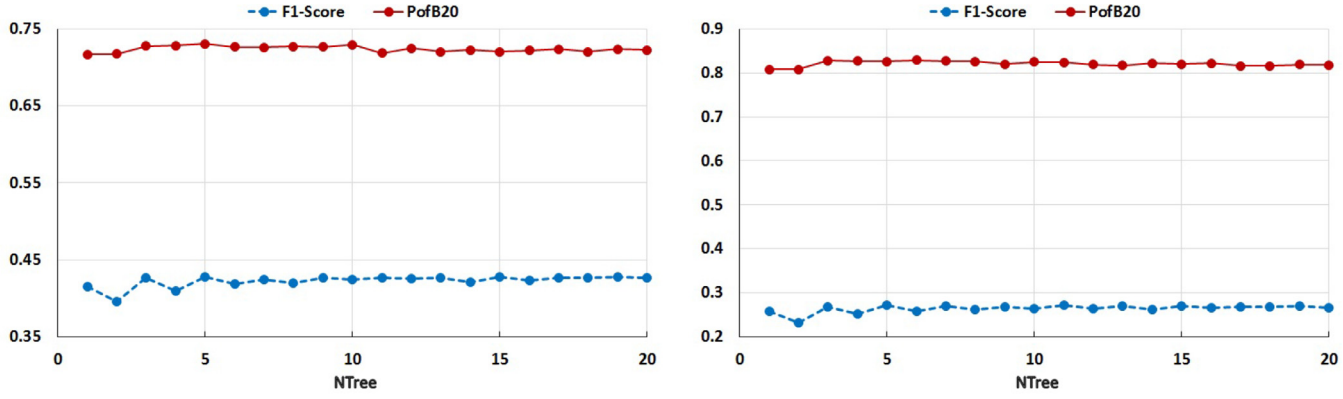
We have investigated six research questions about *TLEL* and shown the superiority of our approach *TLEL*. However, there still exists one point that can be discussed.

TLEL is compared with three baselines. Among them, *Deeper* is a state-of-the-art deep learning approach for just-in-time defect prediction, while *DNC* and *MKEL* are two state-of-the-art ensemble learning approaches. Actually, when comparing different ensemble approaches, it would be good to also see the differences in performance when using the same base learner. However, the base learners of *TLEL* and *DNC* are the same (i.e., decision tree), while the base learner of *MKEL* is SVM. To better demonstrate the superiority of our ensemble learning approach, we create a variant of *TLEL* (referred to as *TLEL_SVM*) by replacing the base learner of *TLEL* with SVM, and we compare *MKEL, TLEL_SVM* and *TLEL*. Note that the experiment setting is the same as the one described in Section 4.

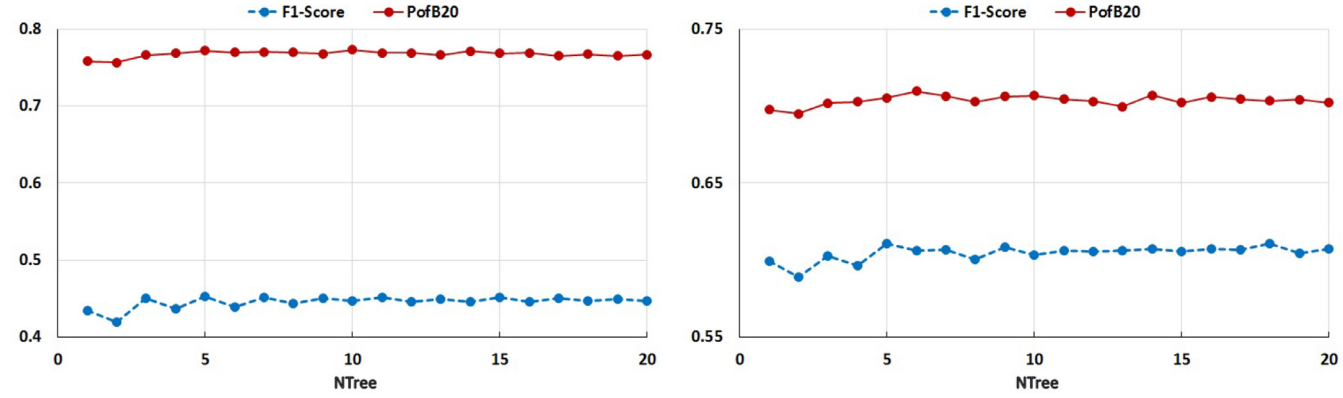
Tables 23 and 24 present the performances of *MKEL, TLEL_SVM* and *TLEL* in terms of PofB20 and F1-score. From these tables, we can see that when using the same base learner, *TLEL_SVM* is better



(a) Bugzilla (b) Columba



(c) JDT (d) Mozilla



(e) Platform (f) Postgres

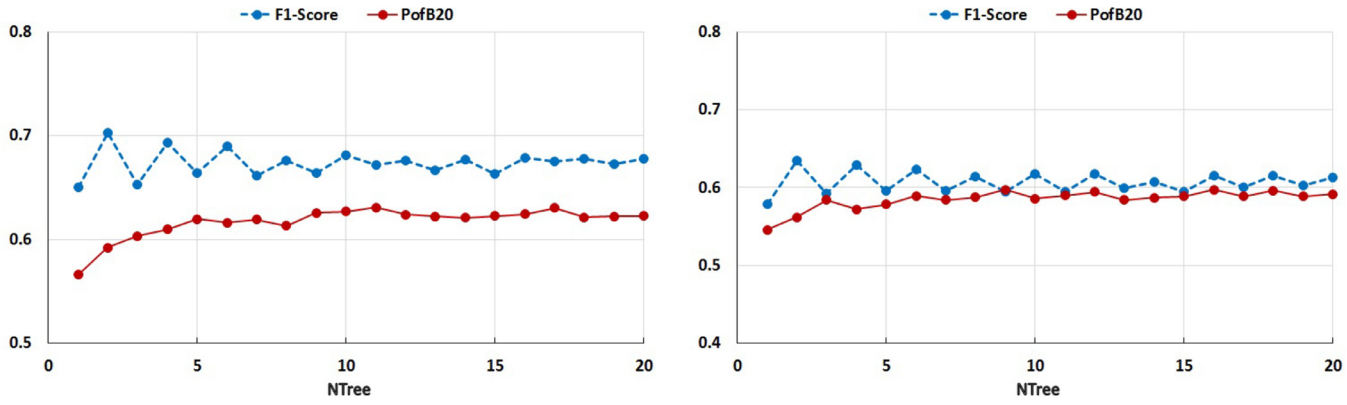
Fig. 4. The effect of varying parameter *NTree* when *NLearner*=10 on the performance of our approach on six datasets.

Table 23
The performance of TLEL compared with TLEL_SVM in terms of PofB20.

Project	MKEL(%)	TLEL_SVM(%)	TLEL(%)
Bugzilla	33.02	55.37	61.67
Columba	30.05	54.45	58.85
JDT	26.00	61.37	72.55
Mozilla	50.98	61.22	82.40
Platform	48.94	61.63	77.08
PostgreSQL	33.33	58.08	70.64
Average	**37.05**	**58.69**	**70.53**

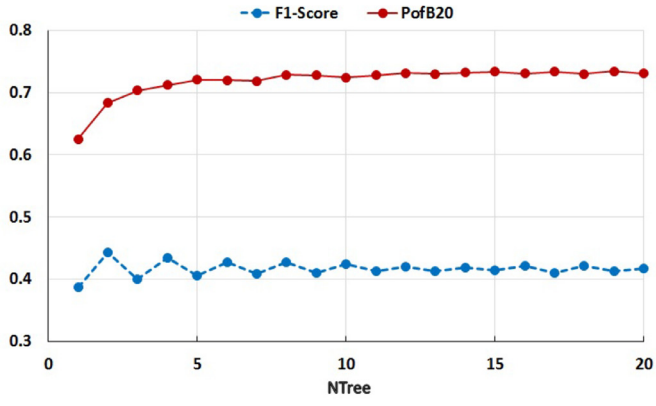
Table 24
The performance of TLEL compared with TLEL_SVM in terms of F1-score.

Project	MKEL	TLEL_SVM	TLEL
Bugzilla	0.5371	0.6061	0.6850
Columba	0.4608	0.5482	0.6065
JDT	0.2488	0.3538	0.4194
Mozilla	0.0987	0.1969	0.2625
Platform	0.2558	0.3435	0.4471
PostgreSQL	0.4000	0.5357	0.6052
Average	**0.3352**	**0.4307**	**0.5043**

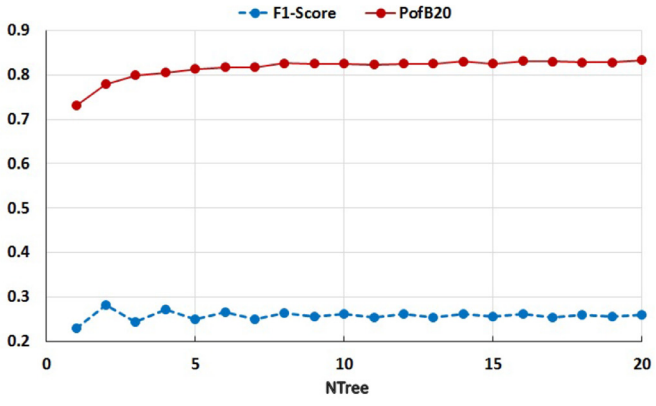


(a) Bugzilla

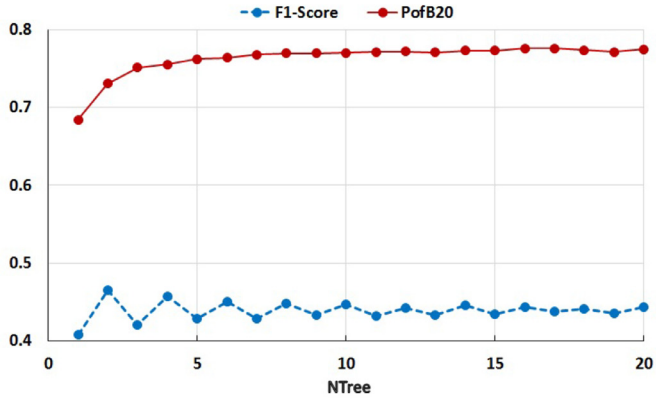
(b) Columba



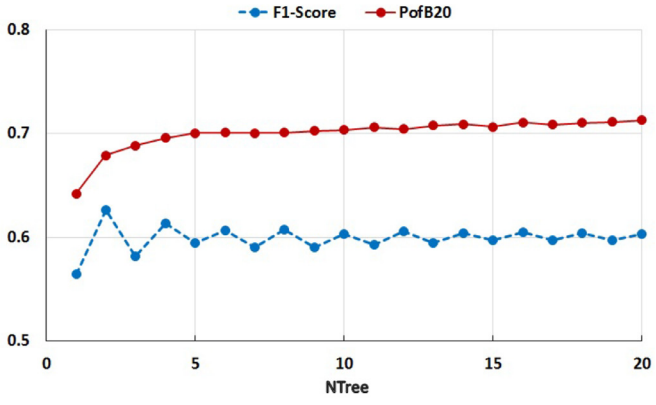
(c) JDT



(d) Mozilla



(e) Platform



(f) Postgres

Fig. 5. The Effect of Varying Parameter *NLearner* When *NTree*=10 on the Performance of Our Approach on Six Datasets.

than *MKEL* for all datasets in terms of PofB20 and F1-score, which further demonstrates the superiority of our ensemble learning approach *TLEL*. In addition, the performance of *TLEL_SVM* is worse than that of *TLEL*. It indicates that decision tree is indeed better than SVM as the base learner, which corresponds to the first observation described in Section 2.3.

5.1. Threats to validity

Threats to internal validity relate to errors in our experiments. We have double checked our experiments and implementations. Still, there could be errors that we did not notice. Threats to external validity relate to the generalizability of our results. We have evaluated our approach on 137,417 changes from six open source projects. In the future, we plan to reduce this threat further by analyzing even more datasets from more open source and commercial software projects. Threats to construct validity refer to the suitability of our evaluation metrics. We use cost effectiveness and F1-score which are also used by past software engineering studies to evaluate the effectiveness of various prediction tech-

niques [12,17–19,21,22,47]. Thus, we believe there is little threat to construct validity.

6. Related work

We classify related work into two parts. The first part is about studies on defect prediction. The second part is about studies on ensemble learning.

6.1. Defect prediction

There are some prior studies on just-in-time defect prediction. Mockus et al. predict defects at change-level in a telecommunication system [27]. They propose a number of measures that characterize a change including change diffusion, change size, change purpose and so on, and use logistic regression to do prediction. All the change measures satisfy three basic conditions: The measure can be computed automatically from changes, the measure can be obtained immediately after changes, and the measure can reflect a property of changes. Kim et al. predict defects at change-level in 12 open source projects [12]. They use Support Vector Machine to predict whether or not a change will lead to a bug. Kamei et al. perform a large-scale empirical study of just-in-time defect prediction [1]. They choose 14 change measures that perform well in traditional defect prediction research and build Logistic Regression models to predict if changes are defective or not.

There are many studies on traditional defect prediction. Zimmermann et al. use network analysis to analyze dependencies between various pieces of code, which can help managers to identify central program units that are more likely to be defective [10]. Zimmermann et al. propose a cross-project defect prediction approach; they train a model on a source project which is selected considering several factors, and use the model on a given target project [48]. Turhan et al. employ a k-nearest neighbor algorithm for cross-project defect prediction, which selects 10 nearest instances from source projects to be used as training data for a target project [11]. D'Ambros et al. present a benchmark for defect prediction and provide an extensive comparison of well-known approaches used for defect prediction in their survey [9]. Rahman et al. analyze code metrics from several different perspectives, and build prediction models across 12 large open source projects to understand the performance, stability, portability and stasis of different sets of metrics for defect prediction [18]. Nam et al. propose TCA+, a novel approach to make feature distributions in source projects similar to that of target projects, which can improve the performance of cross-project defect prediction [21].

6.2. Ensemble learning

In defect prediction, class imbalance is a severe problem. Class imbalance is a situation in which the instances of some classes are much less than those of other classes [36]. Ensemble learning is one of the best solutions to class imbalance problem [49,50]. In addition, ensemble learning can combine strengths of different base learners so that it can achieve much better classification performance [14,15].

There are many studies on applying ensemble learning to defect prediction. Based on the class-imbalance learning method AdaBoost.NC [36], Wang et al. propose a dynamic version of AdaBoost.NC for software defect prediction [2]. The approach uses decision tree as base learner and can adjust its parameters dynamically during the training process. Based on the multiple kernel boosting approach MKBoost [51], Wang et al. propose a multiple kernel ensemble learning approach for software defect prediction [3]. The approach uses boosting method. In each boosting round, different kernels are tried and the SVM with the best kernel is chosen as base ensemble learner. Zheng proposes a boosted neural network with cost-sensitive method to improve the performance of software defect prediction [4]. In the approach the misclassification costs are considered in the weight-update strategy. Sun et al. present a coding-based ensemble learning method for software defect prediction [5]. The approach converts imbalanced binary-class data into balanced multi-class data. Rodriguez et al. suggest a descriptive approach for defect prediction [16]. They use two well-known subgroup discovery algorithms to obtain rules that identify defect prone modules. Different from theirs, our approach is a two-layer ensemble learning approach based on classic classification techniques.

7. Conclusion and future work

In this paper, we propose a two-layer ensemble learning approach *TLEL* for just-in-time defect prediction. The approach has two layers of ensemble learning technique. In the inner layer, we combine Decision Tree and Bagging to build a Random Forest model. In the outer layer, we use random under-sampling to train many different Random Forest models and ensemble them once more using stacking. We evaluate *TLEL* on datasets taken from six large open source projects and use two evaluation metrics which are cost effectiveness and F1-score. We compare *TLEL* with three baselines, i.e., *Deeper, DNC* and *MKEL*. The results show that *TLEL* is the best in terms of the two metrics. For cost effectiveness, our approach can identify over 70% defective changes by reviewing only 20% lines of code, which is much more than the defective changes that can be identified by the three baselines. In addition, our approach achieve an average F1-score of close to 50%.

In the future, we plan to improve the performance of our approach by optimizing parameters of *TLEL*. We also plan to perform experiments on more datasets to reduce the threats to external validity.

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