A Comparison of Source Code Representation Methods to Predict Vulnerability Inducing Code Changes

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Keywords: Software Vulnerabilities, Software Metrics, Embeddings, Abstract Syntax Tree.

Abstract: Vulnerability prediction is a data-driven process that utilizes previous vulnerability records and their associated fixes in software development projects. Vulnerability records are rarely observed compared to other defects, even in large projects, and are usually not directly linked to the related code changes in the bug tracking system. Thus, preparing a vulnerability dataset and building a predicting model is quite challenging. There exist many studies proposing software metrics-based or embedding/token-based approaches to predict software vulnerabilities over code changes. In this study, we aim to compare the performance of two different approaches in predicting code changes that induce vulnerabilities. While the first approach is based on an aggregation of software metrics, the second approach is based on embedding representation of the source code using an Abstract Syntax Tree and skip-gram techniques. We employed Deep Learning and popular Machine Learning algorithms to predict vulnerability-inducing code changes. We report our empirical analysis over code changes on the publicly available SmartSHARK dataset that we extended by adding real vulnerability data. Software metrics-based code representation method shows a better classification performance than embedding-based code representation method in terms of recall, precision and F1-Score.

1 INTRODUCTION

Software security is a significant characteristic of software quality (ISO, 2011). Software professionals monitor and check potential attacks on software systems after development with the help of detection systems and testing approaches. Still, it is practically more useful and easier to maintain vulnerability-free software systems that are designed and built considering security practices (McGraw, 2006). Software vulnerabilities are weaknesses in the protection effort of an asset in a system that an attacker can exploit to gain access to a computer system and negatively affect its security (McGraw, 2008). Although vulnerabilities are rarely observed compared to other software defects, they are inevitable for some software systems and require more effort to address. Therefore, it is critical to detect and mitigate risks of vulnerabilities in the early stage of the life cycle before a software system is released (McGraw, 2006).

Building a vulnerability prediction model is a data-driven process that utilizes historical vulnerability data to classify vulnerable modules at different granularity levels. However, extracting real vulnerability data is challenging as vulnerabilities are usually not directly linked to the related bug reports or associated code changes. Except for studies in which curated labels for vulnerabilities are manually generated by security experts (Şahin et al., 2022), there are also studies that use static code analyzers (Scandariato et al., 2014) or synthetic vulnerability data (Ghaffarian and Shahriari, 2021) to evaluate the performance of vulnerability prediction models. Furthermore, previous studies study at different granularity levels, such as file-component level (Shin and Williams, 2013), release level (Smith and Williams, 2011), or function/method level (Cao et al., 2020; Chakraborty et al., 2021). Although method level is the lowest granularity that pinpoints the location, it can produce many false positives. File level can also be too big to cover if files are large in size.

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Halepmollası, R., Hanifi, K., Fouladi, R. and Tosun, A.
A Comparison of Source Code Representation Methods to Predict Vulnerability Inducing Code Changes.
DOI: 10.5220/0011859300003464
In *Proceedings of the 18th International Conference on Evaluation of Novel Approaches to Software Engineering (ENASE 2023)*, pages 469-478
ISBN: 978-989-758-647-7; ISSN: 2184-4895

In this study, we employ various ML and DL algorithms to classify vulnerable code changes of several projects with real vulnerability data, and compare two different source code representations in prediction. We identify our research question as follows: *To what extent do different kinds of source code representations predict vulnerability inducing code changes?* The contributions of our study are summarized as follows:

- We utilize two different source code representation techniques that are software metrics and AST based embeddings to compare their effects on predicting vulnerable code changes.
- We use SmartSHARK dataset(Trautsch et al., 2021) that is quite comprehensive in terms of commits and software metrics. However, the dataset does not contain the projects' vulnerabilities. We mined vulnerabilities from National Vulnerability Database (NVD)[1] and linked them to their associated fixing commits from project-specific issue tracking systems. We also identified vulnerability-inducing changes using SZZ. Eventually, we propose an extended SmartSHARK in terms of reported vulnerabilities.
- We perform predictions at code change-level instead of file-component or method level, as it gives instant feedback. The proposed method can analyse code changes and predict vulnerabilities after each commit. With this model, we continuously check only code changes, thus, the complexity and the analysing time are reduced.

2 RELATED WORK

To predict vulnerabilities through source code requires some kind of modeling of the code, either in the form of metrics, or other (token, embedding or graphical) representations. Traditional software metrics such as size, complexity, coupling, code churn, and fault history are widely used to predict software defects and results in promising performance (Li and Shao, 2019; Tosun and Bener, 2009). Several studies also investigate the use of software metrics for vulnerability prediction: Shin and Williams (Shin and Williams, 2008) investigate the validity of a hypothesis that asserts software complexity is the enemy of software security. They explore the usage of nine different complexity metrics, commonly utilized in software defect prediction, to predict security issues. Their analysis on Mozilla JavaScript Engine to identify vulnerability-prone code parts report that those nine metrics have a weak correlation with vulnerabilities. Later, Shin and Williams (Shin and Williams, 2013) also validate the aforementioned hypothesis. They observe that the correlations between complexity metrics and vulnerabilities are weak but statistically significant.

Chowdhury and Zulkernine (Chowdhury and Zulkernine, 2011) investigate whether code complexity, coupling and cohesion, i.e., structural metrics, can be used for vulnerability prediction. They built various classifiers using these metrics for 52 Mozilla Firefox releases, and conclude that structural metrics are useful to predict vulnerabilities.

With the growing success of natural language processing models, text-mining-based methods have emerged as an alternative approach for extracting source code features. Alon et al. (Alon et al., 2019) propose code2vec as a neural network-based model to represent source code as a continuous distributed vector. First, the Abstract Syntax Tree (AST) of the code is broken down into a set of paths, and then, the method learns the atomic representation of each path while trying to aggregate them as a set. Lozoya et al. (Lozoya et al., 2021) propose a code embedding technique called comit2vec, based on code2vec. Instead of embedding representation of the code itself, this technique focuses on code change representation to classify security-relevant commits.

Furthermore, word embedding techniques have also been used to transfer the source code into the numerical vector. Harer et al. (Harer et al., 2018) generated popular word2vec embeddings for C/C++ tokens and utilized these for vulnerability prediction. Henkel et al. (Henkel et al., 2018) applied the GloVe model to extract word embeddings from the AST of the C source code. Fang et al. (Fang et al., 2020) propose the FastEmbed technique for vulnerability prediction based on an ensemble of ML models.

Hanifi et al. (Hanifi et al., 2023) proposed 1D CNN based method for vulnerability prediction on function level. While preserving the structural and semantic information in the source code, the method transforms the AST of the source code into a numerical vector. Sahin et al. (Şahin et al., 2022) propose a vulnerability prediction model using different code representations to explore whether a function at a specific code change is vulnerable or not. They represent the function versions as node embeddings learned from their AST, and build models using two Graph Neural Networks with node embeddings and Convolutional Neural Network (CNN) and Support Vector Machine (SVM) with token representations.

Moreover, there exist studies that compare the performance of software metrics-based and text mining-

[1] National Vulnerability Database. https://nvd.nist.gov

based vulnerability prediction models. In an early study, two kinds of vulnerability prediction models are proposed using text mining based and software metrics on PHP web applications (Walden et al., 2014). Also, Kalouptsoglou et al.(Kalouptsoglou et al., 2022) trained an ensemble model using software metrics and Bag of Words (BoW) to detect vulnerabilities in JavaScript codes. According to these studies, text mining-based models outperform software metrics-based models. Although our aim is similar, we differ from these studies in terms of applied source code representation techniques (BoW vs deep learning based embeddings) and software metrics (static vs structural metrics). Additionally, both studies report at function level whereas we predict at code change level.

3 DATASET

To perform empirical analysis, we utilize the SmartSHARK dataset MongoDB Release 2.1[2]. SmartSHARK enables to conduct a comprehensive empirical study and consists of 77 projects belonging to Apache Software Foundation repository which is a well-known ecosystem developed in Java. In the dataset, the projects include between 1,000 and 20,000 commits. SmartSHARK contains 47,303 pull requests, 163,057 issues, and 366,322 commits. Moreover, it has data including refactoring activities, developer information, code changes, clone instance, and bug-fixing activities.

The size of the complete dataset stored in MongoDB is 1.2 TB and some of which is not relevant to our study. Therefore, we created custom MongoDB scripts in the source dataset and converted output from bson format to csv format for analysis. We first determined the collections we need to use. We extracted *commit* collection to generate the labelled data and *project* and *vcs_system* collections to filter the projects we determined. We also extracted *code_group_state* collection, which contains the results of the static analysis run on the repository at each commit, to use in the software metrics-based approach. When obtaining the issue tracking data of the projects, we extracted *issue* collection that contains the data about the issue itself and *issue_system* collection that stores the issue tracking system id.

We extracted the changed files in each project's commits using git commands and parsed those to filter the changed Java files as selected projects were developed in Java language. Also, we filtered out the merged commits during the analysis as they have two parent commits and those commits could lead us to compute the same metric twice.

3.1 Creating the Vulnerability Dataset

To create a suitable dataset for building vulnerability prediction models, we applied the following steps:

Extracting the Vulnerability Information. SmartSHARK dataset does not include the vulnerabilities of projects. Therefore, we extended the dataset by adding the vulnerabilities and their associated fixing commits. To this end, we manually curated the real vulnerability dataset that consists of vulnerabilities analyzed from NVD for 77 projects. Vulnerabilities published in NVD are indexed according to Common Vulnerabilities and Exposures Identifier (CVE ID). After extracting all the CVE IDs, we filtered four projects, namely, Active-MQ, Nifi, Struts, and Tika. Including projects with a few real vulnerability data in the analysis can make the dataset more imbalanced. Thus, we selected the projects with the largest number of real vulnerability data. The filtered dataset includes 154 vulnerability reports as of Nov 2021.

Linking Vulnerabilities to Commits. It is a critical and toilsome problem to link vulnerabilities with classes or packages of the source code of the developed software project as software organizations usually do not well-report those (Croft et al., 2022). Moreover, Apache Software projects do not often have specific templates for security advisories, and vulnerability description reports may not contain references to CVE ID details. Therefore, we manually linked vulnerabilities, which were obtained from NVD, with the fixing commits, which were obtained from project-specific web resources and projects' issue tracking systems. In other words, we review the available information for each vulnerability and try to find the associated fix commit(s) in the issue tracking system for the impacted open-source component. As a result of this pursuit, we identified 75 commits for which vulnerability records were fixed. Furthermore, we utilized the MSR2019 dataset (Ponta et al., 2019) as the ground truth and validated the correctness of our mapping.

Extracting Vulnerability Inducing Commits. After vulnerabilities are linked to their fixing commits, we obtained commits in which these vulnerabilities

[2]https://SmartSHARK.github.io/dbreleases/

Table 1: Descriptive statistics for the projects.

Projects	Commits	Inducing Commits	Fixing Commits	Unique CWE ID	Time Period
Tika	4,933	17	9	3	31/03/07-09/07/18
Nifi	5,376	24	7	6	09/12/14-24/10/18
Struts	6,092	100	35	38	23/03/06-03/06/18
ActiveMQ	12,523	261	24	18	12/12/05-03/12/20

were induced in order to build a vulnerability prediction model. To this end, we performed the SZZ algorithm that is widely used for identifying bug inducing changes(Śliwerski et al., 2005; Sahal and Tosun, 2018). SZZ algorithm analyzes the bug-fixing commits, i.e., commits in which a bug reported on an issue tracking system is fixed, to trace back to their bug-inducing commits, i.e., commits that include the code changes inducing a bug into the system. We matched 75 out of 154 vulnerability fixing commits with 402 vulnerability inducing commits. Table 1 is a summary of the collected vulnerability dataset.

4 METHODOLOGY

In this section, as illustrated in Figure 1, we report our experimental steps for learning source code representations and training vulnerability prediction models. We refer to Software Metric Based Code Representation as Approach1 and Embedding Based Code Representation as Approach2.

4.1 Source Code Representation

Considering that the features used to train the classification model have an essential effect on the classification performance, we employed different feature extraction techniques and compared their outcomes. We considered two feature types both of which are extracted from the projects' source codes: (i)software metric-based, (ii)code embedding-based.

4.1.1 Metric Based Code Representation

We leverage software metrics, which are provided in SmartSHARK dataset, to understand and explore the impact of the metrics on vulnerability prediction. In other words, we investigate the ability of various defect prediction metrics to be used in vulnerability prediction. We utilized complexity, coverage, and dependency metrics of the projects for predicting real vulnerabilities. SmartSHARK dataset utilizes OpenStaticAnalizer as part of a plugin for the SmartSHARK infrastructure in conjunction with an HPC-Cluster to obtain the metrics for each file in each commit of a project. OpenStaticAnaylzer is an open-sourced version of the commercial tool SourceMeter that perform deep static program analysis of the source code of projects by constructing an Abstract Semantic Graph (ASG) from the source code to calculate the code metrics. The summary of the metrics is shown in Table 2. For detailed descriptions of the computed metrics, we refer to the websites and user guides of the tools. Unfortunately, the documentation of tools, libraries and API descriptions of tools published by researchers are insufficient. Thus we cannot provide a fully detailed description or long forms of abbreviations.

Table 2: The categorization of software metrics.

Category	SourceMeter Metrics
Coupling	TNOI, NF, TNF,NIR, NOR
Documentation	CD, CLOC, DLOC,TCD, TCLOC, TDLOC
Complexity	NL, NLE, McCC
Size	LLOC, LOC, NOS,NUMPAR, TLLOC,TLOC,TNOS, TNPC, TNSR,NNC, TNNC, NDS, TNDS

Source-meter proposes the software metrics at various granularities such as method level, file level, package level. We aggregated the metrics from the file level to the commit level in the dataset to compare against the embedding based code representation and to predict vulnerability-inducing code changes. In other words, our model is at commit level indicating that many files exist in a single commit and their metrics must be somehow aggregated to represent the code quality at commit level. We investigated various aggregation techniques (Dixit and Kumar, 2018) and decided to use the following aggregation approach: Over all files in a single commit, we take the sum, mean, median, and standard deviation of each metric and generate in total of 324 metrics for each commit.

4.1.2 Embedding Based Code Representation

To extract embedding features, we utilized natural language processing techniques. Nevertheless, since the structure of source code varies from ordinary texts, we transform the source code into its AST. Sub-

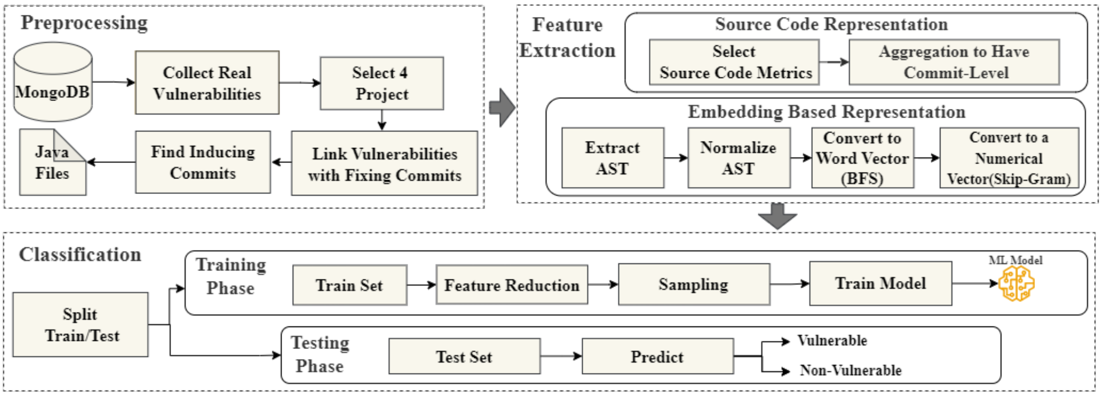


Figure 1: Illustration of proposed experimental setup.

sequently, we utilized Breadth-First Search (BFS) to convert the AST into a vector retaining the location of each node. Next, we employed Skip-Gram, a word embedding technique, to transform it into a numerical vector. The process steps are detailed below:

Step 1. Extracting AST of Source Code. We used AST representation to extract the syntactic structure of the source code. For this, we applied Javalang [3], a third-party open source library designed to analyze Java source codes. Javalang is a pure Python library that provides Java-oriented lexical analyzer and parser. With Javalang, the source code can be translated into an AST that contain several types of nodes. Each node in the AST denotes a construct occurring in the code. Figure 2 shows the AST for the function *multiply* in the code example below:

```
public int multiply(int a,int b){
    return a*b;}
```

Step 2. Normalizing AST Nodes Names. Each node of the AST denotes a construct occurring in the source code. AST represents only structural and content-related details and discards other details, for example, grouping parentheses are implicit in the tree structure, and they are not represented as separate nodes in the AST. However, some of the structural nodes like method names are out of our interest and do not hold information related to vulnerabilities. Thus, before using AST nodes we applied a normalization step in which the nodes that are not essential for vulnerability prediction are replaced with unique predefined names. For example, since the variable and method names are not important in our case, they are all replaced by unique names, such as VARIABLE_NAME and METHOD_NAME. The normalized nodes in the AST of method *multiply* are highlighted as green nodes in Figure 2.

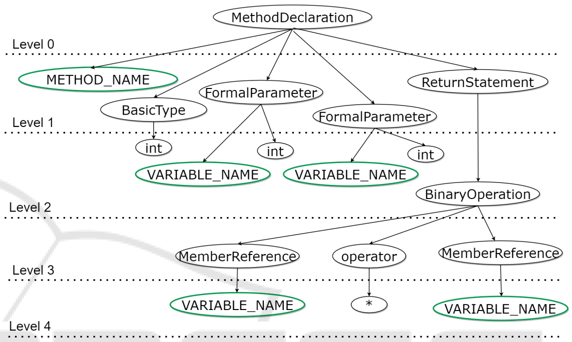


Figure 2: Extracted and Normalized AST of *multiply* func.

Step 3. Convert to Word Vector. In order to convert the normalized AST to a one dimensional array without losing the relations between AST nodes, we used the BFS technique. Yet, the leaf nodes are kept attached to their parent nodes as they are considered features rather than separated nodes. Finally, the extracted array is used as an input to the embedding model to extract the feature matrix.

Step 4. Convert to Numerical Vector (Skip-Gram). We used the Skip-Gram method to convert the formerly mentioned word vector into a numerical vector. Skip-Gram extracts numerical features by considering the relation between the neighbor nodes. Therefore, the context information is preserved and mapped into the numerical vector (Bamler and Mandt, 2017). We transformed each word in code into a numerical vector that captures its features and context through two steps. Firstly, we generated a feature matrix (dictionary) using the Skip-Gram method on SmartSHARK projects during preprocessing. This resulted in an embedding feature matrix that represents each word as a numerical vector based on its location in the code. During model training and testing, we utilized this dictionary to convert code arrays into numerical vectors for processing.

[3]https://github.com/c2nes/javalang

During training and test phases, changed code lines at commit level were extracted, preprocessed, and converted to a numerical vector, where each word was represented with a numerical vector $\in \mathbb{R}^{20\times1}$. Furthermore, it is more practical to use a fixed vector size as an input to the ML model. To decide the best vector size with the least information lost, we analyzed cumulative distribution function (CDF) of the code vectors' sizes, and set the size that captures the maximum information. Vectors with sizes of 6000 (equivalent to 300 words) cover 99.24% of the data. Thus, the vector size was fixed to be 6000 for each commit. The vectors whose sizes are above 6000 were cut, and only the first 6000 tokens were processed. On the other hand, vectors whose sizes are less than 6000 were padded with zeros.

4.2 Sampling

We have an imbalanced dataset in which the instances labelled as vulnerable commits only account for a very small portion of the whole dataset (0.014%). Thus, we applied an elimination approach to address the problem of a serious imbalance between vulnerable and non-vulnerable classes. We selected commits that have files labelled as vulnerable at least once in entire change histories. Meanwhile, we filtered out commits according to the number of their files when selecting. Afterwards, we performed hybrid-sampling, that is, we implemented under-sampling to reduce the number of instances of the major class up to three times that of the minor class, and then we implemented over-sampling until the number of majority class instances is equal to those of minority class instances.

4.3 Dimensionality Reduction Methods

Dimensionality reduction methods are performed when ML algorithms can be adversely affected by an extreme number of features or the correlation between features. We used Principal Component Analysis (PCA) and Independent Component Analysis (ICA) dimensionality reduction methods to evaluate their impact on the performance of classifiers. PCA calculates the eigenvectors of the covariance matrix of the original feature set, linearly transforming a high-dimensional feature vector into a low-dimensional vector with uncorrelated components. ICA aims to obtain statistically independent components in the transformed vectors, instead of transforming unrelated components. We reduced the number of features to fifteen when implementing both PCA and ICA.

4.4 Classification Algorithms

We built the vulnerability prediction model using ML and DL classifiers, namely, SVM, eXtreme Gradient Boosting (XGBoost), Gradient Boosted Tree (GBT), and 1D CNN. We used SVM algorithm with poly kernel hence it outperformed other kernels in predicting vulnerabilities. The optimal parameter set of SVM is identified through k-fold cross-validation. We also employed GBT and XGBoost by tuning the hyperparameters through the grid search. Tuning XGBoost is a difficult task as it has various hyperparameters. Therefore, we implemented the grid search for a limited parameter combination, namely, colsample bytree, gamma, max depth, and min child weight. We also used 1D CNN that consists of two convolutional layers, a max-pooling layer, dropout layers, a fully connected layer, and a softmax layer. Also, a dropout layer is applied to avoid over-fitting the training data.

5 EXPERIMENTAL RESULTS

We obtained different vulnerability prediction models and compare the impact of the two code representation methods (software metrics and embedding) in predicting vulnerabilities. We analyze recall, precision, F1-Score, and inspection ratio of classification results. Even though we have sampled and balanced the training dataset, we conducted our test experiments using the original ratio of positive and negative samples. We split 70% of the data for training and 30% for testing. We repeated the experiments 10 times each with a different random seed on the order of instances and took the average of the overall performance scores. We ensure that the data is split with stratification. Additionally, we applied Friedman and Nemenyi tests to conclude that the differences between the models in terms of each performance evaluation metric are statistically significant ($p < 0.05$).

During our experiments, we first evaluated the performance of vulnerability prediction models using SVM, GBT, XGBoost, and CNN classifiers. Then, to increase the robustness of the prediction model, we assessed feature selection and dimensional reduction methods. Table 3 summarizes the results obtained from the experiments of all vulnerability prediction models built with both Approach 1 and Approach 2. To closely examine the models' performances, we measured their results for predicting vulnerable and non-vulnerable commits separately (shown as: vulnerable commits prediction result/non-vulnerable commits prediction result). In particular, we provide comparisons of the best model using Approach 1 and

Table 3: Software Vulnerability Prediction results of different code representation approaches and classification models.

Model Name	**Approach 1** (Vulnerable/Non-vulnerable) R(%)	P(%)	F1(%)	IR(%)	**Approach 2** (Vulnerable/Non-vulnerable) R(%)	P(%)	F1(%)	IR(%)
XGB	47.0/76.9	11.0/96.0	17.8/85.4	24.5/75.5	24.9/**80.8**	**7.6**/94.7	11.5/**87.1**	**19.5**/80.5
GBT	69.6/48.4	6.9/96.9	12.3/61.9	52.6/47.4	46.2/56.3	7.2/94.4	10.3/65.4	43.9/56.1
SVM	84.1/38.8	7.3/97.1	13.3/54.4	62.2/37.8	**88.8**/23.0	5.5/92.9	10.1/26.0	76.9/**23.1**
CNN	63.2/51.2	8.0/96.5	14.2/65.4	45.2/50.2	34.2/69.7	6.2/94.4	10.3/79.7	31.9/69.6
XGB+PCA	52.1/70.5	9.6/96.1	16.2/81.3	30.8/69.2	39.8/65.6	6.5/94.7	11.2/77.4	34.8/65.2
GBT+PCA	77.7/40.1	7.3/96.8	13.4/56.2	60.9/39.1	53.6/46.7	7.3/84.6	8.0/50.7	53.3/46.7
SVM+PCA	83.7/38.3	7.2/97.0	13.2/53.9	62.7/37.3	77/25.2	4.5/93.5	8.4/29.5	74.7/25.3
CNN+PCA	71.7/51.8	7.8/96.4	14.0/67.2	52.7/50.7	39.1/68.0	5.9/94.3	10.1/78.7	38.1/68.0
XGB+ICA	53.2/71.7	10.3/96.2	17.3/82.2	29.5/70.3	37.2/66.9	6.6/94.7	11.1/78.4	32.7/66.6
GBT+ICA	76.0/42.9	6.8/97.4	12.5/57.3	57.6/41.8	50.0/48.9	4.7/94.2	8.0/56.8	50.5/49.0
SVM+ICA	86.5/39.8	7.6/97.3	13.9/56.4	61.4/38.6	77.1/26.3	5.7/93.5	8.8/31.3	73.6/26.4
CNN+ICA	79.4/52.8	7.5/96.3	13.7/66.8	60.5/51.8	53.4/42.9	6.5/93.5	9.8/55.5	54.2/43.1
XGB+k-best	47.5/75.5	10.5/96.0	17.2/84.5	25.8/74.2	33.6/68.0	6.7/94.3	9.9/75.2	32.1/67.9
GBT+k-best	50.0/70.2	9.2/95.9	15.6/81.0	31.0/69.0	34.3/67.3	6.5/94.3	9.8/74.9	32.8/67.2
SVM+k-best	**92.5**/33.3	7.1/**97.7**	13.2/48.0	67.7/32.3	64.5/44.8	5.9/94.0	10.3/57.7	55.2/44.8
CNN+k-best	69.8/37.6	7.5/97.2	13.4/53.7	53.5/36.6	40.4/50.8	5.7/94.0	9.2/62.9	39.5/50.8
XGB+PCA+k-best	49.4/76.3	11.2/96.1	18.3/85.1	25.2/74.8	36.0/70.6	6.9/94.8	11.6/80.9	29.8/70.2
GBT+PCA+k-best	58.7/65.8	9.4/96.3	16.2/78.2	35.6/64.4	40.8/65.4	6.7/94.8	11.5/77.3	35.0/65.0
SVM+PCA+k-best	84.4/38.3	7.4/97.2	13.4/53.9	66.8/37.2	62.6/33.8	5.8/93.6	8.8/42.6	66.0/34.0
CNN+PCA+k-best	72.3/51.6	7.9/96.6	14.2/67.0	52.5/50.4	40.0/54.6	6.0/94.2	10.3/67.7	39.4/54.6
XGB+ICA+k-best	49.4/**77.0**	**11.5**/96.3	**18.6/85.5**	**24.5**/75.4	35.7/71.7	7.0/**94.8**	11.7/81.6	29.0/71.3
GBT+ICA+k-best	60.4/66.7	10.0/96.7	17.1/78.9	34.5/65.1	45.5/63.0	7.0/94.7	**12.0**/75.6	37.3/62.8
SVM+ICA+k-best	84.6/37.1	7.3/97.2	13.4/53.3	62.7/**36.0**	56.6/44.7	5.6/93.5	9.9/57.6	53.0/44.9
CNN+ICA+k-best	76.0/43.5	7.4/97.0	13.4/59.9	58.9/42.3	65.3/48.4	5.5/93.3	9.3/59.0	69.0/48.6

the best model using Approach 2 when predicting vulnerable and non-vulnerable commits in Figures 3 and 4, respectively. We publish our source codes that consists of entire steps of model training and testing and also includes additional real vulnerability dataset.

Approach 1 - Software Metric Based Vulnerability Prediction. It can be seen that the combination SVM+k-best utilizing Approach 1 has the highest recall rate (92.5%) in predicting vulnerable commits. However, when achieving this recall rate, inspection ratio is high (67.7%). It means that effort is required to review 67.7% of all commits to detect 92.5% of vulnerable commits. In terms of precision and F1-Score, XGBoost+ICA+k-best outperformed the other classifiers. The model achieves 11.5% precision rate and 18.6% F1-Score rates. Also, inspection ratio is more acceptable with 24.5%. When predicting non-vulnerable commits XGB+ICA+k-best utilizing Approach 1 outperformed the other classifiers with recall rate of 77%. This combination has also the highest F1-Score rate (85.5%) and the lowest inspection ratio (24.5%). Meanwhile, SVM+k-best achieve high precision (97.7%).

Approach 2 - Embedding Based Vulnerability Prediction. Results of vulnerability prediction models trained with embedding metrics are also shown in Table 3. Unlike SW metrics based models, embedding based models showed similar performance in both classifying vulnerable and non-vulnerable samples. XGB classifier has the highest Precision rate (7.6%),GBT+ICA+k-best F1-Score rate (12%), and SVM has the highest recall rate (88.8%).

Approach 1 vs. Approach 2. We observed that the outperforming models developed with both approaches achieved high recall rates for the prediction of both vulnerable and non-vulnerable commits. On the other hand, in respect of precision and F1-Score rates, models achieved high rates in predicting non-vulnerable commits, but low rates in predicting vulnerable commits. This variance between recall and precision indicates higher false positive rate in the models predictions. However, this could not be a totally wrong case, as the commits are manually labeled by expert developers and new vulnerability types and continuously discovered. So, some of the vulnerable commits that are now considered as non-vulnerable commits could actually contain vulnerable parts but have not been discovered yet. Moreover, we applied sampling techniques to balance the training set whereas we used the original ratios in the test set. The conducting the experiments on such highly imbalanced test set is another reason to have different prediction rates for samples with different distributions. Figure 3 shows the results (in terms of recall, precision and F1-Score) of the outperforming models in predicting vulnerable commits for both approaches. Also, Figure 4 shows the results of the outperforming models in predicting non-vulnerable commits for both code representation approaches.

As illustrated in Figures 3 and 4, Approach 1, namely, software metrics based code representation, is better at distinguishing vulnerable and non-vulnerable classes as it has better prediction performance in terms of recall, precision and F1-Score. In contrast to prior research, our findings demonstrate that software metrics outperformed text mining methods in detecting vulnerabilities. This deviation can be attributed to the fact that we processed codes at the code change (commit) level, whereas text mining methods have been shown to be most effective when applied to complete texts, such as entire functions in previous studies. Based on these results, we conclude that working at the code change level may be a more cost-effective and flexible option for real-time projects and using software metrics could provide a better measurement attribute in such cases.

Moreover, the projects are heterogeneous in terms of the number of all commits and vulnerability inducing commits. Therefore, to analyse the overall results for each project, we performed additional experiments on each project's test set separately. Figure 5 shows that the performance of the SVM+ICA+k-best model with Approach 1 is better than the performance of the GBT+PCA prediction using Approach 2 over ActiveMQ and Struts. On the other hand, according to the results of Tika, Approach 2 has a better recall rate than Approach 1 (Figure 5a), while has worse precision and F1-Score rates (Figure 5b and Figure 5c). Besides, the results of the experiments on Nifi show that both approaches have similar recall rates while Approach 1 has better precision and F1-Score rates than Approach 2. Our findings show that the performance of software vulnerability prediction models can vary depending on the analyzed project in the dataset.

6 THREATS TO VALIDITY

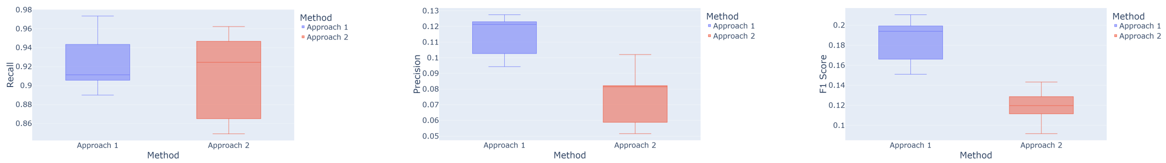
This study is limited to open source Java projects selected from the public SmartSHARK dataset. Hence, we cannot prove the generalization of our results to industrial projects, other open-source projects or projects implemented in other languages. Nevertheless, the dataset used in our study offers a comprehensive data source with 47,303 pull requests, 163,057 issues, 2,987,591 emails, and 366,322 commits. And we selected four projects with the largest number of real vulnerability data. Thus, we can safely argue that our research question have so far been addressed on the largest and most diverse dataset in this field. The dataset includes software metrics collected by SourceMeter tool, and hence metrics that the tool could not identify are excluded. Nevertheless, SourceMeter is able to extract the majority of the most popular metrics. Our conclusions are limited to 4 projects implemented Java, but the prediction results are statistically compared among several representations and models, and validated through non-parametric significance tests.

7 CONCLUSION

We intent to investigate vulnerability-inducing code changes and source code representations that explain those. However, extracting embedding features of changed parts of the code only might have led to missing some of the contextual details, and thus, embedding based models might have underperformed compared to software metrics based models in vulnerability prediction task. To overcome this problem, file based embedding features could be extracted to double check the vulnerability existence in the source code as a whole. Also, pre–trained source code models could be used to generate the embedding matrix/dictionary. Moreover, to improve the performance of vulnerability prediction model, the impact of other code features, such as technical debt, code smell, and refactoring related features could be investigated. Furthermore, our approaches could be evaluated on other projects for increasing the validity of our conclusions. Furthermore, in this study, to extract vulnerability-inducing commits, we used the SZZ algorithm. Vulnerabilities are different from common bugs and a lot of vulnerabilities are foundational, i.e., they are introduced at their initial time. Therefore, to identify vulnerability-inducing commits, vulnerability-specific SZZ algorithm (Bao et al., 2022) could be considered.

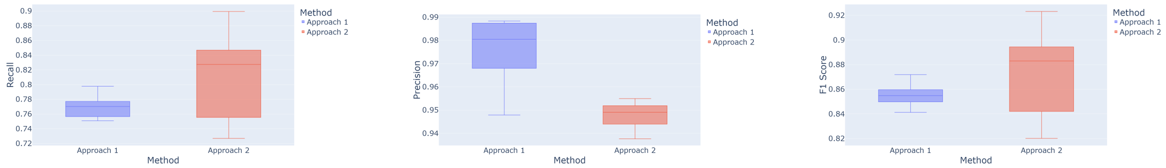
ACKNOWLEDGEMENTS

This work was funded by The Scientific and Technological Research Council of Turkey, under 1515 Frontier R&D Laboratories Support Program with project no: 5169902.



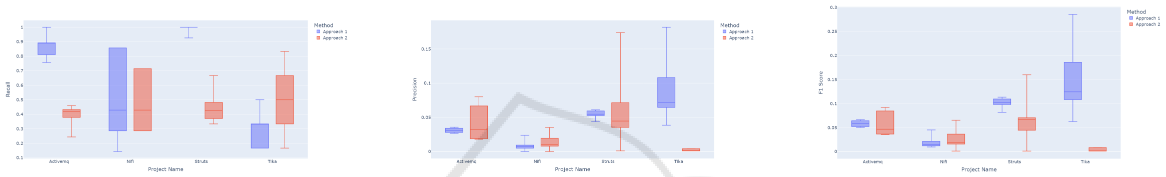
(a) SVM+k-best Recall (b) XGBoost+ICA+k-best Precision (c) XGBoost+ICA+k-best F1-Score

Figure 3: Boxplots of feature representation approaches using models that outperformed in predicting vulnerable commits.



(a) XGBoost+ICA+k-best Recall (b) SVM+ICA Precision (c) XGBoost+ICA+k-best F1-Score

Figure 4: Boxplots of feature representation approaches using models that outperformed in predicting nonvulnerable commits.



(a) Recall (b) Precision (c) F1-Score

Figure 5: Evaluation results of each project.

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