Temporal Convolutional Networks for Just-in-Time Software Defect Prediction

Pasquale Ardimento[1], Lerina Aversano[2], Mario Luca Bernardi[3] and Marta Cimitile[4]

[1]Computer Science Department, University of Bari, Via E.Orabona 4, Bari, Italy

[2]University of Sannio, Benevento, Italy

[3]Department of Computing, Giustino Fortunato University, Benevento, Italy

[4]Unitelma Sapienza, University of Rome, Italy

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Abstract: Defect prediction and estimation techniques play a significant role in software maintenance and evolution. Recently, several research studies proposed just-in-time techniques to predict defective changes. Such prediction models make the developers check and fix the defects just at the time they are introduced (commit level). Nevertheless, early prediction of defects is still a challenging task that needs to be addressed and can be improved by getting higher performances. To address this issue this paper proposes an approach exploiting a large set of features corresponding to source code metrics detected from commits history of software projects. In particular, the approach uses deep temporal convolutional networks to make the fault prediction. The evaluation is performed on a large data-set, concerning four well-known open-source projects and shows that, under certain considerations, the proposed approach has effective defect proneness prediction ability.

1 INTRODUCTION

Software maintenance and evolution are human-based activities that unavoidably introduce new defects in the software systems. Test cases (Myers and Sandler, 2004) and code reviews (A. Ackerman and Lewski, 1989) are two traditional techniques to check if performed modifications introduced new defects in the source code. However, available resources are often limited and the schedules are very tight. An efficient alternative way to perform this task is represented by the adoption of statistical models to predict the defect-proneness of software artifacts exploiting information regarding the source code or the development process (Pascarella et al., 2019). The existing techniques evaluate the defectiveness of software artifacts by performing long-term predictions or just-in-time (JIT) predictions. The former technique allows to analyze the information accumulated in previous software releases and, then, predicting which artifacts are going to be more prone to defect in future releases. For instance, Basili et al. investigated the effectiveness of Object-Oriented metrics (Chidamber and Kemerer, 1994; Bernardi and Di Lucca, 2007) in predicting post-release defects (Basili et al., 1996), while other approaches consider process metrics (Hassan, 2009; Ardimento et al., 2018). However, the long-term defect prediction models have limited usefulness in practice because they do not provide developers with immediate feedback (Kamei et al., 2013) on the introduction of defects during the commit of artifacts on the repository.

JIT technique, instead, overcomes this limitation exploiting the characteristics of a code-change to perform just-in-time predictions.

With respect to other existing JIT defect prediction models (Yang et al., 2015; Kamei et al., 2013; Hoang et al., 2019) this work explores a deep learning framework based on temporal convolutional networks (TCN) to predict in which components code changes most likely introduce defects. The TCNs are characterized by casualness in the convolution architecture design and sequence length (Bai et al., 2018). This makes them particularly suitable to our context where the causal relationships among the internal quality metrics evolution and bug presence should be learned. The proposed approach exploits numerous features about source code metrics previously detected from the available sequence of commits. The evaluation is performed on a large data-set, including 4 open-source projects. The obtained results are satisfactory.

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The paper is structured as follows. In section 2 some background information is provided. In section 3, a brief discussion of related work is reported. The proposed approach is described in Section 4 while the experiment results are discussed in Section 5. Finally, in Section 7 and 8 respectively, the threats to validity and the conclusions are reported.

2 BACKGROUND

2.1 Deep Learning Algorithms

The proposed approach is based on the adoption of Deep Learning (DL) algorithms. DL extends classical machine learning by adding more complexity into the model as well as transforming the data using various functions that allow their representation in a hierarchical way, through several levels of abstraction composed of various artificial perceptrons (Deng et al., 2014; Bernardi et al., 2019). Indeed, DL is inspired by the way information is processed in biological nervous systems and their neurons. In particular, DL approaches are based on deep neural networks composed of several hidden layers, whose input data are transformed into a slightly more abstract and composite representation step by step. The layers are organized as a hierarchy of concepts, usable for pattern classification, recognition and feature learning.

The training of a DL network resembles that one of a typical neural network: i) a forward phase, in which the activation signals of the nodes, usually triggered by non-linear functions in DL, are propagated from the input to the output layer, and ii) a backward phase, where the weights and biases are modified (if necessary) to improve the overall performance of the network.

DL is capable to solve complex problems particularly well and fast by employing black-box models that can increase the overall performance (i.e., increase the accuracy or reduce error rate). Because of this, DL is getting more and more widespread, especially in the fields of computer vision, natural language processing, speech recognition, health, audio recognition, social network filtering and moderation, recommender systems and machine translation.

3 RELATED WORK

Several recent studies have focused on applying deep-learning techniques to perform defect prediction. In (Yang et al., 2015), the authors proposed the usage of a deep-learning approach called Deep Brief Network (DBN). They mainly used the original DBN as an unsupervised feature learning method to preserve as many characteristics of the original feature as possible while reducing the feature dimensions. The authors evaluate the proposed approach on data of 6 large open-source software projects achieving an average recall of 69% and an average F1-score of 45%. In (Phan et al., 2018), the authors proposed a prediction model by applying graph-based convolutional neural networks over control flow graphs (CFGs) of binary codes. Since the CFGs are built from the assembly code after compiling its source code, this model applies only to compilable source code. Some studies (Wang et al., 2016) have used existing deep learning models, such as DBN and long short-term memory, to extract features directly from the source code of the projects. In (Xu et al., 2019) authors used a deep neural network with a new hybrid loss function to train a DNN to learn top-level feature representation. They conduct extensive experiments on a benchmark data-set with 27 defect data. The experimental results demonstrate the superiority of the proposed approach in detecting defective modules when compared with 27 baseline methods. In (Manjula and Florence, 2019), the authors proposed a feature optimization model using a genetic algorithm to select a feature subset used, then, as the input of a DNN. They carried out an empirical investigation on five projects belonging to the well-known PROMISE data-set. They obtained an accuracy value of 98%, that is, to the best of our knowledge, the best result known in the literature. Anyway, the limit of this study is that it is not possible to explore the source code and the contextual data are not comprehensive (e.g., no data on maturity are available). Moreover, in some cases, it is not possible to identify if any changes have been made to the extraction and computation mechanisms over time. Concerning the described approach, our study proposes a JIT software prediction technique. As mentioned in Section 1, JIT permits the developers to check and fix the defects just at the time they are introduced achieving the following advantages:

- large effort savings, over coarser-grained predictions, thanks to identification the defect-inducing changes that are mapped to smaller areas of the code;
- immediate and exact knowledge of the developer who committed the changes;
- freshness of the design decisions made by the developers.

Recently research on JIT techniques applied to software defect prediction (SDP) has increased rapidly. The study reported in (Kamei et al., 2013) proposes a prediction model based on JIT quality assurance to identify the defect-inducing changes. Later on, the authors also evaluated how JIT models perform in the context of cross-project defect prediction (Kamei et al., 2016). Their main findings report good accuracy for the models in terms of both precision and recall but also for reduced inspection effort. In 2015, Yang et al. (Yang et al., 2015) proposed the use of a deep-learning approach for JIT defect prediction obtaining better performance for average recall and F1-score metrics. Later, Yang et al. (Yang et al., 2016a) compared simple unsupervised models with supervised models for effort-aware JIT-SDP and found that many unsupervised models outperform the state-of-the-art supervised models. In (Yang et al., 2017) Yang et al. uses a combination of data preprocessing and a two-layer ensemble of decision trees. The first layer uses bagging to form multiple random forests while the second layer stacks the forests together with equal weights. Afterward, this study was replicated in (Young et al., 2018) where authors applied a new deep ensemble approach assessing the depth of the original study and achieving statistically significantly better results than the original approach on five of the six projects for predicting defects (measured by F1 score). Chen et al. (Chen et al., 2018) proposed a novel supervised learning method, which applied a multi-objective optimization algorithm to SDP. Experimental results, carried out on six open-source projects, show that the proposed method is superior to 43 state-of-the-art prediction models. They found, for example, that the proposed method can identify 73% buggy changes on average when using only 20% efforts (i.e., time for designing test cases or conducting rigorous code inspection). Pascarella et al. (Pascarella et al., 2019) proposed a fine-grained prediction model to predict the specific files, contained in a commit, that are defective. They carried out an empirical investigation on ten open-source projects discovering that 43% defective commits are mixed by buggy and clean resources, and their method can obtain 82% AUC-ROC to detect defective files in a commit. Hoang et al. (Hoang et al., 2019) proposed a prediction model built on Convolutional Neural Network, whose features were extracted from both commit messages and code changes. Empirical results show that the best variant of the proposed model achieves improvements in terms of the Area Under the Curve (AUC), from about 10.00% to about 12.00%, compared with the existing results in the literature. Finally, Cabral et al. (Cabral et al., 2019) conducted the first work to investigate class imbalance evolution in JIT SDP founding that this technique suffers from class imbalance evolution.

Concerning the above discussed JIT methods, our approach proposes a new classification method based on TCNs. Our main assumption is that the TCNs are particularly suitable in the JIT-SDP problem that is characterized by a huge amount of data (extracted at the commit level) organized as multivariate time-series.

4 APPROACH

In this section, we describe the approach used to predict the defect prone system classes using the metrics model. The approach consists of two essential elements: *i*) the feature model, *ii*) and the TCN classifier. In the following subsections, these two components are thoroughly detailed and explained.

4.1 The Proposed Features Model

The proposed features model is reported in Table 1. The table shows the list of the adopted features (i.e., internal quality source code metrics from CK (Chidamber and Kemerer, 1994) and MOOD (Brito e Abreu and Melo, 1996) suites) and their corresponding description.
Figure 1-(a) depicts the tool-chain used for the features extraction.

In the Commits/Bugs analysis all the commits log messages have been analyzed and parsed to extract the description of the changes performed on the files of the code repository. The information about the commits' log messages is extracted by the GIT repository searching for bug identifiers. The information about the bugs is gathered by the bug tracking system (BTS).

In detail, to evaluate the number of commits and bugs for each class we build the log from the BTS repository and extract, for each commit, the files changed, the commit ID, the commit timestamp, the commit parent, the total number and the names of files changed, the commit note. With this information, we can identify fix-inducing changes using an approach inspired by the work of Fischer (Fischer et al., 2003), i.e., we select changes with the commit note matching a pattern such as a bug ID, issue ID, or similar, where ID is a registered issue in the BTS of the project. Hence the ID acts as a traceability link between the GIT repository and BTS repository. Then the issue type attribute is used to classify the issues and to select only bug fixes discarding any other different kinds

Table 1: Source Code Quality Metrics used in the Features Model.

Source Code Metrics	Description
Number of Attributes Defined (Ad)	*Attributes defined within class*
Number of Attributes Inherited (Ai)	*Attributes inherited but not overridden*
Number of Attributes Inherited Total (Ait)	*Attributes inherited overall*
Number of Attributes Overidden (Ao)	*Attributes in class that override an otherwise-inherited attributes*
Number of Public Attributes Defined (Av)	*Number of defined attributes that are public*
Class Relative System Complexity (ClRCi)	*avg(Ci) over all methods in class*
Class Total System Complexity (ClTCi)	*sum(Ci) over all methods in class*
Depth of Inheritance Tree (DIT)	*The maximum depth of the inheritance hierarchy for a class*
Number of Hidden Methods Defined (HMd)	*Number of defined methods that are non-public*
Number of Hidden Methods Inherited (HMi)	*Number of inherited (but not overridden) methods that are non-public*
Method Hiding Factor (MHF)	*PMd / Md*
Inheritance Factor (MIF)	*Mi / Ma*
Number of Methods (All) (Ma)	*Methods that can be invoked on a class (inherited, overridden, defined). Ma = Md + Mi*
Number of Methods Defined (Md)	*Methods defined within class*
Number of Methods Inherited (Mi)	*Methods inherited but not overridden*
Number of Methods Inherited Total (Mit)	*Methods inherited overall*
Number of Methods Overidden (Mo)	*Methods in class that override an otherwise-inherited method*
Number of Attributes (NF)	*The number of fields/attributes*
Number of Methods (NM)	*The number of methods*
Number of Methods Added to Inh. (NMA)	*The number of methods a class inherits adds to the inheritance hierarchy*
Number of Inherited Methods (NMI)	*The number of methods a class inherits from parent classes*
Number of Ancestors (NOA)	*Total number of classes that have this class as a descendant*
Number of Children (NOCh)	*Number of classes that directly extend this class*
Number of Descendants (NOD)	*Total number of classes that have this class as an ancestor*
Number of Links (NOL)	*Number of links between a class and all others*
Number of Parents (NOPa)	*Number of classes that this class directly extends*
Number of Public Attributes (NPF)	*The number of public attributes*
Number of Static Attributes (NSF)	*The number of static attributes*
Number of Static Methods (NSM)	*The number of static methods*
Number of Public Methods Defined (PMd)	*Number of defined methods that are public*
Raw Total Lines of Code (RTLOC)	*The actual number of lines of code in a class*
Specialization Index (SIX)	*How specialized a class is, defined as (DIT * NORM) / NOM;*
Total Lines of Code (TLOC)	*The total number of lines of code, ignoring comments, whitespace.*
Weighed Methods per Class (WMC)	*The sum of all of the cyclomatic complexities of all methods on a class*

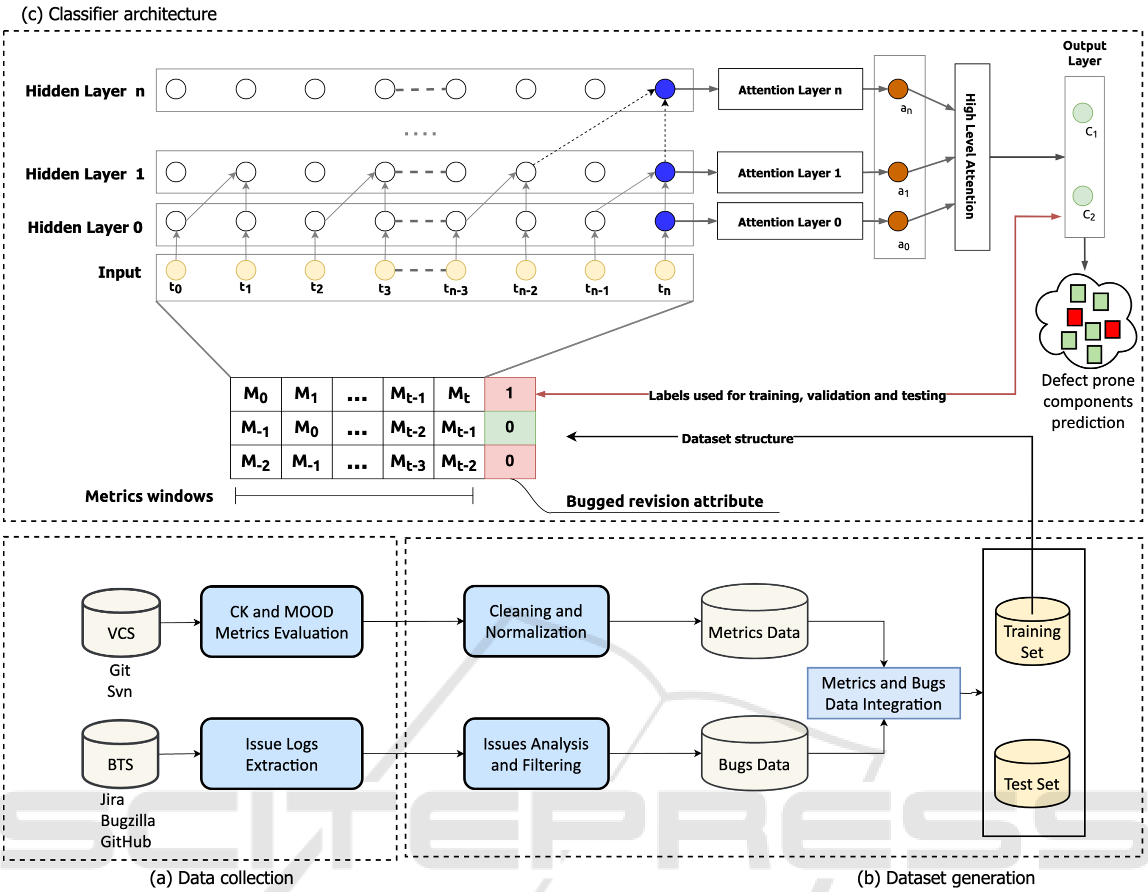


Figure 1: Overall process and classifier architecture.

of issues (e.g., improvement, enhancements, feature additions, and refactoring tasks). This is needed to identify, for each class, only the issues that were related to bug fixes, since we use them to tag faulty revisions of each class. Finally, we only consider issues having the status *CLOSED* and the resolution *DONE* since their changes must be committed in the repository and applied to the components in the context of a commit. This allows identifying bugged classes for each commit in the GIT repository. At the same time, the source code at each commit has been downloaded and analyzed for evaluating the internal quality metrics of Table 1 over time. To this aim, several tools for metrics calculation have been exploited (Hilton, 2020; Aniche, 2015; Spinellis, 2005). Finally, as depicted in Figure 1-(b) the metrics and the bugs data, evaluated at each commit, are merged into a unified training and testing dataset. During this step, the raw data-set is also cleaned by removing incomplete and wrong samples and normalizing the attributes (min-max normalization). The final dataset, for each class of the system, contains the evolution, by commits, of the calculated metrics integrated with bug presence information.

4.2 The Temporal Convolution Network Classifier

The classifier architecture is shown in Figure 1-(c).

The convolutional operations in the TCN architecture are discussed in (Bai et al., 2018). Specifically, the TCN network exploits a 1D FCN (fully convolutional network) and padding to enforce layer length coherence. The architecture applies causal convolutions to ensure that when evaluating the output at current time t only current and past samples are considered. The dilated convolutions specify a dilation factor f_d among each pair of neighboring filters. The factor f_d grows exponentially with the layer number. If the kernel filter size is k_l, the effective history at the lower layer is $(k_l - 1) * d$, still growing exponentially by network depth.

For classification, the last sequential activation of the last layer is exploited since it summarizes the information extracted from the complete sequence in input into a single vector. Since this representation may be too reductive for the intricate relationships (as those present in bugs and internal quality metrics multivariate time-series), we added a hierarchical attention mechanism across network layers inspired by (Yang et al., 2016b). As shown in Figure 1-(c), if the TCN has n hidden layers, L_i is a matrix comprised of the convolutional activations at each layer i (with $i = 0, 1, \dots, n$) defined as:

$$L_i = [l_0^i, l_1^i, ..., l_T^i], L_i \in R^{K \times T},$$

where K is the number of filters present in each layer. Hence layer attention weight $la_i \in R^{1 \times T}$ can be evaluated as:

$$la_i = softmax(tanh(w_i^T L_i))$$

where $w_i \in R^{K \times 1}$ are trainable parameter vectors. The combination of convolutional activations for layer i is calculated as $a_i = a_f(H_i \alpha_i^T)$ where $a_i \in R^{K \times 1}$ and a_f is an activation function (we experimented with ReLU, Mish and Swish). At the output of the hidden-level attention layers, the convolutional activations $A = [a_0, a_1, ..., a_i, ..., a_n]$ (with $A \in R^{K \times n}$) are used to calculate the last sequence representation to perform the final classification:

$$\alpha = softmax(tanh(w^T A))$$

$$y = a_f(A\alpha^T)$$

where $w \in R^{K \times 1}, \alpha \in R^{1 \times K}, y \in R^{K \times 1}$.

The considered architecture can be instantiated with a variable number of hidden layers where each hidden layer is the same length as the input layer.

Referring to Figure 1-(c), we exploited the following three types of layers:

- **Input Layer:** it represents the entry point of the considered neural network, and it is composed of a node for each set of features considered at a given time;
- **Hidden Layers:** they are made of artificial neurons, the so-called "perceptrons". The output of each neuron is computed as a weighted sum of its inputs and passed through an activation function (i.e., mish, swish, and ReLu) or a soft-plus function.
- **Attention Layers:** allows modeling of relationships regardless of their distance in both the input and output sequences.
- **Batch Normalization:** Batch normalization is added to improve the training of deep feed-forward neural networks as discussed in (Ioffe and Szegedy, 2015).
- **Output Layer:** this layer produces the requested output.

The TCN training is performed by defining a set of labeled traces $T = (M, l)$, where each of the M rows is an instance associated with a binary label l, which specifies if a class is bugged or not as exemplified in Figure 1-(c). For each of the M instances, the process computes a feature vector V_f submitted to the classifier in the training phase. In order to perform validation during the training step, 10-fold cross-validation is used (Stone, 1974). The trained classifier is assessed using the real data contained in the test set made of classes (and hence bugs) that classifier has never seen.

During the training step, different parameters of the architecture are tested (i.e., number of layers, batch size, optimization algorithm, and activation functions) in order to achieve the best possible performance as further detailed in the next section.

The considered TCNs architecture was trained by using cross-entropy (Mannor et al., 2005) as a loss function, whose optimization is achieved by means of stochastic gradient descent (SGD) technique. Specifically, we adopted a momentum of 0.09 and a fixed decay of $1e^{-6}$. To improve learning performances, SGD has been configured into all experiments with Nesterov accelerated gradient (NAG) correction to avoid excessive changes in the parameter space, as specified in (Sutskever et al., 2013).

5 EXPERIMENT DESCRIPTION

The experimentation is conducted by using the feature model and the TCN classifier described in Section 4.

Specifically, the tool-chain described in Figure 1 is applied to four different Java open-source projects. The projects are selected by considering the necessity to generalize the obtained results. However, as discusses in (Hall et al., 2012), the data-sets, used in the empirical investigation strongly affect prediction performance. For this reason, the selected projects differ for their application domain, size, number of revisions. Table 2 describes their characteristics: the total number of commits analyzed for each project, the total number of bugs fixed and detected for each project, the analyzed period represented by the date of the first and the last commit detected.

All the projects in the table, have an available Git repository that is active and contains more than one release. Finally, the considered systems are also used in other studies allowing to easily evaluate and compare the obtained results.

The assessment is conducted by identifying the best parameters reported in Table 3 found using a Sequential Bayesian Model-based Optimiza-

Table 2: Analysed Software Systems.

System	Commits	Bugs	Period
Log4j	3275	647	2001-02-28/2015-06-04
Javassist	888	260	2004-07-08/2019-10-14
JUnit4	2397	153	2001-04-01/2019-04-03
ZooKeeper	1939	1787	2008-06-24/2019-10-10

tion (SBMO) approach implemented using the Tree Parzen Estimator (TPE) algorithm as defined in (Bergstra et al., 2011).

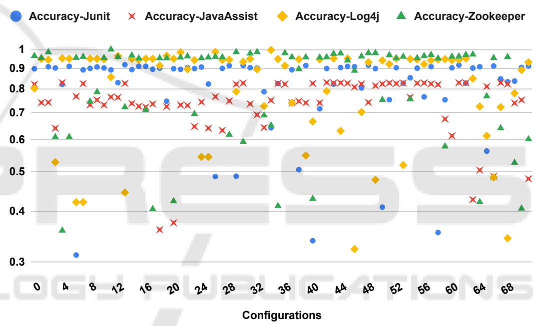
The parameters reported in the table are the following:

- Network Size: we considered two levels of network sizes (small, medium), depending on the actual number of layers. A small size consists of a maximum of 1.5 mln of learning parameters. The medium size is composed of a number of parameters between 1.5 mln and 7 mln;
- Activation Function: we tested three different activations functions: Swish and Mish (Ramachandran et al., 2017) in addition to the well-known ReLu;
- Learning Rate: it ranges from 0.09 to 0.1;
- Number of Layers: the numbers of considered layers is 6,7,9;
- Batch Size: batch size belongs to the set $\{64, 128, 264\}$ and is handled, for a multi-GPU system, as suggested in (Koliousis et al., 2019);
- Optimization Algorithm: we tested the Stochastic Gradient Descent (SGD) (Schaul et al., 2013), RmsProp (Wang et al., 2019), Nadam (Wang et al., 2019).
- Dropout rate: it is fixed to 0.15.

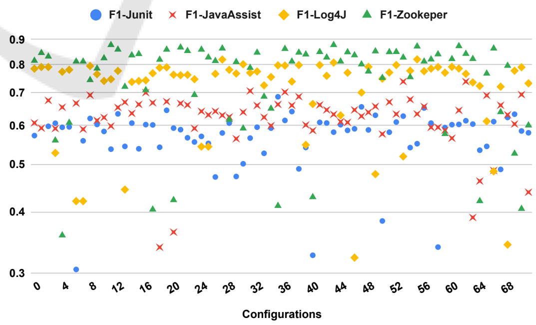
The experiments run on the TensorFlow 2.1 deep learning platform and used PyTorch 1.4 as a machine learning library. The hardware environment of the platform is a workstation with one dual-core microprocessor: two Intel (R) Core (TM) i9 CPU 4.30 GHZ 64GB of RAM, one equipped with NVIDIA Tesla T4 AI Inferencing GPU and the other with Nvidia Titan Xp.

6 DISCUSSION OF RESULTS

The plot depicted in Figure 2 shows the distribution of (a) accuracy and (b) F-measure over the hyper-parameters configurations. As the figure shows, the worst results are obtained for projects having a lower number of detected bug (e.g. Javassist and JUnit4), while satisfactory results are obtained considering data-set with a large number of detected bugs (e.g., Log4J and Zookeeper). The parameters permutations providing the best accuracy and F-measure by the project are listed in Table 4. Most of the models behave consistently and there are quite small differences among networks with six and seven layers. It's also interesting to observe that there is a small set of models that are not able to learn from the data and looking carefully at those models they fall into two categories: (*i*) models with more than nine layers and medium sizes; (*ii*) models trained with learning rates higher than 0.015. For the first case increasing the dataset is needed and it is likely to improve final performances.



(a)



(b)

Figure 2: Scatter plots of distributions of accuracy (a) and F-measure (b) for each model configuration comparing obtained results on the four analyzed systems.

Table 3: Hyper-parameters Optimization and selected ranges.

Hyperparameters	Ranges
Network size	Small, Medium
Activation Function (AF)	Mish, ReLu, Swish
Learning Rate (LR)	[0.09, 0.12]
Number of layers	{ 6, 7, 8, 9 }
Batch size	{ 64, 128, 256 }
Optimization Algorithm (OA)	SGD, Nadam, RMSprop

Table 4: Permutations providing the best validation accuracy for each project.

Project	AF	LR	No. Layers	Batch size	OA	Dropout Rate	Accuracy	Loss	F1	Training Time (sec)
Log4j	mish	9	7	64	SGD	0.15	0.996	0.0512	0.81	10275.51
Javassist	mish	9	6	64	SGD	0.15	0.822	0.1770	0.72	2791.87s
JUnit4	mish	9	8	64	Nadam	0.15	0.916	0.0597	0.65	4534.22s
ZooKeeper	ReLu	9	6	64	SGD	0.15	0.997	0.0002	0.87	6159.53

7 THREATS TO VALIDITY

In this section, the threats to the validity of the research proposed are discussed.

Construct Validity: A threat to construct validity concerns with the source code measurements performed. To mitigate this threat, we used three publicly available tools (Hilton, 2020; Aniche, 2015; Spinellis, 2005). We decided to use more than one tool to check, whenever possible if the measures obtained from one tool are the same calculated by the other ones. Moreover, the fact that both the tools and the OSSs are publicly available makes possible to replicate the measurement task in other studies. Another threat concerns with the class imbalance problem often encountered in SDP. In order to ensure that the results would not have been biased by confounding effects of data unbalance we adopted the SMOTE technique as described in (Chawla et al., 2002).

Internal Validity: Threat to internal validity concerns whether the results in our study correctly follow from our data. Particularly, whether the metrics are meaningful to our conclusions and whether the measurements are adequate. To this aim, an accurate process for the data gathering has been performed.

External Validity: Threat to external validity concerns the generalization of obtained results. To mitigate this threat, in our investigation we considered well-known OSS systems that are continuously evolving and different for dimensions, domain, size, timeframe, and the number of commits. However, our results can not be generalized to commercial systems due to the existing differences between OSS systems and commercial systems such as the nature of reported defects. In OSS systems, defects can be reported by customers, for stable releases, and by developers during development activities. In commercial projects, instead, the defects modeled and therefore studied are only those reported by customers for released versions. Moreover, we limited our investigation to Java systems because the tools exploited to compute the considered metrics only work for this programming language. Thus, we cannot claim generalization concerning systems written in different languages as well as to projects belonging to industrial environments.

8 CONCLUSIONS AND FUTURE WORK

In this work, we defined a deep learning approach based on temporal convolutional networks for just-in-time defect prediction. To predict changes that will introduce software defects, we used a fine-grained quality metrics features model. The approach exploits a large data-set, from four open-source projects, with the assessment of 33 class level source code metrics detected commit by commit. The evaluation carried out shows that the predictions performed with our approach are satisfactory and the accuracy obtained is greater than the 0.90 in most cases, achieving the 0.99 value in the case of the ZooKeeper and Log4J projects. To our knowledge, it is the best result in related literature. However, a limit of our work is that our model, like all prediction models, requires a large amount of historical data to train a model that will perform well. In practice, training data may not be available for projects in the initial development phases, or for legacy systems that do not have archived historical data. For this reason, in the future, we plan to apply our approach in a cross-project context, where models can be trained using historical data from other projects. Moreover, we intend to extend the set of metrics considered as features also including process metrics. Finally, we plan to evaluate the effectiveness of our model in-field, through a controlled study with practitioners to make defect prediction more actionable in practice and support in real-time development activities, such as code writing and code inspections.

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