Machine Learning Based Prediction of Change Request Severity Level: Experimental Results

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***Abstract*—In the context of Change Request (CR) systems, the severity level of a change request is considered a critical variable when planning software maintenance activities, indicating how soon a CR needs to be addressed. However, the severity level assignment remains primarily a manual process, mostly depending on the experience and expertise of the person who has reported the CR. In this paper, we present preliminary findings of ongoing research aimed to predict the severity level of a CR by analyzing its long description, using text mining techniques and Machine Learning (ML) algorithms. Best results were obtained with a classifier based on the Random Forest ML algorithm. This classifier can predict whether the severity level will change (accuracy of 93.681%) and if it will increase or decrease (accuracy of 93.440%). However, preliminary results were not as good when predicting the final severity level in an imbalanced data scenario.**

***Keywords*-software maintenance; change request systems; machine learning; random forest.**

MARIO: GERAL: passar a usar acronimo CR no restante do artigo. Faltam comparacoes dos nossos resultados com a literatura. Figuras e tabelas incluidas e citadas devem ser explicadas, pelo menos um pouco, caso contrario o revisor pode acha-la desnecessaria. Nao usar expressoes absolutas: the best, the worst, the fastest, etc. Evitar primeira pessoa. Voz passiva ok, mas ordem direta eh melhor. Nunca dizer: in section xx we present.... Diga: section xx presents. A conversar com MC: comentar sobre a estrutura hierarquica do texto, com intro-desenv-concl, em cada nivel. Indicar significado das siglas na primeira ocorrencia. Indicar referencia a tecnicas, metodos, artigos, quando citados. Ao citar texto ipsis literis, se for longo, colocar entre aspas e dar o devido crédito. Se preferir usar de passagem, reescreva para nao haver acusacao de plagio. Deve haver um espaco antes de abrir parenteses; ha varios casos sem espaco. Nao usar giria nem apostrofe em verbo isn't e sim is not, etc. Evitar URL no texto, principalmente se for longo; preferir nota de rodape ou referencia (quando for realmente uma referencia); se for curto ok.

I. Introduction

Change Request (CR) systems have played a major role in maintenance process in many software development settings, both in Close Source Software (CSS) and in Open Source Software (OSS) scenarios. This is specially true in OSS, which is characterized by the existence of many of users and developers with different levels of expertise spread out around the world, who might create or be responsible for dealing with several CRs [1].

A user interacts with a CR system often through a simple mechanism called CR form. This form enables him to request changes, to report bugs or to ask for support in a software product [2]. Initially, he or she should inform a short description, a long description, a type (e.g. bug, new feature, improvement, and task) and an associated severity level (e.g. blocker, critical, major, minor and trivial). Subsequently, a development team member will review this request and, case it is not refused for some reason (e.g. request duplication), he or she will complete the information in CR form, indicating, for example, its priority and assigning the person responsible for the CR. MARIO: importante usar terminologia e jargao do ramo: acho que aqui nao eh accomplish e sim assigned for the CR; verificar em outros artigos

The severity level information is recognized as a critical variable in the equation to estimate a prioritization of CRs [3]. It defines how soon the CR needs to be addressed [4]. However, the severity level assignment remains mostly a manual process which relies only on the experience and expertise of the person who has opened the CR [1], [3], [4]. As a consequence, it is a process with high degree of subjectivity, and it may be quite error-prone.

The number of CRs in large and medium software OSS projects [5] is frequently very large. Severity level shifts throughout CR lifecycle may have an adverse effect on the planning of maintenance activities. For example, the maintenance team could be assigned to address less significant CRs before most important ones. There is opportunity for an intelligent software assistant to help developers and maintenance personnel in defining more accurately the field values in a CR form. Currently, Machine Learning techniques have become popular to address this issue and there is quite a few publications in this area in the literature [1].

Machine Learning (ML) techniques have been successfully applied in solving real problems in many areas of knowledge, including those related to CR systems, such as duplication and assignment of CR [1]. However, the accuracy of ML algorithms may be affected by imbalanced datasets [6] —a recurring critical problem in CR repositories [7]. For example, more than 60% of CRs may have a "major" severity level.MARIO: veja a sintaxe para matching double quotesLUIZ: CorrigidoMARIO: eu tinha corrigido e vc voltou a forma errada. O certo eh "assim"
MARIO:
tirei a figura e a referencia. Alias, o texto fala Severity level

shifts throughout CR lifecycle e a figura era sobre os estados do lifecycle. Melhor remover.

MARIO: aqui deveria entrar a motivacao. Motivacao sempre e: melhorar o desempenho de algo; ou suprir um falha de algo. Vc poderia por ex dizer: muitos estudam CR com ML mas nao ha um comparativo entre algoritmos; ou o desempenho esta muito baixo; ou a melhoria com relacao a predicao manual nao eh medida. E preciso justificar porque vc fez o trabalho. Sugestao durante a reuniao: ha muitos trabalhos mas ainda nao satisfatorios. Ha espaco para melhoria e criacao de ferramenta. LUIZ: Despite there are many studies related to predicting the severity level of CRs, none of them is definitive, and none of them have been implemented into popular tools like as Bugzilla, Jira and Redmine. [1]

REMOVED: In this context, our goal is to indicate the best ML classifier to predict the severity level of a CR in an imbalanced data scenario, based on the assessment the accuracy of three traditional ML algorithms: Neural Networks (NN), Random Forest (RF) and Support Vector Machine(SVM). MARIO: discutir em reuniao: eh isso mesmo? Se sao so 3, entao nao eh the best. OUTRA COISA: eu daria destaque para o goal. Eh comum numerar G1, G2, e depois abaixo RQ1, RQ2, etc, inclusive relacionando-as entre si.LUIZ: To (i) evaluate the performance of traditional ML algorithms in the prediction of CR severity level; (ii) indicate the most suitable algorithm to perform such prediction in a scenario where imbalanced data is natural; and (iii) compare the traditional measures (recall, precision and F-measure) with the performance of the user in the assigned CR severity level.

REMOVED: To systematize our evaluation, our experiments should answer the following research questionsNEW: The research questions of this study are:

- RQ_1 : *Will CR severity level change during its lifecycle?* we have investigated the accuracy of the classifiers to answering a binary response question: if CR will remain its severity level or it will change.
- RQ_2 : *Will the CR severity level increase, decrease or remain the same during its lifecycle*? we have investigated the accuracy of the classifiers to answering a ternary response question: if CR will remain, increase or decrease its severity level.
- RQ_3 : *What will the CR severity level at the end of its lifecycle?* Finally, we have investigated the accuracy of the classifiers to answering a question with more than three responses.

MARIO:

A lista de RQ nao deve misturar as perguntas com a estrategia para seu encaminhamento. Uma possibilidade seria (depois da lista) justificar a escolha delas.

This paper aims to deliver the following contributionsMARIO: Vamos conversar sobre isto na reuniao. Ver artigos semelhantes da MSR:

LUIZ: Professor,já são 3:30 da madrugada, Estou sem ideia tenho que pensar mais :-(

1) Indicate the performance of three ML algorithms to answering questions with two, three or more responses in an imbalanced scenario.
2) Propose a new way to measure the performance of ML algorithms in imbalanced data scenario besides the traditional forms used for this purpose.
3) Advance the researches on the topics discussed in this article.

The structure of this paper is as follows. Section II presents related work that are relevant to our research. Section III provides the information background about CR systems, text mining and machine learning techniques necessary to understand our approach. Section IV describes our work. Section V presents final findings and discussion. REMOVED: Finally, we conclude and discuss future work in Section 6NEW: Finally, Sections VII and VIII present the threats to validity of this research, and conclusions and future work, respectivelyMARIO: deixei aqui p vc ver um exemplo de trocar voz passiva pela ordem direta, e tbem remover a primeira pessoa. Ja mudei no resto deste paragrafo.

II. Related Work

MARIO: usar label e ref para ref cruzada

MARIO: aqui vc entrou de chofre. Precisaria fazer uma introducao

Menzies [8] have developed a method, named SEVERIS (SEVERity ISsue assessment), for evaluating the severity of CRs. SEVERIS is based on common text mining techniques (e.g. tokenization, stop word removal, stemming, Tf*Idf and InfoGain) and on the data mining techniques (e.g. RIPPER). The method was applied to five projects managed by the Project and Issue Tracking System (PITS). - an issue tracker system used by NASA. The average of CRs by projects was 775 and LUIZ: The f-measures have gotten by severity level were: (2) 78%-86%; (3) 68%-98%; (4) 86%-92%. Severity level 1 and 5 were excluded from experiment because there was zero or few CRC with this levels.MARIO: Quais foram os resultados ou conclusoes? Em que medida isso eh util p nosso trabalho ou diferente dele? MARIO: Em toda a secao vc cita varias tecnicas e metodos. Discutir necessidade de referencia

Lamkanfi et al. [4] have developed an approach to predict if severity of bug report is non-severe(severity levels:1 and 2) or severe(severity levels: 4 and 5) based on text mining algorithms (tokenization, stop word removal, stemming) and on the Naïve Bayes machine learning algorithm. They have been validated their approach over from three open source project Mozilla, Eclipse, and GNOME and they accomplished that a training set with approximately 500 CRs per severity degree are enough to predict it with a reasonable accuracy LUIZ: (both precision and recall vary between 0.65-0.75 with Mozilla and Eclipse; 0.70-0.85 in the case of GNOME).

In another following work, Lamkanfi et al. [5], these authors compared the accuracy of four machine-learning algorithms (Naïve Bayes Multinomial, K-Nearest Neighbor, and Support Vector Machine) to predict if a bug report is severe or non-severe. They have been concluded that Naïve Bayes Multinomial gave superior performance compared to the others proposed algorithms. LUIZ: The performance have gotten by this classifier was 0.75-0.93 Area Under Curve (AUC)

Valdivia et al. [9] have characterized blocking bugs in six open source projects and proposed a model to predict them. Their model was composed of 14 distinct factors or features (e.g. the textual description, location the bug is found in and the people involved with the bug). Based on these factors they build decision trees for each project to predict whether a bug will be a blocking bug or not. LUIZ: The f-measures achieved by these decision trees was 15-42%.

LUIZ: Tian et al. [3] have develop a method based on similar CR reported in the past to predict severity level of new CRs. The comparison between the past and the new CR was made using BM25 similarity function. Their method was validated on Mozilla, Eclipse and OpenOffice projects over more than 250,000 CR extracted from Bugzilla. The results have gotten by them were F-measure of 13.9-65.3% for Mozilla; 8.6-58% for Eclipse; and 12.3-74% for OpenOffice

III. BACKGROUND

REMOVED: In this section, we describe de CR process. Next we explain the common approach to pre-processing textual documents, and lastly, we highlight the three ML algorithms: Neural Networks, Random Forest and SVM.NEW: This section presents basic background material: CR process and CR Systems (Section III-A; usual approaches to pre-processing textual documents and text mining (Section III-B); and a brief description of three Machine Learning algorithms used in this research, Neural Networks, Random Forest and SVM (Section III-C). Finally, typical Evaluation Metrics are presented (Section III-D).

A. Change Request Systems

CR systems [10] are software employed to keep the recording and tracking information of requests for modifications, bug fixes, and support that could occur during the software life cycle.

Although there is no REMOVED: a common sense NEW: consensus regarding terminology or the amount of information that users must fill in to complete his requisition among popular CR systems (e.g. Bugzilla, Jira, and Redmine) [3], typically, REMOVED: they shall fill in a form containing at least the NEW: a CR form contains the following attributes shown in Table I.

TABLE I: Commom attributes in the CR forms.

Type	Type of request (e.g. bug, new feature, improvement, and new feature)
Title	Short description of request in one line.
Description	Long and detailed description of request in many lines. It could include source code snippets and stack tracing reports.
Severity	Level of severity of request (e.g. blocker, critical, major, minor and trivial).

Once the request has been registered by the user, the development team will assess it and, if it not canceled for some reason (e.g. duplication), REMOVED: they will complement the information with, for example, NEW: will assign the CR to the person responsible for handling it. The development team may include additional information at any time. All these data are stored in a repository, keeping relevant historical data about the system under development. MARIO: este material eh muito basico. Talvez seja desnecessario. Colocar so o que nao eh obvio e eh necessario para o entendimento. Por ex: atributos, problemas de terminologia, historico de alteracao.

B. Text Mining

Text mining is the process to convert unstructured text into a structure suited to analysis [11]. It is composed of three basic activities [12]: tokenization, stop word removal and stemming.

Tokenization is the action to parsing a character stream into a sequence of tokens by splitting the stream at delimiters. In this context, a token is defined as a block of text or a string of characters (without delimiters such as spaces and punctuation) that is recognized as a useful portion of the unstructured data.

Stop words eliminates commonly used words that do not provide relevant information to a particular context, including prepositions, conjunctions, articles, common verbs, nouns, pronouns, adverbs, and adjectives.

Stemming is the process stemming is the process of reducing or normalizing inflected (or sometimes derived) words to their word stem, base form—generally a written word form (e.g. "working" and worked into work). MARIO: Vc copiou algum texto ipsis literis? Caso afirmativo reescreva. Isso vale para toda esta secao.LUIZ: a referência é o [12], esqueci de reescrever

C. Machine Learning

REMOVED: The machine learningNEW: Machine Learning MARIO: So use o the se estiver falando daquele especifico ML. is considered a part of artificial intelligence area whose the primary purpose is to resolve a given problem using experience or example data [13]. It can be seen as an improvement over a set of techniques or methodologies which can make a computer to learn by the study of data sets.

MARIO: Fazer introducao aqui. Enumerar algumas tecnicas e citar que ira descrever x, y, z (ref subsec) por serem mais relevantes nesta area

1) Neural Networks: Neural Network is a learning algorithm that is inspired by the structure and functional aspects of biological neural networks [14]. Computations are structured regarding an interconnected group of artificial neurons, processing information using a connectionist approach to computation.

Modern neural networks are non-linear statistical data modeling tools. They are usually used to model complex relationships between inputs and outputs, to find patterns in data, or to capture the statistical structure in an unknown joint probability distribution between observed variables.

2) Random Forest: The Random Forest algorithm [15] relies on two core principles: (i) in the creation of hundreds of decision trees and the joining them into a single model; and

(ii) in the closing decision based on the ruling of the majority of the forming trees which are treated as equals.

A random forest model is considered a suited alternative for model construction for a many of reasons [12]

- Requires little or no data preprocessing, no data normalization and it is resilient to outliers.
- Requires no variable selections because the algorithm does its own.
- Models resultants from each tree in the forest tend not to overfit to the training dataset because they are built using two levels of randomness (observations and variables).

3) Support Vector Machine: Support Vector Machine is considered the most popular algorithm for supervised learning and an excellent first method to testing [14]. It is a set of related supervised learning methods used for classification and regression. Each example in a set of training data is marked as belonging to one of two categories an the SVM algorithm builds a model that predicts whether a new example falls into one category or the other.

D. Evaluation Metrics

From Information Retrieve (IR) discipline, MARIO: referencia? LUIZ: [11]the three most common performance measures for evaluating the accuracy of classification algorithms are precision, recall, and F-measure.

Recall. The recall for a class can be defined as the percentage of correctly classified observations among all observations belonging to that class. It can be thought of as a measure of a classifiers completeness. More formally [16]: the recall is the number of True Positives (TP) divided by the number of True Positives (TP) and the number of False Negatives (FN), where the TP and FN values are derived from the confusion matrix. A low recall indicates many False Negatives [17]. MARIO: Talvez valha a pena mostrar a matriz de confusao.

Precision. The precision is the percentage of correctly classified observations among all observations that were assigned to the class by the classifier. It can be thought of as a measure of classifier exactness. More formally [16]: the precision is the number of True Positives (TP) divided by the number of True Positives and False Positives (FP), as well as TP and FN, FP also comes from the confusion matrix. A low precision can also indicate a large number of False Positives [17].

F-measure. F-measure conveys the balance between the precision and the recall and combines the two measures in an ad hoc way [11], [17].F-measure can be calculated using the formula $2 * ((precision * recall))/(precision + recall)$. MARIO:
Nao revisei ML e Evaluation

IV. Experiment

This section describes the experiment conducted to address the Research Questions. As in typical methodologies used in ML studies, it comprises the followint steps: Data Collection (IV-A), Data Preprocessing (Section IV-B), and Training and Testing (Section IV-C).

A. Data Collection

This step in the experimental research encompasses sellecting a FLOSS to serve as the data source, studying and interpreting its data structure, and finally extracting relevant data from its repository (feature extraction). In this research, Hadoop, Linux, and Mozilla Open Systems were considered as potential Open Source Systems to study. MARIO: LG: corrigir esta lista; chutei de memoria. In a first approximation, Hadoop was sellected as a data source of CR records, due to the fact it is open, well stablished, has a considerable number of CRs already registered, uses standard repositories, and was under study by other researchers in our research group. According to [hadoop.apache.org], HADOOP is a "framework that allows for the distributed processing of large data sets across clusters of computers using simple programming models. It is considered a specialized and complex OSS project with many users with different levels of expertise. Its CR repository allows for access to all CR contents in XML format. Everything is available (except change history), from CR long description field (with lines with few characters to ones with many lines), including code snippets and exception stack trace.

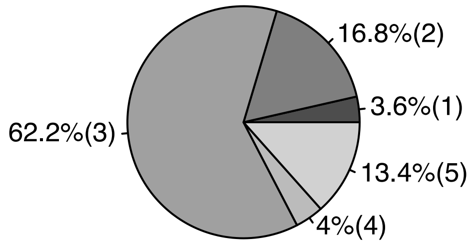
CRs in HADOOP are stored in a Jira based repository [https://www.atlassian.com/software/jira]. Two steps are used to perform data extraction from HADOOP web site[http://issues.apache.org]: (i) copying CR basic data (e.g. status and resolution) from XML contents; and (ii) copying CR changes history from external HTML pages (this may be important for learning). About 10% of the CRs collected in this process changed their level of severity at least once.

CR record data from February 01, 2006 to January 18, 2017 was collected. Only requests from the common module (identifier = HADOOP-*) MARIO: ver se o wildcard esta corretoLUIZ: Ok were considered for retrieval. The total number of CR records retrieved after preprocessing was 7129.

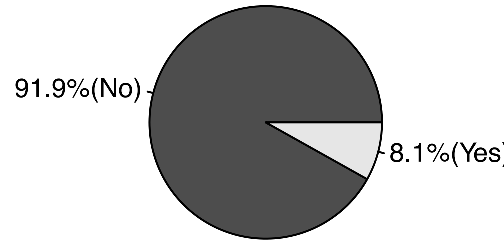
Figure **??** shows how the 7129 retrieved CR records were distributed in terms of severity level and severity level change. Figure **??**(a) shows the severity level distribution: 3.6% have severity 1 (trivial); 16.8% have severity 2 (minor); 62.2% have severity 3 (major), 4.0% have severity 4 (critical), and 13.4% have severity 5 (blocker). Figure **??**(b) shows that only 8.1% have changed their severities levels during the CR lifecycle. Finally, Figure **??**(c) reveals that of these 8.1% CRs which changed their severity, 23.3% decreased it, and 76.7% increased it. One can see that this dataset is clearly imbalanced, posing addicional difficulty to the application of the ML methodology.

B. Preprocessing

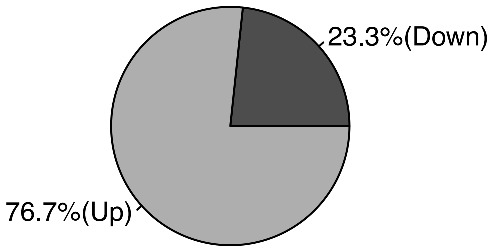
The raw data previously collected from the Hadoop CR Repository was not properly structured to serve as input to ML algorithms, it was in tidy data format [18]. The classical way to address this problem is to run preprocessing procedures to extract, organize and structure relevant information out of the raw data. Specific scripts were written in R language to acomplish this. Preprocessing tasks were executed as follows:



(a) 1a



(b) 1b



(c) 1c

Fig. 1: plots of....

- Extraction of relevant features: key, type, status, resolution status, and long description of CRs; MARIO: title ??
- Filtering CRs with status equals to Closed and resolution equals to Fixed and Implemented.
- Merging CR features with their change history data. This additional information allows for the identification of CRs that have changed severity level during the CR lifecycle, and furthermore, if they have changed for better (decrease) or worse (increase).
- Performing text mining in the long description field to identify the 100 most frequent words. This information is then converted into features for each CR.
- Sorting the CRs in ascending chronological date.

C. *Training and testing*

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Training and testing steps starts with partitioning the already preprocessed dataset in two disjoint subsets: a subset for training, with 60% of the CRs, and a subset for testing, with the remaing 40% of the CRs. MARIO: falar algo sobre sampling choices?? In the training phase, we have used the cross-validation with 3-fold MARIO: seriam as 3 medidas? Ser mais explicito ou citar referencia techniqueLUIZ: [17]to choose the best values for hyperparameters for each classifier algorithm to use them in the test phase.

V. Findings and Discussions

A. *RQ1: Will the CR severity level change during its lifecycle?*

The RQ1 is a simple binary problem, i.e., a question whose answer is true or false. The Table II shows the performance (in percentage) of the classifiers to predict the response to this issue.

TABLE II: Classifiers Performances on RQ1.

Classifier	Precision	Recall	F-Measure
NN	93,381	98,015	95,642
RF	93,801	99,923	96,765
SVM	93,727	99,809	96,627

We tested the classifiers with 2851 (40% of 7129) CR: 2620 have changed their severity level, and 231 haven't changed their severity level. We can observe that the three classifiers performed very closely. However, the Random Forest classifier have achieved a F1-Measure somewhat better than the two others. LUIZ: About the related works, the value of the F-measure of the three classifiers was better, although the research questions are not identical.

Regarding the Random Forest classifier we have done one step further, we have investigated its performance relating to the number of hits and errors made in answer to RQ1. The Figure **??** indicates that its accuracy was 93.681% (2676 divide by 2851).

B. *RQ2: Will the CR severity level increase, decrease or remain the same during its lifecycle*

The RQ2 poses a problem more difficult than a previous question. It is a question with three possible responses related to severity level: (-1) it has decreased; (0) it has remained; and (1) it has increased. The Table III shows the performance (in percentage) of the classifiers to predict the response to this issue.

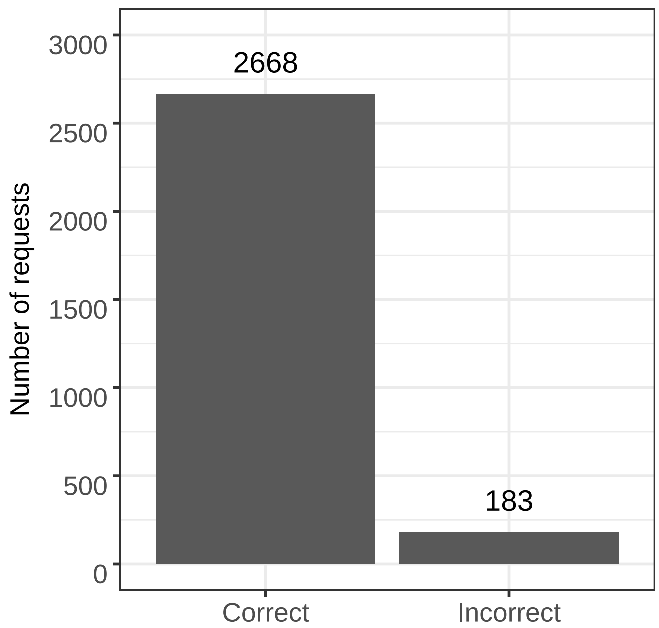

Fig. 2: Performance of Random Forest for RQ1.

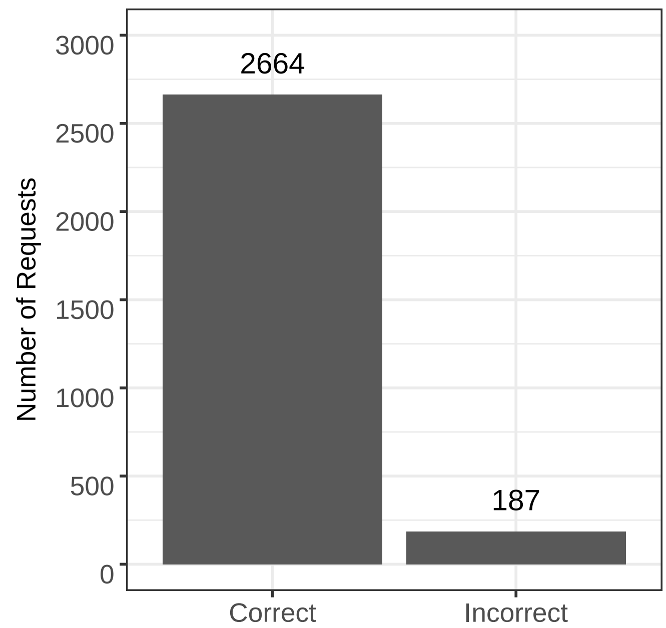

Fig. 3: Performance of Random Forest for RQ2.

TABLE III: Classifiers Performance on RQ2.

	Class	Precision	Recall	F-Measurement
NN	-1	3.703	28.571	6.557
	0	97.663	93.357	95.447
	1	22.598	38.461	28.469
	Average	41.311	53.463	43.491
RF	-1	13.111	85.714	19.672
	0	99.923	93.500	96.605
	1	28.598	90.652	46.199
	Average	47.210	89.955	54.158
SVM	-1	12,962	70,000	21,875
	0	99,923	93,902	96,819
	1	27,118	90,566	41,739
	Average	46,667	84,822	53,477

We have tested the classifiers with 2851 (40% of 7129) CRs. Only now, we have three predicting situations: 2620 haven't changed their severity level, 177 have increased their severity level, and 54 have decreased their severity level. We can observe in the Table III which the classifiers also performed very closely as question 1. However, the Random Forest classifier have achieved F-Measure somewhat better than the two others.

Like as in the RQ1, we have done one step further regarding the best classifier, we have investigated its performance, observing the number of correct and incorrect answers on the test dataset as a whole. The Figure **??** indicates that its accuracy was 93.440% (2664 divide by 2851) in the RQ2 prediction. LUIZ: Não estou certo como comparar essa questão de pesquisa com os outros trabalhos, pois ela não é similar a dos outros trabalhos

C. RQ3: What will the CR severity level at the end of its lifecycle?

The RQ3 is a problem much harder than other two. It is a question with five responses related to severity level: (1) trivial; (2) minor; (3) major; (4) critical; and (5) blocker. The Table V shows the performance (in percentage) of the classifiers to predict the response to this issue.

TABLE IV: Classifiers Performance on RQ3.

	Class	Precision	Recall	F-Measurement
NN	1	4.950	29.411	8.474
	2	18.997	34.469	24.495
	3	88.726	66.273	75.873
	4	16.964	37.254	23.312
	5	17.015	46.099	24.856
	Average	29.330	39.606	31.402
RF	1	4.950	83.333	9.345
	2	16.283	76.470	26.850
	3	98.308	67.387	79.963
	4	30.357	100.000	46.575
	5	25.130	81.355	38.400
	Average	35.005	81.709	40.226
SVM	1	6.930	70,000	12.612
	2	16.283	77.227	26.896
	3	95.478	67.166	78.857
	4	30.357	97.142	46.258
	5	23.036	87.128	36.438
	Average	34.416	79.7326	40.212

We have tested the classifiers with 2851 (40% of 7129) CRs. Only now, we have six predicting situations: 101 are trivial; 479 are minor; 1774 are major; 112 are critical; 382 are a blocker. We can observe in the Table III which the classifiers also performed very closely as questions 1 and 2. However, the Random Forest classifier have achieved a F1-Measure somewhat better than the two others. LUIZ: the value of the F-measure this classifier was better than [3] and not as good as [8].

Like as in the RQ1 and RQ2, we have done one step further regarding the best classifier, we have investigated its performance, observing the number of correct and incorrect answers on the test dataset as a whole. The Figure **??** shows three graphs. The graph (a) shows user range error in the assignment of severity level. The graph (b) shows the classifier error in the assignment of severity level. And the graph (c) compares de Predictor Error (PE) with User Error (UE) in terms of the amount of CR whose predictions. We can note that the random forest performance was also 68,08% (1941 divide by 2851).

Although we can consider that accuracy a good value, the graph (a) shows that user accuracy was 91.18% and graph (c) also shows that 745 CRs, the PE was greater than UE. From a business vision, the predictor have not show suitable performance.

VI. Findings and Discussions

LUIZ: Tabela em CONSTRUÇÃO

VII. Threats to Validity

Runeson [19] recommends that threats to validity should be considered under four aspects: construct validity; internal validity; external validity; and reliability.

Construct validity. Despite existing others metrics to evaluate classifiers [16], which could be more suitable than precision, recall and F1-measure, we prefer to use them because they have been used satisfactorily in related works [4], [5], [8], [9].

Internal validity. We assume that level of severity assignment by the user is correct and that there is an intimate relationship between it and the long description of the CR. This assumption finds echo or support in [3], [4]

External validity. We have considered one single repository and we have extracted 8858 CRs from it. Although we can't generalize the results to others, the characteristics presented by HADOOP repository, particularly regarding the balance of the data, are similars to those shown in the repositories studied [3]–[5], [9].

Reliability. The code developed in the Java language and the R language for preprocessing, training, testing and analysis of results have been carefully checked may contain bugs. To minimize this problem, we rely heavily on libraries offered by them such as XStream (the XML parser), nnet (a neural network R implementation), randomForest (a random forest R implementation) and e1071 (a SVM R implentation).

VIII. Conclusion and Future Work

In this paper, we assess the Neural Network, Random Forest and Support Vector Machine, three popular ML algorithms to CR severity level in imbalanced data scenario. We have considered the CR long description as the main factor to this prediction. The features of machine learning were derived from words (token) from this description. The results on a dataset consisting more than 8,000 CR from Hadoop have shown that random forest performed well to predict the severity level will change and whether severity will increase or decrease with reasonable accuracy, around 93.681% and 93.440% respectively. However, it has provided the accuracy (around 68,08%) to predict the final last severity level on imbalanced data scenario.

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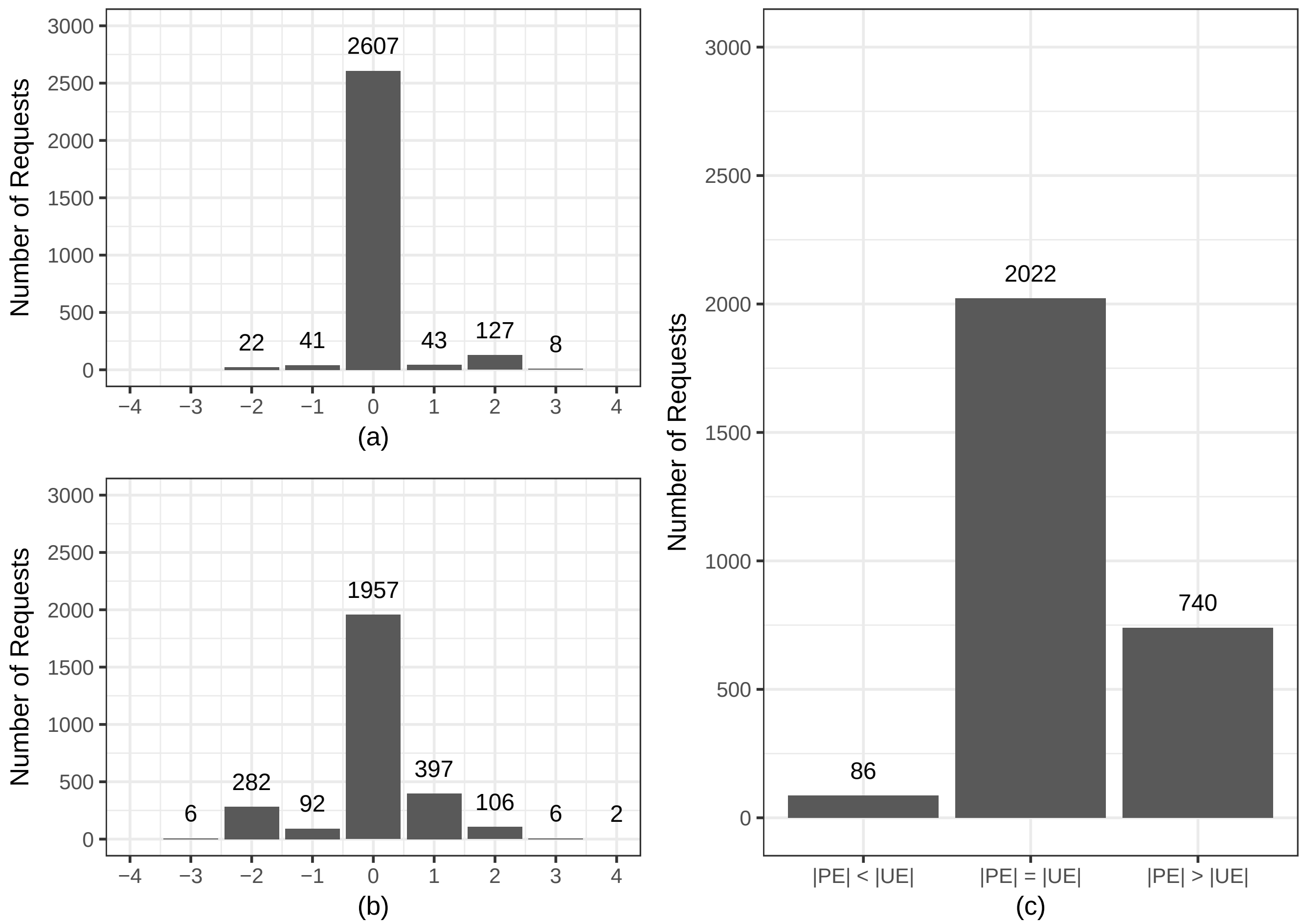

Fig. 4: Performance of Random Forest for RQ3.

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TABLE V: Classifiers Performance on RQ3.

	Research Questions	Repositories	F-measure	Algorithms	Observations
Menzies [8]	NA	pitsA	14-71	RIPPER	
		pitsB	42-90	RIPPER	
		pitsC	53-92	RIPPER	
		pitsD	87-99	RIPPER	
		pitsE	8-80	RIPPER	
Lamkanfi [4]		4.950	83.333	9.345	0
		16.283	76.470	26.850	0
		98.308	67.387	79.963	0
		30.357	100.000	46.575	0
		25.130	81.355	38.400	0
Lamkanfi [5]		6.930	70,000	12.612	0
		16.283	77.227	26.896	0
		95.478	67.166	78.857	0
		30.357	97.142	46.258	0
		23.036	87.128	36.438	0
Valdivia [9]		6.930	70,000	12.612	0
		16.283	77.227	26.896	0
		95.478	67.166	78.857	0
		30.357	97.142	46.258	0
		23.036	87.128	36.438	0
Tian [3]		6.930	70,000	12.612	0
		16.283	77.227	26.896	0
		95.478	67.166	78.857	0
		30.357	97.142	46.258	0
		23.036	87.128	36.438	0
Ours		6.930	70,000	12.612	0
		16.283	77.227	26.896	0
		95.478	67.166	78.857	0
		30.357	97.142	46.258	0
		23.036	87.128	36.438	0