Software Risk Prediction using Supervised Machine Learning Techniques

Sugato Chakrabarty[1], Jhansi Rani Prathuri[2], Kavitha P[3], Pavan Rajkumar Magesh[4], and Richard Delwin Myloth[5]

[1,2]Professor
[3]Assoc. Professor
[4,5]Under Graduate Student
[1,2,3,4,5]Department of Computer Science and Engineering, CMR Institute of Technology, Bengaluru, India

Abstract

Trying to minimize the number of software failures is one of the most important goals in the area of software project management. In software development, which is a part of software project management, incremental changes are typically made to an existing set of code and documents that may be initially empty. This goal becomes more crucial due to short delivery schedules that constrain coding, inspection and testing. In this paper, we deal with one aspect of the above scenario, where we predict, using machine learning techniques, the risk associated with changing a software code segment based on a set of parameters associated with that segment. We decide on a set of features relevant to a segment of code and create different types of machine learning models based on those features to predict the risk associated (in terms of probability of failure) with a change in that segment. We then decide on various evaluation criteria and compare and show the best models that work in this scenario.

Keywords: Machine Learning, Software Engineering, Risk Prediction, Naïve Bayes, Neural Nets, Random Forest

1 Introduction

Though software engineering is one of the most challenging and difficult of all engineering disciplines, this is often not recognized as such, because most of the software is hidden from our eyes in our daily lives.

Software development typically proceeds as a series of changes to a base set of software. Except for new projects, where the base set is initially empty, most projects, however, involve incremental changes to an existing, perhaps large, set of code and documentation. Software developers usually make changes to the code by fixing defects or bugs, adding new functionality, improving performance or reliability, or rewriting the software to improve its changeability or readability, among other tasks. Each change carries with it some possibility of failure, leading in turn to possible software project failures. These failures are often a result of insufficient and ineffective risk information regarding the future. To overcome this, software risk prediction should be performed in advance to allow project managers insight into providing more valuable information for decision making, such as scope coverage, resource allocation, and schedule changes.

Reducing the number of software failures, thus, becomes one of the most challenging problems of software production. It is even more important when tight delivery schedules restrict coding, inspection, and testing intervals. In this paper, we specifically deal with one aspect of the above-mentioned scenario, namely predicting, using Machine Learning techniques, the risk associated with changing a specific software code segment given a set of parameters associated with that segment. Knowing this risk helps project managers to put in place possible risk mitigating tasks (e.g. increasing testing or rescheduling the launch of the software).

The remainder of this paper is organized as follows. In the section immediately below, we review related work. In the next section, we enumerate the methodology adopted where Machine Learning is used to determine the risk associated with a software change. In the sections that follow, the methodology adopted and the results of running the Machine Learning models are shown. Finally, in the last section, the concluding remarks are presented.

2 Related Work

A number of investigations have been done that determine several product measures that predict the likelihood of a code having a fault. A common approach is to use several product measures— determined from a short description of the code—as predictors of fault likelihood, with code size (that is, the number of lines of code) as one of the most important fault prediction measures.

The paper by An, Gustafson, and Melton [1], Basili and Perricone [2] and Hatton [3] connect the defect frequency of code to the file size. An, Gustafson, and Melton[1] also use the degree of nesting to predict the potential for a file to have a fault. Measures of code complexity, such as McCabe's cyclomatic complexity [4] and Halstead's program volume [5] are other product measures that have been linked to failure possibilities. Empirical studies of product measures and fault rates have been conducted and are described by Schneidewind and Hoffman[6], Ohlsson and Alberg[7], Shen et al.[8] and Munson and Khoshgoftaar[9]. Another way to measure modeling fault rates uses data from the change and defect his tory of the program. Yu, Shen, and Dunsmore [10] and Graves et al.[11] use this idea for fault prediction, while Basili and Perricone [2]do a comparison based analysis between new code units and those that borrow code from other places.

The software reliability literature also contains various studies [12, 13, 14, 15, 16, 17] that roughly calculate the number of faults remaining in a software system. This may help in predicting the number of faults in the future. Some studies have also been done with regard to software projects risk prediction [18, 19, 20]. In particular, research has been conducted on prediction models, that attempt to predict the failure likelihood of components of a newly developed software system. Since a software system usually has components described by metrics such as the code complexity and number of pre-release changes, statistical models, such as a decision tree or logistic regression, may be used based on these metrics for predicting a component defect or system failure.

Gupta et al.[21] gives a quantitative model for risk control for a software project called SRAEM (Software Risk Assessment and Estimation Model). Much of the research conducted by industry involve using the data mining of software repositories (MSRs), such as DTSs and version control systems. In this context, Hassan[22] gives the concept of the entropy of changes, which is a measure of code change complexity. Kim et al.[23] propose the change classification technique, which involves learning historical change patterns of bugs, in order to predict whether a new code change will lead to bugs. Zimmermann et al. [24] predict defect proneness based on the defect information extracted from the CVS/SVN repositories. However, most of these techniques try to build a classification model to analyze the code or developer behavior and thereby predict whether the resulting code will have a bug.

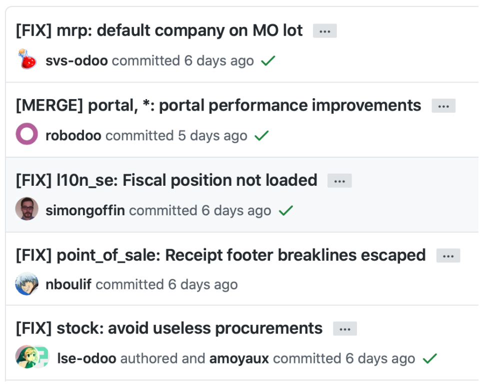
Some work has also been made to automate the software testing process using Machine Learning (ML) which happens to be a sub domain of AI. In [25],[26], evolutionary algorithms have been used to automate generation of test case. In [27], Artificial Neural Networks (ANN) have been used to build a model to determine the effectiveness of the generated test cases. Briand et al. in [28] has proposed a method based on the C4.5 decision tree algorithm to predict potential bugs in a software system. Research seems to suggest that machine learning techniques offer a promising approach to automate the testing processes.

3 Methodology

In this section the overall methodology is discussed. The basic idea is to create machine learning models to predict the risk of introducing a bug to a software code section, when making a change in it, and then compare these models in terms of several criteria.

We use supervised machine learning techniques and so there happen to be features used to create the machine learning model and certain steps that are typically followed in creating such a model. The steps are as follows:

1. Gathering the data: This step is very crucial as the quality and quantity of data gathered will directly determine how good the predictive model will turn out to be. In our case, the data happen to be software code sections from github. An example is shown in Figure 1.


[FIX] mrp: default company on MO lot
svs-odoo committed 6 days ago ✓

[MERGE] portal, *: portal performance improvements
robodoo committed 5 days ago ✓

[FIX] l10n_se: Fiscal position not loaded
simongoffin committed 6 days ago ✓

[FIX] point_of_sale: Receipt footer breaklines escaped
nboulif committed 6 days ago

[FIX] stock: avoid useless procurements
lse-odoo authored and amoyaux committed 6 days ago ✓

Figure 1: Git Commits

2. Preparing the data: After the training data is gathered, the next step of machine learning needs to be done. This happens to be data preparation, where the data is loaded into a suitable place and then prepared for use in machine learning training. In addition to other tasks, the data now also has to be split into two parts. The first part that is used in training our model, will be the majority of the data set, usually around 80 percent (the training set) and the second will be used for evaluating the trained model's performance, usually around 20 percent (the test set).

In this step, the relevant features of the data set are also decided. This is important because choosing the appropriate set of features determines the accuracy of the output. For our work, the features chosen are,

- lines of code added
- lines of code deleted
- number of files changed
- author experience
- commit message categorization
- commit message length

We also decided to use the categorical variable called risk taking the value of 1 (i.e. equal to or greater than 50 percent probability of failure) and 0 (less than 50 percent probability of failure) as the output variable.

3. Choosing the model: The next step is to choose a model among the many machine learning models available. In our case, we've chosen several types of models in order to compare them. These are Naive Bayes, Neural Net, Logistic Regression, Random Forest and Support Vector Machines (SVM).

4. Training the model: In this step, often considered to be perhaps the most important step, the model is trained or created with the training data. This

essentially means that some kind of function is created based on which an input can be mapped to an output. Some models need the user to adjust certain control parameters.

5. Evaluating the model: In this step, once training is complete, the model is evaluated for accuracy or goodness. This is where the test set put aside earlier comes into play. Evaluation allows the testing of the model against data that has never been seen and used for training and is meant to be representative of how the model might perform when used in the real world. There are several ways in which the accuracy of the model may be measured or evaluated. We will use the measures of Precision and Recall, Receiver Operating Characteristic or ROC, and Confusion Matrix to measure the accuracy of the models.

4 Results

In this section the results obtained by running the different machine learning models are presented. The data set has about 4736 code samples taken from the GitHub open source ERP repository, "odoo". An example data has already been shown in Figure 1.

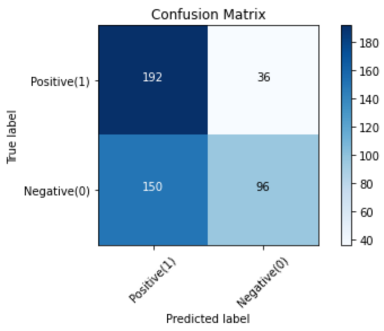
Comparison amongst the used models resulted in a clear observation that the Random Forest model performs the best. Table 1 gives a comparison between these models and the following Precision-Recall Curves, Confusion Matrices, and Receiver Operating Curves further reinforc this claim.

Table 1 shows the classification report in terms of accuracy, precision, recall and F1-score for various machine learning models like Random Forest, Logistic Regression, SVM, Neural Network and Naive Bayes classifier. The parameters used to generate the classification report are,
TP-True Positives, TN-True Negatives, FP-False Positives, FN-False Negatives
Accuracy = (TP+TN)/(TP+FP+FN+TN)
Precision = TP/(TP+FP)
Recall = TP/(TP+FN)
F1 Score = 2*(Recall * Precision) / (Recall + Precision)

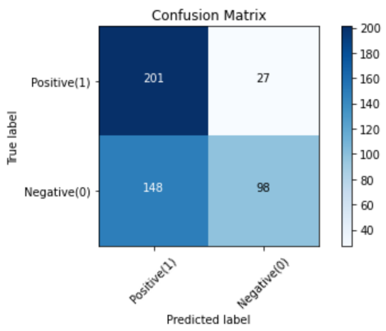
As per the results shown in Table 1, the random forest model gives the best accuracy of 82.2% among the models run, which indicates the false positive and false negatives are almost same. Precision of 81.8% indicates the low false positive rate and recall of 84.5% indicates the model is good as it is above 50%. F1-score of 83.2% indicates the model is good.

Table 1: Classification Report

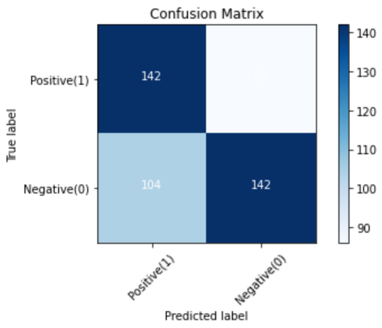
Model	Accuracy	Precision	Recall	F1-score
Random Forest	82.2	81.8	84.5	83.2
Logistic Regression	57.1	66.4	35.3	46.1
SVM	56.1	61.8	40.2	48.7
Neural Network	59.9	62.2	57.7	59.9
Naive Bayes	48.7	66.6	2.43	4.70



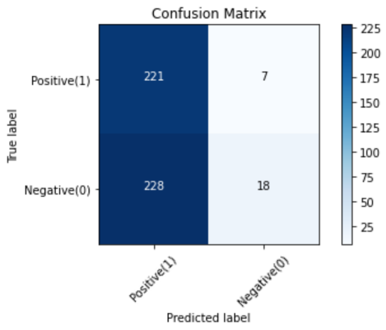
(a) SVM



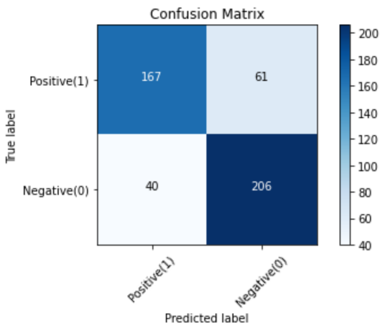
(b) Logistic Regression



(c) Neural Network



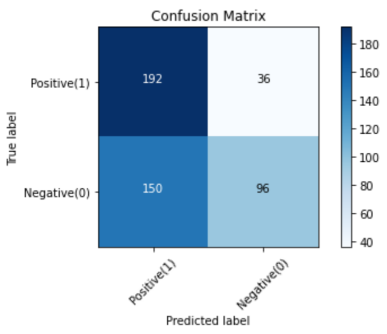
(d) Naive Bayes



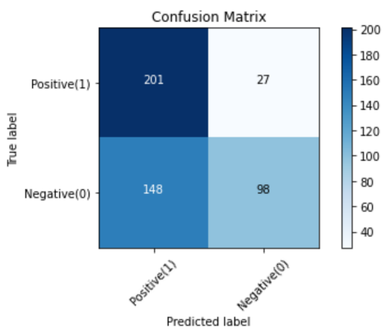
(e) Random Forest

Figure 2: Confusion Matrices

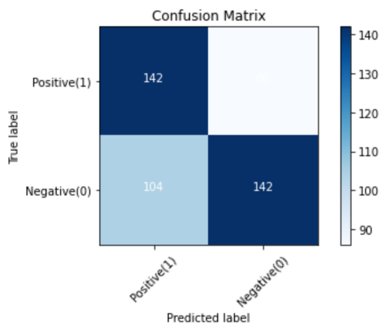
The confusion matrices for the models are shown in Figure 3. Figure 2(a) depicts the confusion matrix for the SVM classifier, and it can be observed that the model predicted a significant number of false negatives and a relatively lower amount of false positives. Logistic Regression as depicted in Figure 2(b) obtained similar values. The neural network predicted almost no false positives while the Naive Bayes classifier performed quite poorly as it can be seen that it predicted a significant 228 false negatives. The Random Forest Classifier depicted in Figure 2(e) performed the best overall.



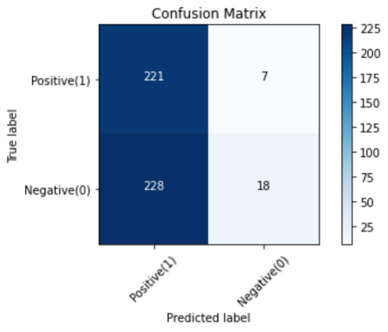
(a) SVM



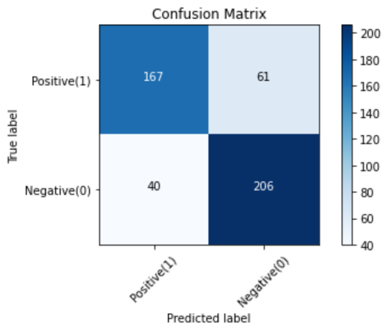
(b) Logistic Regression



(c) Neural Network



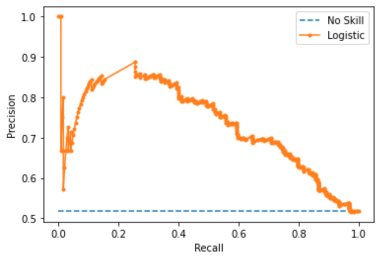
(d) Naive Bayes



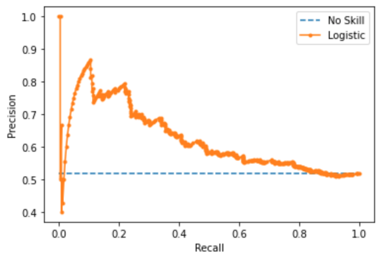
(e) Random Forest

Figure 3: Confusion Matrices

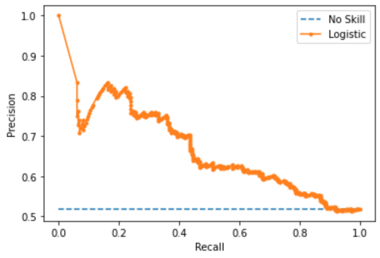
A Precision Recall curve is simply a graph with Precision values on the y-axis and Recall values on the x-axis. The dotted line indicates a no skill classifier and an ideal classifier (indicated by dashed line) would need to be away from this as much as possible, towards the top-right position of the graph. Figure 4 shows the PR curves for Random Forest, Naive Bayes, Neural Nets, SVM, and Logistic Regression models respectively. It can be observed that the random forest model performed the best after interpreting the PR curve for it.



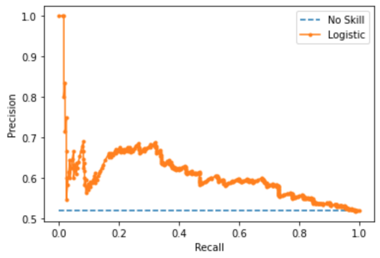
(a) SVM



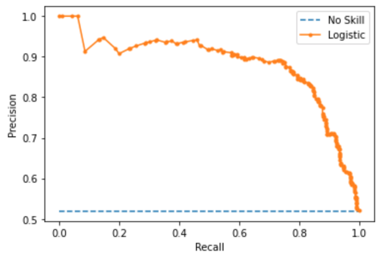
(b) Logistic Regression



(c) Neural Network



(d) Naive Bayes

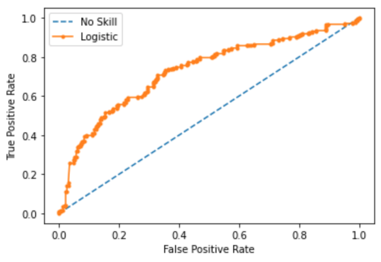


(e) Random Forest

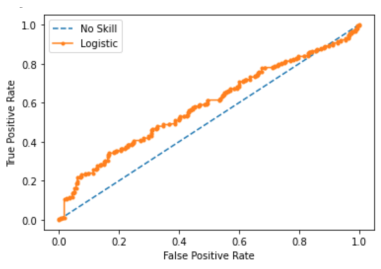
Figure 4: PR Curves

A receiver operating characteristic curve, or ROC curve, is a graphical plot that illustrates the diagnostic ability of a binary classifier system. The ROC curve is created by plotting the true positive rate against the false positive rate at various threshold settings. Figures 5 show the ROC curves for Logistic Regression, Naive Bayes, Neural Nets, SVM and Random Forest models respectively. The dotted line indicates a no-skill classifier and an ideal classifier would position itself along the top-left of the graph. Such a characteristic is seen in the Random Forest curve which performs the best.

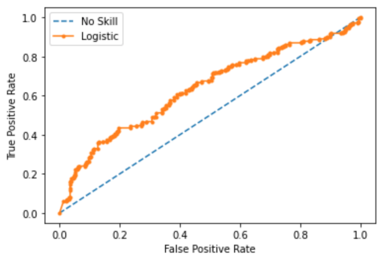
Based on these figures, it is clear that the Random Forest model performs the best. Table 1 gives a comparison between these models and from these it is also clear that the Random Forest model gives the best result in terms of accuracy.



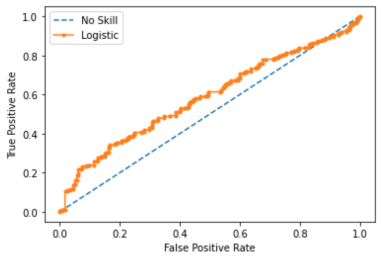
(a) SVM



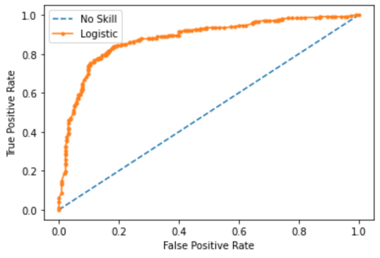
(b) Logistic Regression



(c) Neural Network



(d) Naive Bayes



(e) Random Forest

Figure 5: ROC Curves

5 Conclusions

In this paper, we have collected code samples from GitHub open source ERP and identified the features for determining the risk associated with making a change to a section of software code. Later we have used several machine learning models to predict the risk by generating the classification report consisting, accuracy, precision, recall and F1-score. Then the accuracies of the models have been compared using several measures such as ROC curves, Precision-Recall curves, and Confusion matrices. Based on these results, we have found that among the models chosen, Random Forest seems to give the best results in terms of the above mentioned measures. Future work may involve deciding on which features have the most impact in terms of accuracy of prediction.

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