

PREDICTION OF DESIGN IMPACTFUL CHANGES IN MODERN CODE REVIEW USING MACHINE LEARNING

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DEDICATION

This thesis is dedicated to my loving parents, whose unwavering love, encouragement, and support have been my guiding light throughout this academic journey. Your belief in me has been a constant source of inspiration, driving me to overcome challenges and strive for excellence. This achievement is as much yours as it is mine, and I am forever grateful for your presence in my life.

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ABSTRACT

In today's era most of the companies are using modern code review as one of the most useful technique to monitor the software changes continuously and to improve the software quality. The major purpose for this activity is to detect the design impactful changes as soon as possible that prevent the design degrading of the software after each and every code review.

Anyhow, the modern code review techniques are not enough to prevent the design degradation even after the degradation symptoms results in the rejection of changes done in the code. The design degradation occurs when smells occur due to the symptoms of bad structural decisions that occurs by a change. Technical and Social features may influence the design degradation when it comes to code reviews.

There is no any research that investigates the benefits of the prediction of design impactful changes to the stakeholders of code review using the social and technical features. Using the data provided by the Code Review Open Platform (CROP), an open-source dataset that links code review data to software changes I have used a machine learning approach to predict the design impactful changes with social and technical features in modern code review.

At the end I have evaluated the machine learning algorithm and extracted number of social and technical features and assessed how those features influences the code review. According to the literature review I have chosen Gradient Boosting algorithm. Using technical features leads to more accurate predictions. Anyhow, the social features that are available before the start of a review also be a good aspect for a highly precise prediction. Therefore we can say that technical and social prediction models can be used in the inspection of the changes done in software.

Expanding on the use of modern code review techniques to detect design impactful changes, the limitations of these techniques, the need for incorporating social and technical features, and the implementation of machine learning algorithms for prediction. Modern code review techniques are widely adopted by companies to monitor software changes continuously and enhance software quality. One of the primary objectives of code review is to detect design impactful changes promptly to prevent software design degradation after each code review iteration.

Despite the effectiveness of modern code review, it may not always suffice to prevent design degradation. Even when changes exhibiting degradation symptoms are rejected during code review, design degradation can still occur. This degradation typically arises from poor structural decisions manifested as code smells introduced by changes. Both technical and social factors play significant roles in influencing design degradation during code review. Technical features encompass aspects like code complexity, cohesion, and coupling, while social features include factors such as developer experience, communication dynamics among team members, and team collaboration.

To address the challenge of predicting design impactful changes, machine learning approaches are employed. Utilizing the Code Review Open Platform (CROP) dataset, which links code review data to software changes, machine learning algorithms are trained to predict design impactful changes based on a combination of social and technical features. Among various machine learning algorithms, Gradient Boosting is chosen for its effectiveness in handling complex datasets and producing accurate predictions. Through rigorous evaluation, it's found that incorporating technical features leads to more precise predictions. However, social features available before the start of a code review also prove to be valuable in enhancing prediction accuracy.

In conclusion, the integration of social and technical features into machine learning models facilitates more accurate prediction of design impactful changes during code review. By leveraging both technical and social aspects, stakeholders can gain insights into the potential impact of software changes on design quality, thereby improving the overall effectiveness of code review processes.

Keywords: modern code review, machine learning, design changes

TABLE OF CONTENTS

Declaration	iii
Dedication	iv
Acknowledgement.....	v
Abstract	vi
Table of Contents	viii
List of Figures	xi
List of Tables.....	xii
List of Abbreviations.....	xiii
List of Appendices	xvi
Chapter 1	1
Introduction	1
1.1 Modern Code Review in Today's Era	1
1.1.1 Challenges in Modern Code Review.....	2
1.1.2 How developers Overcome the Challenges in Modern Code Review in General	3
1.1.3 Machine Learning Concept for Modern Code Review	5
1.2 Background and Motivation.....	6
1.3 Our Approach	8
1.3.1 Research Gap	8
1.3.2 Research Objectives	10
1.3.3 Overall Approach	10
Chapter 2	12
Literature Review.....	12
2.1 Introduction to machine Learning in Modern Code Review.....	12
2.2 The Challenges	13
2.3 Existing Machine Learning approaches to overcome the Challenges in Modern Code Review	14
2.4 How Machine Learning helps to overcome the Challenges in Modern Code Review.....	15
2.5 Related Work.....	17

Chapter 3	24
Methodology	24
3.1 Research Gap.....	24
3.1.1 Scenario 1	24
3.1.2 Scenario 2.....	24
3.1.3 Identified Research Problems	25
3.2 Research Objectives	26
3.2.1 Utilizing the Open Source large Training Data Set as much as possible 26	
3.2.2 Explore the use of Social and Technical metrics as features of Machine Learning algorithm.....	27
3.2.3 Build a Machine learning model and Evaluate the prediction ability of the selected features	29
3.3 Proposed Solution.....	30
3.3.1 Research Questions	30
3.3.2 The Approach.....	31
Chapter 4	37
Implementation	37
4.1 Dataset	37
4.2 Technology Adapted	38
4.2.1 Python 3.12.3	38
4.2.2 Machine Learning	39
4.2.3 Gradient Boosting Algorithm.....	40
4.2.4 SVC Linear	41
4.2.5 Feature Engineering	42
4.3 Degradation Symptom Detection in the Reviews	44
4.4 Design impactful change instance identification.....	45
4.5 Features Extraction for Prediction of Design impactful changes.....	47
4.5.1 Technical Features	47
4.5.2 Social Features	49
4.5.3 Features that are derived newly to the Dataset.....	52
4.6 Prediction model development for Design Impactful changes	54
4.6.1 Training and Testing of the model.....	55



4.6.2 Performance Evaluation of the model..... 56

Chapter 5 57

Results and Discussions 57

5.1 Design Impactful changes vs Design unimpactful changes 57

5.2 Performance of the ML Model to Predict design impactful changes 60

5.3 The Technical and Social features’ role in Prediction..... 63

5.3.1 Technical and Social features as Predictors 64

5.3.2 Technical vs Social features vs the combination of features 65

5.4 The features that are best for Prediction 65

5.4.1 The features that are best in isolation for Prediction..... 66

5.4.2 The features that are best in combination of Technical and social for Prediction 70

Chapter 6 74

Conclusion 74

6.1 Fulfillment of Research Objectives 74

6.1.1 Utilizing the Open Source large Training Data Set as much as possible
74

6.1.2 Explore the use of Social and Technical metrics as features of Machine Learning algorithm..... 75

6.1.3 Build a Machine learning model and Evaluate the prediction ability of the selected features 76

6.2 Limitations..... 77

6.3 Conclusion..... 77

6.4 Future Work 78

References 80

Appendix A - Degradation Symptoms Description 85

Appendix B – Mechanisms for the Symptoms Detection..... 87

LIST OF FIGURES

Figure	Description	Page
Figure 1.1	Overview of Modern Code Review Process	1
Figure 3.1	Sample Code review that introduced degradation symptoms	25
Figure 3.2	Overall framework of the Approach	33
Figure 4.1	Architecture Diagram	54
Figure 4.2	Code Snippet of Gradient Boosting Algorithm	55
Figure 5.1	Using Cliff's delta measure and Wilcoxon Rank Sum Test	57
Figure 5.2	Performance of the ML Algorithm	60
Figure 5.3	Performance of the features as Proxy	60
Figure 5.4	Ranking of the features	61
Figure 5.5	Performance of the ML Algorithm for Fine-grained smells	62
Figure 5.6	Performance of the ML Algorithm for Coarse-grained smells	62
Figure 5.7	Performance comparison for Fine-grained smells	63
Figure 5.8	Performance comparison for Coarse-grained smells	64
Figure 5.9	Performance of the features as Proxy for Fine-grained smells	64
Figure 5.10	Performance of the features as Proxy for Coarse-grained smells	66

LIST OF TABLES

Table	Description	Page
Table 4.1	Software systems used in this research	37
Table 4.2	Degradation symptoms used in this research	44
Table 4.3	Design Impactful changes for fine-grained smells	46
Table 4.4	Design Impactful changes for coarse-grained smells	47
Table 4.5	Technical Features	47
Table 4.6	Social Features	50
Table 4.7	Derived Features	52
Table 5.7	Ranking of the Technical features for Fine-grained smells	66
Table 5.8	Ranking of the Social features for Fine-grained smells	67
Table 5.9	Ranking of Technical features for Coarse-grained smells	67
Table 5.10	Ranking of the Social features for Coarse-grained smells	68
Table 5.11	Ranking of Technical features for Fine-grained smells	70
Table 5.12	Ranking of Technical features for Coarse-grained smells	70
Table 5.13	Ranking of the Social features for Fine-grained smells	71
Table 5.14	Ranking of the Social features for Coarse-grained smells	71

LIST OF ABBREVIATIONS

Abbreviation	Description
NSD	Count of code snippets removed during the code modification process
NSU	Count of code snippets modified during the code modification process
NSA	Count of code snippets inserted during the code modification process
NFA	Count of files inserted during the code modification process
NFD	Count of files removed during the code modification process
NLA	Count of lines inserted during the code modification process
NLD	Count of lines removed during the code modification process
CHURN	Number of lines interested to and deleted in the change of code.
IMPR	The code change description contains “improve” word
BUG	The code change description contains “bug” word
REFC	The code change description contains “refactor” word
FEAT	The code change description contains “feature” word
DOC	The code change description contains “document” word
ML	Description’s word count of the change of code
NLANG	Programming language count in the change of code
ME	Changed code’s distribution across the files during the code modification process
NFT	Count of types of Files in the modified code



NCF	Count of files modified in the modified code
NMD	Number of directories changed in the change of code
FD	Number of developers involved in the code change
FM	Number of modification times of the code change file before
NWIC	Total word count of the general comments in the change of code
PWIC	NWIC weighted by using the general comment count
NWGC	Total word count of the inline comments in the change of code
PWGC	NWGC weighted by using the inline comment count
NIC	Inline comment count that are made by the reviewers
NGC	General comment count that are made by the reviewers
DL	Sum of Inline comments and General comments count that are made by the reviewers
NR	The count of code changes in the past that are assigned to the code owner whose code changes to be inspected
NC	The count of code modifications in the past that are submitted by the person who owns the code
NRC	The count of code modifications in the past 120 days that are submitted by the person who owns the code
NDC	The count of code modifications in the past that are submitted by the person who owns the code that contains at least a folder that has been impacted by the code changes
MR	The merge rate of code changes in the past that are submitted by the person who owns the code
RMR	The merge rate of code changes in the past 120 days that are submitted by the person who owns the code

DMR	The merge rate of code changes in the past that are submitted by the person who owns the code that contains at least a folder that has been impacted by the code changes
SB	The total of all pairs shortest path which go with v as a fraction
SKC	The maximal subgraph which consists of degree k 's nodes or more
SD	The centrality of degree for node v that fraction of nodes which are connected through v
SCLUST	The geometric weight of subgraph edges as average
SCLOS	The total count of all the distances to all the other nodes as inverse
SE	The centrality of the neighbors based centrality of a node

LIST OF APPENDICES

Appendix	Description	Page
Appendix - A	Degradation Symptoms Description	84
Appendix - B	Mechanisms For The Symptoms detection	86