A Machine Learning Approach to assist the Prediction of Loan Characteristics

Name: C. L. Perera

Index No: 198767D

Dissertation submitted to the Faculty of Information Technology, University of Moratuwa, Sri Lanka for the partial fulfillment of the requirements of Degree of Master of Science in Information Technology

DECLARATION

I declare that this thesis is my own work and has not been submitted in any form for another degree or diploma at any university or other institution of tertiary education. Information derived from the published or unpublished work of others has been acknowledged. Due references have been provided on all supporting literature and resources.

C. L. Perera

UOM Verified Signature

Date: 25/07/2022 Signature of Student:

Supervised By:

Mr. Saminda Premarathne

Senior Lecturer

Faculty of Information Technology

University of Moratuwa

UOM Verified Signature

Date: 25/07/2022 Signature of Supervisor:

ACKNOWLEDGEMENT

At the outset, I would wish to acknowledge everyone who contributed for the success of the research project and would wish to appreciate their efforts.

First, I am deeply grateful for the supervision throughout my research and the helps received from my supervisor Mr. S. C. Premarathne, Department of Information Technology, Faculty of Information Technology, University of Moratuwa. I have learned so much from our project discussions and his willingness to motivate me contributed tremendously to the study.

Besides, the entire academic staff of the Faculty of Information and technology, who shared their vast awareness throughout, providing me with a good environment that influenced a lot to achieve this goal, is greatly appreciated.

It is with great pleasure that I thank the staff of the University of Moratuwa, Sri Lanka, for all its efforts and facilities that it has contributed towards successful accomplishment of this postgraduate programme. My colleagues, who supported to complete this research successfully, are also greatly appreciated.

Also, my thank goes to the finance institute, which provided me with the dataset and guided throughout the study.

I am as ever, especially obligated to my parents and brother for their affection, inspiration and backing throughout my life to improve my career.

ABSTRACT

The business environment in Sri Lanka has become complex and competitive with the development of the financial sector and the spread of the Covid-19 pandemic. The number of business organizations and individuals applying for loans has increased. The practices that are being used to predict financial allocation for loans of future periods are based on previous experiences and rough estimates. The most challenging risk faced during this process is the credit risk, which is the risk of lending money to unsuitable loan applicants. Lengthy authentication procedures are being followed by financial institutes prior to approving loans. However, there is no assurance whether the chosen applicant is the right applicant or not. Also, predicting the risks of credit loans prior to becoming nonperforming is essential as the outcomes are unbearable except provisions are arranged for anticipated downsides. Thus, this study focused on analyzing the historical data of loans and evaluating customer profiles based on the demographic, geographical, and behavioral data of the customers to enable the prediction of future loan amounts, evaluation of the credit risks of loans and prediction of Non-Performing Loans using Machine Learning (ML) algorithms, in order to help make appropriate choices in the future. An exploratory data analysis was first performed to provide insights on developing marketing strategies based on loan types and to identify the type of customers who can be approached. Thus, three models were devised to predict the identified loan characteristics. Model 1 was devised to predict the future loan amounts with the highest R-squared score of 0.9967 using Light Gradient Boosting Regression. Model 2 was devised to evaluate the credit risk with the highest training and test accuracy of 0.9960 and 0.7842, respectively, using Stacking Ensemble Classification. Model 3 was devised to predict the Non-Performing Loans with the highest training and test accuracy of 0.9999 and 0.9522, respectively, using Random Forest Classification. Finally, the study illustrated a remarkable approach in predicting loan characteristics which ideally suits the ever changing economy. It achieved outstanding results which could enable any financial institute in the country, in minimizing the expected risks.

Keywords: loan characteristics, loan amount, credit risk, Non-Performing Loans, Machine Learning, exploratory data analysis, Random Forest, Boosting Algorithms, Ensemble Learning

Table of Contents

DECLA	ARA'	TION	i
ACKN	OWI	LEDGEMENT	ii
ABSTI	RAC	Γ	iii
List of	Figu	res	viii
List of	Table	es	xi
Abbrev	iatio	ns	xii
Chapte	r 1		1
Introdu	ction		1
1.1	Pro	oblem Background	1
1.2	Pro	oblem Statement	4
1.3	Aiı	m, Objectives and Research Questions	6
1.3	3.1	Aim and Objectives	6
1.3	3.2	Research Questions	7
1.4	Ov	erview of the dissertation	7
1.5	Su	mmary	7
Chapte	r 2		8
Literatu	ıre R	eview	8
2.1	Int	roduction	8
2.2	Fin	ndings of previous studies	8
2.3	Su	mmary	14
Chapte	r 3		15
Techno	logie	es adopted in Predicting Loan Characteristics	15
3.1	Int	roduction	15
3.2	Inv	volvement of Data Mining and Machine Learning	15
3.1	1.1	Data Mining	15
3.1	1.2	Machine Learning	16
3.3	MI	Technologies used to develop models	17
3.3	3.1	Regression	17
3 3	3 2	Naïve Raves (NR)	17

3.3.	3 Decision Tree (DT)	18
3.3.	4 Random Forest (RF)	18
3.3.	5 Artificial Neural Network (ANN)	19
3.3.	6 Boosting Algorithms	20
3.3.	7 Ensemble Learning	21
3.4	Implementation Technologies used to develop models	22
3.5	Summary	23
Chapter	4	24
A Nove	Approach for Predicting Loan Characteristics	24
4.1	Introduction	24
4.2	Overview of the Novel Approach for Predicting Loan Characteristics	24
4.3	Conceptual Design	24
4.4	Research Methodology	25
4.5	Hypothesis	26
4.6	Inputs to the models	26
4.7	Outputs from models	26
4.8	Process in brief	26
4.9	Users	27
4.10	Features	27
4.11	Significance of the study	27
4.12	Summary	27
Chapter	5	28
Research	h Analysis and Design for Prediction of Loan Characteristics	28
5.1	Introduction	28
5.2	Overview of the Proposed Model Design	28
5.3	Attributes Selected for modeling	29
5.4	Data Preprocessing	30
5.5	Devising Prediction Models	30
5.6	Evaluation of Model Performance	32
5.7	Summary	32
Chapter	6	33

Impleme	entation	. 33
6.1	Introduction	
6.2	Data Collection	. 33
6.3	Loading of Data and Libraries	. 33
6.4	Data Preprocessing	. 34
6.4.	1 Feature Extraction	. 34
6.4.	2 Removing outliers	. 35
6.4.	3 Label Encoding of Categorical features	. 35
6.4.	4 Feature scaling	. 36
6.5	Exploratory Data Analysis (EDA)	. 36
6.6	Prediction Modeling	. 38
6.6.	1 Defining the input and target variables	. 38
6.6.	2 Splitting training and test sets	. 38
6.6.	3 Devising of Models	. 38
6.6.	4 Hyperparameter tuning with RandomizedSearchCV	. 39
6.6.	5 Evaluation of Model Performance	. 39
6.7	Deployment of Models	. 40
6.8	Summary	. 40
Chapter	7	. 41
Research	h Findings and Evaluation	. 41
7.1	Introduction	. 41
7.1	Exploratory Data Analysis (EDA)	. 41
7.1.	1 Univariate Analysis	. 41
7.1.	2 Multivariate Analysis	. 45
7.1.	3 Correlation Analysis	. 46
7.2	Findings of Developed Models	. 47
7.2.	1 Model 1: Prediction of the loan amount for future periods	. 47
7.2.	2 Model 2: Prediction of the default risks of Loan customers	. 62
7.2.	Model 3: Prediction of Non-Performing Loans for future periods	. 74
7.3	Deployment of Models	. 86
7.4	Summary	. 87

Chapter 8		88
Conclusions and Future Works		88
8.1	Introduction	88
8.2	Conclusions	88
8.3	Limitations of the Study	89
8.4	Recommended Future Studies	90
8.5	Summary	90
Chapte	r 9	91
Referen	nces	91
APPEN	NDIX A	95
APPENDIX B		98
APPENDIX C		100

List of Figures Figure 6.6: Feature scaling 36

Figure 6.14: Evaluation of Model Performance	. 39
Figure 6.15: Saving of Models	40
Figure 6.16: POST methods to receive the request and post back	40
Figure 7.1:Log_FacilityAmount Distribution and Probability plots	41
Figure 7.2: Distribution, Violin and Box plots	42
Figure 7.3: Loan Count vs. Loan Status	42
Figure 7.4: Loan Count vs. Facility Type	43
Figure 7.5: Loan Count vs. Month	43
Figure 7.6: Average interest rate vs. Month	43
Figure 7.7: Loan Count vs. Year	
Figure 7.8: Loan Count vs. District	44
Figure 7.9: Loan Count vs. Province	44
Figure 7.10: Loan Count vs. Marital Status	45
Figure 7.11: Distribution of Age according to Gender	45
Figure 7.12: Facility Amount vs. Occupation	46
Figure 7.13: Correlation Analysis	46
Figure 7.14: Actual and Predicted Loan Amounts of Linear Regression	48
Figure 7.15: Density plot of Actual and Predicted Loan Amounts of Linear Regression	48
Figure 7.16: Feature importance values obtained using Linear Regression	49
Figure 7.17: Model 1 statistics obtained using Ridge and Lasso Regression	49
Figure 7.18: Actual and Predicted Loan Amounts obtained using Decision Tree	
Regression	50
Figure 7.19: Residual plot obtained using Decision Tree Regression	51
Figure 7.20: Random Forest Regression	51
Figure 7.21: Best parameters obtained using Random Forest Regression	. 52
Figure 7.22: Feature importance values obtained using Random Forest Regression	. 52
Figure 7.23: AdaBoost Regression	. 53
Figure 7.24: Feature importance values obtained using AdaBoost Regression	. 53
Figure 7.25: Gradient Boosting Regression	54
Figure 7.26: Feature importance values obtained using Gradient Boosting Regression	. 55
Figure 7.27: Light Gradient Boosting Regression	. 55
Figure 7.28: Feature importance values obtained using LGB Regression	56
Figure 7.29: Hyperparameter tuning of ANN	56
Figure 7.30: Network Layer Structure and Model Configuration	
Figure 7.31: Training and Validation MAE and loss	
Figure 7.32: MAE values of each fold	. 58
Figure 7.33: Validation MAE per epoch	
Figure 7.34: Actual and Predicted Loan Amounts obtained using ANN	. 59
Figure 7.35: Ensemble Stacking Regression	60
Figure 7.36: Performance Evaluation Statistics of Model 1	61

Figure 7.37: The R-squared scores of Model 1	61
Figure 7.38: Model 2 statistics obtained using Logistic Regression	62
Figure 7.39: Model 2 statistics obtained using Naïve Bayes Classification	63
Figure 7.40: Model 2 statistics obtained using Decision Tree Classification	64
Figure 7.41: Model 2 statistics obtained using Random Forest Classification	65
Figure 7.42: Model 2 statistics obtained using Extra Tree Classification	66
Figure 7.43: Model 2 statistics obtained using Ada Boost Classification	67
Figure 7.44: Model 2 statistics obtained using Gradient Boosting Classification	68
Figure 7.45: Model 2 statistics obtained using Light Gradient Boosting Classification	69
Figure 7.46: Hyperparameter Tuning of ANN	70
Figure 7.47: Loss and Accuracy values during training	70
Figure 7.48: Test accuracy and confusion matrix	71
Figure 7.49: Stacking ensemble classification.	71
Figure 7.50: Model 2 statistics obtained using stacking ensemble classification	72
Figure 7.51: Performance Statistics of Model 2	73
Figure 7.52: Accuracy scores of Model 2	73
Figure 7.53: Model 3 statistics obtained using Logistic Regression	74
Figure 7.54: Model 3 statistics obtained using Naïve Bayes Classification	75
Figure 7.55: Model 3 statistics obtained using Decision Tree Classification	76
Figure 7.56: Model 3 statistics obtained using Random Forest Classification	77
Figure 7.57: Model 3 statistics obtained using Extra Trees Classification	78
Figure 7.58: Model 3 statistics obtained using Ada Boost Classification	79
Figure 7.59: Model 3 statistics obtained using Gradient Boosting Classification	80
Figure 7.60: Model 3 statistics obtained using Light Gradient Boosting Classification	81
Figure 7.61: Hyperparameter Tuning of ANN	82
Figure 7.62: ANN layer structure	82
Figure 7.63: Loss and accuracy values during training	83
Figure 7.64: Test accuracy and confusion matrix	83
Figure 7.65: Stacking ensemble classification	83
Figure 7.66: Model 3 statistics obtained using Stacking ensemble classification	84
Figure 7.67: Performance Statistics of Model 3	85
Figure 7.68: Accuracy scores of Model 3	85
Figure 7.69: Login	86
Figure 7.70: UI for the Prediction of Loan Amount in future periods	86
Figure 7.71: UI for the Prediction of credit or default risk in future periods	87
Figure 7.72: UI for the Prediction of Non-Performing Loans in future periods	87

List of Tables

Table 5.1: Definition of Variables	29
Table 7.1: Model 1 statistics obtained using Linear Regression	47
Table 7.2: Model 1 statistics of Decision Tree Regression	50
Table 7.3: Model 1 statistics obtained using Random Forest Regression	52
Table 7.4: Model 1 statistics obtained using AdaBoost Regression	53
Table 7.5: Model 1 statistics obtained using Gradient Boosting Regression	54
Table 7.6: Model 1 statistics obtained using LGB Regression	55
Table 7.7: Model 1 statistics obtained using ANN	59
Table 7.8: Model 1 statistics obtained using Stacking Ensemble Regression	60

Abbreviations

AI Artificial Intelligence

ML Machine Learning

NPL Non-Performing Loan

EDA Exploratory Data Analysis

ANN Artificial Neural Network

DT Decision Tree

NB Naïve Bayes

RF Random Forest

KNN K-Nearest Neighbor

LGB Light Gradient Boosting

SVM Support Vector Machine

EML Ensemble Machine Learning