MACHINE LEARNING APPROACH TO PREDICT BANK DEFAULT

The report represents a machine learning project aimed at predicting loan defaults using historical data from a German bank. The study involved data exploration, preprocessing data, performing exploratory data analysis, and apply various machine learning models to predict default probabilities. The model's performance was evaluated using accuracy score and ROC_AUC curve. The Ada Boost Classifier and Random Forest Classifier was found to be the most effective model with accuracy 0.74 on the test set and ROC 0.79 and 0.78 respectively. The finding suggests that machine learning can be evaluable tool for financial situation in assessing credit risks.

Introduction

The financial industry has long faced challenges in assessing the creditworthiness of loan applicants. With the advents of machine learning, banks now have an opportunity to improve their prediction of loan defaults, thereby reducing financial risks. This project focus on building and comparing machine learning models to predict whether customers of German bank will default on their loans.

Primary objective of this study is to identify the most effective machine learning model for predicting loan defaults based on historical customer data. By achieving accurate predictions, the bank can make more landing decisions and minimize the incidence of loan defaults.

This report details the methodology used in building the predictive models, the results obtained, and the implications of the finding for credit risk assessment in the bank sector.

Methods and Materials

The dataset used on this study "credit.csv", contains 1000 entries with 16 features and 1 target feature ("default"), related to customer's demographic and account information, as well as their loan repayments status. The data was preprocessed to handle missing values, encode categorical variables, and normalize the features. Detail of data description were showed in Appendix A table1 and table2.

Exploratory data analysis revealed key insight into the relationship between various features and target variable (loan default). Visualization such as histogram and correlation matrix were used to understand the data distribution and features importance. Data visualization can be found at Appendix B image1 and image2.

Several machine learning models were evaluated, including Logistic Regression, K-Nearest Neighbors, Support Vector Machines, Linear Discriminant Analysis, Quadratic Discriminant Analysis, ensemble methods like Random Forest, Gradient Boosting, AdaBoost Classifier, XGB Classifier, LGBM Classifier, Bagging Classifier and Voting Classifier method. Hyperparameters tuning was performed by using GridSearch with cross-validation to optimize each model performance.

The models were trained on 70% of data and tested on remaining 30%. Performance score like accuracy and ROC_AUC were used to assess each model's effectiveness in predicting loan default.

Results

The Ada Boost and Random Forest Classifier achieved the highest accuracy score of 0.74 on the test set with ROC of 0.79 and 0.79, Bagging and XGB Classifier showed highest accuracy score 0.753 however, ROC are low of 0.76 and 0.77. Ensemble methods showed considerable higher accuracy than non-tree-based methods. K-nearest Neighbors showed the lowest accuracy 0.70 with ROC of 0.66.

A comparison of the model's ROC curves indicated that the ensemble methods outperformed the simpler models in terms of both precision and recall. Detail results, included train and test accuracy, ROC_AUC score and ROC curve for each model are presented in appendix C.

Discussion

The superior performance of Ada Boost and Random Forest Classifier suggested that ensemble methods, which combine multiple weak learners to form a strong predictor, are well suited for the problem of loan default prediction. The model's ability to capture complex non-linear relationships in the data likely contributed to its effectiveness.

One limitation of this study is the data set is relatively small, which may impact the generalizability of the findings. Additionally, the model may benefit from the inclusion of more diverse features like economic indicators or credit history.

Future work could explore the use of deep neural network techniques to explore the enhancement of model accuracy. Further research could also investigate to understand the impact of class imbalance on model performance.

Conclusion

This study demonstrates the potential of machine learning models to predict the loan default with the high degree of accuracy. Ada Boost and Random Forest Classifier, in particular, proved to be effective tools for credit risk assessment. The finding of this project could assist the financial institutions in making more informed landing decision and ultimately reduce the incidence of loan defaults.

References

[1] Hastie, T., Tibshirani, R., & Friedman, J. (2009). The Elements of Statistical Learning. Springer.

[2] Brownlee, J. (2016). Machine Learning Mastery. Retrieved from https://machinelearningmastery.com/

[3] Cristian Román-Palacios. Introduction to machine learning course from University of Arizona.

Appendix A: Exploratory Data Analysis – Statistical data.

Table1: Numerical feature's statistical data

Features	count	mean	std	min	25%	50%	75%	max
months_loan_duration	1000	20.90	12.06	4	12	18	24	72
amount	1000	3271.26	2822.74	250	1365.5	2319.5	3972.25	18424
percent_of_income	1000	2.97	1.12	1	2	3	4	4
years_at_residence	1000	2.85	1.10	1	2	3	4	4
age	1000	35.55	11.38	19	27	33	42	75
existing_loans_count	1000	1.41	0.58	1	1	1	2	4
dependents	1000	1.16	0.36	1	1	1	1	2

Table2: Categorical features' statistical data

Features	count	unique	top	freq
checking_balance	1000	4	unknown	394
credit_history	1000	5	good	530
purpose	1000	6	furniture/appliances	473
savings_balance	1000	5	< 100 DM	603
employment_duration	1000	5	1 - 4 years	339
other_credit	1000	3	none	814
housing	1000	3	own	713
job	1000	4	skilled	630
phone	1000	2	no	596
default	1000	2	no	700

Appendix B: Exploratory Data Analysis – Visualization.

Image1: Numeric feature distribution

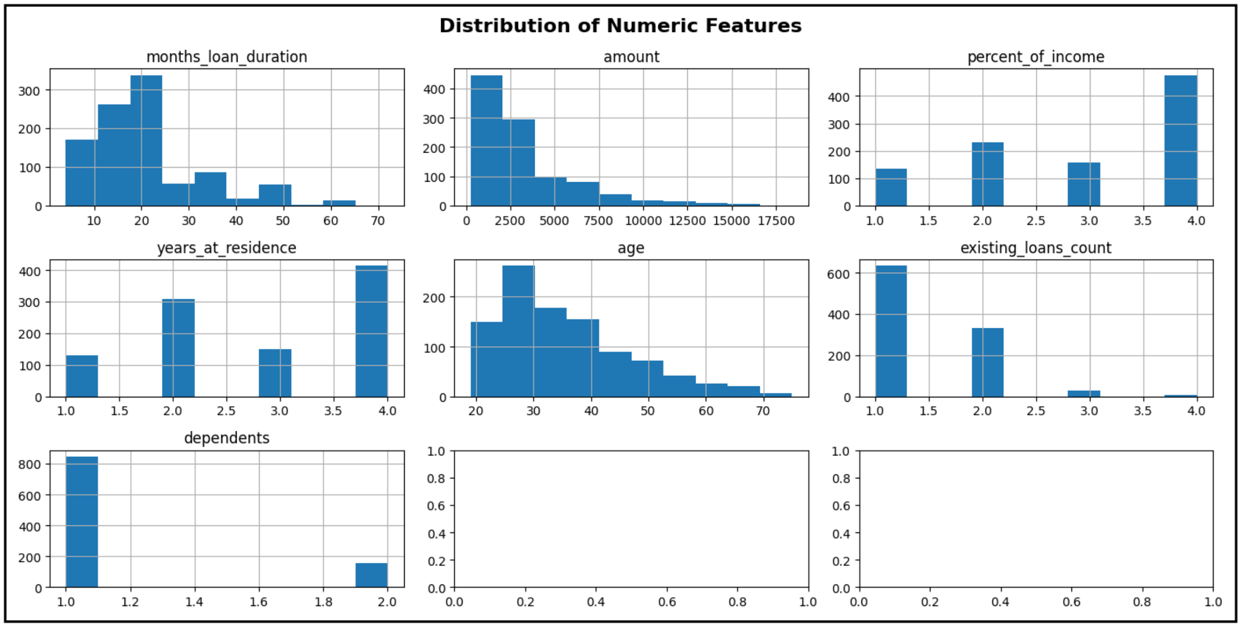
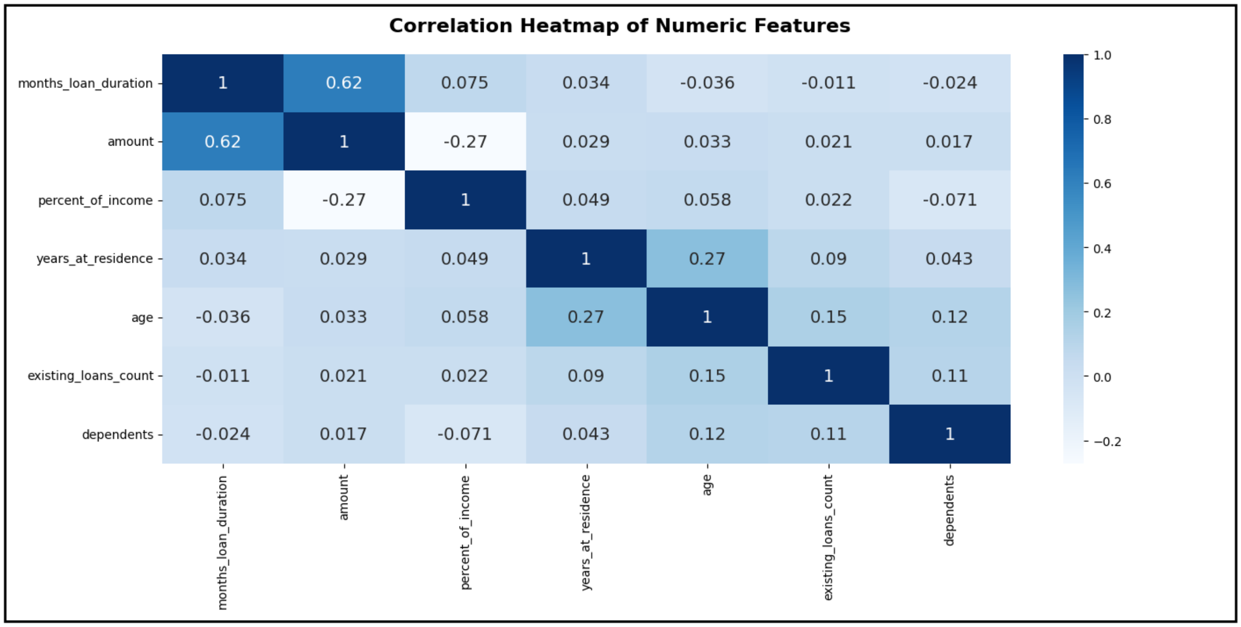
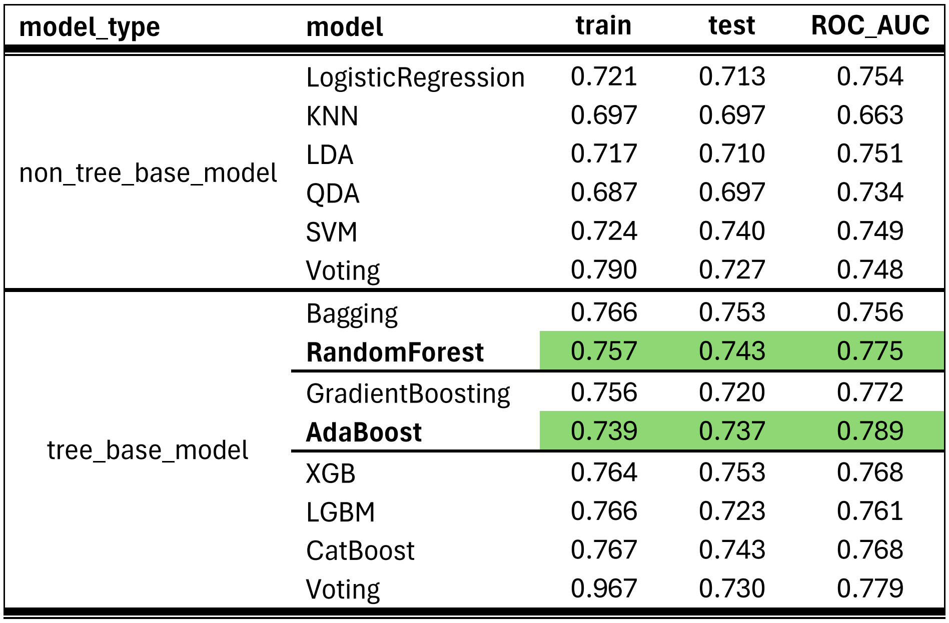


Image2: Numeric Features correlation.



Appendix C: Model performance accuracy and ROC_AUC score

Table3: Model performance comparison in term of train, test accuracy and ROC_AUC score.



model_type	model	train	test	ROC_AUC
non_tree_base_model	LogisticRegression	0.721	0.713	0.754
	KNN	0.697	0.697	0.663
	LDA	0.717	0.710	0.751
	QDA	0.687	0.697	0.734
	SVM	0.724	0.740	0.749
	Voting	0.790	0.727	0.748
tree_base_model	Bagging	0.766	0.753	0.756
	RandomForest	0.757	0.743	0.775
	GradientBoosting	0.756	0.720	0.772
	AdaBoost	0.739	0.737	0.789
	XGB	0.764	0.753	0.768
	LGBM	0.766	0.723	0.761
	CatBoost	0.767	0.743	0.768
	Voting	0.967	0.730	0.779

Image3: Model type performance

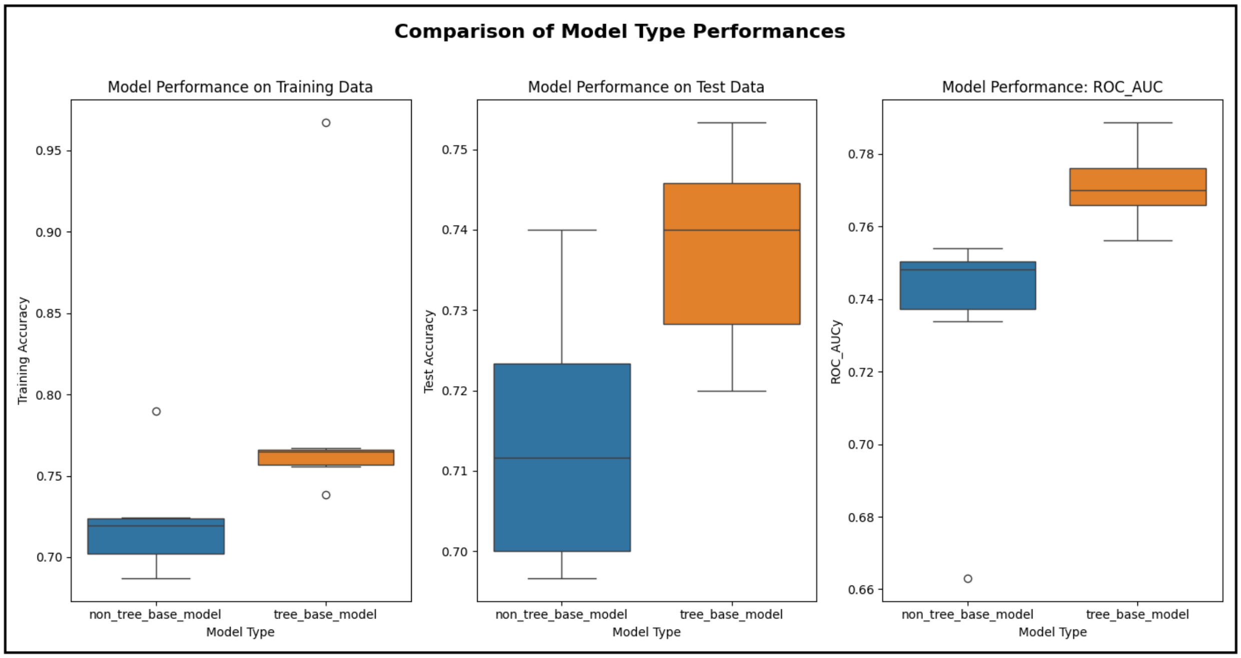


Image4: Model performance comparison.

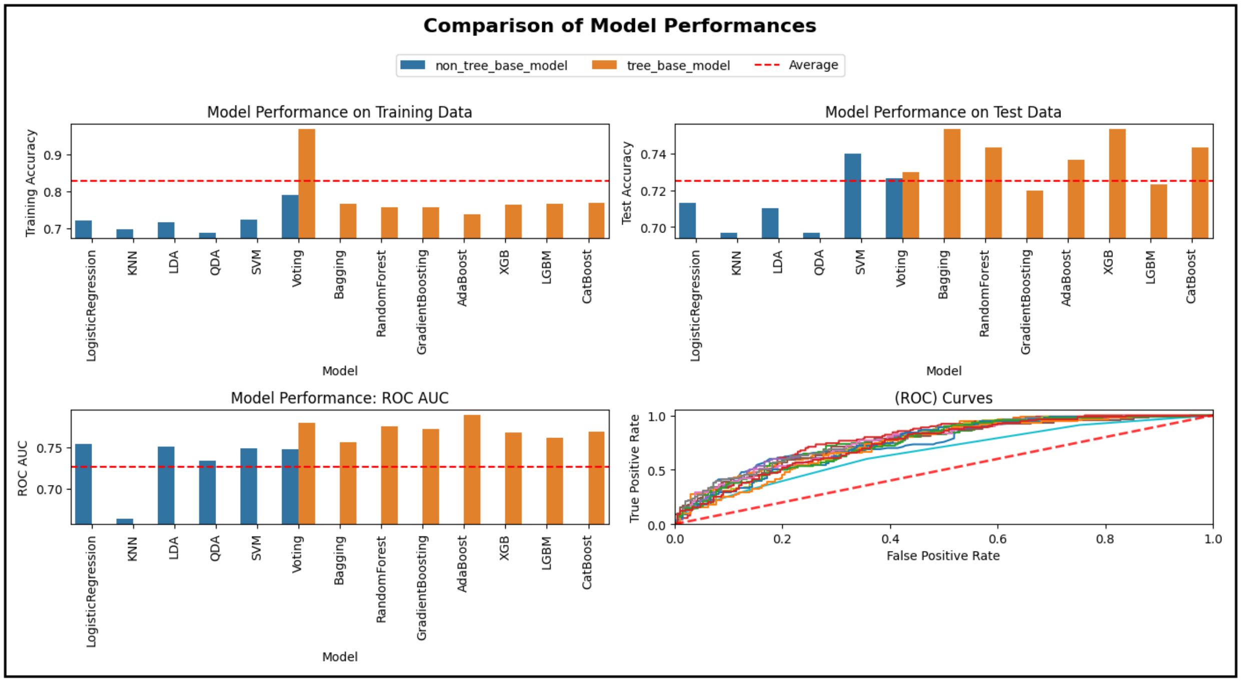
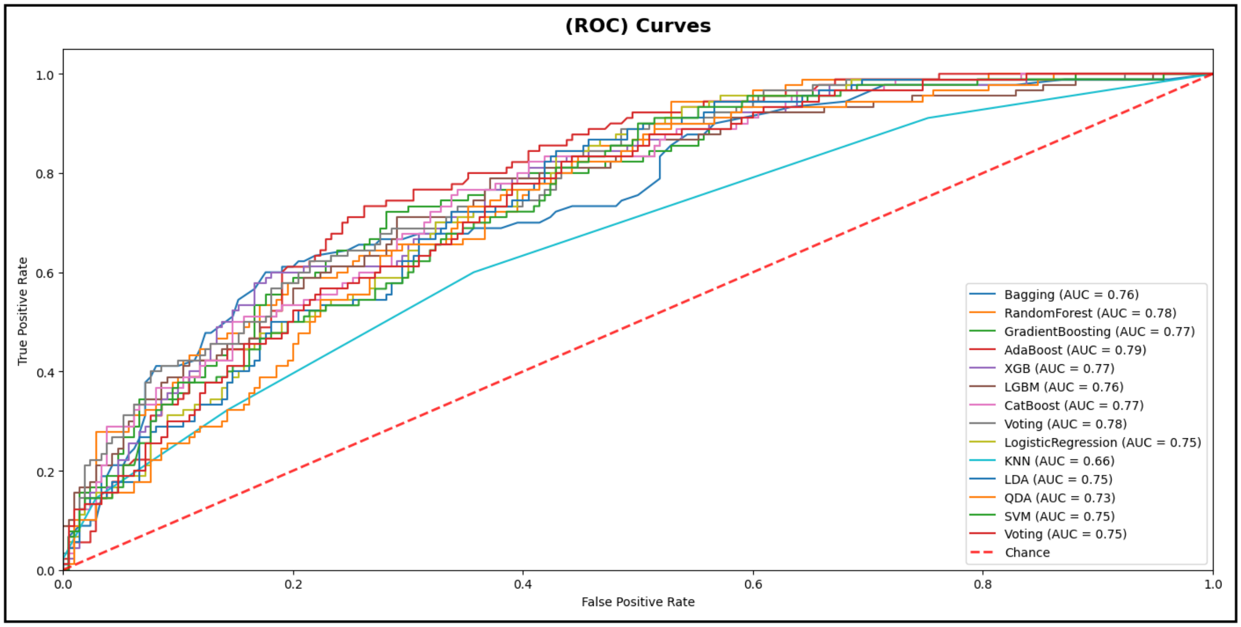


Image5: ROC_AUC curve


(ROC) Curves
True Positive Rate
False Positive Rate
Bagging (AUC = 0.76)
RandomForest (AUC = 0.78)
GradientBoosting (AUC = 0.77)
AdaBoost (AUC = 0.79)
XGB (AUC = 0.77)
LGBM (AUC = 0.76)
CatBoost (AUC = 0.77)
Voting (AUC = 0.78)
LogisticRegression (AUC = 0.75)
KNN (AUC = 0.66)
LDA (AUC = 0.75)
QDA (AUC = 0.73)
SVM (AUC = 0.75)
Voting (AUC = 0.75)
Chance