

LOAN CREDIT RISK PREDICTION

Presented by
Gilang Wiradhyaksa

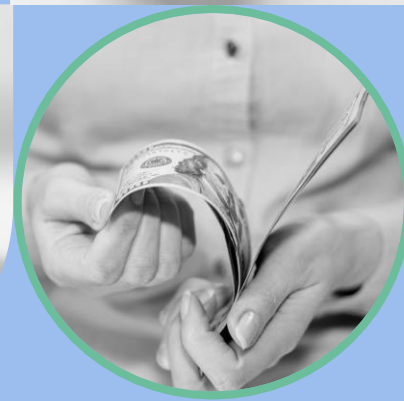


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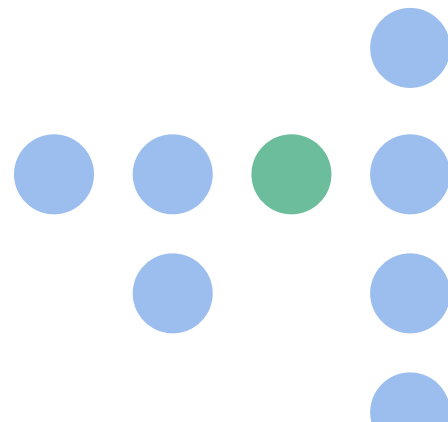
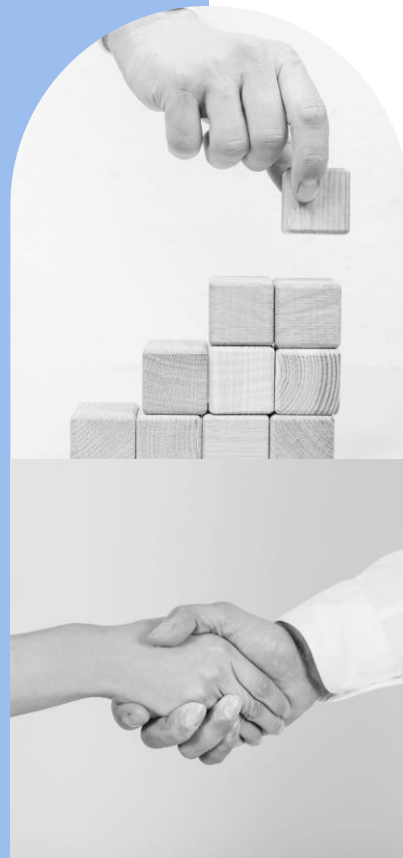
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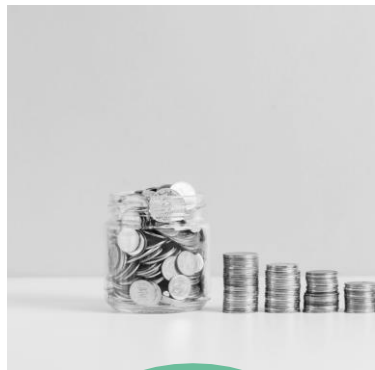
Conclusion of the project

01

ABOUT THE PROJECT

A predictive machine learning
project





PROJECT INTRODUCTION

In the dynamic landscape of financial services, lending institutions face the formidable challenge of balancing risk and reward when extending credit to borrowers.

Our project focuses on leveraging machine learning algorithms to predict the credit risk associated with loan applicants.



PROBLEM

Manual prediction relies on human judgment, which can be subjective and prone to bias.

Manual prediction is inherently limited by human capacity and resources.

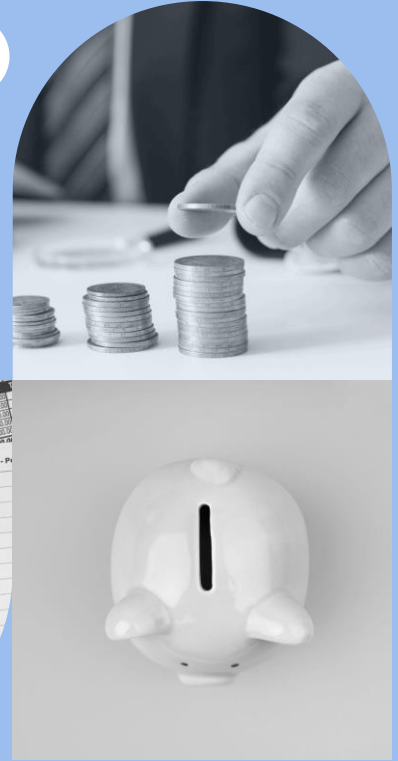
Manual prediction lacks consistency across different decision-makers and time periods.



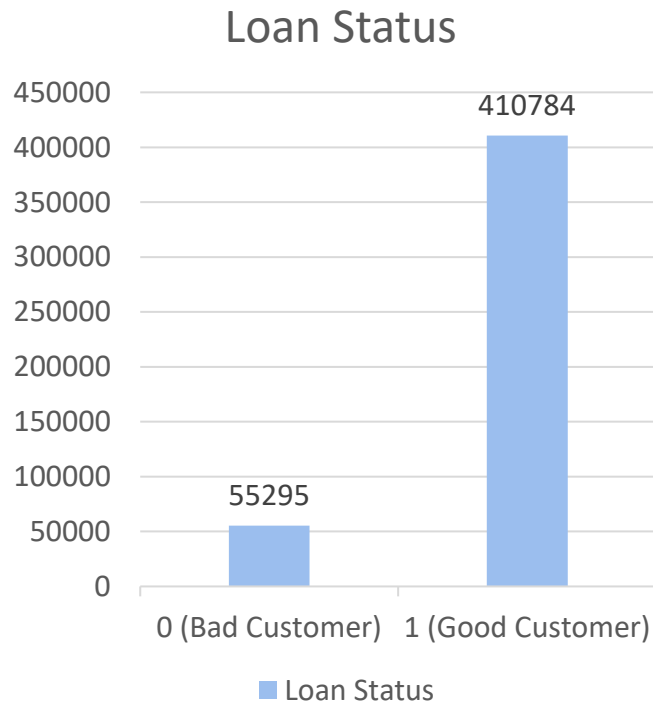
GOALS

In contrast with manual prediction, machine learning approaches offer several advantages, including scalability, objectivity, efficiency, and adaptability.

Machine learning models can analyze vast amounts of data, identify complex patterns, and provide more accurate and consistent predictions of loan credit risk.



LOAN STATUS DISTRIBUTION



The data is imbalanced, most of the targets are positive.



Imbalanced data is normal for credit cases, because normally most customers always pay their debt.

MODEL EVALUATION

Three Best Algorithm

 **Logistic Regression**

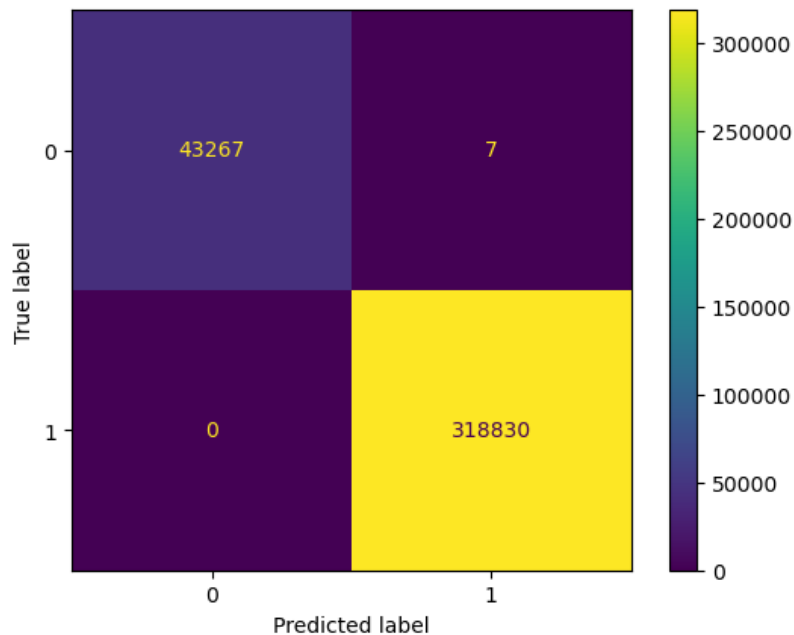
Precision Score : 90%

 **K-Nearest Neighbors**

Precision Score : 93%

 **Random Forest**

Precision Score : 99%



Random Forest Confusion Matrix

You can check this project [here!](#)

MODEL ANALYSIS



Metrics

To analyze this model, we use **Precision** metrics because we want to **minimize False Positive**.

In this case False Positive is customer whose **actually Bad** or Negative but **predicted as Good** Customer or Positive.



False Positive

Why is it better to **minimize** False Positive ?

For this loan case, it is **better** if the **Lending Company reject good customer** rather than **provide loan to a bad customer** who have no intention or unable to pay.



Cross Validation

After performing Cross Validation check on **Random Forest** model we still get very good result for the model which mean it's **not a coincidence** this model have a very good result which is 99% Precision Score.

You can check this project [here!](#)

CONCLUSION



This dataset is having **imbalance data**. For a better result this needs to be handled. Technique like **SMOTE** can be used to handle imbalance dataset.



This model weakness is even with 99% precision score, when we check using **cross validation** we only get about **94% of precision score**. Less than the train result but it's still very good result.



Out of 3 model we tried, the best model is **Random Forest**. This model give 99% Precision score which mean it can correctly predict 99 out of 100 data.



For next **improvement**, we can try **oversampling** data using **SMOTE** technique and try to do **hyperparameter tuning** for our model. With those we might be able to improve the model even better.

You can check this project [here!](#)

ABOUT ME

Gilang Wiradhyaksa

Data Scientist

I am a Fullstack Software Developer transitioning to Data Science. Experienced in building a Web Application, API Web Service and Background Service.

Possess an understanding of statistical analysis, machine learning, and data visualization techniques, combined with strong programming skills in Python and proficiency in SQL.

My experience includes data preprocessing, feature engineering and model development.



LinkedIn : [in/gilangwiradhyaksa/](https://in.gilangwiradhyaksa/)

Email : gilang.wirad@gmail.com

GitHub : github.com/gilangwd



THANK YOU