iNeuron.ai

Credit Card Default Prediction

Low Level Design (LLD) Documentation

Himanshu Banodha 5-30-2024



Document Version Control

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1. Introduction

1.1. Why this Low-Level Design Document?

The purpose of this document is to present a detailed description of the credit card default system. It will explain the purpose and features of the system, the interfaces of the system, what the system will do, this document is intended for both the stakeholders and the developers of the system and will be proposed to the higher management for its approval.

1.2. Scope

This software system will be a web application, and this system will be designed to predict whether the credit card holder will default the payment in the upcoming month or not.

1.3. Risk

Document specific risks that have been identified or that should be considered.

1.4. Out of Scope

Delineate specific activities, capabilities, and items that are out of scope for the project.

2. Technical Specifications

2.1. Dataset Information

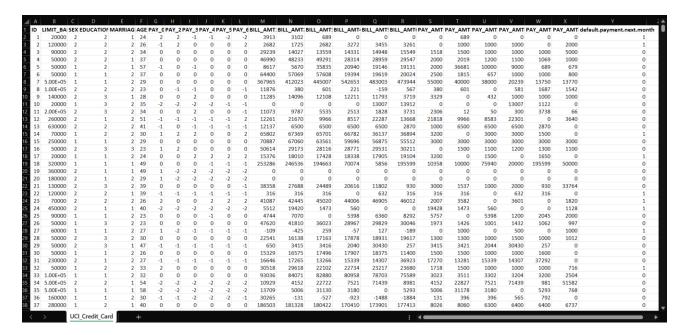
Here we got the dataset from Kaggle (Credit Card Default Prediction Dataset) this dataset contains information about default payments, demographic factors, credit data, history of payment, & bill statements of credit card clients in Taiwan from April 2005 to September 2005.

There are 25 variables:

- **ID**: ID of each client
- LIMIT_BAL: Amount of given credit in NT dollars (includes individual and family/supplementary credit
- **SEX**: Gender (1=male, 2=female)
- **EDUCATION**: (1=graduate school, 2=university, 3=high school, 4=others, 5=unknown, 6=unknown)
- **MARRIAGE**: Marital status (1=married, 2=single, 3=others)
- **AGE**: Age in years
- PAY_0: Repayment status in September, 2005 (-1=pay duly, 1=payment delay for one month, 2=payment delay for two months, ... 8=payment delay for eight months, 9=payment delay for nine months and above)
- **PAY_2**: Repayment status in August, 2005 (scale same as above)
- **PAY_3**: Repayment status in July, 2005 (scale same as above)
- **PAY_4**: Repayment status in June, 2005 (scale same as above)
- **PAY 5**: Repayment status in May, 2005 (scale same as above)
- **PAY_6**: Repayment status in April, 2005 (scale same as above)
- **BILL AMT1**: Amount of bill statement in September, 2005 (NT dollar)
- BILL_AMT2: Amount of bill statement in August, 2005 (NT dollar)
- **BILL_AMT3**: Amount of bill statement in July, 2005 (NT dollar)
- **BILL AMT4**: Amount of bill statement in June, 2005 (NT dollar)
- **BILL_AMT5**: Amount of bill statement in May, 2005 (NT dollar)
- BILL AMT6: Amount of bill statement in April, 2005 (NT dollar)



- PAY_AMT1: Amount of previous payment in September, 2005 (NT dollar)
- **PAY_AMT2**: Amount of previous payment in August, 2005 (NT dollar)
- PAY_AMT3: Amount of previous payment in July, 2005 (NT dollar)
- PAY_AMT4: Amount of previous payment in June, 2005 (NT dollar)
- PAY_AMT5: Amount of previous payment in May, 2005 (NT dollar)
- PAY_AMT6: Amount of previous payment in April, 2005 (NT dollar)
- default.payment.next.month: Default payment (1=yes, 0=no)



3. Technology Stack

Front end	HTML/CSS
Back end	Flask

4. Architecture Description

4.1. Data description:

The Dataset was taken from Kaggle (https://www.kaggle.com/datasets/uciml/default-of-<u>credit-card-clients-dataset</u>), This dataset contains information about default payments, demographic factors, credit data, history of payment, & bill statements of credit card clients in Taiwan from April 2005 to September 2005.

4.2. Data Preprocessing:

In this step we will import the necessary Python libraries such as Pandas, NumPy, Matplotlib, Seaborn, Scikit-learn etc.

And importing the dataset as pandas DataFrame.



4.3. Exploratory Data Analysis:

In this step we handled null values, changed the columns names, plotted multiple graphs & charts in Seaborn and Matplotlib to understand the data properly and also the distribution of the data.

As there were no missing values in the data so we proceed with the visualization and analysis. For each specific feature, by analysing the data we got to know about some key points which can impact the final predictions.

4.4. Data Ingestion:

In this step, we divided the data into 3 CSV files, raw.csv, train.csv & test.csv. with the help of Train Test Split, we divided the data into train and test set, in the ratio of 80-20%, where 80% data got for training the model(train.csv) and 20% is for testing the model(test.csv).

4.5. Data Transformation:

In this step, we performed feature scaling using scikit-learn.

First, we divided the both train & test dataset into 2 categories, categorical data & numerical data. Then we apply the scaling by using the fit-transformed method. Also, we have read the train and test data and changed them into arrays. Then saved this as preprocessor.pkl file for further steps.

4.6. Model Trainer:

In this step, we train the model using multiple algorithms and find the best algorithm with highest accuracy. We used Logistic, SVM, Decision Tree, Random Forest etc. algorithms to train the model.

4.7. Prediction:

Random Forest got the highest accuracy score 82.22

4.8. Saving the Model:

Here we saved the model using pickle library, which

4.9. Deploy In Localhost:

We have created an HTML template and deployed the model using Flask