



**CREDIT CARD DEFAULT** 

**PROBABILITY PREDICTION** 

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### **DOCUMENT VERSION CONTROL**

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# **DOCUMENT VERSION CONTROL**

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18/10/2022	1.0.1	First Draft	Namdeo Patil
20/10/2022	1.0.2	Added Technical specifications	Namdeo Patil
20/10/2022	1.0.3	Added Technology stack, Proposed solution and Workflow	Namdeo Patil



#### **ABSTRACT**

Financial threats are displaying a trend in the credit risk of commercial banks as the incredible improvement in the financial industry has arisen. In this way, one of the biggest threats faces by commercial banks is the risk prediction of credit clients. The goal is to predict the probability of credit default based on the credit card owner's characteristics and payment history.

With the help of Data Science and Machine learning technology, I developed an application, which allows a banker to determine the probability Of Default in just a few second

### 1) Introduction

### 1.1 Why this Low-Level Design Document?

The goal of LLD or a Low-level design document is to give an internal logical design of the actual program code for the Concrete Compressive Strength Prediction System. LLD describes the class diagrams with the methods and relations between classes and program specs. It describes the modules so that the programmer can directly code the program from the document.

### 1.2 Scope

Low-level design (LLD) is a component level design process that follows a step-by-step refinement process. This process can be used for designing data structures, required software architecture, source code and ultimately, performance algorithms. Overall, the data organization may be defined during requirement analysis and then defined during data design work.



# 2) Technical Specifications

#### 2.1 Dataset Overview

For training and testing the model, I used the public data set available in Kaggle, "Default of Credit Card Clients Dataset" by UCI.

URL - <a href="https://www.kaggle.com/datasets/uciml/default-of-credit-card-clients-dataset">https://www.kaggle.com/datasets/uciml/default-of-credit-card-clients-dataset</a>

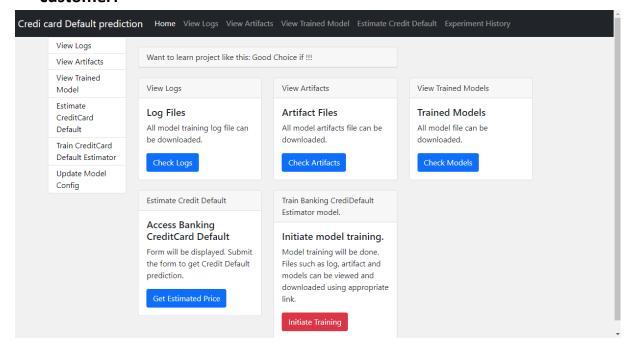
NAME	DATA TYPE	MEASUREMENT	DESCRIPTION
LIMIT_BAL	QUANTITATIVE	NT DOLLAR	INPUT
<u>SEX</u>	CATEGORIC	INT	INPUT
EDUCATION	CATEGORIC	INT	INPUT
MARRIAGE	CATEGORIC	INT	INPUT
AGE	QUANTITATIVE	YEARS	INPUT
<u>PAY_o-6</u>	CATEGORIC	INT	INPUT
BILL_AMT-o-6	QUANTITATIVE	NT DOLLAR	INPUT
PAY_AMT-o-6	QUANTITATIVE	NT DOLLAR	INPUT
default.payment .next.month	CATEGORIC	BINARY	OUTPUT



### 2.2 Predicting Credit card default probability

The web application must be loaded properly for the users without any technical glitches like server timeouts.

- It must display the input fields and the "Predict" button to the users who accessed the application and allow the user to enter the values with respect to the attributes of the customer.
  - The user gives the required information.
- Then the application should be able to predict the probability of default based on the information given by the user about the customer.



### 2.3 Logging

We should be able to log every activity done by the user.

- The system should be able to log every step in the program flow.
- System should not be hung even after using so many loggings.
  - Logging makes debugging much easier, like we can directly go to that specific line of code, having bugs.
    In this project, logs will be written in the files
- "development\_logs.log" and the "deployment\_logs.log" respectively.

# 2) Technology stack



Front-end	HTML with CSS styling
Back-end	Python version 3.7, Flask version 2.0.1
Deployment	Heroku, gunicorn version 20.1.0

#### 3) Proposed solution

The solution proposed here is a web application, which takes the details of the customer and those details will be taken by a machine learning model in the backend, which will then predict the probability of default and display it on the front-end page of the user.

# 4) Workflow

## START DATA -→ INGESTION DATA

- -→ Data validation-→ MODEL Transformation
- -→ Model Trainer -→ Model EVALUATION
- -→BEST MODEL-→ MODEL Pusher
- -→DEPLOYMENT-→ APPLICATION START
- -→INPUT FROM USER



# -→PREDICT PROBABILITY OF DEFAULT -→ END