Architecture

Credit Card Default Detection Application

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Abstract

The architecture of the Credit Card Default Detection machine learning project is outlined in this document, serving as a comprehensive guide to the underlying structure and implementation intricacies of the system. This architectural overview delves into key design decisions and specifications crucial for the successful development and deployment of the Credit Card Default Detection application.

The document provides insights into the system architecture, elucidating the relationships and interactions among various components. It details the selected classification algorithm, its architectural nuances, and the essential input features. Furthermore, the document offers a comprehensive understanding of model training methodologies and validation techniques employed to ensure the predictive accuracy of the system.

API design considerations form a crucial aspect of this architectural documentation, encompassing endpoint definitions, input validation procedures, error handling mechanisms, and robust security measures, including token authentication. Deployment strategies, along with environment specifications and containerization details, are meticulously outlined to facilitate a seamless and efficient implementation process.

The document also addresses testing methodologies, both at the unit and integration levels, ensuring the reliability of both the machine learning model and the API functionalities. Logging mechanisms and monitoring metrics are defined to enable effective debugging and continuous assessment of the system's health.

A strong emphasis is placed on documentation planning, covering code documentation with a focus on docstrings and comments. Additionally, a comprehensive user guide is provided to assist both developers and end-users in navigating the system, fostering a smooth and user-friendly interaction.

Security measures are integrated to address data privacy concerns, outlining strategies to safeguard sensitive financial data. Model explainability techniques are incorporated to enhance transparency in predictions, providing stakeholders with a clear understanding of the Credit Card Default Detection system.

This abstract serves as a succinct reference, encapsulating the essential features of the architectural design document for stakeholders involved in the evolution of the Credit Card Default Detection system.

1 Introduction

1.1 Purpose and Significance of Architecture Document?

This architectural document aims to provide a comprehensive overview of the design and structure underlying the Credit Card Default Detection system. It outlines the purpose and significance of the architecture, emphasizing its role in guiding the development team and stakeholders through the intricate details of the system's construction. By detailing key architectural decisions, this document ensures a shared understanding of the system's blueprint, fostering efficient collaboration and informed decision-making.

1.2 Scope

The scope of this architecture document extends to elucidating the fundamental design elements, relationships between components, and the overall structure of the Credit Card Default Detection system. It is intended for a diverse audience, including stakeholders and developers, providing them with a detailed insight into the architectural decisions that define the system. This document, proposed for approval by higher management, serves as a guiding resource throughout the development lifecycle, facilitating a cohesive and well-informed approach to system architecture.

2 Technical specifications

2.1 Dataset

The dataset includes information on each client's personal details, credit limit, demographic data, repayment history, bill statements, previous payments, and whether they defaulted on the next month's payment. This comprehensive dataset can be utilized for developing predictive models to assess credit risk and predict the likelihood of default for each client. The information is spread across multiple tables, mirroring the structure of a relational database, providing a rich source for analyzing and modeling credit card default detection.
There are a total of 2,2500 records in the training set and 7,500 records in the testing set, and 3,5018 records in the training set and 11,710 records in the testing set after resampling

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA
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2.2 Predicting Credit Card Default

- The system presents a form with fields representing the client's information, similar to historical data attributes (e.g., credit limit, gender, education, marital status, age, repayment history, bill amounts, payment amounts).
- The user fills in the required information for the client in question.
- Upon confirmation, the system processes the input data through the selected prediction model.
- The prediction output is displayed, indicating whether the model predicts a default or non-default for the given client.

2.3 Logging

1. User Activity Logging:
Ensure comprehensive logging of all user activities within the system.

2. Dynamic Logging Identification:
The system intelligently determines the appropriate steps in the workflow where logging is necessary.

3. System Flow Logging:
Enable logging for every step and aspect of the system's flow to capture detailed information.

4. Flexible Logging Methods:
Developers have the option to employ various logging methods, including database logging or file logging.

5. Optimized System Performance:The system should maintain optimal performance even when employing extensive logging methods, such as database or file logging.

6. Logging for Debugging:
Emphasize the importance of logging for debugging purposes; it is a mandatory practice to facilitate issue identification and resolution.

2.4 Database

1. Data Storage:
The system must store every credit card default detection request in the database, ensuring a format that facilitates easy model retraining.

2. User Interaction:
The user selects the credit card default detection option and provides the necessary information.

3. Comprehensive Data Storage:
The system systematically stores all user-provided data or received information related to credit card default detection in the chosen database, allowing flexibility between MongoDB and MySQL.

2.5 Deployment

Deployment, in the context of software development, refers to the process of making a software application available and operational in a specific environment. It involves transferring a developed and tested software system from a staging or development environment to a production environment, where it becomes accessible to end-users. In the case of this particular project, AWS (Amazon Web Services) was utilized for the deployment, leveraging its cloud infrastructure and services to host, scale, and manage the application in the production environment.

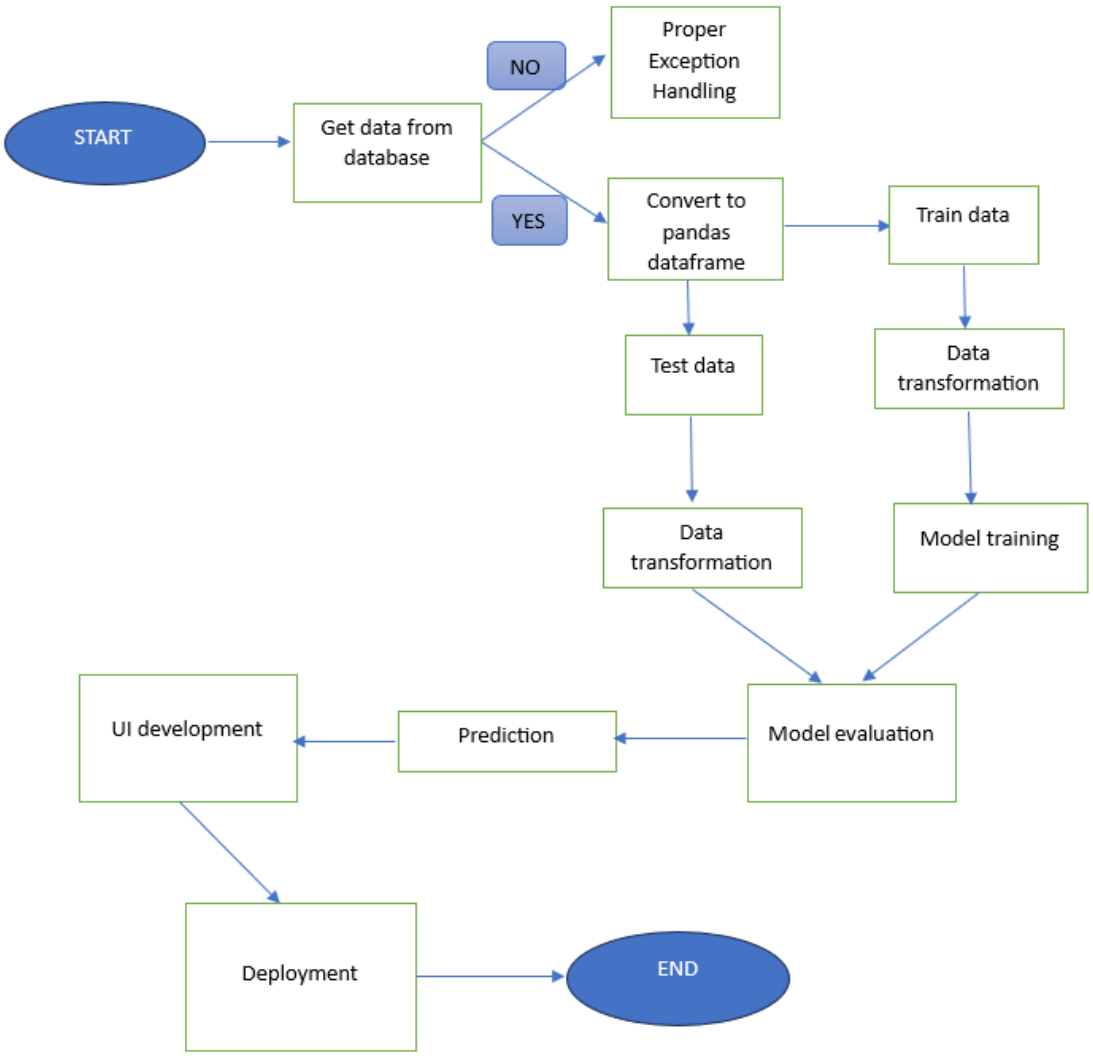
3 Technology stack

The technology stack comprises a dynamic blend of HTML, and CSS for an engaging front-end user experience. Python powers the back end, handling logic and data processing seamlessly. MongoDB, a NoSQL database, offers flexibility in managing evolving data structures. Amazon Web Services (AWS) for deployment ensures a scalable, reliable, and secure cloud infrastructure. This stack is not only versatile but also prioritizes user-centric design, emphasizing a visually appealing and interactive interface. The integration of these technologies streamlines development and deployment workflows, creating a robust foundation for credit card default detection system.

Front End	HTML/CSS
Backend	Python
Database	MongoDB
Deployment	AWS

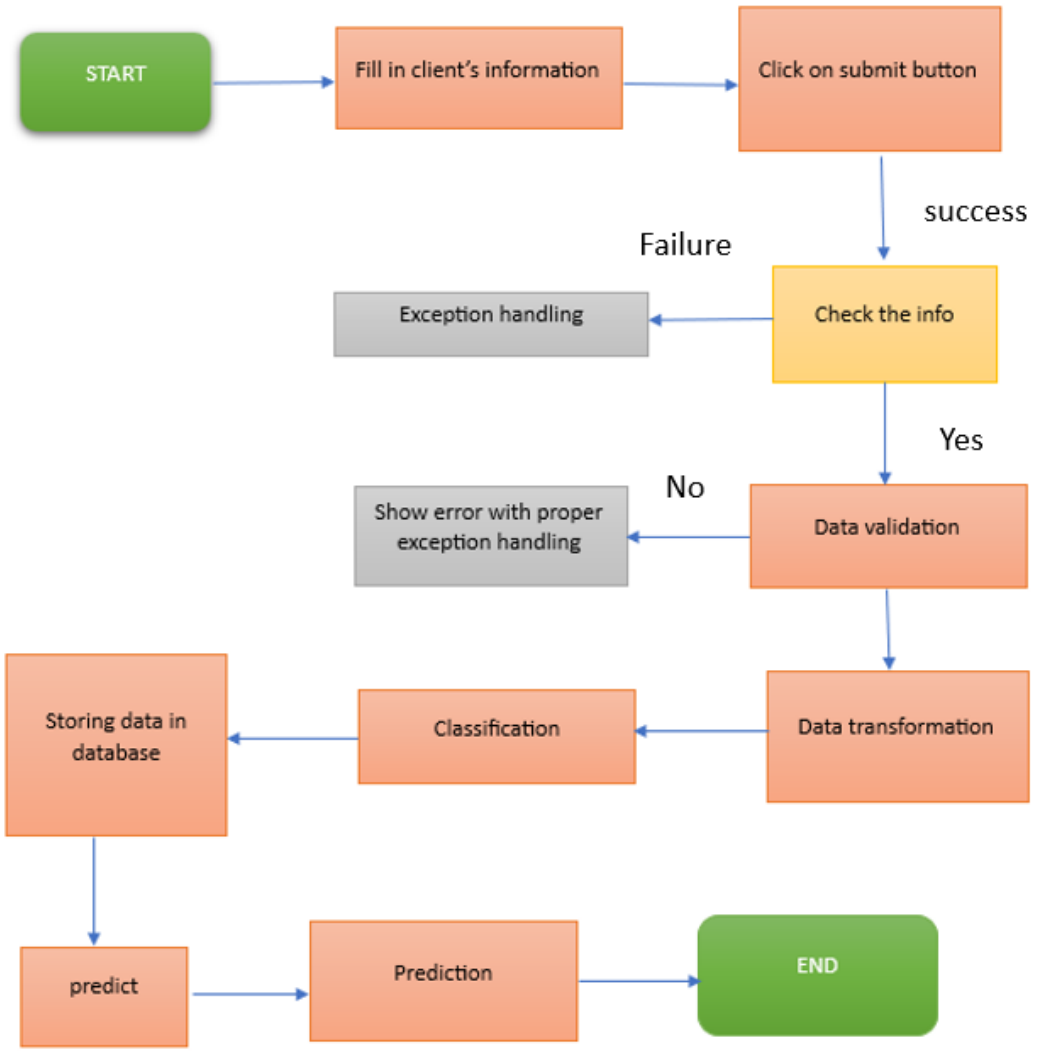
4 Model training/ validation workflow

The model training and validation workflow involves several key steps to ensure the effectiveness of the credit card default detection system. Initially, a dataset is collected and preprocessed to prepare it for training. Features such as credit limit, gender, education, and repayment history are selected. The data is then split into training and test sets. A supervised learning classification model, built using Python and popular machine learning libraries, is trained on the labeled data. The model's performance is assessed using test data, employing metrics such as accuracy, precision, recall, and F1 score. The final trained model is then ready for deployment in the credit card default detection system, providing accurate and reliable predictions based on user inputs.



5 User I/O workflow

The User I/O workflow for the credit card default detection system involves a user-friendly interface designed with HTML, and CSS. Users initiate the process, select the credit card default detection option, and provide relevant information such as credit limit, gender, education, and repayment history. The system incorporates exception handling to address errors or incomplete information, guiding users to correct input. Upon successful validation, the system uses a pre-trained supervised learning classification model, built with Python, to predict the likelihood of credit card defaults. The results, including prediction and additional insights, are presented to users through a clear and visually appealing interface, enhancing the overall user experience.



6 Conclusion

The architecture document for the Credit Card Default Detection system provides a thorough blueprint for the application's design and implementation. It covers critical aspects such as system architecture, classification algorithm details, API design considerations, deployment strategies, testing methodologies, and security measures. This document serves as a vital reference for stakeholders, offering insights into the system's robustness, reliability, and user-friendliness.
As the system evolves, the architecture outlined herein will guide its development, ensuring a well-informed and cohesive approach to the Credit Card Default Detection application.