Introduction

Businesses in the banking sector experience substantial losses due to the natural tendency of customers to leave their financial relationships. Financial institutions need to grasp customer churn prediction because keeping current customers proves less expensive than acquiring new customers [1]. The Bank Customer Churn Prediction Web App implements machine learning to forecast bank customer departure likelihood through its web platform. The application employs predictive analytics to help financial institutions find customers at high risk while enabling them to build ahead-of-time retention techniques.

A pre-trained machine learning model inside the application evaluates different customer data points, starting from account usage metrics to transaction history and customer identification characteristics and engagement records. The features enable the model to generate churn risk scores for each customer so banks can conduct preventive measures before their customers depart. The integrated banking system enables analysts to perform data-driven customer retention assessments by using the platform.

Significance of Customer Churn Prediction

The matter of customer departure poses a major threat to banks since it negatively affects financial performance and market duration. Research confirms that acquiring new customers requires five to twenty-five times more expense than keeping current customers [2]. Predictive capabilities regarding customer churn enable banks to develop client retention programs which reduce total business revenue loss. The utilization of learning models in churn prediction allows banks to transition above basic heuristic methods by embracing data-driven methods [3].

Development Workflow

A structured workflow leads to the development of the Bank Customer Churn Prediction Web App, which delivers accuracy alongside efficiency and scalability. Building a bank customer churn prediction web app requires three main development stages:

1. Data Collection and Preprocessing

Any predictive model is built on the foundation of data. Historical customer data is collected from historical transaction logs, customer feedback, demographics, and account usage history for churn

prediction. Data pre-processing includes dealing with missing values, encoding the categorical variable and transforming the numerical variable to make data consistent and accurate when training the model. Meaningful insights are extracted to systematically improve the predictive capability of the model using feature engineering techniques [4].

2. Machine Learning Model Training and Evaluation

Logistic regression, decision trees, support vector machines, and deep learning methods with networks like artificial neural networks are the ones employed for churn prediction. We depend on the algorithm to choose from based on the interpretability requirements of the underlying dataset. Previous churn outcome is known for the unlabeled dataset. To measure the performance of the model [5], the such as accuracy, precision, recall, and F1-score are used. Model performance is optimized using hyperparameter tuning techniques like grid search and cross-validation.

3. Integration of the Model into a Web-Based Platform

This is followed by training the machine learning model and validating it; then, the machine learning model is integrated with a web application. The integration here has been to create an end-to-end user interface where the bank analysts and decision makers can feed in the customer data and have the churn prediction made immediately. Streamlit is used in building the application, streamlit for backend processing and the front end utilizes HTML, CSS, and JS for a perfect user experience on streamlit cloud. [6].

4. Deployment to a Cloud-Based Hosting Service

To make the application easy to access for financial institutions it is deployed on a cloud-based platform, Streamlit Cloud. It provides scalability, security and remote accessibility. To achieve seamless integration with the existing banking system it presents API endpoints which allow running automated churn predictions without input of any manual data. [7]

Target Audience and Impact

The main focus of this project is assisting bank analysts as well as banks and decision-makers who intend to improve their customer retention strategies using predictive analytics methods. Banks can use machine learning models to improve customer satisfaction, decrease churn rate and improve overall profitability. Through actionable insights, the web application provides actionable

advice for decision-makers to customize personalized retention strategies through targeted promos, rate change, customer support services, etc. [8].

Technical Details

1. Data and Preprocessing

The banking records database includes the following attributes:

- **Demographic Information:** Age, gender, country.
- **Account Details:** Balance, tenure along with number of products used.
- **Transaction Patterns:** Estimated salary, credit score.
- **Behavioral attributes:** active status and customer satisfaction scores.
- **Target Variable:** Churn (Yes/No).

Preprocessing Steps

Multiple data preparation methods were implemented to make data uniform and strengthen the modelling results:

Any missing values were filled through imputation methods.

The application of one-hot encoding served to transform the categorical variables between gender and country.

Standardization methods were used to scale numerical features because they make models more effective at prediction.

Bootstrap Resampling served as one technique for balancing the dataset according to documented research by [9].

2. Machine Learning Models Used

- XGBoost
- Random Forest Classifier

- CatBoost
- Neural Networks (MLP)
- LightGBM

The final model selection was based on evaluation metrics such as accuracy, precision, recall, and F1-score. The best-performing model was fine-tuned and saved for deployment [10].
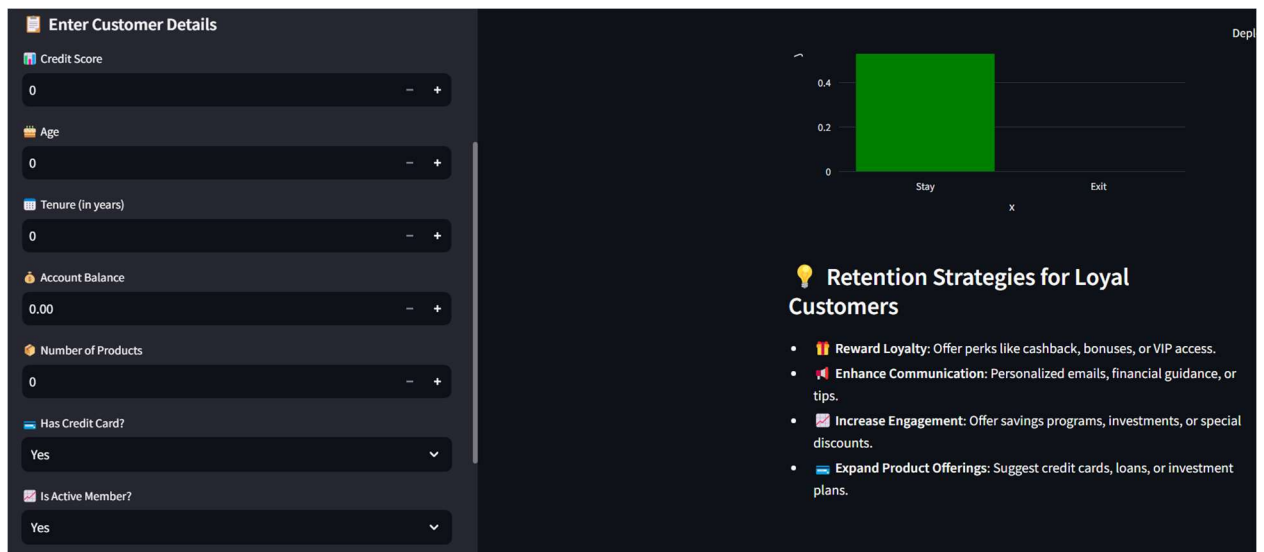
3. Web Application Development

The web application was developed using Streamlit for backend integration and HTML/CSS for the frontend interface. The key functionalities include:
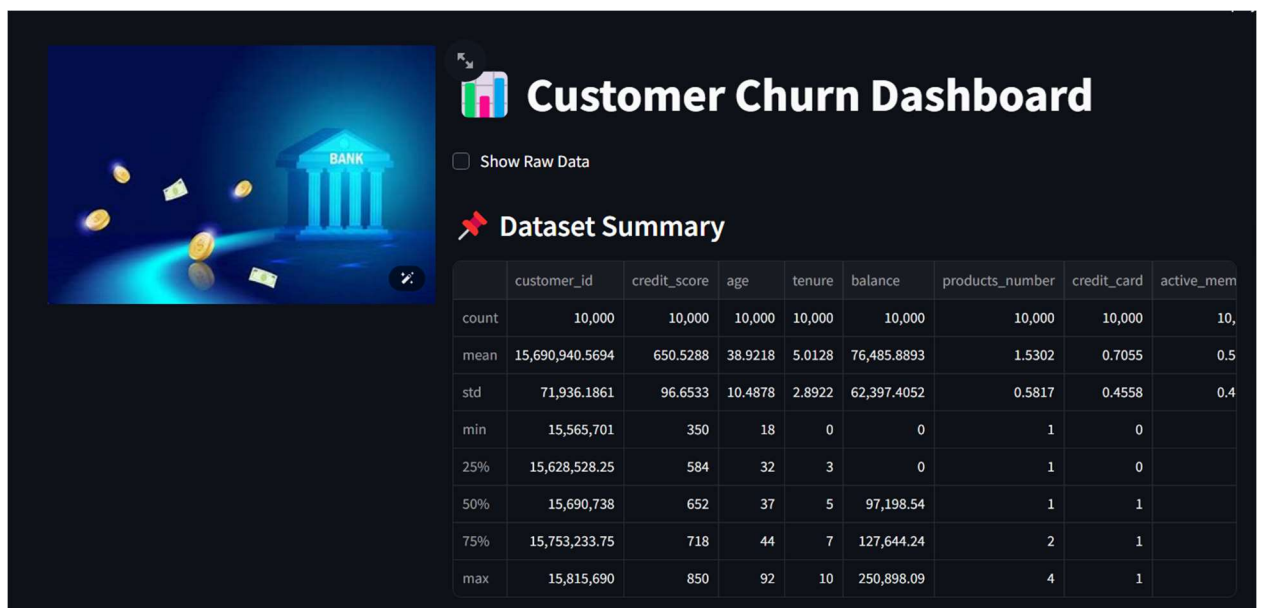
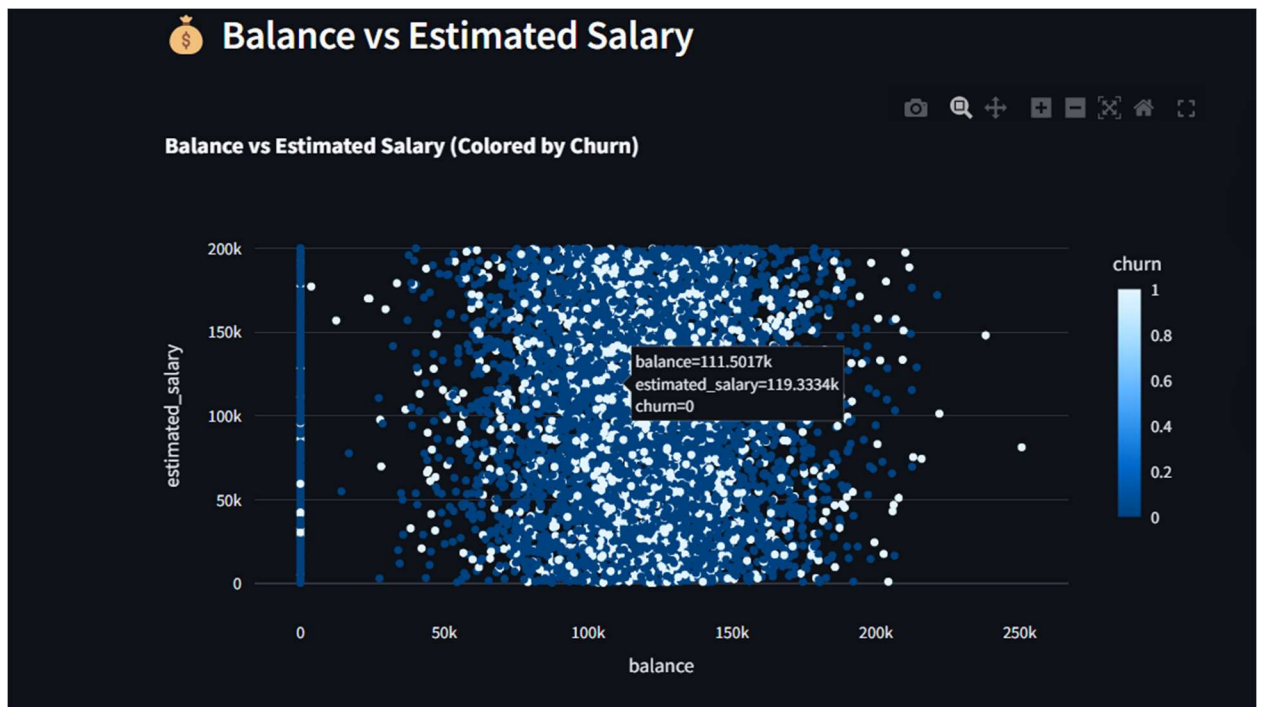- **User Interface**: A simple and intuitive UI for users to input customer data.
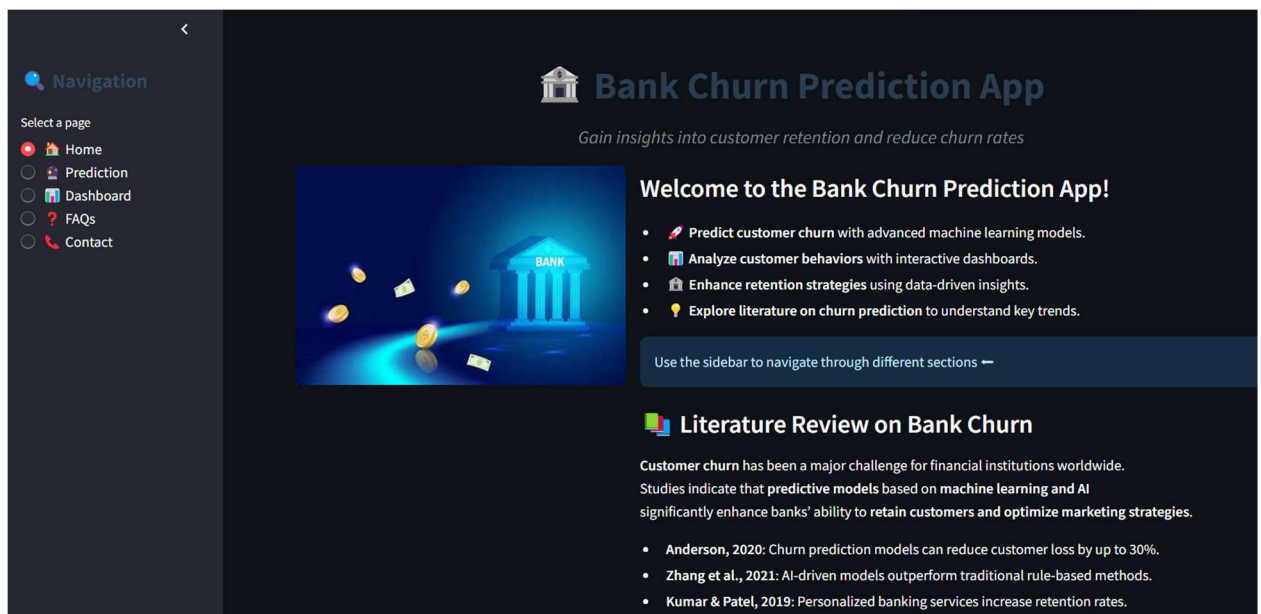
- **Model Prediction**: The backend processes the input data and returns the probability of churn.

- **Visualization Dashboard**: Displays insights such as customer trends and churn predictions [11].

- **FAQ**: Frequently asked questions are also answered.

- **Contact**: The contact information of the project owner is stated.

4. Deployment

The application was deployed on streamlit cloud for cloud accessibility. The deployment process involved:

- **Version Control**: The source code was pushed to GitHub for continuous integration.
- **Deployment Automation**: The platform was configured to automatically build and deploy the latest version of the application [12].

5. Code Documentation

a. Data Processing Pipeline

- Read input customer data.
- Apply necessary transformations (encoding, scaling, feature engineering).
- Input the processed data into the trained model for prediction.

b. Model Integration

- Loads the pre-trained model file (Pickle Saved Model format).
- Runs the model to generate churn probability scores in percentage.

c. API Endpoints

- **/predict**: Accepts user inputs via HTTP requests and returns churn predictions.
- **/dashboard**: Provides analytical visualizations of churn trends.

Results and Analysis

The deployment model selection falls on CatBoost because it demonstrates the highest performance through ROC AUC (0.7725) and Recall (0.7051) metrics evaluation. The chosen model achieves an ideal balance between correct churn detections while maximizing actual case identification efficiency, which fulfills the requirements for customer churn prediction. CatBoost enables the model to execute a reliable data-driven strategy, improving customer retention methods and sustaining predictive accuracy.

The developed model revealed three main insights through its analysis:

➢ High churn likelihood among customers with low transaction frequency and minimal banking engagement.

➢ The length of customer accounts along with their credit history have a strong influence on churn likelihood because established customers demonstrate lower churn rates.

➢ The predictive analysis indicates that organizations should implement customized loyalty programs and proactive customer services because these retention strategies reduce customer loss.

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