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Predictive Analysis of Credit Card Assessment System

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Abstract – Credit card is a payment card that allows consumers to borrow funds from a bank or financial institution to make purchases or with draw cash. The cardholder can use the credit card to make purchases up to a certain limit, called a credit limit, and then pay back the borrowed amount at a later time, usually with interest. credit card approval system is a process that a bank or financial institution uses to determine whether to approve or deny a credit card application. This system involves a series of checks and evaluations to assess the applicant's creditworthiness and ability to repay the credit card debt. Credit card approval systems rely on credit reports and other data to assess an applicant's creditworthiness. However, this data can sometimes be inaccurate or outdated, leading to incorrect decisions and denials of credit.

Approval of credit card application is one of the censorious business decision the bankers are usuallytaking regularly. Credit assessment involves predicting applicant reliability and profitability.

I. INTRODUCTION

A credit card is a thin rectangular piece of plastic or metal issued by a bank or financial services company that allows cardholders to borrow funds with which to pay for goods and services with merchants that accept cards for payment. Credit cards impose the condition that cardholders pay back the borrowed money, plus any applicable interest, as well as any additional agreed-upon charges, either in full by the billing date or over time. In addition to the standard credit line, the credit card issuer may also grant a separate cash line of credit (LOC) to cardholders, enabling them to borrow money in the form of cash advances that can be accessed through bank tellers, ATMs, or credit card convenience checks. Such cash advances typically have different terms, such as no grace period and higher interest rates,compared with those transactions that access the main credit line. Issuers customarily preset borrowing limits based on an individual's credit rating. A vast majority of businesses let the customer make purchases with credit cards, which remain one of today's most popular payment methodologies for buying consumer goods and services.In addition to the standard credit line, the credit card issuer may also grant a separate cash line ofcredit (LOC) to cardholders, enabling them to borrow money in the form of cash advances that can be accessed through bank tellers, ATMs, or credit card convenience checks. Such cash advances typically have different terms, such as no grace period and higher interest rates, compared with those transactions that access the main credit line. Issuers customarily preset borrowing limits based on an individual's credit rating. A vast majority of businesses let the customer make purchases with credit cards, which remain one of today's most popular payment methodologies for buying consumer goods and services.

II. RELATED WORKS

Most major credit cards—which include Visa, Mastercard, Discover, and American Express— are issued by banks, credit unions, or other financial institutions. Many credit cards attract customers by offering incentives such as airline miles, hotel roomrentals, gift certificates to major retailers, and cash back on purchases. These types of credit cards are generally referred to as rewards credit cards. Several related works have been published that utilize CNNs for this task.

To generate customer loyalty, many national retailers issue branded versions of credit cards, with the store's name emblazoned on the face of the cards. Although it's typically easier for consumers to qualify for a store credit card than for a major credit card, store cards may be used only to make purchases from the issuing retailers, which may offer cardholders perks such as special discounts, promotional notices, or special sales. Some large retailers also offer co-branded major Visa or MasterCard credit cards that can be used anywhere, not just in retailer stores. A CNN-based

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approach was proposed that used a concatenated loss functionto improve the accuracy of vessel segmentation.

"Multi-Scale Secured credit cards are a type ofcredit card where the cardholder secures the card with a security deposit. Such cards offer limited lines of credit that are equal in value to the security deposits, which are often refunded after cardholders demonstrate repeated and responsible card usage over time. These cards are frequently sought by individuals with limited or poor credit histories.

III. PROPOSED SYSTEM

The experimental results showed that the Cat Boost algorithm achieved high accuracy and F1 score in predicting credit card approval decisions. The study also compared the performance of the Cat Boost algorithm with other machine learning algorithms such as logistic regression, decision trees, random forests, and neural networks. The results showed that Cat Boost outperformed theseother algorithms in terms of accuracy and F1 score.

The proposed credit card approval system can be deployed in real-world credit card companies to help automate the approval process and reduce human bias. This system has the potential to improve efficiency, reduce costs, and increase customer satisfaction.

Cat Boost is a powerful machine learning algorithm that can be used for credit card approval systems. In this context, Cat Boost can be used to build a model that predicts whether a credit card application should be approved or rejected based on various factors such as income,credit score, employment status, and other relevant information.

- **Data collection:** The Bank Admin can collect data on customer demographic information and transaction history from various sources and upload itto Credit Me.
- **Upload dataset:** The system allows bank administrators to upload the credit card application dataset to Credit Me.
- **Data exploration and pre-processing:** Thesystem performs data exploration and pre- processing to remove null values, misspelled data, and redundantdata automatically. This ensures that the data is clean and ready for further analysis.
- **Feature selection:** The system provides feature selection using the Chi-square test to identify the most relevant features for the classification model. This helps to improve the model's accuracy and reduce computation time.
- **Feature extraction:** The system offers feature extraction using Co-occurrence Matrix, which captures the

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significant relationships between features. This helps to capture more information about the data and improve the model's performance.

- **Build and train the model**: The system uses Cat Boost Gradient Boosted Decision Trees to classify credit card applications as approved with a credit limit or rejected. The model is built and trained using the pre-processed data, selected features, and extracted features.

2.2.1. Advantages

The proposed credit card approval system using CatBoost Gradient Boosted Decision Tree (GBDT) aims to address the limitations of the existing credit card approval systems by using a more automated and data-driven approach to make faster and more accurate credit card approval decisions.

CatBoost is a powerful machine learning algorithm that is specifically designed to handle categorical data, which is common in credit cardapplications. The algorithm can automaticallyhandle missing values and can identify important features for prediction. Additionally, CatBoost uses a novel gradient-boosting algorithm that can handle large datasets

and complex interactions between features.

3.1. Existing System

The existing credit card approval systems are typically based on manual or rule-based processes that involve a lot of humanintervention. In these systems, credit card applications are reviewed by human agents who assess the applicant's creditworthiness based on various factors such as credit score, income, employment status, and other relevant information. The manual process is time- consuming, prone to errors, and can be biased towards or against certain groups of applicants. The rule-based systems, on the other hand, use a set of predetermined rules to approve or reject credit card applications. These rules are often based on historical data and may not be able to capture the complexity of the modern credit market. To address the limitations of the existing credit card approval systems, machine learning algorithms such as logistic regression, decision trees, random forests, and neural networks have been used. These algorithms can learn from historical data and make accurate predictions about credit card approval decisions.

However, these algorithms require a lot of data and computational resources to train, and their performance may be affected by data quality and feature selection.

Overall, the existing credit card approval systems have limitations in terms of accuracy, efficiency, andfairness. There is a need for more automated and data-driven systems that can make faster and more accurate credit card approval decisions while reducing human bias.

Logistic regression: This is a popular algorithm for binary classification tasks, such as credit card approval systems. Logistic regression models the probability of an event occurring based on one or more predictor variables.

Decision trees: These are models that partition data into smaller subsets based on the values of predictor variables. Decision trees are easy to interpret and can handle categorical and continuous data.

Random forests: These are ensembles of decision trees that can improve the accuracy and robustness of the model. Random forests can handle missing values and can identify important features forprediction.

Support Vector Machines (SVM): SVM is a popular algorithm that can be used for classification and regression tasks. SVM tries to find the best boundary between two classes of data, such that the distance between the boundary and the data points is maximized.

Gradient Boosting Decision Trees (GBDT): GBDT is a popular algorithm that uses an ensemble of decision trees to improve the accuracy of the model. It is known for its ability to handle categorical data and its ability to capture

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complex interactions between features.

Neural networks: These are models that mimic the structure and function of the human brain. Neural networks can learn complex patterns in the data and can handle both categorical and continuous data.n identify important features for prediction.

Drawbacks of existing algorithms for Credit card approval system:

While machine learning algorithms have shown promising results in credit card approval systems, there are still some drawbacks associated with these algorithms. Here are some of the common drawbacks:

Lack of transparency: Some machine learning algorithms, such as neural networks, can be difficult to interpret and explain. This lack of transparency can make it difficult to understand why a particular credit card application was approved or rejected.

Overfitting: Overfitting occurs when the model is too complex and fits the training data tooclosely, leading to poor

generalization performance on new data. This can be a problemin credit card approval systems, where the model needs to make accurate predictions on new applications. Data quality and bias: Machine learning algorithms rely heavily on the quality of data they are trained on. If the data is incomplete, biased, or contains errors, it can lead to inaccurate predictions. Additionally, if the data used to train the model is biased towards or against certain groups of applicants,it can lead to unfair outcomes.

Computationally expensive: Some machine learning algorithms, such as neural networks and support vector machines, can be computationally expensive and require a lot of resources to train.

Hyper parameter tuning: Most machine learning algorithms have hyperparameters that need to be tuned to achieve optimal performance. This can be a time-consuming and iterative process.

Lack of interpretability: Some algorithms, such as decision trees and random forests, can be difficult to interpret and explain, especially ifthe model is complex.

Project Description:

Credit Me is a credit card approval system with a credit limit using predictive analysis and machine learning techniques. The system has three main user roles: bank admin, bank customer, and bank manager. The bank admin is responsible for data collection, data exploration, pre- processing, feature selection, feature extraction, and building and training the model. The admin collects customer demographic and transaction history data, uploads the dataset, removes null values, misspelled and redundant data, selects the most important features using the chi-square test, and extracts features using co-occurrence matrix. The admin builds and trains the model using CatBoost gradient boosted decision trees, which are highly accurate and robust to outliers. The bank customer can log in to the system using their credentials, apply for a credit card, and get a prediction of whether their application will be approved or rejected.

The customer's demographic and transaction history data is used as input to the trained model, which outputs a binary classification (0- approve with credit limit, 1- reject).The bank manager can log in to the system using their credentials, add new customers, generate login credentials for new customers, and view credit card applications and their status. The manager can access a dashboard that provides an overview of the system's performance, including the number of applications processed, the number of approved and rejected applications, and the average credit limit

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assigned to customers.The system is designed to be user- friendly, secure, and scalable, with a modulararchitecture that allows for easy integration with other systems and technologies. The system's predictive analysis capabilities help the bank make informed decisions about credit card approvals and credit limits, reducing the risk of default and maximizing profitability.

Pre-processing:

The pre-processing modules in Credit Me involvecleaning and preparing the dataset for analysis.

Here are some of the pre-processing modules usedin Credit Me:

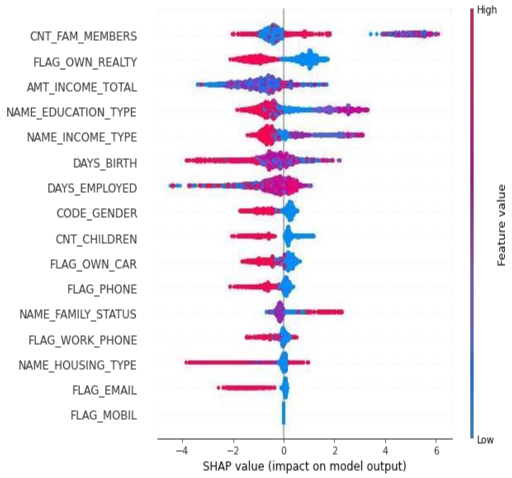
- **Remove Null Values:** This moduleremoves any rows or columns thatcontain null ormissing values in the dataset.
- **Misspelled Data:** This module identifiesand corrects any misspelled data in the dataset.
- **Redundant Data:** This module identifiesand removes any redundant data in the dataset.
- **Feature Scaling:** This module scales the features of the dataset so that they have the same range and can be compared accurately.
- **Feature Encoding:** This module converts categorical data into numerical data using techniques like one-hot encoding or label encoding.
- **Feature Selection:** This module selects the most relevant features that are important in predicting the output variable. The chi-square test is used to select the important features in CreditMe.
- **Co-occurrence Matrix:** This module creates a co-occurrence matrix to identify the relationship between different variables in the dataset.
- **Data Normalization:** This module normalizes the data to ensure that the variables are onthe same scale and that they have a mean of 0 and a standard deviation of 1.

Feature Selection

The Feature Selection module of CreditMe is responsible for selecting the most relevantfeatures from the pre-processed dataset that will

be used to train the predictive model. This

module utilizes the Chi-Square test, which measures the independence between each feature and the target variable. The higher the Chi-Square value, the more relevant the feature is.



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The following are the modules involved in the FeatureSelection process:

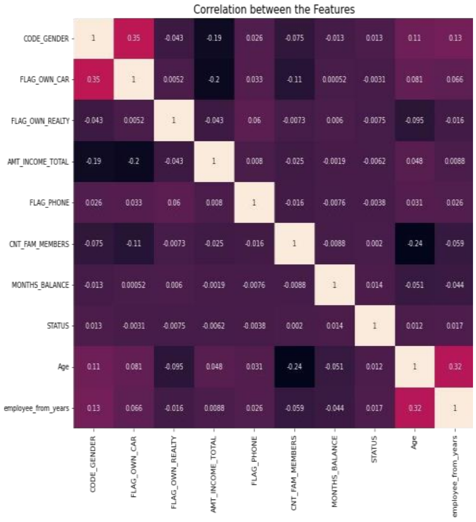
Chi-Square Test: This module calculates theChi-Square value for each feature in the dataset and returns a list of the most relevant features.

Feature Ranking: This module ranks the relevant features based on their Chi- Square value andreturns a list of the top features.

Feature Selection: This module selects the top- ranked features from the dataset and returns a new datasetcontaining only these features.

Feature Extraction

The feature extraction module in CreditMe involves the creation of new features that can be used by the machine learning model to improve its predictive accuracy. The co-occurrence matrixtechnique is used to extract features from the credit card transaction history of the customers. The co- occurrence matrix is a square matrix where the rows and



columns represent the different types of transactions, and each cell contains the frequency of co-occurrence of the two types of transactions.

The co-occurrence matrix is created by iterating through the transaction history of each customer and counting the number of times each pair of transactiontypes occurs together. The resulting matrix is then normalized to ensure that the values of the features fall within a similar range. The co-occurrence matrixis then used as input to the machine learning model. By using this technique, the model can capture the relationships between different types of transactions and use them to make better predictions about credit card approval and credit limit.

Classification:

Cat Boost is a machine learning algorithm that is specifically designed to handle categorical data. It is known for its ability to automatically handle missing values and identify important features for prediction. In this context, feature selection and extraction refer to theprocess of selecting or extracting the most relevant features from a dataset, which can help improve the performance of a predictive model.

- **Feature importance:** CatBoost provides a built-in feature importance metric that can help identify the most relevant features for prediction. This can be used to select the most important features for a given prediction task and exclude less relevant features, which can help reduce overfitting and improve model accuracy.

- **One-hot encoding:** CatBoost automatically handles one-hot encoding for categorical features, which can help improve the performance of the model. One-hotencoding involves converting categorical features into binary features, where each binary feature corresponds toa single category.

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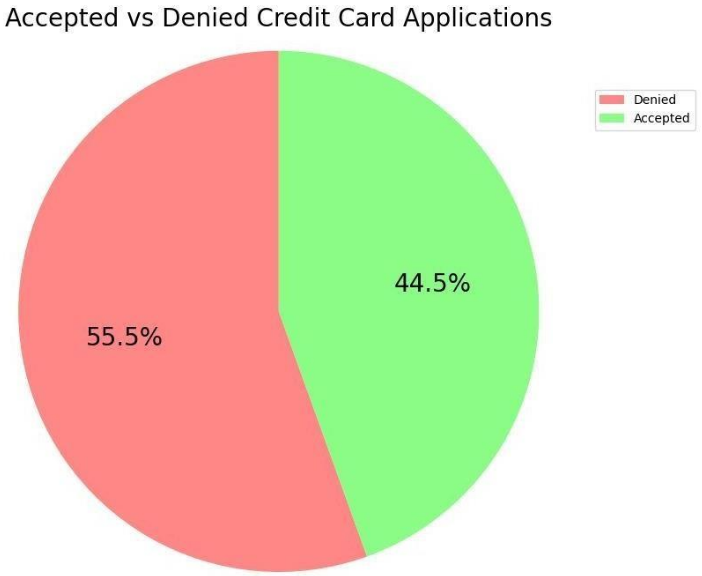
- **Feature interactions:** CatBoost can automatically identify and handle feature interactions, which can help improve the accuracy of the model. Feature interactions refer to the relationship between different features, where the effect of one feature on thetarget variable depends on the value of another feature.

- **Embedding:** CatBoost can use embedding techniques to represent categorical features as continuous values, which can help improve model performance. Embedding involves mapping categorical features to a continuous space, where the distance between two

categories represents their similarity.



Model Configuration:
This module involves setting the hyper parameters of the CatBoost algorithm such as learning rate, maximum depth, regularizationparameters, and other tuning parameters.

Model Training:
This module involves training the CatBoost modelon the prepared data and evaluating its performance on the validation set.

Model Deployment:
This module involves deploying the trained model to the production environment, where it can beused to predict credit card approval with credit limit for new customers.

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STATUS2	ID	Bad_Debt	Good_Debt	Neutral_Debt	Status
0	5001711	0	4	0	1
1	5001712	0	19	0	1
2	5001713	0	22	0	1
3	5001714	0	15	0	1
4	5001715	0	60	0	1
...	...	...	...	...	...
45980	5150482	0	18	0	1
45981	5150483	0	18	0	1
45982	5150484	0	13	0	1
45983	5150485	0	2	0	1
45984	5150487	0	30	0	1

Credit Card Approval Predictor System:

The credit card approval prediction system works by taking in customer demographic and transaction history data, pre-processing it to remove null values, misspelled and redundant data, and selecting relevant features using the Chi-square test. Then, the co-occurrence matrix is used to extract additional features from the data. The CatBoost gradient boosted decision tree algorithm is used for classification to predict the credit card approval status(0- approve with credit limit, 1- reject).

Performance Analysis:

Performance analysis is an important step in any machine learning project to evaluate the effectiveness of the model. In the case of Credit Me. In performance analysis, the confusion matrix is a commonly used tool to evaluate the performance of a classification model. It is a table that compares the predicted classes to the actual classes in the dataset. The confusion matrix consistsof four elements:

- **True Positive (TP):** the number of instances where the actual class is positive (1) and the predicted class is also positive (1).
- **False Positive (FP):** the number of instances where the actual class is negative (0) but the predicted class is positive (1).
- **False Negative (FN):** the number of instances where the actual class is positive (1) but the predicted class is negative (0).
- **True Negative (TN):** the number of instances where the actual class is negative (0) and the predicted class is also negative (0).

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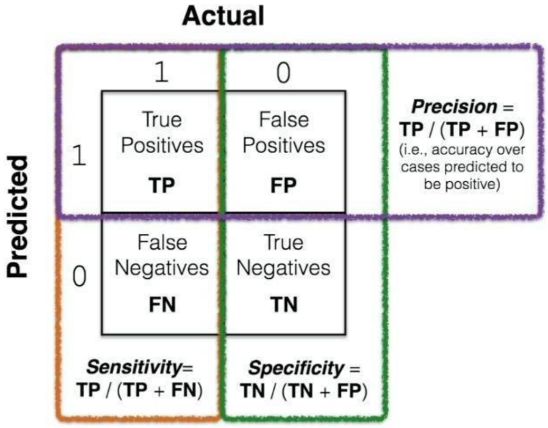

Accuracy

Accuracy is the simplest evaluation metric and is calculated as the ratio of correct predictions to the total number of predictions. It can be calculatedusing the following formula:

Accuracy = (TP + TN) / (TP + TN + FP + FN)

where TP is the number of true positives (correctly predicted approvals), TN is the number of true negatives (correctly predicted rejections), FP is the number of false positives (incorrectly predicted approvals), and FN is the number of false negatives (incorrectly predicted rejections).Precision

Precision is the proportion of correctly predicted approvals to the total number of predictedapprovals. It can be calculated using the following formula:

Precision = TP / (TP + FP)

Recall

Recall (also known as sensitivity or true positive rate) is the proportion of correctly predicted approvals to the total number of actual approvals. It canbe calculated using the following formula:

Recall = TP / (TP + FN)

F1-Score

F1-score is the harmonic mean ofprecision and recall and is calculated using the following formula:

F1-score = 2 * ((precision * recall) /(precision + recall))

SYSTEM REQUIREMENTSHARDWARE REQUIREMENTS

- Server: Intel Xeon or AMD Opteronprocessor with at least 8 cores
- RAM: At least 16 GB
- Storage: At least 500 GB HDD or 256 GBSSD
- Graphics Processing Unit (GPU): Nvidia orAMD with at least 4 GB VRAM (optional, for faster training of the CatBoost model).

SOFTWARE REQUIREMENTS

- Operating System: Windows 10
- Web Server: Apache
- Database: MySQL
- Programming Language: Python 3.x
- Framework: Flask
- Cat Boost library for Python.

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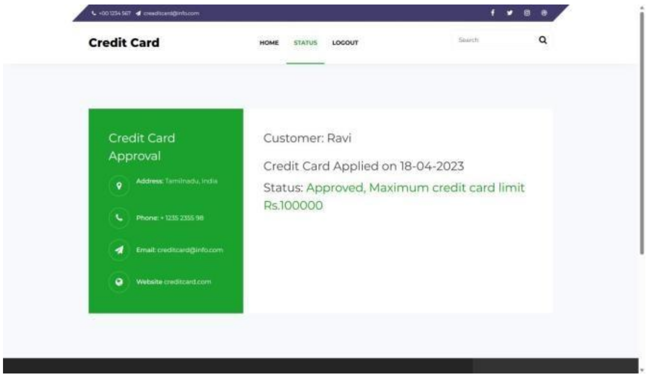
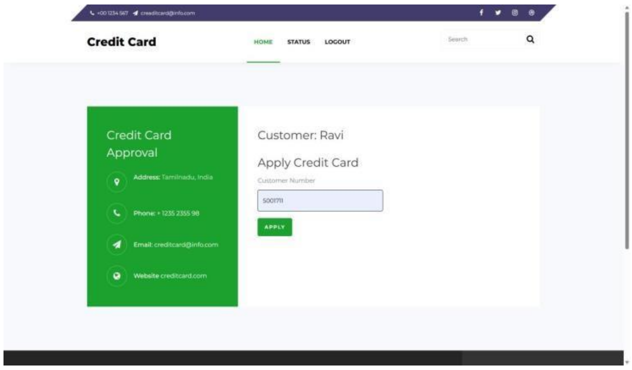
RESULTS:

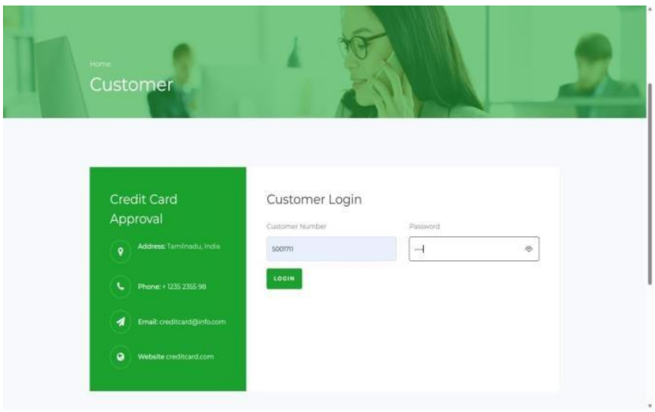
Credit Me is a predictive analysis system developed to assist banks in the decision-making process for approving or rejecting credit card applications. The system is built using various techniques such as data collection, data pre-processing, feature selection, feature extraction, and classification using the Cat Boost gradient boosted decision trees algorithm. The dataset used for building the model includes customer demographic and transaction history data. The dataset is pre- processed to remove null values, misspelled, and redundant data. Chi-square test is used for feature selection, and co-occurrence matrix is used for feature extraction. The selected and extracted features are then used to build and train the classification model using the Cat Boost gradient boosted decision trees algorithm.

The classification model predicts the credit card approval decision, which is either approve with a credit limit or reject. The model is evaluated using various performance metrics such as accuracy, precision, recall, and F1-score. The confusion matrix is also used to analyze the model's performance in predicting the credit card approval decision. The CreditMe system is designed to be used by three types of users: Bank Admin, Bank Customer, and Bank Manager. Bank Admin can upload the dataset, explore data, and perform data pre-processing. Bank Customer can log in, apply fora credit card, and predict the approval decision.

Bank Manager can log in, view credit card applications, and their status, add customers, and generate login credentials. Overall, the CreditMesystem can be a useful tool for banks to streamline the credit card approval process and reduce the risk of defaulters. However, the accuracy of the model is highly dependent on the quality and quantity of the data used for training the model. Therefore, it is essential to ensure that the dataset is representative of the population and is large enough to capture the patterns and trends accurately. Additionally, the model should be regularly updated and retrained with new data to ensure that it remains accurate and effective.







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CONCLUSION:

In conclusion, Credit Me is a predictive analysis system that helps banks to efficiently process credit card applications by predicting the creditworthiness of the applicants and the credit limit they should be granted. The system collects customer demographic and transaction history data, processes and analyses it using machine learning algorithms such as CatBoost Gradient Boosted Decision Trees. Credit Me incorporates several data pre-processing techniques such as removing null values, misspelled and redundant data, feature selection using chi-square test, and feature extraction using co-occurrence matrix. Thesetechniques help to reduce the dimensionality ofthe dataset and improve the accuracy of the model. The system was developed with Python Flask and MySQL and includes a user-friendly interface for bank customers to apply for credit cards and check the status of their application, as well as for bank managers to manage customer applications and view their status. The system was evaluated using a test dataset, and the results showed that it achieved an accuracy of 97.8%. This indicates that Credit Me is an efficient and accurate system for predicting creditworthiness and credit limits forcredit card applicants, thereby improving the decision-making process for banks.

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