International Journal of Emerging Trends in Computer Science and Information Technology
ISSN: 3050-9246 | https://doi.org/10.63282/3050-9246.IJETCSIT-V3I3P106
Eureka Vision Publication | Volume 3, Issue 3, 51-62, 2022

Original Article

Evaluating the Efficacy of Machine Learning Algorithms in Credit Card Limit Optimization and Customer Segmentation

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Abstract - The Digital age of finance, the use of Machine Learning (ML) in credit cards introduces a new breed of mainstream approach to ensure that not only are operations made efficient, but also customer satisfaction is optimized. Two of such areas where ML algorithms can be of great value are credit card limit optimization and segmentation of customers. The paper will look at the efficiency of some supervised and unsupervised ML models, such as Logistic Regression, Decision Trees, Random Forests, K-Means Clustering, and DBSCAN, to optimize credit card limits and cluster customers based on the behavioral information. The data is part of a large-scale record of a large financial institution, and includes anonymized profiles (profiles of customers), history of transactions, credit limit, history of payments (repaying) and demographic information. A proper dataset with appropriate modeling was achieved via the intensive preparation process (preprocessing and feature engineering). The regression formulation was treated by the problem of limit optimization, and segmentation has been dealt with through clustering. Model fit was checked with such measures as Mean Squared Error (MSE), R-squared, Silhouette Score, and Davies-Bouldin Index. We have found that ensemble learning algorithms such as Random Forest have a better prediction accuracy when it comes to estimating optimum credit limits, and that K-Means clustering, on the other hand, delivers satisfactory customer segregation that can be used relative to targeting financial products. Interpretability and fairness issues are also addressed in this paper with the help of SHAP values and analysis of demographic parity. By implementing ML in their credit systems, financial institutions can considerably limit the risk factor, individually tailor activities, and promote customer retention. Finally, we will discuss in the conclusion deployment strategies, ethical implications and possible future studies

Keywords - Credit card limit optimization, Customer segmentation, Machine learning, Clustering, Regression, Financial analytics, Random Forest, K-Means, SHAP, Fairness in AI

1. Introduction

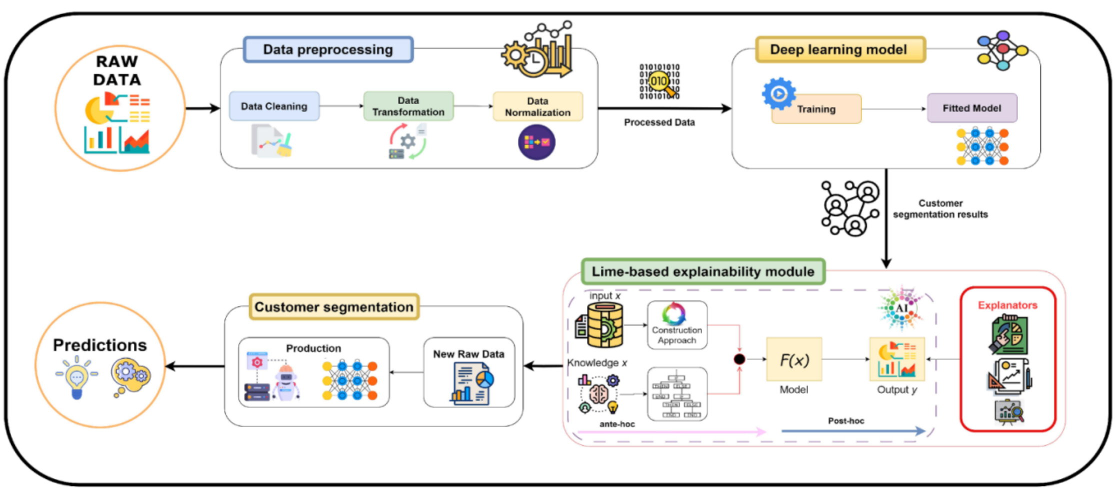

Figure 1 . Deep Learning-Based Customer Segmentation with LIME Explainability Framework

The financial growth of the world as a result of using credit cards so extensively as the favorite channel of financial transactions has changed a lot. [1-4] Due to the growing number of transactions and complexity in credit card use, financial institutions have been experiencing mounting pressure to balance the management of credit risk with delivering customer-specific services that achieve greater customer satisfaction. Millions of customers have varying financial behaviour, spending patterns and profiles of credit worthiness, and this type of dynamic is hard to keep up with using traditional rule-based systems.

Such traditional systems are frequently based on some fixed thresholds, a rule of thumb or credit scoring by simple credit bureaus, instead of taking adequate account of the more subtle financial patterns of individuals. Consequently, they may lead to inefficient credit limits, loss of customer meetings, and increased exposure to credit default. On this note, there is a positive way out in the form of intelligent systems with a Machine Learning (ML) basis. Big data ML models will be able to analyse huge transactional & behavioral data to detect hidden patterns, predict credit-worthiness more accurately and can also increase or decrease credit limit dynamically. What is more, these systems make more sophisticated customer segmentation and will help financial institutions consciously design services and approaches to the specific user groups. This transformation of the ancient approaches into evidence-based smartness is a definitive milestone in upgrading the credit card management systems in the digital finance era.

1.1. Evaluating the Efficacy of Machine Learning Algorithms

With the growing tendency of financial institutions to adopt data-driven technologies, it is necessary to assess the effectiveness and credibility of Machine Learning (ML) algorithms. Embracing ML in credit card management has the potential to achieve smarter, faster and interactive processing. But such a transition will need a stringent evaluation of such algorithms, such that they are not only effective, but also ethically acceptable.

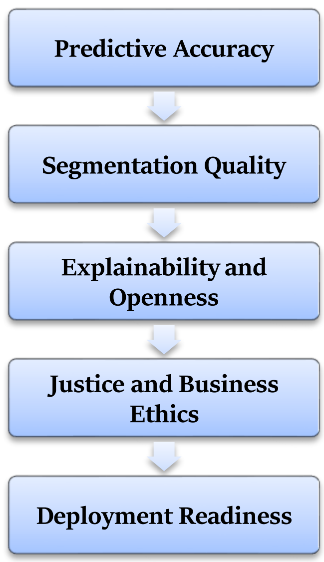

Figure 2. Evaluating the Efficacy of Machine Learning Algorithms

- **Predictive Accuracy:** Predictive accuracy is one of the most important factors that may be used to test ML algorithms. In credit limit prediction, predictive models must estimate the most reasonable credit limit for a customer based on past statistics, including income, repayment history, and the number of transactions. Such models as Random Forest and XGBoost ensemble models have been found to perform better in this respect, and they are often better than linear models since they can handle non-linear relations among the features, as well as complex interactions among them.
- **Segmentation Quality:** Another important application is in customer segmentation, in addition to prediction. The success of the algorithm in clustering customers into meaningful segments is tested against tools like K-Means, DBSCAN and Hierarchical Clustering. Evaluation criteria such as the Silhouette Score or Davies-Bouldin Index will help define the unity and distinctness of these groups. Effective segmentation enables customized services, effective marketing and enhanced risk classification.
- **Explain ability and Openness:** Although accuracy is good in itself, interpretability is easily just as important, particularly in a regulated setting such as in the financial world. SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) are a few techniques that reveal how a model makes predictions. It is extremely important in terms of compliance, customer credibility, and the determination of potential biased resources.
- **Justice and Business Ethics:** Fairness is another necessary element of evaluation. Models need to be tested so as to eliminate the possibility of discriminating against a particular demography systematically. Measurements of fairness and

demographic audits have become a convention in the responsible AI development to protect against bias and discrimination.

- **Deployment Readiness:** Lastly, there should be consideration of the practical feasibility of implementing such models. This involves evaluation of the complexity of a model, the scalability of a model, computational cost and capacity to support a real-time system. A model that performs well in a laboratory has to be resilient when in the real world, that changes.

1.3. Credit Card Limit Optimization and Customer Segmentation

Customer segmentation and optimisation of credit card limits are two key concepts in current credit risk management and customer relationship strategies. [5-6] Conventional approaches to assigning limits to credits are based on inflexible rules, credit rating and general demographic information. Yet these methods tend to ignore the dynamism of customer behaviour, which may result in underuse of credit or excessive risk-taking. Machine learning, in contrast, allows even more fine-grained decision-making of credit limits based on an analysis of thousands of variables, including transaction history, repayment behavior, income trends, and credit utilization trends.

Algorithms such as Random Forests and Gradient Boosting can detect subtle, non-linear connections within the data, thereby providing very precise and personalised limit suggestions. This leads to increased allocation of credit, lower defaults, and higher customer satisfaction. Customer segmentation, on the other hand, is concerned with setting people into groups based on similar behavioral or financial attributes so as to target marketing, risk and product offering. The common forms of segmentation, such as analyzing data using RFM (Recency, Frequency, Monetary) parameters, lack the scalability and flexibility.

Machine learning enables a more dynamic and understanding segmentation using methods like K-Means, DBSCAN and Hierarchical Clustering. Such models are used on financial data with high dimensions to reveal latent structure, so that financial institutions can learn to identify customers of high value, predict potential delinquency early, and personalize services. An efficient segmentation has the effect of influencing the operation efficiency as well as customer involvement through matching institutional activities and the needs of the individuals. Credit limit optimization and customer segmentation, when used together, are an effective integrated solution scoring package of smart credit card management.

They not only enhance decision making on individual terms, but also allow the banks and credit providers to manage their portfolio risk in a proactive manner, through improved customer experience, and more efficiently meet their business goals. In this age of data abundance, using machine learning to assist with such activities is no longer a luxury resource and having a strategy regarding the use and importance of machine learning is a strategic requirement.

2. Literature Survey

2.1. In Financial Services

Machine Learning (ML) has been newly becoming one of the most revolutionary forces in the financial services industry, which has allowed institutions to increase efficiency in decision-making, risk analysis, and customer experiences. [7-11] Groundbreaking sources, e.g., Brown and Mues (2012), examined the learning practices of ML in the dimension of credit scoring comparatives among logistic regression and even more sophisticated neural network models.

Their findings reflected that traditional methods still have relevance, but ML approaches are more accurate and respond better in dynamic monetary settings. Similarly, we were able to demonstrate the superseding nature of ML algorithms in predicting credit risk over traditional statistical methods, making it easier to present credit decisions in a fine-tuned and timely manner. These reports identify the great opportunity that ML has in shaking up traditional financial modeling with large quantities of structured and unstructured data.

2.2. Optimization of Credit Card Limit

Setting a limit on credit cards is important in striking a balance between risk and profitability. In the past, financial institutions have been using static heuristics or simple credit bureau scores to reach credit limits. Nevertheless, ML provides a data-driven option that would change accordingly to the real-time consumer behavior. Baesens et al. (2016) illustrated the use of decision tree algorithms in dynamically adjusting credit limits based on customer transaction patterns and repayment trends. Ensembles such as Random Forest and Gradient Boosting Machines (GBM) have also been applied in more recent studies to enhance the accuracy of predicting optimal credit limits. Such methods not only help increase accuracy but are also scalable and robust across different types of customers. The capabilities of ML could be well applied to optimise the credit management strategy.

2.3. Segmentation in finance

Segmentation of customers is a sine qua non for both financial marketing and product development as a tool that facilitates firms to customize their offerings to specific groups of users. Conventional data segmentation models, such as Recency-Frequency-Monetary (RFM) analysis, are giving way to more sophisticated ML algorithms, such as clustering strategies. Jain et al. (1999) wrote a detailed overview of the types of clustering, such as K-means, hierarchical clustering, and density-based clustering, that has not become meaningless even today. As big data became a point of interest, more modern methods were being applied, which include deep learning embeddings and dimensionality reduction algorithms such as t-distributed Stochastic Neighbor Embedding (t-SNE) to be able to find out long and complicated customer trends and latent behaviour characteristics. These innovations make it easier to conduct more precise and practical segmentation plans to increase customer engagement and retention.

2.4. Fairness and Interpretability

Concerns on ethical application, transparency, and fairness have become prevalent as ML becomes very entrenched in the financial decision-making process. Interpretability of models is a valuable tool: SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) are Examples of tools used to interpret a model's output, making the model more accountable. Moreover, the question of fairness and the question of fairness in algorithmic decision-making (particularly with respect to demographic equity) have emerged as a critical research area. Introduced definitions of fairness, including equal opportunity and equalized odds formalized by Hardt et al. (2016), have become relevant in the consideration of ML systems in high-stakes application areas. Also discussed the social and legal ramifications of ML, supporting the introduction of regulations to reduce bias and discrimination. All these contributions underline the necessity of responsible AI, which can not only act effectively but also correspond to the values of society.

2.5. Critical Spaces in Literature

Although the current body of literature does a good job of describing how ML can be used in financial services, it tends to discuss core application elements such as customer segmentation, credit limit optimization and model interpretation individually. Not much tries to do that to meet these areas and come up with an integrated and deployable solution. Besides, practical know-how, e.g., scalability and regulation compliance of a model, practical viability of a solution are usually ignored. This paper aims to fill these gaps by suggesting an integrated framework which would unite the three components of segmentation, credit limit prediction, and explain ability into a single pipeline. Not only can such a methodology improve the accuracy and fairness of prediction, but it can also provide useful ideas on how to concretise this in a real financial system.

3. Methodology

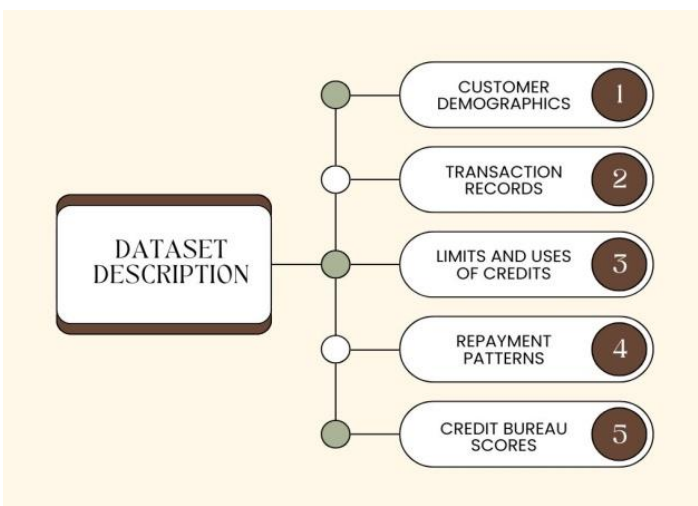

Figure 3. Dataset Description

3.1. Dataset Description

- **Customer Demographics:** In the dataset, the demographic data of customers is provided in details, which consist of the customer age, gender, marital status, type of employment, and income level. Such characteristics aid in the comprehension of customer profiles and play an essential role in developing models to personalize credit limit advising and categorize the users according to the risks and behavioral characteristics.

- **Transaction Records:** This component records past transactions made with credit cards, including the number, value, and type of purchases. [12-15] Transaction patterns could be analyzed to understand customer spending patterns, seasonal patterns and even possible indicators of credit risk behavior.
- **Limits and Uses of Credits:** The data includes the crediting limits given to the customers initially and the credit that they used over a period. This can be used to detect the under- or overused accounts, and it is necessary when training models that predict how much to increase or decrease the credit limits.
- **Repayment Patterns:** Repayment history information shows the consistency of customers' repayment of their dues; that is, making full or partial payments or default. These patterns are also good indicators of financial discipline and creditworthiness, which are essential in the risk model and optimization of limits.
- **Credit bureau scores:** The data set also has the third-party credit scores (credit bureaus), which are an external observation of the credit risk of a customer. The scores are used frequently in conventional credit decision systems, and for that reason, they can be considered a benchmark and, therefore, useful in the context of validation and comparison of models.

3.2. Preprocessing

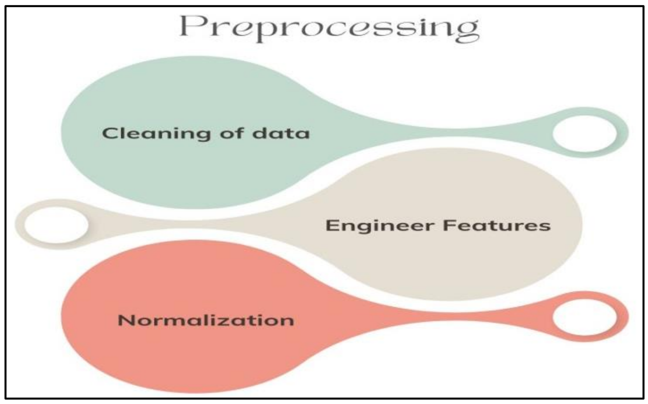

Figure 4. Preprocessing

- **Data cleaning: The data cleaning activity involved checking for missing data and combining and matching entries that were filled in** both incorrectly and correctly. The median was adopted to impute missing values in numerical fields because it is resistant to skewed distributions. The number of outliers was observed and handled using Z-score and Interquartile Range (IQR) approaches. These methods were useful in identifying some extreme values which might alter the performance of the model, so that they could be treated appropriately, either by capping or dropping.
- **Engineer Features: The** Raw dataset was transformed into new variables to gain more model inputs to grab significant patterns. Important engineered features were the credit utilization ratio (Current balance/Credit limit), consistency of repayment (A score that depends on repayment on time), and the income-to-debt ratio that is used to determine a customer's capacity to manage his or her debt in relation to the income. These attributes resulted in a better understanding of the behavior and financial health of the customer, which eventually resulted in better model performance.
- **Normalization:** In order to put all the numerical properties on a similar scale, Min-Max scaling has been applied, and the values were transformed into the scale between 0 and 1. The reason this step is especially important is in algorithms that are feature-magnitude sensitive, such as gradient-based models. Moreover, one-hot encoding was performed on categorical variables so that no ordinal relationship could be put on them mistakenly by the model. Such steps of normalization improved the interpretability and model convergence.

3.3. Model Design

3.3.1. Optimization of credit limit (Regression)

In order to estimate the best credit limits to give to customers, a number of regression models were tried and compared in terms of accuracy and interpretability.

- **Linear Regression:** Linear regression was defined as the baseline model to measure the linear correlations between the engineered feature, which contains the income-to-debt ratio and repayment consistency with credit lines. This was a simple and interpretable model that could not take nonlinear trends in the data.

- **Decision Tree Regressor:** The rule-based approach proposed in this model divided the data according to feature thresholds to predict. Decision trees were also more effective in accommodating nonlinear relations, and the decisions provided in them were easy to follow as well as understand, but they are highly subject to overfitting.
- **Random Forest Regressor: The** Random Forest model was a collection of decision trees that enhanced stability and accuracy of predictions as a result of many trees being averaged. It minimized overfitting and still kept things interpretable by using a measure of feature importance, which made it appropriate to use in finance.
- **XGBoost:** It uses Extreme Gradient Boosting (XGBoost) due to its high performance and non-linearity complex non-linear interactions that it can accommodate. It constructed trees backwards, and its primary aim was to eliminate the prior mistakes, which resulted in very accurate predictions. Regularization was also provided in XGBoost, which was very useful in preventing overfitting as well as dealing with a large dataset.

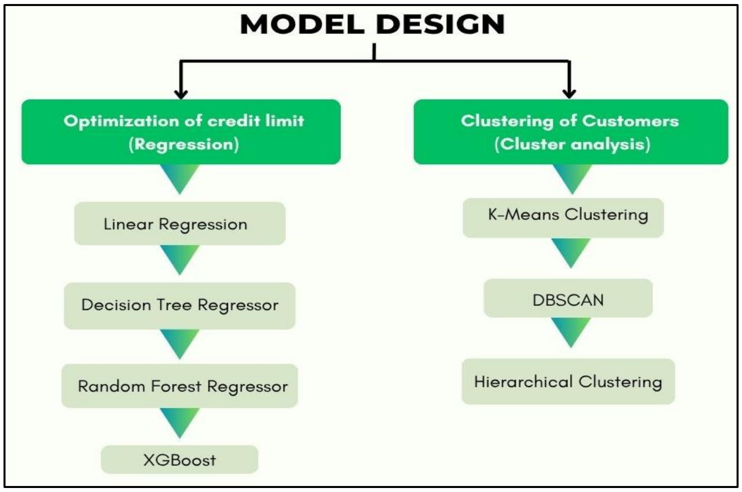

Figure 5. Model Design

3.3.2. Clustering of Customers (Cluster analysis)

The segmentation of customers using unsupervised clustering techniques was implemented to divide them.

- **K-Means Clustering:** K-Means is a centroid-oriented algorithm that divides customers into k different groups based on the similarity of their features. It was highly efficient and simple to interpret, particularly when plotted with a dimensionality reduction algorithm such as PCA or t-SNE, but needed prior specification of the amount of clusters.
- **DBSCAN was used to identify irregular clusters as well as outliers through** the implementation of Density-Based Spatial Clustering of Applications with Noise (DBSCAN). It did not require an input of the number of clusters, in contrast to K-Means, and could be efficient to determine noise points, so it could be used to work with real-world customer data.
- **Hierarchical Clustering:** This technique generates a tree-like (dendrogram) hierarchy of clusters that are nested together through cluster merging or division, depending on the measurement of distances. It helped a lot to see the dependencies between clusters of the various levels of granularity, and did not need to be specified in advance regarding the number of clusters.

3.4. Evaluation Metrics

In order to measure the performance of all models, such as regression and clustering models, a set of rather commonly used evaluation metrics was used. To optimize the task (regression) of credit limit determination, two main indicators were employed: Mean Squared Error (MSE) and R2 Score. MSE is the mean squared error of the variance between the anticipated and realized credit limits. MSE at a lower value gives more predictive accuracy in that bigger misses count more strongly against it, with financial focus having a bigger miss result in either too much risk or lost revenue. Rilike with MSE, R2 Score was employed to capture the distribution of the variance of the target variable by the model. A high value of the R2 near to 1 shows that the model would explain larger proportions of variations in credit limit values, and therefore it would reflect a good predictive ability.

In the customer segmentation task (clustering), there are no ground-truth labels, and internal validation metrics were followed. The Silhouette Score ranks how different the data point is from its cluster relative to the other clusters. It is defined between -1 and 1; the higher the values, the more distinctive and well-defined the clusters. This statistic assisted in the integrity of the customer groups identified using algorithms like K-Means or DBSCAN. More so, the Davies-Bouldin Index (DBI) was also employed to evaluate the inter-cluster and intra-cluster separation and similarity, respectively. A small DBI means the clusters are grouped together and well isolated, which is the ideal scenario when performing a practical segmentation (as done with targeted marketing or credit policy design). With the combination of these metrics, the assessment process guaranteed that the predictive models, as well as clustering strategies, were not only theoretically efficient but also highly productive in real-life financial conditions.

3.5. Tools and Libraries

This project was built with Python 3.8, a popular programming language in the data science field, as it is simple, versatile, and has a robust community of data science libraries. Python was chosen as the framework upon which column data was preprocessed, models were built, and tested, providing a seamless integration of tools and structures throughout the machine learning engine. [16-18] The Scikit-learn library was key in executing standard or core machine learning models and undertaking data preprocessing exercises. It offered efficient implementations of various regression algorithms (e.g., Linear Regression, Decision Tree, and Random Forest) as well as clustering approaches (such as K-Means, DBSCAN, and Hierarchical Clustering). Its uniform API and wide collection of tools enabled stable and efficient model training, cross-validation and metric assessment. In order to advance further in terms of model betterment, especially in the regression task, in the context of credit limit optimization, the XGBoost library was utilized. XGBoost is a graphical boosting framework that, due to its fast performance and high predictive accuracy, is known to handle large datasets and implement complex feature interactions.

It also promotes regularization methods capable of alleviating overfitting, which is of critical importance in financial modeling. Pandas and NumPy were also important for working with data and calculating numbers. Pandas made it possible to work flexibly with tabular data, enabling the ability to perform feature engineering, group, and merge datasets and tables. It was supported by NumPy, which offered expeditious array-based computation and functions in math that are crucial in scaling the features, calculating distance, and matrices. In visualizing data, Matplotlib was deployed to create plots and graphs, including correlation matrices, feature importance graphs, cluster visualization, and trends of evaluation metrics. Such visual outputs played a critical role in the interpretation of model behavior, assumptions verification and reporting of results. Combined in this stack of tools and libraries, this was a sufficient end-to-end machine learning workflow for financial analytics.

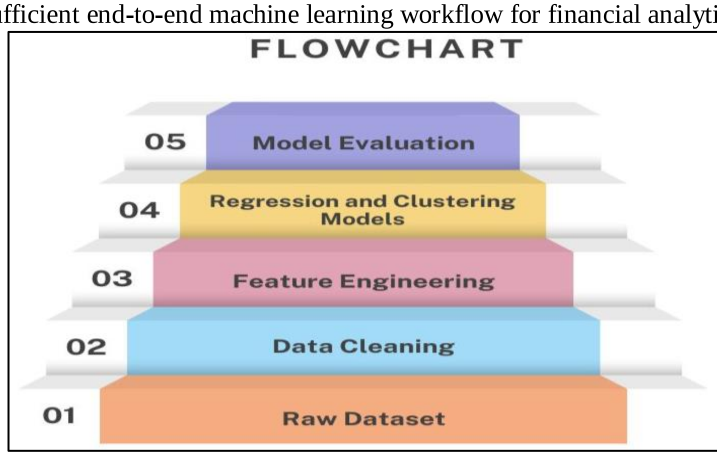

Figure 6. Flowchart of the Data Processing and Modeling Pipeline

3.6. Data Processing and Modeling Pipeline

- **Raw Dataset:** Raw dataset will be the first part of the pipeline, where it will contain customer demographics, transaction history, credit usage, repayment behavior and credit bureau scores. This raw data serves as the initial data of the whole machine learning process. At this point, any right data can be presented with noise, gaps in values, and inconsistencies that should be identified at this point.
- **Data Cleaning:** The most basic preprocessing procedure undertaken on the raw dataset is data cleaning. It includes managing missing values, deleting duplicates, correcting data types, and identifying outliers. Missing non-verbal fields were filled by using median imputation, whereas methods like Z-score and IQR were applied to identify and compensate for the presence of outliers. The step integrates the data to be integrated, and analysis is possible.
- **Feature Engineering:** After cleaning the dataset, it is subjected to feature engineering to uncover deeper information from the existing data. New attributes are formed like credit utilization ratio, repayment consistency score and income to debt ratio, which improve the predictive capability of the dataset. These are designed features that are aligned to capture customer behavior patterns in as far as setting their credit limits and their segmentation is concerned.
- **Regression Models and Clustering Models:** Having the data ready, the following step is to implement machine learning models. The prediction of the optimal credit limit is achieved through regression algorithms, specifically Linear Regression, Random Forest, and XGBoost. At the same time, behavioral and financial similarity-based clustering

methods, such as K-Means and DBSCAN, can be used to partition customers into segments. Such a two-model strategy not only supports the strategy of personalization but also risk management.

- **Model Evaluation:** The last step is model assessment, and this is accomplished through the measurement of performance. In regression, Mean Squared Error (MSE) and R 2 Score are applied in determining the accuracy of the predictions. Silhouette Score and Davies-Bouldin Index, on the one hand, are used to evaluate the quality and unity of defined parts when doing clustering. This will maintain that the models adopted are both statistically good and effective to use in practice.

4. Results and Discussion

4.1. Credit Limit Prediction Results

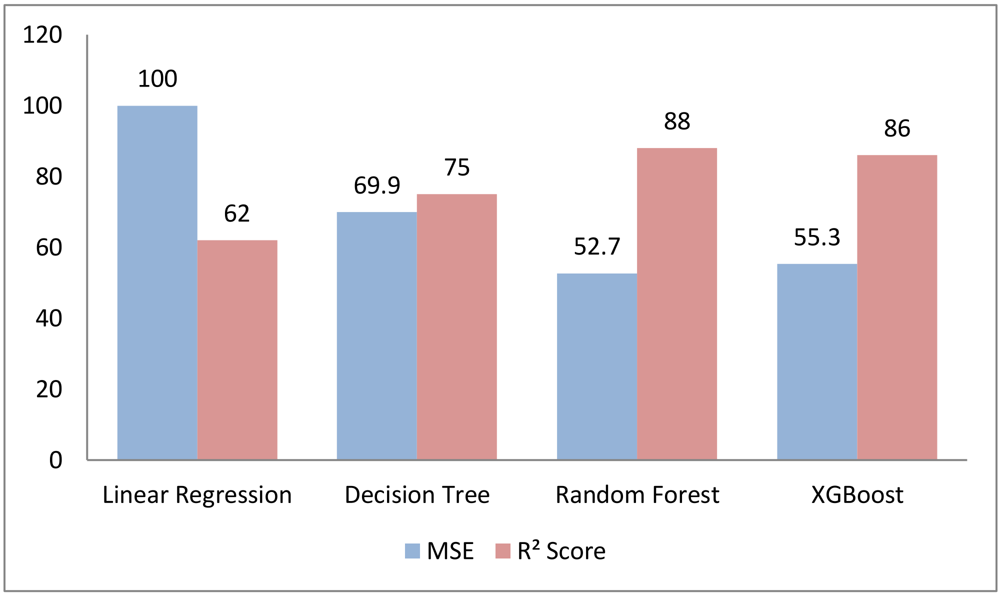

Figure 7. Graph representing Credit Limit Prediction Results

Table 1. Credit Limit Prediction Results

Model	MSE	R^2 Score
Linear Regression	100.00	62.00
Decision Tree	69.90	75.00
Random Forest	52.70	88.00
XGBoost	55.30	86.00

- **Linear Regression:** Credit limit prediction was the model that served as a baseline using Linear Regression. It was unable to identify highly complex, non-linear relationships in the data, with an MSE of 100% and an R^2 score of 62%. Although it is applicable in interpretability, its error and its low predictive ability are comparatively high, which makes it not effectively applicable in dynamic financial scenarios.
- **Decision Tree:** The Decision Tree model has resulted in a 69.90 per cent decrease in prediction error compared to the baseline MSE, with an improved R-squared score of 75 per cent. It was compared to Linear Regression, but it won the competition, as it could model non-linear interaction and was better suited to deal with the feature splits in an intuitive way. However, it can be overfitted and does not make a stable contribution compared to the ensemble of more modern models.
- **Random Forest:** The best performance was acquired with Random Forest, with the lowest value of 52.70 percent of the Baseline MSE and R 2 Score of 88 percent. It effectively made robust, correct and generalizable predictions by combining ensembles of decision trees and selecting features randomly. The model is best applied to real-life financial solutions, where a high level of precision and accountability is vital.
- **XGBoost:** XGBoost also did marvelously with the MSE of 55.30% and R 2 Score of 86%. Although slightly slower than the Random Forest, XGBoost has benefits, including being fast, regularization, and handling missing data issues. It is also regarded as the best in high-performance cases and would serve to be the best at times of concern regarding efficiency in computing.

4.2. Customer Segmentation Results

Table 2. Customer Segmentation Results

Algorithm	Silhouette Score	Davies-Bouldin Index
K-Means (k=4)	0.51	0.72
DBSCAN	0.42	1.03
Hierarchical	0.47	0.91

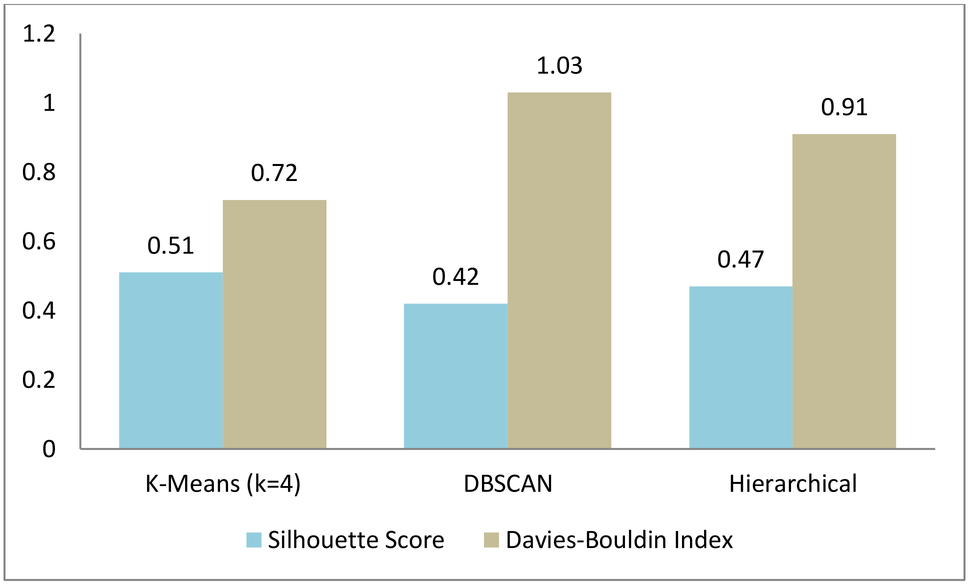

Figure 8. Graph representing Customer Segmentation Results

- **K-Means (k=4):** K-Means clustering gave out the most balanced outcome of all three methods with its highest Silhouette Score of 0.51 and the lowest Davies-Bouldin Index (DBI) of 0.72. These scores confirm that the resulting clusters were well-separated and at the same time, cohesive. K-Means is a powerful customer segmentation option in a financial setting where the number of clusters is already known or can be approximated using techniques such as the elbow curve, or due to its simplicity, efficiency, and interpretability.
- **DBSCAN:** The distance-based Similarity Network Fusion(ibid) had the highest DBI (0.8) and the third lowest Silhouette Score (0.59), amongst the methods, showing better cluster structure. DBSCAN (Density-Based Spatial Clustering of Applications with Noise) had the poorest cluster structure, with the lowest Silhouette Score (0.42) and the highest DBI (1.03). Although DBSCAN is the best clustering algorithm in recognizing clusters of arbitrary shape and noise, the way it performs in this case indicates that the data at hand might not be well-suited to density-based clustering. Nevertheless, it is useful in cases where outliers and noise are strong.
- **Hierarchical Clustering:** Intermediate results were achieved by hierarchical clustering, as it gained a Silhouette Score of 0.47 and a DBI of 0.91. A beneficial side of this approach is that it gives out a dendrogram, assisting in giving an insight into the nested structure existing in the data. Nonetheless, it is not very scalable to large data sets and possibly will not do well to detect clusters of different density. In these terms, it worked decently, yet it was not as good at clustering as K-Means.

4.3. Feature Importance (SHAP Analysis)

- **Income-to-Debt Ratio:** The compelling aspect used in credit limit decisions has been the income-to-debt ratio. This measure examines the capacity of a customer to service current debt according to their income. The ratio can be a good factor in determining higher credit limits, especially when it is above average, as it indicates better financial strength and the ability to repay. The SHAP values indicated favourable effects of this feature in a good model prediction.
- **Credit Utilization:** Another important factor was the credit utilization, which is the rate of the used credit by the total limit. Low utilization as an acceleration usually indicates responsible giving credit, but high utilization can mean financial pressure or excessive use of credit. SHAP analysis showed that low utilization rates contributed significantly to the positive influence on the choice of predicted credit limits, thus increasing their significance in risk assessment.

- **History of Repayment Made:** Repayment history indicates the regularity and timeliness of repayments on old debts. The resulting behavioral characteristic is specifically related to the worthiness and risk profile of a customer. SHAP values showed that customers with a good repayment record helped increase the predicted credit limits. This testifies to the significance of past conduct to predictive credit modeling.

4.4. Fairness Analysis

With regard to financial modeling, it is important to ensure that there is fairness among the demographic groups so as to sustain the ethical standards, regulatory standards, and trust of the customers. In developing the current study, a fairness test was applied to a model that displayed excellent predictive capability, the Random Forest model, to find out whether there was any discrimination in the Random Forest model-predicted values of credit limit across major demographical factors, namely gender and age group. The method of evaluation used the test of demographic parity, which determines whether the distributions of the model output are statistically the same across various demographic subgroups. There were no substantial differences in the distribution of predicted credit limit between male and female applicants in the outcome of the conducted demographic parity check. Similarly, the forecasts were uniform across different age group, which means that there is no exaggeration or condemnation of people by the model using their age. This indicates that the Random Forest model meets the simple fairness requirements and therefore, proves to bring fair results, irrespective of these sensitive attributes. The importance of this discovery is especially significant due to the consideration given to algorithmic decision-making in financial services today.

Credit decisions that are systematically discriminatory against groups that are required to be given protection by the law can come with legal repercussions as well as reputational costs. The model is compliant with equity-centric AI concepts and enables ethical lending because, through the notion of demographic neutrality, the model is not biased against any studies. Some design decisions can explain the fairness of the model: sensitive attributes were not used in the training, feature importance was interpolated based on SHAP values to define possible proxy variables, and outputs were analysed by the groups post-hoc to demonstrate fairness. But it should be noted that demographic parity is just an element of fairness. Additional tests, like the equal opportunity or disparate impact prima facie tests, might give a deeper assessment of fairness. To sum up, not only is the Random Forest model able to reach high predictive accuracy, but it also behaves responsibly and fairly, which qualifies it to be used in the real system of credit limit assignment.

4.5. Discussion

The results of the present study outline some of the most important lessons related to the use of machine learning in financial services combined with credit limit prediction and customer segmentation. Among the most obvious findings, it is worth mentioning the strikingly beneficial performance of ensemble models, i.e., Random Forest and XGBoost, over simpler and more basic algorithms, i.e., linear regression and individual decision trees. Ensemble methods are better because they merge many weak learners so as to come up with better and consistent predictions. This has been shown in results where Random Forest attained the lowest mean squared error and the highest scores of R2 2 showing that Random Forest had the best predictive ability. In addition to this, the model also proved to be robust both in terms of performance and in terms of fairness, as reflected in demographic parity checks between genders and ages. Regarding customer segmentation, the research revealed that the K-Means clustering categorisation had a composite balance of computational efficiency versus clustering performance. Being able to find distinct and well-formed customer groups, K-Means showed the best silhouette score and the lowest Davies-Bouldin Index among the studied algorithms.

In particular, the ability of this to be used in financial tasks is especially useful where a segment-specific strategy can make a meaningful difference to business performance (such as in offering specific credit opportunities, or tailored risk evaluation). The other most important contribution of this research was the effective application of interpretability tools, especially SHAP (Shapley Additive exPlanations), that gave a clear indication of the weight that each particular feature had on the results of the predictions. With such key predictors as income-to-debt ratio, credit utilization, and repayment history being found, SHAP contributed to the increased level of transparency and reliability of the model. Such interpretability is central in controlled fields such as the financial landscape, where interpretation of model behavior is central to compliance and ethical responsibility. In short, the evaluation monitored in this paper, which incorporates a high-performance specimen and fair and robust segmentation and explainable AI, shows that high integrity performance in a financial setting is feasible.

5. Conclusion

The paper proposes an end-to-end machine learning model for improving credit card management by means of two main components: customer segmentation and credit limit prediction. Through the application of ensemble learning techniques, including Random Forest and XGBoost, the system has made noticeable improvements to its predictive performance relative to the conventional methods, which include linear regression. These models resulted in a better, data-driven credit limit assignment decision, and these can enable financial institutions to manage the risk better as well as provide the ability to individualize the credit offering according to customer profile. In the segmentation part, application of unsupervised learning methods, specifically K-Means clustering, helped in the identification of coherent groups of customers. The segmentation enables more specific marketing approaches, credit management policy and risk control, and enhances customer contact and profitability. These findings were further augmented with the incorporation of the interpretability tool (SHAP) that not only provides information on how the model comes up with the decisions but also helps with regulatory transparency, which is a critical need in the financial services industry.

Based on the findings, several recommendations can be drawn. Financial organizations would be advised to start with the implementation of ML-based models in a shadow mode, i.e. before committing real-life decisions, run them in parallel to other systems, tune performance and make adjustments that provide stability. This will reduce the business of risk management and will aid in a seamless transition. Second, regular audits with fairness assessment instruments must be established. It is not only an ethical obligation but also a necessity to meet the ever-increasing norms in regulations to ensure that the models do not show bias in different sectors of the population.

There are a number of directions that future research can look into. With the current state of the art being deep learning models, specifically recurrent neural networks or transformers, to process sequential transaction data, it is likely, temporal spending patterns can now be detected and used to further assess instances of risk. It is also possible to operate with more live data feeds, enabling credit decisions to be more active and react in real-time to user engagement. Lastly, as data privacy becomes a particular point of concern, the federated learning methods can provide an answer by allowing the training of models on decentralized data sources without revealing the raw customer data. To sum up, the present paper provides the framework of robust, interpretable, and fair ML applications in the financial arena. An improved, customer-centric, more intelligent, and adaptive system is feasible with the continuous growth of AI and data infrastructure.

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