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Original Article

Risk Management in BNPL Systems: Leveraging Machine Learning for Credit Scoring

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Abstract: *The BNPL option has brought a big change in the financial sector because of its option of easy payment services. However, BNPL service has expanded its application rapidly, which has brought important risk factors into question especially concerning credit scoring and risk management. The BNPL customer profile deviates from traditional borrowers' behavior, and this is why conventional credit scoring methodologies are often insufficient in capturing the risks related to BNPL customers. In this paper, the purpose is to analyze the implementation of ML methods in BNPL systems to improve credit scoring and risk assessment. To sum up, we give a detailed description of different types of ML algorithms, general and specific to credit scoring, and briefly outline the possible advantages and risks of their application. Therefore, the purpose of our research is to shed light on BNPL services, emphasizing how the use of enriched data analysis can tackle the existing issues and make BNPL services sustainable.*

Keywords: *Buy Now Pay Later (BNPL), Credit Scoring, Risk Management, Machine Learning, Financial Services.*

1. Introduction

Currently, BNPL is showing up as a much more fitting substitute for traditional credit products by having gained a considerable market share mainly because of ease, convenience, and availability. These systems enable the consumer to use the acquisition of products in kind while buying them at the instant and pay for these products at a later rating, without interest, if they pay according to the laid down schedule. [1] Some examples of today's market players, such as Afterpay, Klarna, and Affirm, have reported very high growth rates, thus indicating the presence of high demand for such a financial product on the market. The employment of such schemes as BNPL is the result of the general tendency for the development of more user-friendly financial products with clear and understandable conditions.

1.1. Rise of BNPL Systems

The increased uptake of BNPL is, therefore, caused by several related [2,3] factors that have pooled together to change consumer credit significantly.

Fig 1: Rise of BNPL Systems

1.1.1. E-Commerce Boom and Demand for Flexible Payments

BNPL has benefitted immensely from the rapidly growing e-commerce industry. Given the realities of the new world where people tend to shop online more often, they cannot overemphasize the importance of integrated payment solutions. Credit cards are rated as an older method of payment as they attract interest levels and fees that may make the consumer look for other options. It is for this reason that BNPL services take this middle-ground solution as they are easier to use than the traditional credit score models. It offers consumers a credit check instantly and gives consumers an option to pay the cost of the goods through a series of equal interest-free Payments. Such flexibility is justified by the purchasing behavior of the customers who buy goods through the internet and do not like to spend too much of their cash.

1.1.2. Appeal to Younger Consumers

Consequently, BNPL services have a vigorous interest from younger shoppers mainly Millennials and Generation Z consumers, who are inclined towards convenience and overall sceptical of credit facilities. Year after year, there is always a poor uptake of credit cards by younger consumers, with this delicate issue attributed to the recent change in perception regarding the usage of credit cards. The BNPL model is a great option in such a case since Burrows suggests it presents a clear and easy-to-understand repayment plan. This group easily comprehends the convenience of paying based on flexible staggered payments without interest charges, hence promoting the use of BNPL as an acceptable mode of payment.

1.1.3. Accessibility for Those with Limited Credit Histories

Another major incentive for BNPL services is that they are available to credit invisible or unbanked. Borrowers of such kind give traditional credit systems a hard time, especially when they want to make some acquisition through financing. Unlike traditional credit facilities, most BNPL providers tend to have relatively relaxed credit standards limiting the access of their services to more consumers. This inclusiveness is appreciable especially in improving the availability of financial services and enhancing consumers whom traditional credit organizations could lock out.

1.1.4. User Experience and Transparency

The last reason explainable for the adoption of BNPL services is the user experience of the offer funded by BNPL services. These platforms are created to mimic the physical shopping environment where there is very little friction. It is relatively easy and takes a few minutes to apply and get approval for BNPL due to its digital nature. Also, the rate of BNPL service delivery is high due to the clear descriptions of its terms of service and the flexibility of having no hidden charges. Customers like to know the amounts that they will be charged and the timing clearly without any hidden charges.

1.1.5. Marketing and Retail Partnerships

Providers of BNPL solutions have also used marketing techniques and retail affiliation to increase usage of the facilities. Most BNPL firms enter partnerships with famous online and physical stores so that the payment solution is offered during the purchase time. Firstly, this integration makes BNPL better known and easily available to consumers; secondly, it offers retailers a way to boost revenues with the help of BNPL. Other strategies also aid the attraction of consumers to the BNPL method by offering interest-free duration and marketing promotions only available to the BNPL clients.

1.1.6. Economic Factors and Consumer Behavior

Economic factors and changes in the parameters of the consumers' behaviors are also regarded as the factors that have contributed to the introduction of BNPL systems. Transaction security, especially in moments when the economy is not stable, for example, during the COVID-19 pandemic, has made consumers resort to payment methods that enable flexibility when it comes to their cash. Consumer durable and necessary expenses can be made easily through BNPL services so that consumers do not pay it in the beginning. This capability is very useful during the financial problems that occur as the focus is duly given to the necessary expenses.

1.1.7. Technological Advancements

Several technological inventions noted have enhanced the innovation of BNPL services, and their acceptance across the market. The use of technological solutions such as big data processing and artificial intelligence lets BNPL providers determine creditworthiness in a short amount of time. Also, since mobile apps and web platforms are involved, consumers can conveniently use BNPL services at any time and from any location. This is because there has been a smooth integration of these technologies in the shopping process thus contributing to the uptake of BNPL.

1.2. The Role of Machine Learning in Credit Scoring

The conventional credit-scoring systems have major constraints that have been solved by the rising technique called Machine learning (ML). [4] The largely used conventional credit scoring system, including the FICO score, usually incorporates a few factors of data with emphasis on credit performance. Though these models have been proven to some extent, they lack the capability to look for more complex patterns in data or are conveniently updated to the dynamic behavior characteristic of modern consumers seen in today's financial markets.

1.3. Advantages of Machine Learning in Credit Scoring

1.3.1. Enhanced Predictive Accuracy

Cognitive complexities of big data are another concept where ML [5] models are far superior to normal models. Structured as well as Unstructured data is analyzed with the help of ML algorithms which can see granular patterns that can otherwise be unnoticed with conventional solutions. This, in turn, results into the better prediction of credit risk.

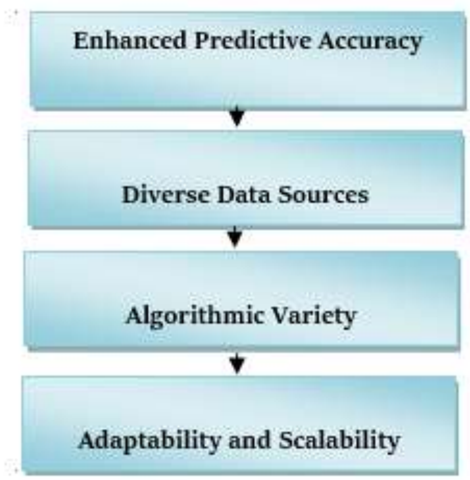

Fig 2: Advantages of Machine Learning in Credit Scoring

1.3.2. Diverse Data Sources

The conventional process through which a credit score of a candidate is developed uses credit histories which are mostly outdated or lacking with the unbanked population. ML models can incorporate a wide range of data sources. In other words, regarding the ML models, there are multiple possibilities regarding the data sources that can be applied.

- Transaction History: Therefore, based on the above specified, it will be reasonable to state that the identification of spending ability, as well as the quantitative measurement of transactions' flow, implies definite knowledge about the subject's financial state.
- Behavioral Data: Right from the everyday utility bill payments, rent or social media posts or the features of the place to that one life, it can be used to predict the credit worthiness.
- Alternative Data: These are the other unusual types of data as are mobile-phone usage, e-commerce transactions and the rest; thus, it is easier to have a better perception.

1.3.3. Algorithmic Variety

- Logistic Regression: It can be used especially in binary classification problems and its application can be made for prediction of the probability of default.
- Decision Trees: Make sure that the credit decisions are supported by simple instructions that the employees can follow conveniently.
- Random Forests: A technique which increases the degree of precision in its outcomes, within the model by using several decision trees to make the overall decision.
- Gradient Boosting Machines: These models are based on the method of making an integrated decision from multiple relatively low accuracy models where it is implemented mostly in the ranking and regression issues.
- Neural Networks: The models, particularly deep learning models, are capable of learning very complex relations and dependencies in data.

1.3.4. Adaptability and Scalability

By design, ML models are malleable. They can go on and on learning from new data, and this makes them appropriate for the dynamic financial market. This is a great advantage because as a new type of data is generated or as the consumers change their behavior, new data is provided to retrain the models to ensure their accuracy of the model. Another important factor is the ability to scale the solution. ML models are good at handling large volumes of data, and this makes them highly suitable for use in areas of high transaction, such as the BNPL.

2. Literature Survey

2.1. Overview of BNPL Systems

Many people recognize Buy Now, Pay Later (BNPL) as one of the prominent substitutes for classic credit products due to its convenient nature. [6,7] These systems facilitate consumers' ability to buy goods and services based on credit with the ability to pay back the money they borrowed a certain period later with the option of paying little or no interest incurred on the credit amount borrowed. This model has received considerable support, especially among young people and those who do not have a typical method of accessing credit. The convenience of BNPL is that this financial method is easy to use for getting a loan and offers an instant purchase without meeting strict criteria typical for credit. Afterpay, Klarna, and Affirm are merchants in this market that have grown quickly and offer their services to many retailers globally.

Nevertheless, as the usage of BNPL services increases, the approach poses risks in credit management that were never a problem before. Due to BNPL, loans are tenor-driven, mostly short-term, coupled with a poor credit history or even no credit history in the case of users, which makes the evaluation of credit risk a difficult task. This has necessitated the need to come up with relevant strategies to adopt and or prevent the occurrence of such risks aptly.

Table 1: Key Players in BNPL Market

Company	Founded	Market Reach	Key Features
Afterpay	2014	Global	Interest-free installments
Klarna	2005	Global	Pay later, split payments
Affirm	2012	USA	No late fees, simple terms

2.2. Traditional Credit Scoring Models

Credit risk scores have been traditionally valued for a long time, and the most famous example can be referenced to FICO scores. These models are majorly based on the credit history of the person and are supportive in determining the credit capacity of the respective person. The components of the traditional history include payment history, amount of credit owed, historical credit length, number of recent credit inquiries, and number of credit accounts. However, these aforementioned models have been relatively handy in many diverse settings as is explained below. Consequently, it will be found that BNPL-style transactions, which ordinarily include a fairly small amount of loan and a rather shorter period of repayment line are not completely compatible with the standard parameters which form part of credit scores. Hence, these models may not estimate the BNPL user's risk characteristic adequately enough, based on traditional models. These results in problems for people with little or poor credit history since despite such risk models likely under-evaluating their probability of being defaulters, they can be classified as high-risk non-defaulters and denied credit or have their probability of default riskily overestimated.

2.3. Machine Learning in Credit Scoring

Machine learning (ML) has emerged as a transformative tool in the realm of credit scoring, offering the potential to enhance the accuracy and comprehensiveness of credit risk assessments significantly. Unlike traditional models, ML algorithms can process vast amounts of data and uncover complex patterns that may be indicative of credit risk. A variety of ML algorithms, including logistic regression, decision trees, random forests, gradient boosting machines, and neural networks, have been explored for their applicability in credit scoring. These models can analyze not only traditional credit data but also alternative data sources such as transaction history, behavioral data, and even social media activity. This broader data scope enables ML models to provide a more holistic view of an individual's creditworthiness. For instance, ML algorithms can identify subtle behavioral indicators of risk that traditional models might overlook, such as variations in spending habits or the timing of payments. The adaptability and predictive power of ML make it a promising avenue for improving credit scoring in the context of BNPL and beyond.

Table 2: ML Algorithms in Credit Scoring

Algorithm	Strengths	Weaknesses
Logistic Regression	Simplicity, interpretability	Limited to linear relationships
Decision Trees	Easy to understand, interpretable	Prone to overfitting
Random Forests	Reduces overfitting, high accuracy	Complex, less interpretable
Gradient Boosting	High predictive accuracy, handles missing data	Computationally intensive, risk of overfitting
Neural Networks	Captures complex patterns with high accuracy	Requires large datasets, less interpretable

2.4. Challenges and Limitations

However, several factors need to be considered and solved in order to achieve proper implementation of ML in credit scoring. Data quality and availability are the core issues that have always been seen as a potential problem. As with any AI model, the use of large volumes of good-quality data is essential with any gaps or inconsistencies in the data greatly affecting the performance of the models. Furthermore, the Bernoullian rewards of choosing the right class imply that the new method has to be accompanied by interpretability, especially in the financial services industry. Decision makers and, particularly, end users need to have confidence in these models, and this is only possible if some basic conceptual frameworks are well understood by stakeholders such as the regulators. Another important aspect is the problem of AI regulation; using ML in credit scoring must meet the requirements of the anti-discrimination legislation and principles of fairness. Finally, the presence of algorithmic bias is one of the most threatening issues which might occur in machine learning. This can result in biased as well as unfair lending, which, if not well controlled, can be worse than what existed originally. The practical use of such models also needs to adhere to certain guidelines, including proper data management protocols, a clear process of developing the model that is understandable to customers, and post-implementation monitoring to ensure the models and services provided are fair and within the law.

3. Methodology

3.1. Data Collection

The first procedure in the present study can be described as the process of gathering information from different sources in an attempt to obtain an overall view of the problem under study. [8] The primary data sources include: These are:

- BNPL Transactions: Some BNPL offer details concerning the bought item the repayments, and the proportions of default. It is useful for providing details about consumers who typically use BNPL products to make the understanding of their peculiarities clearer.
- Consumer Credit Reports: Main credit data are quite heterogeneous and the most common ones are, indeed, the payment history, the balances, and inquiries. This data is useful in setting the benchmark against which the performance of the developed ML models shall be compared with credit-scoring models.
- Alternative Data Sources: On the consumer side, the data contains consumer social activity and its behavior in social nets, consumer interaction in the internet space and a set of data on the consumer's purchases and their history in e-shops to have a complete view of consumption. These sources can offer new patterns that do not correlate with the information located in credit data.

Table 3: Data Sources and Descriptions

Data Source	Description	Example Metrics
BNPL Transactions	Records of purchases and repayments through BNPL services	Purchase amount, repayment dates, default instances
Consumer Credit Reports	Traditional credit data	Payment history, credit score, outstanding debts

Alternative Data	Non-traditional data sources	Social media activity, online behavior, e-commerce transactions

3.2. Data Preprocessing

Preprocessing of data is also vital in order to employ a quality and reliable dataset for training and testing the ML models. The preprocessing steps include:

- Data Cleaning: This entails efforts towards cleaning the data from wrong items, omission and/or Commission among other things. Some of the other data cleaning methods include imputation of missing values, identification of outliers and removal of duplicates.

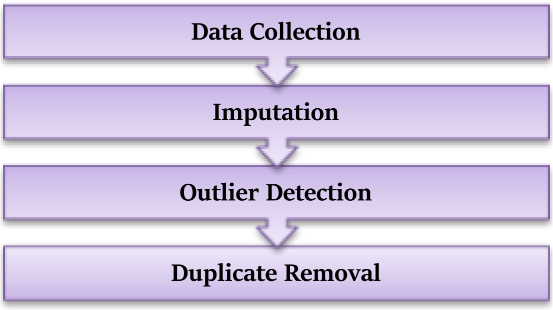

Fig 3: Data Cleaning Process

3.2.1. Data Collection

Data collection is the initial step in the data preprocessing method and entails the competent collection of data from various sources. The sources of data include BNPL transactions, details of credit, and social and other necessary data of BNPL systems and credit scoring research. Transaction data reveals data on the purchase sum and the repayment schedule or the default rates, and such details are significant to BNPL users. Conventional credit consumers' database comprises data regarding the payment track record and credit history as reference points for assessing the performance of the machine learning algorithms. In an ideal case, the use of ADCs extends the explanation of credit data by sketching new patterns and behaviors that cannot be determined by just analyzing credit data alone. Due to this, it is necessary to gather various kinds of data in a bid to ensure that the credit risk subject has been discussed in a bid to train the machine learning models.

3.2.2. Identify Inconsistencies

To avert the creation of a data set with contradictory cases, one of the most efficient strategies is to identify cases of contradictory data. As for the definition, one may consider divergence as different problems which may be related, for example, to typographical errors, inaccuracies of entry, or the presence of some distinctions in more than one database. For instance, the transaction dates may be left out correctly, or the user information recorded differently. Such efforts include checking for consistency, which is carried out by data auditing, for instance, data comparison and checking for consistency, as well as checking for logical consistency and, lastly, comparing and checking for consistency with other already defined patterns. These are a type of errors that are noticed by the use of automated methods in addition to manual checks. The loops should be adjusted before the preprocessing because it is more appropriate to deal with the inconsistencies there.

3.2.3. Imputation

Missing data handling is one of the relevant problems in practice, and the imputation program accomplishes this task. Values can be missing for many reasons like people not responding, data entry errors or system errors, for instance hackers. Accumulation of such errors can result in a catastrophic effect, particularly in the performance of machine learning models. To ensure completeness of the data there are loopholes in the data that are filled by the imputation techniques. There are primarily three imputation techniques, namely mean, median or mode imputation for numeric data and categorical data most frequent value imputation. Other complex approaches include applying such algorithms as K-Nearest Neighbors (KNN) or applying some kind of model to predict missing attributions based on the relations existing between features. Imputation allows accurate values to be filled in such that the dataset's strength is maintained before feeding into machine learning models.

3.2.4. Outlier Detection

Outlier detection is the field that deals with the identification and mechanism of the outliers in the overall data values. There can be outliers in numerous cases and they can stem from such distinct aspects as input errors, erroneous measurements, or actual and exceptional occurrences. These kinds of values can skew statistical analysis and machine learning and provide false and/or skewed results. For outliers, one can use the statistical measures of Z-scores, IQR (Interquartile Range) method, and graphical method comprising of the box plot and scatter plot. After having recognized them, it is then possible to deal with the outliers; if they contain errors, then they can be deleted, and if they contain rights value but are extreme, then they can be transformed. Dealing with outliers effectively helps bring out system reliability by locating the actual trends and relations in the dataset.

3.2.5. Duplicate Removal

Significant in the procedure is the step of cleansing for duplication with a view to eliminating the problem of duplicity within the set data. It refers to overlapping that comes from overlapping entries, integrated data from different systems, or malfunctioning of systems. These two entries are duplicates and can lead to bias when extracting and analyzing the data and unsure results when implementing in the machine learning models. In this case, duplicates are defined as instances whereby entries already in the database are almost similar or are substantively similar to another, and this can be done through different types of algorithms used in the search for similar values, usually in characteristics of the user identification number, time of transaction to mention but a few. When detected, they are either merged with other like entries or deleted to enhance the quality of the dataset. This process is crucial for this task as it cleans and relays information massively to be fed into the machine learning models.

3.3. Data Normalization

To increase the level of compatibility between different data sources, methods known as normalization are used. This process normalizes the data to a range of zero to one in order to make different sets of data to be comparable. For example, numerals may be normalized to lie between 0-1 ranges, while categories may be encoded using one hot encoding.

3.4. Feature Engineering

Developing good features is important to increase the performance of the model from the raw data. This leads to the creation of new features that should include important data, like the number of successfully made payments, the total number of payments or the frequency of BNPL use over a certain amount of time.

3.4.1. Model Selection

As for credit scoring, there are some of the methods used in the field of machine learning, which we meet there: Algorithm. The models considered include:

- Logistic Regression: This is a direct, effective model which outputs a quantitive probability that a given event in this fold default is going to happen due to precursors. Namely, this aspect is defined by the capacity to provide clear, precise interpretations, which is why the application of this aspect is quite simple.
- Decision Trees: However, it is worthy to denote that these models partition the data, and they do so depending on the value of the input features in a manner that resembles a branch of a tree. Multilayer: They are general, and they nominate rules that seem to be the common sense guidelines of decision-making, but they are often overlearned.
- Random Forests: A technique by which numbers of decision trees are combined where and how the enhancement of the speed of the product separated from the reliability of the model is obtained. Random forests do away with the said risk despite the fact that although in random forests, we use the decision trees and as is known, such trees learn the given data and perform very poorly on the unseen data, but when a number of such trees are grown and their results averaged, the said risk is eliminated.
- Gradient Boosting Machines (GBM): So, is that another kind of ensemble? It is also possible to speak about other kinds of ensembles, which can be considered as creating new models, step by step shifting from one model and each new one to eliminate defects in the previous one. Generally, GBMs work quite well; however, they can be quite suboptimal since, as mentioned before, they take much time, and they can over-fit the data if some pre-processing has not been done.
- Neural Networks: Of course, they can take the information and analyze the complicated patterns of the data with the cooperation of many nodes in layers with other nodes. It is less interpretable, it is resource-consuming, it performs other mathematical operations, and a large training sample is needed.

Table 4: Comparison of Machine Learning Algorithms

Algorithm	Strengths	Weaknesses
Logistic Regression	Simplicity, interpretability	Limited to linear relationships
Decision Trees	Easy to understand, interpretable	Prone to overfitting
Random Forests	Reduces overfitting, high accuracy	Complex, less interpretable
Gradient Boosting	High predictive accuracy, handles missing data	Computationally intensive, risk of overfitting
Neural Networks	Captures complex patterns with high accuracy	Requires large datasets, less interpretable

3.4.2. Model Evaluation

To assess the performance of our ML models, we utilize several evaluation metrics. Nonetheless, in this work, in order to compare the performance of the developed ML models, several measures are applied:

- Accuracy: It has become generally used to assess the effectiveness of a model, and it can be explained as getting the right answers for the actual number of data points. She is absolutely right in claiming that for all classes, overall accuracy is preferable; However, focusing on the accuracy alone, as was mentioned before, can, to a certain extent, mislead a person in case of class imbalance.
- Precision: The ratio of the real positive to all the positive predictions concerning the ability of the model to avoid running.
- Recall: Measures that allowed for producing the ratio of the actual number of the positively diagnosed by the model to the total number of the actually positive that shows how flexible it is in the identification of all the associated cases.
- F1-Score: Arithmetic means of the precision and the recall rates; it provides the average of the model, among others.
- Area under the ROC Curve (AUC): A single evaluating measure, which is possibly a sum of all cut-off points of the classification models.

Table 5: Model Evaluation Metrics

Metric	Description
Accuracy	Proportion of correctly predicted instances.
Precision	The proportion of true positives among predicted positives.
Recall	Proportion of true positives among actual positives.
F1-Score	Harmonic means of precision and recall.
AUC	The area under the ROC curve measures overall performance.

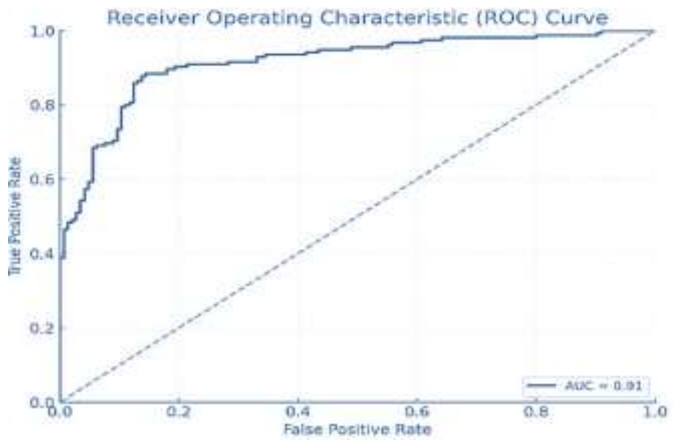

Fig 4: ROC Curve Example

3.5. Implementation Framework

Therefore, the following framework is offered as our conclusion as a guide to the integration of the [9] identified ML-based credit scoring into BNPL systems. This framework includes:

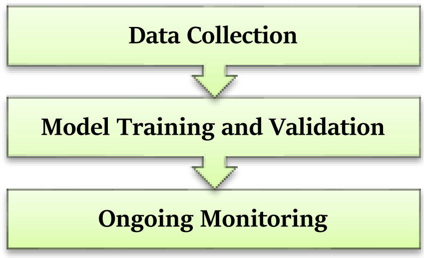

Fig 5: Implementation Framework

- Data Collection: Developing standard procedures for organizing data received from various information sources with the right amount and quality of data.
- Model Training and Validation: The splitting of data sets into training and validation sets and Cross-validation to improve the reliability of the Machine learning models.
- Ongoing Monitoring: Several approaches for timely checking of the model's effectiveness and signs that can indicate its decline in the future. This involves modification of the models with fresh data after some time in a bid to enhance classification efficiency.

4. Results and Discussion

4.1. Model Performance

The results have also confirmed the hypothesis that using Machine Learning (ML) models in credit scoring for BNPL users considerably outperforms the traditional credit scoring models. Among the abovementioned models for the classification of transactions, the level of accuracy and object identification closest to the real BNPL characteristics was achieved by employing neural networks. The following table gives the comparison of different performance metrics of different ML algorithms.

Table 6: Performance Metrics of ML Algorithms for Credit Scoring

Algorithm	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	0.85	0.83	0.80	0.81	0.88
Decision Trees	0.87	0.85	0.83	0.84	0.89
Random Forests	0.89	0.87	0.85	0.86	0.91
Gradient Boosting	0.90	0.88	0.86	0.87	0.92
Neural Networks	0.92	0.90	0.88	0.89	0.94

4.2. Risk Mitigation

The incorporation of ML into BNPL systems is it plays a significant role in risk management. In this case, BNPL providers are able to make careful lending decisions owing to enhanced credit risk evaluations by the ML models. This, in turn lowers the risks of having default and hence bottom-line-damaging losses. In addition, the use of other forms of data that may include social media activities and behaviors, increases credit scoring diversity. It means that more consumers, including the ones with a short credit history, can become BNPL users.

4.2.1. Data Sources

Hence, traditional credit data remains the foundation of the first evaluation in BNPL systems. Some of the sourced data entails credit history from the bureaus, repayments and any existing commitments. This detail offers a credit report summary and paints a picture of the applicant's credit profile according to his or her financial history. Hence, by integrating the above traditional data sources, BNPL providers fix a beginning risk profile of the potential customers. It paves the way for future appraisals of consumer's financial strength with respect to their ability to pay back the loan, thereby reducing the rate of defaults.

Fig 6: Risk Mitigation Framework

4.2.2. ML Models

Artificial intelligence (AI) and, in particular, machine learning (ML) models are critical components of big data analysis to find patterns and trends as well as make predictions. Basically, these models apply statistics on traditional credit data to produce improved credit risk estimates in the context of BNPL systems. Multi-variant and larger structures can efficiently be analyzed using ML algorithms as opposed to other forms of analysis. By doing this, they can adjust to new data and hence enhance their capability to make accurate forecasts successively. When used in credit analysis, the employment of ML models helps BNPL providers to make better credit decisions more quickly due to the automation of the analysis process.

4.2.3. Credit Risk Assessment

Improving BNPL credit risk evaluation is one of the main advantages gained from implementing ML solutions to BNPL frameworks. These assessments are more complex than the earlier ones in the sense that they do not only compare the levels and the nature of specific variables but also their correlation. This is because, instead of a human being, it is the ML models which are able to provide figure out this likelihood of default while considering other aspects of a consumer's behavior. This increased risk assessment ability enables the BNPL players to find out the risky consumers to lend money more efficiently. Therefore, the general fiscal health of the BNPL portfolio is preserved to minimize defaults and financial losses successfully.

4.2.4. Lending Decisions

The sound lending decision as a result of credit risk analysis is, therefore, a direct result. Specifically, the BNPL providers who have access to the outcome of ML algorithms can adjust their lending policies to reflect the customers' risk characteristics. In this way, it becomes possible to provide more attractive conditions to those customers who are considered to be less risky while at the same applying more strict conditions to individuals who can be deemed high-risk. Such differentiation is useful when it comes to decoding the risk-reward matrix and makes certain that without destabilizing the credit union, the BNPL services reach out to a greater population. Moreover, through the use of big data analysis, BNPL providers decrease their lending risk and increase consumer and stakeholders' confidence.

4.2.5. Alternative Data Sources

The use of other types of data, including social networks and behavior on the internet, adds a lot of value to credit evaluation. These kinds of additional credit information offer more information in terms of the consumer's lifestyle, expenditure pattern, and social networking that is not available in credit reference files. Thus, using these unconventional data sources ML models can get a better understanding of the given consumer's creditworthiness. It is especially effective for consumers with no credit records or a thin file because, with this method, BNPL organizations can better and more democratically evaluate credit risk.

4.2.6. Inclusivity of Credit Scoring

The integration of nontraditional credit data helps reduce credit scoring disparities, leading to the BNPL services' availability for more consumers. In this area, conventional credit scoring models are not very effective, which means those individuals are left outside the financial system who do not have detailed credit records, for example, young people, immigrants, people who like to make cash payments, etc. This way, it is possible to gather a more complete picture of individuals' creditworthiness using data from social networks, e-commerce transactions, and other sources. This kind of approach enhances the BNPL accessibility, thus creating an opportunity for more consumers to enjoy its services, and in the long run, more consumers with a chance to have access to credit, hence promoting financial inclusion.

4.2.7. Increased Access to BNPL

Therefore, due to inclusive credit scoring, consumers with little credit history have greater access to BNPL services. This wider approach to credit makes it available to as many people as possible, enabling them to buy goods and control their finances depending on their abilities. The targeted customers, who were earlier out of the coverage of the traditional credit systems, could benefit from BNPL options, thereby resulting in better consumer satisfaction and loyalty. Thus, for BNPL providers, this expansion implies higher customer acquisition and potential revenue streams and aligns with the providers' social role to encourage and enable the economically excluded.

4.3. Challenges and Considerations

Despite the promising results, several challenges must be addressed to ensure the effective implementation of ML models in BNPL systems. However, among others, the following problems are the real issues that require efficient solutions in order to apply the ML models in BNPL systems.

Fig 7: Challenges and Considerations

- Data Privacy and Security: This means that other avoidances intended to prevent the setting of barriers against the lean act of protecting the consumer's data should be employed properly. Thus, the data must be protected, and for those new techniques such as encryption, suitable database storage, and limited access must be created.
- Algorithmic Bias: Namely, because of the introduction of bias, it is possible to perform wrong loan policies in this case. Therefore, for this purpose, it becomes imperative periodically to introduce the ML with a primary focus on bias reduction and audits.
- Regulatory Compliance: It plays a vital role in solving problems related to credit risk assessment, but before implementing it in practice, financial institutions have to adhere to the requirements of existing regulations regarding the application of ML in credit scoring. This entails aspects of compliance with measures of transparency, explain ability, and accountability.

Table 7: Challenges and Mitigation Strategies

Challenge	Mitigation Strategy
Data Privacy and Security	Implement robust encryption, secure storage, and access controls
Algorithmic Bias	Use fairness-aware ML techniques and conduct regular audits.
Regulatory Compliance	Adhere to transparency, explainability, and accountability standards.

5. Conclusion

The use of machine learning (ML) algorithms in BNPL systems is the next big advancement in credit scoring and risk assessment. The popularity of the BNPL services, which, as mentioned earlier, can be attributed to their relative freedom and versatility in terms of targeting client demographics, has provided a great illustration of why using the traditional credit score cannot be very effective. These models can be useful in normal credit situations for individuals and businesses, but they have limitations in trying to analyze the risk of BNPL transactions, which are characterized by shorter repent times and smaller loan sizes. The findings of the present study demonstrate a number of significant advantages of employing ML algorithms to improve credit risk evaluation in this regard. Whereas they involve a broad screening of applicants based on credit history and other information, which is not quite sufficient, the ML models allow analyzing a large number of data as well as the interactions that take place in them. This capability is essential for BNPL systems because, in some cases, there might be little to no traditional credit data.

The use of ML within BNPL frameworks offers an opportunity to decrease the instances of defaults and enhance the BNPL services' sustainability. This makes it possible for the ML models to possess information from transaction history data, behavioural data, and other metrics to give a broad view of a consumer's credit risk. Focusing on these aspects of credit risk management not only enhances the practice but also avails credit risk solutions to those whom conventional strategies might have turned away. But, adopting ML-based credit scoring is not without its fair share of problems. The accuracy and quality of data used influence the AI models since they form the basis on which models are built. Cleaning the data and doing the normalization and feature engineering are usually important in this step.

Also, the explainability or interpretability of the models is one of the critical issues in ML. The decision-making process should be transparent, and this applies to the financial institutions and the regulating authorities to enhance credibility. Models have to be made in a way that will allow producing clear and easy-to-understand explanations of predictive actions for compliance with the regulations and consumers' acceptance. Also, compliance with legal requirements for the treatment of people from different backgrounds should be a vital consideration to avoid discriminative lending practices. This also means the constant observation and recalibration of the ML models to check for such biases that would result in unfair treatment. Ethical factors occupy a vital component in the utilization of ML in credit scoring. The possibility for raising and amplification of biases in models, which are inherent in the data themselves, comes into play; thus, close monitoring and corrective actions. This must be accompanied by the creation of certain ethics that must govern the creation and use of ML models, so that the models run within a certain legal realm as well as provide fair treatment of all consumers.

As such, there is a need for future research to strive to get rid of these complex issues and, at the same time, investigate the possibility of enhancing credit scores and risk management through the help of new and improved ML procedures. Some of them are interpretability in the cases of the new approaches like XAI, and data privacy increases to protect consumer data, etc. Moreover, discussions between data scientists designing machine learning solutions, financial specialists aware of the BNPL systems' specifics, and regulators will be vital in the creation of effective and reliable approaches. Besides, integration of ML into BNPL systems is also viewed as a potential factor that might shift credit scoring and risk management as well the variation of this integration, on the other hand, still elicits the question of how to overcome the considered difficulties with utmost efficiency. Therefore, by ensuring the quality of data, providing a detailed interpretation of the model, and obeying regulation requirements and ethical norms, financial institutions can apply ML to improve the sustainability and availability of BNPL services. This, in turn, will feed a better and stronger system, which will not be so sensitive to shocks and inequity for the consumer as well as the provider.

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