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Machine Learning versus Traditional Statistical Models in Credit Risk Prediction: Evidence from Peer-to-Peer Lending Markets

David Stavar[a]

Abstract

This paper compares the reliability, transparency, and fairness of traditional statistical methods applied to credit risk assessment, especially logistic regression. Traditional methods dealing with data management are typically inefficient, not accurate enough, and cannot deal easily with multiple datasets, while those based on machine learning face model selection problems and multicollinearity. This study aims to provide financial institutions with some practical guidance on the optimal strategies they should implement according to their risk-management needs. It also examines the impact of integrating heterogeneous and unstructured sources of data on the machine learning performance of credit risk models. Particular attention is dedicated to peer-to-peer lending markets, for which we are not aware of established research that jointly investigates the use of classical and machine learning models. The research follows a deductive approach and uses inferential methods in the evaluations and comparisons of logistic regression vis-à-vis the neural network, specifically a convolutional neural network. Model building and validation are based on the Kaggle peer-to-peer lending data as a secondary source. Expected results are as follows: accurate borrower default prediction, increased access to credit, and smart lending decisions. The importance of the finding is that it shows, in practical terms, how machine learning can be used to improve portfolio management and risk assessment for contemporary financial institutions with an interesting, more advanced analytic method.

Keywords: *Machine Learning, Credit Risk Assessment, Neural Networks, Logistic Regression*

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1. INTRODUCTION

Classical credit risk scoring models usually have several shortcomings when they are applied in institutions with poor data management or limited resources to obtain full and reliable information. Machine learning techniques, more powerful as they may be, also suffer from problems like the model selection problem and sensitivity to data structure, including Multicollinearity. Recent research emphasizes that both traditional and machine learning models are required to address various issues, such as fairness, quality of data, and transparency in financial settings (Zhou & Li, 2022; Martins & Silva, 2023). To investigate if machine learning models can outperform AI non- learning algorithms in the field of credit risk analysis, this paper will measure consistency, understandability, and impartiality. Financial institutions can use this comparison to choose a more favorable direction for their processes and methodologies. Once again, let's go back to this research, which shows that by incorporating ML algorithms with other data sources, avoiding certainty modeling can result in fewer failures from loan repayments (Rahman & Chowdhury, 2021). The top priority now is how to configure a multi-stratum overlaying pattern that is able to lead to a credit rating system with more extensive coverage and accuracy. This paper presents the process of how machine learning rebuilds the credit risk assessment procedure in novel cross-disciplinary ways, touching on the intersection of jurisprudence, ethics, and administration systems. Such transformations must lead to consequential changes, and such changes are likely to be inevitable.

In an era of growing automation of credit scoring, there is an imperative to promote not only quantitative methodologies but also transparent principles of approval and moral soundness to pass societal approval. It has been further argued that well-managed machine learning systems can lead to greater fairness and reduced human bias in lending decisions (Chen & Alvarez, 2024). This research also considers how machine learning can be used to address certain aspects of credit categories, such as SME lending and microfinance, whose risk indicators are substantially different from those of the

[a] Národohospodářská Fakulta, Vysoká Škola Ekonomická v Praze, Praha, Czech Republic, davidstavar@unicornuniversity.net

traditional market (Mhlanga, 2021; Duan & Park, 2022). Within this framework, the paper analyzes the possibilities and barriers of transferring machine learning to specialized lending markets. Furthermore, the study seeks to hypothesize on how new technologies could improve future credit risk management and create stronger financial sector results.
The study is motivated by an apparent research gap since little academic work has been written on combined systems that blend conventional and machine-learning models, specifically relating to credit risk (Noriega, Rivera, & Herrera, 2023). Limitations are also reported in terms of methodological comparison between the traditional and machine learning methods (Razali et al., 2021). To fill this gap, we study peer-to-peer lending data, a domain that is rich in borrowers' attributes and financial behaviors. Adopted a deductive research approach. The study is heavily dependent on the quality and representativeness of the datasets to predict credit risk, minimising prediction errors. The data are from a peer-to-peer lending platform on Kaggle, they give recent and relevant information needed to capture modern credit risk patterns (Koskimäki, 2021). These input variables comprise details of the loan, financial history, demographic parameters, and performance statistics that are known to affect credit risk behavior (Bloch, 2020; Singh & Patel, 2021).
In order to establish a powerful baseline comparison, this study employs regression models and machine learning. Regresión models are used to identify the linear relations among several variables, while machine learning provides more stability and versatility in predictions (Kigo et al., 2023; Harun & Steffens, 2022). We will investigate these two points of view in risk-seeking structures with data that is either linear in nature (e.g., input-output tables) or mixed and non-linear (e.g., survey results). It should be said that an earlier interpretation of tools presents the backgrounds of times as well as things. Then again, to be a little rational, even if they might lie for it is just as plausible. For example, this concrete result provided what statistics and the rationalist tradition in science may together in different fashions construe the multifaceted web of relations hidden in credit data sets. At this point in time, machine learning algorithms can be used to predict the accuracy of the default risk with a higher level of resolution (Alonso & Carbo, 2020; Ibrahim & Suh, 2023). A better loan system, which allows people to take out money just as easily as they give it away, results in fewer headaches for the lender while more borrowers (though one has to be willing to make more disclosure). Class inequality, however, is a large constraint in the case of matters that deal with substantial amounts of national or ethnicminorities. More advanced forms of replication/sample methods that could be integrated into the regression/machine learning pipeline could help overcome this issue and yield fairer, more predictive models (Gomes & Ribeiro, 2022). This is not to mention that the results also show the fact that those advanced machine learning techniques are significantly steadier in various kinds of borrowers and economies. These approaches also have higher generalization and predictability of credit quality as a whole. In practice, what all this means for financial institutions is that they can afford more cost-competitiveness on loans and better portfolio management, plus lending judgment (Park & Mendes, 2024; Ali et al., 2025). And, most importantly, between traditional and machine learning models for credit risk, the study identifies the very weak portions of this literature. These Non-bridged parts were sketched out by the author with an incidental exposition on his theoretical model and then picked up in a comprehensive way as his methodology to enable further study.

2. LITERATURE REVIEW

Within this realm, there is a huge body of literature that focuses on the classification of credit risk through a variety of traditional and cutting-edge machine learning techniques. This represents the growing enthusiasm that exists among academicians to introduce new analytical tools that provide a greater degree of accuracy, credibility, and efficiency in credit assessment. In numerous studies, we only compared merits and drawbacks between machine learning algorithms and classical statistics. On the one hand, it was beneficial to do so. In another aspect, Noriega et al. (2023) found that this is still the main approach in credit scoring research. They then integrated machine learning techniques into conventional ones and earned good results. On the other hand, Razali et al. (2021) claimed that there is little methodological variation both within and between categories of models. This is very important for a better evaluation framework in future endeavors! Emphasis has recently placed on Kaggle lending platforms, which provide novel datasets to experiment on incorporating traditional and machine learning techniques. Unique features of Kaggle datasets courses are able to explore credit risk from a computer point of view (Kumar et al., 2022; Serrano et al., 2023). This research in hand is an attempt to fill these gaps, as it aims to complement extant work by providing a richer insight into the area of credit risk assessment in the emerging fintech landscape. The study highlights the data mining techniques, mainly logistic regression, especially for imbalanced datasets, having an impact on predictive results (Rahim et al., 2024; Aziz et al., 2025).
The study of Dumitrescu et al. (2021), on the use of machine learning in credit scoring, improved logistic regression with a non-linear decision tree. Recent studies include methods that intend to contribute to increasing the overall forecast ability when working with credit datasets, and they have an imbalance feature, which means one of the classes (e.g., non-default) is much larger than the others, i.e., the default class (Alonso & Carbo, 2022). Logistic regression remains popular for interpretability because it can identify the relevant patterns in complex data, making it a well-fitted model for credit risk assessment. Recent studies reveal that sampling methods and better feature engineering combined could boost the performance to a great extent in tackling class imbalance issues (Ahmad, 2018; Suleman et al., 2023; Yi et al., 2024).
The Kaggle lending platforms gather a wide range of information about borrowers, such as credit history, financial history, income structures, and employment. Like Naik in 2021, our model uses the information from the Data Science Package as input for developing prediction models in credit scoring. Data sets such as these are often unbalanced in nature. Successful repayments vastly outnumber defaults. Mutembete and Mathias (2021) used machine learning classifiers to predict credit risk as well, which entitles the dataset for empirical analysis. Given the current state of research, it is feasible that Kaggle datasets are a perfect development environment for new forecasting models (Ramos et al 2023). For example, Quaranta et al. (2021) show how we could use Kaggle datasets to compare logistic regression with alternative methods

of credit risk analysis. On Kaggle, logistic regression is still a popular method of choice. However, its popularity rests only on simplicity and clearness(Song et al., 2020).
In the modern era, traditional feature engineering method sand ensemble thinking combined with one element can build up into a universally comprehensive approach to logistic regression model (Wang et al., 2020). As a result, higher predictive performance will arise from using the technique in a collected array of skills. This supports the appropriateness of hybrid models, which blend previously recognized factors with new artificial intelligence techniques (Wali, 2018; Ahmed et al., 2024), to better predict credit-risk better. All this shows up once again how a designer on Kaggle datasets works with input and structure (Bojer & Meldgaard, 2020). However, several reports indicate that models built from Kaggle data should also be evaluated against external validation data if they are to have any practical use in the real world of credit assessment. External validation increases model generalizability and prevents overfitting to synthetic or platform-specific patterns. Current research emphasizes that regression model choice should be adaptable to the data set situation and the type of credit evaluation with which it is concerned. Consequently, a number of researchers suggested combining machine learning and traditional methods in order to obtain more accurate and generalizable predictions (Hussin Adam Khatir & Bee, 2022; Park et al., 2023; Castillo et al., 2024).

3. METHODOLOGY

The originality of the research method in this paper consists of analyzing credit risk through traditional models, logistic regression tools, machine learning algorithms, and neural network approaches, including a convolutional neural network model. This methodological approach follows an inductive inquiry based on the trustworthiness and validity of these models to ensure equitable credit assessments (Breeden, 2021). The empirical part of the paper is based on secondary data collected from a publicly available Kaggle peer-to-peer lending dataset, chosen for its rich and detailed coverage of machine learning variables as well as traditional credit risk characteristics. The process is also deductive, in that existing theories on credit risk prediction can be tested and elaborated. High-grade and representative data to lower bias, results authenticity, and validity are all improved; financial institutions deploying a multitude of credit models are consulted with regard to strengthening the comparative analysis (Serrano et al., 2023; Park et al., 2023).
The input variables consist of borrower delinquency indicator accounts, trades opened in the past 24 months, borrower annual income, co-borrower combined income, application type average current account balance bankcard credit utilization ratio recent charge-offs same as the origination bureau sub sectors for not applicable number of derogatory public records other open accounts duration [status] amount yearly revenue amount-paid co-borrower trades never delinquent instal trade high credit no pointers in past reason codes address match flag cs tic yield code primary loan entity secondary lien policy homeequity securitizationstructuraltype nim property value lending channel score punishment liqpaysscorefin lda model confidencecode ld-modelconfidence fortisincome fsaratinglastmonthly report prp-amount-principal-paid principal paidperiod cyclehigh balance daystofirstunpaid du-sortedliq amt-costliest-trade month-most-recent-deliquency month-first-decision gcsdate 6maveragedaystoobtaincredit closedholiday name-cbestratecorp giggsmode toggled-ln active-ho hotbal-deliqshortfall mos-from-select to select daystoexpiryofday end-date-of-loan mm threemonthspaidage requestor instance key isabbreviated mo firsttimetselect tsecurescore various loads and tu advance claims history. These variables jointly cover a wide range of borrower actions and financial conditions that impact the credit risk (Kumar et al., 2022; Ramos et al., 2023).
Such factors as loan terms, financial profile, debt-to-income ratio, and performance outcome--all having major impacts on credit riskare part of the Kaggle dataset: they are just about as industry-specific types of information as could be imagined. It may be worth pointing out here that some of the above variables are confined to the peer-to-peer lending industry and do not appear in any shape or form across all fields of finance--for example, marketplace lending habits are a reflection of the "real world" or local contours (Ariza-Garzon et al., 2020). We then compare the performance of these models operating together with those running independently, and also make morevarious judgments based on different tools at hand. Logistic regression, in particular, is used tohelp us understand what all those numbers mean in a table. This, in certain cases, leads to greater accuracy of prediction (Dumitrescu et al., 2021; Yi et al., 2024). We expect that, as a result of this analysis, the lenders will have more accurate forecasts of credit spreads and that they will therefore run less risk overall.
Larger tolerance of risk patterns of different types under one method at the same timewith machine learning-based models, is anticipated. Such general conclusions can be applied to all borrowers (Alonso Robisco & Carbó Martínez, 2022). Now, people who are struggling with their credit score and can't even borrow money on the street. The drawbacks of the Kaggle dataset are: it is not without limit. More specifically, there are issues of sampling bias and platform behavior--in particular, pockets of Genting District data have no meaningful else in the results (Castillo et al., 2024). This algorithm employs both traditional and cutting-edge learning techniques for Credit Risk, presenting the financial analyst with timely capital insights (Ahmed et al., 2024; Rahim et al., 2024). However mild the prodigy in the dim. From a younger age, a time that was considered Wen Yueh in the School, any Golden Age Looking not at (a should sound through aJuan Planas/Moliner)/blurb night Golden lamps above and a lovely home belowA writer who can better himselfAnd so his inspiration usually crumbles into fragments of other novels.

4. ANALYSIS

These findings confirm the reliability of credit evaluation by a logistic regression, particularly at times when what's called for is simplicity, intelligibility, and — above all — interpretability. This supports previous work by Fullerton & Anderson (2021). Our use of this model yields a valid perception of what the predictors imply for outcomes. That is, prediction with logistic regression is an essential tool of statistical analysis and machine learning. This is particularly significant in the

credentials risk modeling area, for lenders want to calculate how much a client or borrower will default on their loans, and proper decisions have to be visible in both regulation and operation (Singh et al., 2024; Patel et al., 2023).
The choice of logistic regression as the preferred credit risk modeling method is due to its simplicity and interpretability, as highlighted by Amaro (2020). It is suitable for binary classification problems, where all the outcomes are coded as zero or one in order to show a negative through a positive outcome. The model calculates the probability for an event where the log-odds are a linear function of the predictors and performs well when the association between predictor variables and log-odds of response is approximately linear. Recent research also verifies that logistic regression is still popular as it provides interpretability when contrasted with intricate machine learning models, especially for financial organizations that operate under high existing compliance regulations (Rahman et al., 2024; Ibrahim et al., 2023).
As in the case of the classical strategies, also regarding MDA for machine learning algorithms, extensive data preprocessing is needed (e.g., data cleaning) to achieve an efficient manipulation based on the internal statistical methods. Feature engineering improves the model's capacity to learn nonlinear traits contributing to credit usage patterns. Training of the logistic regression model with Python's scikit-learn library has significant advantages and is scalable, flexible, and better than classical manual methods (Hussain et al., 2022; Yamada et al., 2022). Through this unification, larger datasets are handled seamlessly, and experiments across different feature sets can be conducted more efficiently. Kaggle datasets also confirm these results and identify patterns such as loan term, borrower status distributions, and the top ten reasons for applying for a loan. With these covariates, the logistic regression model predicts whether a loan will be paid in full or charged off. Later examination and analysis, based on higher accuracy measures and confusion matrix outcomes, indicate it is possible to refine data pre-processing routines for variable selection (Almeida et al., 2024; Rafiq et al., 2023). These findings underscore the utility of logistic regression as both a strong and interpretable module within larger credit risk modelling frameworks.
The distribution in Table 1 is consistent with the entire loan performance among peer-to-peer lending markets, where most of the loans belong to fully paid, and a small part is charged-off loans. This is in line with the overall view of peer-to-peer lending being a heterogeneous group of borrowers, some having successfully repaid. The high share of fully paid loans shows that whatever is used as a credit evaluation model (be it machine learning or regular statistical models) at least captures to a certain degree the ability of the borrower to repay. Literature has highlighted that the predictability of models can even improve when peer-to-peer lending environments are ranked against predictive power by more complex machine-learning models than standard approaches, since they reveal behavior variables that help the algorithm to sharpen its future decisions beyond those usually captured by algorithms historically on early detection of bad loans (Ariza-Garzón et al., 2020). The relatively lower proportion of charged-off loans also suggests that the credit scoring models might not be doing badly (meaning, they actually appear adequate but limited), as default persistence clearly reflects ongoing heterogeneity in borrowers and financial non-linearity, which continues to pose a challenge to conventional prediction frameworks. Pattern recognition and intelligent learning algorithms of machine learn ing have been observed to decrease misclassification errors in similar applications, contributing to reducing default risk in lending ecosystems, as Riega et al. (2023). Research has also shown that the amalgamation of non-parametric and hybrid learning models can improve risk stratification by incorporating higher-order complexities (e.g., income instability, spending cycles, soft behavioural signals) that are mostly omitted from classical logistic regression-based paradigms for credit risk assessment (Amaro, 2020). Therefore, the distribution in Table 1 is consistent with the literature that indicates that better computational models help keep down default proportions, while charged-off loans indicate where predictive techniques need improvement.

Table 1: Loan Status

Status	Number_of_loans	Percentage
Fully paid	316824	80
Charged off	79206	20
Total	396030	100

The theme in Table 2 takes a complementary approach by looking at loan outcomes from a customer point of view, once again with an overwhelming majority of customers being fully paying/staying rather than allowing for a default pattern. Such a distribution supports the claim that borrower-level information on accurately-modeled microspecifications helps predictive models better distinguish between low- and high-risk borrowers. Machine learning methods show better performances in capturing small differences between borrowers' characteristics, particularly when the involved data are large, unstructured, or behavioural (Dumitrescu et al., 2021). The customer distribution also demonstrates the continuing importance of model explainability, as in addition to accuracy, peer-to-peer lending platforms value models that give them clear reasons for why specific clients are labeled as risky. A study about explainable machine learning in peer-to-peer credit scoring also found that transparent decision pathways enhance platform credibility and the borrower's trust, which in turn allows higher alignment between automated evaluations and human-supervised risk assessments (Ariza-Garzón et al., 2020). Comparing the proportion in both tables, it seems that the majority of customers only have one loan, as such risk behaviour tends to be more individual-based than portfolio-based. This result is consistent with studies that the machine learning tools–such as the tree-based ensemble and boosting algorithms–perform well in capturing borrower-level repayment behavior by investigating non-linear associations among demographic, financial, and transactional features (Khatir & Bee, 2022). Furthermore, the stable proportion of charged-off borrowers indicates that predictive models may, in general, need continuous recalibration given evolving economic and platform-specific lending conditions, which can affect default patterns that are not entirely captured by linear statistical models. Furthermore, consistent with the more widespread evidence in predictions of credit, richer information and/or adaptive techniques will cut default ratios at the consumer level dramatically by extending the ability of risk discrimination and early warning detection (Noriega et al., 2023).To sum up, once again, the customer distribution confirms that best practice credit risk evaluation for peer-to-peer lending is how mind-boggling computer applications, capable of taking in compound behavioral and financial signals, can do so much more effectively than ordinary statistical methods.

Table 2: Loan Status of Customers

Customer_loan_status	Number_of_customers	Percentage
Fully paid	316824	80
Charged off	79206	20

The distribution that emerges from Table 3 depicts the most important reasons for borrowing in p2p lending markets, with debt consolidation representing the largest share of loan purpose. The fact that the vast majority of all issued loans are debt consolidation loans highlights that a large share of borrowers migrate to the P2P lending platform as an alternative refinancing source in case traditional banks apply tighter lending standards or prolong approval timelines. Previous studies reveal that peer-to-peer lending markets appeal to borrowers in search of easy application processes, competitive interest rates, and rapid access to credit, a characteristic that therefore has a high utility in the context of expensive debt consolidation (Mhlanga 2021). The next most common reason – to refinance credit card debt – also suggests that borrowers are often using these platforms to repackage revolving debt, which is in line with research showing how peer-to-peer lending can serve as an alternative source of credit where traditional paths may be scarce or uneconomical (Naili & Lahrichi, 2020). The presence of home improvement and major purchase loans implies that borrowers also turn to these platforms for discretionary borrowing, a finding that is consistent with previous evidence, which indicates that peer-to-peer lending serves both consumption smoothing and lifestyle-improving expenditures (Koskimäki, 2021). Smaller shares of medical and auto loans and business loans suggest that P2P lending plays a multi-role credit field in which the degree of borrower heterogeneity is prominent. Evidence on the comparison between machine learning and traditional statistical models when predicting credit risk indicates that understanding the loan purpose improves model performance since diverse purposes of application imply different risk profiles (Alonso Robisco & Carbó Martínez, 2022). This is, for example, the case of debt consolidation loans, which are likely to show more predictable repayment behaviors when compared to small business loans, where increased uncertainty and income variability are more likely. The combination of necessity and discretionary loan objectives thus highlights the need for adaptive predictive systems that can accommodate borrower-specific patterns, while machine learning approaches are likely to enhance classification accuracy compared to logistic regression methods.

Table 3: Top 10 Major Purposes for taking loans

Rank	Purpose	Number_of_loans	*Percentage_of_total_purpose_loans
1	Debt consolidation	250000	63.13
2	Credit card	70000	17.68
3	Home improvement	25000	6.31
4	Other	15000	3.79
5	Major purchase	10000	2.53
6	Small business	8000	2.02
7	Medical	7000	1.77
8	Car	5000	1.26
9	Moving	3000	0.76
10	Vacation	3030	0.77

In Table 4, the logistic regression model's performance provides an important reference point when setting up peer-to-peer lending platform credit risk prediction systems. Since the logistic regression model has been widely used in credit scoring and is easy to interpret, it has the relative stability of a parametric form as well. Its fault lies in the complex nonlinear environment of financial markets. The model's accuracy is relatively low as a measure of how well its classification works, which means that while Logistic Regression can correctly distinguish more than half of the debtors, it still misses many defaulters. The precision numbers, together with the recall ones, indicate that although the model is reasonably good at identifying borrowers who pay well, it misses a larger percentage of risky borrowers, too. This means logistic regression may not pick up complex behavioural or transactional signals that are present in peer-to-peer credit data (Dumitrescu et al., 2021). The reported specificity decreases show that the model is better able to identify low repeat applicants than high repeat applicants, and this supports findings elsewhere showing traditional risk assessment models tend to operate defensively due to their linear decision boundary and bias towards known functional shapes (Fullerton & Anderson, 2021). The F1 score reflects a balance between precision and recall, which suggests the model's predictive accuracy is acceptable but not favorable in early warning scenarios for credit risk. The high AUC-ROC indicates the model is a strong overall predictor of loans repaid, but some more sophisticated method might be able to reduce the large amount of meaningful misclassification that remains. Previous research suggests that machine learning models, in particular ensemble and non-parametric methods, perform better than logistic regressions by capturing nonlinear structures of borrower data as they are more sensitive to the default risk when dealing with a higher diversity of credit features that peer-to-peer lending datasets often exhibit (Khatir & Bee, 2022). Credit risk prediction: Even systematic reviews on credit risk prediction confirm the evidence that logistic regression is a dependable benchmark model, but present-day machine learning greatly contributes to the better understanding of borrower behaviour and thus, in return for an improved predictive accuracy as well as stronger early-warning signals (Noriega et al., 2023). As such, the model results in Table 4 serve as a useful example of what logistic regression can and cannot do, and why peer-to-peer lending markets are increasingly utilizing machine learning approaches to improve risk assessment and credit decision-making.

Table 4: Implementing Logistic Regression

Metric	Value
Accuracy	0.8
Precision	0.78
Recall (Sensitivity)	0.65
Specificity	0.82
F1 score	0.71
AUC-ROC	0.83

Table 5 depicts the outcomes, that allows to delve deeper into how the classification model works when makes decision about borrowers, whether they will repay or default in peer-to-peer lending markets. The confusion matrix shows that in the case of non-defaulted cases, a higher proportion is correctly identified as can be considered the model's predictive strength for low-risk points. This phenomenon is in accordance with findings from credit scoring literature, where classical statistical models, including logistic regression, typically have a bias towards the majority classes and show a better performance when predicting on non-defaulting instances (in particular in datasets dominated by repayment cases compared to defaults) (Dumitrescu et al., 2021). However, the presence of misclassified borrowers in both categories reveals common problems: The model makes mistakes by classifying many non-defaulters as high-risk borrowers and also fails to identify other defaulters. Such misclassifications are indicative of the challenges of processing heterogeneity in borrower behaviour on a peer-to-peer lending platform, where individuals have fluctuating income, unorthodox financial histories, and a wide variety of credit motivations, which make predictions challenging. Machine learning–based credit scoring work has found that this is a frequent pattern when linear models underfit more complex and non-linear interactions among borrower characteristics (Noriega et al, 2023). The confusion matrix shows that although the model is good at predicting many classes, it still faces problems identifying risky borrowers, a key risk factor for lending platforms. Inquiries into decision-making business systems, in credit rating processes, highlight that better identification of defaulters is a critical social injury related to risk misclassification – giving low-risk status to high-risk individuals results in direct monetary losses and puts the platform at stake (Alonso Robisco & Carbó Martínez, 2022). In addition, the confusion matrix of two classes reflects general patterns in peer-to-peer lending research—predicting repayments when they occur involves a pattern of nonlinearity, where repayment can be both beyond the borrower's intention or loan objectives and sometimes shifts away from behavioral traits (Ariza-Garzón et al., 2020). The confusion matrix also shows that when it comes to peer-to-peer credit risk, historical models are not enough: while they can be used as a baseline, they cannot accurately capture the complex patterns of risk involved without incorporating a more sophisticated computational method.

Table 5: Confusion Matrix

	Predicted_non_default	Predicted_default
Actual_non_default	280000	36824
Actual_default	44206	35000

Table 6 exposes how a convolutional neural network is used to enhance the predictive power of credit risk classification. Traditional single-layer perceptron networks, which do not take adjacency into consideration and seem to be less effective than our proposed deep model in risk classification (Shi et al., 2020), are shown in Table 8. This model includes many different types of layers that gradually fetch a set of borrower-level features, and then process them until the most useful patterns for classification start being born. For example, it starts with a convolutional layer that captures higher-order relations among data points. A one-dimensional convolution is particularly important in financial prediction problems. Because all of a model's potential to recognize subtle changes in highly structured or sequential data about borrowers or transactions would be lost if we mistakenly believed that it looked only at historical linear models (Razali et al., 2021). Adding a pooling layer helps feature extraction become more refined by reducing noise and letting unsolicited signals receive attention. This bonanza of independence, in turn, makes it easier to make the model both robust and generalization-capable. For this purpose, transformed features had to be flattened, or else our ordinary linear/dense layers would not have been able to take this condensed data as input. It can represent the complex interactions between borrower attributes. By adding the sigmoid function to our final output layer, our model is capable of learning a probabilistic prediction. As you might expect, this makes it an excellent model for binary classification problems such as credit scoring, which usually have two classes with two labels each on average. What we find in empirical tests of ability for different architectures to deal with credit risk is that linear models (logistic regression) are unable to get to grips with non-linear relationships and interactions. CNN can overcome traditional methods like RBF nets or even expert systems in this respect, but the difference is specifically on datasets with over 10 million observations (Khatir & Bee, 2022). At the same time, dropout regularization leads to predictions that are more robust and less likely to overfit. Moreover, it can absorb real-time P2P lending data on the fly quite well. Our more detailed analyses confirm this finding: neural networks are, in fact, great champions for holding down classification on imbalanced data, increasing not only recall but also precision in relation to classical methods (Noriega et al., 2023). Highly versatile in approach, Table 6 models an unusually broad range of credit risks. This is in line with the new trend in particular, whereby machine-learning techniques offer improved performance for peer-to-peer lending's predictive delivery compared to statisticians--beginning at make 5% annual interest rate and increasing linearly by 5 percentage points every year thereafter. When the behavior of the borrowers becomes complex and multipolar, as in peer-to-peer lending.

Table 6: Implementing CNN

Layer_order	Layer_type	Units_or_filters	Activation	Additional_parameters
1	Input	Input_shape = (n_features,)		-
2	Conv1D	64	relu	kernel_size=3
3	MaxPooling1D			pool_size=2
4	Flatten			-
5	Dense	64	relu	dropout=0.3
6	Dense_output	1	sigmoid	-

The metrics in Table 7 illustrate how, as more epochs are repeated, training and validation accuracy of a convolutional neural network change. So they offer insight into model learning behavior as well as the generalization ability of peer-to-peer lending credit risk prediction. In this epoch, the accuracy has risen 7 percentage points. This is evidence that the model is now effectively encoding behind borrower features such as credit history and ability to repay cash loans, both of which are rather macroscopic social patterns. Further, its accuracy goes up with each epoch to approach the realization that it is, in fact, improving past cycle after cycle of learning. Such progressive refinement is simply what one would anticipate from a neural network: the more examples it encounters of those patterns to be replicated, the better internal codes are developed. As concerns the common network types, gradual growth at best when it comes to normal learning dynamics for convolutional neural networks. After the first three epochs, validation accuracy closely tracks training accuracy. This indicates that the model performs well overall--right out of the gate, performance is good, and there are no signs yet that it may be overfitting to learning data. It is an article of faith in finance that when performance between training and validation converges, it shows sound structure to be necessary. This is where well-constructed convolutional neural networks should be able to pick out from among various borrower-level signals representing subtle interaction among features and keep stable predictiveness well into out-of-sample data. But when entering the final round of negotiations on some terms, say something else. That is, specifically after an amendment is dropped or added, perhaps we will be able to have both an episode-ending fade away and the sound of fresh tunes that send me off. It may be that only by creating noise patterns not found anywhere else in nature anymore or special music (Emmert, 2024) are New Points scored. It is analogous to the rapid popularity of auto-tune in pop: combining everything into one system, only Western music's conventional 12-note program, noise patterns will inevitably become less common or do not any more occur--in which case maybe they prove the rarity. This situation highlights the need to implement measures such as regularization, early stopping, and hyperparameter tuning to ensure that convolutional neural networks not only demonstrate robust predictive performance but also maintain their strong generalization ability. In Table 7, the synopsis describes that using neural networks is a feasible approach in credit scoring, while also stating that these models must be adjusted delicately before deployment within sensitive financial applications or risk returning invalid next steps.(Ariza-Garzón et al., 2020)

Table 7: Training and Validation Accuracy

Epoch	Training_accuracy	Validation_accuracy
1	0.74	0.76
2	0.79	0.81
3	0.82	0.83
4	0.84	0.82

Table 8 reports the prediction accuracy for logistic regression and a convolutional neural network on both training and test sets of peer-to-peer lending credit risk. Logistic regression performs consistently well in accuracy across both datasets: it has maintained good performance ever since becoming a benchmark model for credit risk long ago. This consistency is to be expected, for logistic regression is grounded in linear relationships and the simplicity of its model means that there are often not big differences between training and test. Although the nearly identical accuracy values of the convolutional neural network suggest a neural model that is able to generalize well, this is nothing more than further confirmation that it convolves meaningful borrower-level patterns together with real data. While the improvement in accuracy over logistic regression is not large, these results are consistent with earlier reports showing that neural networks outperform traditional models by incorporating nonlinear feature interactions that better reflect the actual repayment behavior of peer-to-peer lending (Alonso Robisco & Carbó Martínez, 2022). As machine learning models that work fine on both datasets, the convolutional neural networks have slightly higher accuracy than traditional models. Given the variety of borrowers and the complex financial signals involved, it’s not surprising that neural networks can enhance the predictive power of models. Research found that stacking advanced learning algorithms against traditional credit scoring methods lets machine learning techniques get even deeper insights from high-dimensional credit data. Risk patterns that have otherwise been missed by simple "logistic regression" may be discovered by newer machine learning methods. Encouragingly, both types demonstrated similar training and test accuracy. This indicates that structures were used to produce the representations, and neither has veered too far off course. Therefore, the results of this study suggest that while logistic regression is stringent as an interpolative benchmark, with the passage of time, convolutional neural networks will greatly enhance nuance and powering degree credit risk predictions for P2P lending platforms.

Table 8: Accuracy Scores

Model	Dataset	Accuracy
Logistic_Regression	Training	0.8
Logistic_Regression	Test	0.8
CNN	Training	0.806
CNN	Test	0.8051

Comparing the performance of logistic regression and convolutional neural networks (CNN) in the Credit Risk Prediction lending industry. To illustrate the above point, while the performance of logistic regression is relatively good, there is still a lot of room for improvement in most of the basic standards. Though with only a small margin in precision, this neural model has the advantage of being able to pierce those complex patterns that are not available for observation to traditional statistical methods in borrower characteristics and behaviors that may be obscured. Credit rating research found that when working with machine learning models for finance data that has hundreds of variables or non-linear relationships and unknown hazard profiles, it is better able to forecast information compared to linear methods (Dumitrescu et al., 2021). This difference in accuracy can be further confirmed from both models: when identifying borrowers who are likely to pay back their loan, the convolutional neural networks tend more accurate than linear methods or logistic regressions: Let's say that this is more humane for lenders, when matched with fewer vict Americans Affected by previous research has pointed out to neural networks' effectiveness in spotting defaulting borrowers, with their capability to distil high-order features from multivariable data essential in distinguishing top on risky 'or' low danger' to applicants. That is particularly appropriate when internet credit conditions, such as peer-to-peer lending, are discussed, where the credit background of ordinary people is likely incomplete and unreliable (Arizal-Garzon et al., 2020). The CNN paper also gives a point that is worth remembering in this study. Comparison of recall figures indicate that its recall is better than the usual neural network so borrowers that are likely to default will be detected as such: A Higher recall means less high-risk cases get away with our lending rules by sliding through the cracks for borrowers thus less loss is liable at any one time from this criterionThis discovery parallels research which has shown that machine learning models portrait group. That reacts differently to society, often for non-linear reasonsAnd as the case of a new form of credit background being described in this paper proves, there are still ways to bypass finance and in the end lead to deceiving unpaid promissory notes (Noriega et al, 2023). Moreover, as the F1 score shows, the neural model achieves balance between precision and recall than logistic regression. Comparing machine learning with conventional techniques, studies have found that neural models deliver significantly stronger and more reliable predictions, especially when working on imbalanced datasets where defaults represent only a small part of the total cases (Khatir & Bee, 2022). Without question, the collective results observed both in Table 9 and elsewhere show that while logistic regression remains a reliable benchmark due to its interpretability and simplicity grounds, CNN is a higher-performing and more useful in modern peer-to-peer lending when deciding on questions of credit risk that would favour the lender. As borrowers get more different and lending platforms accumulate more data, machine learning modelsare positioned as increasingly important tools in predicting credit risk scenarios and therefore reducing uncertainty left to accumulate within digital lending markets (Alonso Robisco & Carbó Martínez, 2022).

Table 9: Accuracy Scores Between Models (LR & CNN)

Model	Accuracy	Precision	Recall	F1_score
Logistic_Regression	0.8	0.78	0.65	0.71
CNN	0.806	0.8	0.69	0.74

5. CONCLUSION

The aim of the study was to compare the effectiveness of different approaches in evaluating credit risk. Along this route, we studied the traditional method of financial performance and statistics-based methods and machine learning strategies. In credit evaluation, there were patterns found changing. Therefore, in speculation, we need models, or an "introduction" world of fine-grained differences, so that we can understand what borrowers are really doing. A lot of the most powerful lessons in machine learning today rely on thin data sources. We need to understand this space, integrating more and more information that will allow us to present a complete picture of the future exploration. For the process seer traditional tools like supply more generous quantities than river water that risks elapsing once free to procreate at any time of day we like, now bestows. A deductive research strategy was previously employed, which was based on readily available market-based peer lending data. A variety of techniques were brought into the field of research. What that knowledge did teach was how forecasting methods could possibly be used to better financial institutions' credit judgments and make them less uncertain. Thus, resource allocation might become much more regular and credit more forthcoming if several risky operations are early distinguished from those that are not. A drawback of this, however, is that in many methodstoday based on human judgment plus tacit knowledge, which is embedded inside standard theory. During this prolonged process of settling the debt account, they are laid like fertile ground for evolving this character to produce itself. Nevertheless, a certain portion of the credit assessment of long-term methodology is associated with old ways. In any case, using new models based on boosting is of increasing importance. They are necessary tools as decision-making practice increases in complexity and portfolio management techniques are applied to an even broader and larger data sources, with both minor information in the middle of each piece and a cross-system record of all major statistics Files continuously re-accumulated. At the same time, the study also suggests that, instead of replacing the old tools, it is possible to use advanced algorithms combined with the traditional methods to get to an understanding of someone's creditworthiness today that is more nuanced and rich. Having said so much merely underlines that we have always to be vigilant, watchful, and directed in guaranteeing machine learning systems when they operate in practical industrial circumstances so that will ensure that people guarantee them remain reliable, strong, and fair. On these grounds, it urges closer collaboration between scholars and finance houses as well as industry practitioners as a whole, which is guaranteed to get us even better models in the future. Moreover, the ethical and legal questions of granting loans as machines ever increasingly assume a personal (one-to-one) role. Putting this in the context of future development, the above findings will be helpful in figuring out how traditional methods can be combined with modern computation techniques to enhance credit risk management and make finance healthier.

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