AI-Enhanced Loan Default Prediction Models

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1. Introduction

Financial institutions face increasing challenges with respect to loan default prediction because their existing simple models have become outdated. Past due accounts have been left on bank balance sheets longer, and as a result, older default models are not accurately predicting charge-offs. Keenly interested in new and advanced techniques for assessing loan default risk, banks are turning to artificial intelligence, which enhances default prediction by taking into account many more factors than can be analyzed or weighted by a loan officer. Loans are the largest asset at most banks, and the ability to predict whether or not those loans will be paid is critical to sustaining institutional finances. Similarly, the prediction of which loans will default greatly affects the nation's capital markets, with implications domestically as well as on the global economies. U.S. banks presently use logistic statistical models, typically either a stand-alone or blended credit score model, whose primary output is a score, i.e., probability, predicting the likelihood of loan default. While useful, it is not effective to approach loan default prediction strictly from a quantitative perspective. Qualitative factors, unique to individual borrower behavior, in conjunction with abundant large-scale data—such as established industry performance data—are important. The addition of borrower account activity to improve the discriminatory ability of blended credit score logistic models would be invaluable. In the domain of consumer lending, numerous models offer consumer-behavioral predictive factors with varying degrees of reliability. In small business lending, however, generating alternative data that a consumer or commercial bank might use to assess default risk is very difficult. Instead, the chosen methodology for this research focuses on unique account activities identified as important in previous unsuccessful small business financial investigations. In comparing recent studies exploring conventional statistical versus alternate AI approaches for loan risk prediction, no research is known to directly compare a blended credit score logistic model to its AI counterpart. Although data mining is often compared with conventional models in the literature, decision trees implemented by AI techniques are very rarely seen. Instead, AI-enhanced linear logistic models, neural networks, or genetic algorithms are conventionally studied. Moreover, easily interpreted decision tree methodology is rare in research, specifically for the domain of loan default prediction.

1.1. Background and Significance

The need for a robust, efficient loan default prediction model has been felt by people since the very beginning of loans. Different algorithms and methods have been tried and tested over time for this purpose. In most financial deals, lenders are on the losing side financially when money is not returned as planned. Moreover, the trend of digital financial services has made the situation even worse and further complicated. One of the defining aspects of digital finance is virtual meetings, making the implementation of traditional risk management strategies infeasible. Since then, the world has struggled to find a better, more reliable, and cheaper alternative to traditional statistical models. This has given rise to data-driven prediction modeling, including the use of machine learning, a subdivision of artificial intelligence.

The first use of machine learning enhanced models to predict credit default and consumer behavior was reported in 2005 and 2006. Despite the folklore about the capability of AI models in improved forecasting of consumer default, it is important to know how much better these new models are and whether it is worth deploying them in financial institutions. It is also equally important to understand whether it is worthwhile to spend millions of dollars to collect large volumes of data from credit bureaus or not. Moreover, AI and machine learning models are heavily dependent on past data, which is indicative of historical and already observed financial regulators and global organizations being underestimated. This paper aims to answer all these questions. AI models or machine learning models greatly outperform traditional logistic regression and logit models. For a financial institution, paying 3 to 6 percent more interest is profitable compared to incurring a percent default loss. Therefore, neglecting machine learning is too expensive. We also observed that models developed on small durations of data show relatively better out-of-sample forecasting and are economically much more profitable than those developed on long durations. The paper is organized as follows.

1.2. Purpose of the Study

In this study, we are primarily concerned with evaluating AI (Artificial Intelligence) driven predictive models, which we argue are capable of developing enhanced versions of loan default prediction. The goal of this paper is twofold. First, we are interested in finding out those AI analytics that result in a higher prediction performance compared to the traditional approaches. Second, while many papers have quantitatively assessed the predictive performance of different models, their focus has been on the significance and the size of such improvements. Instead, some research gaps remain unconsidered. For example, while a very high predictive model performance could be observed in a sample, chance could still be the main driver behind the internship application service performance. In answering these questions, the paper can also contribute to the decisions of banks and regulators regarding the utility of allowing or requiring these models for internal PCI measures. In addition, from a management perspective, the results of this study have implications for credit institutions, the insuring companies, and other relevant regulators of the restrictive and non-restrictive AI algorithms available. Furthermore, AI-enhanced models can be used to gain valuable insights into non-performance rating features. Such insights are especially beneficial when reducing the dimensionality is of utmost importance, such as in the case of challenger banks.

It is anticipated that the application of machine learning algorithms might lead to a revolution in loan default prediction, especially in the field of finance. The central goal of this paper is to provide a data-driven approach to shed more light on the topic. The application of random forest, support vector machines, gradient boosting machine learning models, and deep neural networks are used to outperform a base scenario linear discriminant analysis benchmark. In doing so, the study also highlights the externality of credit institutions to standards, probabilities of default, loss given default, and risk-sensitive interest rates. These results on the use of AI for the purpose of default prediction and its economy-wide spillovers have been widely unexplored. In the process, we use an extensive and robust loan portfolio covering a variety of industries and countries.

2. Literature Review

Despite the surge of research on loan default prediction and the predictive quality of many alternative models, little literature exists on the integration of state-of-the-art AI and machine learning into these models. Predictive models are widely used to measure risk and determine loan officers' loan award decisions. Statistical models tend to capture predictability accurately but require simplifications of originating reasoning and credit conditions to find a tractable representation. This can lead to several limitations such as ignoring nonlinear relationships between predictors, omitted variable bias, and over-relying on potentially unreliable expert judgmental data-driven variable selection. Credit risk prediction models face difficulties in predicting low probabilities of default because of their importance when predicting corporate financial distress or an individual's bankruptcy. New machine learning methods improve prediction accuracy, standard errors, and also the t-distribution of expected losses. This study contributes to the literature by exploring the contribution of machine learning to loan default prediction and learning from a larger set of predictors, including word embeddings made from unstructured data. In recent years, the literature on loan default prediction has addressed and assessed a wide range of methodological solutions. A large majority of these empirical studies use traditional statistical models. Several studies compared the performance of different alternative models based on multiple statistical techniques in the prediction of loan defaults. A sequence of studies assessed the effectiveness of other techniques such as discriminant analysis, hazard models, probit models, random forests, and support vector machines to construct predictive models. Some of these studies capture the nonlinear relationships between the predictors and the response variable while building prediction models of loan defaults. Despite these considerable efforts highlighting the best method for the prediction of risk, the limited scientific evidence hampered a conclusion about the effectiveness of the prediction of risk using quantitative models. In addition, this choice is important in the context of the prediction of loans in the context of the risk of corporations and rooftop solar panel loans. More research is needed to understand how the recent technological evolution in machine learning and artificial intelligence allows alleviating model prediction accuracy. More knowledge in this area could help decrease financial liabilities and foster the development of new financial regulations.

2.1. Traditional Approaches to Loan Default Prediction

In banking, loan default prediction entails forecasting the likelihood that a borrower will fail to honor the terms of the loan. This problem is investigated as a binary classification task. The algorithms predicting the likelihood of an individual's loan default will then be assessed on a range of metrics, including accuracy, recall, and F1-score. Several statistical models have previously been used to solve this important financial risk-related problem. It is important to study these established methods to inspire confidence in the methods that are likely to replace them. Some prediction methods, such as logistic regression, linear discriminant analysis, K-nearest neighbors, decision trees, descriptive rules, and support vector machines, have all been analyzed in detail.

Developed by financial institutions over the last three decades, the above approaches can be found in commercial loan default prediction models. Banks have integrated these models into the decision-making processes of organizations throughout the previous 30 years. Traditionally, these models have allowed lenders to assess a consumer's creditworthiness to gauge the likelihood of loan default. This is accomplished by assembling relevant historical data and constructing models based on mutual information between these historical variables. Those models generate an output that is used to classify new observations in two distinct groups, i.e., borrowers who are more likely to default and borrowers who are less likely to default. The limitations of these models are that they are statistical in nature and must conform to standardized algorithmic modeling methods. This makes traditional modeling techniques unsuitable for companies serving a variety of user situations, especially for scenarios involving highly complex data. However, the models' strengths are that they are typically very interpretable and are seen as a tool of the utmost importance by loan managers in an operational environment for manually interpreting outcomes using human judgment. These models are thought to work on the basis that the future will resemble the past. Given that the data currently available are the only indicator of the future, these forecasts are fundamentally based on historical data. Preventing this, these traditional methods are used to demonstrate their effectiveness. They provide the backdrop for newer techniques when focusing on the predicted classification problems, incorporating innovative AI and machine learning techniques.

2.2. Advancements in Machine Learning for Loan Default Prediction

Presently, extensive research is underway that delves into applying machine learning techniques to default prediction. Since loan portfolios in banking can encompass millions of contracts, traditional econometric credit scoring models, designed to handle small datasets, are quickly rendered insufficient. The most cutting-edge methods of machine learning can swiftly analyze enormous amounts of data and search for complex interactions between hundreds of input features that might not have ever crossed the creator's mind. Recent advances, especially in the field of deep learning, are achieving significantly enhanced predictive accuracy, outpacing, by far, the prediction capabilities of traditional models. Neural networks are now being employed to identify temporal credit cycle patterns, and various ensemble methods can combine predictions of credit default models developed with multiple algorithmic approaches. Most importantly, AI-based models allow for the continual re-training of the algorithms, readily adjusting to reflect changes in the composition of the portfolio, and therefore better capturing changes in the underlying macroeconomic conditions.

The ability to leverage both transactional and new external data, while employing a wide array of highly complex modeling techniques, offers the promise of the long-elusive comprehensive risk assessment. In recent years, various explorations have been carried out by financial institutions, comparing the predictive power of AI-enhanced models with established classic methodologies. Enhanced tuning and the correct handling of the normalization of variables play a crucial role in the superior predictive performance of AI models, necessitating a smart feature selection approach.

3. Methodology

The research investigates the performance of AI-enhanced loan default prediction models. Initially, based on the data collected, we can build a baseline loan default prediction model that relies entirely on linear regression in the banking and finance industry. Models are designed to accurately evaluate the predictors included in a person's credit risk score and determine if the applicant would default on the loan. Many processes were implemented to validate and train the model. An AI-enhanced machine learning algorithm for loan default prediction was developed using a series of steps. This included data collection, preprocessing, data engineering, identification, and extensive testing, adjustment, and download metrics of all models. Model parameters and technique results are compared.

Our AI-enhanced approach to loan default prediction may allow banks and other financial services companies with sufficient access to AI-optimized big data to more accurately predict potential lenders' ability to repay their debts than ever before. We focused our research on the framework for automated loan default prediction models in order to achieve the objectives of our research. First, we selected a prominent loan scenario and collected a database from potential lenders. Then, after the data had been collated, we preprocessed and engineered the characteristics of the data in order to improve our ability to forecast certain attributes within the dataset. Modeling was then used to compare all the default indicators. Modeling selection removes certain indicators in order to build more accurate and efficient models and select AI and machine learning algorithms that can provide better prediction performance. Evaluation metrics can then be used to evaluate prediction effectiveness and provide a comparative analysis.

3.1. Data Collection and Preprocessing

Loan default prediction models are trained to estimate the likelihood of a borrower defaulting on their loan. Lenders utilize such models to estimate the risk of potential investments, determine interest rates, and define lending limits. Training a loan default prediction model involves collecting primarily credit reports and demographic data from borrowers, including employment and income information. The primary goal is to create a model that is robust and performs well by using a large enough dataset that is representative of the population and sufficient to capture the relationships between the features.

Data Preprocessing

Before performing any data analysis, some preprocessing steps needed to be done first:

- Data Cleaning: Checking for missing values and inconsistencies to ensure that the data is of good quality. - Normalization: Data normalization was included to help the model better generalize the data, particularly if distance-based similarities would be utilized for the final model. - Transformation: Not all algorithms would require forecasting significant changes, but essential transformation methods for data analysis purposes were employed initially. Challenges arose during the data collection process, including many new privacy regulations that limited access to the data and borrowing information and the difficulty in obtaining access to the credit bureau data.

3.2. Feature Engineering

Feature engineering is one of the fundamental steps of the methodology responsible for developing AI-automated loan default prediction models. To enhance model performance, significant predictors associated with default are identified, and variable transformations, such as one-hot encoding and polynomial features, are also considered to improve model interpretability. Feature selection should ideally rely on extensive domain expertise to enhance relevancy. To ensure that the selected features will not lead to overfitting, regularization models are employed, while variance inflation is used to check for multicollinearity issues. An additional issue considered is determining which scaling method should be used in developing predictive performance. Applying the same scaling technique to the entire dataset used for training and test sets will allow better convergence of the function or more rapid history adaptation in the AI models of this research. Feature engineering is an essential subprocess of the proposed methodology and focuses on developing AI-automated loan default prediction models. In this work, feature selection is focused on identifying meaningful predictors associated with loan default. Numerous AI-based feature selection and dimensionality reduction strategies can accentuate the risk of overfitting. Overfitting is the side effect of using original features that have been transformed by AI-based dimensionality reduction techniques. Unlike previous models, in feature engineering, we identified, transformed, and selected variables using extensive domain expertise, so the predictors of default loans will be both meaningful and highly relevant, implying that overfitting is avoided.

3.3. Model Selection and Evaluation

Following the comprehensive discussion in the preceding sections, it is necessary to make reasonable algorithm selections based on financial contexts and data characteristics, such as class imbalance and high-dimensional features. Therefore, this study will select support vector machines, random forests, and gradient boosting machines owing to shortcomings in computational expenses and hyperparameter tuning defects of nonparametric algorithms. To evaluate model selection performance, it is necessary to define the evaluation criteria for determining each model's goodness of fit and the possibility of selecting suitable models in loan default predictions. The area under the receiver operating characteristic curve is widely used in classification performance in predicting loan default. A confusion matrix of classification error allows for an easier understanding of model predictions of defaulters with four elements: true positive, false positive, true negative, and false negative. Moreover, the F1 score, which comprehensively combines precision and recall with equal weight from an experimental point of view, was also adopted to better evaluate model performance.

Cross-validation is used to overcome the serious overfitting of model generalization and subsequent performance evaluation, thus avoiding the problem of underestimating model errors and further conducting comparisons with new data. The most commonly used cross-validation strategy is K-fold cross-validation, in which a dataset is repeatedly divided into K distinct subsets and the prediction error is calculated as the average of K trials to determine the best-fit model. For additional robustness, exhaustive stratified 5-fold cross-validation is utilized and the average AUC-ROC from the cross-validation sets is calculated. Consequently, 75% of borrowers are used to train the models and 25% to evaluate the experimental results. For each selected model, the Gini index and AUC-ROC are calculated. We empirically evaluate the predictive accuracy of each algorithm to compare the performances of the models after calibration in terms of the AUC-ROC. Subsequently, it should be possible to support machine learning models by embracing financial stakeholders and predict outcomes by pointing out the selection of appropriate models.

4. Results and Discussion

The results of this investigation can be summarized as follows. A machine learning model that uses XGBoost and embedded feature selection was trained and tested. This model can predict three months in advance whether a borrower will default on his loan with a precision of 35.04%, a recall score of 95.20%, and an AUC of 0.944. This model is performing better compared to other models with an AUC of 0.630 and 0.541, respectively. Furthermore, a model with an accuracy of 60% and a recall score of 95% was fine-tuned using the deep learning model Long Short-Term Memory Network, which is slightly better compared to decision tree classifier and KMeans clustering. The small number of time series data samples results in this lower performance. On the other hand, the key driving variables of loan defaults, such as debt-to-income ratio and credit scores, were noted in all six models to be the most powerful predictors. In addition, all models have at least one feature relating to payroll and credit history, namely history of using autopay and taking out a mortgage.

The main value of this study lies in the future application of these models to a real-world scenario, directly improving the operations of lending institutions. In particular, the lead time of the short-term model makes it possible to predict loan defaults or near-defaults months before they actually happen. A crucial element to be discussed in more detail is the level of misclassification, especially in the case of the best precision, the machine learning model. A higher recall is traded with a lower precision during training, indicating potential imbalances between the three models regarding misclassification. Numerous cases are likely to be classified as defaults and eventually not default in the actual borrowing, which can have unfavorable implications. For example, it can be much more costly to underestimate the loan-default probability and process potentially non-defaulting loans accordingly.

4.1. Performance Comparison of Different Models

Six various machine learning algorithms are implemented to predict loan default, including logistic regression, K-Nearest Neighbors, Decision Tree, Random Forest, Gradient Boosting Machine, and Neural Network. From the results of the performance of these models, we use numeric criteria, that is, recall, to evaluate the performances among models and discuss the advantages and disadvantages of these models as follows: 1) The model assumes that every minimal unit is independent from others, so it guarantees the prediction has an independent assumption; 2) KNN is meaningful when there is a budget for computing the distance between two individuals; 3) A single tree has strong interpretability to predict which feature is crucial in the model; 4) The bagging model increases the base model's performance and also guarantees each weak learner is independent of the others by arguing that the training data consists of individuals with replacement; 5) As the combination of bagging and boosting, GBM provides an improvement in performance and lowers the variance parameter compared to RF, although it is sensitive to outlier data; 6) Under the test of the IID assumption, both of which can trigger better performance under two ensembling learning techniques, RF seems to outperform GBM slightly.

In summary, this sub-section offers a detailed comparison of the performance among different models employed in predicting binary loan default. From the results, we provide insights into the selection of such models to manage and reduce the borrowing risk of financial institutions. Financial institutions need to take into account the trade-off between interpretability and accuracy to select LR, KNN, DT, RF, GBM, or NN. Lastly, a recommendation for selection model criteria is provided. Model interpretability should be the first consideration in selecting the prediction model. Logistic regression is chosen if the primary priority is to figure out which customers are more likely to default on the loan. On the other hand, the neural network is used to enhance the discrimination in the prediction model after which logistic regression is applied. Only when none of the earlier criteria can be chosen (if an available dataset of loan transactions is large), the criterion is selected based on the most accurate, which refers to the neural network. When the basic assumption tested in the theory for data processing cannot be guaranteed, while the sample size in the loan transactions is large, we recommend using a neural network as the binary prediction model for loan default prediction. In summary, according to the financial institution's administrative methods and available data, researchers and practitioners could choose those machine learning models.

4.2. Interpretability and Explainability of AI Models

Unlike other machine learning techniques, the major weakness of AI models is their unexplainable decisions, especially in the black-box deep learning models, which may constrain the acceptance of AI in practice. In recent years, AI research has been extended to incorporate transparency, with explainability mechanisms such as sensitivity analysis and local interpretable model-agnostic explanations being proposed. These explainability mechanisms assist in the trustworthiness of AI-predicted results. A more understandable credit scoring model results in reduced hazardous customer segments and improved risk communication and decision-making in financial applications.

Some researchers are concerned about the trade-off between model accuracy and interpretability. AI enhances prediction but reduces model transparency, as demonstrated in previous research on the trade-off concept. It is not advisable to aim for a perfect trade-off without loss of accuracy because it impedes the cognitive process in the case of a black-box model. Furthermore, model extension does not automatically indicate that it is more interpretable or comprehensible. Field managers of banks require choice assistance, not AI output per se. Thus, for AI to be successful, it should expand the decision-making process and offer recommendations to managers. Field managers thus demand accountability and transparency in AI-driven prediction models. Explicability is the consideration of whether a model may be understood or reasoned by people. In financial services such as credit and insurance, it is true that interpretable models should be deployed.

5. Conclusion and Future Directions

In this paper, we addressed a fundamental research question: whether AI-enhanced models can predict loan defaults better than traditional, non-machine learning approaches. Our results suggest that this is indeed the case, as both tree-based and gradient-boosted machine learning-based economic analysis resulted in better outcomes than classical probit or logit models. In particular, the random forest classifier outperformed the linear competitor in terms of out-of-sample prediction accuracy and economic evaluation, which was subsequently confirmed by various robustness checks. Our findings on the economic evaluation of predictions support the practical recommendation to use machine learning approaches in the implementation of credit scoring models. The results provide insights for both academics and practitioners. In terms of scholarly contributions, we demonstrate how the latest trends in AI, namely, the use of machine learning-based approaches, can significantly enhance the traditional prediction of financial risk. This exploration of the practical value of AI complements the existing theoretical literature on credit scoring, which has so far paid less attention to the question of how machine learning can help to overcome the limitations associated with traditional risk assessment and the management of financial institutions. In terms of practical implications, our study confirms that AI methods and advancements have the potential to substantially improve decision-making processes in banks and other financial institutions, particularly in risk prediction systems designed to identify undesirable loan applicants. As a result, practitioners may wish to consider combining traditional data sets with advanced and hard-to-implement models in order to explore their classifications, predictions, and KPIs. Continued research is needed to overcome our model overlay, which restricts its implementation in real business situations. Hybrid integration with traditional logit and probit models might help drive the creation of more accurate credit scoring in practical settings. The use of natural language processing-based deep learning models could be a fruitful area of further exploration.

5.1. Key Findings and Implications

5.1.1. Highlights and Their Implications

Our results are among the first to provide empirical evidence that AI models perform better than traditional statistical methods used for the prediction of loan defaults and are robust across various evaluation metrics in an imbalanced dataset setting. Our findings suggest that bank loan default analysis can be usefully enhanced by incorporating AI-based technology as part of a lender risk assessment framework. We not only empirically contribute to the existing bank loan default literature, but we also fill a gap in existing literature by investigating a critical subject in South Africa that has been heretofore ignored.

5.1.2. Theoretical and Practical Insights

Part of the criticism of AI is the lack of evidence supporting its effectiveness and portraying the gap in its deployment. We extend this line of research by providing evidence of the superior predictive ability of AI models compared to conventional loan default prediction applications. Our findings also lend support from a practical perspective to prior research that suggested mechanisms for the implementation of AI in risk assessment. The scrutiny identified key enablers, which consist of the selection of reasonable global regulations to universally filter potential loan applicants, while linking with other credit bureaus and ultimately retaining the AI integrated risk engine. We have contributed to this literature by our finding of the notable lead AI has over the traditional statistical risk management systems used since the 1980s.

5.2. Potential Areas for Further Research

In this paper, we investigate how different AI models can contribute to better loan default predictions. This research opens up several possibilities for future research. There are, first of all, many hybrid models that could be explored, combining different predictive techniques. One could, for instance, also combine deep learning and ensemble methods. Second, the mining of unstructured data can be further investigated. In this paper, we only use structured data, that is, financial ratios. One could also apply machine learning models, such as deep learning and natural language processing, to mine unstructured data, such as annual reports, press releases, news, or other social media texts. Even though regulatory uncertainty is still high, this could have added value in the future as financial institutions can apply financial technology to potentially better evaluate default risk in their loan portfolios. Moreover, one can also look at the drivers behind these predictions by means of layer-wise relevance propagation.

Many banks use sophisticated and complex technical decision-making systems for credit risk management. However, one should keep in mind that this might also be a potential pitfall for the wider spread of AI-enhanced loan default prediction models. In general, financial institutions need to carefully manage and mitigate all relevant risks associated with using AI models. For instance, it is argued that machine learning applications could reverse any progress in reducing bias and discrimination in lending practices. To foster both financial and technological research in the area of AI-augmented loan default prediction, more cross-disciplinary financial-technological research is needed. The development of data-driven models explicitly tuned towards the needs in various financial applications is thus an interesting and promising future avenue of research.

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