Default Probability Estimation Under Data Scarcity: Machine Learning Algorithm Development for Robust Credit Risk Modelling

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1. Introduction to Credit Risk Modeling

Credit risk modeling involves using statistical models for evaluating the creditworthiness of individuals and companies, enabling lenders to make informed investing decisions. In the financial sector, assessing the risk of loan defaults is critical for credit approval, loan pricing, and credit limit decisions. Inaccurate credit risk assessments and valuations can result in business losses, and thus lending institutions are at risk. These and other concerns have motivated ongoing advancements in credit risk modeling. As a result, more advanced and powerful analytical techniques are being employed in credit risk models. This has led to a remarkable increase in the need for research and development in credit risk modeling techniques. Therefore, the present research focuses on the role of artificial intelligence in credit risk modeling and is intended to contribute new and different results.

The limitations of traditional credit risk assessment techniques for analyzing extensive amounts of data have fueled the growth of AI-based scoring and financial decision-making techniques. Traditional means of assessing credit risk have been adopted over time. However, despite the substantial technological advancements made in the field of finance, the credit process has stayed largely unchanged. Over time, credit scoring has also developed from a judgmental mode to a complex replica of the judgmental mode. The efficient management of risk has emerged as a critical factor in enhancing financial stability due to the technological advances observable in the electronic transfer of funds and financial liberalization. There is, therefore, a pressing need for lenders to adapt and implement the most recent technology advancements in their appraisals, assessments, and risk management.

1.1. Importance of Credit Risk Assessment in Financial Services

Credit risk is a crucial issue in real life. It is an integral part of financing and investment decisions for profit-maximizing organizations, both large and small. It is especially important if the borrower is a large institution. Thus, all financial organizations have had to develop sensible credit risk measurement criteria and strategies. These estimations help outline the relevant costs and revenues of originating and conducting the business of various loans. They assist in reducing default rates by running a credit profile through the adoption of a focus and associated credit standing cut-off. Additionally, they help to optimally distribute debt and liabilities throughout the loan portfolio. Moreover, in the presence of abrupt redundancy, a large institution can identify the compromised sector at random. It can ascertain the high-risk sector and significantly decrease its overall losses.

The rationale propels substantial interest in credit risk modeling algorithms. From the institutional view, loan output is directly related to its risk rating. The correlation between the borrower's default rating and the likelihood of loan loss is negative. Thus, there is considerable interest in the chance that a borrower will default on a single credit contract or on a portfolio of credit contracts. Furthermore, business success is highly correlated with how effectively they govern credit risk. In the recent financial collapse, mismanagement of credit liabilities was identified as the determining variable. Regulatory bodies have placed significant emphasis on managing credit risk by banks and thrift institutions in their risk-based capital over the past decade. In the presence of risk management platforms, a bank may lose trust in market financing without platform-to-lender transparency. The importance of having the appropriate loan default estimator for the marketing strategy of a lending institution is notable. There is a connection between the acceptance criterion used in the offline decision-making method and the prediction performance of final component borrowers that are almost exclusively critical.

1.2. Traditional Approaches vs. AI-Based Approaches

Data analysis on credit risk can be mainly divided into the following two approaches. On the one hand, the traditional approach is to use historical data to estimate various risk persistence parameters and the breakpoint of default, and to use those to make assumptions about the loss distribution of a given period. In doing so, the traditional view usually uses regimental data of economic cycles and identifies different regulatory capital amounts needed to cover the likelihood of low-probability, high-severity events in the low regulatory capital setting. On the other hand, AI-based approaches use sophisticated techniques that create models that are more flexible and adaptable over time, as well as powerful in providing forecasts, results, and recommendations. While the traditional approach stresses empirical regularities and forecasting and model risk via a top-down process, the AI-based approach rests upon the potential for finding new features in the data that describe complex patterns that may be difficult to treat in practice by human experts in a bottom-up process.

There are, however, critical challenges in the application of AI-based models in financial risk analysis. The first is explainability. It is usually not clear why AI-based approaches arrive at their predictions or classifications, and calculating a solution for this so-called black box problem is not straightforward. Therefore, the emphasis is that AI-based approaches that consider personal data of individuals cannot be fully data-driven, particularly in the area of consumer finance. Currently, few AI experts think automatic AI-based approaches that do not require human reviewers should be fully trusted for credit scoring. The second issue is the need for interpretable and robust approaches that not only address the limitations of historical data and can capture changes, but also prevent the deliberate or non-deliberate interference of evaders in the control environment. These motivations suggest an inevitable direction to develop hybrid models that integrate the latest AI that absorbs signals and could provide a unique and powerful enhancement to existing methods but also takes into account traditional wisdom. Indeed, empirical studies in the industry have shown that after the AI-powered tools are launched in practice, the proportion of credit commitments scored has begun to decrease somewhat: some have maintained the AI-generated scores for a long time, while some have continued with the traditional expert-based scores. Only recently has there been an increase in scorecards.

2. Fundamentals of Machine Learning in Credit Risk Modeling

Machine learning is a powerful tool for credit risk modeling, and credit risk is a promising application context for this technology. There is a broad consensus that in circumstances of minimal data and limited available information, the additional predictive performance gains that machine learning can offer become less significant.

However, machine learning has a potential edge in contexts where it is possible to capture more of the complexity of the underlying data generating processes. When it comes to credit scoring, machine learning has demonstrated its ability to outperform classical rating approaches. In particular, machine learning can identify non-linear variations in the relationship between predictors and an outcome.

A broad distinction can be made between supervised learning methods and unsupervised learning methods. Supervised learning methods require a dataset consisting of a set of feature values and an outcome that we are interested in predicting. By contrast, unsupervised learning methods are used only with the objective of finding hidden structures, patterns, or trends in an unlabeled dataset. Some commonly used concepts or techniques in machine learning are the learning algorithm, models, model parameters, features, and target variables. Adequately handling big data has been one of the most important advantages of machine learning and big data processing tools. This is of more practical relevance in the case of intelligent credit scoring, since more observations will increase data variability, complicating the initial classical techniques described in credit risk assessment. Several machine learning algorithms can be used in credit risk assessment. The ultimate techniques selected are usually literature-based, though practitioners play an important role in the decision associated with the assessment of the best solution. Success is conditioned by the quality of the database under analysis, and sometimes it is not possible to reveal the most appropriate segments in credit risk situations during the training of these models due to the low volume of segments; consequently, a new model must be trained, since the performance metrics may evolve. In sum, machine learning is emerging as a new wave in credit risk assessment. In this context, classic models are limited. Their behavior, which we can implement, may change when we go from the sample used to build the same sample. This limitation cannot yet be overcome because of the sample volume and/or the nonexistence of sufficient rate variation.

2.1. Supervised Learning Techniques

Labeled datasets are used for training supervised learning models to predict whether an applicant is at risk or safe based on past data, which are categorized as risky or safe. Historical data is utilized by trained models to predict future problems. Model development and then model validation is the general framework for these procedures.

This algorithm could be characterized by its capacity to enhance solutions automatically. To categorize applicants into specific risk classes, supervised learning models have been used. Linear regression, logistic regression, decision trees, random forests, support vector machines, naive Bayes, and neural networks are some commonly used supervised learning models in the finance sector. Linear and logistic regressions are used for assessments based on certain requirements, as they may be used to calculate applicants' credit scores and categorize and characterize potential risk. Complex relationships might be identified by decision trees that consist of trees and hierarchical nodes leading to decisions. A broad set of variables is chosen by random forests, and multiple decision trees are created, from which the most prevalent category is selected by vote. The ability to combine linear and nonlinear relationships is also displayed by support vector machines. Additionally, there are neural networks and deep learning techniques. Algorithms that imitate the brain's cells and nervous functioning are called neural networks. They are able to conduct nonlinear regression, classification, segmentation, and outlier analysis, in addition to modeling multi-dimensional economic data. The application of artificial intelligence with increasingly layered neural networks is known as deep learning. All of these models try to overcome issues with simultaneous and overlapping government powers. Deficiency and excess of analysis in these models may lead to errors, such as underfitting and overfitting models.

These overfitting models and their excesses need to be adjusted to maximize their performance. Challenges involve preparedness and improvement of the training subset, the research method, and model operation. Because of the sophisticated and deep nonlinear relationships they encapsulate, a large amount of data is frequently required for neural networks and deep learning algorithms. It is anticipated that one large portion is reserved to form the training sample, whereas the rest are used to train and assess the model. Furthermore, cross-validation studies should be conducted using one of at least two methods. Unlock a portion of the full set, confirm the rest, and compare the findings with the expenditure in the training collection. Those are the performance indicators that can be considered when predicting extreme outcomes. It is also critical that the models have criteria to assess their outcomes. The actual degree of accuracy is known as the degree of precision. As an outcome, the model's output differs from the current rank in reality. Approval of the programmer or misplaced beliefs is analyzed to establish a price for the dog, which is referred to as the value assessment. Additionally, the programmer's instruction and the credit rating will be compared to determine the risk of rejection. Credit scores will determine the rating scale. These data provide the underpinning for modern solutions for risk in government initiatives.

2.2. Unsupervised Learning Techniques

Unsupervised learning aims at working without labeled outcomes, either to find hidden structures in data or new composite features. As such, while all accepted algorithms may also apply to regression or classification proxies of credit risk, unsupervised methods can be applied on their own labeled data, prior to any definition of the outcome. As a primary application, borrowing data can be analyzed with techniques such as clustering algorithms, especially when prospecting prior to any credit risk assessment; in this case, the objective is the segmentation of the space of individuals based on patterns that are not directly observed or on the credit score that cannot be used as input to unsupervised algorithms. Indeed, provided that it is unsupervised, clustering techniques can also be used for anomaly detection, i.e., to highlight cases with a structure not directly linked to the others, to identify exceptions and even potential cases of high credit risk that need to be supported by further analysis. The key focuses on implementing this approach are the requirement of meaningful interpretation of results to perform model validation and to guarantee that the outcomes of the analysis are indeed actionable. In conclusion, unsupervised learning is a prime candidate to further develop and explore to advance the functionality of the toolbox in the most common applications for practitioners, confirming its growing pervasiveness in a number of credit risk evaluation literatures.

3. Data Preprocessing and Feature Engineering for Credit Risk Modeling

In many cases, raw data is not directly useful for machine learning models and needs to be preprocessed. Raw data may contain inconsistencies, duplicates, and various errors, causing its quality to be very poor. Cleaning this data is time-consuming and often requires domain knowledge about the data and the process it represents. Multiple properties of this data lead it to be more prone to credit risk, one of which is imbalanced datasets. This has a great impact on the way machine learning models are trained and evaluated.

Despite preprocessing, evaluating each data transformation is also necessary. Multiple feature selection and extraction approaches can be used to shape more sophisticated data, which, in most cases, leads to an increase in model performance and generalization. Feature selection techniques preserve the already existing number of features while improving performance. In contrast, feature extraction techniques reduce the dimensionality of raw data to a simpler representation, typically acting as a latent structure by producing a reduced number of feature sets. In credit risk assessments, it has been proven that the richer and more meaningful new features are, the better the model's predictive accuracy. Sparse and high-dimensional datasets are being analyzed using techniques that construct more humble and low-dimensional features. That said, this process is iterative and affects models because each potential preprocessing technique applied may lead to different results. In data preprocessing, there are several techniques that reproduce better results for a specific dataset, which directly influences the development of models as a predictive tool.

3.1. Handling Imbalanced Datasets

The issue of imbalanced datasets is common in the credit risk domain, where the ratio of non-default to default observations almost always deviates significantly from 1. During the training stage, the scarcity of defaults can lead to overgeneralization from the majority class and, consequently, biased model predictions. Besides, this overprediction can be achieved without necessarily improving classification performance. Because of the effects discussed, the recognition of class distribution has become a crucial step in the practical application of such models. Imbalanced scenarios can be managed via a variety of strategies, such as properly designed sampling schemes. Strategies for dealing with imbalanced data are classified into two groups: sampling techniques and algorithmic solutions. Sampling techniques include the application of different levels of randomness, i.e., random over-sampling, based on the creation of clones of the class members, and random under-sampling, removing some number of class members. There are also algorithms used for forming synthetic data. Algorithmic solutions, on the other hand, use classifiers and create regions of interest outside the margin of the classifier.

The general scenarios of working with imbalanced data can be successfully realized in the context of credit risk studies. Data preprocessing methods have a significant impact on model performance, outperforming a model's natural ability to draw out discriminatory aspects. So, taking care of the data is essential—either too little or too much bias can lead to overlapping models or, even worse, inappropriate model fairness and/or accuracy. Correct model evaluation using the appropriate performance metrics is even more critical when using algorithms to handle imbalanced data. For example, if we choose F1-score as a model performance measure, which incorporates both precision and recall, we can detect severe imbalances in the training and test data. The general improvement of predictive performance measured by the area under the curve can then be supplemented by the application of proper metrics concerning minority examples. Only a proper use of these will establish that a model built on dynamically handled data samples meets the standards required.

3.2. Feature Selection and Extraction

In the majority of machine learning problems, one of the first steps is to prepare the data. For the task of credit risk modeling, many modern methods such as deep learning techniques require a lot of data, automatically pre-processed and free of noise for accurate decisions. Due to this, feature selection and extraction are usually used to obtain more reliable results. This process of preparing data for training a credit scoring model is called feature selection, which tries to select all features that are useful to predict the credit risk of an applicant. Moreover, interpreting and selecting the most important characteristics is vital in credit risk modeling. Therefore, several studies on feature selection techniques based on statistical tests and information theory have been proposed to measure the importance of the selected features regarding the concept to identify. Two big categories are used: filter methods based on statistical tests and model-based approaches. There exist other methods to select the member features. For example, dimensionality reduction techniques like Principal Component Analysis can be utilized to select the first principal components of the member features that contain the maximum amount of variance in the data.

Having irrelevant features in the feature set significantly decreases the performance of the classifier because the model is trained on noisy data. On the other hand, training the model with redundant features complicates the prediction and does not provide any additional information. Actually, some of the machine learning algorithms, such as decision trees and genetic algorithms, implicitly possess feature selection capability. We can also merge some of the features to create a new variable called variable engineering. A new member called average amount of transaction from big cities was added to the member who has a transaction frequency feature, and the prediction rate was improved. Let the machine decide with a lot of data or let the expert decide with a little data? This is actually a question on the balance between the complexity of the selected features and the interpretability of the model.

4. Popular Machine Learning Algorithms for Credit Risk Modeling

There is a wide range of machine learning algorithms used by practitioners while conducting credit risk modeling. Every algorithm has its own unique features and performs better to some extent compared to other algorithms. Here, we introduce some popular machine learning algorithms that are frequently used for credit risk modeling, covering logistic regression, decision trees, random forests, K-Nearest Neighbors, and Support Vector Machines. These algorithms are experimentally compared with each other, and it is also shown how the algorithms vary when applied to different datasets.

Logistic regression is widely used and highly effective when considering binary classifications. Decision trees are easy to interpret and are widely used by practitioners. Random forests are also easy to understand. They help manage the trade-off between high variance overfitting models and low variance underfitting models, making them very popular. Support vector machines can be an extremely powerful classifier method. They split data efficiently into classes, and in some cases can analyze high-dimensional spaces accurately. When selecting a particular algorithm to use in predicting creditworthiness, it is crucial to remember that each algorithm has its strengths and weaknesses. Based on business objectives, it is important to choose an algorithm that fulfills a company's expectations. At the same time, the expertise on model technique can affect a company's decision. It is highly recommended to consider available data and research to select the most appropriate algorithm. When considering business decisions based on predictive scores, it is important to know whether the model is more effective at setting a target rate or reducing the expected loss. Trade-offs among features in analysis checkpoints: when implementing credit risk models in business, it is important to recognize that there are trade-offs between profitability and risk.

4.1. Logistic Regression

Logistic regression is the first and often most essential method for binary classification tasks such as default prediction in consumer finance. The strengths of logistic regression include its ability to provide interpretable coefficients, encode non-linearities with manually created features, and good performance in practice. The model can be used to interpret the impact of each coefficient on the estimated probability of default, which is an approachable average risk proxy. A key feature of the logistic function is that it constrains its output into the [0, 1] domain to denote probabilities, a critical requirement for statistical modeling of rare events such as loan defaults.

This model is sensitive to multicollinearity between the explanatory variables, which can lead to unstable, or even meaningless, coefficients. Furthermore, the function exhibits poor performance when input features have different scales. To ensure fair and accurate results in credit risk models, normalizing the raw input features to a common scale is vital. Additionally, logistic regression includes overfitting risks in rare events, including loan defaults, and regularization techniques such as lasso and ridge regression models must be used. In practice, logistic regression is widely used to model credit risk, from traditional retail banks to fintech companies. Although this technique was developed in the 1960s, the model remains one of the most popular risk modeling methods worldwide.

4.2. Decision Trees and Random Forests

Decision trees are simple decision support tools with valuable applications in credit risk modeling. This subsection provides an overview of decision trees as well as their ensemble variant, random forests, and a discussion on their applicability in credit risk management. A decision tree is an interpretable prediction model with the advantage of representing structured human decisions. The resulting model can be visualized to show the segments. A tree is constructed through recursive partitioning of the data based on feature values. For classification problems, the leaves contain the probability of target variable classes given the segment feature vector. Decision trees have demonstrated outperformance in credit scoring applications, and their application is intuitive and easy to understand. However, the simple adaptive structure of decision trees is usually challenged by overfitting.

A single decision tree may not be optimal and could not boost the prediction accuracy. A random forest is a popular ensemble method based on the decision tree, which creates a host of decision trees during the training phase to improve accuracy. All the trees then vote for the most popular prediction. Constituent decision trees will lessen the risk of developing an overfit model and increase accuracy. An out-of-bag estimate indicates the performance of a random forest. The decision tree is a popular non-linear classification and prediction algorithm, which has been widely used in the financial industry, including credit rating, asset pricing, operational management, and so on. Since the split of nodes is completely determined by sample IDs, the algorithm is robust and not sensitive to noisy samples. It outperforms in some scenarios compared with frequentist methods. However, the overfitting hazard may reduce accuracy as the tree grows deeper. The splits are essentially determined by the Gini index at each node, which makes analyzing parameter importance inadequate. From a business perspective, the risk factors derived from the decision tree model are more interpretable and feasible compared with GBDT.

4.3. Support Vector Machines

Support vector machines, also known as SVMs, are considered one of the successful algorithms among all machine learning technologies that have the ability to handle high-dimensional spaces and provide efficient classification. The basic concept of SVM is to find hyperplanes or decision boundaries that separate different classes in the dataset. Hyperplanes that maximize the marginal distance between support vectors from different classes can create more effective classifiers. Kernel functions are a fundamental concept that has made support vector machines feasible for solving non-linear problems. If the pattern seems to be difficult to separate clearly without a line, the kernel function can transform the original dataset into a higher-dimensional space where clear separability is apparent. For a wide variety of complex applications in real life, SVMs have been proven to provide a good level of accuracy since their performance highly depends on the selected kernel function.

It is well-known that SVMs have numerous benefits in comparison with traditional methods, which include their ability to deal with non-linearity, their small effect caused by outliers, and their classification that is not sensitive to class representations that are even disguised by other classes. Hence, there are many effective applications of support vector machines in various diverse fields, particularly in areas that consist of highly complex problems and large datasets, like text classification, gene expression data, image analysis, and credit scoring. However, due to their dependence on searching for the best parameter combinations based on the training set and labeled data, support vector machines still have some limitations that hinder their practical application. There are some parameter values that need to be optimized properly in order to attain a better performance model, such as the regularization parameter, kernel function, and the kernel width values. The strong discriminating ability of the SVM framework to classify risky as well as non-risky loans has been verified and validated across numerous domains, including mobile telecommunications and energy markets.

5. Evaluating and Interpreting Credit Risk Models

To ensure reliable predictions, we need to evaluate our credit risk models. Various performance metrics for classification problems exist, including accuracy, precision, recall, AUC-ROC, and F1-score. The evaluation of credit risk models, especially the black-box models, is not straightforward as for other problems. Methods for robust model evaluation are needed in order to avoid overfitting and to measure the generalization performance of the model. In addition, our credit risk scoring or classification models should be designed to offer a proper trade-off between model complexity and accuracy.

Interpretable and explainable models are easy to understand by non-technical practitioners and stakeholders and are useful for decreasing the risk of model misinterpretation. Whereas a traditional credit scoring model is typically straightforward and interpretable, many machine learning credit risk models are black-box models because they are relatively more complex, and therefore, the communication should be clear and explained in an intelligible manner. The interpretation of AI-based black-box models includes making the model explainable and ensuring practitioners' and customers' trust in using the interpretable model. In addition, proper communication is necessary in order to avoid misleading interpretation of the AI-based black-box models. Interpretation of the model's prediction results does not mean interpreting the AI's internal model.

Moreover, practitioners should interpret the model's prediction results with caution, especially if they have time-based and distributional data that may violate some of the model assumptions. Misinterpretation may cost the company in many ways, such as a refusal to grant credit to a good customer, or vice versa, approving credit to a potentially bad customer. In conclusion, evaluation and interpretation of the credit scoring model is necessary to determine the value of the credit scoring model.

5.1. Performance Metrics for Model Evaluation

Credit risk models utilize various performance metrics to evaluate the model's goodness. There are various performance metrics for binary classification and they may be categorized into model-based, probability-based, and misclassification-cost-based. From model-based metrics, the metrics of accuracy, precision, recall, and F1-score are traditionally considered. These metrics are used to determine if the model is correct on average in classifying the samples from both classes. The appropriateness of these metrics in the credit risk problem needs to be adjusted with regard to the context of the problem, the characteristics of the collected dataset, and the imbalance of the classes. To better interpret the model outputs, we should use visual tools such as confusion tables to understand the output of the models more holistically and conduct a holistic model evaluation. Although one metric is often used to evaluate the performance of a predictive model on a creditworthiness problem, many argue that just a single metric is not sufficient to provide a clear picture of the classification outcome and that the three metrics must be analyzed together. Accuracy is believed to not always be the best metric, especially in the case of imbalanced data. For example, in credit card fraud detection using a scoring system, it is important to control sensitivity because the higher the sensitivity, the higher the success in detecting fraudulent transactions. Classifiers with the highest sensitivity are generally considered to exhibit superior performance. Moreover, to adjust the metrics to the cost-sensitive issues, the misclassification costs are taken into account, where a higher misclassification cost on a certain class should lead to a higher precision and a lower sensitivity for that class.

5.2. Interpretable vs. Black Box Models

Interpretable models are the opposite of black box models. Interpretable models are models that humans can understand, for example, decision trees or linear models. Black box models are models that are too complex to be understood by humans, like artificial neural networks. Though black box models could theoretically provide higher accuracy, achieving this does no good because they cannot be trusted by humans who do not understand their inner workings. In the application domain of credit risk, interpretability is of utmost importance: a bank making a prediction about an individual's creditworthiness will have to base the decision solely on the statistical prediction. The model will have little predictive value if the explanation for why the individual is a credit risk is, "the model said so," as opposed to an easily understandable explanation. Interpretable models have the advantage of being transparent, with decisions that are easy to comprehend and do not require time-consuming and error-prone guesswork to determine what specific inputs would have to be modified in order to obtain a desired result.

Apart from having a consistent explanation like that of the advantages described above, interpretable models are also able to guide analysts in identifying outliers and data quality problems and to prevent racial, gender, and other forms of discrimination by allowing audit of model predictions. Although black box models other than decision trees, like random forests and gradient boosting machines, are difficult to understand on their own, a large variety of model-wide and local interpretability techniques have recently emerged to provide post-hoc explanations of the predictions generated by those models. For instance, one of the popular techniques for delivering local explanations is called LIME. LIME approximates individual decisions of any model by choosing a small subset of all the input variables and fitting a linear model to predict the output. However, it is important to note that LIME and all other model-agnostic explanation techniques can be sensitive to input perturbation and, hence, deliver explanations that only approximately provide the actual model's behavior. Most real-life tasks exist in a gray zone where the use of interpretable models cannot be summarized with slight sacrifices in predictive accuracy. Within that gray zone, undertaking that trade-off between predictive power and interpretability is a crucial consideration that may need assessments, estimations, and risk management in any industry, including banking.

6. Future Direction

Dealing with future directions in terms of technology trends, recently, deep learning techniques and their application in predictive models are becoming more popular in credit risk modeling due to their superior performance as well as new technologies. Moreover, in this era of big data, there is a perception in both industry and academia that, with the huge amount of data available to provide more informed decisions, we can achieve a greater depth of insight in terms of credit risk assessment and improve the potential of our models. While there are many opportunities for developing new credit analytics, a close look must be paid to the ethical challenges that will emerge from AI and data analytics, particularly in the banking sector. AI with predictive analytics and developing credit scores is giving the power to "decide" who gains or cannot access financial services. Consequently, the design and use of AI in financial institutions must further consider the importance of using "fairness, transparency, and interpretability" without forgetting regulatory compliance. Finally, researchers have to address the issue of the heyday of AI, where data privacy, model transparency, and model efficiency combined with superior models are the key drivers to create sustainable innovations. In developing AI models, the importance of student involvement in industry-academia collaboration becomes influential in creating a compliant solution in AI and model risk management. Many available AI models may not be used for such decision-making processes as model building is not straightforward for credit risk. Credits are a combination of formalization, social behavior, and trust. Aid in credit applications, however, is considered part of this trust relationship. In response to the increasing volume of credit applications and the limited capacity of human credit analysts, advances in AI, machine learning, as well as alternative data and building models with related analytical technologies are not unknown. AI and digital transformation are also seen as the twin engines that have the power to redefine the customer banking experience. It can be predicted that over the next 5 to 10 years, this bank will continue a positive pattern where increasingly more will be spent on data and analytics than on security. AI and customer experience will make the second wave to enrich human experience, particularly in the banking and credit industry. With regard to regression applications, prediction and recognition have become the forefront of AI calculations for underlying credit analysis, being intelligent in various ways while dealing with a large amount of data. The remaining ambition is to produce a highly sophisticated model for AI training with insightful detection of anomalies, detection of fraudulent behavior, customer engagement, as well as personalization.

7. Conclusion

Traditional and advanced modeling techniques might be used in financial industry to face the credit risk challenges. In this direction, machine learning models demonstrate the capability to extrapolate structures and hidden information within the data. The empirical part examines several machine learning models that might be successfully used for credit scoring and credit risk assessment. Based on historical data pertaining Romania, a series of models have been developed and compared. The obtained performances are conclusive and provide answers to a number of issues in the field. The comparative analysis starts from three logistic regression, which is used as benchmark, and is completed based on KMeans method. The model results indicate a linear dependency of the approved loans on the main drivers, showing an almost similar pattern in all models. Moreover, machine learning models, especially neural networks, offer relevant performances in developing hybrid models relying on data quality. The model driven methodology is very promising and requires academic and financial attention, as it could help on decision making process and could contribute with a relevant new basic results, delivering a more complete better understanding the main factors and how they influence the financing process. The scope is to provide a comprehensive approach in order to develop and apply hybrid classification models in the credit risk evaluation field. The proposed technology framework brings several contributions for both financial and academic staff interested in finance and risk modeling. Model performances confirm the importance of efficiency scores. The correlation driven approach is delivering good performances in credit risk models. Model evaluation should be based on both accuracy and interpretability and addressing any of them should be done after discussing with end-users which are the main requirements. Future research might further investigate hyperparameters, and also in the future the field of learning / models might also extend to a such point in which it is based on a deep research in combination with the legal and regulatory framework and complemented by the operational and security framework that supports real-world data. Mainly, it is important to assess if the dyad model (completing the algorithm driven model with financial ratios) generates also in this case non-linear results. Additionally the Financial Ratios Model could also be tested based on an assessment of logistic regression. Such models might provide a more complete view upon representatives in these industries. The following research have as starting point the subject of regulations, and focus in determining Efficient Market Hypothesis in most significant stock from stock markets. Further analysis on forecasting will be considered, and their viability will be tested. We are continuing the research in the subject of AI and finance practices, in a way to test the viability of trading stock and commodities in most important stock markets. An efficient market is one where the whole present information is included in the prices of assets being traded. Finding if our local markets are becoming efficient or are we still enjoy a professional informational advantage is considered important because it allows us to position ourselves and develop a strategy regarding the new risk of our stock market. There is only very little literature on testing the efficient market hypothesis. One other reason they are considered important is because they make assumptions that are essential in agency and fiduciary laws. We live in a digital age and that has influenced how architectures, tools and processes are designed. To work in a digital environment has become inevitability. When we speak about data and the intelligence behind it, relevance and meaning are brought by means of tooling and methods such as AI and Big Data. Consequently, it is critical for tooling and methods in AI and Big Data to be an indisputable part of the working life of every part of society, including finance professionals. In other words, practices in finance-AI, as well as their benefits, should be well-understood by all finance professionals. When it comes to regulations and standards in finance, styles, tools and methods need to be considered as an integrated part. A practice in finance involves developing and deploying AI models globally in a standard way and under consideration of ethical and security principles. Conducting a deeper investigation of the method's viability in finance practices is relevant and the proposed investigation based on financial credits offered to households except revolving credit score would offer meaningful intelligence. Balancing between performance levels and interpretative power remains the core element in assessing the ability to support the decision making for investment and loans. Financial institutions and academic experts are interested in knowing that a customer is likely to decide on some days in advance of their financial commitment when it comes to the new financial credit. Additionally, applying the modern techniques to different data would constitute a need for further research.