

MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE IN CREDIT RISK PREDICTION FOR COMMERCIAL BANKS: A REVIEW

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ABSTRACT

Credit risk prediction is a fundamental function of commercial banking, directly influencing financial stability, profitability, and regulatory compliance. With the rapid growth of digital financial data and advances in computational capabilities, machine learning (ML) and artificial intelligence (AI) have emerged as transformative tools in credit risk assessment. This review paper provides a comprehensive synthesis of the existing literature on ML and AI applications in credit risk prediction for commercial banks. It examines the evolution from traditional statistical models to advanced ML techniques, including classical algorithms, ensemble learning methods, and deep learning approaches. The study develops a conceptual framework that integrates data inputs, pre-processing techniques, modelling approaches, decision processes, and governance mechanisms, highlighting the multi-layered nature of AI-driven credit risk systems. A comparative analysis of different models is presented, emphasizing their strengths, limitations, and applicability in various banking contexts. The review also identifies key challenges, including data quality issues, model interpretability, class imbalance, regulatory constraints, and ethical concerns such as bias and fairness. Furthermore, the paper outlines future research directions, including explainable AI, dynamic modelling, alternative data integration, and privacy-preserving techniques. Practical implications for banks and regulators are also discussed, focusing on the need for robust governance and responsible AI adoption. Overall, this review contributes to the literature by providing a structured and critical understanding of how ML and AI are reshaping credit risk prediction in modern commercial banking.

Keywords: Credit Risk Prediction, Machine Learning, Artificial Intelligence, Commercial Banking, Explainable AI

1. INTRODUCTION:

Credit risk the probability that a borrower will default on debt commitments in a contract- is one of the greatest sources of financial instability in the commercial banking (Abiola, 2025). Proper risk evaluation of credit is not only a key to profitability and sustainability of banks, but also to systemic stability of the financial ecosystem (Addy et al., 2024). In the past, commercial banks have been using the old methods of statistics like logistic regression, discriminating analysis, and credit scoring

systems that are based on expert judgment (Adewale et al., 2022). Although these methods have given a systematic way of assessing risks, they do not always tend to deliver the nonlinear, complex, and high-dimensional relationship that are present in the current financial data (Adewuyi et al., 2023a).

The accelerated process of digitalization of financial services and the vast increase in the amount of data produced by various sources, including transaction records, social media, mobile banking, and other financial services,

have changed the future of credit risk modeling fundamentally (Adewuyi et al., 2023b). This rich data environment has revealed the weaknesses of traditional models which often assume linearity, independence of variables and fixed relationship. Consequently, the paradigm has shifted to more advanced, data-oriented methods that can reveal latent trends and adjust to a dynamic financial environment (Ali).

Artificial Intelligence (AI) and Machine Learning (ML) have become the strong forces in predicting credit risks. ML methods - such as decision trees, random forests, support vector machines, gradient boosting models, and neural networks allow modeling complex nonlinear relationships and interactions among variables without having parametric conditions (Aloun). In recent years, the development of deep learning, ensemble learning, and hybrid AI models has further enhanced predictive accuracy and robustness. They are especially applicable to modern banking contexts that are volatile and uncertain because these approaches are capable of processing large-scale and high-dimensional datasets and never-endingly learning new information (Amarnadh and Moparthi, 2023).

Other than enhanced predictive capabilities, AI-based credit risk models have further benefits of automation, scalability, and the presence of other data sources. This is especially the case with financial inclusion where the conventional credit scoring systems are not usually able to evaluate individuals or small enterprises that have a limited credit score (Anh and Phuong, 2021). Unconventional data such as behavioral patterns, digital footprints and transactional metadata can be used by AI models to offer more inclusive and granular risk evaluations (Barngatuny, 2025).

Nevertheless, there are no problems with the adoption of ML and AI in credit risk prediction. Problems of model interpretability, transparency, and regulatory compliance have become a greater concern particularly in bank industries that are highly regulated (Bello, 2023). Black-box models are not always explainable, yet they are accurate, which is problematic among regulators and other stakeholders who need clear justification of credit decisions. In addition to that, data quality, model bias, overfitting, and cybersecurity risk are other challenges that

impede successful implementation of AI-based systems (Bhatore et al., 2020).

Considering such opportunities and challenges, an increasing body of literature exists about the use of ML and AI methods in credit risk prediction among commercial banks. Current research is diverse regarding the methods, data sets, performance measures, and evaluation systems, and it is hard to conclude the similar conclusions or find the best practices (Bhatt et al., 2023). Besides, the field is changing very fast and algorithms, computational capabilities, and regulatory views are constantly being improved. Thus, this review paper tries to present the role of Machine Learning and Artificial Intelligence in credit risk forecasting of commercial banking in the most in-depth and systematic way possible. To be more precise, the paper aims at (i) discussing the history of the development of credit risk modeling methods, (ii) comparing the performance and usefulness of different ML and AI methods, (iii) determining the main challenges and limitations that are linked to the use of these solutions, and (iv) pointing out the latest trends and research directions in the given field.

This review can serve as a valuable contribution to the academic literature and practical practice by summarizing the available literature and providing critical insights into the potential of AI-based credit risk assessment to transform modern banking by helping researchers, practitioners, and policymakers to comprehend the topic.

2. LITERATURE REVIEW

2.1 Evolution of Credit Risk Modelling

The evaluation of credit risk has been continuously developed during the last decades due to the increased availability of data, computing capability, and analysis methods. The logistic regression, linear regression, and discriminant analysis were the main statistical techniques used in the traditional credit risk models in commercial banking (Bhatt et al., 2023). These models became widely accepted as they were simple, interpretable and could be regulated easily. Early credit scoring models, such as the Z-score invented by Altman and models based on the Basel framework helped to create a standard method of assessing the risk of borrowers (Bhattacharya et al., 2023).

Although the traditional models have practical use, they have various assumptions such as linear relationships between predictors and outcomes, independence of variables, and inability to handle high dimensional data (Chitturi, 2025). These constraints impaired predictive effectiveness of classical methods as financial markets grew more interrelated and complex. As a result, scientists started investigating other methodologies that can describe nonlinear patterns and relationships between variables (Gafsi, 2025).

2.2 Emergence of Machine Learning Techniques in Credit Risk Prediction

The incorporation of machine learning (ML) in credit risk modelling is a paradigm shift in hypothesis-based modelling to data-based modelling. The first uses of ML were on classification algorithms like decision trees, k-nearest neighbors (KNN), and support vectors machines (SVM) (Khan et al., 2025). These models had a higher predictive accuracy than the conventional statistical models because they successfully represented nonlinear relationships and highly interactive features.

The interest in decision tree-based models such as Classification and Regression Trees (CART) was driven by the fact that they are easy to interpret and could be used in analyzing both numerical and non-numerical data. Ensemble learning models like the Random Forest (RF) and Gradient Boosting Machines (GBM) were then used to further improve the performance of the model by using a combination of multiple weak learners to minimize variance and bias. According to empirical research, ensemble techniques have always been more accurate, robust, and capable of generalizing, in comparison to single classifiers (Krasniqi et al., 2023).

Credit risk prediction has also seen the use of support vector machine as it has a solid theoretical basis and is useful in high dimensionality. Nonetheless, their functionality is also sensitive to the choice of kernel and parameter optimization, which can restrict scalability with large datasets (Md Manarat Uddin et al., 2025).

2.3 Deep Learning and Advanced AI Approaches

The last several years have seen an explosion of the use of deep learning and advanced artificial intelligence methods in credit risk prediction. ANNs, especially deep neural networks (DNNs) have been shown to perform better when it comes to modeling nonlinear relationships that are not linear in large financial datasets. These models are able to automatically compute hierarchical features, thus, eliminating the process of manually engineering features (Nahar et al., 2024).

Further architectures, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been investigated to address particular tasks, including sequential transaction analysis and time-series prediction of default risk. A type of RNNs is called Long Short-Term Memory (LSTM) networks, and it is especially useful to capture temporal dependencies in the behavior of a borrower (Naili and Lahrichi, 2022b).

It has also been suggested that hybrid models, i.e. models that combine several AI methods, like neuro-fuzzy systems, genetic algorithms with neural networks and ensemble deep learning, can be used to enhance the predictive capability (Naili and Lahrichi, 2022a). The approaches will be used to capitalize on the strengths of various methodologies and reduce the weaknesses of individual methodologies.

2.4 Role of Alternative Data in Credit Risk Assessment

The increased access to alternative data has also had a major impact on the creation of AI-powered credit risk models. The old credit scoring approach is extremely dependent on credit bureau and financial history, both of which are not available to every borrower. Conversely, non-traditional sources of data, including the use of mobile phones, social media, e-commerce and behavioural patterns, can be incorporated in ML and AI models (Naumenkova et al., 2020).

Research shows that the addition of other data enhances model precision and increases the access of credit to underbanked groups. This has been especially applicable in the developing economies, whereby a significant percentage of the population and small enterprises do not

have formal credit histories (Noor et al., 2025). Nonetheless, the application of alternative data is associated with the issue of data privacy, ethical implications, and bias in digital footprints (Samson-Onuorah, 2025).

2.5 Model Performance and Comparative Studies

There is a significant amount of literature devoted to the comparison of the work of traditional statistical models and ML-based ones in terms of credit risks prediction (Wang et al., 2020b). The majority of empirical analyses come to the conclusion that ML models - especially ensemble techniques and deep learning algorithms - are more effective than traditional techniques in predictive accuracy, Area Under the Curve (AUC), and default classification (Shiraguppi, 2025).

The advantage of ML models is not omnipresent. Certain researchers point out that the performance improvements are slight in case of a small dataset, or in case features are optimally designed to fit standard models. Also, ML models can be quite resource-intensive in terms of computational resources and expertise and may be restricted in smaller financial institutions (Shittu, 2022).

2.6 Explainability, Interpretability, and Regulatory Challenges

The trade-off between model accuracy and interpretability is one of the most important issues in the implementation of ML and AI in credit risk prediction (Wang et al., 2020a). Conventional approaches like logistic regression are transparent by nature and the stakeholders are able to know the contribution of each variable to the final decision. Conversely, most ML models, especially deep learning models are black box, which implies that their predictions cannot be interpreted (Shittu, 2022)

Regulatory rules, including Basel III and IFRS 9, argue that risk modelling should be transparent, accountable and explainable. This has given rise to the popularity of Explainable AI (XAI) methodologies, such as SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-Agnostic Explanations) and partial dependence plots. These approaches are meant to make complex models easier to interpret without much damage to their predictive capabilities (Shiraguppi, 2025).

2.7 Research Gaps and Future Directions

However, even though there has been a substantial improvement, a number of gaps in the research in using ML and AI to predict credit risk still exist. First, there are no unified evaluation frameworks, thus, it is not that easy to compare the findings between the studies. Second, data quality, imbalance, and bias remain an issue that impacts the reliability and fairness of the models. Third, it is essential to consider operational issues such as model governance, scalability, and cybersecurity to integrate ML models into the banking system of reality. New opportunities like federated learning, explainable AI, and ethical AI may also be explored to enhance credit risk assessment and remain in line with the regulatory standards. The next generation of research should also aim at designing hybrid models that can be predictive and interpretative as well as robust.

The literature indicates that there is a shift towards utilizing the more advanced AI and ML methods of credit risk forecasting in place of the traditional statistical models. Although the predictive capabilities and flexibility of the ML models are superior, issues of interpretability, regulation, and data governance should be tackled to enable the high adoption of the models in commercial banking.

Table 1: Studies on Machine Learning and AI in Credit Risk Prediction

Author(s) & Year	Methodology / Model	Dataset / Context	Key Findings	Limitations
Lessmann et al. (2015)	Benchmark ML models (SVM, RF, LR)	Credit scoring datasets	ML models outperform traditional methods	Limited real-world deployment
Baesens et al. (2016)	Logistic regression vs ML models	Banking datasets	ML improves predictive accuracy	Interpretability concerns

Brown & Mues (2012)	SVM, Random Forest	Consumer credit data	Ensemble models outperform single models	Data-specific results
Khandani et al. (2010)	Machine learning algorithms	Consumer lending data	ML captures nonlinear risk patterns	High computational complexity
Malekipirbazari & Aksakalli (2015)	Random Forest	Peer-to-peer lending	RF improves default prediction	Limited generalizability
Xia et al. (2018)	Ensemble learning	Credit datasets	Boosting methods yield best performance	Parameter sensitivity
Zhang et al. (2020)	Deep learning (ANN, DNN)	Financial datasets	Deep learning captures complex patterns	Black-box issue
Addo et al. (2018)	Hybrid ML models	Banking sector	Hybrid models improve robustness	Complexity in implementation
Louzada et al. (2016)	Review of credit scoring models	Multiple datasets	ML dominates modern credit scoring	Lack of standard evaluation
Recent studies (2021–2024)	XGBoost, LightGBM, LSTM	Large-scale & fintech data	Ensemble & deep learning outperform traditional models	Explainability & regulatory challenges

3. CONCEPTUAL FRAMEWORK OF MACHINE LEARNING AND AI IN CREDIT RISK PREDICTION

Credit risk prediction in the commercial banking setting has been transformed by the traditional statistical methods to cutting-edge data-driven approaches. Judging by the literature reviewed, it is possible to create a conceptual framework that will help to summarize the contribution of machine learning (ML) and artificial intelligence (AI) to credit risk assessment (Shittu et al., 2022). The framework does not reflect a single model but is a combination of key elements that have been discovered in previous researches, which focuses on the relationship between data, analytical methods, and decision-making processes (Schwarz et al., 2007).

AI-based prediction of credit risk exists as a multi-layered system, which contains the inputs of data, the modelling of analytical predictions, predictive outputs, and governance. This architecture indicates how the traditional credit rating approaches are giving way to smart, responsive and information-based risk evaluation models (Ullah et al., 2025).

3.1 Data Layer: Foundation of Credit Risk Modelling

The initial element in the framework is the data layer and this forms the basis of any predictive models. The literature has emphasized the need to move to the use of traditional financial information and the incorporation of various and high-dimensional information (Sousa et al., 2016).

The conventional credit risk models have considered structured financial factors like income, debt ratios, payment history and collateral value. Recent research, however, puts strong emphasis on the increasing significance of alternative and behavioral data, such as transactional records, mobile banking activity, digital payment trends and social or e-commerce data (Derera et al., 2016).

This increases the capacity of ML models to capture the heterogeneity of borrowers and the ability to predict better, especially individuals or firms with a limited credit history. Meanwhile, the literature highlights the issues of quality of data, privacy, and possible bias of non-traditional data sources (Abi et al., 2025).

3.2 Data Processing and Feature Engineering Layer

The second element is the data preprocessing and feature engineering which converts raw information to meaningful inputs of the ML models. In the literature, it is stressed that the performance of AI-based credit risk prediction strongly relies on the methods of data preparation (Gafsi, 2025).

The main processes that have been found in the previous research are data cleaning, missing values, normalization, feature selection, and dimensionality reduction. Class imbalance is the most common problem in credit risk datasets with the number of default cases being significantly smaller than non-default cases. Because of this, resampling techniques and cost-sensitive learning are noted in many studies as a solution to this challenge (Bhattacharya et al., 2023).

The process of feature engineering is important as well since it allows the mining of informative variables that would improve the performance of the model. The literature says that the effective features could greatly enhance both the conventional and ML-based models (Bhatt et al., 2023).

3.3 Modelling Layer: Machine Learning and AI Techniques

The central element of the framework is the modeling layer, in which the ML and AI algorithms are used to model credit risk. These models have been divided into various groups in the literature depending on their growing complexity and predictive abilities.

The use of the traditional statistical models, including logistic regression, still remains a benchmark because it is interpretable and acceptable to the regulatory bodies. Nonlinear relationships have however been shown to be better captured by classical ML models such as decision trees, support machine learning and k-nearest neighbour (Šarlija et al., 2017).

More sophisticated algorithms, especially the ensemble learning techniques (e.g. random forest, gradient boosting), are highly identified in the literature as being superior with regard to predictive performance. By increasing the number of learners, these models minimize overfitting and enhance generalization. Over the past years, deep learning networks, such as

artificial neural networks, recurrent networks, etc., have received attention due to their capability to process large and complex datasets. These models come in handy especially in sequential or behavioural data (Moradi et al., 2020).

In general, it is recommended in the literature that more advanced models are used, but none of them are universally the best. The choice of models is frequently determined based on the trade-off of accuracy, interpretability, and operational feasibility.

3.4 Prediction and Decision Layer

The prediction layer is the translation of model outputs into operational credit risk measures. According to the literature, the most frequent products are probability of default, credit ratings, classification of the borrowers (non-default and default), and risk ratings (Khan et al., 2025).

Commercial banks use these outputs to aid in making critical decisions that include; loan issuance, allocating credit limits, price-based risks, and maintaining a portfolio. Moreover, ML-based systems will be able to produce early warning signals, which will allow mitigating risks in advance (Barngetuny, 2025).

The literature has pointed out that, the worth of AI in credit risk prediction is not only in its increased accuracy, but also in its role in supporting faster, automated, and scalable processes to the extent of decision-making.

3.5 Governance, Interpretability, and Regulatory Layer

One of the fundamental aspects that are pointed out in the literature is the governance and interpretability layer which determines the responsible use of ML and AI models in controlled banking contexts (Anh and Phuong, 2021).

Advanced models are generally more predictive, but they are usually not transparent. This has contributed to the growing interest in explainable AI (XAI) methods that attempt to make complex models easier to understand. Techniques like SHAP and LIME are often mentioned as the ways of explaining how the model behaves (Shittu, 2022).

The regulatory frameworks stipulate that the decision to give credit should be transparent, fair

and justifiable. Hence, banks are in a dilemma of maximizing predictive accuracy and minimizing interpretability as well as compliance. Other issues that have been brought up in the literature include biasness, fairness, and ethical use of data especially when other sources of data are involved (Wang et al., 2020a).

3.6 Feedback and Model Adaptation Layer

The last element of the structure is the feedback and adaptation layer that demonstrates the dynamics of credit risk. The literature points out that credit risk model should be continuously

reviewed and revised in order to be effective (Zhang et al., 2025).

Model drift can be caused by the variations in economic environment, borrower behaviour and financial markets and hence predictive accuracy will decrease with time. Consequently, continuous validation, recalibration and performance monitoring is necessary. This is a feedback process that brings out the transformation of nonadaptive credit scoring systems to adaptive and learning-based systems, which adapt to new information and updated environments (Suryanto et al., 2022).



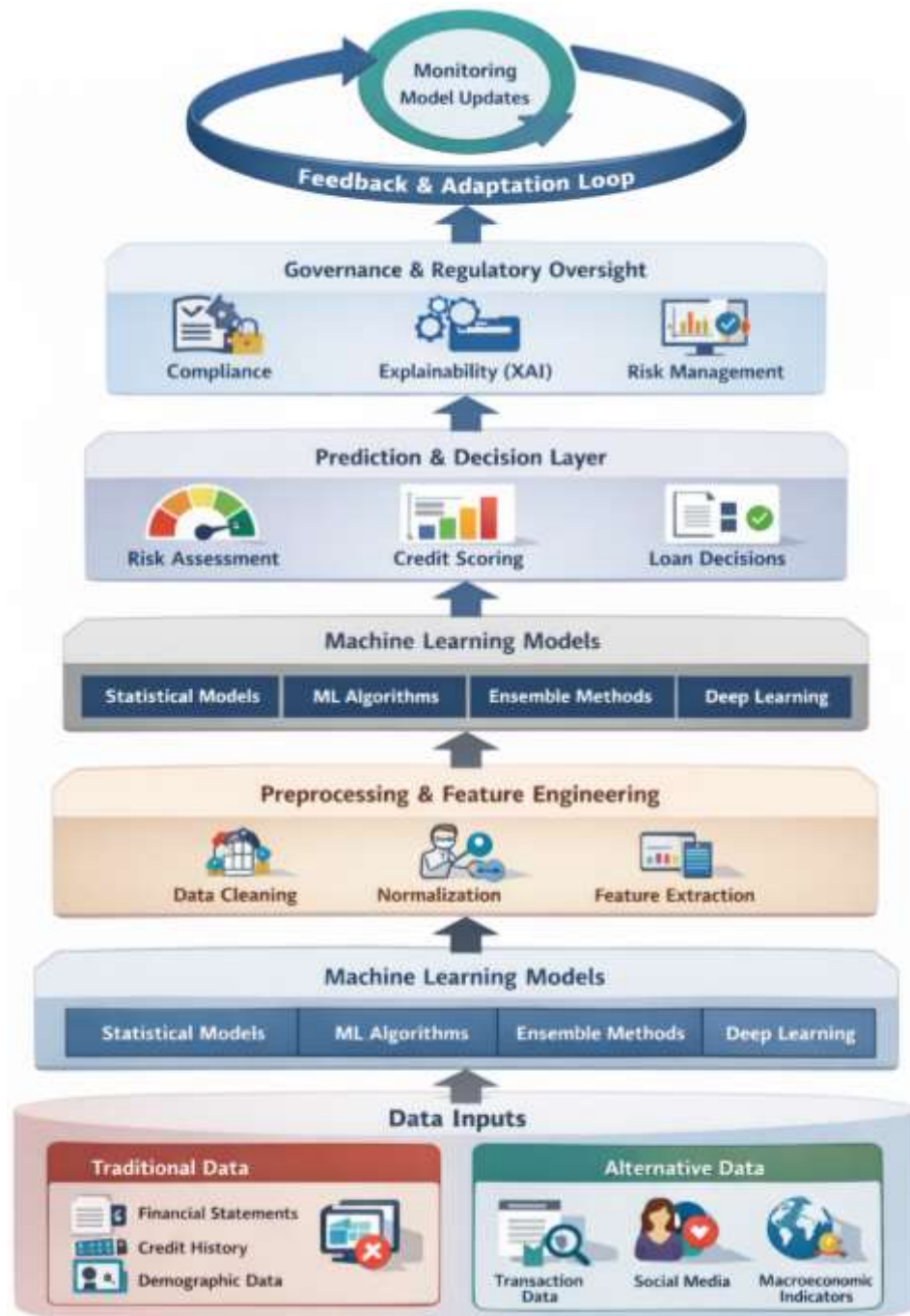


Figure 1: Conceptual Framework of AI-Driven Credit Risk Prediction in Commercial Banks

Figure 1 is a conceptual framework that shows how artificial intelligence (AI) and machine learning (ML) applications are integrated to predict credit risks in commercial banks. The framework emphasizes on a multi-layered system where various data sources, analytical procedures and decision-making processes interrelate towards the effective and sound credit risk evaluation.

The first layer of the framework is the data input layer comprising of both conventional financial

data (income, debt ratios, and repayment history) and non-conventional data (transactional behaviour, digital footprints and macroeconomic indicators). Heterogeneous data increases the comprehensiveness of risk profiles in a borrower that the AI models capture (Karami and Igbokwe, 2025).

This data is then fed through a step of data pre-processing and feature engineering where raw data undergoes processing to become meaningful features. The step also entails the

cleaning of data, normalization, missing values and the issue of class imbalance, important steps to ensure the models work well (Nahar et al., 2024).

The processed data are then analysed in the modelling layer where several machine learning and AI algorithms are run. Among them, there are classical machine learning algorithms, traditional statistical models, ensemble algorithms, and deep learning. According to the literature, this layer is a key component that is involved in extracting intricate patterns and enhancing the predictive accuracy (Noor et al., 2025).

The results of these models enter into the prediction and decision layer where the main risk indicators including probability of default, credit scores, and classifications of borrowers are created. These outputs can help in making critical banking decisions such as the approval of loans, risk-based pricing, and portfolio management (Shiraguppi, 2025).

The other notable feature of the framework is the governance and regulatory layer, which makes AI-based decisions transparent and fair and adherent to financial regulations. Such techniques as explainable AI (XAI) are becoming more common to promote interpretability and establish confidence in automated credit decisions (Wasif; Wu, 2022; Yanenkova et al., 2021).

The framework will have a feedback and adaptation loop, which will focus on the dynamic nature of credit risk prediction. The system can be adjusted to the evolving economic situations and borrower behavior by continuous monitoring, model validation, and recalibration, which will guarantee the effectiveness of the model in the long term. The framework indicates the agreement in the literature that the effective prediction of credit risk by AI is not only based on the advanced algorithms but on the efficient data management, interpretability, and compatibility with regulations.

4. COMPARATIVE ANALYSIS OF MACHINE LEARNING MODELS IN CREDIT RISK PREDICTION

The relevant literature on credit risk prediction in commercial banks shows that there has been a distinct methodological change in the traditional statistical methods to more

sophisticated machine learning and artificial intelligence models. The general use of comparative studies is to assess these models based on the predictive accuracy, robustness, interpretability, scalability, and applicability to various forms of banking data. Even though no one model can be considered better in every situation, the existing literature displays significant differences in the strengths and weaknesses of the major families of models (Abiola, 2025).

Standard statistical models, especially logistic regression, are still significant references in credit risk modeling. The fact that they are interpretable, simple, and matchable with the regulation requirements has contributed greatly to their relevancy (Addy et al., 2024). The logistic regression works well enough in the case of structured dataset, relatively constant relationships, and where explanatory transparency is of importance (Bello, 2023). Nonlinear interactions, high-dimensional variables or complicated temporal patterns however limit its predictive power when the behaviour of borrowers is determined by them. This is why numerous comparative studies recognize logistic regression as a beneficial foundation, as opposed to the most effective predictive method (Md Manarat Uddin et al., 2025).

Classical machine learning algorithms like decision trees, support vector machines, k-nearest neighbours and Naive Bayes are an intermediate phase in the development of credit risk analytics. The decision trees are appreciated as being transparent and rule structured, which can be explained easier in credit decision situations (Karami and Igbokwe, 2025). Single-tree models are however unstable and most of the time, they overfit. It has been widely stated that support vector machines perform better than the conventional statistical models, especially when the boundary of a dataset is nonlinear with high dimensionality (Chitturi, 2025). However, they are less widely used in the recent literature due to their sensitivity to parameter tuning, computational complexity and comparatively low interpretability, many of which can cause their performance to degrade on noisy, imbalanced, or large scale financial data.

Of all the model categories, the ensemble learning methods have been most aided in the recent research. Random forest, gradient boosting, XGBoost, LightGBM, and many others are always superior to predictive results in structured credit data. They are strong because they are able to model nonlinearities, minimize variance, and better generalization to a wide range of borrower characteristics. Ensemble models are specifically effective where credit risk prediction is associated with non-homogeneous features and asymmetric classes. Boosting algorithms are known to perform better than traditional models and the single machine learning classifier on these main metrics AUC, F1-score, and recall, in many comparative reviews. Nevertheless, better predictive effectiveness of ensemble models is usually associated with less transparency and higher complexity of model calibration.

Deep learning neural networks, artificial neural networks and recurrent networks, such as LSTM, have also become more prominent in the literature. The models come in particularly handy when the goal is to utilise high-dimensional, large-scale, or sequential data (Yu et al., 2019). This is because of their ability to learn nonlinear feature representations and hence they can be used in behavior credit scoring, transaction analysis and dynamic monitoring of borrowers. However, empirical evidence indicates that deep learning is not necessarily more effective than the ensemble approaches on conventional tabular banking data. Gradient boosting models are still more effective and competitive in a high number of commercial banking scenarios compared to deep neural networks particularly when the amount of data is moderate and structured (Carmona et

al., 2019). Moreover, deep learning models are also associated with significant difficulties associated with explainability, the cost of computation, and deployment.

The other trend that is reflected in the literature is the increased relevance of hybrid and smart models. These are genetic algorithm-based neural network optimization, neuro-fuzzy, stacked ensembles, and explainable-enhanced predictive systems. The purpose of such approaches is frequently to address the limitations of single-model systems by balancing predictive power with flexibility or understandability. Despite the potential of hybrid models, the common aspect is that they are not yet fully implemented in the field of practice because they present greater complexity in architecture and because they are not regularly evaluated in studies (Gülmez et al., 2025).

In general, the comparative literature indicates that model performance in credit risk prediction depends on the character of the data, the period of prediction, the degree of interpretability required, and the working environment of the bank (Siddikov et al., 2024). Logistic regression is useful when transparency is important, the advantages of using support vector machines and classical ML are better in nonlinear classification, ensemble models can be the most effective predictors of structured data, and deep learning models seem to be most effective in large-scale and behavior-rich settings (Musa et al., 2013). That is why, in commercial banking, the choice of models must be determined not only by predictive accuracy, but also by the possibility to explain, governability of models, and institutional preparedness.

Table 2: Comparative Analysis of Major ML Models in Credit Risk Prediction

Model Category	Representative Models	Main Strengths	Main Limitations	Suitability in Banking
Statistical models	Logistic regression, probit	Interpretable, simple, regulator-friendly	Limited nonlinear modeling	Traditional scorecards, compliant environments
Classical ML	Decision tree, SVM, k-NN, Naive Bayes	Better nonlinear classification, flexible	Tuning sensitivity, moderate explainability	Borrower classification in structured data

Ensemble learning	Random forest, XGBoost, LightGBM	High accuracy, robustness, strong generalization	Lower transparency, higher complexity	Default prediction, portfolio risk scoring
Deep learning	ANN, DNN, LSTM, CNN	Strong nonlinear learning, suitable for large/behavioral data	Black-box nature, data-intensive, costly	Transactional and dynamic credit datasets
Hybrid models	GA-ANN, neuro-fuzzy, stacked models	Combines strengths of multiple methods	Difficult implementation, lack of standardization	Advanced institutional applications

5. CHALLENGES AND LIMITATIONS IN AI-BASED CREDIT RISK PREDICTION

Although machine learning and artificial intelligence have become more successful in predicting credit risk, there are still a number of challenges in the literature that can be called concerning and restrict the implementation of machine learning and artificial intelligence in commercial banking. These are not just technical but also operational, ethical and regulatory (Bhattacharya et al., 2023).

Data quality and availability is one of the most discussed issues. The credit risk models developed using AI require a lot of trustworthy data that is representative in large quantities. Nevertheless, banking data is usually described as incomplete values, dirty data, out-of-date borrower records, and unequal standards of reporting (Bhatore et al., 2020). Moreover, alternative data can also cause additional complexity, since this data can be unstructured, partial, or hard to validate. Low quality data can greatly compromise the model and can result into unstable or inaccurate predictions (Bhatt et al., 2023).

Class imbalance is also another significant difficulty and is an intrinsic feature of credit risk prediction as the cases of default are typically much fewer than those of non-default. This skew may make the models favour the majority group leading to high overall accuracy, but less detection of real defaults. It has been indicated in the literature that a number of studies aim at alleviating this problem by resampling, generating synthetic data or by cost sensitive learning. Nevertheless, the best strategy in terms of various datasets and the type of model remains a controversial issue (Chitturi, 2025; Gafsi, 2025; Karami and Igboke, 2025).

Another weakness is related to model interpretability and transparency. Most of the most precise ML models, especially ensemble and deep learning models, are a black-box. This presents grave issues in commercial banking where the credit decision should be explainable to the regulators, internal auditors and consumers. Lack of clarity in explaining why a loan was approved or denied may impede the trust in automated systems and cause legal or compliance risks. The literature indicates that even though explainable AI methods have become a potential solution, they are still in their development phase and may not address the transparency gap in its entirety (Khan et al., 2025; Krasniqi et al., 2023).

Another problem that the literature also raises is the problem of algorithmic bias and fairness. In case historical training data can be considered biased in social, economic, or institutional terms, then the production of discrimination in lending patterns can be reproduced or even enhanced by the use of ML models (Naili and Lahrichi, 2022b). This is particularly relevant when other sources of data are employed, because the digital behaviour can inductively capture delicate socioeconomic features. Consequently, equity has taken a centre stage of AI-based credit risk modelling, although it is not well developed in most of the predictive literature (Samson-Onuorah, 2025).

The other notable restriction is overfitting and low external validity. Models that are effective in one dataset cannot necessarily be effective in a different borrower population, economic or banking system (Shittu, 2022). A significant number of published studies use benchmark data or samples of a single institution, thus restricting the external validity of their results. This begs the question of whether the

performance gains reported can be applied into the actual commercial banking operations.

In terms of operations, the deployment and integration issues are still significant. Numerous researches are dedicated to model creation and testing, but they lacked any consideration of practical challenges connected to the integration of AI systems into existing banking systems. Practical implementation demands scalability, low latency processing, 24/7 monitoring, cybersecurity protection, and liaison with human credit officers. The lack of these factors can make even the best models on paper unrealistic.

Last but not least, regulatory uncertainty remains one of the key limitations. Commercial banks are surrounded by a very strict environment, whose decisions that involve credit, capital allocation and risk management face close monitoring. Most regulatory frameworks tend to support transparency, stability, and accountability, whereas most developed AI models are more inclined to predictive power. This tension introduces the unsureness in the models that can be used in the real world, the ways of their validation, audit, and regulation (Barngetuny, 2025; Bhatt et al., 2023).

Collectively, these issues point to the fact that the future of AI in credit risk prediction will be based not solely on improving algorithms but also on the emergence of data governance, equitable models, interpretable systems, and institutionally viable strategies of deployment.

6. FUTURE RESEARCH DIRECTIONS

The research on machine learning and artificial intelligence in credit risk prediction has grown at a fast rate, but multiple fields are not researched thoroughly. Subsequent studies ought to go beyond mere model comparison and concentrate on the creation of integrative, transparent and situation-focused methodologies that would better reconcile predictive innovation with the dynamics of commercial banking.

One of the key research directions in the future is the design of models that can optimally combine predictive performance and interpretability. Accuracy and explain ability are discussed in much of the current literature as conflicting goals. Future studies must thus

venture into model architectures and post hoc explanation techniques that can enable the banks to enjoy the advantages of advanced analytics without compromising regulatory and operational transparency. In this respect, explainable AI is probably going to become a key element of credit risk systems of the future.

The other opportunity is the growth of dynamic, time sensitive credit risk modelling. Most of the available literature takes default predictions as a fixed time classification problem whereas borrower risk changes with time. The studies in future would give more focus to longitudinal modelling, survival analysis, sequential learning, and concept-drift detection such that the models could capture the changes in the behaviour of borrowers and macroeconomic conditions over time. The necessity of further research on alternative data integration is also high. Although the literature is more accepting of the predictive quality of digital and behavioural data, further research is needed on which type of alternative data has the highest quality of information, reliability, and ethical suitability. It would also be of particular interest to compare the evidence across the countries and borrower groups to see if these data enhance a better prediction or are applicable only in a narrow range of situations.

Another area of research that is of primary importance is the topic of fairness-conscious and ethical AI systems. In the future, fairness measurements, bias reduction strategies and ethical assessment systems should be integrated directly in credit risk modelling as opposed to being considered minor issues. This is especially crucial in commercial banking, where automation can lead to significant consequences of financial inclusion and social equity.

Future studies of privacy-preserving and collaborative learning, including federated learning, would also be beneficial to the literature. Such practices could allow organizations to have more resilient models trained on decentralized data without necessarily providing sensitive information on customers. In controlled financial settings, the research has the capacity to settle the predictive improvement and confidentiality and data protection requirements.

One more possible area is the investigation of graph-based and network-aware models.

Interactions between borrowers, firms, guarantors, and transactions are frequently found to be in interlocking financial network as opposed to in isolation. Future studies may explore the role of graph neural networks and relational learning models in enhancing the identification of latent risk connectivity, contagion and credit patterns of fraud. More cross-country and cross-institution comparative studies are also required. The majority of the existing research is carried out in closed datasets and in closed regulatory settings. The transferability of models in different banking systems, economic scenarios, and legal environments should be examined in future studies. This type of work would be more powerful to support the generalizability and practical applicability.

The human-in-the-loop decision systems and hybrid decision systems should be addressed more. Algorithms are seldom exclusively used to make credit decisions. Future research ought to consequently examine how the ML models can be employed efficiently in conjunction with expert judgment, in-house policy regulations and government frameworks. It can result in more realistic and institutionally acceptable ways of AI implementation in commercial banking. The proposed research in the future must strive to create more precise and more interpretable, fair, adaptable, privacy-sensitive, and banking operations-oriented credit risk models.

7. PRACTICAL IMPLICATIONS

The increased research on the topic of AI-based credit risk prediction has significant practical implications on commercial banks, regulators, and policymakers. The implementation of the technologies of ML and AI provides both the strategic opportunities and the managerial tasks as banks strive to modernize the risk assessment process.

In the case of commercial banks, the most important implication is the possibility to enhance accuracy and efficiency of credit evaluation. High-end ML models may help to increase the number of risky borrowers identified, decrease losses on defaults, and assist in the management of credit (Bello, 2023). Moreover, automated and information-based credit scoring mechanisms can speed up the loan assessment procedures enabling banks to react

faster to the clients and decrease the manual processing loads. The other implication that can be made practically is the potential to expand financial inclusion. Banks can potentially evaluate the creditworthiness of borrowers with no formal credit history, e.g. small businesses, informal workers or first-time borrowers by adding alternative and behavioral data. This will be able to help more inclusive lending policies, especially in emerging and digitally growing financial systems. This opportunity should be, however, balanced with effective protections against prejudice, privacy breaches and unfair dismissal (Di Maggio et al., 2022).

To the bank management, the literature indicates that the successful implementation of AI in credit risk prediction would need institutional preparation and not technical procurement. Banks require data infrastructure that is resilient, model governance, and internal verification, as well as interdisciplinary coordination among data scientists, risk managers, and compliance officers. That is, the usefulness of AI is determined by the extent of its integration in organizational processes and management systems (Ahmed et al., 2025).

To policy-makers and regulators, the literature indicates that there is a necessity to establish effective governance models of responsible AI implementation in the banking sector. The attention of the regulations should be directed toward interpretability, fairness, accountability, and auditability (Wijethilake et al., 2025). Regulatory agencies might have to come up with new benchmarks of certifying machine learning models, algorithmic risk examination, and keep the automated lending choice clear and unrestricted (Lee et al., 2024). It is also suggested in the literature that banks should not just consider predictive performance as the only basis in selecting a credit risk model. Practically, model selection must represent a trade-off between accuracy, explainability, compliance, and operational feasibility. A slightly better statistical model can still not be acceptable as long as it cannot be validated, explained and integrated into the decision architecture of the bank (Sudjianto et al., 2024).

The review identifies that the future of AI in credit risk prediction is in augmentation of decision-making over complete replacement of human judgment. In practice, the most common

use of ML models is to enhance expert credit analysis, instead of doing away with it. This anthropocentric strategy can enhance the trust, accountability, and the better incorporation of AI into the commercial banking practice. The practical implication of the literature is evident: AI and machine learning can substantially change the process of credit risk forecasting, although they may be successful only when used in a cautious set of institutional governance and regulation.

CONCLUSION:

In this review paper, the author discussed machine learning and artificial intelligence as potential tools to predict credit risks in commercial banking with references to the shift to more sophisticated data-driven methods instead of traditional statistical methods. This analysis has shown that both ML and AI methods, especially ensemble and deep learning models provide serious gains in predictive accuracy and ability to generalize complex and nonlinear relationships of financial data. The results also show that there are significant issues associated with the adoption of these sophisticated models. Data quality, class imbalance, interpretability, and regulatory compliance problems continue to pose essential obstacles to their large-scale adoption. The issue of trade-off between predictive performance and explainability remains a major worry, particularly in a highly-regulated banking setting. The theoretical framework that has been built in this paper highlights the fact that successful credit risk forecasting is a multi-layered process that includes data management, modelling, decision-making, and governance. It emphasizes the necessity of combining technical innovation and institutional and regulatory issues. Further studies are needed in coming up with models that offer a balance between accuracy and transparency, use dynamic and alternative data sets and deal with fairness and ethical issues. Practically, the successful implementation of AI in credit risk prediction must be supported by effective governance structures, ongoing monitoring, and alignment with regulatory requirements. Finally, ML and AI can contribute to the improvement of credit risk assessment considerably, yet their usefulness depends on the

responsible use and integration into the overall banking ecosystem.

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