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Survey of Data-Driven Approaches for Credit Risk Evaluation in Banking Using AI Techniques

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***Abstract*—Credit risk measurement is one of the most prominent problems in modern banking and financial services that has a direct impact on the lending operations, profitability, and stability. Conventionally, qualitative, experience-based methods have been applied in assessing credit risk based on transactional jeopardy, inherent peril and concentration risk in loan portfolios. Nonlinear patterns and dynamic risk behavior are however usually not well captured using the traditional methods, particularly due to increasing complexity of the financial markets, as well as due to the profile of diverse borrowers, and the presence of large volumes of data. Credit risk assessment has been transformed by recent advancements in AI and ML, which have made it data-intensive, adaptable, and scalable. When dealing with high-dimensional, unbalanced, and heterogeneous financial data, the approaches that have proven to be effective include logistic regression, random forests, gradient boosting machines, and deep neural networks. Additionally, alternative sources of data, such as transactional, demographic, behavioral, and social data can be utilized to predict credit scoring with increased accuracy and reduced bias with the aid of advanced preprocessing and feature engineering. In addition to risk evaluation, AI is also used to identify fraud, predictive analytics, regulatory compliance, and chatbots. Although the above advantages are there, there are still issues of data privacy, ethics and model interpretability. The paper indicates traditional and AI-based methods of credit risk assessment.**

***Keywords*—Machine Learning (ML), Data-Driven Approaches, Credit Risk Evaluation, Banking Sector, Artificial Intelligence (AI), Deep Learning (DL).**

I. INTRODUCTION

The banking sector is a key financial intermediary that helps in the effective circulation of the funds between the savers and the borrowers hence supports businesses and individuals in financial transactions [1]. The fact that it is a pillar in economic growth highlights the significance of sound financial intermediation processes which have a close relationship with financial innovation, the scope of banking and the financial system structure. The decision between universal and functionally separated banking is likely to have a considerable impact on institutional incentives to undertake financial innovation, the source of financing of borrowers and the cost of capital attached to it [2]. In addition, system-related causes, including industry fragmentation, consolidation, and path dependence also influence the development of banking practices.

Credit risk assessment is one of the fundamental roles of a bank, and involves a thorough evaluation of the borrower traits, such as credit history, consistency of income, and current existing debt commitments [3][4]. Proper assessment of credit risks helps the banks to be aware of the likelihood of loan failure and implement appropriate mitigation steps, which is vital to financial stability. Quality assessment also helps in better loan approval rates, interest rates and efficiency in operations.

Conventional financial risk management has been based on regulatory systems, statistical modeling and intuition to reduce credit, market, operational and liquidity risks [5]. But with the advent of the AI technologies, the traditional methodology has changed, allowing risk management to be done based on data, adaptive, and predictive strategies [6]. ML, DL, NLP, and robotics make it possible to score credits automatically, perform risk monitoring, and detect anomalies, which give the banks more analytical opportunities, and more responsive to the changing financial environment.

AI has been applied to banking, not only in the back-end functions, but also in the front office, with chatbots, voice recognition, and even personalized advisory systems [7][8]. The AI-based solutions reduce operations such as credit underwriting, loan issuance, and risk analysis, increasing efficiency and satisfaction of the client experience. However, the adoption of AI-based solutions is still hampered by such challenges as digital literacy, insufficient technological infrastructure, and digital divide [9]. Addressing these barriers is essential to fully leverage data-driven approaches for credit risk evaluation and to ensure equitable access to AI-enhanced banking services.

A. Organization of the Paper

The paper structure is as follows. Section II reviews credit risk evaluation in banking. Section III discusses AI and data-driven techniques, including ML and deep learning models. Section IV presents data sources and preprocessing methods. Section V highlights applications in banking and financial services. Section VI outlines challenges and future directions, and Section VII concludes the paper.

II. CREDIT RISK EVALUATION IN BANKING

Credit is a legal concept in banking whereby a lender grants a borrower immediate valuables in exchange for a promise to repay the lender at a later date [10]. Credit risk is the potential for a decline in the value or complete disappearance of a bank's assets, particularly its loans. The borrower's inability or unwillingness to fulfil the agreed-upon obligations leads to this. Credit risk, in its simplest form, is the possibility that a bank or other asset may be at risk because a borrower does not pay back loans or otherwise fulfils other obligations as promised [11]. Three modules make up a bank's loan portfolio's credit risk.

- **Transactional Jeopardy:** Transactional Jeopardy is concerned with the erratic nature of earnings and credit quality as a result of how the bank evaluates specific loan transactions. Underwriting, selection and operations are the three parts of transaction jeopardy
- **Inherent Peril:** The risk present in some business ventures and advances made to specific industries is its main idea. Construction loans for salable real estate are fundamentally riskier than money lent to consumers. An industry or line of business' vulnerability to historical, prognosticative, and lending risk variables is addressed by intrinsic risk. e industry or company line's past success and stability are covered by historic aspects.
- **Concentration on single borrower:** Lending to a single borrower, a single sector of the economy, a single region of the country, or a single line of business can result in risk of concentration, which equals to the accumulation of inherent and transactional danger within the bank's portfolio[12]. For each of these aggregations, the bank must specify acceptable portfolio concentrations. A significant objective is achieved via portfolio diversification.

A. *Traditional Methods of Credit Risk Assessment*

The common credit risk can be defined in two ways: either as a broad credit risk or as a more specific credit risk. Credit risk encompasses all possible losses that may occur as a result of a counterparty's inability to fulfil their financial commitments [13]. So, the possibility of suffering a loss as a result of a variety of credit transactions is credit risk. When customers make commitments to repay credit loan principal and interest, spend the money, or do anything comparable, commercial banks face a risk. Financial organizations (such commercial banks) and organizations that assess credit often do credit risk assessments, which include checking the evaluation target's dependability and capacity to meet contractual obligations, to arrive at a credit grade. "Traditional" and "modern" procedures are the two mainstays of risk assessment in today's academic and corporate circles, respectively [14]. In the past, commercial banks and other financial organizations employed what is known as "traditional" credit risk evaluation to express their qualitative assessments of clients based on their prior activities. Credit lending is where most of these ideas and approaches come together in the hands of commercial banks.

B. *Impact of Credit Risk on Financial Institutions*

Credit risk, including the likelihood of late or default payments, is complex and requires knowledge of its intricacies on the part of lenders, banks, non-banking financial institutions, and Fintech businesses that deal with money. Credit risk is the potential for monetary loss as a result of nonpayment of debt. There are many different kinds of credit risk.

1) *Concentration Risk*

The risk of concentration increases when a lender focusses on a limited set of borrowers, companies, or occupations for their lending activity. A bank that mostly loans to car firms is very vulnerable to concentration risk since its very survival depends on the car industry's performance. If the industry is struggling financially, lenders stand to lose even more money.

2) *Default Risk*

Credit risk may take many forms, but default risk is one of the most obvious and common. When lending money to someone, every lender runs the danger of default, which is short for "credit risk" [15]. For instance, the lender faces default risk in the event that the borrower fails to return the loan. All credit transactions, from mortgages and loans to derivatives and bonds, have the risk of default.

3) *Downgrade Risk*

Providing loan to a borrower whose credit has declined exposes the lender to the danger of a downgrade. For instance, in the event that a borrower or business is unable to pay back their debts as agreed, CIBIL reduce their credit score.

4) *Institutional Risk*

Financial institutions run the danger of "institutional risk" when they are unable to fulfil their commitments due to bankruptcy, fraud, insolvency, or any other reason. Just like concentration risk, institutional risk impacts almost every link in the value chain. This includes regulatory bodies, creditors, shareholders, investors, and many more.

III. AI AND DATA-DRIVEN TECHNIQUES IN CREDIT RISK

An artificial intelligence (AI) system is one that can mimic human intelligence, which is "a thinking power created by humans." This means that AI systems can employ algorithms that are capable of working independently of human intellect, eliminating the need for preprogramming. Among other machine learning techniques, it employs neural networks for RL and deep learning.

A. *Machine Learning Approaches*

ML is essentially the process of developing algorithms that enable a computer to learn. This is dependent on the algorithm's input and the result that is intended. Some of the ML methods used mimic human strategies for solving problems [16]. As seen in Figure 1, a number of mathematicians and computer scientists have proposed answers pertaining to methods and approaches for machine learning.

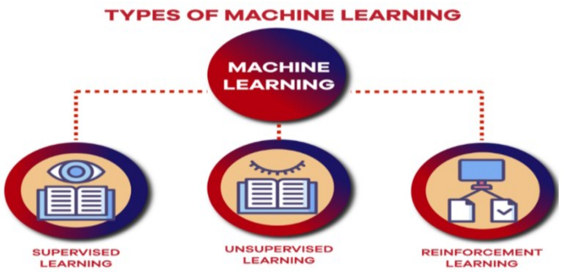

Fig. 1. Machine Learning Techniques

- **Supervised Learning:** The data source already has a valid categorization given to a data sample in supervised learning. Additionally, it may be viewed as an attempt to codify a certain principle of learning from instances involving inputs and outputs.

- **Unsupervised Learning:** This approach requires a bit more effort than supervised learning. The reason behind this is that can't explicitly teach a computer something new. Instead of producing categorization, this learning strategy maximizes rewards through decision-making.
- **Reinforcement Learning:** A favorable result is either predetermined or highly contingent on the choices made using this method. Learners are unaware of the appropriate course of action until they are presented with a specific scenario.

B. Machine Learning Models

Machine learning revolutionizes credit scoring as it builds dynamic and flexible models [17]. It can model high-dimensional data, find nonlinear dependencies, and make predictions on complex interdependencies where classical statistical methods cannot. The popular ML models are as follows:

- **Logistic Regression (LR):** Used as a baseline because it is simple and interpretable, but may underperform with nonlinear relationships [18].
- **Random Forests (RF):** Offers better performance than logistic regression by capturing interactions and reducing overfitting but can be computationally intensive for large datasets.
- **Gradient Boosting Machines (GBM):** Light GBM and XG Boost have a stellar reputation for accuracy, especially when dealing with credit scoring datasets that are skewed.
- **Neural Networks:** They are effective for complicated situations with predominance of nonlinear patterns, but they are resource-intensive and need massive datasets [19].

C. Deep Learning Models

Deep supervised, unsupervised, hybrid, and reinforcement learning are the four main types of DL models [20]. With examples of models in each area, Figure 2 displays the key types of DL. The following are brief explanations of various groups.

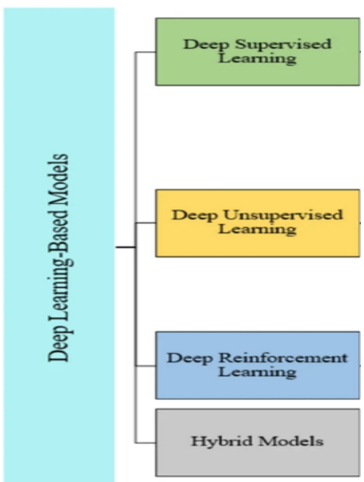

Fig. 2. Deep Learning Models

1) Deep Supervised Learning

A labelled training dataset is used to train one of the most frequent forms of DL models, which is called deep supervised learning-based models. To see how well these models work, utilize the loss function. The weights are fine-tuned until an acceptable level of error minimization is achieved.

2) Deep Unsupervised Learning

An increasing number of people are looking at deep unsupervised models as a potential option for deep learning. Systems that can be trained with a small number of unlabeled instances are often constructed using these models.

3) Deep Reinforcement Learning

The purpose of RL is to find the optimal answer in every particular situation such that the learner's reward is maximized. Through interactions with one's surroundings, one can attain optimum behaviour. An agent may make decisions, see the outcomes, and modify its approach to deliver in RL.

4) Hybrid Deep Learning

Hyperparameter tuning settings and data exploration are two areas where deep learning models excel and where they fall short. Because of their shortcomings, these models may not be suitable for use in all contexts.

IV. Data Sources and Preprocessing for Credit Risk

Data clean-up, data conversion, data integration, and data discretization are the primary methods for converting credit card information into a format that data miners can utilize [21]. Take note of the steps used to get the data ready. There was a plethora of dirty data in the original database, including wrong attribute values, duplicate entries, null values, inconsistent values, acronyms abound, and breaches of referential integrity, among other things [22]. This is due to a variety of factors. Data mining and decision support can benefit from the data if it is transformed into high-quality data. Consequently, prior to using the data, a data preprocessing method called data cleaning should be employed to clean up the unclean data.

- Organize the data There is customer data in the customers database and recorders reflecting customer transactions in the card trading log table. Consequently, the customers' data should be deleted from the customer’s table.
- Handle vectors that are empty the original database has some null values because some fields are unnecessary. First, it mostly handles null values by doing the following. Since the majority of families consist of four people, the null values in the family population field have been replaced by customer recorder statistics showing that this is the case.
- Clean up inaccurate information use the query analyzer to search and analyzes the data in the spreadsheet for any values that don't fit the fields. While it may be challenging to rectify inaccurate data, it is often possible to estimate the value of one field and use it as a basis to assess the value of another.

A. Types of Data in Credit Risk

There are some types of data in credit risk as follows:

- **Transactional Data –** Includes information on customer payment histories, credit card transactions, loan repayments, and account balances. This data captures financial behavior over time and helps identify default risks.
- **Demographic Data –** Typical borrower profiles and repayment ability estimates include age, gender,

profession, income, marital status, and degree of education [23].

- **Behavioral Data –** Digital footprints such as online purchase habits, mobile banking activities, spending patterns, and social interactions are increasingly considered to enhance predictive accuracy.
- **Alternative Data –** In emerging nations, where official credit records are few, sources including telecom usage, utility bill payments, e-commerce activity, and even social media presence are utilized.

B. *Feature Engineering and Selection*

ML end goal is to develop learning models that can accurately categorize both visible and invisible data. Data is plentiful and enormous datasets may be discovered and created from various sources nowadays [24]. The dimensionality curse makes it necessary to pick and choose which dataset samples seem to have a greater impact on distinguishing the desired values. Feature selection is an essential step in reducing the amount of training sets and, by extension, the noise introduced by features that are not statistically significant.

- The intensity of the correlations between each feature and the label is indicated by a weight vector that is established by the univariate feature selection. In order to determine the weights vector, these methods rely on statistical testing.
- In recursive feature removal, less important characteristics are removed. Prioritizing characteristics in a predefined model is the foundation of the recursive selection process.
- Constructing a classifier utilizing all accessible characteristics constitutes the feature significance determination, also known as model-based feature importance. After that, use the model's ranking to choose the K most significant attributes.
- A feature's (predictor's) information value shows how well it can distinguish between two binary target variables, such the good and bad types of customers in the credit scoring problem.

C. *Data Imbalance Challenges*

The final open challenge addressed in this paper is associated with the escalating complexity of data. Compelled to create computationally efficient solutions for the processing of the vast quantities of information that modern systems generate. Class imbalance can also impact big data, which presents a greater challenge to learning systems [25].

- SMOTE-based oversampling methods have a tendency to fail when implemented in distributed environments, such as MapReduce. As a result of randomly dividing up the data for each mapper, which introduces samples based on real objects without any spatial correlations, this might happen.
- In mining big data, they are interested in the value that it can gain out of this process [26]. One of the prospective directions is to develop approaches through which by evaluating the nature of imbalance capable of understanding given problem better.
- Machine learning algorithms face limitations when dealing with such data sets, which are increasingly common in unbalanced and big data analytics.
- Imagine a scenario where the majority class has a huge sample size while the minority class has a tiny one. This might lead to imbalanced big data. The other is when the imbalance is present yet there are many representatives from both groups.

V. Applications in Banking and Financial Services

AI is changing the face of banking and financial services by helping businesses automate tasks, obtain insights, and provide better client experiences [27]. Some examples of AI in action in the banking and financial industries in Figure 3:

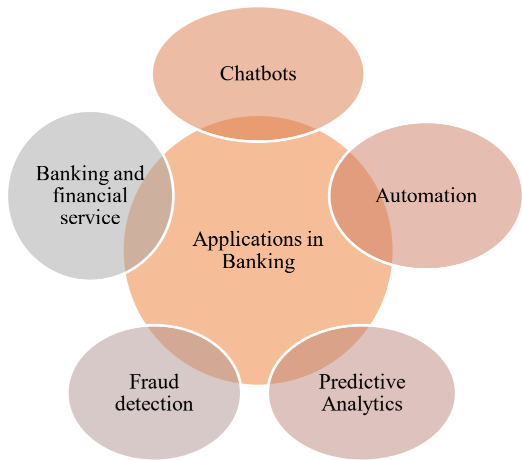

Fig. 3. Applications in Banking and Finance

- **Chatbots:** A chatbot is a piece of software or an application that allows users to hold conversations virtually. Talking to a chatbot is like having a conversation with a real person; it uses AI and NLP to mimic human speech and writing. Customers may access chatbot support at their convenience, day or night, from any location. Customers are more satisfied as a result of support provided by chatbots.
- **Automation of Financial Reports and regulatory compliance:** AI software placed within the system can automate the process of retrieval and report preparation. Financial reports, performance matrices, regulatory compliance statements, and legal compliance statements may be generated using this tool with less room for error compared to equivalent processes involving human data entry and account reconciliation.
- **Predictive Analytics:** Big data mining, statistics, modelling, machine learning, and artificial intelligence are all components of predictive analytics, a subfield of data analytics [28]. By utilizing statistical approaches such as pattern analysis and regression procedures, predictive analytics systems sift through massive amounts of data in search of trends and patterns.
- **Fraud detection:** Banks and other financial organizations have long worried about fraud. Crimes including money laundering, credit card fraud, and identity theft cost the economy billions of dollars every year [29]. More recently, AI has shown great promise as a weapon against fraud.
- **Banking and Financial Services:** "The RPA Systems Market is anticipated to Reach USD 12 Billion By 2023," it states, referencing the banking and financial services industry. It's hardly surprising that banking and other financial services employ more than one-third of the world's bots, since these businesses were

among the first to embrace automation (36% of all use cases according to the Forrester report).

VI. Literature of Review

The following is a summary of research that looks at sophisticated models for detecting fraud and assessing credit risk in the banking and finance industries using ML, DL, and ensemble methods. The research highlights improvements in predictive accuracy, stability, and scalability while addressing challenges in data complexity, high-dimensional features, and multi-entity modeling.

Diao et al. (2025) the rapid advancements in internet and big data technologies, coupled with the growing demand for credit services, have introduced significant challenges to traditional credit risk assessment models. To overcome the limitations of conventional approaches in managing data complexity and nonlinear relationships, this study presents an XGBoost-based credit risk prediction model. In laboratory experiments, XGBoost beats more traditional models such as DT, RF, and SVM on several metrics, including precision, accuracy, recall, and AUC [30].

Yepuri et al. (2025) uses a dataset with several borrower characteristics to forecast credit risk using ML and DL techniques in addition to statistical methods. With a 98.1% accuracy, the LGBM classifier outperformed the other models in this investigation and demonstrated the capacity to identify intricate risk patterns. The other machine learning models also shown outstanding performance; however, the statistical and deep learning frameworks were unable to achieve the same accuracy levels as machine learning methods [31].

Hassan et al. (2024) There are a number of ML models whose AUC values are investigated using the Kaggle Family Credit Default Risk dataset. Credit scoring may be greatly improved with the use of modern ML algorithms like LSVM and RF. This application case is well-suited to ensemble models like LightGBM because of its benefits, such as enhanced forecasts and increased stability. Outperforming methods such as XGBoost, SVMs, and logistic regression, combining predictions from several models typically produces less noisy results than using a single model [32].

Zhang et al. (2024) proposes a credit risk evaluation model that considers distributed adjustable resources such as conventional generators, energy storage operators, controllable loads, and electric vehicles. Firstly, a market entity credit rating index system and method that takes into account transaction behaviors are constructed. Secondly, the traditional credit metrics model is specifically improved to build a credit risk evaluation model suitable for multiple entities in the electricity market [33].

Bhatt, Kumar and Kumar (2023) aims to reveal Bank of Maharashtra-related financial wrongdoing in India and the consequences of internet banking on clients. Examine the background and present situation of fraud in the Indian financial system, touching on subjects including the effects of internet banking and how common it is, in this paper's introduction. In the literature review part, two themes are selected and analyzed which are fraud cases in Indian banking industry and evolution of internet banking in India [34].

Sharma et al. (2023) provides an innovative and strong model architecture that was developed to address a field problem with credit risk modelling and scoring prediction. Data cleansing, feature engineering, and assessment with different matrices are all part of the novel framework introduced in this study. The data collection originates from Lending Club, a P2P lending network with over 450,000 features. Use the Chi-square test and the ANOVA F-statistic to identify features [35].

Credit Risk Evaluation in Banking Can Be Summarized in Table I, Which Includes: Study, Approach, Key Findings, Challenges, and Future Directions.

TABLE I. Summary of a Study on Credit Risk Evaluation in Banking Using AI

Author	Study On	Approach	Key Findings	Challenges	Future Directions
Diao et al., (2025)	Credit risk prediction	XGBoost-based model using individual and corporate credit data	XGBoost outperforms traditional models (Decision Trees, Random Forest, SVM) in precision, recall, AUC, and accuracy	Managing data complexity and nonlinear relationships	Further optimization of objective functions and regularization; testing on larger, diverse datasets
Yepuri et al., (2025)	Credit risk forecasting	ML (including LGBM) and DL techniques, plus statistical methods	LGBM achieved 98.1% accuracy; ML models capture intricate risk patterns better than DL or statistical methods	Deep learning and statistical models underperform	Explore hybrid ML-DL approaches to improve accuracy and interpretability
Hassan et al., (2024)	Credit scoring	Comparison of ML models (Random Forest, SVM) and ensemble techniques (LightGBM)	Ensemble models improve prediction stability and reduce noise; outperform single models like XGBoost and logistic regression	Need for combining predictions from multiple models to reduce variance	Development of more robust ensemble frameworks; application to other financial datasets
Zhang et al., (2024)	Credit risk evaluation in electricity market	Improved traditional credit metrics; market entity credit rating index	Model accounts for transaction behaviors and multiple distributed entities; tailored for electricity market	Complexity in modeling multiple entities and adjustable resources	Extend model to real-time monitoring; integration with smart grid systems
Bhatt, Kumar & Kumar, (2023)	Fraud detection in Indian banking	Literature review on banking frauds and evolution of internet banking	Highlights increasing fraud incidents; significance of internet banking for consumers	Limited empirical modeling; focus mainly on descriptive analysis	Development of predictive fraud detection models for Indian banks; impact analysis of internet banking security measures
Sharma et al., (2023)	Predicting scorecards and modelling credit risk	Incorporating data purification and feature engineering into new modelling frameworks; selecting features using a Chi-square test and an ANOVA F-statistic	Systematic framework for large-scale Lending Club dataset; robust feature selection improves prediction	Handling over 450,000 features; high-dimensional data challenges	Apply model to other P2P platforms; integration with automated feature selection pipelines

VII. Conclusion and Future Work

Credit risk evaluation is a cornerstone of banking and financial services, directly influencing lending strategies, portfolio management, and financial stability. Conventional credit risk assessment techniques, though useful, rely on past experience and subjective judgment, limiting their ability to capture the complex dynamics of borrowers and market environments. With the emergence of AI and ML, banks and financial institutions can now build flexible, data-driven, and highly predictive models. These approaches leverage diverse data sources, from transactional and demographic to behavioral and alternative data, enhancing accuracy, efficiency, and fairness in credit scoring. AI is also applied in fraud detection, predictive analytics, customer engagement, and compliance, showcasing its transformative role in finance. However, regulatory compliance, data privacy, ethical concerns, interpretability of black-box models, data imbalance, bias in training data, and integration of unstructured or real-time data remain key challenges.

Future studies should focus on developing explainable and responsible AI frameworks, incorporating real-time data, exploring federated learning for privacy-preserving assessments, and combining traditional risk assessment with advanced AI techniques for a more ethical, robust, and inclusive credit risk evaluation system. "

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