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RECENT ADVANCES AND CHALLENGES IN AI-BASED CREDIT SCORING MODELS: A SURVEY ON FAIRNESS AND BIAS MITIGATION IN FINANCIAL

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Abstract: Data-driven models introduced by Artificial Intelligence (AI) have fundamentally transformed credit scoring, making the process more accurate, faster, and fairer. AI-based credit scoring leverages machine learning, deep learning, and hybrid models to uncover complex patterns across diverse data sources, including alternative and behavioral data, thereby surpassing traditional methods that rely solely on limited historical financial data. Explainable AI (XAI) adds transparency and interpretability, addressing the long-standing "black box" issue in automated credit decisions. However, AI-powered systems still face challenges related to algorithmic bias, data privacy, and security concerns. Recent research advocates adopting fairness-aware frameworks and bias-mitigation techniques, such as adversarial debiasing and continuous validation, to ensure equitable credit evaluations. Furthermore, global regulatory standards like GDPR, ECOA, and FCRA promote ethical AI practices and safeguard consumer rights. The success stories of fintech companies such as Tala and Lenddo illustrate AI's transformative potential to promote financial inclusion for the unbanked and underbanked, while highlighting the need for responsible, explainable systems. Ultimately, integrating fairness-by-design principles ensures that lending decisions remain unbiased and sustainable, marking AI-based credit scoring as a pivotal advancement toward a transparent, inclusive, and ethically governed financial ecosystem.

Keywords: Credit Scoring, Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Fairness, Bias Mitigation.

1 INTRODUCTION

The financial crisis has been a lingering global challenge that has deeply influenced the economies and financial systems of the world. Over the last few years, numerous small and medium-sized enterprises (SMEs) that were in poor condition due to a lack of growth and market volatility have been reporting very low profits or even heavy losses. [1]. On the other hand, the number of large-scale bankruptcies has been increasing rapidly. This has caused a financial distress scare, affecting firms of all sizes and sectors. The large losses resulting from these failures have heightened criticism of financial institutions. The majority of the criticisms concern the insufficiency of the traditional credit risk evaluation methods. The financial sector is being transformed by the era of digital transformation in ways different from before. It is mostly a consequence of rapid technological advancements, data-driven innovation, and changing socio-economic priorities. [2]. One of the key features of this transformation is the rise of sustainable finance, which aims to reconcile the financial systems with ecological and social needs in the long run.

Credit scoring has been one of the main tools that has helped financial institutions make decisions most efficiently for a long time [3]. In the beginning, credit scoring mechanisms were carried out manually, subjective, and largely depended on the judgment of experts. Around the 1950s, credit scoring began to be done statistically, largely due to the work of Fair Isaac and Company (FICO). The latter was one of the first standardized and most broadly adopted scoring models to introduce [4] such models. These models relied on quantitative variables, such as payment history, debt ratios, and credit utilization, to produce a numerical representation of credit risk.

On the other side, credit scoring methods that are based on traditional statistics have been less effective in the complex financial market of today. The volume of financial and behavioral customer data is growing rapidly, and models that can handle nonlinear relationships and dynamic patterns without the need for local statistical tools are required. In such a scenario, artificial intelligence (AI) and machine learning (ML) have become powerful tools for modernizing credit risk assessment. AI-driven models can uncover hidden patterns, increase prediction accuracy, and hence, decision-making becomes more time-efficient [5] By using large datasets. Nevertheless, the introduction of 'black-box' AI systems into the practice of regulated industries such as finance, where traceability, accountability, and fairness are still required, poses a major concern.

Explainable AI (XAI) has been considered a potential solution that maintains a model's predictive power while also providing transparency in response to the raised problems. The XAI-based credit risk evaluation involves the use of interpretable machine learning models and an algorithm that provides easy-to-check, comprehensible results to both decision-making agents and regulators [6]. Using statistical and ML techniques, raw financial and behavioral data can be transformed into a unified quality metric commonly known as a credit score that quantifies the probability of default or repayment capability [7]. In addition, the recent revolution in deep learning (DL) has opened new horizons for credit risk models. DL frameworks such as recurrent and convolutional neural networks are very effective in domains where data depend on time or space [8]. DL has been instrumental in business analytics and financial operations for modeling sequential data, such as transaction histories, stock prices, and macroeconomic indicators.

1.1 Organization of the paper

This research is organized in the following way: Credit risk assessment models based on AI, machine learning, deep learning, and explainable AI techniques have been reviewed in detail in Section 2. The problems of fairness and bias reduction in credit scoring are resolved in Section 3. Section 4 focuses on AI and Ethical Financial Inclusion in AI Credit Card Scoring. The summary of the literature review, along with the key findings, is outlined in Section 5. Section 6 provides final thoughts and future research suggestions.

2 RECENT ADVANCES IN AI-BASED CREDIT SCORING.

The various ML algorithms that analyze data and predict creditworthiness have been implemented to power an AI-driven credit scoring system that has undergone modifications. The main AI models are based on regression, neural networks, and ensemble methods. Conventional linear and logistic regression models identify relationships between input features and credit risk, thereby providing transparency and interpretability. At the same time, they are efficient in handling continuous and binary outcomes.

2.1 Machine Learning Models in Credit Scoring

ML techniques serve the credit scoring process to improve both predictive accuracy and decision-making capabilities [9]. Decision trees categorize borrowers by risk based on a series of factors, providing simple systems for understanding and interpretation.

2.1.1 Supervised Learning

A supervised model can only learn a mathematical function that represents the relationship between input and output if the dataset is labeled, implying that labeled datasets are the only way to train supervised models. The fundamental purpose of learning a target function for class value prediction in supervised or inductive machine learning is to achieve this. Underneath Figure 1 is the procedure for implementing supervised ML to a practical problem. Management-Oversight Machine Learning System:

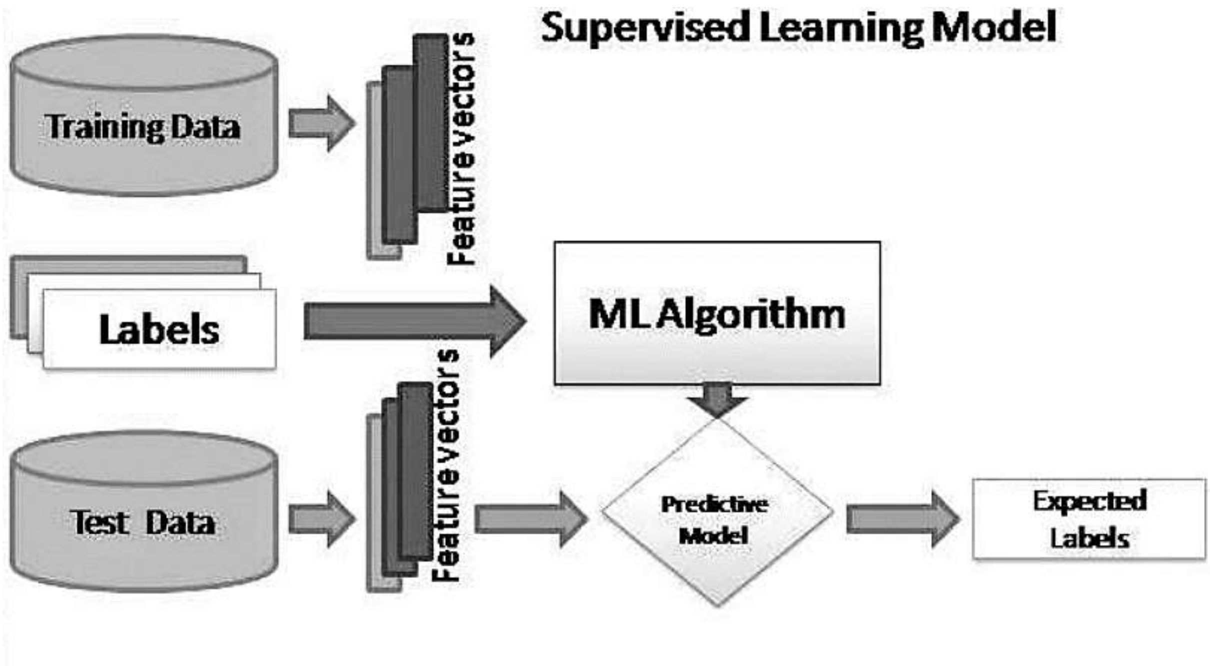

Figure 1: Supervised Machine Learning Model

2.1.2 Unsupervised and Semi-Supervised Learning

The goal of unsupervised learning is to discover groups and associations in unlabeled data rather than to predict future outcomes. Using this approach, previously unknown groups of borrowers or risk factors can be located. Semi-supervised learning achieves more accurate predictions than unsupervised approaches while remaining faster and cheaper than fully supervised learning by adding a small amount of labeled data to a large unlabeled dataset.

2.2 Deep Learning Models

DL refers to a set of techniques within ML that has been developed from the previous "shallow" learning methods. Deep learning models can autonomously create hierarchical representations of data, unlike shallow models that rely heavily on manually engineered features. This allows them to spot intricate patterns and correlations that more traditional approaches would miss [10]. Such a feature makes deep learning a very powerful tool for representing complex, nonlinear credit risk behaviors.
CNNs are a type of DL framework that have been widely used for handling spatial data in computer vision. 1D CNNs, also called time-delayed neural networks, can be used for sequential or temporal data, for example, in transaction histories or time series of financial behavior. The architecture of CNNs is derived from brain science, specifically the anatomy and function of the visual cortex, thus allowing the network to recognize hierarchical patterns in the supplied data.

Besides CNNs, other DL architectures such as RNNs, LSTMs, and Transformer-based models are being used in credit scoring to deal with sequential and structured data. These models can capture temporal dependencies, recognize subtle trends, and adapt their behavior to the new borrower data.

2.3 Hybrid and Ensemble Approaches

Hybrid and ensemble models are combinations of multiple machine learning techniques that aim to achieve higher predictive performance and robustness in credit card scoring. These strategies use the advantages of various algorithms to lessen the drawbacks of individual models and increase the accuracy of the results as a whole [11]. Hybrid Models fuse data mining methods with machine learning algorithms, which may be organizex`d in either serial or parallel configurations:

- **Serial Architectures:** Models function one after another, whereby the result of one program is used as the resource for the subsequent one. Such a method works well for descending feature extraction and classification, thus allowing more precise predictions.
- **Parallel Architectures:** Several models are run at the same time, and their results are combined by means such as majority voting, weighted averaging, or stacking. Hence, the overall system becomes more stable and robust because the ensemble compensates for the errors of individual models.

Ensemble Learning is a category of hybrid methods that merge the outputs of several models to achieve higher precision. Ensemble techniques, which combine diverse and independent algorithms, can reduce generalization error and improve prediction trustworthiness. Popular ensemble techniques in credit scoring include bagging (e.g., RF), boosting (e.g., Gradient Boosting, XGBoost), and stacking, all of which have demonstrated superior performance compared to single-model approaches. In general, when dealing with complex, non-linear data patterns or diverse client profiles, hybrid and ensemble approaches offer a more reliable and accurate framework for credit card scoring.

2.4 Use of Explainable AI (XAI) in Credit Scoring

The use of explainable AI, or XAI, in credit scoring is rapidly changing how financial institutions decide to grant credit. The traditional metrics for creditworthiness assessment, such as income, credit history, and employment status, have long been utilized in credit scoring [12]. But modern AI-powered credit scoring uses complex mathematical models fed massive datasets to search for anomalies that characterize a borrower's capacity to repay a loan. Even though these models are very accurate, they exhibit a decision-making style called a "black swan." Problems with trust, compliance, and dissatisfied customers have resulted from a lack of clarity regarding what comes next [13]. By delivering AI model clarity while maintaining prediction accuracy, XAI approaches address these challenges.

2.5 Challenges and advantages in Ai-Based Credit Scoring

Credit scoring models driven by AI have outperformed more conventional approaches across performance prediction, inclusivity, and risk management. In addition to reducing default rates and increasing the number of loans granted to applicants with little or no credit history, machine learning and deep learning models can uncover complex patterns in vast volumes of data. Traditional credit scoring systems also overlook data sources that AI may utilize, such as a user's mobile phone use, social media activity, and utility payments [14]. The impact of AI on credit scoring can be seen through the successful implementation of various case studies, especially in developing countries, where AI models have proved to be a viable means of giving credit to those who have been excluded from the financial sector [15]. For example, a fintech company in Kenya developed a model that analyzed mobile phone usage patterns —such as call volume, SMS activity, app usage, and mobile money transactions —to assess the creditworthiness of the unbanked population. However, these advantages come with some hurdles that still need to be overcome:

2.5.1 Privacy Concerns

Privacy is about controlling the release of one's personal information, and also the right to know how this information is collected, used, and shared. The usage of large volumes of personal and sensitive data without clear consent or transparency is where the problem of privacy in AI-based credit scoring arises[[16]. Because AI models need a significant amount of data for them to be able to make correct predictions, it becomes very important to collect the data ethically and obey legal rules to safeguard the rights of individuals.

2.5.2 Data Security

Data security refers to the many precautions taken to prevent data breaches, misuse, or unauthorized access. To enhance their performance, AI systems frequently combine several data sources, which in turn, exposes them to potential security threats. Therefore, technical precautions like encryption, access controls, and secure storage must be employed to not only guarantee the confidentiality but also the integrity of sensitive financial and personal information at every stage of its lifecycle [17] .

Credit scoring that incorporates AI is a revolutionary technology with the potential to improve predictive accuracy and open new markets for financial inclusion. Nevertheless, it is essential to address privacy, security, fairness, and regulatory considerations to do so responsibly and ethically.

3 FAIRNESS AND BIAS MITIGATION TECHNIQUES IN CREDIT SCORING

The Infusion of Artificial Intelligence and Machine Learning in the credit scoring system has been a game-changing development. These technologies generate data-driven insights that not only increase the precision of risk assessment but also facilitate the extension of financial inclusion. Nevertheless, these models can suffer from algorithmic bias that, if not handled appropriately, can result in unfair or discriminatory effects [18]. Bias in AI-powered credit scoring can be traced to three major sources, i.e., data, design, and deployment, and tackling these issues necessitates a mix of technical, ethical, and organizational measures [19]. For instance, Figure 2 shows the comparative effectiveness of different bias-detection and mitigation methods in AI-based credit scoring. In this work, Counterfactual Fairness and Bias Auditing reach the highest effectiveness. In contrast, Fairness Constraints obtain a relatively lower performance, thereby underlining the significance of continuous assessment and explainability in giving fair credit decisions.

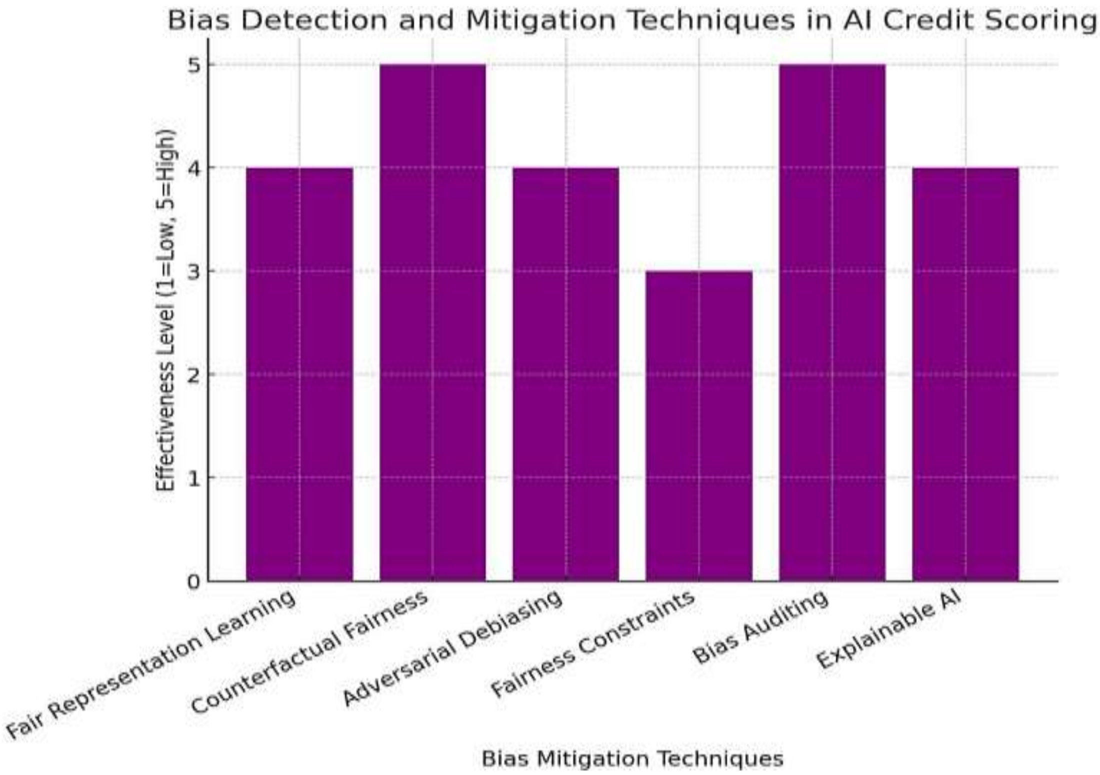

Figure 2: Bias Detection and Mitigation Techniques in AI-Credit Scoring

3.1 Sources of Bias in AI Models

Algorithmic bias is a type of discrimination that is systematic and unfair and is a result of defects in the design, data, or implementation of AI (Artificial Intelligence) systems [20]. The bias may be traced back to three major areas: data, design, and deployment.

- Data bias Bias in AI is a problem that occurs when training data does not adequately represent the diversity of the population or is based on historical quality of lines. One example is the perpetuation of systemic prejudice through the use of credit-scoring models trained on data that does not accurately reflect minority populations.

- Design bias happens when the organization or goals of an AI model implant assumptions or take that, if not checked, produce unfair results. As an example, if a fraud detection system is created to lessen false positives, it can unintentionally raise false negatives [21] without a proportional increase in the affected population, which can be those who are less privileged and depend on non-traditional financial transactions for their livelihood.
- Deployment bias occurs when the application of AI systems is different from their expected usage or when they are not adjusted to real situations. To illustrate, an AI-powered credit system used in a locality with vastly different economic conditions from those in the training data may lead to biased and unjust decisions.

3.2 Mitigation Strategies for Bias Reduction

Data diversity and quality should be seen as the very core of the effort to lower algorithm bias in artificially intelligent systems. Different datasets thus provide a far more representative training base for models, and consequently, the possibility of biased results that disproportionately affect underrepresented groups is very low. By leveraging demographic data from various regions, socio-economic backgrounds, and user behaviors, AI systems can become more generalizable across populations, resulting in fairer outcomes in financial decision-making. Innovative model design and rigorous testing procedures are major factors in the complete removal of algorithmic bias in artificial intelligence systems in challenging scenarios, particularly in the financial sector, which has high stakes. Besides making AI-driven decisions fairer and more equitable, these methods also contribute to the establishment of trust and accountability in the technological solutions offered.

3.2.1 Bias-reduction algorithms

One of the strongest instances to illustrate this is adversarial debiasing, which involves constructing AI models using adversarial networks that continuously detect and challenge bias in predictions. The adversary compels the model to find a compromise between achieving high performance and being fair to different demographic groups. Essentially, the method serves as a means to ensure that features such as race, gender, or socioeconomic status are not heavily employed to produce the results.

3.2.2 Continuous testing and validation

They are indispensable for figuring out and removing bias that is present in the entire AI life cycle. Normal testing techniques, which are usually restricted to the stages before the system is put into use, do not consider the changing nature of the data from the real world. Continuous testing means checking how well the model performs in a production environment continuously, keeping AI systems up to the task and fair when data distributions change over time.

3.2.3 Organizational Policies and Training

Organization policies and staff training are the pillars that support the raising of a culture of justice, responsibility, and openness when creating and applying AI systems. Especially the presence of internal diversity, equity, and inclusion (DEI) policies plays a significant role in not only defining the moral principles that guide the AI teams but also in influencing the entire ethical framework, Figure 3 Framework for Bias Mitigation in AI Systems, within which these teams operate. The policies mentioned above establish standards for fair AI practices and guarantee that being diverse and inclusive remain at the organization's heart.

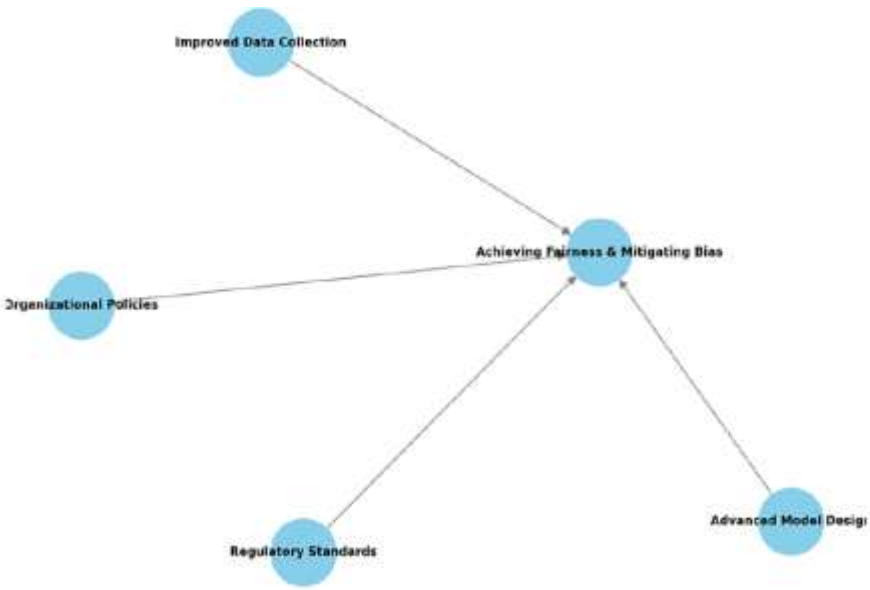

Figure 3: Framework for Bias Mitigation in AI Systems

3.3 Recent Advances in Fair AI for Credit Scoring

Recent research has identified the fairness strategies for AI-powered credit scoring that can be applied to various domains [22]. One can classify the procedures as either "pre-processing," "in-processing," or "post-processing.":

- **Pre-Processing Techniques:** These techniques emphasize changing the input data prior to model training in order to eliminate or decrease the discrimination patterns. Some examples are reweighting, resampling, and data augmentation that are used to equalize representation of demographic groups.
- **In-Processing Techniques:** These changes focus on the model's learning behavior, where fairness constraints are enforced during training. Adversarial debiasing and regularization are two methods that penalize biased forecasts when they violate fairness-aware objectives.
- **Post-Processing Techniques:** These methods are used to change the predictions or the decision thresholds in order to get fair results. A post-processing step is very helpful, for instance, in the case of a model or data that cannot be altered directly, thus it makes it possible to remove biases by means of calibration and by using fairness-aware optimization that is guided by the metric chosen.

4 AI AND ETHICAL FINANCIAL INCLUSION IN AI CREDIT CARD SCORING

Fairness, transparency, and consumer protection have been ensured by legislative frameworks put in place in response to the growth of AI-powered credit scoring. By prohibiting bias and guaranteeing personal information, the regulations aim to ensure that technical progress does not impede ethical accountability [23]. The United States has a regulation called the Equal Credit Opportunity Act (ECOA) that forbids discrimination in credit based on several characteristics and requires reasons to be provided in the event of negative outcomes, even those made by AI. Consumers have the right to access and dispute information about their credit reports under the Fair Credit Reporting Act (FCRA), and the Consumer Financial Protection Bureau (CFPB) is a staunch supporter of providing explanations for automated decision-making [6].

According to the General Data Protection Regulation (GDPR), which is part of the European Union, individuals are allowed to question decisions that have been made only by automated means, and, moreover, they should be provided with understandable explanations [24]. The European Banking Authority (EBA) guidelines on the use of machine learning in credit risk assessment, which focus on human supervision and risk mitigation, also back up this idea. Similarly, both China and India have implemented regulations that ensure that AI credit models are not just transparent but also unbiased and that they remain fair, particularly in the case of small businesses and the unbanked.

AI has limitless abilities, and one such ability can be allowing the poor to have access to credit, which is a great move towards financial inclusion. Financial companies can evaluate a person's creditworthiness without a traditional financial record by analyzing non-traditional data like mobile phone use, online shopping, and geolocation [25]. Workers in the informal sector, entrepreneurs in rural areas, women, and youth, who are usually left out by the traditional banking system, are the major beneficiaries of this new method. Several fintech platforms have been positioning themselves as future leaders in this field through their innovative AI-powered inclusive lending models that are now practical and replicable.

4.1 Real-World Implications of AI in Credit Scoring

AI has revolutionized credit scoring with its superior predictive analytics, which improve the accuracy, efficiency, and inclusivity of financial decision-making. By processing non-traditional data sources, AI-powered lenders are able to accommodate the so-called “credit invisible” or “thin-file” individuals, thus extending the access to finance to previously unbanked and marginalized groups. Besides, ethically developed AI models have the potential of lessening discrimination issues as they rely on strictly factual, data-driven variables instead of socioeconomic ones, which is in line with the principles of fairness. Furthermore, AI’s capability of handling enormous amounts of data almost instantaneously empowers financial institutions to spot very subtle trends and early-stage risks, thus leading not only to increased predictive accuracy but also to a more sophisticated and timely risk assessment approach [10]. These institutions’ readiness to quickly adapt to the ever-changing economic environment is thereby further enhanced through risk management and portfolio resilience. In effect, the credit evaluation part of loan applications, which is essentially a workflow of repetitive tasks, has been automated, thus the process of loan approvals has been greatly expedited, which is a good thing for customers as well as the institutions’ productivity [26]. Moreover, AI-compliant systems that are based on data allow for more impartiality and uniformity between different credit decisions, which in turn lessens the possibility of bias on the part of humans and increases the trust of consumers.

4.2 Case Studies and Model Simulations

This section provides real-world case studies and model simulations as evidence of the power of machine learning and alternative data in enabling more equitable credit evaluation for the underprivileged groups.

4.2.1 Case Study 1: Tala – Mobile Data for Microloans

Tala is a financial technology company that serves markets such as Kenya, the Philippines and India. Those without a traditional credit history can nevertheless get a good score by analyzing their mobile phone use, SMS information, and app installation patterns. More than 85% of the customers of the company at the time of the study had been left out of the formal financial system [27]. Although this method opens up new credit opportunities, it also raises issues of privacy and the risk of bias that may not be apparent if certain mobile behaviors happen to be associated with gender or socioeconomic status. This fact highlights that privacy protection, transparency, and fairness audits are indispensable.

4.2.2 Case Study 2: Lenddo – Social Media and Online Footprints

Creditworthiness in the Asian and Latin American markets is determined by Lenddo using less traditional digital data like social media activity, web browsing, and email metadata. Although this method allows quick onboarding of unbanked people, it creates problems related to surveillance, informed consent, and algorithmic transparency [28]. An empirical study revealed that the predictive performance was robust; however, the fairness differed among demographic subgroups. For instance, older and rural users were sometimes at a disadvantage. Hence, testing subgroup fairness is mandatory prior to implementation.

4.2.3 Model Simulation: Traditional vs. Fairness-Aware Models

Comparisons of three strategies were made through simulations on a synthetic dataset of an underprivileged community:

- Baseline logistic regression with conventional features,
- Gradient boosting with both traditional and alternative data,
- Fairness-aware adversarial debiasing incorporating fairness constraints.

One of the key results was that the demographic disparity was the largest in the boosting model, although it had the highest accuracy. The fairness-aware model kept a competitive accuracy and also was able to reduce the disparate impact by more than 30%, thus emphasizing the benefit of the integration of fairness constraints.

4.2.4 Policy Simulation: Regulatory Constraints

Simulations assessing the effect of regulatory measures, for instance, "right to explanation" mandates and demographic parity targets, showed that changes made to ensure fairness after the fact frequently lead to a decrease in accuracy. On the other hand, models that incorporated fairness-by-design features showed higher compliance and an equitable balance between performance and fairness.

5 LITERATURE OF REVIEW

Massive datasets, including not just traditional financial measures but also non-traditional data like social media activity and utility payments, are no problem for AI-driven models. In principle, these AI models sound like a great solution for banks to cut required time and increase lending accuracy. Unfortunately, that is not the full story, as these models raise important issues of being unbiased and open to public scrutiny.

Cahudhari *et al.* (2025) Customized credit scores were evaluated, which gave farmers the possibility to get loans even if they did not have formal credit histories. Two neural network models were developed and tested for the prediction of loan approval: an FNN and a DNN, with the help of data on employment, credit history, and demographics. The dataset was prepared for analysis by employing essential preprocessing procedures such as feature scaling, categorical encoding, and handling missing values. In order to avoid overfitting, both models utilized the Adam optimizer and categorical cross-entropy loss [29].

Kumbhar *et al.* (2024), The suggested approach enhances credit risk assessment, particularly for self-employed individuals, by using an RF classifier ensemble learning model on an Indian dataset of two-wheeler motorcycles. Credit line predictions with the help of ensemble learning on random forest are being used to give loan amount estimations along with risk considerations, either by considering bank statements or other financial data. The proposed system is committed to producing correct results for those who need help from financial institutions. The explainable AI graph is a great resource for openness and comprehension in AI systems, which in turn helps users to trust and interpret the model's decisions more efficiently [30].

Beeram and Suganyadevi (2024). utilizes AI techniques such as ML and statistical analysis to increase the precision and speed of credit score-based risk assessment. These algorithms, which mix past and present data, are capable of finding patterns and anomalies in credit statistics, thus resulting in better decisions for mortgage approvals and risk assessments. The utility of AI-based optimization algorithms in credit score threat assessment gives several advantages to financial institutions. First of all, it could reduce the effort and time required to acquire and examine information, thereby facilitating faster decision-making [31].

Widagdo *et al.* (2023) intended to address the requirements of investors and industry participants to quantify credit risk in a more forward-thinking manner through the use of artificial intelligence (AI) rather than conventional, non-forward-thinking methods. In this meta-analysis of nine research papers, find that analysts who must rely on AI computation to inform their decisions have a general and favourable impression of the efficacy of these applications in improving forecast power. Overall, the economy benefits from AI's improved forecasting capabilities and, when applied properly, its ability to make it easier for less fortunate people to get loans [32].

Sadok, Sakka and El Maknouzi (2022) deduces the consequences of banks' and other financing organizations' usage of artificial intelligence (AI) for credit inspection. With the rise in computational power and the special characteristics of AI models, new data sources (big data) are accessible for creditworthiness evaluations. Combining AI with huge data allows them to spot subtle indications that traditional credit scoring systems might overlook. Weak signals may indicate non-linearities or interactions among the explanatory factors that appear to enhance predictions. This impact is observed throughout the global economy, leading to estimations of positive growth rates. Deploying AI in credit analysis, on a lesser scale, has the impact of increasing financial inclusion and making it simpler for lower-income borrowers to access the market [33].

Milana and Ashta's (2021) The study depict the AI-powered financial risk identification system that comprises the key stages primarily used for the identification of financial risk and subsequently its classification by types. The established and continuing process of financial risk reduction via artificial intelligence includes multiple processes that are employed to reduce possible risk. Additionally, there is an in-depth discussion of the methods employed by AI to reduce various types of financial risk. In sum, this research delves into the speedy gains from utilizing contemporary technologies to lessen monetary hazards. Financial organizations can also employ AI-based financial risk identification and mitigation methods to precisely assess massive data sets [34].

Table 1 summarizes key studies that have applied AI and DL techniques to develop or enhance credit scoring models, including study, approach, findings, challenges and future work.

Table 1: Literature on Artificial Intelligence-Based Credit Scoring Models in Financial

Author	Study On	Approach	Key Findings	Challenges
Cahudhari et al. (2025)	Customized credit scoring for farmers without formal credit histories	FNN and DNN preprocessing, feature-scale, categorical-encoding, and missing-value handling; Adam optimizer, categorical cross-entropy loss, and early stopping.	Both models effectively predicted loan approval; enabled credit access for underserved farmers	Potential overfitting (mitigated via early stopping); limited by dataset size and quality
Kumbhar et al. (2024)	Credit risk assessment for self-employed individuals, especially two-wheeler owners	Random Forest Classifier Ensemble Learning; credit line prediction; explainable AI graphs	Ensemble learning improved accuracy in credit risk assessment; XAI graphs enhanced transparency and trust	Dependent on quality and completeness of financial data; may require more generalization across diverse populations
Beeram et.al. (2024)	AI-based credit risk assessment for mortgages	AI techniques combining machine learning and statistical analysis; historical and real-time data integration	Improved accuracy and efficiency in credit risk assessment; faster decision-making; better anomaly detection	Complexity in integrating diverse data sources; reliance on algorithm tuning and computational resources
Widagdo et al. (2023)	Forward-looking AI applications for credit risk forecasting	Literature review of nine AI studies on credit risk forecasting	AI provides better forecasting power; supports financial inclusion for underserved borrowers; positive economic implications	Understanding AI outputs may be challenging for analysts; adoption may be limited by interpretability concerns
Sadok, et.al. (2022)	AI in credit analysis for banks and financing institutions	AI models leveraging big data to capture weak signals and non-linear relationships	Improved prediction of creditworthiness; increased access to credit for underserved borrowers; positive macroeconomic impact	Data privacy concerns; reliance on quality and representativeness of big data
Milana et.al. (2021)	AI-based financial risk detection and mitigation framework	Outlined stages of AI-driven financial risk identification, classification, and mitigation using intelligent data processing	Demonstrated that AI enhances early risk detection and enables proactive risk management in finance	Lack of standardized AI risk frameworks; challenges in transparency and interpretability of complex models

6 CONCLUSION AND FUTURE WORK

Credit scoring powered by AI is a game-changer in the world of modern finance; it makes credit risk appraisal more accurate, inclusive, and efficient. Banks and other financial organizations may now evaluate complicated and non-traditional data more quickly and fairly using hybrid models, ML, and DL. The application of Explainable AI (XAI) enhances transparency and accountability, addressing the interpretability issues of black-box models. Fairness-aware algorithms and regulatory compliance frameworks ensure that credit evaluations are conducted fairly and without bias. Innovative companies like Tala and Lenddo exemplify how AI can expand credit access for the unbanked and disadvantaged. However, challenges in data privacy, security, and algorithmic bias persist, requiring continuous monitoring, fairness audits, and policy integration to build trust and encourage long-term adoption. The integration of AI ethics with innovation will shape the next era of global financial inclusion.

Future studies should focus on developing AI models that ensure interpretability and privacy protection. Additionally, embedding blockchain in data-sharing protocols will enhance security and support fairness standards, while combining XAI with federated learning and ethical governance will promote transparency and trust

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