Developing AI-powered Credit Scoring Systems for Underserved Populations

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Abstract

The rapid evolution of fintech and AI-driven credit scoring systems presents transformative potential for financial inclusion, particularly in low- and middle-income countries (LMICs) where traditional credit systems often exclude underserved populations due to reliance on collateral, formal identification, and historical financial data. This research explores how AI and machine learning (ML) leverage alternative data sources such as mobile phone usage, social media activity, and transaction histories—to assess creditworthiness, enabling lenders to uncover hidden financial reliability among underbanked groups. Case studies, including MyBucks in South Africa, demonstrate AI's efficacy in reducing default rates by 18%, highlighting its capacity to enhance lending accuracy. However, challenges persist, including algorithmic bias, lack of transparency in "black-box" models, and regulatory compliance. Ethical considerations around fairness, discrimination, and data privacy necessitate frameworks to balance innovation with equity. The study underscores the need for inclusive, interpretable AI models and collaborative efforts among policymakers, financial institutions, and regulators to ensure ethical deployment. By addressing these challenges, AI-powered credit systems can democratize financial access while mitigating risks of perpetuating systemic inequalities.[1]

Keywords

AI credit scoring, Financial inclusion, Underserved populations, Machine learning, Alternative data, Algorithmic bias, Ethical AI, Fintech innovation, Credit risk assessment, Regulatory compliance.

Introduction

The global fintech revolution has been markedly accelerating since mid-2010s, democratizing access to financial services in ways that have proved most successful in the Global North. As a crucial example, alternative lenders can often approve a loan in minutes using advanced AI algorithms, a stark contrast with traditional banks and credit unions which can require weeks to complete the same application [1]. Yet globally, and especially in low and middle-income countries (LMIC), the gains are uneven. In Tanzania, local entrepreneurs point to the difficulty of accessing credit due to a lack of access to collateral and formal identification as keys barriers to their financial inclusion. This research asks how fintech AI credit scoring algorithms can be used to uncover the hidden creditworthiness of populations that have been "traditionally underbanked" by current financial markets.

There is rapidly growing literature on how AI, in the form of machine learning credit scoring, can improve accuracy compared to human agents. This growing literature focuses in many places, though primarily in high-income countries, on the use of cutting edge AI techniques to compare human and computer accuracy on the basis of sets of commonly used historical financial indicators like previous loans and debt. Yet in LMIC and especially the Global South, traditional financial data such as credit bureau data is often hard to come by, as it is expensive to collect and is often limited and of poor quality. There is thus an opportunity and need to explore how alternative, often overlooked data sources can contribute to the construction of more accurate credit scoring systems which can better capture "soft" predictive information about repayment history that conventional credit risk analysis misses.

Scope and Significance

The credit scoring system, which is traditionally used for evaluating whether to issue financial products to a potential borrower, was not formed due to the inability to confirm the collateral or identification easily. AI technology and machine learning techniques have been innovating this situation. Scoring Profiles for Lending were generated by scraping data from the mobile phones of borrowers, who must sign a waiver for the scraping, and the data was used for credit assessments by AI technology. In South Africa, where MyBucks was previously working, the default rate on the loan portfolio was reduced by 18% in the financial year 2017/2018. Discussion implies considerable use of AI in financial markets. This research investigates the current status and future of AI-powered credit scoring systems. Credit risk is an important issue, because the issuance of loans is essentially promising to increase funds to another agent, so it is important to assess the likelihood of recovering the money. [1] discusses that people who are unable to use traditional banks for various reasons even though they have income (collectively referred to as the underbanked) are increasing in prevalence. These people have difficulty accessing traditional forms of collateral or identification widely required by creditors. Refers thus to efforts to utilize technology to find solutions to these concerns, and AI goes further, noting that there are companies that generate and sell big data by scraping the smartphone data of customers to AI, trying to make their financial profiles from there.

Traditional Credit Scoring Systems

Credit scoring models are widely used to assist lenders in consumer credit decisions. The development of alternative credit scoring systems for certain categories of individuals and the methodology used to assess and compare predictive performance are presented. The proposed credit scoring models are developed by using one of the most attractive and fastest-growing applications of data analytics and artificial intelligence (AI) - machine learning. The models are then compared with a traditional scoring mechanism that is widely used in finance, logistic regression [3]. Several findings and suggestions are reported which have significant implications for lenders and credit bureaus in emerging economies.

Access to credit is an essential springboard for people and companies in both developed and developing economies. Consumer credit, in particular, can spur economic growth and strengthen social cohesion by facilitating consumption and investment, as well as by expanding the opportunity frontier for households. To make informed loan decisions, financial intermediaries must evaluate the creditworthiness of a borrower which, when conducted in consumer markets, is commonly referred to as the credit scoring process [4]. When undertaken prudently, it is a critical device that helps the banking sector, in particular, to increase the efficiency of capital allocation by limiting the possible incidence of non-performing loans (NPLs) and personal bankruptcies. Given the increasing need for consumer credit (NPLs and personal bankruptcies in retail lending) and more than half of the global adult population unable to access savings or simple credit facilities, pushing them to utilize informal lending arrangements with strict or predatory conditions, credit scoring constitutes a paramount challenge in the current financial arena.[2]

Limitations and Biases

Credit scoring applications have a profound effect on modern society, as they speed up the repayment process of non-cash transactions and are an important factor in reducing the risk of sudden shocks in the supply-demand equilibrium of numerous businesses. The expansion of transaction types in the domestic and foreign markets has focused on the development of digital ecosystems and has become a source of significant wealth mobility. As a result, the approval process of loans in consumer credit markets has increasingly migrated from human decisions to complex algorithmic decisions. Manual assessment mechanisms based on expert knowledge of the applicant, small group samples, or rough heuristics have limitations on the considerable increase in application volume and data dimension, and recent financial regulations that want more consistent and auditable approval processes. [5]

In light of this, automatic scoring tools using various data processing tools such as decision trees, support vector machines, and neural networks have been devised to predict whether the applicant is likely to violate the repayment agreement. However, such a business reality raises questions regarding the supervision of such automated decisions. The interpretability of the models used has long been a source of concern for industry regulators. While FinTech companies consider the models used for credit scoring as proprietary information, there is demand for regulators, consumers, and subprime borrowers to provide information on why the rejection reasons arise from black-box type models. An automatic decision, even if it can be interpreted, may give different treatments to groups or certain individuals based on information asymmetry, eventually causing discrimination.[6] In general, certain financial assistance regulations explicitly cover some factors of discrimination such as race, gender, ethnicity that are not relevant to a legitimate credit operation. However, there are concerns that other unlimited commercial information from smart contracts, office furniture purchases, business mergers, participation in blockchain technology tend to give rise to discrimination against vulnerable groups such as the homeless, foreign workers, and temporary laborers. On the other hand, rich information from external information sources such as public sources and social networks can be interpreted as correlated information not directly related to a protected attribute, but having important applications such as purchasing power, reputation, and influence can be used as instrumental variables for the protected attribute.

AI and Machine Learning in Credit Scoring

The application of artificial intelligence (AI) is pivotal in making precise credit decisions, identifying emerging threats to financial institutions, as well as meeting compliance obligations. There is a recent evolution toward the use of AI and machine learning tools in the assessment and management of credit risk, among other reasons in the context of financial inclusion. The evolution of AI and machine learning has become increasingly significant in finance as well as in the management and assessment of credit risk. AI refers to the capacity of a machine to imitate intelligent human behavior through the application of advanced mathematical modeling techniques.

Existing literature shows that the integration of machine learning tools has substantially transformed the field of finance as well as the assessment and management of credit risk. Banks and other financial institutions need a risk prediction model capable of detecting individuals bearing a higher chance of defaulting on loans. With the advent of advanced machine learning techniques, it is now possible to develop highly robust machine learning models, enabling banks as well as their clients to have a better understanding of behaviors potentially detrimental to their credit scores.

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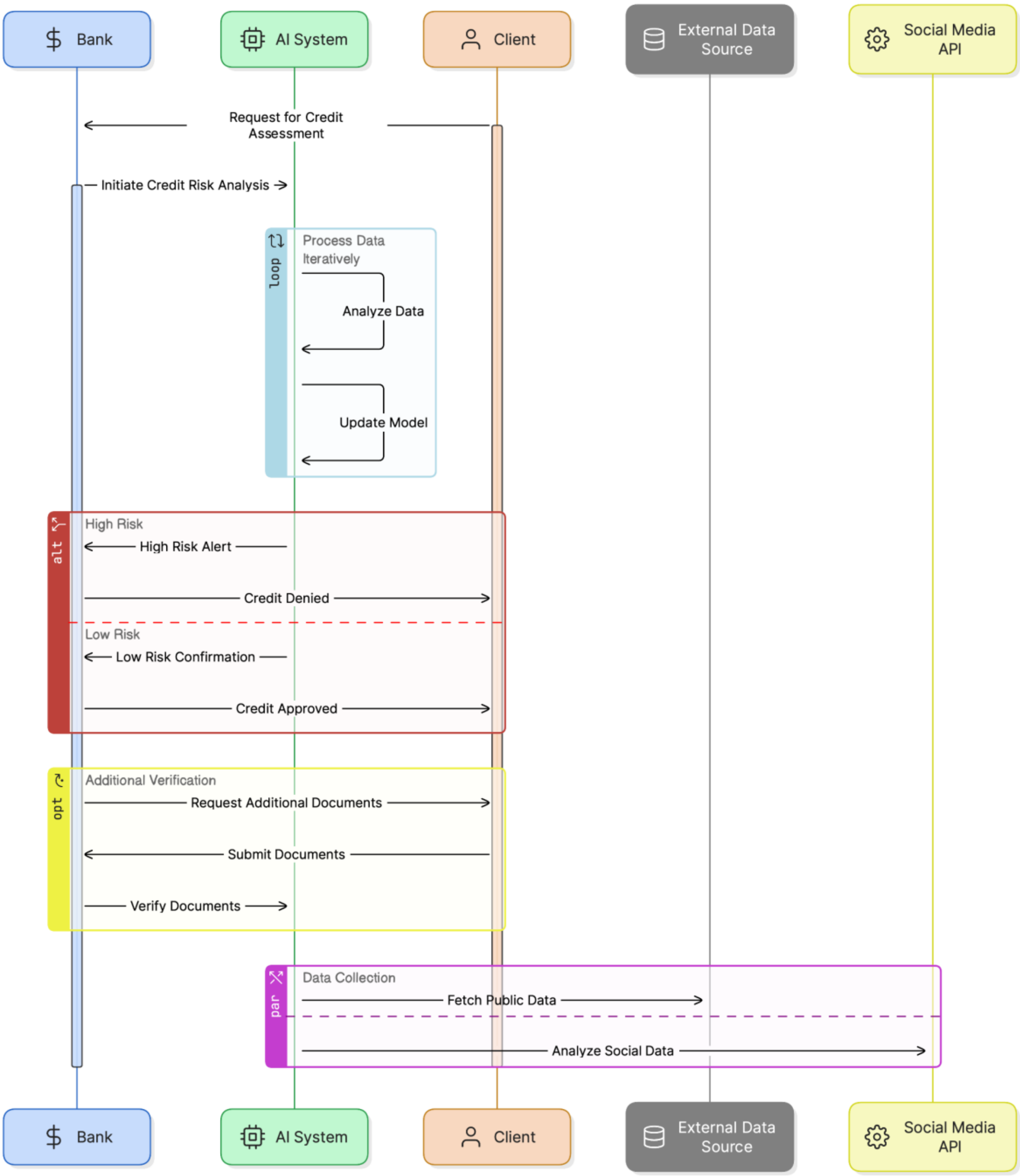

The ever-rising ease of collecting and storing vast amounts of personal data has made it increasingly simpler for banks, financial companies, as well as other enterprises to evaluate the creditworthiness of an individual or entity on the basis of data-driven machine learning models [1].

Advantages and Potential

availability of internet services, the increasing application of smartphone devices and decreasing costs of data bundles have all played a significant contribution in the growth of FinTech mobile services delivery. It also acts as an enabler for service providers to discover new territories at a more rapid pace than ever before. Moreover, strict financial regulations on the one side and increased, on the other side, an appetite for financial inclusion in some economies, e.g. reserve banks, has seen an increasing policy and industry attention been given to financial inclusion. It is an emerging challenge in the application of Machine learning (ML) and Artificial Intelligence (AI) in an assessment of credit risk and corresponding algorithms. Over the past decade, the predominantly formal sector based and multiplicative collateral factor imposed economies of large ID and traditional forms of collateral requirements on credit seekers, hence excluding individ-uals whom in general struggle to comply with such formal requirement, e.g. entrepreneurs in the informal African business sector. A greater leap of credit also goes to the financially most established, most often locked in an ivory tower, while the greater majority, the underbanked find exclusion at the bank's door. Machine learning (ML), AI and Alternative information avenues for credit risk assessment in financial inclusion age where a vast data ocean exists. The probability of the ability to repay a loan is enhanced through applying ML and AI on various data inputs, including sometimes hard to assess unstructured data such as social media data, public data on environmental factors, on personal habits, etc. on the potential borrower and/or customer [1].

Challenges and Ethical Considerations

Automatic decision making applications are becoming increasingly important and widespread. They are now used for automated decisions in a wide range of areas such as the judicial system, recruitment, police profiling, traffic surveillance, or university admission. Credit scoring applications are of particular interest to the financial sector, playing an essential role in modern society. The loan approval process is increasingly based on algorithmic decisions that are deemed to be more objective. They are perceived as being neutral to political, social, or cultural factors, and they deliver consistent decisions over time. A possible drawback is that the rationale behind the decision process is much more complex than checking whether a predefined rule applies. This may lead to a lack of transparency for non-experts, a significant drawback for the trustworthiness of such applications.

An extensive literature has emerged in recent years on the interpretability and fairness of models implemented by such decision making algorithms. The credit scoring model is used to score borrowers, and so assign them a loan decision, e.g., to grant credit with fixed characteristics, to condition the amount of the loan, or to set the lending interest rate. The regulator has to ascertain that a financial institution is not unfairly treating potential customers. This implies checking also the overall discrimination. To this end, the relative yield ratio is often computed, with a value above a certain threshold prompting a more in-depth investigation. There may be other undisclosed criteria that are also in place, but the public attention is mostly attracted by those.

Underserved Populations in Credit Markets

In banking and finance, credit risk is a major concern as it looks to assure that economic agents that are granted loans will repay them, generating monetary benefits for the creditors. This is a broad issue when assessing the creditworthiness of individuals, resulting in a wide focus on using new techniques and sources of data. Issuing a loan requires assessment of possibilities related to receiving the money back, often the most costly use of capital is lending it. Therefore, the goal is to finance risky but profitable activities and borrowers. For loans issued to individuals there is also a worry of lending to a bad customer, defined as someone who does not repay the loan taken. Banks cannot recover the face value of the loans, quickly generating losses in their balance sheets.

Literature mostly focuses on what predicts loan repayment and whether it is catching up with a high coverage of the uninsured. There is now a significant body of work exploring the impact of this intensive margin of access to credit using credit registers combined uniquely with building permits or business data. These papers do not focus on passive or observed outcomes deriving from exclusion. The primary focus is on how the ability to obtain personal credit loans shapes the investment path of firms or high productivity potential entrepreneurs shying away from limited fixed costs. This body focuses on the mechanism through which financial frictions hinder investment, employment, and possibly the emergence of financially dependent firms.

Trade credit and access to finance. Data and disparities in consumer credit present summary statistics of borrower and credit drivers in the universe of mortgage applications, analyzed annually from 1999 until 2014, making it a total of 16 cohorts. The observations reflect lender decisions on prequalifying applications, so in most cases the application pipeline follows origination of a loan in that year of application. Application year indicators are mapped to macroeconomic controls conveniently forwarded for the purpose of analysis and split according to subsequent domination of the mortgage market. MIs are characterized by dummy variables in columns and dummy variables in another column. The dependent variable is not restricted to lenders that fully originate the loans but instead features all lenders that have access to pre-applicant credit report data, accommodated by a much wider set of dummies. Standard errors are shown in parentheses. All reported estimates scale explanatory variables by their own standard deviation.

Defining Underserved Populations

Financial service providers, predominantly in the banking sector, often rely on credit scores or credit assessment systems to assess the ability of borrowers to pay back loans. However, there are a number of individuals and businesses who do not have traditional credit scores and are therefore often excluded from the market's access to credit. The inability to present a traditional credit score is a frequently cited reason why many individuals avoid banks and other financial service providers seeking quick financial help when emergency borrowing is needed [1]. The peculiar condition of underbanked individuals such as women, youth, poor rural families, and small businesses in emerging economies is well documented. Due to cultural traditions, women in Sub-Saharan Africa are expected to sign their husband's names and forego independent financial control, causing difficulty in accessing any possible credit due to low financial literacy and insecurity of legal contract. Traditional credit scores mainly rely on the presence of land or significant real assets, often priced under the ambiguous counter-market value. Hence, entities without traditional bond to show, such as small businesses, can hardly be considered as creditworthy clients exposing lenders to substantial risk. These circumstances exemplify the significant difficulty faced by the financial service providers of underbanked emerging economies in granting fair access to credit. Addressing these growing concerns in a data-rich environment, this study aims to better understand and disentangle the systemic informational bias associated with the credit assessment system to the peculiar condition of underbanked individuals and small businesses. The intent is to offer practical and straightforward guidelines for financial service providers on the application and development of credit scoring systems, as well as how some improvements can be made with the use of machine learning and artificial intelligence technologies. With a view to sustainability, the suggestions provided do not require an immoderate amount of initial resources; this is crucial for newly founded microfinance and peer-to-peer lending institutions that appear as fresh alternative to traditional banks.

Barriers to Accessing Credit

The extensive availability of new data sources and new techniques for analyzing them has the potential to greatly impact credit markets. The tools used in the consumer credit scoring process range from classical scorecards using a small number of financial characteristics to models that rely on machine learning and artificial intelligence [1]. Credit scores are used as a signal of applicant quality in high-stakes decisions involving borrowing, renting, insurance, and offers of employment. Use and reliance on credit scores are widespread, in part due to algorithmic decision-making automating screening decisions based on them. This trend is particularly visible in the United States as commercial credit scores are increasingly relied on by lenders. They are stand-ins for a host of financial characteristics important for predicting default and competition dictates that lenders use them to decide who to extend credit to. Despite their importance, credit scores and the mechanisms underlying their calculation are opaque to consumers and sometimes even to the financial institutions using them [7]. Academia and the general public often express concerns about whether credit scores contribute to disparities across social and economic groups.

The ongoing shift towards algorithmic underwriting in the US mortgage market is particularly interesting in this regard because this market is the single largest source of consumer credit and, historically, one of the most important sources of US wealth accumulation. Despite the significant development of the mortgage market, concerns persist about persistent gaps in homeownership and wealth between whites and minorities. Historically, because the operational costs and decision complexity of making a mortgage loan are high, the mortgage market is one of the last consumer credit markets where automated credit scores were used widely. Importantly, in this setting, we argue that financial institutions face high uncertainty when assessing the default risks of traditionally underbanked groups, which can exacerbate existing inequalities in the credit market.

AI Solutions for Credit Scoring in Underserved Markets

Trying to fit round pegs into the square holes of traditional credit scoring systems is a difficult task. As such, the need to develop alternative custom data and AI-powered credit risk assessment methodologies has always been pressing. The discussion in this document development of AI synthetic data generation of unlabeled data and supervised models built from custom features obtained through the analysis of non-traditional sources such as social media, bank transactions, mobile phone calls and SMS, satellite images, etc. Implementation of these scoring systems into powerful AI software is described, utilizing AI decision trees, boosting, neural networks, and methods for spotting complex nonlinear dependencies. Historically, these systems open the black box of credit scoring models and they dictate an in-depth analysis of both model and creditworthiness predictions, allowing for a profound overhaul of the credit risk assessment domain. AI solution is presented that has been deployed successfully in numerous countries custom tailored for specific underbanked segments of plenty of companies with the aim of financial inclusion. A causal inference architecture for random forest based AI operations in strategic business areas is discussed. The commercially implemented application of the said patent is described for AI intervention guidelines gleaned from the analysis of supervised models.

Key Features and Components

Financial institutions started using data-driven credit scoring as an integral part of the credit granting process. The main component of credit scoring systems (CSS) is a statistical model that captures the system's expected future good/bad applicants. The data used by a CSS to train the model is primarily made up of applicant credit reports. The main features are credit utilization ratio (CUR), payment history, etc. Additional sources of data include customer demographics, employment history, income, etc. [8]. To prepare an applicant's data for the model, different pre-processing steps are carried out, such as standardization or one hot encoding. Financial institutions moving online are developing automated CSS, which provides scalability and lessens human resources costs. Many financial institutions work on a global scale. As each country exhibits a different internal customer behaviour and social values, local financial institutions often serve the underserved population in such a credit export. Consequently, models built abroad usually perform poorly. Developing a CSS for such populations is crucially important in the scope of responsible and ethics in credit provision [9]. Including less data, developing techniques that disregard the data distribution, missing values imputation, and alternative credit reporting (ACR) are common features of the data. Traditional statistical models do not perform well on such data, thus creating the need for more advanced models. Backward selection is used to train the best statistical model, the application score is calculated as model-specific instalments-to-net-income (I/T) ratio, and the explainability of the CSS is thoroughly analyzed. To facilitate future research on this topic, the application form of the automized system is described in detail.

Case Studies and Best Practices

Access to fair consumer credit has an important impact on individuals, households, and the wider economy. While credit is an indispensable ingredient for economic development and well-being, it remains an underserved segment in many countries, especially among the most vulnerable and marginalized populations. Credit scoring is the most common credit assessment technique used by lenders worldwide. Following the digitization of finance, AI-powered credit scoring technologies are commonly used with the promise of eliminating human biases.

An interdisciplinary critical analytical review of AI-powered credit scoring was conducted, with a particular focus on serving the interests of underserved populations. This review aims to translate academic scholarship into actionable insights for key stakeholders such as policymakers, regulators, lenders, academics, and nongovernmental organizations. It brings the discussion on AI-powered credit scoring closer to civil society, welfares, and consumer advocacy groups, which are often excluded from these debates. Central to the endeavor are consumer protection and fairness considerations, leading to a re-consideration of algorithmic fairness from a broader perspective beyond technical benchmarking [5].

The discussion draws on insights from technical, legal, and policy scholarship. It is ultimately suggested a set of data-based best practices for the fair design and enforcement of AI-powered credit scoring systems, especially in the interest of underserved population. The second part of the discussion provides a critical review of recent academic scholarship on AI-powered credit scoring from the unique perspective of serving the interests of underrepresented and marginalized population.

Ethical and Regulatory Considerations

As AI and machine learning techniques are increasingly widespread among financial institutions, it is of paramount importance to scrutinize the ethical impact that the credit scoring algorithmic decisions may have on sensitive/vulnerable groups [5]. Ironically, the ongoing public concerns on the issue are mainly focused on the new machine learning algorithms, which are less opaque than the old-fashioned techniques, such as linear models. A consistent pressure aimed at the enforcement of the "right to explanation" to foster the deployment of novel credit scoring algorithms could elicit perverse effects and much worse outcomes for the most vulnerable, as the logistic regression is widely known to be significantly less affected by the Simpson's Paradox as opposed to more complex decision trees or black box models. At the same time, an overestimation of the interpretability of primitive credit scoring systems could lead to a discount of real improvements and a biased self-denial of the advantages of the new predictive-aware paradigm. The new data-driven credit scoring methods are designed to be more accurate than earlier approaches, while preserving, and often increasing, the fairness over different demographic groups. They do not require to use sensitive attributes, aiming to avoid direct discrimination, and are more resilient to non-sensitive attributes that could be used to infer the sensitive ones. With a strong reliance on data, the model is more likely to consider diverse borrowers so to improve its performance. The advantages of the new credit scoring methodology over earlier ones are enabled by technology, specifically the widespread availability of data that paint an adequate picture for credit scoring without using sensitive attributes. Given a model, it is practical to use many combinations of non-sensitive attributes to gauge the effect of them towards the sensitive one.

Fairness and Bias Mitigation

By assessing the creditworthiness of loan applicants, financial institutions are able to evaluate which applicants have a high likelihood of repaying their debts. As data-driven approaches have become increasingly popular in evaluating loan applications, machine learning presents the opportunity of assessing a large range of features, patterns and relationships that human experts would otherwise oversee. Although the effectiveness of machine learning in this context has been demonstrated for a long time, recently there has been an increase in concern over whether such automated decision-making processes as a whole may result in unequal treatment among different groups, potentially leading to discriminatory outcomes. This is highlighted by its growing body of scholarly work, as well as by a series of legal instruments regulating the use of machine learning in various decision-making processes [5]. As an example of this, in the US, the Equal Credit Opportunity Act and the Fair Credit Reporting Act regulate the use of credit scores for any form of lending.

Substantially less attention has been paid to methods that mitigate bias in conjunction with fairness metrics. To date, these methods, promoted by a series of studies in the machine learning community, have been solely evaluated in terms of their effectiveness across various fairness metrics. This paper extends the scope of this research by comprehensively evaluating bias mitigation methods in terms of their effectiveness across a set of commonly-used fairness metrics, while also assessing their accuracy and potential profitability for financial institutions, in a controlled experimental setting. Concerning bias mitigation methods, this paper identifies challenges associated with achieving fairness while maintaining accuracy and profitability and highlights both the most and the least successful mitigation methods. Finally, the research serves to bridge the gap between experimental machine learning studies, with a focus on correctly evaluating algorithms, and its practical applications in the finance industry.

Compliance with Legal Frameworks

Complex machine learning (ML) algorithms are increasingly deployed in applications with high stakes, such as hiring decisions, judicial proceedings and credit scoring. In the US and Europe, ML models are proliferating rapidly in credit markets, faced with critical debate on their impact during the recent COVID-19 crisis. On the one hand, ML is expected to fine-tune credit assessment and enable financial services in hard-to-serve populations, as it is being attempted in digital and branchless banking in the developing world. Yet strong concerns have emerged on the fairness of such opaque scoring models, especially towards disadvantaged groups [6]. Discrimination can result from the training data, when it historically perpetuates unequal treatment towards qualified applicants, and from the model specification, when it assigns unfavorable predictions to similar individuals, as demonstrated mostly on proprietary data. Litigation and bad media attention can stem from referee models, despite their efficiency, thus their interpretability may become profitable. Meanwhile, high legal and regulatory uncertainties around ML models impede financial service providers to innovate and invest in new screening technologies. Lenders—who are, with the model-developing tech companies, the focus of lawsuits—frequently lack a clear view on how to prove that their opaque models output fair results, once they cease to provide statistical assessments from. The US Supreme Court has twice declined to define whether and how the Equal Credit Opportunity Act (ECOA) is implied to scoring. In the tech industry, the key reasons for not expanding ML to important products are related to unfair algorithm outcomes, and yet there are no regulatory obligations for the merely utilization of black box algorithms. Consequently, despite out-of-sample experiments exploring precise, practical implications of grade design, implementation may have to be quiet because of substantial legal risks. The last two decades also saw banks and financial startups in the EU reluctant to adopt high-performing ML algorithms they had developed in the anticipation of stringent provisions around transparency, as in the General Data Protection Regulation (GDPR). Effort should be devoted to provide a more comprehensive and empirical understanding of the fairness of ML scoring technologies in large, public data and innovative modeling [5]. Thereof, a methodology enabling to formally test the null hypothesis of fairness at the model's application level is proposed. Such a framework may also be of the interest of lenders as well as regulatory bodies when an alternative credit scoring model, that happens to be opaque. It may help them to identify important factors contributing to an unfair downgrading, and allow them to accurately assess a suspicious model from a small subset of account applications, which the proprietary assessment does not provide for. Industries seek technically based guidelines with which to assess trade-offs between fairness and other product performance metrics established by industry-driven initiatives for manufacturers of image-based credit-scoring technologies. They aim to develop an imbalanced data processor for ML models trained on digital footprints from which lenders can red flag, for further interpretation, any form of group discrimination at marginal cost. Nearly 40% of the American population have low or no credit score. Machine learning algorithms, by training on a wide set of predictors such as detailed bank transactions, may provide a more comprehensive assessment of their creditworthiness. These applicants are therefore generally rejected by baseline scorecards for lack of sufficient financial information and instead get the opportunity to explain their credit history through a conversation and additional, alternative evidence. The competitive settings engenders 300 million refusals post-campaign. At the same time, while machine learning technologies have allowed banks to gradually lower their minimum profitable amount account packet; however, the Explainable AI (XAI) tools are scarce in fintech due to strong competitive advantage reasons of opacity. In the recent rulings, the European Court of Justice has qualified as a likely sentence the French bank BPCE for deploying opaque algorithms that oversee the downgrading of mortgage applications whose merit can be demonstrated by the use of only a limited set of fuzzy rules output by a rival modeling approach. New guidelines and tools to red flag discrimination appear against a general background of in its use in the financial sector: the so-called black-box banking recession debate in the US Congress.

Conclusion:

The study was aimed at providing an overview of the application of artificial intelligence (AI) in credit risk assessment and the credit decision-making process. Digital financial services and AI-powered credit scoring systems can modernize and increase efficiency in the credit process. However, when using AI-powered credit scoring systems, some necessary precautions should be taken into consideration to avoid potential negative implications on underserved populations. The research questioned and later analyzed how the use of AI-powered credit scoring systems can impact credit risk assessment and credit decisions in a potential negative manner. As a result of data mining and experiments, it was found that the scoring systems of fintechs rated borrowers faster, and the same borrower was rated more favorably by financial institutions with comparable predictive performance [1]. There was considerable underbanked growth across the globe in 2020. In line with EU conjectures, the most populous nation-state in Eastern Europe and the Balkans, Turkey, has seen a substantial decline in bank credit-to-GDP in both retail loans and general-purpose loans since 2016. In parallel, digital finance, the pilot fintech commercial instrument, saw rapid emergence of AI-powered credit scoring systems in the open market. Observing free versions of such systems outdated by various fintechs, financial institutions that offer only an integrated credit product also started to use AI-powered credit scoring systems.

References:

[1] D. Mhlanga, "Financial inclusion in emerging economies: The application of Machine learning and artificial Intelligence in Credit Risk assessment," 2021. [PDF]

[2] D. C. Hsia, "Credit Scoring and the Equal Credit Opportunity Act," 1978. [PDF]

[3] H. Abdou and M. Tsafack, "Forecasting creditworthiness in retail banking: a comparison of cascade correlation neural networks, CART and logistic regression scoring models," 1970. [PDF]

[4] O. Koc, O. Ugur, and A. Sevtap Kestel, "The Impact of Feature Selection and Transformation on Machine Learning Methods in Determining the Credit Scoring," 2023. [PDF]

[5] D. Moldovan, "Algorithmic decision making methods for fair credit scoring," 2022. [PDF]

[6] C. Hurlin, C. Pérignon, and S. Saurin, "The Fairness of Credit Scoring Models," 2022. [PDF]

[7] L. Blattner and S. Nelson, "How Costly is Noise? Data and Disparities in Consumer Credit," 2021. [PDF]

[8] A. El Qadi, N. Diaz-Rodriguez, M. Trocan, and T. Frossard, "Explaining Credit Risk Scoring through Feature Contribution Alignment with Expert Risk Analysts," 2021. [PDF]

[9] S. Albanesi and D. F. Vamossy, "Predicting Consumer Default: A Deep Learning Approach," 2019. [PDF]