Application and effectiveness of artificial intelligence in credit assessment

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Abstract: This article examines the application and effectiveness of artificial intelligence in credit assessment. The article first describes the emergence of artificial intelligence in the financial sector and then examines the limitations of traditional credit scoring methods, including data limitations, human biases and accuracy issues. The importance of credit assessment is then highlighted. The application of artificial intelligence to credit assessment is then examined in detail, including machine learning, natural language processing and block-chain technology. The impact of AI on credit assessment is then analysed, including improved accuracy, reduced bias and increased efficiency. Next, the article describes the challenges and risks faced, including data privacy, interpretation issues and reputational risk. Finally, the article discusses future trends, including the proliferation of artificial intelligence tools, evolving regulatory frameworks and the application of deep learning. These trends will continue to shape the financial sector and create opportunities and challenges for the financial system and borrowers.

1. Introductory

The emergence of Artificial Intelligence (AI) has attracted a great deal of attention and investment globally. In recent years, breakthroughs in AI technology, particularly in the areas of deep learning and big data analytics, have sparked a revolution in many industries, including finance. Financial organisations are increasingly aware that AI is not only a technological trend, but also an inevitable choice to remain competitive and improve customer service. In the financial sector, the use of AI has been rapidly gaining popularity in a number of areas, including risk management, portfolio management, customer service and credit assessment.

Credit scoring also plays a key role in maintaining economic stability; correct credit scoring reduces the risk of default and maintains the health of the financial system. With more accurate credit scores, financial institutions are able to extend credit to people without a traditional credit history, thereby improving access to financial services and contributing to socio-economic development[1]. The goal of our study is to understand how AI techniques can be used to improve credit assessment methods and to assess the effectiveness of these methods in improving the accuracy, fairness and efficiency of credit assessment.

2. Limitations of traditional credit assessment methods

2.1 Definition of traditional credit assessment methods

Traditional credit assessment is a financial practice designed to assess the credit risk of an individual or entity, i.e. the ability and willingness of a borrower to repay a loan or fulfil a contractual obligation on time. It usually involves assessing and analysing the borrower's credit history, financial situation, sources of income and repayment record. The purpose of a traditional credit assessment is to help financial institutions, credit card companies, lenders and other financial service providers make informed credit decisions and ensure that their borrowers have the ability to fulfil their financial commitments. It relies on traditional credit reports and credit scores that are rated based on an individual's credit history and financial activity. Credit reports include information such as a borrower's borrowing history, credit card usage, repayment history, outstanding debt, and number of

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open credit accounts. Credit scores, on the other hand, are scores calculated from this information and are used to measure a person's credit risk.

2.2 Dependence on limited data sources

Traditional credit assessment methods typically rely on limited data sources, primarily historical credit reports and credit scores. The drawbacks of these data sources are obvious, as they do not provide complete information about the customer. Financial information is incomplete, and historical credit reports typically contain only information about the borrower's interactions with the financial institution, such as loans, repayments and late payments. While this information is important, it does not provide a complete picture of the borrower's financial situation. For example, it does not include information about the borrower's assets, investment portfolio, real estate, other financial commitments, and other information that is important for assessing credit risk. In addition, the traditional approach does not take into account the vast amount of other data available, such as a customer's employment history, educational background, social media activity, etc[2]. Reliance on limited data sources is also unsuitable for new forms of finance such as P2P and cryptocurrency lending, which lack relevant historical data.Most importantly, traditional methods often fail to generate personalised scores that fully take into account the unique circumstances of each borrower, which can lead to unfair credit scoring and financial inequality. These shortcomings highlight the importance of employing artificial intelligence and other data sources to improve the accuracy and fairness of credit scoring.

2.2 Susceptible to human bias

A significant problem in traditional credit assessment methods is their susceptibility to human bias. Assessors may be influenced by individual differences, race, gender, age, etc., which can create unfair bias in assessing borrowers. E.g., blind trials: in a well-known blind trial, researchers showed participants two photographs, one of a white male and the other of a non-white male. They then asked participants about their credit risk assessment of the two males. The results showed that despite the two males having the same credit history, many participants were more inclined to perceive the non-white male as a higher credit risk, demonstrating the existence of ethnic bias. Gender Bias Experiment: Researchers conducted an experiment in which bankers were shown identical loan applications, only the gender of the borrower was changed to male or female. The results showed that when borrowers were identified as female, they were more likely to be denied or receive a higher interest rate, despite being in the same financial situation. These biases may lead to unnecessary loan denials or high interest rates, harming the financial interests of borrowers and generating unfair controversy in the community.

Individual differences and subjectivity are a central concern. Traditional credit assessment methods often rely on the subjective judgement of the assessor, which makes the assessment vulnerable to individual differences. Different assessors may make different decisions on the same credit application, which may lead to unfair results.

In addition, research has shown that race and gender biases exist in traditional credit assessment methods. A borrower's race and gender may influence an assessor's decision-making, resulting in certain groups being more likely to be denied or receive unfavourable loan terms. Similarly, age and income level may trigger bias, making younger, older, or lower-income groups more vulnerable to discrimination.

Social and cultural factors are also not adequately taken into account, with traditional methods often failing to reflect differences in borrowing habits and repayment capacity among different social groups. The introduction of AI technology can help mitigate the impact of these human biases as AI assessments are based on data and algorithms that are more objective and fairer.AI is not influenced by personal emotions or subjective factors, and can make decisions based on objective data, thus improving the fairness of credit assessments[3]. This not only helps borrowers get a fairer deal, but also enhances the stability and sustainability of the financial system.

2.3 Limited prediction accuracy

Another notable limitation of traditional credit assessment methods is their limited predictive accuracy, especially in situations of economic instability or dramatic market changes. These methods are usually based on historical data and cannot predict future credit risk well. This limited accuracy is manifested in the following aspects:

(1) Traditional valuation methods usually rely on past credit history data, which may be outdated. In a rapidly changing economic environment, real-time data is critical to accurately assess credit risk. However, it is difficult for traditional methods to access and analyse real-time data.

(2) Financial markets can change dramatically in a short period of time, such as financial crises or industry changes. Traditional methods often fail to adapt quickly to these changes because their models are built on relatively stable historical data.

(3) Traditional methods usually fail to take into account the impact of external factors on credit risk. For example, natural disasters, political events or global economic trends can have a significant impact on a borrower's credit profile, but traditional methods struggle to capture these factors.

(4) There may be complex non-linear relationships between factors in credit assessment, which traditional methods fail to adequately take into account. This leads to inaccurate prediction of credit risk, especially in complex financial products and transactions.

The predictive accuracy of traditional credit assessment methods is usually measured by the evaluation of credit score models. These models use historical credit data and other financial information to predict the likelihood of a borrower defaulting in the future. Common metrics used to evaluate these models include:

FICO Score: The FICO Score is a commonly used credit assessment model with scores typically ranging from 300 to 850.Higher scores indicate lower credit risk, while lower scores indicate higher risk. The predictive accuracy of an assessment model is usually measured by the accuracy of the FICO score and the prediction of whether the borrower will default.

AUC-ROC Curve: area under the receiver operating characteristic curve (AUC-ROC) is another common metric. It measures the trade-off between the model's true case rate and false positive case rate at different thresholds.The closer the AUC-ROC value is to 1, the better the model's performance.

Confusion matrix: the confusion matrix includes the number of true cases, false positive cases, true negative cases and false negative cases, which can be used to calculate the model's precision, recall, F1 score and other metrics [4].

AI can improve the predictive accuracy of traditional credit assessment methods many times over, and the exact multiplier or order of magnitude of improvement may vary depending on the AI model used, the quality of the data, the specific task, and the business context. Overall, however, the use of AI in credit assessment typically achieves significant predictive accuracy improvements, thereby providing financial institutions with more reliable credit assessment tools that can help reduce the risk of non-performing loans and improve the accuracy of lending decisions. This is because AI can handle large-scale unstructured data and utilise complex algorithms for pattern recognition and data analysis to more accurately predict a borrower's credit risk.AI models can take into account a wider range of features, including social media data, online shopping habits, device usage information, etc., which cannot be effectively utilised by traditional models. In addition, AI is able to update the model in real time to reflect the borrower's latest behaviour and credit status, improving the accuracy of dynamic credit assessment.

Introducing AI technology can improve the predictive accuracy of credit assessments.AI models can handle large-scale, real-time data and use sophisticated algorithms to uncover non-linear relationships between data. This allows AI to better respond to market changes and external factors and improve the accuracy of credit risk predictions. By combining traditional and emerging data sources, such as social media activity and consumer behaviour, AI can also provide a more comprehensive picture of the customer, helping to assess credit risk more accurately. Improving forecast accuracy is therefore a key motivation for introducing AI technology to improve credit assessment methods.

3. Application of Artificial Intelligence in Credit Assessment

3.1 Machine Learning Algorithms

The use of machine learning algorithms in credit assessment has become an important trend in the financial world, and they provide a powerful tool for improving the accuracy, efficiency and fairness of credit assessments[5]. The key applications of machine learning in credit assessment are the following:

(1) Feature engineering and data mining

The success of machine learning models relies on appropriate feature selection and engineering, as well as deep data mining. Financial institutions can use machine learning to discover new features relevant to credit risk, such as a customer's social media activity, online shopping habits or mobile app usage. This helps build richer credit assessment models.

(2) Model automation and migration learning

Machine learning models have the ability to learn and adapt automatically to new data. This enables financial institutions to continuously improve their credit assessment models to adapt to market changes and emerging risk factors. Migration learning can also be used for credit assessment across different markets and product types, thus increasing the generalisability of models.

(3) Risk Scoring Models

Machine learning models can build more accurate risk scoring models for predicting a borrower's probability of default. These models can better identify high-risk borrowers and offer more favourable loan terms to low-risk borrowers, thereby reducing credit risk.

(4) Real-time decision support

Machine learning models can analyse data in real time and provide real-time decision support to financial institutions. This means that loan decisions can be made in seconds, speeding up the loan approval process while ensuring accuracy.

3.2 Natural Language Processing (NLP) for Credit Report Analysis

The application of Natural Language Processing (NLP) technology in credit assessment, especially in analysing credit reports[6], has had a significant impact.The main applications of NLP in credit assessment are in the following areas:

(1) Sentiment Analysis

NLP can analyse the text in a credit report to capture the sentiment and tone of voice within it. This is essential for understanding the borrower's credit behaviour and attitude. For example, by analysing the annotations of credit card statements in a credit report, it is possible to detect any malicious attempts to avoid repayment or any signs of financial difficulties.

(2) Credit Report Verification

NLP can help verify the accuracy of credit reports. It can automatically compare the information in a credit report with information from other sources, such as financial documents, tax records or employer confirmations. This helps detect false information or fraud.

(3) Text summarisation and tagging

NLP can automatically generate a summary of a credit report, providing a quicker and more concise way to understand the key elements of the report. In addition, NLP can tag the text to categorise different parts of the information, making it easier for machines and humans to understand.

(4) Risk factor identification

NLP technology can help financial institutions identify risk factors in credit reports. It can automatically detect keywords or phrases that indicate potential loan default risks. For example, if there are frequent default, delinquency or bankruptcy-related words in a credit report, NLP can warn of the risk.

For example, LendingClub is an online lending platform that uses NLP technology to analyse borrowers' online social media activity and public information. They use NLP to identify a borrower's social media posts, comments, and articles to get more information about the borrower's creditworthiness. According to LendingClub, they have improved their loan approval rates through NLP technology. Specifically, they found that by analysing borrowers' online social media data, they increased their loan approval rates by about 15 percent. This meant that more borrowers were able to get loan approvals, which improved the borrower's chances of getting financing. The Credit evaluation model is shown in figure 1:

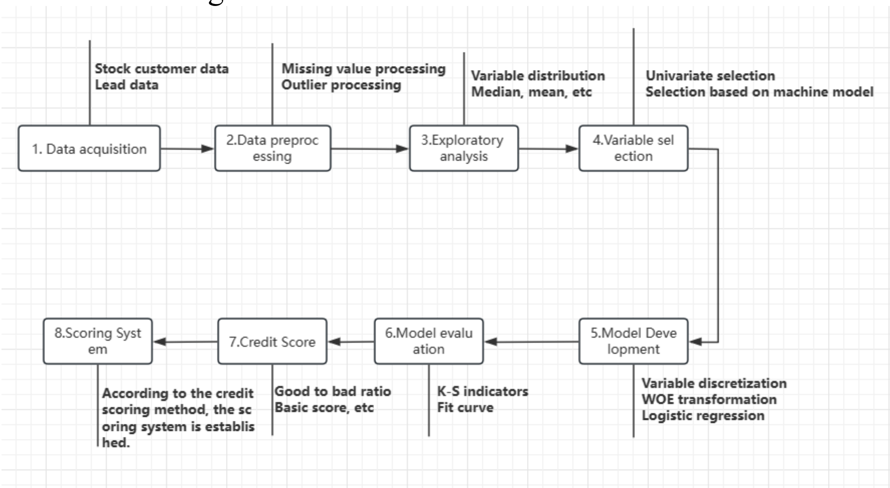

Figure 1 Credit evaluation model

3.3 Application of Blockchain Technology

The application of blockchain technology in the field of credit assessment has the potential to improve the transparency, security and credibility of credit assessment. There are several aspects about the application of blockchain technology in the field of credit assessment:

(1) Secure storage of credit history records

Blockchain can provide secure distributed storage for storing borrowers' credit history records. These records can include not only information from traditional credit reports, but also other financial transactions and credit-related data. This ensures the integrity and immutability of credit history records.

(2) Decentralised authentication

Blockchain can be used for decentralised identity verification, giving borrowers greater control over their personal identity and credit information. This helps to reduce identity theft and fraud while improving data privacy and security.

(3) Smart Contracts

Smart contracts on the blockchain automate credit agreements, automatically releasing funds or performing other actions based on predetermined conditions. This reduces the need for third-party intermediaries, improves the efficiency of transactions, and reduces operational risk.

(4) Transparency in credit assessment

Blockchain provides complete transparency in the credit assessment process, where all transactions and decisions can be recorded on a tamper-proof blockchain. This helps regulators to better monitor the credit assessment practices of financial institutions and ensure compliance.

4. Effectiveness of Artificial Intelligence in Credit Assessment

4.1 Improved the accuracy of credit assessment

The use of Artificial Intelligence has significantly improved the accuracy of credit assessments.AI models can process large-scale data, including traditional and non-traditional credit-related information, to provide a more comprehensive picture of the customer[7]. This comprehensiveness helps to more accurately assess a borrower's credit risk. In addition, machine learning algorithms can uncover complex relationships between data and identify hidden patterns, which improves the accuracy of predictions. By applying big data analytics and machine learning to credit assessment, financial institutions are able to better identify high-risk borrowers and reduce the risk of default, as well as improve credit availability to low-risk borrowers, thereby reducing lending rates.

4.2 Reduced human bias in credit assessment

Traditional credit assessment methods are susceptible to human bias, leading to unfair credit assessments. The introduction of Artificial Intelligence (AI) has helped to reduce this bias.AI assessments are based on objective data and algorithms and are not influenced by individual differences in assessors, race, gender or other subjective factors. This makes credit assessments fairer and does not discriminate against specific groups, helping to reduce financial inequality. By ensuring fair credit assessments, AI helps the financial system better serve all groups and improves the sustainability of the financial system.

4.3 Improved the efficiency of credit assessment

The application of AI also improves the efficiency of credit assessment. Traditional manual assessment methods are usually time-consuming and cumbersome, requiring a lot of human resources. AI, on the other hand, can automate many appraisal tasks, thus speeding up the loan approval process. Machine learning models can analyse large amounts of data in real time, providing financial institutions with rapid decision support. This not only improves the customer experience, but also reduces the operating costs of financial institutions.

4.4 Practical Case Analysis

Take the example of Kreditech, a German fintech company that focuses on providing loan services to those who cannot be covered by traditional credit assessment methods. They use machine learning and big data analytics to improve the credit assessment process.

Problem: Traditional credit assessment methods were facing serious challenges in certain markets because most borrowers lacked a traditional credit history, resulting in many creditworthy borrowers not being able to obtain loans.

Solution: Kreditech took an innovative approach that leveraged big data and machine learning. They analysed a large amount of non-traditional data, including borrowers' social media activity, online shopping habits, mobile phone usage patterns and more. By analysing this non-traditional data, they build highly personalised credit assessment models. These models can more accurately predict the credit risk of borrowers, especially those without a traditional credit history.

RESULTS: Kreditech's innovative approach was a remarkable success. They were able to lend to more borrowers, especially those that traditional banks might have rejected. Their default rate was significantly lower compared to traditional credit assessment methods, while increasing loan availability. This success story demonstrates the real-world effectiveness of machine learning and big data analytics in improving credit assessment and provides an example of innovation in the fintech space. The application of Artificial Intelligence in the field of credit assessment is shown in figure 2:

Figure 2 The application of Artificial Intelligence in the field of credit assessment

5. Strategies to Address Challenges and Risks

5.1 Strategies for Coping with Data Privacy and Security Issues

Data privacy and security issues are particularly important in AI applications, especially when it comes to sensitive financial data. The primary strategy for addressing these issues is to ensure compliance and regulatory compliance. Financial institutions and enterprises should have a thorough understanding of international, national, and regional data privacy and security regulations, such as the GDPR in Europe, the CCPA in the U.S., and other similar regulations. Understanding the requirements of these regulations is fundamental to ensuring compliance. Assemble a dedicated compliance team to oversee and manage data privacy and security matters. This team should consist of regulation experts, legal counsel, information security specialists, and data protection officers, among others, to ensure immediate response to regulatory changes. This team is supposed to develop a clear privacy policy to detail the collection, storage, processing, and application purpose of data. Firstly, it aims to ensure the policy is easy to understand and clearly informs users how their data will be used, review contracts with third-party data providers, data processors and other partners, ensure that these contracts include compliance clauses for data privacy and security; secondly, updates them as needed, categorise and label different types of data to ensure that sensitive data is appropriately protected; thirdly,establish an access control and permissions system that restricts access to sensitive data to authorised employees only; fourthly,develop real-time monitoring and auditing systems to track data access, usage and transmission, identify and respond to potential data security threats in a timely manner, use strong data encryption, both in data transmission and data storage, to protect data from unauthorised access; fifthly,conduct regular data privacy and security training for employees to educate them on the proper handling of sensitive data and identify potential risks; finally, conduct regular risk assessments to identify possible threats and vulnerabilities and establish contingency plans to respond to data breaches or security incidents, and comply with data breach notification regulations to ensure that regulators and users are provided with timely notification and appropriate corrective actions are taken in the event of a data breach. Compliance and regulatory compliance are key to ensuring data privacy and security, while also helping to maintain the reputation of the organisation. Financial institutions and businesses need to continually update their compliance strategies to adapt to the evolution of regulations and emerging data privacy challenges.

5.2 Interpretive vs. Interpretable Response Strategies

The use of interpretable AI models in credit assessment is one of the key strategies to address interpretability and explainability challenges. These models can provide a clearer and more transparent decision-making process and help users and regulators understand assessment results. Because the decision-making process for these models is easier to explain and understand, thus AI models that are more interpretable, such as decision trees, linear regression, logistic regression, or rule-based models, are prioritised, and a feature importance analysis tool is used to help users understand how much attention the model pays to different features. This helps in identifying which factors influence the final evaluation results. Local interpretable methods such as LIME (Local Interpretable Model Interpretation) or SHAP (SHapley Additive exPlanations) are used to explain the reasons for individual decisions. These methods can provide explanations for each specific assessment result. Using visualisation tools and graphical interfaces, the decision-making process of the model is presented visually to the user and assessor. This helps users to better understand how the model works. If rules or weighting methods are used to make decisions, ensure that these rules and weightings are transparent and can be explained to users and regulators. Train assessors and regulators so they can understand and explain how AI models work. Provide regular training and resources to strengthen their capacity. Explainable AI models help to increase the credibility and acceptance of the model, as users and regulators can more easily understand the model's decision-making process. Financial institutions should consider these strategies to ensure that their credit assessment models are sufficiently interpretable.

5.3 Reputational risk response strategies

Reputational risk is one of the challenges that financial institutions need to pay special attention to when using AI in credit assessment. Establishing a quality control and monitoring system is one of the key strategies to address reputational risk. Developing a precise quality control process, including data quality, model, and result validation, can ensure data accuracy and enhance model credibility. Establish monitoring metrics to track model performance and results in real time. These metrics can include accuracy, bias, error rate, etc. Utilising automated tools and algorithms to monitor model output can help detect anomalies or biases, thus mitigating reputational risk. Establishing an anomaly detection system for identifying unusual model behaviour or predictive results is crucial. They are taking timely corrective action if anomalies occur. Track the actual results of the model and compare them with the model's predictions. Take immediate action if inconsistent or misleading results arise. Regular internal audits should examine how the model works and the decision-making process to help identify potential problems and make improvements. Considering an external audit in which an independent third-party organisation assesses the quality and compliance of the model. External audits can enhance the credibility of the model. If problems or anomalies are identified, corrective actions are taken in a timely manner and the model's performance and processes are continually improved. Establishing a quality control and monitoring system is an important step in maintaining reputation. Financial institutions should ensure that their models are always operating at a high quality and are able to respond quickly to any potential problems.

6. Conclusion

The use of AI in credit assessment has already led to significant changes, improving accuracy, reducing human bias, increasing efficiency, and providing greater opportunities for financial institutions and borrowers. However, this progress has been accompanied by a number of challenges and risks, including data privacy and security concerns, interpretive vs. explainable dilemmas, and the threat of reputational risk. In the future, we can expect wider use of AI-based credit assessment tools, which will enable more personalised and flexible credit assessments and improve financial inclusion. Compliance and regulation will become more stringent to ensure the legitimacy and fairness of AI credit assessments. Advanced AI techniques such as deep and reinforcement learning will further improve the quality and predictability of credit assessments.

However, we also need to be wary of the risks that new technologies may bring, especially in terms of data privacy and model opacity. While pursuing innovation, measures must be taken to protect the rights and interests of borrowers and ensure the credibility and fairness of credit assessment. Ultimately, the use of AI in credit assessment will continue to shape the future of the financial sector, providing equal financial opportunities for more people and contributing to the stability and sustainability of the global financial system.

References

[1] Arutyunov V V .Application of artificial intelligence methods in solving information security problems: effectiveness and relevance of research results of Russian scientists[J].Scientific and Technical Libraries, 2021(11):105-116.DOI:10.33186/1027-3689-2020-105-116.

[2] Xu Y Z, Zhang J L, Hua Y, et al. Dynamic credit risk evaluation method for e-commerce sellers based on a hybrid artificial intelligence model[J]. Sustainability, 2019, 11(19): 5521.

[3] Mhlanga D .Financial Inclusion in Emerging Economies: The Application of Machine Learning and Artificial Intelligence in Credit Risk Assessment[J].International Journal of Financial Studies, 2021, 9. DOI:10.3390/ijfs9030039.

[4] Locatelli R , Pepe G , Salis F .Artificial Intelligence and Credit Risk[J].Springer Books, 2023.

[5] Biecek P , Chlebus M , Gajda J ,et al.Enabling Machine Learning Algorithms for Credit Scoring -- Explainable Artificial Intelligence (XAI) methods for clear understanding complex predictive

models[J]. 2022. DOI:10.48550/arXiv.2105.06736.

[6] Chowdhury A I .A hybrid model for credit risk assessment: empirical validation by real-world credit data[J].Journal of Risk Model Validation, 2021, 14(4):1-39.DOI:10.21314/JRMV.2020.228.

[7] Yang K , Yuan H , Lau R Y K .PsyCredit: An interpretable deep learning-based credit assessment approach facilitated by psychometric natural language processing[J].Expert Systems with Applications, 2022, 198:116847-.DOI:10.1016/j.eswa.2023.116847.