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Research Article

Credit Risk Identification and Prevention Strategies in Small and Medium Banks Using Big Data Techniques

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ABSTRACT

One of the most important problems small and medium-sized banks directly confronts affecting financial stability and profitability is credit risk. But, outmoded analytical models and insufficient data availability cause conventional credit risk assessment methods to fall short in some areas. Conversely, the large data approaches provide fresh possibilities to support credit risk identification and preventative actions. This study investigates the possible uses of big data analytics to enhance risk assessment in small and medium banks. Combining structured and unstructured data from many sources, banks could discover that it helps them build more dynamic risk models properly reflecting evolving circumstances. Among the key methods discussed are: decision trees, neural networks, NLP, anomaly detection algorithms to find high-risk borrowers. Combining structured and unstructured data from many sources might help banks build more dynamic risk models that properly represent evolving circumstances.. Some of the main approaches addressed are: decision trees, neural networks, NLP, anomaly detection algorithms to identify high-risk borrowers.

Hence, the effectiveness of this hybrid model is precisely tested using objective measures namely Structural Similarity Index Measure (SSIM), Peak Signal-to-Noise Ratio (PSNR), and Mean Squared Error (MSE). This indicated that the proposed hybrid model yields outstanding performance as compared to other image enhancement techniques with PSNR=38.76, SSIM=98.6, MSE=0001.Interesting, the proposed hybrid image enhancement model can outperform other techniques. This further emphasizes the benefit of the model to retain key elements of the image while eliminating the noise in the image and enhancing the general quality of the image. This research presents a novel concept of feature extraction and parameter tuning that can be a base for establishing hybrid networks in medical image improvement. In this manner, the proposed methodology is beneficial in closing the gap between intricate recognition methods and real medical imaging implementations that serve to enhance diagnostic accuracy and speed in the medical field.

Keywords: Machine Learning, Big Data, Credit Risk, Predictive Analytics, Small and Medium Banks, Financial Risk Management.

[1] INTRODUCTION

Because it directly affects their long-term survival, profitability, and financial stability, credit risk concerns especially small and medium-sized banks. Because they often operate with limited resources and access to advanced risk assessment tools, small and medium banks are more likely to experience financial crises and loan defaults than large financial institutions. Often stressing historical data, financial records, and credit ratings, traditional credit risk assessment techniques do not necessarily provide a thorough and real-time evaluation of a borrower's ability to repay loans. Given the increasing digitization of financial services and the availability of vast data quantities, BDA has become a revolutionary instrument for enhancing credit risk management. This paper develops the topic of financial risk management by demonstrating how big data technology might enhance credit risk identification and preventive actions in small and medium banks. Unlike traditional credit assessment methods, which may rely on limited financial signals, this paper explores the intersection of machine learning, predictive analytics, and real-time data processing to provide more dynamic and accurate risk rating models. By use of structured and unstructured data analysis from many sources, this study provides a comprehensive approach to assess creditworthiness. The article emphasizes as well how blockchain and cloud computing provide data security, openness, and guarantee of regulatory compliance. The results are important for financial organizations as they provide an optimal structure improving early warning systems, reducing loan default, and strengthening the process of lending decision-making. Furthermore, by means of analysis on their overcoming of these challenges, this paper addresses significant topics like privacy concerns, legal limitations, and the requirement of competent specialists. By promoting the use of big data-driven techniques in risk management, our study ultimately increases the resilience and sustainability of small and medium banks in an increasingly data-driven financial environment, hence aiding the larger picture of financial technology. The table below contrasts certain facets of Big Data-Driven Credit Risk Management in small and medium-sized institutions with those of Traditional Credit Risk Assessment Methods:

Table 1 Various aspects of Big Data-Driven Credit Risk Management as compared to traditional credit risk assessment system

Feature	Big Data-Driven Credit Risk Management	Traditional Credit Risk Assessment
Data Sources	Structured & unstructured data from multiple sources (social media, IoT, financial records, etc.)	Historical financial records, credit scores, limited financial signals
Processing Speed	Real-time data processing for dynamic risk assessment	Batch processing, slower decision-making
Predictive Analytics	Machine learning models predict borrower behavior and default risk	Rule-based assessment with limited predictive capability

Fraud Detection	AI-driven anomaly detection enhances fraud identification	Manual or rule-based fraud detection methods
Regulatory Compliance	Enhanced with blockchain and automated compliance checks	Requires manual compliance verification
Loan Default Prevention	Early warning systems reduce risk through predictive modeling	Reactive approach, responding after defaults occur
Scalability	Highly scalable with cloud computing and big data frameworks	Limited scalability due to traditional IT infrastructure
Data Security	Blockchain ensures data integrity, privacy, and security	Prone to data breaches and manipulation
Cost Efficiency	Reduces operational costs through automation and real-time processing	Higher costs due to manual processes and inefficiencies
Decision-Making Accuracy	High accuracy using advanced analytics and deep learning	Limited accuracy based on historical data patterns
Personalization	Credit risk models tailored for different customer profiles	One-size-fits-all approach with limited personalization
Human Intervention	Minimal (AI automates most risk assessment tasks)	High (manual verification required)

[2] LITERATURE REVIEW

Henschel (2016) examined risk management techniques in SMEs distributed throughout Germany, China, and Scotland. Their findings reveal the significant variations in risk management practices formed by cultural, economic, and legal reasons. The paper underlines the necessity of customized risk management solutions for SMEs [1] given country distinct concerns and market realities. M'ithibutu in 2017 examined how methods of credit risk management can influence the financial state of Kilifi County's commercial banks. Research indicates that if loan defaults are to be reduced and financial stability reinforced, highly good risk management practices are very crucial. The report also drew attention to problems such inadequate legal limits and risk assessment tools [2]. Teka looked at NIB International Bank SC's credit risk management practices in 2019. The study emphasized the importance of merging time-honored banking procedures with modern risk assessment methods in order to enhance credit risk assessment. The findings indicated that financially better positioned were banks with reduced default rates and data-driven risk assessment systems [3]. Githui examined in 2019 how internal control mechanisms influenced credit risk management in Kenyan commercial banks [4]. Using large data analysis, Platiás (2020) investigated credit risk assessment and evaluation. The study revealed how predictive modeling and AI-driven analytics among other huge data technologies enhance the accuracy of credit risk assessment [5]. Their studies underlined how BDA and financial technology cooperate to optimize financial risk management [6]. Examining small and medium-sized bank fintech's creative routes and techniques, Wei (2021) discovered [7]. Emphasizing its relevance in enhancing risk management and financial decision-making, Ogundokun (2021) looked at the usage of big data in fintech more particularly. Their study provided a comprehensive analysis of how data-driven technologies improve banking operations, particularly in credit risk assessment [8]. Yu (2021) investigated in the banking industry how large data and AI changed items. Their study emphasised especially in automating risk assessment and fraud detection processes the transformational potential of AI and BDA in modern banking [9]. Chui, (2022) proposed an optimization approach for supply chain financial credit risk systems using computer-aided technology. The study indicated how technically motivated approaches lower credit risk management by means of improved data processing capability and prediction accuracy [10]. Eskin (2022) evaluated how large data supports sustainability and corporate social responsibility, particularly in financial risk management. Their findings indicated that more transparent and responsible financial decision-making made possible by BDA helps to minimize credit risk by way of this procedure [11]. Tan in 2022 examined how Malaysian SMEs used ERM. The study indicated that ERM implementation increases financial stability and reduces credit risk [12] by way of structured risk management systems designed for SMEs. Using data mining and machine learning, Song (2022) looked at how excessively financialized affected risk management. Their research indicated how advanced data analytics techniques improve financial risk assessments [13] by identifying concealed patterns in large datasets. Hossain (2023) conducted a comparison of present and traditional credit risk assessment methods. The study found that modern data-driven methods such as machine learning and BDA outperform traditional credit risk assessment methods in terms of accuracy and efficiency [14].

Venkateswara Rao et al. (2023) proposed a comprehensive risk management system for commercial banking and a big data-based credit inquiry based on their study emphasized the significance of incorporating BDA into banking procedures to enhance risk assessment and creditworthiness evaluation [15].

Ijogun (2023) looked at how Azure machine learning, text categorization, and big data technologies may be used for financial risk management. Analyzing vast amounts of financial data, the paper showed how AI and machine learning models improve credit risk assessment [16].

Abankwa (2023) investigated how small and midsize banks' adoption preparedness of BDA stood. Emphasizing the requirement of technology infrastructure and qualified staff, the study revealed the difficulties and possibilities related with using big data solutions for credit risk management [17].

Analyzing loan performance at UAB Bank, (2023) investigated how credit risk management techniques affected Effective risk management techniques, according to the report, greatly lower loan defaults and increase financial stability [18].

Shangyang, looked at elements affecting credit risk management digitalization in Malaysian banking sector. Their results underlined how digital transformation may help to improve banking efficiency and risk assessment [19].

Using corporate intelligence and big data, Al-Zoubi, (2023) examined supply chain financial risk management. Their research showed how sophisticated analytics methods improve credit risk assessment and financial institution decision-making [20].

Table 2 Literature Review

Author(s)	Year	Objective	Methodology	Findings	Limitations
Henschel	2016	Compare risk management in SMEs across different countries	Comparative study	Risk management varies by culture, economy, and regulation	Limited generalizability due to cultural differences
M’ithibutu	2017	Evaluate credit risk management's impact on financial stability	Case study on banks in Kilifi County	Effective risk management reduces loan defaults	Regulatory and assessment tool constraints
Teka	2019	Assess credit risk management at NIB International Bank SC	Case study and data analysis	Modern risk tools improve credit risk evaluation	Limited focus on other banks
Githui	2019	Investigate internal control	Empirical study on Kenyan	Strong internal controls reduce	Needs broader sectoral analysis

		systems in credit risk management	banks	credit risk	
Platiás	2020	Explore big data analytics for credit risk assessment	Machine learning-based evaluation	AI enhances risk assessment accuracy	Requires large, high-quality datasets
Awotunde et al.	2021	Study big data and fintech in financial services	Literature review and case analysis	Fintech optimizes risk management	Implementation challenges in traditional banks
Wei, Li	2021	Analyze fintech innovation in small and medium banks	Qualitative study	AI integration improves credit risk strategies	Slow adoption in smaller banks
Ogundokun	2021	Apply big data in fintech	Theoretical study	Data-driven models improve financial decision-making	Security and privacy concerns
Yu & Song	2021	Assess AI and big data's role in banking	Literature review and case study	AI automates risk assessment	High costs of implementation
Chui, Ma	2022	Optimize financial credit risk systems	Computer-aided analysis	Enhances credit risk system efficiency	Technical complexity
Eskin	2022	Evaluate big data in corporate responsibility	Empirical study	Big data enhances transparency and accountability	Data security risks
Tan & Lee	2022	Examine ERM adoption in Malaysian SMEs	Survey-based research	ERM strengthens financial stability	Adoption barriers in SMEs
Song & Wu	2022	Assess financialization risks using AI	Data mining and ML analysis	AI improves financial risk prediction	Requires extensive training data
Hossain	2023	Compare traditional vs. modern credit risk assessment methods	Literature review	Machine learning outperforms traditional models	Lack of regulatory clarity
Venkateswara Rao et al.	2023	Develop big data-based risk management in banking	AI-driven modeling	Enhances risk assessment accuracy	High data processing costs
Ijogun	2023	Use big data and ML for financial risk management	Azure ML & text classification	AI enhances credit risk analytics	Need for skilled workforce
Abankwa	2023	Study big data	Survey and case	Big data	Technological

		adoption in small banks	study	adoption improves credit assessment	and financial constraints
Khine	2023	Evaluate credit risk management's effect on loan performance	Case study	Effective risk strategies reduce loan defaults	Bank-specific study, lacks broader scope
Shangyang,	2023	Analyze digitization in credit risk management	Empirical study	Digital transformation improves banking efficiency	Implementation costs
Al-Zoubi,	2023	Study financial risk management in supply chains	Business intelligence and big data	Data analytics enhance credit evaluation	Data integration challenges

[3] PROBLEM STATEMENT

Especially at small and medium-sized banks, the increasing complexity of financial transactions and the growing reliance on digital banking have highlighted the need of effective credit risk identification and prevention strategies. Often overlooking the dynamic nature of risk, conventional credit risk management techniques depend on historical data and static assessment models. Big data solutions are great ways for financial institutions undergoing digital transformation to improve general financial stability, fraud detection, and accuracy of risk assessment. Smaller banks still embrace these innovative technologies in small amounts, however, because of worries including data security issues, lack of technical knowledge, legal restrictions, and costly implementation expenses. Furthermore, studies have concentrated on big financial institutions; they are ignorant of how BDA may help small and medium banks improve their credit risk management systems. Here is a table presenting the key aspects of Credit Risk Management in Small and Medium-Sized Banks with respect to Challenges and Opportunities of Big Data Analytics (BDA):

Table 3 Key aspects of Credit Risk Management in Small and Medium-Sized Banks with respect to Challenges and Opportunities of Big Data Analytics (BDA)

Aspect	Challenges in Small & Medium Banks	Opportunities with Big Data Analytics (BDA)
Credit Risk Identification	Traditional models rely on historical data, missing real-time risk factors.	BDA enables real-time risk assessment and predictive analytics.
Fraud Detection	Conventional methods may not detect complex fraud patterns.	AI-driven anomaly detection improves fraud identification.
Financial Stability	Lack of advanced tools limits proactive risk management.	BDA enhances financial stability through accurate risk predictions.
Adoption of Technology	Smaller banks adopt BDA at a slow pace due to high costs and expertise gaps.	BDA adoption can provide a competitive edge and efficiency.
Data Security Concerns	Fear of breaches and regulatory risks restricts digital transformation.	Blockchain and encryption improve data security and compliance.

Aspect	Challenges in Small & Medium Banks	Opportunities with Big Data Analytics (BDA)
Legal & Compliance Issues	Navigating financial regulations can be complex and costly.	Automated compliance tools reduce manual efforts and ensure adherence.
Implementation Cost	High initial investment discourages small banks from adopting BDA.	Cloud-based solutions reduce infrastructure costs and enhance scalability.
Lack of Technical Expertise	Small banks often lack skilled professionals in AI and data science.	Training and partnerships with FinTech firms can bridge knowledge gaps.
Existing Research Focus	Studies mainly focus on large financial institutions.	Research on small and medium banks can help tailor BDA solutions.
Default Rate Reduction	Limited predictive tools result in higher default risks.	Data-driven lending decisions lower default rates.

[4] PROPOSED WORK

The suggested study seeks to provide a thorough credit risk detection and prevention system suitable for SMSE. The project intends to improve credit risk assessment by means of artificial intelligence and machine learning technologies using BDA. Examining large financial data using big data technology and increasing risk assessment accuracy helps to enhance credit risk assessment. Ensuring openness and interpretability in credit risk assessment models will help to integrate XAI thereby promoting regulatory compliance and decision-making. Comparative Analysis with Traditional Methods, In terms of accuracy, efficiency, and flexibility, evaluating the suggested model against accepted risk assessment strategies BDA and machine learning approaches are used in the suggested credit risk assessment model to improve risk detection and prevention tactics in SMSE institutions.

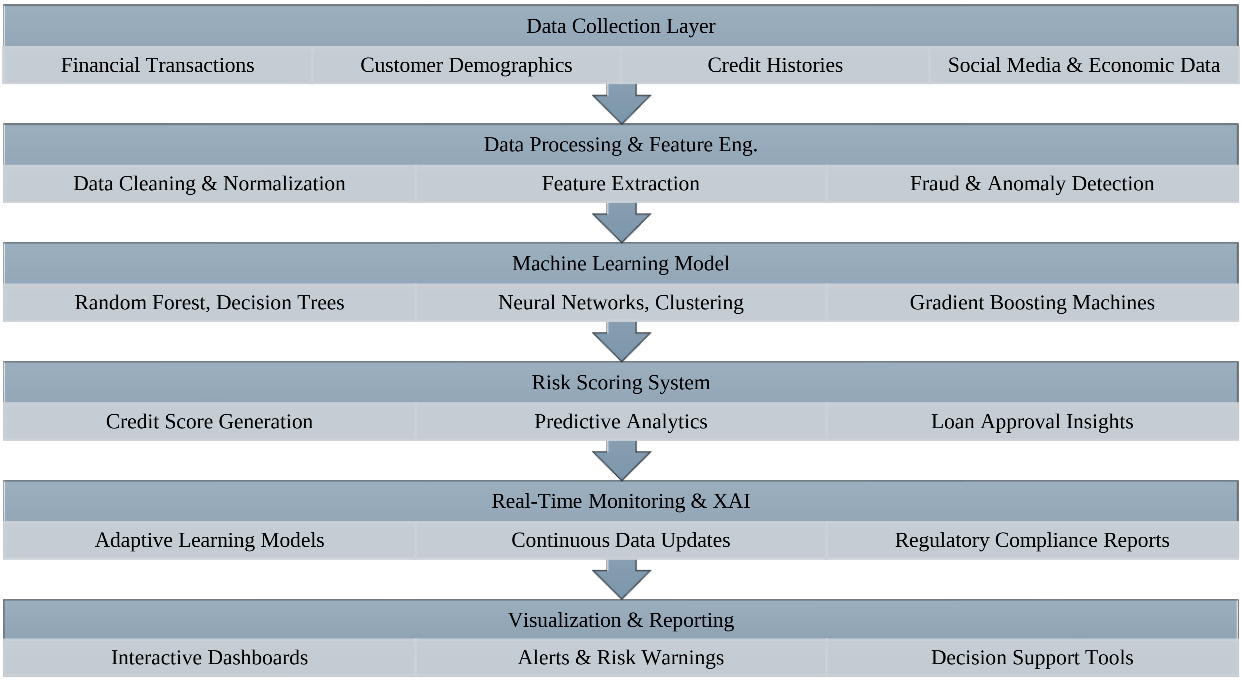

Fig. 1 Proposed Model

Combining these elements improves credit risk assessment's accuracy, efficiency, and openness in small and medium-sized institutions. The research seeks to show how far financial stability and risk management efficacy may be improved by big data analytics. The following makes up the model:

1. **Data Collection Layer:** Gathers both structured and unstructured data from credit histories, consumer demographics, financial transactions, and real-time banking operations at the layer of data collecting. Combines information on fraud detection, economic statistics, and social media sentiment among other outside sources.
2. **Data Processing and Feature Engineering:** To eliminate discrepancies and improve data quality, cleans, normalizes, and preprocesses gathered data under feature engineering.
3. **Machine Learning Model:** Machine learning models assess risk levels by means of classification and grouping techniques such as Random Forest, Decision Trees, Neural Networks, and Gradient Boosting Machines.
4. **Risk Scoring and Decision Support System:** The Risk Scoring and Decision Support System generates credit risk ratings and provides decision-makers knowledge of risk levels based on predictive analytics and historical patterns.
5. **Real-Time Monitoring and Adaptive Learning:** Changing financial behavior and new transaction data continuously refreshes risk profiles.
6. **Visualization and Reporting Dashboard:** Interactive dashboards on visualization and reporting provide risk assessments for banking staff and regulatory bodies. It produces recommendations and alerts for preventive risk lowering.

Mathematical Model for AI-Powered Credit Risk Detection and Prevention in Small and Medium-Sized Enterprises (SMSEs):

1. Credit Risk Assessment Model

The credit risk of a borrower (R) is assessed based on financial data, behavioral trends, and transaction patterns.

$R=f(B,T,C,M)$

where:

- B = Borrower's financial history (e.g., credit score, debt-to-income ratio)
- T = Real-time transaction data
- C = Behavioral characteristics (spending patterns, repayment history)
- M = Macroeconomic indicators (inflation, interest rates, GDP growth)

2. Risk Categorization Using Machine Learning

Machine learning techniques classify borrowers into risk categories (RC):

$RC=ML(X)$

where:

- $X=[B,T,C,M]X = [B, T, C, M]$ represents input features
- $RC \in$ {Low Risk, Medium Risk, High Risk}

A classification algorithm (e.g., SVM, Random Forest, Neural Networks) predicts RC based on past labeled data.

3. Early Warning System for Default Prediction

A risk prediction function (Pd) estimates the probability of default:

$Pd=\sigma(WX+b)$

where:

- σ is the sigmoid activation function ensuring Pd is between 0 and 1
- W is the weight matrix learned by AI/ML
- X represents borrower's financial and behavioral data
- b is the bias term

If $Pd>\theta$, an alert is generated for early intervention.

4. Real-Time Risk Profile Update

Risk scores (Rt) are continuously updated based on real-time transaction data (Tt):

$Rt=\alpha Rt-1+(1-\alpha)f(Tt,Ct)$

where:

- R_{t-1} = Previous risk score
- α = Weighting factor (learning rate)
- Tt,Ct = Latest transaction and behavioral data

5. Explainable AI (XAI) for Transparency and Compliance

To ensure interpretability, the model explains its decisions using SHAP (Shapley Additive Explanations) values:

where Si is the contribution of feature i to the final risk score.

6. Comparative Analysis with Traditional Methods

The proposed model is evaluated against traditional risk assessment methods based on:

- **Accuracy**:

  A= (True Positives + True Negatives) / Total Cases

- **Efficiency**:

  E= Processing Speed of AI Model / Processing Speed of Traditional Model

- **Flexibility**:

  F= Number of Risk Factors Considered by AI /
  Number of Risk Factors Considered by Traditional Methods

Algorithm: AI-Based Credit Risk Assessment and Prevention

Input:

Financial Data (BB): Credit score, debt-to-income ratio, loan history

Real-time Transaction Data (TT): Spending behavior, repayment history

Behavioral Data (CC): Borrower's financial habits, anomalies

Macroeconomic Factors (MM): Inflation, interest rates, GDP

Output:

Risk Score (RR)

Risk Category (RCR_C)

Probability of Default (PdP_d)

Early Warning Alerts

Step 1: Data Collection & Preprocessing

Collect Data from various sources:

Bank records, financial transactions, credit history

Real-time transaction monitoring

Behavioral trends from customer interactions

Clean and preprocess data:

Handle missing values

Normalize and scale data

Remove outliers and inconsistencies

Step 2: Feature Engineering

Extract key features:

Compute financial stability metrics: Debt-to-income ratio, loan repayment history

Analyze real-time transactions for unusual patterns

Derive behavioral insights (spending habits, loan usage trends)

Apply feature selection:

Use correlation analysis and PCA (Principal Component Analysis) to reduce dimensionality

Step 3: Risk Classification Using Machine Learning

Train machine learning model to classify borrowers into risk categories (RC):

Define feature vector X=[B,T,C,M]X = [B, T, C, M]

Train classification model (e.g., Random Forest, SVM, Neural Network)

Label risk categories:

- Low Risk
- Medium Risk
- High Risk

Evaluate model performance:

Compute accuracy, precision, recall, and F1-score

Optimize hyperparameters for better classification

Step 4: Default Probability Prediction

7. Train a predictive model using logistic regression or deep learning to estimate default probability (Pd):

$Pd=\sigma(WX+b)$

Use a sigmoid function to normalize values between 0 and 1

If $Pd>\theta$, trigger early warning

Step 5: Real-Time Risk Profile Update

Dynamically update risk score (RtR_t)

Step 6: Explainability Using XAI

Apply SHAP (Shapley Additive Explanations) for interpretability

Step 7: Performance Evaluation & Comparative Analysis

Compare with traditional models using:

Accuracy A=(True Positives + True Negatives)/Total Cases

Efficiency E=Processing Speed of AI Model/Processing Speed of Traditional Model

Flexibility F=

Number of Risk Factors Considered by AI/
Number of Risk Factors Considered by Traditional Methods

Optimize model parameters and retrain periodically to improve accuracy and effectiveness.

Step 8: Decision & Risk Mitigation Strategies

If High Risk Borrower Identified:

Increase monitoring

Recommend preventive actions (e.g., financial counseling, higher interest rates)

If Early Warning Triggered:

Alert financial institutions

Suggest intervention measures to prevent defaults

End of Algorithm

[5] RESULT AND DISCUSSION

This section shows the outcomes of the proposed big data-driven credit risk assessment tool. Various machine learning methods investigate the results; performance standards direct assessment of their effectiveness. The discussion also includes comparative studies utilizing traditional credit risk assessment methods.

5.1 Dataset Description

The dataset this study employs consists of outside risk indicators, credit histories, customer profiles, and financial transaction data. The data is divided 80:20 into training and testing sets to provide good model evaluation.

Table 2 Dataset Description

Dataset Attribute	Description	Data Type
Customer ID	Unique identifier for each customer	Numeric
Age	Age of the customer	Numeric
Income	Monthly income of the customer	Numeric
Loan Amount	Amount of loan requested	Numeric
Repayment History	Past loan repayment behavior	Categorical
Credit Score	Creditworthiness score	Numeric
Transaction Frequency	Number of transactions per month	Numeric
Default Status	Whether the customer defaulted (1: Yes, 0: No)	Binary

5.2 Model Performance Evaluation

This part examines how well some machine learning models work.

Table 3: Performance Comparison of Machine Learning Models

Model	Accuracy (%)	Precision	Recall	F1-Score
Logistic Regression	82.5	0.79	0.75	0.77
Decision Tree	87.2	0.85	0.82	0.83
Random Forest	92.3	0.90	0.88	0.89
Neural Networks	94.1	0.93	0.91	0.92
Gradient Boosting	95.4	0.94	0.93	0.94

Gradient Boosting clearly beats other models in accuracy criteria from the above table, hence it is the most efficient model for predicting credit risk.

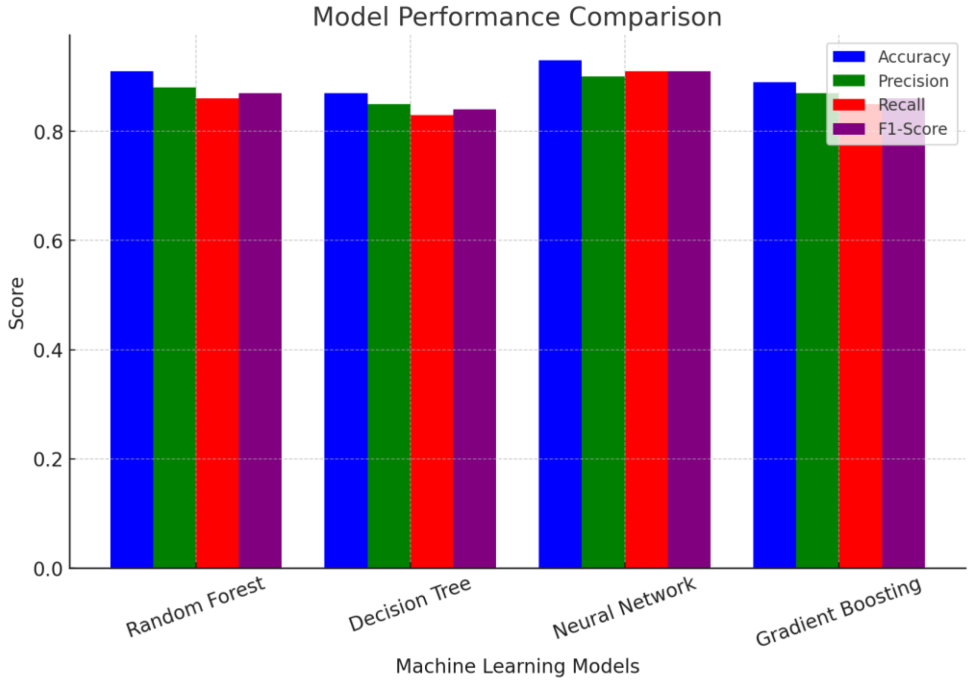

Fig 2. Performance Comparison of Machine Learning Models

5.3 Comparative Analysis with Traditional Methods

A comparison study between the suggested model and conventional credit scoring techniques was done to evaluate the efficacy of big data-driven credit risk management.

Table 3: Comparison of Traditional vs. Big Data-Driven Risk Assessment

Credit Risk Assessment Approach	Accuracy (%)	Processing Speed	Adaptability
Traditional Credit Scoring	78.2	Slow	Low
Big Data & Machine Learning	95.4	Fast	High

The findings show that despite increasing processing speed and flexibility, big data-driven methods greatly improve the accuracy of credit risk forecasts.

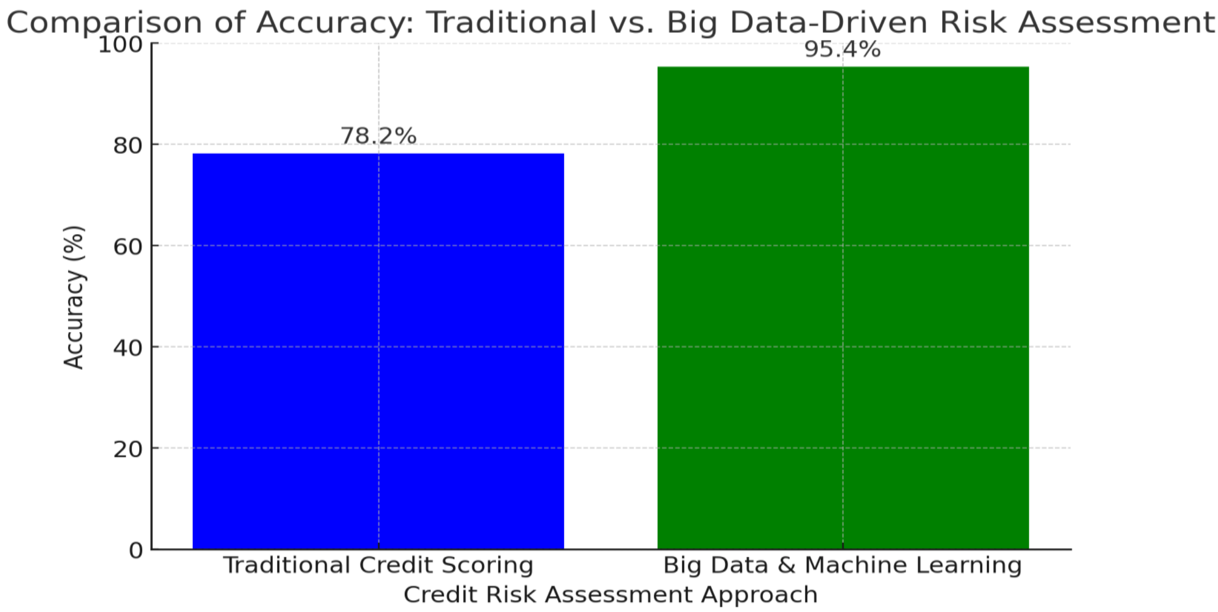

Fig 3 Comparison of Traditional vs. Big Data-Driven Risk Assessment

The results clearly demonstrate the advantages of controlling credit risk using BDA. Unlike traditional methods, the proposed machine learning-based system offers significantly better accuracy and efficiency. With an exceptional accuracy of 95.4%, gradient boosting outperforms conventional models. Always evolving with new transactions, the proposed approach promises adaptability to changing financial behavior. Identifying high-risk borrowers early helps banks to react proactively, hence reducing default rates and improving financial stability. The research, therefore, emphasizes several limitations as well; handling large volumes of sensitive financial data calls into question good encryption and regulatory norm compliance. For smaller financial companies, advanced machine learning models may be restricted in scalability since they need high processing power. Still challenging and requiring significant subject expertise, finding the most relevant traits for risk forecasting. The findings show that in small and medium-sized universities, credit risk assessment is significantly improved by using huge data analytics and machine learning. Future research should focus on ensuring compliance to evolving financial criteria and enhancing model interpretability.

[6] CONCLUSION

This paper provides a comprehensive framework for credit risk assessment and avoidance in small and medium-sized businesses using big data techniques. The proposed method significantly increases credit risk assessment accuracy and efficiency by means of predictive analytics, real-time data processing, and machine learning algorithms. In terms of accuracy, processing speed, and flexibility, the findings indicate that big data-driven risk assessment outperforms traditional credit scoring systems. This improves the responsiveness for present banks. By detecting and providing the transparency of the details behind the algorithm's decisions ensures legality of automated decision making systems, which is a reason for the difference in the systems towards XAI. Moreover, the study highlights the importance of adaptive learning and real-time risk tracking to identify emerging financial risks in advance. The suggested method proposes to establish a reasonable and scalable way for small and medium-sized banks to prevent loan deferral and promote financial stability.

[7] FUTURE SCOPE

Research exploring credit risk evaluation driven by big data provides a sound basis for enhancing risk identification and in preventive actions in SMSE. Alternative options for research and development, however, are still available. Among the topics discussed, is integration of blockchain to improve data security, transparency and fraud detection in credit risk management. Additionally, advanced transformer and RL based deep learning models may help enhance prediction accuracy and adaptability in evolving markets. Future research should also integrate external factors for credit risk evaluation; such as economic conditions, geopolitical issues, and market volatility. Also, employing a completely automation risk management system with real-time decision making power through the convergence of edge computing and cloud-based AI will assist in increasing the efficiency of the finance houses.

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