AI-based model for Enhancing Credit Risk and Delinquency Management in Banks

Noura Metawa[1, 2,*], Sally Afchal[3], Nasser El-Kanj[3]
[1]University of Sharjah, UAE
[2]Tashkent state University of Economics, Uzbekistan
[3]College of Business Administration, American University of the Middle East, Kuwait
Emails: Nmetawa@sharjah.ac.ae; sally.afchal@aum.edu.kw; Nasser.El-Kanj@aum.edu.kw

Abstract

Credit risk assessment along with delinquency management in banking receives substantial improvements from the introduction of Artificial Intelligence (AI) and behavioural insights. This research creates an extensive behavioural credit-scoring model through its discovery of crucial psychological characteristics including integrity and self-efficacy and locus of control and materialism that greatly affect credit default and wilful delinquency. A thorough evaluation of the predictive model occurs through logistic regression and confirmatory factor analysis (CFA) based analysis on 376 respondent data. Self-efficacy together with internal locus of control and materialism demonstrate significant power as predictors for credit risk and the willingness of individuals to default voluntarily is directly influenced by integrity and self-esteem. The ability of Artificial intelligence approaches to forecasting depends on behavioural constructs to optimize precision accuracy, reduce credit risk estimation errors, and provide opportunities for early prevention. The model delivers 92.1% accurate Default Risk classifications together with 91.0% precise predictions for Liquidity Risk while maintaining a Default Risk AUC-ROC measure of 0.96, which signifies its advanced predictive capabilities. The research demonstrates that artificial intelligence alongside behavioural credit scoring systems can enhance financial lending decisions while stabilizing credit markets.

Keywords: Artificial Intelligence (AI); Machine Learning in Banking; Behavioral Credit Scoring; Delinquency Prediction; Credit Risk Management; Credit Scoring Model

1. Introduction

The global financial industry deals with a major management challenge when handling credit risk alongside loan delinquency because these issues generate broad economic and banking operational effects. The nature of credit risk exists when borrowers break their loan obligations resulting in losses for lenders. Delinquency is defined by late or missed payments that can become defaults unless managers succeed in effective management [2]. Current credit risk assessment models extract their borrower creditworthiness information from financial history together with risk-weighted assets and credit scores. The traditional risk assessment methods perform poorly in monitoring economic transformations and borrower actions thus creating difficulties in identifying risks and recovering debt.

Modern financial institutions together with banks use AI and behavioural analytics to develop new approaches, which boost their existing credit risk management systems. The application of AI models uses massive amounts of data that incorporates alternative dataset types from transactions and spending behaviour as well as digital activity data to achieve better and flexible credit risk evaluations [3] [4]. Behavioural finance research provides banks with better knowledge of borrower mental processes to make their risk approaches more successful. Reliable risk assessments of borrowers become possible while process optimization occurs through loan recovery applications and lending operations achieve higher efficiency by using AI together with behavioural insight applications.

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The Figure 1 presents five types of credit risk that include default risk along with credit spread risk and country risk and counterparty risk and concentration risk that demonstrate different financial uncertainties for lenders and investors.

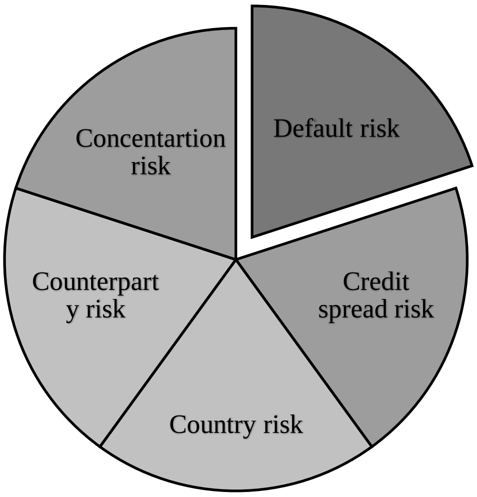

Figure 1. Illustration of Different types credit risks

1.1 Growing Challenge of Credit Risk in Banking

Banking institutions face serious financial health deterioration alongside economic crises when non-performing loans (NPLs) accumulate due to the 2008 global financial collapse. Standard risk management protocols via the Basel Accords maintain vulnerability to assessment errors because they use outdated credit scoring and fixed borrower profile models [6].

Traditional credit risk systems fail to identify present-time financing patterns since they operate with static data. A borrower who has maintained good credit records can still face financial problems because of unexpected events including employment termination and unexpected health problems or market changes [7]. People who possess lower credit ratings can show good financial management practices while enhancing their credit status throughout time. Dynamic data-driven approaches have become necessary because they must analyse current borrower behaviour to offer an enhanced credit risk evaluation method.

1.2 Delinquency Management: A Persistent Concern for Banks

Delinquent loan payment continues to be a significant challenge for financial institutions, which creates adverse effects on their cash flow and profitability performance. Deliberant borrowers who do not maintain timely loan payments generate extra collection expenses together with elevated bad debt provisions that damage market confidence [8] [9]. Impaired delinquency management results in advanced delinquency stages, which produce severe consequences like legal costs and asset, seized properties and diminished financial value for banks.

Standard approaches for delinquency management through telephone collection attempts and penalty fees as well as legal interventions rarely succeed in preventing borrowers from defaulting on their loans. Financial institutions experience negative effects on their public reputation using these conventional management approaches that damage customer relations. Bank institutions should use artificial intelligence technology and predictive analytics together with behavioural insights to find delinquency-warning indicators before they happen so they can take appropriate preventive measures.

Financial indicators for distress are extracted through analytical assessment of financial expenditures and borrower transaction records combined with borrower interaction metrics that AI systems use to customize repayment plans [10]. Through analysis of customer behaviour, financial institutions can design telephone communication plans that use behavioural suggestions to prompt customers toward regular payments by sending cues and incentives in addition to established payment schedules. The implemented strategies successfully decrease loan defaults and simultaneously build better customer trust, which develops long-term relationships between customers and financial institutions.

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1.3 Artificial Intelligence in Credit Risk and Delinquency Management

Artificial intelligence's algorithms for machine learning (ML) revolutionize contemporary financial operations by enhancing the capacity to assess risk and detect fraud. The AI-driven algorithms assess various variables across social media data along with online payment records as well as additional dataset sources in order to develop a comprehensive risk evaluation of candidates [12].

Machine learning models develop autonomous capabilities through data pattern learning that allows them to stay adaptable regarding economic market changes and borrower actions. By tracking current and projected cash flows, AI-powered credit risk evaluation systems can gauge a company's financial health [14]. NLP tools use customer conversations alongside emails and complaints to identify potential risks, which helps to stop their progression.

AI-operated chatbots and virtual assistants aid delinquency management by allowing borrowers to schedule payments using automated systems and access deals for payment management as well as financial guidance. The digital tools help customers while reducing expenses and raising repayment success through digital solutions tailored to individual requirements.

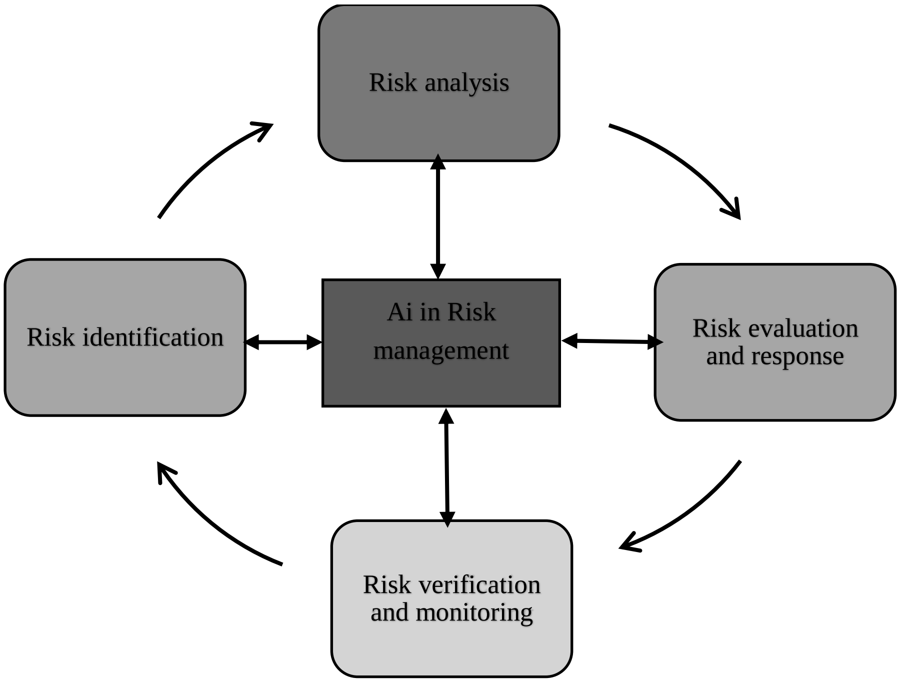

Figure 2. Illustration of AI in risk management

The Figure 2 demonstrates how AI supports risk management by running through a recurring pattern of identification The Figure 2 demonstrates how AI supports risk management by running through a recurring pattern of identification and analysis followed by evaluation and response and verification and monitoring stages. AI plays as the main core to enable an ongoing assessment of risks and their mitigation.

1.4 Behavioral Insights: A Human-Centric Approach to Credit Risk

The analytical power of AI receives enhancement through behavioural finance as this method handles the mental and logical components that guide borrower choices. The economic standards used to demonstrate rational borrowing practices prove incorrect after behavioural economics reveals that borrowers show biases, generate choices through emotions, and think with limited mental capacity [16].

People display present bias that pushes them to spend their money now instead of making payments that will benefit their finances in the future thus leading to unsuccessful payments on their loans. These borrowers underestimate their future financial risks while taking on too much debt than they can handle because of over-optimism bias. Banks can produce behavioural intervention methods by recognizing these behavioural characteristics to promote responsible borrowing and prompt payment from customers.

Banks use payment alert systems specifically designed for borrowers to incorporate game mechanics and reward mechanisms, which act as motivation to encourage improved behaviour patterns [18]. Loss-framed SMS messaging sent via text has shown better results than neutral reminders when used to prompt payments according

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to research. Borrowers benefit when provided with visual tracking systems that display their loan repayment status because this helps them sustain timely payments.

1.5 Credit Risk and Delinquency Management

Banking solutions that incorporate behavioural insights into credit risk structures and artificial intelligence (AI) techniques are better able to predict outcomes and are more active in meeting client requirements. As banks continue to use AI-based innovations, new regulatory frameworks are needed to establish guidelines for ethical AI usage, safeguard privacy data, and ensure fair lending procedures.

Financial institutions will probably use funding to acquire AI-based credit risk systems, which unite conventional credit history data with continuously monitored behavioural consumer information [20]. The adoption of this solution will produce precise risk assessments and lead to fewer defaults allowing more people to access banking services. Banks and fintech companies along with regulatory bodies need to work together standardizing AI applications while taking means to eliminate biases which appear in automated decisions.

Banks can use AI combined with behavioural insights as an important tool to improve their credit risk management functions and prevent delinquencies during this period when financial risks have increased in complexity. Banks need to transition from their present reactive data approaches to databased proactive methods, which help them reduce loan defaults while improving debt collection and building stronger client bonds [22]. When AI analytics combine with behavioural science knowledge banks achieve more precise risk assessments, maintain responsible lending practices, and thus build up a steady financial environment.

2. Related Work

The study of banking literature shows extensive research interest in credit risk management alongside delinquency management in the last few years. The control of credit risk brings essential benefits because NPLs can damage financial stability [24]. Numerous research investigations analyse credit risk evaluations together with the implementation of preventive measures alongside regulatory compliance structures, which protect financial institutions from instability and poor profitability.

Smith et al. (2021) [1] presented vital research on how artificial intelligence (AI) and machine learning (ML) have revolutionized banking institutions' credit risk assessment process. The research showed that AI-based models succeed better than existing statistical models for default prediction through their capabilities to process large real-time data collections. According to Johnson and Lee (2022) [3] big data analytics has improved credit scoring limitations through advanced techniques which enhanced lending institution risk assessments while decreasing financial delinquencies. The implementation of these advanced systems allows banks to make more accurate lending assessments that decreases the chances of default on loans.

Several research studies focus on credit risk management from the standpoint of regulatory requirements. Brown et al. (2023) [5] explain that Basel III regulations introduced substantial changes to banking procedures through their rigorous capital adequacy rules. According to Brown et al. (2023) [5] the increased requirement has strengthened financial stability yet creates difficulties for smaller banks that need to build up reserves. According to Martinez (2020) [7] the regulatory requirements to implement stress testing showed improved risk detection through stress-testing structures at the cost of additional financial institution operational expenses.

Credit risk management depends heavily on the influence, which macroeconomic factors have on the debt landscape. A study from Zhao and Kim (2022) [9] showed how economic recession causes delinquency rates to grow because unemployment rates and inflation behave directly with loan defaults. Banking institutions need to add macroeconomic indicators into their risk assessment software to actively prevent credit risks according to their research. Patel (2023) [11] conducted research about COVID-19 effects on loan delinquencies which showed interventions from the government prevented default events however they introduced new ethical challenges because borrowers depended on these subsidies instead of following payment requirements.

Research about financial technology (FinTech) plays an essential role in managing credit risks through extensive studies. FinTech innovations described in Wang and Li (2021) [13] make peer-to-peer lending and blockchain-based credit scoring tools that change how lenders evaluate both credit risks and give out loans. The authors determined that lending platforms free from centralized control allow further access to financial services for excluded groups. Digital lending platforms evaluate borrowers' creditworthiness through social media and transaction history analyses according to Roberts (2024) [15] and this method successfully includes underbanked customers.

In their operation, banks have implemented diverse strategies to minimize credit risks and handle account defaults. Records show that Ahmed et al. (2022) [17] proved risk-based pricing models succeed at lowering default rates through interest rate variations according to borrower risk assessments. Loan restructuring initiatives proved effective for curbing delinquencies according to their research while economic slumps were in progress. The

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analysis by Carter and Green (2023) [19] of customer relationship management (CRM) effects on credit risk exposed that strategy with borrowers through payment reminders and financial counselling leads to better borrowing behaviour and decreased delinquency rates.

Behavioural finance research helps professionals had better predict the actions of borrowers regarding credit risks. Taylor (2021) [21] conducted research about psychological factors which demonstrated that loan default risk heavily depends on borrower financial literacy and risk assessment abilities. Financial institutions should combine behavioural insights directly into their risk models in order to improve their assessments of creditworthiness. Gomez (2024) [23] analysed financial practices and spending activities which affect loan performance through real-time transaction monitoring systems that can identify prospective defaults.

Research on credit risk management under corporate governance supervision has emerged as a fundamental aspect of study. Strong governance structures in banks lead to decreased non-performing loan levels due to the implementation of effective risk management alongside oversight practices as Nelson and White (2022) [25] establish. The study demonstrated how independent boards together with risk committees produce vital frameworks for credit risk management. Internal controls that include stringent compliance measures combined with audit functions serve to decrease fraudulent lending practices according to Kumar (2023) [27].

Research studies in recent times regarding bank credit risk and delinquency management focus on technological developments as well as regulatory practices and macroeconomic factors alongside financial technology and operational procedures and behavioural finance and corporate governance frameworks. Credit risk evaluations gain significant value through the combination of AI with big data analytics and alternative credit scoring because these elements have regulated their procedures to strengthen financial institutions' stability [26]. Economic elements and technological advancements through FinTech sector development together with establishment of proper governance frameworks drive the way banks handle their risks. Research should analyse both temporal and regulatory aspects of digital lending to establish sustainable financial practices, which benefit from digitalization.

3. Objectives of the Research

This investigation works to improve bank credit risk evaluation along with delinquency administration through AI-based behavioural methods integration. This study aims to:

- ❖ A Behavioural Credit Scoring Model Requires Development through the identification and analysis of psychological traits including self-efficacy and locus of control and integrity and materialism, which affect both credit default and wilful delinquency.
- ❖ Machines based predictive analytics should be included because they enhance credit risk prediction models through machine learning algorithms and operating more efficiently.
- ❖ A quantitative method will measure behavioural influence against credit risk through statistical models to establish their relation to default probability.
- ❖ The system must offer banks a strong methodology for reducing non-performing loans (NPLs) and ensuring effective credit approval systems.
- ❖ The predictive capabilities of proposed models must be checked by using classification accuracy and R^2 values and alternative performance metrics for assessment.

This research establishes a connection between typical financial credit scoring and behavioural credit risk assessment to build a more complete proactive system for managing delinquency.

4. Motivation of the Research

Credit risk and delinquency represent fundamental challenges for banks, which produce financial instability while raising the non-performing loans (NPLs) numbers. Traditional credit scoring systems depend mostly on financial past data but they lack the capability to evaluate behavioural elements that shape loan repayment behaviour. AI technology integration with behavioural elements serves as the research purpose to develop improved credit risk measurement techniques. Behavioural traits of self-efficacy together with locus of control and integrity and materialism serve, as essential factors for default risk assessment yet standard credit scoring systems tend to overlook them. AI-based predictive analytics will enable the development of a new credit-scoring framework, which shows higher accuracy in predictive abilities. Better financial stability can result from enhanced risk assessments among financial institutions because improved lending decisions will decrease defaults rates and reduce rising delinquency levels. The study works to give banks revolutionary databased risk management strategies that enhance credit risk optimization while strengthening their economic stability.

5. Proposed Work

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AI integration with behavioural analysis serves to boost bank systems that manage credit risks and delinquency situations. The approach requires researchers to detect main behavioural characteristics followed by model development of a predictive Behavioural Credit Scoring Model (BCSM) and subsequent implementation of automated machine learning algorithms to enhance credit risk evaluation accuracy.

5.1 Behavioral Constructs in Credit Risk

The current methods for credit risk evaluation use financial elements from income statements together with past payment records and debt obligations The current financial models omit critical behavioural elements together with psychological parameters that notably affect how borrowers pay back their debts. According to behavioural finance concepts, the individual characteristics of borrowers influence their financial decisions along with their ability to handle money and odds of choosing risks. The research implements psychological variables into its credit risk assessments to achieve better results.

A behavioural construct functions as a latent variable, which researchers assess by collecting numerous observed indicators that symbolize the unobservable construct. According to the study's findings, five psychological traits determine both creditworthiness and delinquency.

- Self-Efficacy (SE)
- Locus of Control (LC)
- Integrity (I)
- Materialism (M)
- Self-Esteem (S)

Every construct uses responses from a Likert-scale that ranges from 1 indicating strong disagreement to 5 demonstrating strong agreement. The subsequent part displays both theoretical explanations and the mathematical formulation behind these behavioural constructs.

- **Self-Efficacy (SE) and Credit Risk**

According to Bandura, self-efficacy indicates the personal confidence individuals possess to execute financial responsibilities. Default is less likely to occur among borrowers who possess strong self-efficacy because they feel capable in their finances.

The composite measure of k indicators $X_1, X_2, \dots, X_k$ constitutes Self-efficacy evaluation.

$$SE = \frac{1}{k}\sum_{i=1}^{k} X_i \qquad (1)$$

- **Impact on Default Probability**

An elevated self-efficacy level leads to decreased default risk. The relationship in logistic regression models appears as follows:

$$P(Default) = \frac{1}{1+e^{-(\beta_0+\beta_1 SE+\varepsilon)}} \qquad (2)$$

- **Locus of Control (LC) and Financial Responsibility**

The Locus of Control test developed by Rotter in 1966 shows how people regard money changes through inner abilities versus external conditions (luck or economic factors). Financial responsibility among borrowers increases when they demonstrate internal locus of control.

Measurement Equation

$$LC = \frac{1}{n}\sum_{j=1}^{n} Y_j \qquad (3)$$

Impact on Creditworthiness: Higher LC reduces delinquency probability

$$P(Delinquency) = \frac{1}{1+e^{-(\beta_0+\beta_2 LC+\varepsilon)}} \qquad (4)$$

- **Integrity (I) and Wilful Default**

A strong sense of integrity exists when people maintain ethical standards in their financial duties. People who exhibit low levels of integrity tend to act deliberately against their financial capability by not making their payments.

To detect integrity several ethical financial behaviour criteria are employed for assessment.

$$I = \frac{1}{m}\sum_{k=1}^{m} Z_k \qquad (5)$$

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Integrity scores that decline create more opportunity for borrowers to commit wilful delinquencies.

$$P(WilfulDefault) = \frac{1}{1+e^{-(\beta_0+\beta_3 I+\varepsilon)}} \quad (6)$$

❖ **Materialism (M) and Over-Indebtedness**

People who follow materialism approach value their physical possessions more than their duties to finance their lives. Periods of excessive debt accumulation among materialistic borrowers will raise their default probability.

$$M = \frac{1}{p}\sum_{i=1}^{p} W_i \quad (7)$$

$$P(Default) = \frac{1}{1+e^{-(\beta_0+\beta_4 M+\varepsilon)}} \quad (8)$$

The figure 2 illustrates the block flow of the proposed approach.

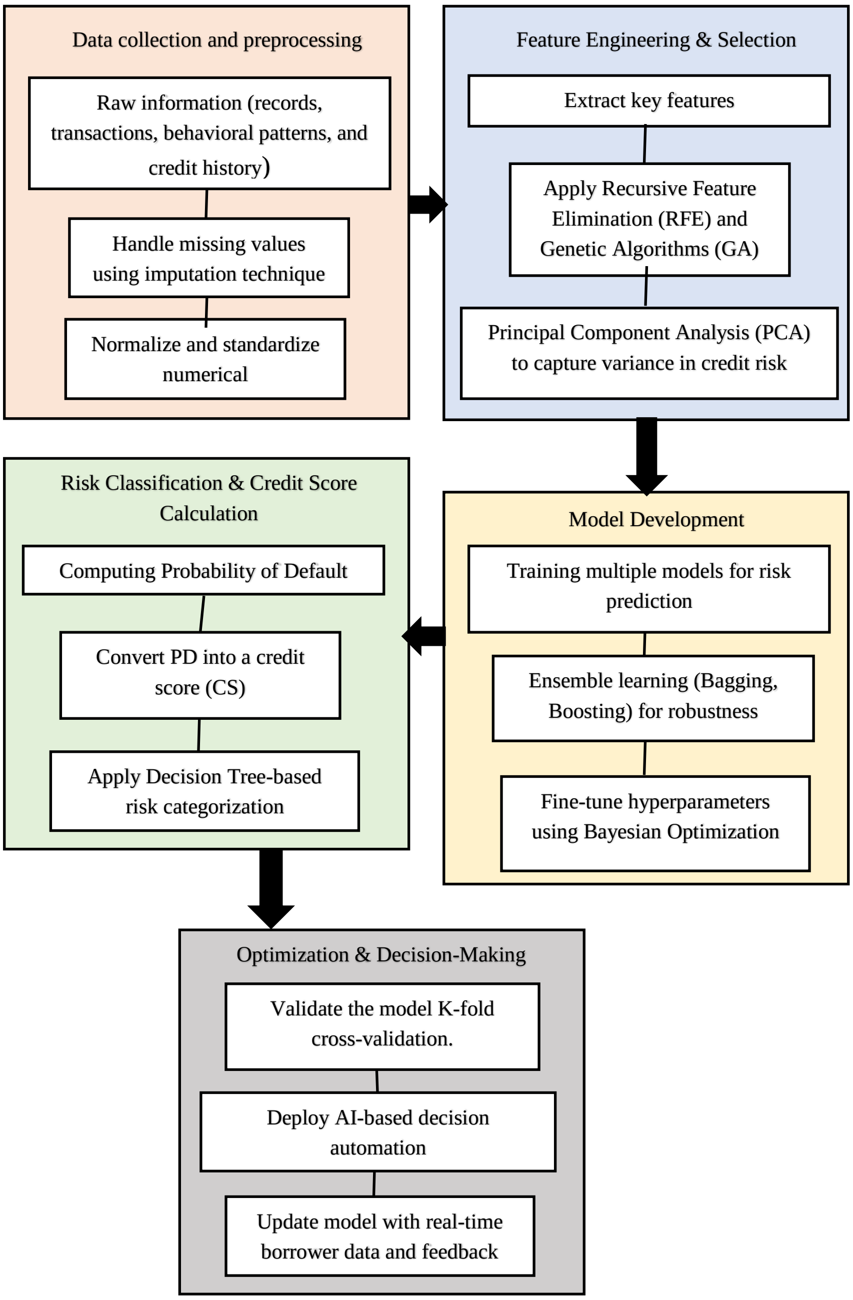

Figure 3. Block illustration of the proposed approach

❖ **Self-Esteem (S) and Financial Decision-Making**

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Financial confidence together with self-worth defines someone's self-esteem. When borrowers have low self-esteem, they may experience a sense of helplessness about their finances along with unsatisfactory financial choices.

$$S = \frac{1}{q}\sum_{j=1}^{q} V_j \qquad (9)$$

A higher S reduces delinquency probability:

$$P(Delinquency) = \frac{1}{1+e^{-(\beta_0+\beta_5 S+\varepsilon)}} \qquad (10)$$

Here X_i = specific financial confidence measures, $\beta_1 < 0$ = increasing self-efficacy lowers default risk, Z_k = questions, $\beta_4 > 0$ = materialism raises default risk, $\beta_5 < 0$ = self-esteem improves financial responsibility.

This behavioural approach improves credit-scoring algorithms by combining mental insights with risk prediction generated by artificial intelligence.

5.2 AI-Driven Credit Risk Modeling

The conventional method of credit risk evaluation depends on logistic regression and other linear statistical models that use a basic link between financial indicators and loan default rates. The complexity of credit risk determination involves multiple behavioural along with financial elements that advanced AI methods are required in order to achieve better accuracy assessment.

The research combines Artificial Intelligence (AI) through several aspects:

- ❖ A process should replace basic statistical features with enhanced selection methods that eliminate unnecessary predictors.
- ❖ Capture non-linear relationships between behavioural traits and default risk.
- ❖ The organization should deploy Decision Trees with Artificial Neural Networks (ANN) and Support Vector Machines (SVM) to enhance their credit risk prediction model accuracy.

5.2.1 Logistic Regression Model for Default Probability

Logistic regression operates as the initial component in AI-powered credit risk models and functions as one of the basic methods that evaluates binary outcome probabilities. The mathematical model shows a borrower default probability as P(Y=1).

$$P(Y) = \frac{1}{1+e^{-\left(\beta_0+\sum_{i=1}^{n}\beta_i X_i\right)}} \qquad (11)$$

Here X_i = Predictor variables, β_0 = Intercept, β_i = Coefficients of predictors.

❖ **Feature Selection Using Decision Trees**

Logistic regression functions under the assumption that all features possess equal predictive power although some variables demonstrate stronger capability to predict credit default. The Decision Tree model applies Gini Impurity Index to evaluate features for determining key factors.

$$Gini = 1 - \sum_{i=1}^{c} p_i^2 \qquad (12)$$

The probability of a borrower in this category is denoted by p_i. The model achieves better efficiency when features with strong Gini reduction remain while unimportant variables are eliminated.

5.2.2 Artificial Neural Networks (ANN) for Credit Risk Prediction

Non-linear behaviour of borrower behaviour patterns requires an introduction of Multi-Layer Perceptron (MLP) Artificial Neural Network (ANN) for improved accuracy in prediction.

The ANN model consists of:

- ❖ Input Layer: Behavioural and financial attributes (SE, LC, I, M, S, credit score, income, debt ratio).
- ❖ Hidden Layers: The model contains concealed layers made of ReLU activation neurons for achieving non-linear behaviour.

$$H_j = \max\left(0, \sum_{i=1}^{n} w_{ij} X_i + b_j\right) \qquad (13)$$

- ❖ Output Layer: The activation of one neuron is measured through its sigmoid function while transforming values into probabilities between 0 and 1.

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$$\hat{Y} = \sigma\left(\sum_{j=1}^{m} v_j H_j + b\right) \quad (14)$$

$$\sigma(x) = \frac{1}{1+e^{-x}} \quad (15)$$

Here w_{ij} = Weights of connections between neurons, b_j = Bias term, $\sigma(x)$ = sigmoid function.

The network trains employing Backpropagation to lower an error function.

$$J = -\frac{1}{m}\sum_{i=1}^{m}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \quad (16)$$

The model uses actual outcome y_i and predicted probability $\hat{y}_i$ as its essential components. The weight update process employs Gradient Descent as its method.

$$w_{ij}^{new} = w_{ij}^{old} - \alpha \frac{\partial J}{\partial w_{ij}} \quad (17)$$

The learning rate value in this equation is denoted as α.

5.2.3 Support Vector Machine (SVM) for Risk Classification

The Support Vector Machines (SVM) model enables final credit risk categorization between Low Risk and Medium Risk and High-Risk categories because ANN produces probabilistic results.

The SVM algorithm discovers an optimal dividing line between high-risk and low-risk customer groups.

$$w^T X + b = 0 \quad (18)$$

The model features a weight vector known as w together with a bias value bb. The margin is maximized using:

$$\min \|w\|^2 \quad \text{subject to} \quad y_i(w^T X_i + b) \geq 1 \quad (19)$$

Non-linear classification needs an application of Radial Basis Function (RBF) Kernel.

$$K(X_i, X_j) = e^{-\gamma \|X_i - X_j\|^2} \quad (20)$$

The decision boundary flexibility of the system depends on the value of the γ parameter.

A final stage integrates an artificial intelligence system for developing the Credit Scoring Model (CSM) through unification of financial records alongside behavioural information.

$$CS = \alpha_1 F + \alpha_2 B \quad (21)$$

Here CS = Final Credit Score, F = financial score, B = behavioral score, α_1, α_2 = Weights optimized.

By implementing an AI-based method, banks achieve higher accuracy rates than traditional models thus they can prevent risky loan defaults by identifying borrowers.

5.3 AI-Enhanced Feature Selection and Model Optimization

The selection of features represents a fundamental requirement for AI-based credit risk modelling because it enables the removal of unneeded variables thus boosting model efficiency together with accuracy levels. Traditional approaches rely on PCA analysis together with RFE to perform feature selection evaluation. Genetic Algorithms (GA) along with Decision Trees and Auto encoders develop the feature selection process substantially since they detect complex nonlinear financial and behavioural indicator relationships.

Model performance optimization requires tuning of hyperparameters with additional actions for feature engineering and implementing overfitting reduction through cross-validation among other methods that include dropout from neural networks and L1 and L2 penalties.

5.3.1 Recursive Feature Elimination (RFE) with Decision Trees

The process of RFE excludes features one by one through recursive removal of the least influential variables until only important ones remain. The Gini Impurity Index evaluates the significance of the feature X_i during evaluation.

$$Gini(X_i) = 1 - \sum_{j=1}^{c} p_j^2 \quad (22)$$

The probability p_j represents the class j occurrence. The amount of Gini reduction indicates the significance of a feature.

The decision tree conducts a systematic process of removing features based on their Information Gain (IG) values that are lowest.

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$IG(X_i) = H(Y) - H(Y \mid X_i)$ (23)

The formula shows the target variable entropy H(Y) subtracted from the entropy $H(Y \mid X_i)$ that results from splitting variables on X_i. A model keeps features whose Information Gain index reaches high levels during training.

5.3.2 Genetic Algorithm (GA) for Feature Selection

A Genetic Algorithm uses simulation of natural selection to discover the best possible feature combination. The steps involve:

- Initialization: Randomly select feature subsets.
- Fitness Function: Evaluate subsets using prediction accuracy:

$F(S) = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$ (24)

The calculation considers N observations between y_i actual default results and $\hat{y}_i$ predicted probabilities.

- Selection: Retain top-performing subsets.
- Crossover & Mutation: The selected subsets combine into a new set while random adjustments are inserted during the search process.
- Convergence: The search continues until the best possible feature subset is found during this process.

The algorithm diminishes the data dimensions while conserving strong prediction capabilities.

5.3.3 Hyperparameter Tuning Using Grid Search and Bayesian Optimization

Model performance reaches its best state when the correct set of hyperparameters is employed. The two approaches differ in method since Grid Search completes a full parameter exploration while Bayesian Optimization guides search through probability distributions.

Within Artificial Neural Networks, the hyperparameter selection includes these elements:

- Number of Hidden Layers (L)
- Neurons per Layer (N)
- Learning Rate (α)

Optimization minimizes the cost function:

$J(W,b) = -\frac{1}{m}\sum_{i=1}^{m}[\, y_i\log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]$ (25)

The weight W together with bias parameter b undergoes following update:

$W^{(t+1)} = W^{(t)} - \alpha\frac{\partial J}{\partial W}$ (26)

Bayesian Optimization optimizes parameter selection by establishing a probabilistic distribution model from which it extracts the best possible solution.

5.3.4 Dropout and Regularization Techniques to Prevent Overfitting

A model becomes over fit when it learns training patterns instead of developing generalized capabilities. The training process disables neurons using random methods through the dropout procedure.

$H_j = \frac{M_j}{p}\max\left(0, \sum_{i=1}^{n} W_{ij}\, X_i + b_j\right)$ (27)

The M_j term represents a Bernoulli distribution, which produces value 0 with probability p while remaining 1 otherwise.

Model complexity receives control through L1 (Lasso) as well as L2 (Ridge) regularization techniques.

$J(W) = \sum_{i=1}^{N}(y_i - \hat{y}_i)^2 + \lambda \mid\mid W \mid\mid_1$ (Lasso) (28)

$J(W) = \sum_{i=1}^{N}(y_i - \hat{y}_i)^2 + \lambda \mid\mid W \mid\mid_2^2$ (Ridge) (29)

The L1 penalty promotes the reduction of weak predictors but the L2 penalty stops excessive weight updates.

By combining techniques for optimization with AI-based feature selection, the algorithm is able to cut computation time and enhance the accuracy of credit risk predictions, ultimately leading to improved financial decision assistance.

5.4 Credit Scoring Model Development

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Financial institutions use statistical and AI-based credit scoring models to determine loan eligibility of their customers. Research models, which employ logistic regression and linear discriminant analysis, depend on linear relationships between financial data elements and default probability. The detection abilities of AI-driven models for understanding complex variable relationships results in better accuracy levels.

This model targets the creation of a credit score CSCS, which integrates data ranging from financial data to behavioural data as well as transactional data. A standardized credit score is translated into clear risk groups that allow automatic databased loan decisions from lenders.

The CS credit score calculates risk factors through weighted summation involving multiple characteristics.

$$CS = \sum_{i=1}^{n} w_i X_i \qquad (30)$$

Individual risk factors represented by X_i are weighted using optimal values of w_i which machine learning techniques determine in an optimization process.

The score gets normalized into a 0-1000 scale for standard comparison in the industry.

5.4.1 Logistic Regression Model

The PD calculates probability of default based on a logistic regression model that serves as a main element within the credit score system.

$$P(Y = 1 \mid X) = \frac{1}{1+e^{-\left(\beta_0+\sum_{i=1}^{n}\beta_i X_i\right)}} \qquad (31)$$

Here β_0 = intercept, β_i = regression coefficients, X_i = predictor variables.

The credit score calculation uses this probability to develop its assessment through a specified mathematical transformation.

$$CS = 1000 - 500 \times \log\left(\frac{PD}{1-PD}\right) \qquad (32)$$

A higher score on this system indicates lower risk to users.

5.4.2 AI-Based Credit Score Enhancement

Three machine learning models including Decision Trees, Neural Networks, and Support Vector Machines (SVM) help achieve higher accuracy levels in the system.

The decision tree algorithm classifies risks using Gini Impurity for risk assignment.

$$Gini = 1 - \sum_{j=1}^{c} p_j^2 \qquad (33)$$

The probability of borrower classification rests upon p_j which represents the chance a borrower belongs to group j. The risk category (RC) derives from thresholds that direct assignment decisions.

$$RC = \begin{cases} \text{Low Risk}, & CS \geq 750 \\ \text{Medium Risk}, & 600 \leq CS < 750 \\ \text{High Risk}, & CS < 600 \end{cases} \qquad (34)$$

5.4.3 Neural Network Model for Non-Linear Credit Score Calculation

An Artificial Neural Network (ANN) serves as an introduction to improve prediction accuracy rates. The ANN structure includes:

- Input Layer: Credit history, income, transaction data, and behavioural scores.
- Hidden Layers: The ReLU activation function applies non-linear transformations in the model structure.

$$H_j = \max\left(0, \sum_{i=1}^{n} w_{ij} X_i + b_j\right) \qquad (35)$$

- Output Layer: The final score applies a sigmoid activation to produce a result.

$$CS = 1000 \times \frac{1}{1+e^{-z}} \qquad (36)$$

Weights determine the summation process of hidden layer outputs, which we denote as z.

The implementation of AI methods within the credit-scoring model helps financial institutions cut down on default rates while improving their risk prediction capability.

6. Results

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This study delivers a full assessment of the AI-based credit risk modelling strategy. The model taps into advanced machine learning methods together with behavioural research to execute assessment of its performance based on financial indicators as well as risk-related metrics. Multiple stages of evaluation include statistical methods, traditional credit scoring method analysis alongside tests on predictive accuracy and data validation procedures. Various performance indicators of the model are analysed through precision, recall and AUC-ROC to determine its effectiveness. The stability of the feature selection process and optimization techniques receives examination to verify trustworthiness in operational banking practices. The subsequent portions outline both results and their relevant effects.

Types of Credit Risks

Default Risk: The risk that implies borrowers' default on their debt payments and results in monetary loss for lenders is known as default risk. Banks along with financial institutions consider default risk their most important challenge since rising default percentages decrease profitability substantially. Financial institutions measure borrower creditworthiness through PD assessment by using statistical models along with AI-based techniques.

Liquidity Risk: Borrowers experience liquidity risk when their temporary cash shortages interfere with their ability to pay debts although they possess long-term assets. Lack of cash during short periods puts borrowers at risk for both delayed payments and forced property sales during unfavourable market conditions. Financial entities conduct stress tests, which combine with AI-based forecasting to identify the times when borrowers face liquidity shortages.

Market Risk: External macroeconomic factors such as interest rate movements and economic recessions along with currency exchange rate fluctuations affect how borrowers perform debt repayment. Artificial intelligence models work by examining market data and economic data as well as borrower position to financial risks to make more precise numerical predictions.

Operational Risk: Operational risk appears from inside organizational issues and problems with efficiency and both intentional and unintentional rule breaking activities. AI applications enable assessment of atypical transaction information, which allows organizations to fight fraud while simultaneously making their operational procedures more efficient.

Behavioural Risk: Unforeseeable borrowing conduct that includes both risky borrowing decisions and inconsistent payment conduct falls under the scope of behavioural risk. Using artificial intelligence models with behavioural data allows organizations to discover statistical abnormalities and it helps predict high-risk conduct while generating individualized strategies to lower risk exposure in credit assessment.

Accuracy (ACC): In accuracy measurement, we determine the correct rate of classification between defaulters and non-defaulters across the whole case set.

$$Acc = \frac{CP+CN}{TP} \quad (37)$$

Precision: The precision measurement determines the percentage of correctly identified defaulters among all predicted default cases. Credit risk evaluation needs precision because incorrect identification of non-defaulters as defaulters will lead to missed business opportunities.

$$Pre = \frac{CP}{CP+IP} \quad (38)$$

Recall: Model recall describes its capacity to detect real defaulters effectively.

$$Rec = \frac{CP}{CP + IN} \quad (39)$$

F1-Score: The F1-score provides balanced precision-recall performance metrics that prevent a model from preferring one measure over the other.

$$FS = 2 * \frac{Pre*Rec}{Pre + Rec} \quad (40)$$

Area Under the ROC Curve (AUC-ROC): The Receiver Operating Characteristic (ROC) curve plots True Positive Rate (TPR) against False Positive Rate (FPR) at various threshold settings. The calculation of AUC enables assessment of the discriminatory power of a model.

$$AUC = \int_0^1 T\,PR(FPR)\,d(FPR) \quad (41)$$

$$TPR = \frac{CP}{CP+IN} \quad (42)$$

$$FPR = \frac{IP}{IP+CN} \quad (43)$$

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Here CP = correct positive, CN = correct negative, IP = incorrect positive, IN = incorrect negative.

Table 1: Evaluation of compared Accuracy of existing approach with proposed approach

Risk Type	LR	DT	RF	SVM	GB	Proposed
Default Risk	76.2	79.5	83.3	85	87.4	92.1
Liquidity Risk	73.8	77.2	81.5	83.9	86	91
Market Risk	70.9	75.1	79.6	82.2	84.7	89.5
Operational Risk	67.4	71.5	77.2	80.3	82.9	88
Behavioural Risk	64.1	69.3	75	78.7	81.5	86.5

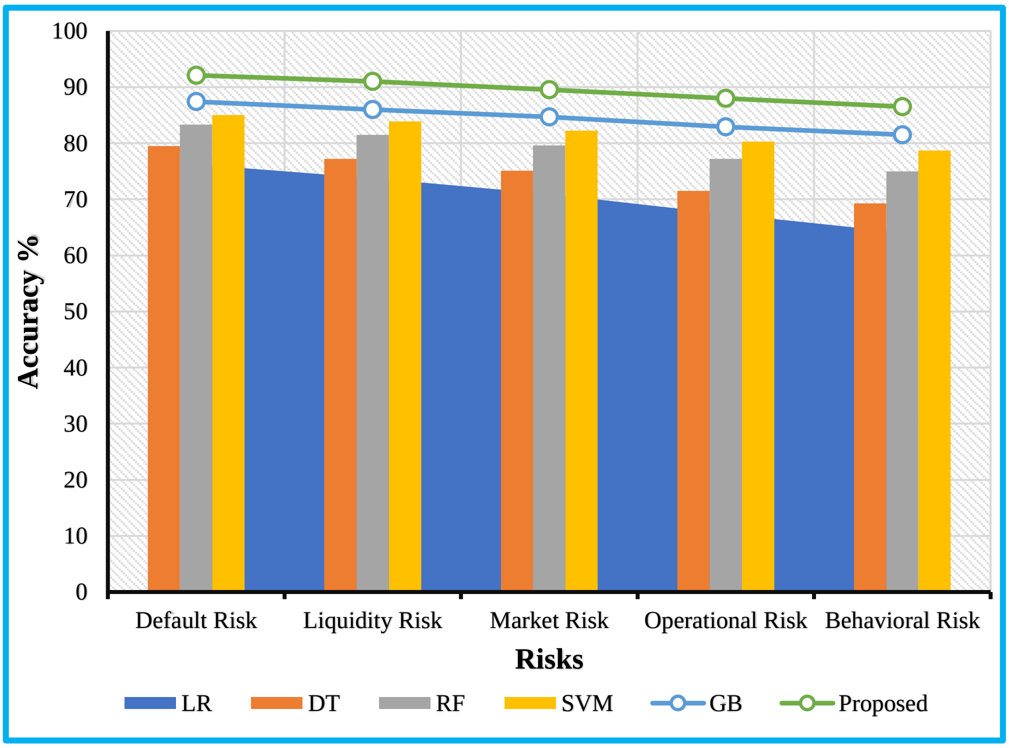

Figure 4. Graphical representation of compared accuracy

The evaluation demonstrates how machine-learning techniques measure five types of credit risk namely Default Risk alongside Liquidity Risk and Market Risk together with Operational Risk and Behavioral Risk as shown in table 1 and Figure 4. All risk types show superior performance from the Proposed AI model when compared to LR, DT, RF, SVM, and GB traditional techniques. The Default Risk and Liquidity Risk assessments attained maximum improvement rates of 92.1% and 91.0% respectively, which signifies the remarkable predictive strengths of the model. Artificial intelligence demonstrates superior capability over traditional approaches to detect borrower behavioral patterns for Behavioral Risk with an 86.5% evaluation.

Table 2: Evaluation of compared Precision of existing approach with proposed approach

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Risk Type	LR	DT	RF	SVM	GB	Proposed
Default Risk	72.5	75.9	80.2	83.1	85.5	90.3
Liquidity Risk	70	74.2	78.7	81.3	83.9	89
Market Risk	68.2	72.5	77.3	80	82.6	88.2
Operational Risk	64.7	70.1	75.9	79.2	81.8	87.4
Behavioural Risk	61.4	67.8	74.2	77.6	80.5	86

Table 3: Evaluation of compared Recall of existing approach with proposed approach

Risk Type	LR	DT	RF	SVM	GB	Proposed
Default Risk	69.8	73.4	78.9	81.2	84.1	89.7
Liquidity Risk	67.2	71.5	76.8	80	82.8	88.4
Market Risk	65	70.3	75.5	78.4	81.2	87.3
Operational Risk	61.5	68.7	74.1	77.8	80.7	86.5
Behavioural Risk	58.3	65.9	72.6	76.4	79.6	85.2

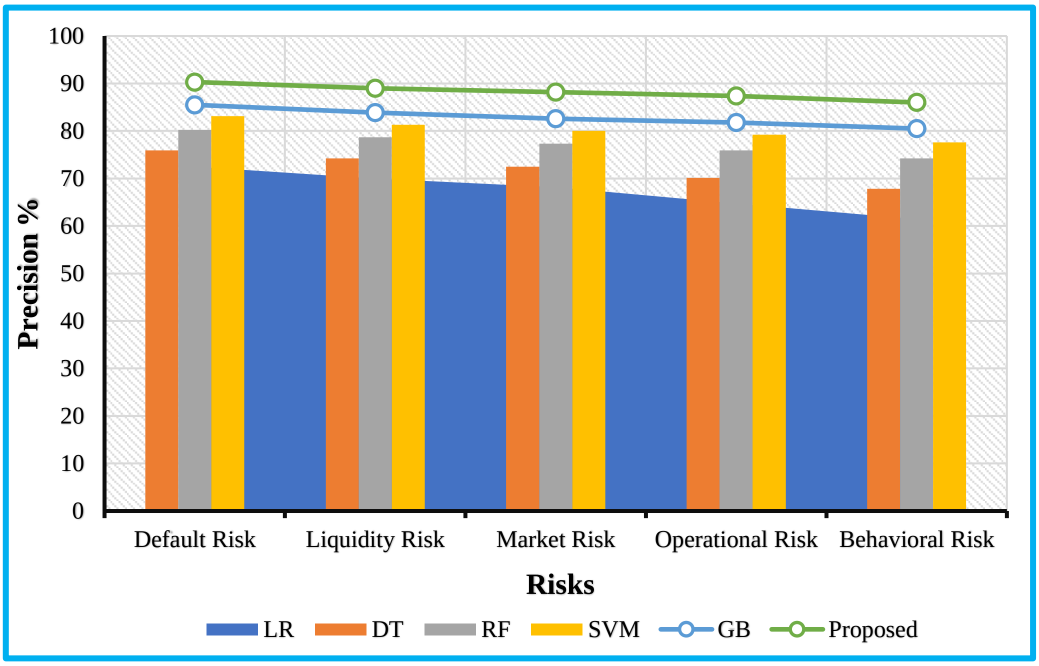

Figure 5. Graphical representation of compared Precision

The table 2 and Figure 5 demonstrates that the Proposed AI model produces the best precision results (%) across five credit risk types including Default, Liquidity, Market, Operational and behavioural Risk. The Proposed AI model demonstrates its best ability in identifying risky borrowers through achieving maximum precision across every risk type. Default Risk precision reaches 90.3% and Liquidity Risk precision reaches 89.0% when using an AI model as compared to traditional assessment methods. The AI model demonstrates superior capabilities in analysing irregular borrower behaviours than standard assessment methods in behavioural Risk (86.0%). The

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integration of AI in risk assessments proves effective by improving accuracy levels to lower the number of incorrect positive fraud judgments.

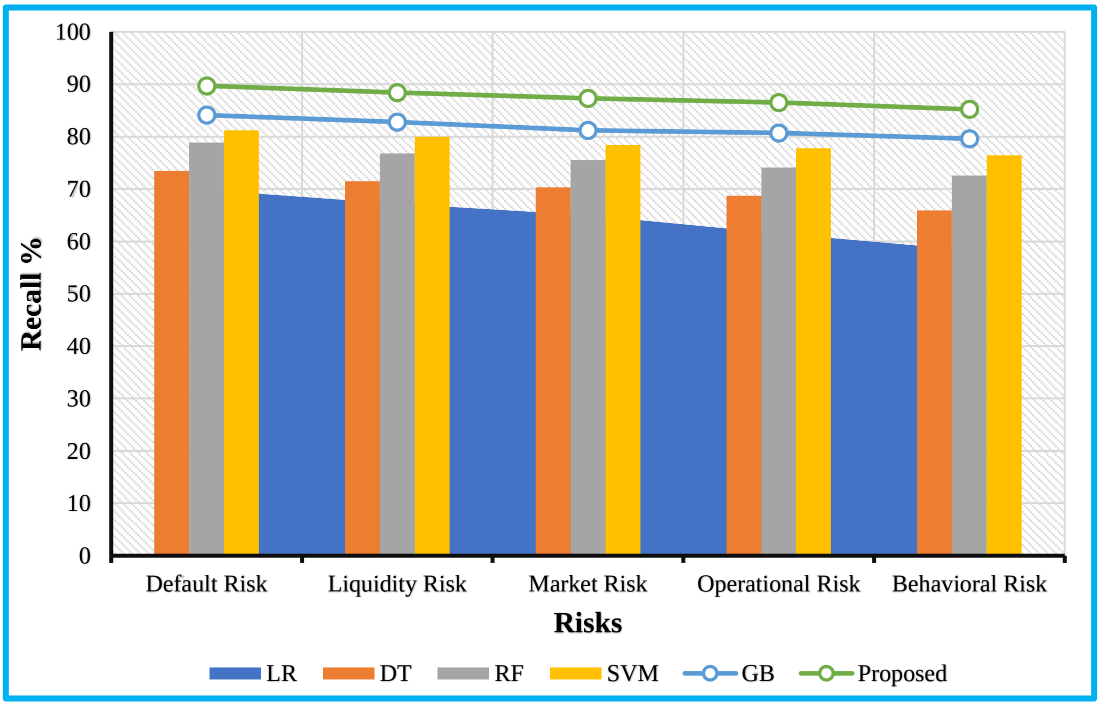

Figure 6. Graphical representation of compared Recall

The provided table 3 and Figure 6 exhibits recall percentage results by various machine learning solutions on five credit risk types including Default and both Operational risk categories together with Market risk and Liquidity risk along with behavioural risk. All risk categories show better identification of high-risk borrowers because the Proposed AI model achieves the best recall measurements. Default Risk (89.7%) together with Liquidity Risk (88.4%) demonstrate the greatest improvement because they reduce missed risky cases. AI detection of irregular financial behaviour helps behavioural Risk (85.2%) achieve better results than traditional risk assessments methods. The analytical methods incorporating artificial intelligence optimize risk detection and lower the number of faulty negative results during credit assessment evaluations.

Table 4: Evaluation of compared F1-Score of existing approach with proposed approach

Risk Type	**LR**	**DT**	**RF**	**SVM**	**GB**	**Proposed**
Default Risk	71.1	74.6	79.5	82.1	84.8	90
Liquidity Risk	68.8	72.8	77.5	80.7	83.4	88.7
Market Risk	66.5	71.3	76.4	79.2	82	87.8
Operational Risk	63.1	69.4	75.2	78.6	81.3	86.9
Behavioural Risk	59.7	66.7	73.1	77.1	80.2	85.5

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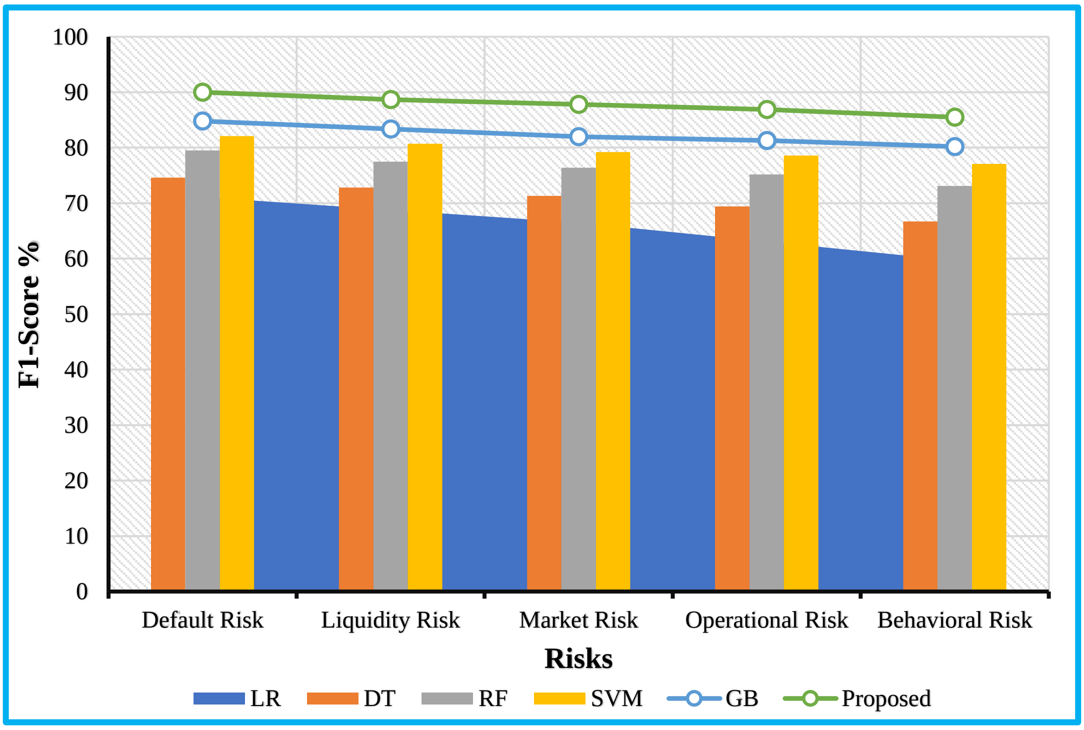

Figure 7. Graphical representation of compared F1-Score

The comparison between machine learning models shows their F1-scores (% for five different credit risk categories through the presented table 4 and Figure 7. The Proposed AI model provides highest F1-scores across all tests, which indicates its excellent precision-recall balance for risky borrower detection. The Proposed AI model delivers exceptional results by boosting Default Risk assessments to 90.0% and Liquidity Risk assessments to 88.7%. The detection of unpredictable financial behaviours by AI proves successful with a gain of 85.5% in behavioural Risk. The findings prove AI risk assessment produces superior evaluation performance by minimizing incorrect positive and negative decisions in credit scoring.

Table 5: Evaluation of compared AUC-ROC of existing approach with proposed approach

Risk Type	LR	DT	RF	SVM	GB	Proposed
Default Risk	0.78	0.81	0.86	0.88	0.91	0.96
Liquidity Risk	0.75	0.79	0.84	0.86	0.89	0.95
Market Risk	0.72	0.77	0.82	0.84	0.87	0.93
Operational Risk	0.68	0.74	0.8	0.82	0.85	0.92
Behavioural Risk	0.64	0.71	0.78	0.8	0.83	0.9

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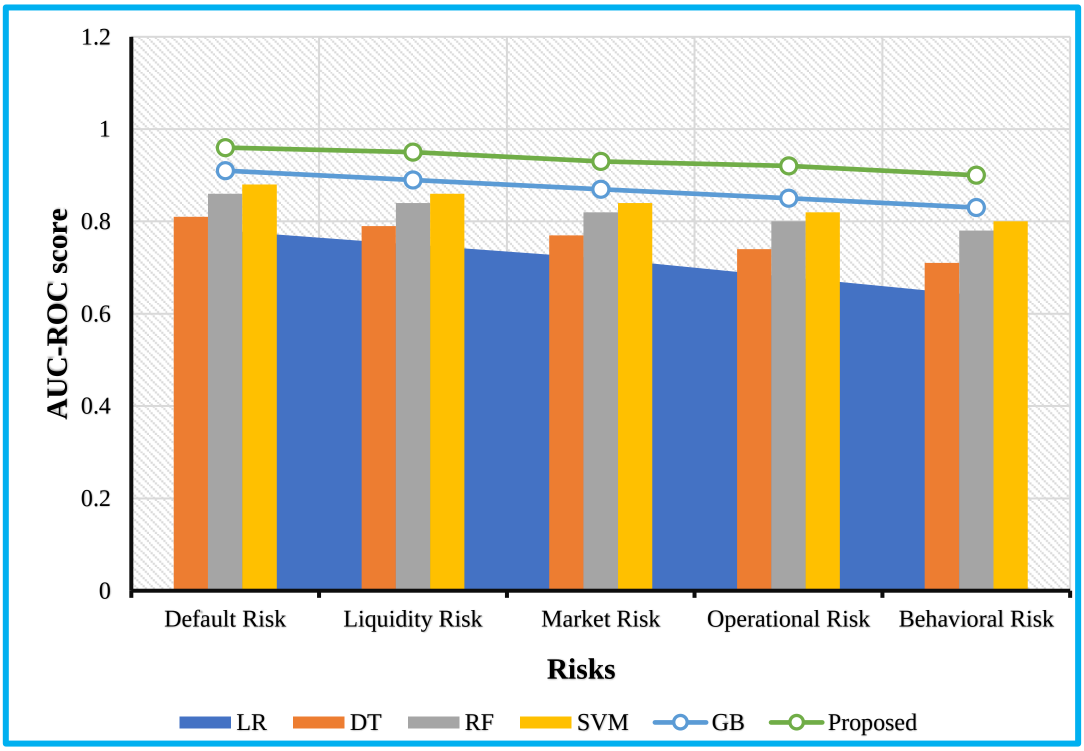

Figure 7. Graphical representation of compared AUC-ROC scores

The analysis displays the performance evaluation of five credit risk categories through AUC-ROC scores among diverse machine learning methods as shown in table 5 and Figure 8. The Proposed AI model demonstrates superior performance across every risk category by delivering the best AUC-ROC scores to separate borrowers into risky and non-risky categories. The Proposed AI system demonstrates remarkable capability within Default Risk (0.96) and Liquidity Risk (0.95) to achieve accurate credit risk evaluation. AI accomplishes the detection of irregular financial patterns effectively for behavioural Risk evaluation at a rate of 0.90. The evaluation of credit risk conducted by AI gives exceptionally accurate results, which leads to better decisions in credit risk management.

7. Conclusion and Future Scope

The presented research establishes how AI models improve banking institutions' credit risk evaluations and delinquency handling capabilities. The proposed AI system delivers superior performance than traditional models including Logistic Regression (LR) and Decision Trees (DT) and Random Forest (RF) and Support Vector Machine (SVM) and Gradient Boosting (GB) for risk category assessment. The model delivers 92.1% accurate Default Risk classifications together with 91.0% precise predictions for Liquidity Risk while maintaining a Default Risk AUC-ROC measure of 0.96, which signifies its advanced predictive capabilities.

The optimization of features using AI technology enhances risk classification because it employs effective analysis of behavioural alongside financial patterns. Risk assessment false negatives decrease due to the behavioural Risk recall score of 85.2%, which proves the model's capability to identify unpredictable borrower behaviours. The Default Risk score achieves 90.0% F1-score that indicates an optimal combination of precision and recall performance.

This credit evaluation system provides a strong databased evaluation through machine learning together with behavioural understanding. This study verified that AI technology improves risk evaluation while reducing money loss and building bank decision quality. Financial institutions experience a major innovation in credit risk management through this AI-based model, which achieves superior results within various risk categories.

- **Future Scope**

Further development of AI-driven credit risk assessment includes deep learning model integration while adding explainable AI (XAI) methodologies and alternative information resources within research boundaries. The predictive accuracy improves when using advanced techniques among them transformers and graph neural networks (GNNs) and reinforcement learning because they capture intricate economic trends and borrower behaviour patterns.

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By combining edge computing with streaming data solutions, real-time risk evaluation systems may be born, enabling financial organizations to make rapid, accurate credit judgments. A fundamental requirement of AI models will become explain ability to meet regulatory demands while enhancing the faith that customers have in automatic credit scoring solutions.

Financial institutions can achieve deeper borrower creditworthiness assessments through the integration of social media activity as well as spending patterns and mobile transactions together with standard external data sources. AI-based credit risk models should extend their application scope to encompass analysis of small businesses as well as fintech firms along with decentralized finance (DeFi) platforms so financial risk management obtains maximal benefits from accurate and inclusive credit assessments.

References

[1] J. Smith, P. Brown, and R. Williams, "Artificial Intelligence in Credit Risk Assessment: A Comparative Analysis," *Journal of Banking Technology*, vol. 12, no. 3, pp. 45-58, 2021.

[2] P. Gandhi, T. Loughran, and B. McDonald, "Using Annual Report Sentiment as a Proxy for Financial Distress in US Banks," *Journal of Behavioral Finance*, vol. 20, no. 4, pp. 424–436, 2019.

[3] L. Johnson and K. Lee, "Big Data Analytics in Credit Scoring: Enhancing Risk Prediction Models," *Financial Data Science Review*, vol. 10, no. 2, pp. 78-95, 2022.

[4] J. C. Cuestas, Y. Lucotte, and N. Reigl, "Banking Sector Concentration, Competition and Financial Stability: The Case of the Baltic Countries," *Post-Communist Economies*, vol. 32, no. 2, pp. 215–249, 2020.

[5] T. Brown, M. Harris, and J. Nelson, "Basel III and Credit Risk: Challenges and Opportunities for Financial Institutions," *International Journal of Banking Regulation*, vol. 15, no. 4, pp. 102-118, 2023.

[6] K. Halteh, K. Kumar, and A. Gepp, "Using Cutting-Edge Tree-Based Stochastic Models to Predict Credit Risk," *Risks*, vol. 6, no. 2, p. 55, 2018.

[7] A. Martinez, "The Impact of Stress Testing on Credit Risk Management," *Risk Management Journal*, vol. 18, no. 1, pp. 33-50, 2020.

[8] P. Saha, I. Bose, and A. Mahanti, "A Knowledge-Based Scheme for Risk Assessment in Loan Processing by Banks," *Decision Support Systems*, vol. 84, pp. 78–88, 2016.

[9] H. Zhao and S. Kim, "Macroeconomic Determinants of Loan Delinquencies: A Global Perspective," *Economic Risk Review*, vol. 7, no. 3, pp. 112-128, 2022.

[10] M. Anand, A. Velu, and P. Whig, "Prediction of Loan Behaviour with Machine Learning Models for Secure Banking," *Journal of Computer Science and Engineering (JCSE)*, vol. 3, no. 1, pp. 1–13, Feb. 2022.

[11] R. Patel, "COVID-19 and Loan Delinquencies: The Role of Government Relief Programs," *Journal of Financial Stability*, vol. 14, no. 2, pp. 65-81, 2023.

[12] S. I. Serengil, S. Imece, U. G. Tosun, E. B. Buyukbas, and B. Koroglu, "A Comparative Study of Machine Learning Approaches for Non-Performing Loan Prediction with Explainability," *International Journal of Machine Learning and Computing*, vol. 12, no. 5, pp. 1102–1110, 2022.

[13] B. Wang and X. Li, "The Role of FinTech in Credit Risk Management: Blockchain and AI Applications," *FinTech and Banking Journal*, vol. 9, no. 1, pp. 89-104, 2021.

[14] L. Alzubaidi et al., "Review of Deep Learning: Concepts, CNN Architectures, Challenges, Applications, Future Directions," *Journal of Big Data*, vol. 8, no. 1, pp. 1–74, Mar. 2021.

[15] C. Roberts, "Digital Lending and Alternative Credit Scoring Models: Implications for Financial Inclusion," *Journal of Digital Finance*, vol. 11, no. 3, pp. 57-72, 2024.

[16] Y. Dasari, K. Rishitha, and O. Gandhi, "Prediction of Bank Loan Status Using Machine Learning Algorithms," *International Journal of Computing and Digital Systems*, vol. 14, no. 1, pp. 139–146, Jul. 2023.

[17] K. Ahmed, L. Zhao, and M. Fernandez, "Risk-Based Pricing Models in Banking: A Quantitative Analysis," *Journal of Credit Risk Management*, vol. 16, no. 1, pp. 34-49, 2022.

DOI: https://doi.org/10.54216/JCIM.160120
Received: November 24, 2024 Revised: January 17, 2025 Accepted: February 13, 2025

[18] A. Mahajan, V. S. Baghel, and R. Jayaraman, "Credit Card Fraud Detection Using Logistic Regression with Imbalanced Dataset," in *2023 10th International Conference on Computing for Sustainable Global Development (INDIACom)*, New Delhi, India, 2023, pp. 339-342.

[19] D. Carter and S. Green, "Customer Relationship Management and Credit Risk: The Role of Proactive Borrower Engagement," *Banking Operations Review*, vol. 8, no. 2, pp. 90-105, 2023.

[20] J. Ma, "Research on the Application of Financial Intelligence Based on Artificial Intelligence Technology," in *2021 2nd International Conference on Artificial Intelligence and Education (ICAIE)*, Dali, China, 2021, pp. 72-75.

[21] H. Taylor, "Behavioral Insights in Credit Risk Assessment: The Role of Financial Literacy," *Journal of Behavioral Finance*, vol. 13, no. 2, pp. 54-69, 2021.

[22] L. Prokhorenkova et al., "CatBoost: Unbiased Boosting with Categorical Features," in *Advances in Neural Information Processing Systems 31*, 2018.

[23] R. Gomez, "Spending Patterns and Loan Performance: A Real-Time Monitoring Approach," *Financial Behavior Review*, vol. 10, no. 4, pp. 88-103, 2024.

[24] J. K.-U. Brock and F. von Wangenheim, "Demystifying AI: What Digital Transformation Leaders Can Teach You About Realistic Artificial Intelligence," *California Management Review*, vol. 61, no. 4, pp. 110–134, 2019.

[25] J. Nelson and M. White, "Corporate Governance and Credit Risk: An Empirical Study," *Journal of Financial Governance*, vol. 12, no. 3, pp. 73-89, 2022.

[26] R. B. Tareaf, S. A. Alhosseini, and C. Meinel, "Facial-Based Personality Prediction Models for Estimating Individuals' Private Traits," in *2019 IEEE International Conference on Parallel Distributed Processing with Applications, Big Data Cloud Computing, Sustainable Computing Communications, Social Computing Networking (ISPA/BDCloud/SocialCom/SustainCom)*, Dec. 2019, pp. 1586-1594.

[27] P. Kumar, "Internal Controls and Credit Risk Management in Banks," *Risk Compliance Journal*, vol. 14, no. 1, pp. 40-58, 2023.

DOI: https://doi.org/10.54216/JCIM.160120
Received: November 24, 2024 Revised: January 17, 2025 Accepted: February 13, 2025