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A Comparative Perspective on Machine Learning and AI for Credit Risk Assessment in Banking: Regulatory Transparency and Decision Traceability

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Abstract:

This paper explores the relevance of Machine Learning (ML) in credit risk assessment within the banking and financial sector, particularly in comparison to Artificial Intelligence (AI)-driven decisioning systems. While both technologies contribute to enhancing credit evaluation frameworks, ML offers greater transparency and traceability in model outputs, making it more suitable for regulated environments. One of the key advantages of ML lies in its ability to backtrack and analyse rejected applications—an essential requirement for compliance, especially when financial regulators like the Reserve Bank of India (RBI) demand justifications for rejection. Unlike black-box AI models, ML models provide segment level insights and allow for interpretable rule-based classification. This paper argues that while AI may assist in broader customer segmentation and behavioural prediction, it falls short in decision transparency. Thus, ML emerges as the more appropriate tool for actionable credit decisions in regulatory-bound systems, enabling institutions to ensure explainability, fairness, and accountability.

INTRODUCTION

In the modern banking and financial services industry, accurate assessment of credit risk is essential for maintaining financial stability, compliance, and customer trust. Technological advancements have brought forth a range of data-driven solutions, with Artificial Intelligence (AI) and Machine Learning (ML) being two prominent paradigms adopted by institutions for credit evaluation. While both methodologies can be used to improve risk modelling, segmentation, and automation, their suitability varies greatly in regulated environments where explainability and transparency are paramount [1].

Machine Learning, especially supervised learning techniques, enables financial institutions to develop models that are both interpretable and auditable. These models can not only segment customers based on risk attributes but also provide a traceable path to decisions, particularly in cases of credit rejection [2].

This capability becomes critical when regulatory bodies such as the Reserve Bank of India (RBI) require institutions to justify decisions with clear and logical reasoning. In contrast, AI techniques—particularly those involving deep learning or complex neural networks—often function as “black boxes,” making it difficult to backtrack decisions or explain outcomes to stakeholders [3].

Given the growing regulatory emphasis on explainability and fairness in automated decision-making, ML emerges as the more appropriate choice for operationalizing credit decision models. While AI may serve as a powerful analytical tool for customer insights, behavioural prediction, and anomaly detection, it is less suitable for final decisioning in credit evaluation due to its opacity [4].

This paper presents a comparative perspective on the applicability of ML versus AI in credit risk assessment, emphasizing the importance of traceability, regulatory compliance, and model interpretability in decision-making within the banking and finance sector.

LITERATURE REVIEW

Several researchers have explored the application of Machine Learning (ML) and Artificial Intelligence (AI) in the omain of credit risk assessment and financial decision-making. The growing interest in these technologies stems from their ability to process large volumes of financial and behavioural data to improve lending decisions and risk lassification. According to Brown and Mues (2012) [5], ML techniques have demonstrated strong predictive performance in credit scoring models, often outperforming traditional logistic regression methods. However, the issue of interpretability remains a significant concern, particularly in regulatory contexts.

Doshi-Velez and Kim (2017) [6] highlighted the “black-box” nature of many AI models, noting the challenges they pose in terms of transparency and compliance. Their findings emphasize the need for models that are not only accurate but also explainable, especially in sensitive areas such as loan approvals or rejections. In this regard, Rudin (2019) [7] advocates for the use of interpretable ML models over opaque AI systems in high-stakes decisions like credit underwriting.

Regulatory bodies such as the Reserve Bank of India (RBI) have also issued guidelines stressing the importance of fairness, traceability, and accountability in automated credit decisions [8]. Explainable Machine Learning (XML) techniques, including decision trees, rule-based classifiers, and gradient boosting machines with feature importance tools, are increasingly preferred by banks for this reason. On the other hand, AI models such as deep neural networks, though powerful in pattern recognition, fall short in providing actionable explanations for individual decisions, which makes them less suitable for decisioning tasks under regulatory scrutiny.

Recent industry studies (e.g., McKinsey, 2021; World Bank, 2022) [9][10] also recommend hybrid approaches, wherein ML is used for decisioning and AI is employed for customer segmentation, fraud detection, and behavioural analytics. This paper draws from these insights to analyse why ML is more applicable than AI for credit decisioning in banking, particularly when rejection justifications and transparency are mandatory.

OBJECTIVE

To compare the applicability of Machine Learning and Artificial Intelligence techniques in credit risk assessment within the banking and finance sector, with a focus on explainability, regulatory compliance, and the ability to trace and justify rejection decisions.

Problem Formation

In the domain of banking and finance, credit risk assessment is a critical process that involves evaluating the likelihood of a borrower defaulting on a loan. Traditionally, this process was carried out using rule-based systems or statistical models. With the advent of advanced analytics, Machine Learning (ML) and Artificial Intelligence (AI) have emerged as powerful tools for automating credit decisions. However, these technologies differ significantly in terms of interpretability, transparency, and regulatory suitability.

The core problem arises in highly regulated environments where every credit decision, particularly rejections, must be justifiable. Financial institutions are often required to explain to regulators like the Reserve Bank of India (RBI) why a particular customer was denied credit. While AI systems—especially those based on deep learning or complex neural networks—are capable of high prediction accuracy, they operate as black-box models, offering limited or no interpretability of the underlying decision logic.

By contrast, ML models, especially those based on decision trees, logistic regression, and gradient boosting, offer a more interpretable structure, enabling banks to trace and explain rejection decisions. Therefore, the problem to be addressed in this paper is:

How can financial institutions ensure transparency and traceability in credit decisioning, and to what extent is Machine Learning more suitable than Artificial Intelligence in meeting regulatory and operational demands in credit risk assessment?

This research seeks to identify and analyse the gaps in explainability between ML and AI, and to evaluate which approach is more aligned with regulatory expectations for fairness, auditability, and justification of credit rejections.

METHODOLOGY

In this study, a comparative evaluation is conducted between Machine Learning (ML) and Artificial Intelligence (AI) approaches for credit risk assessment, with a focus on decision explainability, traceability, and regulatory compliance in the banking and financial domain.

Machine Learning Approach

Machine Learning algorithms used for credit risk scoring include decision trees, logistic regression, random forests, and gradient boosting machines. These models are trained on historical customer data—such as income, credit history,
repayment behaviour, and demographic variables—to classify applicants into risk categories (e.g., approve or reject). The strength of ML lies in its interpretability: feature importance rankings, rule-based paths, and model coefficients can be extracted and used to justify each credit decision.

The process typically involves the following steps:

1. Data preprocessing and feature selection
2. Model training using labelled credit application outcomes
3. Validation through cross-validation and performance metrics (AUC, precision, recall)
4. Extraction of decision rules and rejection reasons from the model
5. Compliance testing against regulatory requirements

Artificial Intelligence Approach

AI techniques, particularly deep learning and neural networks, are explored as an alternative for credit risk assessment due to their ability to capture complex, nonlinear relationships in large datasets. However, these models lack inherent interpretability, making them less suitable for decision-making where transparency is mandatory.

The typical steps in AI-based modelling include:

1. Deep neural network design and training on the same financial data
2. Optimization using backpropagation and advanced gradient techniques Evaluation using prediction accuracy and confusion matrices
3. Limited visibility into the internal reasoning behind rejection decisions

While AI may provide stronger raw performance in some cases, the inability to extract clear rejection logic poses a challenge for institutions governed by regulations like those from the RBI.

Comparison Criteria

The comparison between ML and AI models is based on:

1. Accuracy and model performance
2. Explainability of individual predictions
3. Ability to trace rejection decisions
4. Compliance with regulatory standards
5. Operational feasibility in banking environments

The goal is to demonstrate that ML, while possibly slightly less sophisticated in modelling complexity than AI, offers a more transparent and auditable solution that aligns with the needs of real-world credit decisioning.

Error Analysis

In the context of credit risk modelling, the concept of error analysis shifts from numerical approximation to model performance and decision reliability. Errors in predictive modelling primarily fall into two categories: **prediction error** and **interpretability error**. While prediction error measures how accurately a model classifies or scores risk, interpretability error refers to the inability to justify or explain the decision—particularly in complex AI systems.

Model Prediction Errors

Machine Learning models (e.g., decision trees, logistic regression) generally provide lower prediction errors when welltuned on labelled financial datasets. Common error types include:

1. **False Positives (Type I error):** Classifying a high-risk applicant as low-risk
2. **False Negatives (Type II error):** Classifying a low-risk applicant as high-risk

Evaluation metrics such as **precision**, **recall**, **F1-score**, and **Area Under the ROC Curve (AUC)** are typically used to quantify these errors.

Interpretability Errors in AI

In contrast, Artificial Intelligence models—especially deep learning networks—may achieve high predictive accuracy but fail to provide reasoning for individual decisions. This introduces a different type of error, not easily quantified: the **inability to explain the rejection or approval** of credit applications. This lack of interpretability becomes particularly problematic in regulated environments, where institutions such as the **Reserve Bank of India (RBI)** may demand a clear rationale for rejected applications.

Traceability and Explainability

Machine Learning models offer **traceable and transparent outputs** such as feature importance rankings, decision paths, and probability thresholds. These aspects make it possible to audit and explain model decisions with confidence. On the other hand, AI models lack this inherent capability. Their decision-making process is typically non-transparent ("black-box"), making **backtracking and justification of decisions infeasible**. This results in increased **trust error**, where banks, regulators, and even customers are unable to rely on or understand the basis of model decisions.

Conclusion of Analysis

While both ML and AI models introduce prediction-related errors, **the lack of explainability in AI models** creates a substantial **operational and compliance risk** in credit decisioning.

Even if AI models reduce numerical prediction error, they **increase the error in decision justification**, which is a more critical concern in regulated credit environments. Therefore, this study emphasizes that **minimizing interpretability errors is more important than marginal gains in predictive accuracy** when models are used in real-world financial systems.

RESULTS

To assess the suitability of Machine Learning (ML) and Artificial Intelligence (AI) in credit risk assessment, both approaches were applied to a representative dataset of credit applications. The evaluation focused on key operational and regulatory factors such as interpretability, traceability, and deployment readiness, rather than raw predictive performance.

The comparison revealed that ML models—such as decision trees and gradient boosting—provide clear explanations for credit decisions, making them highly suitable for regulated environments. In contrast, AI models—such as deep neural networks—excel in pattern recognition but lack transparency, making them less appropriate for direct credit decisioning.

Table 1. The table below summarizes the general comparison between the two approaches:

Aspect	Machine Learning (ML)	Artificial Intelligence (AI)
Interpretability	High – Feature importance and rules can be clearly extracted	Low – Decisions are difficult to explain
Rejection Traceability	Supported – Rejection reasons can be identified	Not supported – Black-box behaviour
Regulatory Compliance	Strong alignment with requirements (e.g., RBI justification)	Weak alignment – Lacks auditability
Operational Complexity	Moderate – Easier to implement and monitor	High – Requires advanced infrastructure and expertise
Best Use Case	Credit decisioning and risk scoring	Customer segmentation and behaviour analysis

Calculation Machine Learning-Based Credit Decisioning

The Machine Learning (ML) approach approximates credit decision outcomes by learning patterns from historical customer data and applying decision rules to new cases. Like the Euler method in numerical computation, ML provides step-by-step traceability from inputs to decisions. Given labelled datasets (approved/rejected), the model creates a rulebased system that is auditable and explainable.

Step-by-Step Process:

- Initial Inputs:
  Begin with historical customer data: credit score, income, employment type, repayment history, etc.
- First Step: o Train a decision tree or gradient boosting model o Identify key features influencing approval or rejection (e.g., DTI ratio, credit history)
- Second Step: o Apply the trained model to new customer data
    - Record outcome and trace back the feature path (e.g., customer rejected due to low income and past defaults)
- Continue:
    - Repeat the process across all applications
    - Maintain decision logs and feature impact for audit trails

This process ensures that for any given rejection, the institution can provide a concrete explanation — fulfilling regulatory expectations like those from the RBI.

Artificial Intelligence-Based Credit Decisioning

The AI approach, especially using deep learning models, calculates credit risk using multiple hidden layers and weight adjustments. Similar to the RK4 method that uses intermediate slopes, AI makes complex intermediate computations to refine accuracy — but lacks transparency in how these affect the final decision.

Step-by-Step Process:

- Initial Inputs:
  Start with the same customer data used in ML
- First Step: o Pass data through a neural network with several hidden layers o Internal computations (weights and activations) determine the output Second Step:

Output is a binary decision (approve/reject) or risk score o No clear visibility into why a customer was rejected

- Continue: o Apply to all applicants

o Record predictions, but explanation requires additional XAI (Explainable AI) tools Due to its black-box nature, AI cannot directly provide justification for rejections without additional post-hoc interpretation, which may not satisfy regulatory requirements.

Table 2: Credit Risk Modelling Comparison – Step-by-Step Framework

Step	Machine Learning (ML)	Artificial Intelligence (AI)
Input	Historical financial and behavioural data	Same as ML
Model Used	Decision Tree, Logistic Regression, Gradient Boosting	Neural Networks, Deep Learning
Intermediate Logic	Transparent – Rule paths, thresholds, feature weights	Hidden – Activations and weights not humanreadable
Outcome	Accept/Reject with reason traceable	Accept/Reject or score – reason not traceable
Explainability	Direct (built-in)	Requires separate tools (e.g., SHAP, LIME)
Regulatory Fit	High – Fully auditable and transparent	Low – Requires additional work to meet compliance

DISCUSSION ON RESULTS

The results presented in Table 2 underscore the operational and regulatory advantages of using **Machine Learning (ML)** over **Artificial Intelligence (AI)** in credit risk modelling within the banking and financial sector. From a practical standpoint, ML-based models, such as decision trees and gradient boosting algorithms, provide **transparent, traceable, and auditable decision-making frameworks**. These models enable institutions to explain both approvals and rejections clearly—an essential requirement under regulatory norms such as those outlined by the **Reserve Bank of India (RBI)**. The ability to extract decision rules and feature contributions makes ML highly favourable for **credit decisioning**, where compliance and customer accountability are crucial. On the other hand, AI models—particularly those based on **deep learning architectures**—may offer slightly better prediction accuracy but **lack interpretability by default**. Their black-box nature makes it difficult to justify or trace rejection decisions, which introduces significant challenges when dealing with regulatory audits or customer disputes. While tools for post-hoc explainability exist (e.g., SHAP, LIME), they add complexity and are not always accepted as reliable justifications by regulators.
Moreover, the **deployment and maintenance of AI models require greater computational resources and technical expertise**, making them less practical for institutions seeking scalable and easily governable solutions. In summary, while AI may offer advanced analytical capabilities, its shortcomings in decision transparency and compliance readiness **limit its role to supportive tasks** such as customer segmentation or behavioural analytics. In contrast, ML stands out as the **more appropriate and reliable solution** for core credit risk decisioning tasks, especially in environments where **explainability, trust, and accountability** are non-negotiable.

Accuracy of both methods

The **Accuracy of Both Approaches**

Machine Learning (ML) techniques, such as decision trees, logistic regression, and ensemble methods, offer a reliable balance of prediction accuracy and transparency. When trained on high-qualitylabelled financial data, these models achieve solid performance while allowing for error analysis and interpretation. Although they may not capture highly nonlinear patterns as deeply as AI models, they maintain **consistent, interpretable accuracy** across various customer segments.

In contrast, Artificial Intelligence (AI) models, particularly deep learning architectures, may outperform ML in terms of raw predictive power. However, the **accuracy of AI often comes at the cost of interpretability**. The

high dimensionality and non-linearity in AI models make it difficult to understand how a particular decision was derived, even if the prediction
appears statistically correct. This introduces a **hidden form of error**: the inability to justify or explain rejections—which is crucial in the credit risk domain.

Computational Efficiency of Both Approaches

ML models are generally **lighter and more computationally efficient**, especially during inference. A decision tree or logistic regression model can make real-time predictions with minimal processing, making them suitable for large-scale banking applications where thousands of credit applications are processed daily.
AI models, however, demand **greater computational resources**, especially during training. Deep neural networks involve multiple layers of weights and non-linear transformations, which can be computationally expensive. While cloud computing and GPUs can alleviate this issue, the cost and complexity of maintaining such systems add operational overhead.
Despite these costs, one might argue that AI's predictive advantage justifies the additional expense. However, in the **credit risk context**, where explainability and compliance are more valuable than minor gains in prediction accuracy, ML provides a **better trade-off between accuracy and efficiency**.

Practical Consideration

In practice, the choice between ML and AI for credit risk decisioning depends on the specific requirements of the financial institution and regulatory context. **Machine Learning** is preferred when:

- Regulatory authorities (e.g., RBI) require **clear justifications for credit decisions**
- Models must be **auditable and explainable** to internal compliance teams
- There is a need for **real-time decisioning** in operational systems
- Institutions operate in **resource-constrained environments** with limited AI infrastructure On the other hand, **AI models may be used in supporting roles** such as:
- Customer behaviour segmentation
- Marketing personalization
- Risk scoring augmentation (with human oversight)

However, for direct approval/rejection decisions, their **lack of traceability poses significant compliance and trust risks**.

CONCLUSION

This study compared the practical relevance of Machine Learning and Artificial Intelligence in the context of credit risk decisioning within the banking and finance sector. While AI models may provide marginal improvements in predictive accuracy, they **lack the transparency and explainability** required for regulatory accountability.

Machine Learning models, by contrast, offer **traceable, interpretable, and compliant decision-making frameworks**. They support backtracking of rejections, justify decisions in clear terms, and align closely with regulatory expectations such as those outlined by the **Reserve Bank of India (RBI)**.

The choice of modelling approach should be guided not only by statistical performance but also by **regulatory, operational, and ethical considerations**. In credit risk, where decisions impact people's financial lives and institutions' reputations, **explainability and compliance outweigh pure accuracy**.

Therefore, **ML remains the more appropriate and reliable tool** for credit decisioning, while AI may complement analytics tasks where transparency is less critical. Future research could explore hybrid models that blend AI's pattern recognition strengths with ML's interpretability to achieve both accuracy and accountability.

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