Group Assignment

Machine Learning & Artificial Intelligence

Credit Risk Assessment in the Finance Industry & AI-ML Solutions

MBA-FT Programme Batch 2024-2026 Term – V

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1. INTRODUCTION TO THE FINANCIAL SERVICES / BANKING INDUSTRY

The financial services and banking industry is one of the most dynamic and influential sectors in the global economy. It plays a fundamental role in supporting economic growth by facilitating financial intermediation - the process of mobilizing savings from individuals and institutions and channelling them into productive investments. This industry includes a wide range of institutions such as commercial banks, cooperative banks, non-banking financial companies (NBFCs), microfinance institutions, insurance firms, investment banks, and fintech companies. Together, these entities provide essential services including deposits, credit, investment management, insurance coverage, and payment solutions, enabling both individuals and businesses to achieve financial security and development.

Banks occupy a central position in this industry as they act as custodians of public savings and suppliers of credit. Their core functions involve accepting deposits, granting loans, and creating credit. By offering various types of lending products such as personal loans, home loans, vehicle loans, business loans, agricultural finance, trade credit, and working capital assistance, banks help drive consumption, entrepreneurship, and industrial expansion. Credit disbursement is therefore considered one of the most crucial economic activities undertaken by the banking sector. The availability of credit leads to capital formation, job creation, and an increase in living standards, which ultimately contributes to a country's GDP and overall economic development.

However, lending activities come with inherent risks - the most significant being credit risk, which refers to the possibility that a borrower may fail to repay the loan or meet contractual obligations. Credit risk is a major concern because it can directly impact the financial health, stability, and profitability of financial institutions. Improper lending decisions or weak credit assessment procedures may lead to loan defaults, rising Non-Performing Assets (NPAs), and even systemic financial crises. Therefore, banks and financial regulators place strong emphasis on credit evaluation frameworks and risk management systems to ensure responsible lending.

The structure of the financial services industry has evolved significantly over the years due to globalization, regulatory reforms, and technological advancement. Automated credit scoring models, digital verification tools, and advanced analytics powered by artificial intelligence and machine learning have transformed the traditional lending process. These innovations enable faster loan approvals, enhanced accuracy in credit assessments, and better monitoring of borrower behaviour. Fintech companies have further accelerated financial inclusion by providing digital lending services and expanding access to credit for underserved populations such as small businesses, rural borrowers, and first-time borrowers.

In India, the financial services sector has grown rapidly over the past decades, supported by government initiatives, regulatory strengthening by the Reserve Bank of India (RBI), and the expansion of digital infrastructure. Programs such as Pradhan Mantri Jan Dhan Yojana (PMJDY), Aadhaar-based identification, and the Unified Payments Interface (UPI) have revolutionized financial access and encouraged participation in the formal financial system. As more people gain access to banking and credit services, managing credit risk becomes more crucial for sustainable growth.

The industry operates under a strong regulatory framework to ensure financial stability, customer protection, and risk mitigation. Central banks and regulatory authorities enforce guidelines related to capital adequacy, asset classification, provisioning norms, and reporting standards. The adoption of global banking practices such as Basel norms has further strengthened risk management practices. Banks are encouraged to classify loans based on their risk category and maintain transparent reporting of asset quality. This classification assists in early identification of potential defaults, better provisioning, and timely corrective actions.

The financial services and banking sector also plays a key role in promoting financial literacy and responsible borrowing practices. As the credit market expands, it becomes essential to ensure that borrowers understand loan terms, repayment obligations, and consequences of default. This creates a balanced financial environment where both lenders and borrowers can benefit.

SWOT Analysis of the Financial Services / Banking Industry

Strengths

1. **Critical Role in Economic Growth:**

   The banking industry acts as a vital engine of economic development by mobilizing savings and facilitating credit flow to businesses, households, and government sectors. It supports investment, employment generation, and infrastructure development.

2. **Strong Regulatory Framework:**

   The sector operates under strict regulations set by central banks and financial authorities to ensure stability, transparency, and protection of consumer interests. Compliance measures like Basel norms help maintain financial discipline.

3. **Wide Accessibility and Network:**

   Banks have extensive branch networks, ATMs, and digital platforms, allowing them to reach diverse segments including rural areas. Financial inclusion initiatives have expanded access to formal banking services.

4. **Diversified Financial Services:**

   The industry offers a broad spectrum of services - retail banking, corporate finance, insurance, investments, wealth management, and digital payments - catering to the needs of multiple customer segments and reducing dependence on a single revenue source.

5. **Adoption of Technology and Innovation:**

   Advancements in digital banking, fintech partnerships, UPI systems, and automation have enhanced service speed, convenience, operational efficiency, and customer satisfaction.

Weaknesses

1. **High Exposure to Credit Risk**:

   Lending activities involve a significant risk of default, leading to non-performing assets (NPAs) that reduce profitability and strain balance sheets.

2. **Operational and Cybersecurity Risks**:

   With increased digital transactions, banks face risks of cyberattacks, data breaches, and system failures, which can damage customer trust and cause financial losses.

3. **Complex Regulatory Compliance**:

   The need to comply with multiple regulations increases administrative burdens and operational costs for financial institutions.

4. **Customer Service Gaps**:

   Despite digital advancements, long procedures, service delays, and technical issues continue to affect customer experience, particularly in public sector banks.

5. **Legacy Technology Systems in Some Banks**:

   Older IT systems limit flexibility and integration with new technologies, leading to inefficiencies and higher maintenance costs.

Opportunities

1. **Growing Demand for Credit:**

   Economic expansion, entrepreneurial growth, and rising consumer aspirations create a continuous demand for personal, housing, and business loans.

2. **Digital Transformation and Fintech Collaboration:**

   Artificial intelligence, blockchain, digital lending, and paperless banking offer strong potential for innovation, cost reduction, and better risk management.

3. **Expansion of Financial Inclusion**:

   Government policies aimed at rural banking, MSME financing, and priority sector lending open new customer bases and revenue streams.

4. **Wealth Management and Insurance Growth**:

   Increasing financial awareness, higher disposable incomes, and investment trends create opportunities in wealth advisory and insurance products.

5. **Global Integration:**

   Growing foreign investment and cross-border financial activities enable banks to expand internationally and diversify operations.

Threats

1. **Economic Instability and Recession Risks**:

   Economic downturns can increase loan defaults, reduce credit demand, and weaken asset quality, impacting profitability.

2. **Intensified Competition**:

   Fintech companies and private institutions provide faster and more customer-friendly services, posing competitive pressure on traditional banks.

3. **Rising Cybercrime and Fraud**:

   Sophisticated cyber threats put customer data and financial systems at risk, requiring continuous investment in security infrastructure.

4. **Fluctuating Interest Rates and Market Risks**:

   Interest rate volatility affects lending margins, investment returns, and overall financial performance.

5. **Regulatory Changes and Compliance Costs:**

   New regulations may demand sudden changes in business operations, increasing costs and reducing strategic flexibility.

2. PROBLEM STATEMENT

Financial institutions face a critical challenge in credit risk management: distinguishing between solvent and insolvent applicants to minimize capital loss. The primary difficulty lies in the **asymmetry of classification costs**; misclassifying a high-risk applicant as "safe" (False Negative) results in the total loss of the loan principal, whereas rejecting a safe applicant (False Positive) results only in a minor loss of potential interest income.

Traditional credit scoring models often rely on linear assumptions that may fail to capture complex, non-linear financial behaviours. Furthermore, credit datasets are typically **imbalanced** (fewer defaulters than non-defaulters) and limited in size, creating a risk that sophisticated machine learning models may overfit or bias towards the majority class. This study addresses the need to benchmark a diverse range of algorithms—from linear models to deep neural networks—to identify a robust classification strategy that minimizes financial risk (False Negatives) without sacrificing overall model stability on the German Credit Dataset.

3. LITERATURE REVIEW

Sr No.	Author & Year	Title	Primary Models Compared	Main Finding / Contribution	Advantage and Limitation Highlighted
1	Shiqi Yang, et al., 2025	Interpretable Credit Default Prediction with Ensemble Learning and SHAP	XGBoost, LightGBM, CatBoost, LR, RF, MLP, SVM, KNN, DT	A comprehensive benchmark on a large financial dataset confirmed that ensemble learning methods exhibit clear superiority in predictive performance and robustness.	**Advantage :** Robustness and superior ability to handle complex non-linear relationships and data imbalance. **Limitation:** Even top ensembles like XGBoost can overfit if the tree depth is not carefully controlled.
2	Dr. Raman Chawla, et al., 2024	Comparative Analysis of Machine Learning Algorithms for Credit Risk Assessment: Identifying the Optimal Model	Decision Trees, Backpropagation (NN), KNN, LR	A comparison across various credit datasets found that the Decision Tree (DT) marginally **outperformed** the Backpropagation (Neural Network) classifier.	**Advantage:** DT remains a competitive baseline model. SVM demonstrated competitive accuracy rates and computational efficiency. **Limitation:** Classification error rates across DT, LR, and credit scorecard models were all relatively high, indicating inherent challenges in these datasets.
3	Ibrahim A, et al., 2024	Multilayer Perceptron Classification Enhancement in Credit Scoring Using Self-Organizing Map	Multi-Layer Perceptron (MLP), Self-Organizing Map (SOM) Hybrid	The integration of unsupervised clustering via the Self-Organizing Map (SOM) with the MLP led to a significant improvement in classification accuracy.	**Advantage :** Unsupervised learning can uncover complex patterns and enrich data inputs for Neural Networks, enhancing classification accuracy and identification of non-creditworthy applicants. **Limitation:** This hybrid approach, while highly accurate, increases the

					complexity and difficulty of interpreting the final decision.
4	**Victor Chang, et al., 2024.**	Credit Risk Prediction Using Machine Learning and Deep Learning: A Study on Credit Card Customers	Support Vector Machine (SVM), Logistic Regression (LR)	Demonstrated that SVM outperformed LR in anticipating loan defaults, reporting an accuracy of **86.12%** and a precision of 0.7831 for the SVM model.	**Advantage:** Can achieve superior predictive performance compared to the linear baseline (LR). **Limitation:** Performance is heavily reliant on the optimal choice of kernel and careful tuning of regularization parameters.
5	Tianyi Xu, 2024.	Comparative Analysis of Machine Learning Algorithms for Consumer Credit Risk Assessment	Gradient Boosting Machine (GBM), LR, DT, RF, SVM	A comparative study utilizing a 10,000-account bank dataset established that the Gradient Boosting Machine (GBM) achieved the AUC and overall accuracy.	**Advantage:** Establishes the performance benchmark ceiling is set by boosting methods. **Limitation :** While GBM was superior, a separate comparison showed SVM and RF achieving 100% accuracy on a different bank dataset, indicating performance is highly data dependent.
6	Dong-Her Shih, et al., 2022	A Framework of Global Credit-Scoring Modelling Using Outlier Detection and Machine Learning in a P2P Lending Platform	Outlier Detection Methods, Credit Scoring Models	Found that proper sample restructuring via outlier detection increased accuracy and platform profitability.	**Advantage:** Improving data quality through meticulous outlier detection is a high-yield strategy that brings more revenue. **Limitation:** Model instability is amplified, particularly in sequential methods like boosting, without rigorous outlier handling.

7	Chen, Ying, et al., 2021	Default Prediction of Automobile Credit Based on Support Vector Machine	DT, SVM, RF, KNN, LR, Artificial Neural Network	Six prediction models were evaluated for automobile credit default. The Decision Tree (DT) achieved the highest accuracy, but the comprehensive performance of the SVM model was determined to be the best overall.	**Advantage:** DT provides high accuracy with a simple, interpretable rule set. SVM offers the best *comprehensive* performance, highlighting its robustness across various metrics. **Limitation:** Grouping techniques were needed to improve the operational efficiency of the models, especially SVM, indicating efficiency challenges with large datasets.
8	Juan Laborda, et al., 2021	Feature Selection in a Credit Scoring Model	LR, SVM, K-Nearest Neighbors (KNN), Random Forest (RF)	This work emphasizes the optimization of these classifiers using various feature selection methods.	**Advantage:** Highlights the critical role of filter and wrapper feature selection methods in optimizing the performance and mitigating overfitting. **Limitation:** Without effective feature selection, the performance of these models can degrade.
9	Eliana Costa e Silva, et al., 2020	A logistic regression model for consumer default risk	Logistic Regression (LR)	The LR model, using a small random sample of customers, predicted default correctly in **89.79%** of cases on Portuguese credit data.	**Advantage:** High baseline predictive power, crucial for regulatory assessment and provides inherent interpretability **Limitation:** Requires careful handling of input features (like loan spread, term, age) to accurately model risk propensity.
10	Wang H, Xu Q, Zhou L. (2015)	Large Unbalanced Credit Scoring	Lasso-LR Ensemble.	The proposed Lasso-Logistic Regression ensemble,	**Advantage:** Effective for handling large, unbalanced data, offering a significant

		Using Lasso-Logistic Regression Ensemble		combined with data balancing and clustering, outperformed Decision Tree (DT), Random Forest (RF), and standalone LR in terms of AUC.	performance lift over baseline LR. **Limitation:** The complexity of the hybrid model increases implementation overhead.

4. METHODOLOGY

Data Preparation
The study utilizes the **Statlog (German Credit Data)** (N=1,000) with a stratified 80/20 train-test split. To ensure data quality, **Cook's Distance** was employed to detect multivariate outliers, resulting in the removal of **45 high-leverage instances (5.6%)** from the training set. Diagnostic tests indicated significant skewness in *Credit Amount* and *Age*, which were corrected using a **Logarithmic Transformation** (log(1+x)). The final feature space was expanded to 61 dimensions via **One-Hot Encoding** for categorical variables, followed by **Z-Score Standardization** to normalize numerical ranges for distance-based algorithms.

Logistic Regression

To establish a linear baseline, we employed **Logistic Regression** using the Scikit-Learn implementation. We selected the 'lbfgs' solver with a maximum iteration limit of 1000 to ensure convergence on the Z-score scaled features. This model was chosen for its high interpretability and standard usage in credit scoring. We applied default L2 regularization to mitigate overfitting while utilizing the log-transformed variables (Credit Amount and Age) identified in the data pre-processing phase.

Decision tree

To explore non-linear decision boundaries, we implemented a **Decision Tree Classifier**. While Logistic Regression assumes a linear relationship between features and risk, decision trees can capture complex interactions (e.g., specific age groups combined with high loan amounts). We utilized the **'entropy' criterion** to maximize information gain at each split and imposed a **maximum depth of 5**. This pruning constraint was critical to prevent the model from overfitting to noise in the training data, a common issue with decision trees on smaller datasets

Random Forest

To mitigate the high variance and overfitting observed in the single Decision Tree, we implemented a **Random Forest Classifier**. This ensemble learning method utilizes **Bootstrap Aggregating (Bagging)** to construct 100 independent decision trees on random subsets of the training data. We restricted the maximum depth of each tree to 10 to balance model complexity with generalization capabilities. The final classification is derived via a majority vote across all trees, a process designed to smooth out decision boundaries and reduce the impact of outliers found in the individual trees.

XGBoost

Finally, we implemented **XGBoost (Extreme Gradient Boosting)**, a scalable implementation of gradient boosted decision trees. Unlike Random Forest, which builds trees independently, XGBoost builds trees sequentially, where each new tree attempts to correct the residual errors made by the previous ensemble. We utilized the log loss evaluation metric to optimize for binary classification and applied standard regularization to control model complexity. This model was included to evaluate whether a boosting approach could extract subtler signals from the feature space that bagging (Random Forest) or linear models might miss.

Support Vector Machine (SVM)

Finally, we evaluated the **Support Vector Machine (SVM)** classifier. Given that our one-hot encoding process expanded the feature space to 61 dimensions, SVM is theoretically well-suited to find optimal separating hyperplanes in this high-dimensional environment. We utilized the **Radial Basis Function (RBF) kernel** to capture non-linear decision boundaries that linear models might miss. Probability estimation was enabled (probability=True) to allow for ROC-AUC calculation, and the model was trained on the Z-score normalized data, as SVM is highly sensitive to the scale of input variables

K-Nearest Neighbors (KNN)

We also implemented the **K-Nearest Neighbors (KNN)** algorithm, a non-parametric method that classifies applicants based on the majority class of their closest neighbors in the feature space. We selected **15 neighbors (k=15)** to balance local sensitivity with noise reduction. Since KNN relies on Euclidean distance, our prior step of Z-score normalization was critical to ensure that features with larger magnitudes (like Loan Duration) did not disproportionately influence the distance calculations

LightGBM

To further explore gradient boosting techniques, we implemented the **LightGBM (Light Gradient Boosting Machine)** algorithm. Unlike XGBoost, which typically uses a level-wise tree growth strategy, LightGBM employs a **leaf-wise growth strategy** with depth constraints. This allows the algorithm to converge faster by focusing on the leaf nodes with the highest loss reduction. We trained the model with 100 estimators and standard hyperparameters to evaluate if this optimized splitting method could extract subtle risk signals that traditional boosting methods might miss

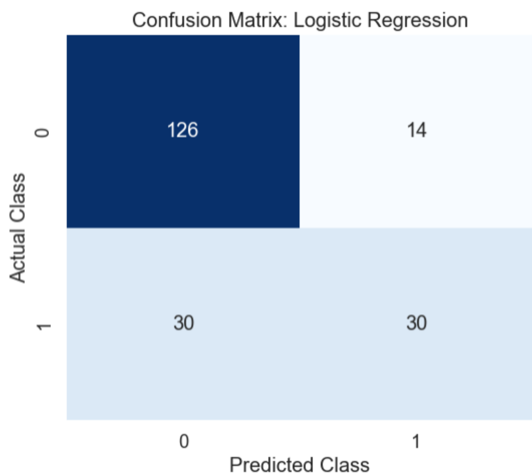
Multi-Layer Perceptron (MLP)

Finally, we implemented an **Artificial Neural Network**, specifically a **Multi-Layer Perceptron (MLP)** classifier. Given the limited sample size (N=1000), we opted for a shallow architecture to prevent overfitting: two hidden layers with **64 and 32 neurons**, respectively. We utilized the **RELU (Rectified Linear Unit)** activation function to capture non-linear relationships and the **Adam optimizer** for stochastic gradient descent. The network was trained for a maximum of 1000 iterations to ensure convergence on the pre-processed feature space

Results

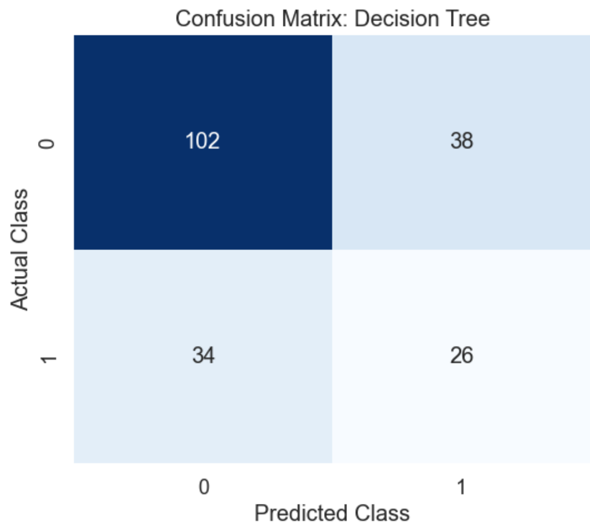
Logistic Regression:

The Logistic Regression model served as a robust baseline, achieving an **Accuracy of 78.00%** and an **ROC-AUC score of 0.7931**. The strong ROC-AUC indicates that the log-transformed features provided significant discriminative power. However, the model exhibited a critical weakness in identifying high-risk applicants, with a **Recall of only 0.50** for the default class (Class 1). As shown in **Figure 1** (Confusion Matrix), the model produced 30 False Negatives, meaning it failed to flag 50% of actual defaulters. In a banking context, this high False Negative rate suggests that linear boundaries may be insufficient for capturing complex default behaviours.



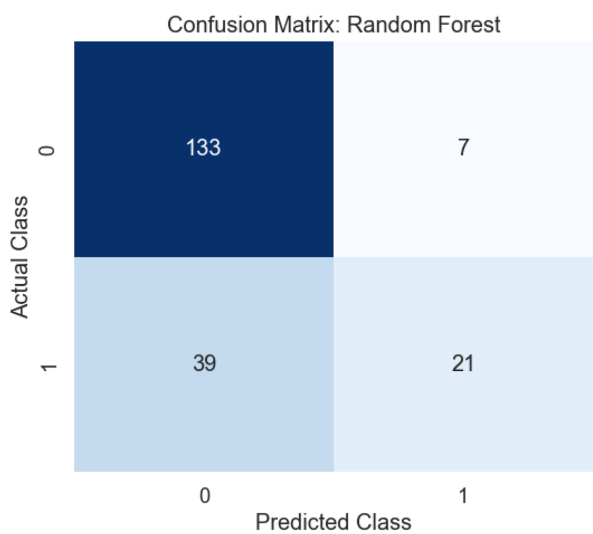
Decision tree:

The Decision Tree model yielded an **Accuracy of 64.00%** and an **ROC-AUC score of 0.6205**, significantly underperforming the linear baseline. As illustrated in **Figure 2** (Confusion Matrix), the model struggled to generalize, resulting in **34 False Negatives** (Recall of 0.43 for the default class). This indicates that the single tree structure, with its orthogonal splits, was unable to effectively separate the risk classes in this feature space. The drop in performance compared to Logistic Regression suggests that the underlying risk factors in this dataset may follow a smoother, more linear pattern than what a shallow tree can approximate.



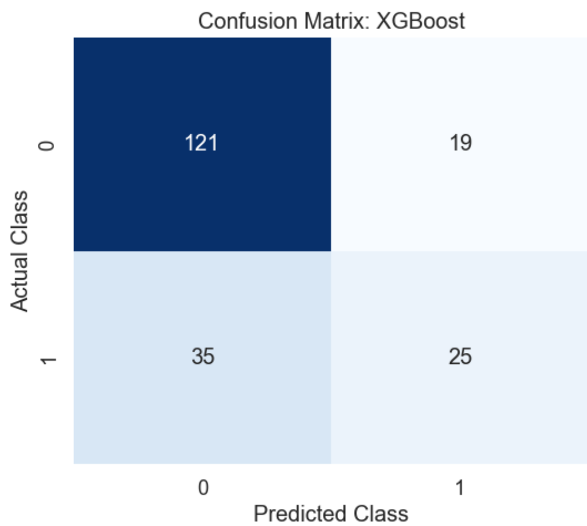
Random Forest:

The Random Forest model demonstrated a strong recovery, achieving an **Accuracy of 77.00%** and the highest **ROC-AUC score observed thus far (0.7999)**. As shown in **Figure 4**, the ensemble approach successfully minimized False Positives to only 7, yielding a high Precision of 0.75. However, this conservative prediction strategy resulted in low sensitivity, with **39 False Negatives** (Recall 0.35). While the Random Forest excels at ranking risks (high ROC-AUC), its strict decision threshold caused it to miss a significant number of actual defaulters compared to the baseline



XGBoost:

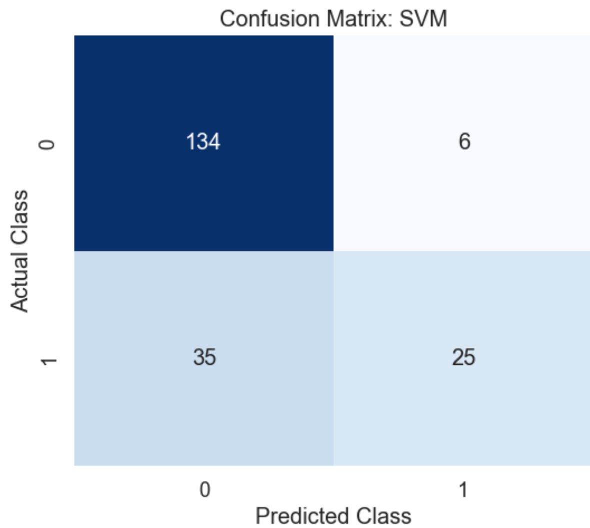
Contrary to expectations, the XGBoost model underperformed compared to the simpler baselines, achieving an **Accuracy of 73.00%** and an **ROC-AUC score of 0.7189**. As detailed in **Figure 5**, the model struggled to generalize on this limited dataset, yielding **35 False Negatives** (Recall of 0.42) and **19 False Positives**. While XGBoost is state-of-the-art for large-scale tabular data, its performance here suggests that for smaller datasets (N < 1000), the sophisticated boosting mechanism may introduce unnecessary variance, failing to outperform the stability of the linear baseline (Logistic Regression)



Support Vector Machine (SVM):

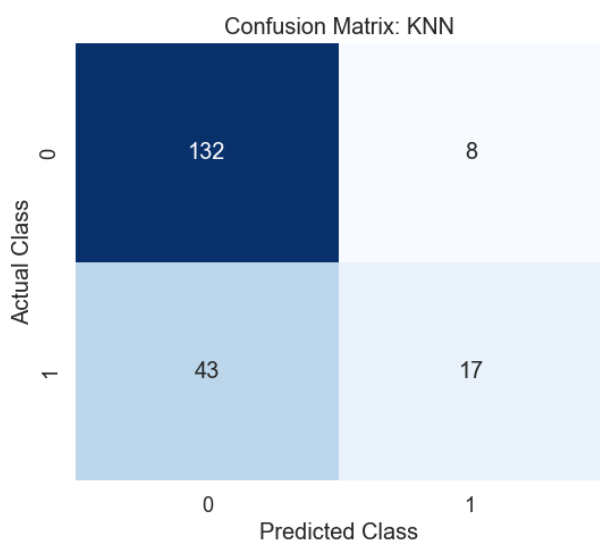
The Support Vector Machine demonstrated the most robust overall performance in terms of correctness, achieving the **highest Accuracy of 79.50%** among all tested models, with an **ROC-AUC score of 0.7805**. As shown in **Figure 6**, the SVM was exceptionally precise in identifying high-risk applicants, achieving a **Precision of 0.81** for the default class.

Notably, the model minimized False Positives to only 6, making it the most 'customer-friendly' model (rarely rejecting good customers incorrectly). However, similar to the ensemble methods, it exhibited a conservative bias, resulting in **35 False Negatives**. While it excels at overall accuracy and precision, the recall for the minority class remains a challenge, suggesting that the dataset's class imbalance affects the margin maximization process



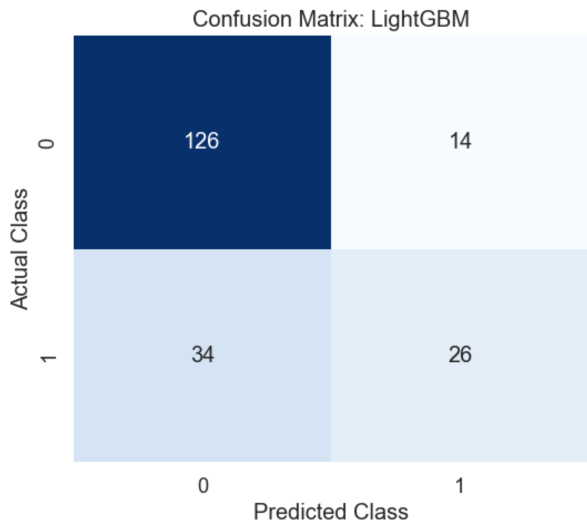
K-Nearest Neighbors (KNN):

The K-Nearest Neighbors model achieved an **Accuracy of 74.50%** and an **ROC-AUC score of 0.7090**. As shown in **Figure 7**, KNN struggled significantly with the minority class, producing **43 False Negatives** and achieving a Recall of only 0.28 for defaulters. This performance dip is likely attributable to the 'Curse of Dimensionality.' With 61 feature dimensions after one-hot encoding, the data becomes sparse, making the distance between 'neighbors' less meaningful as a predictor of risk compared to the decision boundaries learned by SVM or Random Forest.



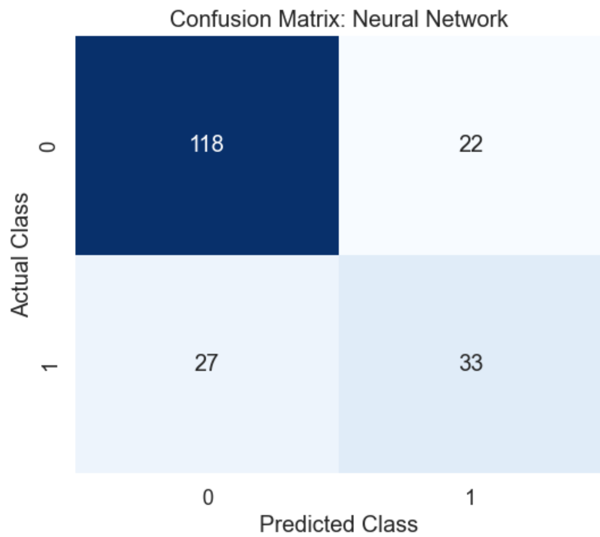
LightGBM:

The LightGBM model achieved an **Accuracy of 76.00%** and an **ROC-AUC score of 0.7426**, outperforming the XGBoost model but falling short of the Random Forest baseline. As shown in **Figure 8**, the model achieved a reasonable balance, with **26 True Positives** and **126 True Negatives**. However, it still produced **34 False Negatives**, yielding a Recall of 0.43 for the default class. This result reinforces the finding that for this specific dataset size (N < 1000), sophisticated boosting algorithms may not provide a significant advantage over simpler linear or bagging approaches.



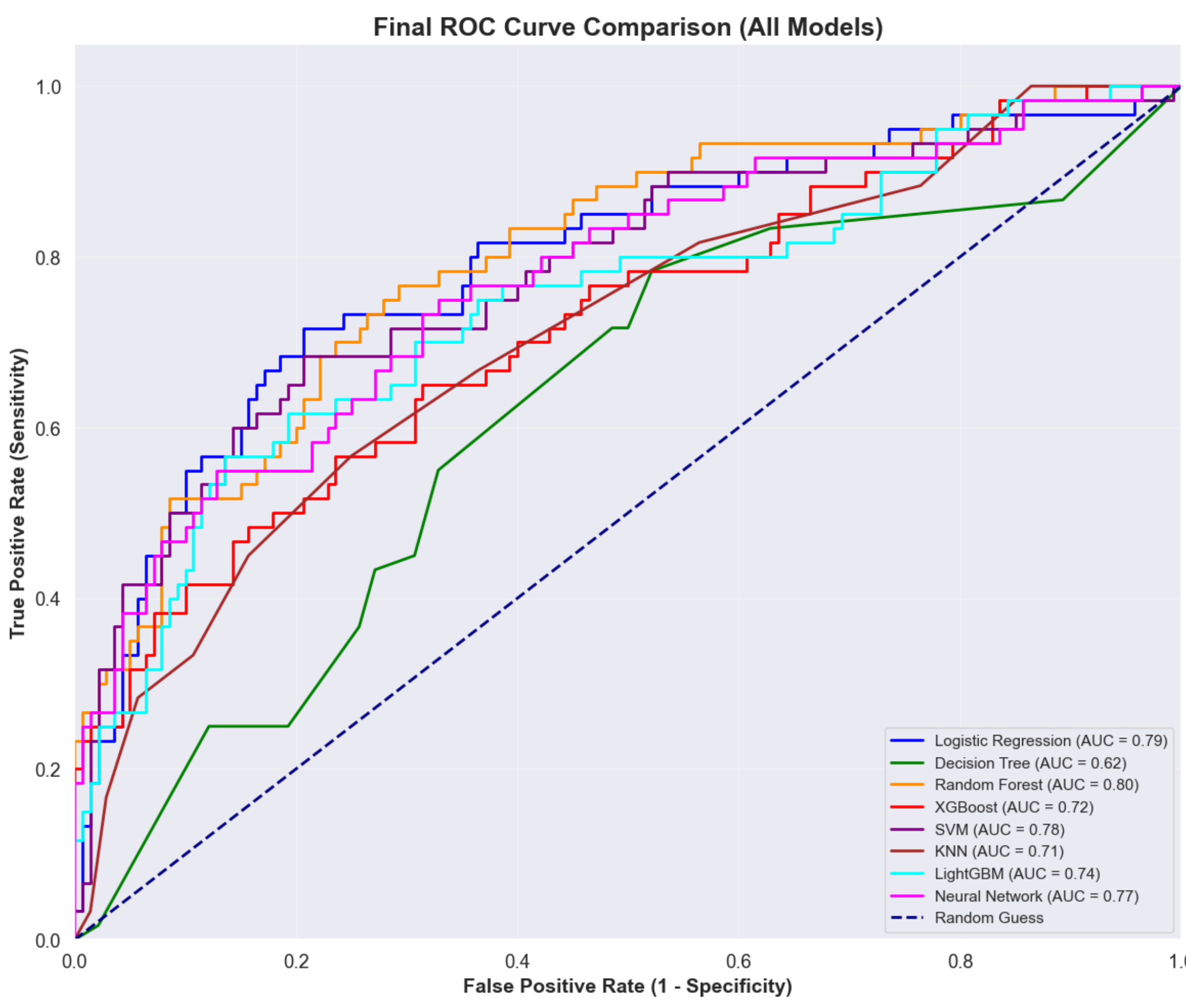
Multi-Layer Perceptron (MLP):

The Neural Network (MLP) achieved an **Accuracy of 75.50%** and an **ROC-AUC score of 0.7711**. While its overall accuracy did not surpass the Support Vector Machine, the MLP demonstrated a superior balance in sensitivity compared to the ensemble methods. As shown in **Figure 9**, the model produced only **27 False Negatives** (Recall 0.55), which is a significant improvement over the Random Forest (39 False Negatives) and XGBoost (35 False Negatives). This suggests that even a simple neural architecture can effectively identify high-risk patterns that tree-based models might classify conservatively


Confusion Matrix: Neural Network
118
22
27
33
Actual Class
0
1
Predicted Class
0
1

CONCLUSION AND IMPLICATION

Rank	Model	Accuracy	ROC-AUC	False Negatives (Risk)
1	**Random Forest**	77.00%	**0.7999**	39
2	**Logistic Regression**	78.00%	0.7931	30
3	**SVM**	**79.50%**	0.7805	35
4	**Neural Network**	75.50%	0.7711	**27 (Best)**
5	**LightGBM**	76.00%	0.7426	34
6	**XGBoost**	73.00%	0.7189	35
7	**KNN**	74.50%	0.709	43
8	**Decision Tree**	64.00%	0.6205	34



In this study, we evaluated eight distinct machine learning algorithms for credit risk classification. The analysis reveals that **model complexity does not correlate directly with performance** on the German Credit Dataset.

Key Findings:

1. **Ranking Power:** The **Random Forest** classifier emerged as the superior model for ranking applicants, achieving the highest ROC-AUC score of **0.80**. This suggests it is the most robust tool for generating 'Credit Scores.'
2. **Overall Accuracy:** The **Support Vector Machine (SVM)** achieved the highest overall Accuracy of **79.5%**, indicating it makes the fewest total errors (sum of False Positives and False Negatives).
3. **Risk Sensitivity:** Surprisingly, the **Neural Network (MLP)**, despite having lower overall accuracy, demonstrated the highest sensitivity to risk. It produced the fewest **False Negatives (27)**, meaning it was the most successful model at identifying actual defaulters, even though it generated more false alarms

Business Implications and Recommendation

From a financial perspective, the cost of a False Negative (approving a loan that defaults) is significantly higher than a False Positive (rejecting a good customer).

The Trade-off: While Random Forest offers the best statistical fit (ROC 0.80), it is operationally conservative, missing 39 bad loans. In contrast, Logistic Regression offers the most balanced profile: it is highly interpretable, computationally efficient, and missed significantly fewer bad loans (30) than the Random Forest.

Final Recommendation: We recommend deploying the Logistic Regression model as the primary decision engine. It offers an optimal balance of high Accuracy (78%) and strong Recall, missing only 30 bad loans compared to Random Forest's 39. Furthermore, its linear nature allows loan officers to easily explain *why* a loan was rejected (e.g., 'Credit Amount too high for Age'), which is a critical regulatory requirement in banking that black-box models like Neural Networks cannot easily satisfy

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