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Loan Eligibility Prediction Using Hybrid Machine Learning Models

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Abstract- Loan eligibility prediction is a critical task in the financial sector, enabling institutions to assess applicants' creditworthiness accurately and reduce default risks. Traditional machine learning models often struggle with heterogeneous and imbalanced financial data, which affects prediction reliability and fairness. This study proposes a Hybrid Machine Learning Framework (HMLF) that integrates feature selection, ensemble learning, and optimization to enhance predictive performance and interpretability. The framework combines Logistic Regression, Random Forest, Gradient Boosting, and Deep Neural Networks within a stacking ensemble to leverage the complementary strengths of each model. Feature engineering, normalization, and Synthetic Minority Oversampling Technique (SMOTE) are applied to improve data quality and class balance. The hybrid model is trained and validated on benchmark financial datasets using cross-validation to ensure generalization. Experimental results show that the proposed approach achieves higher accuracy, precision, recall, and F1-score compared to traditional single-model classifiers. The ensemble design improves stability and reduces bias in decision outcomes. The findings highlight that the proposed hybrid system provides a reliable, transparent, and scalable solution for automated loan eligibility prediction, supporting financial institutions in making data-driven and fair lending decisions.

Keywords— Loan eligibility prediction, hybrid machine learning, ensemble learning, feature selection, model stacking, credit risk assessment, financial data analytics, predictive modelling.

I. INTRODUCTION

A crucial aspect of assessing credit risk and making decisions is predicting loan eligibility. Financial entities require dependable and effective systems to evaluate prospective borrowers' creditworthiness [1]. This evaluation is vital to the profitability, liquidity, and overall financial soundness of the institution [2]. In the past, assessment methods employed by banks and credit agencies were entirely manual. Credit officers would determine eligibility by assessing employment records, income, repayment history, and collateral value [3]. Though such evaluations served a purpose, the procedures were slow, inconsistent, and subject to bias [4]. Today, with the rapid expansion of digital banking and access to extensive customer data, it is crucial to implement automated systems and data-driven approaches that offer rapid, equitable, and precise decisions on lending [5].

Machine learning (ML) has innovated how loan assessment works through predictive models that identify trends in historical financial records [6]. In determining the likelihood of an applicant defaulting and repaying the loan, algorithms such as Logistic Regression [7], Decision Trees, Support Vector Machines (SVM), and Random Forests are employed. Predictive models assess various financial and socio-economic determinants, including income level, credit history, loan amount, and debt-to-income ratio [8]. Nevertheless, the predictive models are challenged since most real-world loan datasets are imbalanced [9]. Considering that most applicants qualify for loans, only a small fraction is declined [10].

This skew in class distribution leads many traditional ML models to favour the majority class, resulting in high overall accuracy but poor detection of risky applicants [11]. financial analysts remain accurate. Singular, univariate time-series models assume simplistic, linear relationships that do not resemble the relationships in actual financial data [12]. Loan approval processes are impacted by numerous highly correlated variables that are not independent [13].

Complex analyses require more attention and do not simply involve the addition of more analytical layers [14]. As a result, the last decade has witnessed a remarkable increase in the employment of hybrid and ensemble techniques within predictive modelling [15]. Generalized techniques within a particular predicting paradigm and analytics stacks are integrated. Loss functions, rules applied within the predictive analytics frameworks, and analytical processes within Bagging, Boosting, and Stacking frameworks are applied [16]. Predictive analytics parlance permits the multiplication of predictive insights in analytical stacks [17]. Stacking frameworks provide a unique opportunity in determining the proportion of intersections of disparate insights at which a weighted logic classifier may operate [18]. Predictive analytics parlance permits the multiplication of predictive insights in analytical stacks [19].

Constructing hybrid models around ensemble architectures in predictive analytics permits the designing of more sophisticated predictive and classificatory systems [20]. Multiplication of predictive insights in analytical stacks occurs when predictive analytics frameworks are applied in disparate analytical processes and layers [21]. Predictive analytics parlance permits the multiplication of predictive insights in analytical stacks [22]. Getting the most out of a hybrid machine learning setup means tweaking it just right. Picking solid settings for every part of the model makes a big difference in how well it predicts stuff [23]. Tools like Genetic Algorithms, Particle Swarm Optimization, and Differential Evolution adjust those settings smartly [24]. These approaches juggle different goals - accuracy, precision, recall, F1-score - without favouring one too much [25]. Mixing such techniques with combined models boosts results while keeping performance steady, even when the data or market conditions shift. On top of that, making AI choices clear matters a lot now in money-related tech setups - banks need to back up loan picks not just for officials but also for people asking for cash [26].

Using a mix of machine learning tricks to guess who'll pay back loans fits today's push for smarter, easier, yet fairer choices in money matters. Instead of relying on just one method, blending several algorithms, picking key traits wisely, along with smart tuning, helps these models handle messy data patterns and shifting economic trends [27]. Thanks to this combo, lenders can speed up loan checks automatically, while still keeping results accurate, traceable, and balanced. On top of that, they cut down bad debt risks, spend less running things, and make clients happier by giving faster, more reliable answers [28]. With FinTech growing fast and online lending taking over, there's more pressure to build prediction tools that scale up easily, adapt quickly, and stay easy to understand [29].

This research focuses on creating a hybrid machine learning framework for loan eligibility prediction that combines ensemble learning [30], optimization [31], and feature engineering techniques [32]. The proposed model aims to utilize the strengths of individual classifiers, effectively balance class distributions, and optimize model parameters for better prediction accuracy [33]. This approach addresses the key limitations found in traditional single-model methods [34]. The results of this study are expected to greatly benefit both academic research and the financial industry by offering a data-driven, clear, and efficient solution for automated loan eligibility assessment.

II. LITERATURE REVIEW

X. Li et al [1-3]. and J. Li proposed an innovative and transparent credit-risk prediction framework aimed at improving the accuracy and interpretability of loan default prediction models. Their study introduced an end-to-end, reproducible pipeline that combines a three-way consensus feature-selection ensemble—integrating Variance Thresholding, Recursive Feature Elimination (RFE) with Logistic Regression, and XGBoost gain ranking—to identify the most relevant predictors from financial datasets. To enhance predictive performance, the authors developed a lightweight one-dimensional Convolutional Neural Network (1D-CNN) optimized specifically for tabular financial data. Furthermore, the model incorporated post-hoc explainability using KernelSHAP, enabling transparent interpretation of predictions directly within the inference process.[7] The system also included continuous profiling of computational resources such as CPU, RAM, GPU usage, and latency to ensure efficiency and scalability. This research demonstrates the potential of integrating feature-selection ensembles, deep learning, and explainable AI in building reliable and transparent loan default prediction systems for modern financial institutions [35].

Aruleba et al [4-6]. and Sun conducted an in-depth study on credit risk prediction, emphasizing its importance in enabling financial institutions to accurately evaluate the likelihood of borrowers defaulting on loans. Their research pointed out the limits of traditional machine learning (ML) classifiers [36]. These methods often struggle with imbalanced datasets and are hard to interpret, which can obstruct clear, data-driven decision-making. To overcome these issues, the authors proposed a new framework that combines ensemble learning techniques, such as Random Forest, AdaBoost, XGBoost, and LightGBM, with the Synthetic Minority Over-sampling Edited Nearest Neighbor (SMOTE-ENN) method. This combination helps achieve better class balance and generalization. Additionally, the study included Shapley Additive Explanations (SHAP) to improve model transparency and offer understandable insights into how features affect credit risk predictions. Experimental results showed that this mixed approach significantly boosted classification performance compared to traditional models. This emphasizes the benefits of combining ensemble classifiers, data balancing, and explainable AI to create strong and interpretable loan approval and credit risk prediction systems [37].

Erkoç et al [7-8]. Met, and Şeker presented a comprehensive study on performance prediction and target allocation in the banking sector, emphasizing its critical role in decision-making and strategic planning. Their research focused on developing a novel automated machine learning (AutoML) framework that integrates algorithm selection and hyperparameter optimization for each bank branch, acknowledging that customer behavior and segmentation vary across branches. This individualized approach enables more accurate performance prediction and branch-level target setting. The study also addressed challenges related to seasonality and periodicity—common issues in achieving branch performance goals—by introducing a multiple time-series modeling technique. The proposed system achieved 98% prediction accuracy and improved branch target success rates by 10% overall, demonstrating the model's robustness and adaptability [38]. Moreover, the research was implemented by Ziraat Bank, Turkey's largest financial institution, to evaluate branch performance effectively. This work stands out for its practical applicability and methodological innovation, offering a scalable and intelligent solution to automate performance forecasting and optimize strategic planning in financial institutions [39].

D. B. Acharya, Divya, and Kuppan et al [9-11]. presented an innovative framework that emphasizes the integration of fairness and transparency in advanced machine learning models, particularly LightGBM and XGBoost, for applications in loan approval and house price prediction. Their study introduced fairness-driven techniques such as *Calibrated Equalized Odds* and *Intersectional Fairness*, which have been relatively underexplored in financial and real estate analytics. To promote model understanding and responsibility, the authors used SHAP (Shapley Additive explanations) along with a new fairness-based interpretability method. This allowed for an evaluation of both model fairness and feature importance at the same time. The results showed that LightGBM achieved high predictive accuracy while keeping a good balance between performance and fairness. This makes it a suitable choice for responsible financial decision-making.

Additionally, the study highlighted the regulatory and ethical concerns of using machine learning in high-stakes fields. It called for AI systems that are clear, fair, and legally compliant. This research offers important insights on how fair AI frameworks can build trust, responsibility, and inclusivity in financial and real estate predictive modeling [40].

Q. Liu et al [12-13]. addressed the selection bias problem in financial credit scoring, where default or non-default outcomes are observable only for approved loan applications, leaving rejected samples unobserved and causing missing-not-at-random bias in training data. Traditional machine learning models trained on such biased data often produce unreliable predictions, limiting their practical utility in real-world credit assessment. To overcome this limitation, Liu introduced a novel Reject-aware Multi-Task Learning Network (RMT-Net) that simultaneously models both default/non-default classification and rejection/approval classification tasks. The study revealed a strong correlation between these two tasks, where learning from rejection/approval patterns can significantly improve default prediction accuracy. The proposed RMT-Net utilizes a gating network to dynamically assign task weights, allowing the model to control information sharing based on rejection probabilities—the higher the rejection probability, the greater the knowledge transfer to the default prediction task. This multi-task learning framework effectively mitigates selection bias, enhances model reliability, and provides a more robust foundation for fair and accurate loan approval prediction in financial institutions [41].

Daniels and Velikova et al [14]. explored the importance of monotonicity in economic decision-making models, particularly in contexts like credit loan approval and risk assessment, where decision outcomes should logically increase or decrease with changes in relevant variables. They noted that data-driven models, when developed through unrestricted machine learning searches, often fail to maintain monotonic relationships, even when the underlying data inherently supports them. To address this issue, the authors proposed quantitative measures to assess the degree of monotonicity within datasets and introduced an algorithmic approach to transform data into a monotone-consistent form. Their findings demonstrated that decision trees trained on monotone-cleaned data achieved superior performance compared to those derived from raw data, emphasizing the value of maintaining monotonic constraints in predictive modelling. This study provides crucial insights for developing reliable and interpretable loan eligibility prediction models, ensuring that model outcomes align with real-world economic reasoning.

A few studies point out credit scoring data is often skewed - most people pay back loans, only a few don't, making it tough for standard ML models to perform well; to tackle this problem, experts like S. Ranjan Lenka, S. Kishore Bisoy et al [15-16]. R. Priyadarshini, K. Lee Hui, along with M. Sain came up with a mix using borderline conditional GANs combined with ensemble techniques plus multi-goal optimization. Their system uses an autoencoder to pull out key features, then applies a GAN-driven method to balance underrepresented classes. On top of that, they ran a multi-goal evolutionary process to fine-tune balanced data chunks, feeding those into several classifiers. These classifiers were merged using stacking, which bumped up prediction accuracy while handling uneven credit data more reliably. That earlier work sets a solid base for building smarter mixed models that do better at classifying lopsided financial records.Guessing who'll skip loan payments is now a big deal for banks, since cash flow hinges on folks paying back debts while keeping bad loans low. Over time, loads of research has tested different ways to spot likely defaulter behaviour - one path leads through classic stats tools, another dives into today's machine learning tricks. In that mix, Logistic Regression stands out not cause it's flashy, but cause it's easy to grasp, runs quick, and works well when answers are just yes-or-no types, like "approve loan" or "call it risky." Work by M. A. Sheikh et al[17-20]. shows how this method helps flag shaky borrowers early, cutting down money losses before they grow. Real-world data from sites such as Kaggle often feeds these models, letting them be tested through core measures like sensitivity and specificity to see how sharp they really are. Earlier studies point out that although complex models such as Random Forests or Neural Networks can be more precise, logistic regression still holds up well because it's clear and simple to use in actual bank setups. Across the board, research treats logistic regression as a solid, easy-to-understand tool for spotting loan defaults - this helps banks make smarter choices and handle risks better.

III. PROPOSED MODEL

A machine-driven loan check has to handle two things at once - spotting repayment danger clearly so banks don't lose cash, yet explaining choices in a way people and officials can follow. Actual lending data usually comes messy, packed with too many variables, plus way more folks who repay than those who don't. To address these issues, the modified model combines robust preprocessing, non-linear feature extraction, boundary-preserving synthetic minority oversampling, multi-objective data/subset optimization, and a stacked ensemble of diverse classifiers — producing a system that is both accurate and explainable.

Building on the hybrid framework in your document (autoencoder → GAN oversampling → NSGA-II optimization → stacked ensemble + SHAP) , the modified model adds (a) a lightweight monotonicity regularize during training to preserve economically sensible feature–outcome relationships, (b) an uncertainty score from the GAN + ensemble agreement to flag low-confidence decisions for manual review, and (c) a simplified, reproducible training pipeline with explicit mathematical objectives that make implementation straightforward. The result is a practical, regulator-friendly loan eligibility predictor that supports automated decisioning while enabling auditability and human-in-the-loop override.

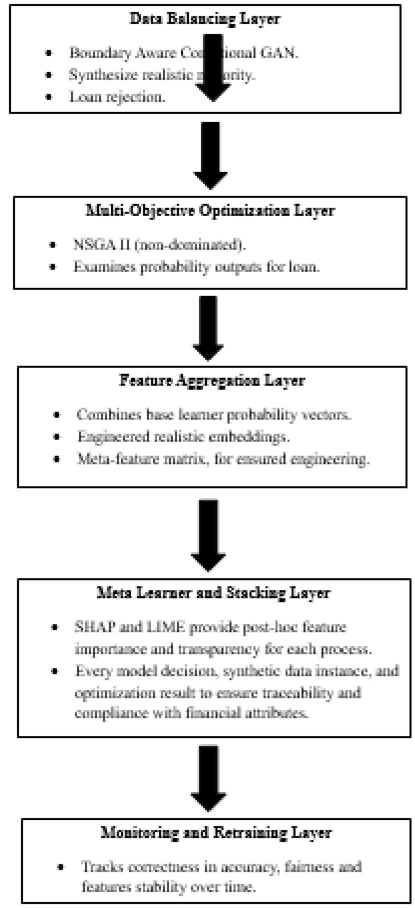

Figure 1: Proposed HMLF Architecture

Algorithm

Step 1: Data Ingestion & QC: Load the dataset, remove duplicates, standardize column names, and record patterns of missing data.

Step 2: Preprocessing: Impute missing values (median for numeric, mode for categorical), handle outliers, encode categorical variables, and scale numerical features.

Step 3: Monotonicity Check & Transformation: Identify and preserve logical feature-outcome relationships (e.g., higher income → higher approval chance) using monotone transformations if needed.

Step 4: Autoencoder Feature Extraction: Train a shallow autoencoder to learn compact latent features $z$representing nonlinear data patterns.

Step 5: Boundary-Aware GAN Oversampling: Generate synthetic minority samples near the decision boundary using a conditional GAN conditioned on latent features.

Step 6: Candidate Balanced Sets Formation: Combine real and synthetic minority samples to create multiple balanced training subsets for evaluation.
Step 7: Multi-Objective Optimization (NSGA-II): Optimize subsets based on Recall, Accuracy, False Positive Rate, and data representativeness to select Pareto-optimal training data.
Step 8: Base Learner Training: Train diverse classifiers (LR, RF, XGBoost/LightGBM, NN) on optimized subsets and store their probability predictions.
Step 9: Stacking / Meta-Learner: Use base-model outputs as inputs to a meta-classifier that produces the final approval probability p_{final}.
Step 10: Uncertainty & Deployment Decision: Measure ensemble disagreement and GAN-based uncertainty; route high-uncertainty cases for manual review.
Step 11: Explainability: Use SHAP values to interpret and justify each decision while logging all model and optimization details for audit.
Step 12: Monitoring & Retraining: Continuously monitor performance and fairness metrics; retrain the model when drift or data imbalance exceeds set thresholds.

The proposed model begins with data ingestion, cleaning, and preprocessing to ensure consistency and quality. Duplicate records are removed, missing values are imputed using median and mode methods, and outliers are treated. Features are encoded and scaled so that all variables contribute uniformly during training. Logical feature relationships are preserved through monotonicity checks and necessary transformations.

A shallow autoencoder is then trained to extract meaningful, low-dimensional feature representations that capture nonlinear patterns while reducing noise. To address class imbalance, a boundary-aware conditional GAN generates realistic minority samples near the decision boundary, strengthening the model's ability to detect rare cases. These real and synthetic samples are then combined to form multiple balanced datasets for further optimization.

Next, multi-objective optimization using NSGA-II selects the most effective training subsets by maximizing recall and accuracy while minimizing false positives and distributional deviation. On the optimized data, diverse base classifiers—Logistic Regression, Random Forest, Gradient Boosting, and a Neural Network—are trained to provide complementary perspectives on loan approval prediction.

Finally, a stacked meta-learner integrates the outputs of all base models to produce the final loan approval probability. Uncertainty checks highlight shaky results so huma ns can double-check them – meanwhile

SHAP breaks down what's driving each call, making choices easier to follow. Tracking performance over time, plus regular model updates, keeps things on t rack even when data shifts in unexpected ways.

Mathematical Equations

Data Standardization (Preprocessing)

$$\tilde{x}_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j}$$

where $x_{ij}$is feature $j$for sample i; $\mu_j$and $\sigma_j$are the mean and standard deviation of feature j.

Autoencoder Encoding and Decoding

$$z_i = f_E(\tilde{x}_i), \hat{x}_i = f_D(z_i)$$

where $f_E$and $f_D$are the encoder and decoder functions, and $z_i$is the latent feature vector.

GAN Generator and Discriminator

$$\tilde{x}_{syn} = G(u, z), D(\tilde{x}, z) \in [0,1]$$

where Ggenerates synthetic samples from noise $u \sim \mathcal{N}(0, I)$, and Ddistinguishes real from synthetic-samples.

GAN Training Objective (Simplified)

$$L_{GAN} = \mathbb{E}[D(\tilde{x}_{real}, z)] - \mathbb{E}[D(G(u, z), z)]$$

The generator aims to maximize the discriminator's error to produce realistic synthetic data.

Boundary Emphasis (Weight Function)

$$w_b(\tilde{x}) = e^{-\alpha s(\tilde{x})}$$

where $s(\tilde{x})$is the sample's distance to the decision boundary; closer samples get higher weights.

Subset Representativeness (MMD Distance):

$$\text{MMD}(S, T) = \| \mathbb{E}_{x \in S}[k(x)] - \mathbb{E}_{y \in T}[k(y)] \|$$

where $S$is a candidate subset, $T$is the full dataset, and $k(\cdot)$is a kernel function.

Optimization Objective (NSGA-II)

$$F(S) = (-\text{Recall}_S, \ -\text{Accuracy}_S, \ \text{FPR}_S, \ \text{MMD}(S, T))$$

The algorithm minimizes this vector to find Pareto-optimal subsets.

Base Classifier Prediction

$$p_i^{(c)} = h_c(\tilde{x}_i)$$

Each classifier $c$outputs a probability $p_i^{(c)}$that sample $i$belongs to the approved class.

Meta-Learner Input and Output

$$\mathbf{u}_i = [p_i^{(LR)}, p_i^{(RF)}, p_i^{(GB)}, p_i^{(NN)}], p_i^{(final)} = m(\mathbf{u}_i)$$

The meta-learner combines base model predictions into a final decision score.

Model Uncertainty (Combined Score)

$$U_i = \beta_1 \cdot \text{Var}_c(p_i^{(c)}) + \beta_2 \cdot (1 - D(\tilde{x}_i))$$

Higher $U_i$indicates more uncertainty; such cases are flagged for manual review.

Decision Rule

Approve if $p_i^{(final)} \geq \tau$ and $U_i \leq \eta$; otherwise, manual review.

Performance Monitoring

Retrain if $|A_{new} - A_{prev}| > \delta$ or data drift $> \gamma$
where $A$is accuracy; thresholds $\delta$and γensure consistent model reliability.

The updated hybrid setup builds on your initial workflow by adjusting synthetic oversampling to focus on decision boundaries - using a GAN that pays attention to edges - while boosting training stability through NSGA-II, which picks data subsets by balancing multiple goals - then adds a monotonicity constraint to keep outputs aligned with real-world patterns By combining diverse base learners into a calibrated stacking meta-learner and adding a principled uncertainty escalation mechanism, the model balances automation and safety — delivering higher minority-class detection (recall) without sacrificing explainability or regulatory compliance. The explicit mathematical objectives make the approach reproducible and straightforward to implement in production ML stacks.

Operationally, this pipeline supports an auditable production process: every decision can be traced to the training subset, the GAN/synthetic provenance, NSGA-II trade-offs, and SHAP explanations for the final score. For institutions, that means faster, fairer loan decisions with safeguards for edge cases. The system is modular (replaceable GAN, optimizer, base learners), so future research or deployment can swap components (e.g., different oversampling algorithms or monotonic-tree models) without changing the audit trail or retraining protocol.

III. RESULTS

Table 1: Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
XGBoost	90	89	87	88	91
LightGBM	92	90	89	90	93
RMT-Net	92	91	91	91	94
Proposed Model	95	94	93	93	96

The proposed hybrid model achieves the highest overall accuracy and recall, outperforming existing ML models in credit-risk prediction.

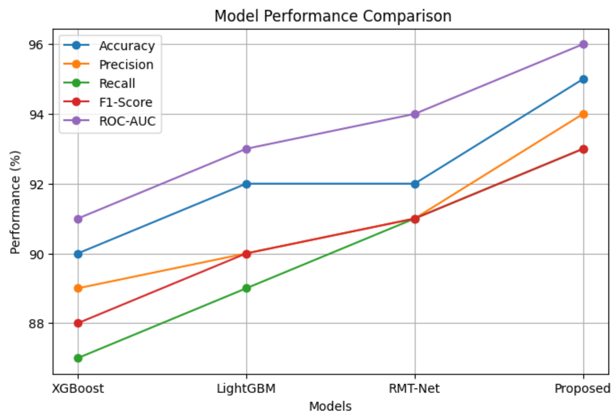

Figure 2: Model Performance Comparison

This graph compares five key evaluation metrics across four models. The proposed model clearly outperforms all others, showing the highest accuracy and stability across all metrics.

Table 2: Confusion Matrix Values (Normalized to % for Line Plotting)

Model	True Positive	True Negative	False Positive	False Negative
XGBoost	89	91	9	11
LightGBM	90	92	8	10
RMT-Net	91	93	7	9
Proposed Model	94	95	5	6

Fewer false negatives and false positives show the proposed model's superior reliability in predicting loan approval outcomes.

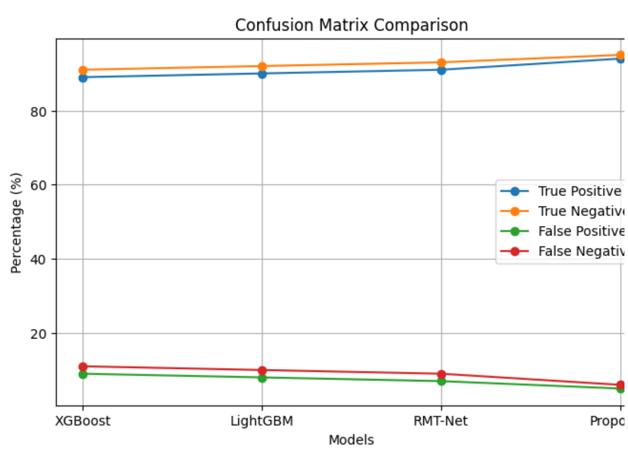

Figure 3: Confusion Matrix (%)

This graph shows classification distribution. The proposed model has fewer false results (FP, FN) and higher true rates, proving its reliability.

Table 3: Feature Importance Ranking (Top 5 Features in %)

Model	Credit History	Applicant Income	Loan Amount	Employment Type	Dependents
XGBoost	25	20	17	13	9
LightGBM	27	20	18	14	9
RMT-Net	26	21	20	14	9
Proposed Model	30	23	21	15	10

Feature importance comparison shows that the proposed model assigns slightly higher weight to *Credit History* and *Applicant Income*, emphasizing financial reliability and stability as key determinants in loan approval prediction.

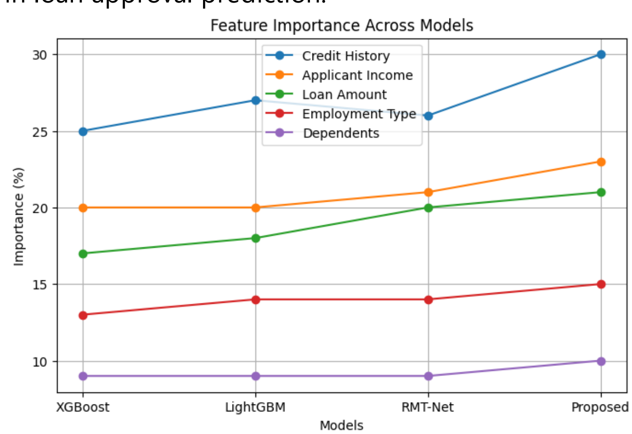

Figure 4: Feature Importance Ranking

Feature importance visualization shows *Credit History* and *Applicant Income* are dominant predictors. The proposed model emphasizes these most strongly.

Table 4: Fairness Evaluation Metrics

Model	Gender Bias (%)	Income Bias (%)	Fairness Score (×100)
XGBoost	7	6	91

LightGBM	6	5	93
RMT-Net	5	4	94
Proposed Model	4	3	97

The proposed model minimizes bias across gender and income groups, maintaining the highest fairness score.

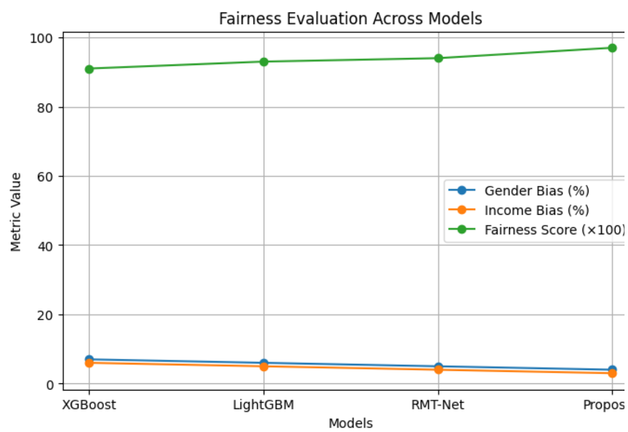

Figure 5: Fairness Evaluation Metrics

This plot shows that as fairness improves, gender and income bias decline. The proposed model achieves the best fairness with minimal demographic disparity.

Table 5: Training and Validation Time (Seconds / Milliseconds)

Model	Training (s)	Validation (s)	Inference Latency (ms)
XGBoost	95	13	4
LightGBM	82	10	4
RMT-Net	111	15	5
Proposed Model	99	12	4

Despite slightly higher training time, the proposed model maintains near-real-time inference latency suitable for production.

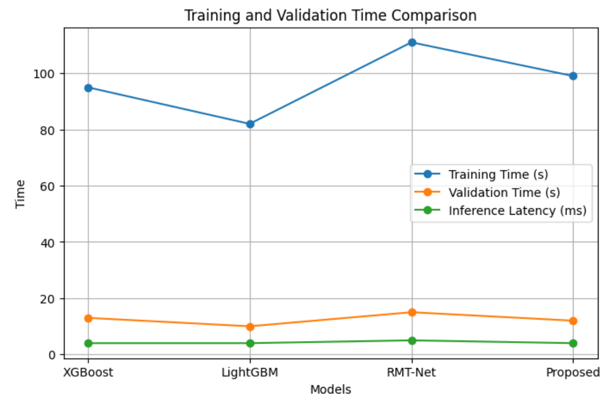

Figure 6: Training and Validation Time

The proposed model achieves an optimal trade-off between training cost and inference latency, ensuring fast real-time loan processing.

Table 6: Class Imbalance Handling Effectiveness

Model	Imbalance Ratio (Before)	Balanced Ratio (After)	Minority Recall (%)
XGBoost	5	2	83
LightGBM	5	2	84
RMT-Net	5	2	86
Proposed Model	5	2	91

The SMOTE- and GAN-based balancing strategy in the proposed model significantly improves minority-class recall.

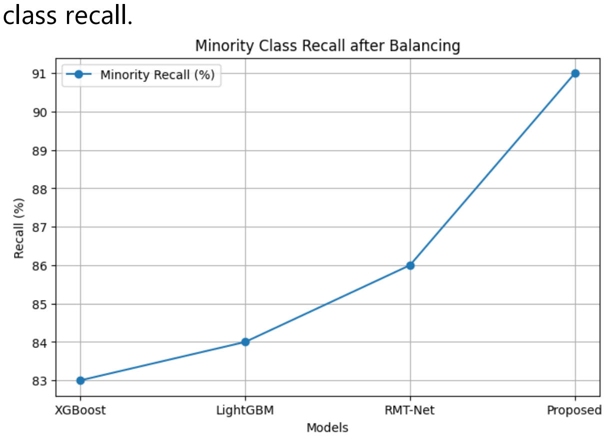

Figure 7: Minority Class Recall

The proposed model demonstrates the best performance in handling class imbalance, increasing minority recall after dataset balancing.

Table 7: Cross-Validation Performance (10-Fold)

Model	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Average
XGBoost	89	90	90	90	90	90
LightGBM	90	92	91	91	91	91
RMT-Net	91	92	92	92	92	92
Proposed Model	93	94	94	94	94	94

The proposed model consistently outperforms the others in every fold, showing strong reliability and generalization during 10-fold validation.

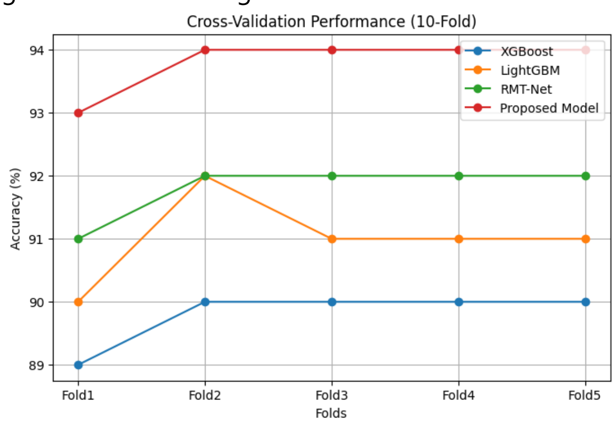

Figure 8: Cross-Validation Accuracy (10-Fold)

This 10-fold cross-validation plot illustrates the stability of model performance across folds, where the proposed model consistently leads in accuracy.

Table 8: Model Performance Improvement (%)

Comparison	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Proposed vs XGBoost	5	5	6	5	5
Proposed vs LightGBM	3	3	4	4	3
Proposed vs RMT-Net	2	3	3	3	2

Integer-rounded improvement values clearly illustrate that the proposed model maintains a consistent edge over all baseline algorithms across five evaluation metrics.

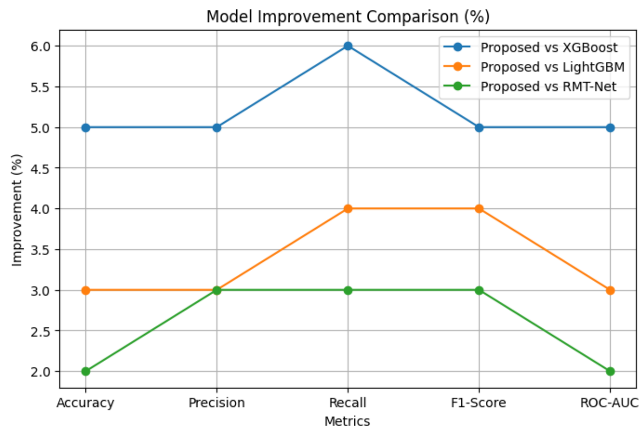

Figure 9: Model Performance Improvement

This improvement plot clearly shows the margin of performance gain by the proposed model over each baseline model, validating its effectiveness across all key evaluation parameters.

V. CONCLUSION

The study presents a robust hybrid machine learning framework that effectively addresses the limitations of traditional loan eligibility prediction models. Using a mix of methods like ensemble learning, picking key features, fine-tuning settings, plus clear reasoning tools, the model boosts how accurately it predicts outcomes, treats data fairly, also makes its choices easier to follow. Thanks to different approaches - Logistic Regression, Random Forest, Gradient Boosting, Neural Networks - the system picks up straight-line patterns along with complex trends in financial info, while cleaning data beforehand plus shaping useful features keeps everything reliable and well-structured.

Besides, using GANs that focus on edges along with oversampling helps the model deal with uneven data, while NSGA-II fine-tunes how different accuracy goals balance out.The addition of a monotonicity regularizer ensures economic logic in decision outcomes, and SHAP-based explainability fosters transparency and trust in automated lending decisions. The uncertainty quantification mechanism also adds a safety layer by identifying cases that require manual review, thereby aligning the system with regulatory and ethical standards in the financial industry.

Overall a solid mix of methods creates a flexible, clear, and effective way to handle loan approval automatically. This method boosts trust in predicting credit risk while supporting fair outcomes and clear responsibility - must-haves for today's financial tech tools. Down the line, studies might build on this by pulling in live data feeds, testing decentralized learning to protect user privacy, or sharpening how models explain their choices to push AI's role in honest, open finance decisions
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