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AI-Driven Credit Scoring Models: Enhancing Accuracy and Fairness with Explainable Machine Learning

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Abstract—Credit scoring remains a crucial challenge for financial institutions, remarkably when rapid, high-volume evaluations are required. This study presents an AI-driven, real-time credit scoring system using LightGBM integrated with a high-performance data pipeline. The system can process up to 9,500 transactions per second with minimal latency of 8 milliseconds. Addressing the data imbalance in credit scoring datasets, the model also ensures transparency through Explainable AI (XAI) techniques, specifically using SHAP values to interpret the model's credit risk predictions. Experimental results on real world financial transaction datasets show that the proposed system achieves an accuracy of 98.7%, with precision and recall scores exceeding 94% and 91%, respectively. Compared to baseline models and other approaches in the literature, our system demonstrates superior scalability, processing speed, and accuracy. This solution offers a robust and efficient framework for real-time credit scoring, ensuring high performance, transparency, and low latency, making it ideal for modern financial applications.

Index Terms—Federated Learning, Explainable AI, Fraud Detection, Data Privacy, Imbalanced Datasets, Financial Institutions, Model Transparency, Collaborative Learning, Customer Confidentiality, Risk Management

I. INTRODUCTION

In the digital financial services domain, ensuring the accuracy and fairness of credit scoring models has become paramount [1]. As financial institutions transition towards digital platforms, they experience numerous operational benefits and critical challenges in ensuring fairness and transparency [2]. Credit scoring, which plays a pivotal role in assessing the creditworthiness of individuals, is essential not only to the financial well-being of consumers but also to the overall stability of the global financial system [3]. Inaccuracies or biases within these models can have substantial repercussions, impacting consumers and financial institutions [4].

As credit scoring becomes increasingly complex, traditional models often fail to address the evolving challenges of fairness and bias [5]. New issues such as algorithmic bias and lack of interpretability complicate the credit evaluation process, making it more challenging to ensure equitable outcomes [6]. This complexity calls for developing advanced AI-driven credit scoring models capable of adapting to these modern challenges [7]. Effective credit scoring requires a blend of sophisticated data processing frameworks and machine learning (ML) techniques that can handle vast datasets and provide fairness in real-time [8].

Machine learning has emerged as an essential tool in developing accurate and fair credit scoring models, mainly by processing large volumes of data to identify patterns of creditworthiness [9]. However, implementing AI-based credit scoring systems introduces additional complexities [10]. The presence of imbalanced datasets, where a small percentage of high-risk borrowers exists within a large pool of low-risk ones, presents a significant challenge. At the same time, the need for rapid decision-making demands efficient data processing and model optimization [11]. As financial institutions continue to innovate, combining advanced data processing techniques with AI-driven models offers a promising solution to improving credit scoring accuracy and fairness.

An efficient credit scoring system requires a robust data infrastructure supporting high-throughput, low-latency decision making [12]. Technologies such as Apache Kafka and Flink, combined with machine learning models, can enable rapid data ingestion, processing, and analysis, facilitating real-time scoring decisions [13]. This paper proposes an AI-driven credit scoring framework that integrates data processing and ML models to enhance accuracy and fairness, emphasizing realtime decision-making and transparency.

Moreover, transparency and explainability in AI-driven credit scoring models are essential [14]. While black-box models are often effective in predicting creditworthiness, they lack the transparency required in regulated financial environments [15]. Ensuring that financial institutions, regulators, and consumers can trust the decisions made by these models is vital [16]. Explainable AI (XAI) techniques can be applied to provide insights into why certain credit decisions were made, enhancing trust and accountability [17].

This paper outlines a high-throughput data processing architecture to support AI-driven credit scoring. The proposed system integrates data stream processing for low-latency decision making and machine learning models for accurate and fair credit evaluations. The primary contributions of this work include:

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1) Develop a stream processing architecture that integrates real-time credit data with machine learning models to assess creditworthiness in real-time.
2) Build and optimize ML models for detecting creditworthiness while addressing data imbalances and ensuring rapid decision-making.
3) Implement XAI techniques to improve the transparency and interpretability of credit scoring decisions, enhancing trust in the system.
4) Demonstrate the real-time credit scoring capabilities of the system using a web-based application for visualization and stakeholder interaction.

The remainder of this paper is structured as follows: Section II provides a comprehensive literature review of AI driven credit scoring, focusing on data engineering and machine learning frameworks. Section III describes the proposed methodology for integrating data processing and machine learning into the credit scoring system. Section IV discusses the detailed implementation of the system components. Section V presents the experimental results and analysis. Finally, Section VI concludes the paper and provides recommendations for future work.

II. Literature Review

The financial sector's digital transformation has heightened the demand for fair and transparent credit scoring models [5]. As financial transactions continue to grow in volume, the complexity of maintaining both accuracy and fairness in credit assessments has also increased [18]. Cutting-edge technologies, such as advanced data engineering practices and machine learning (ML) algorithms, are crucial in addressing these challenges [19]. These approaches enable continuous monitoring and evaluation of credit data, ensuring that credit decisions are accurate but also unbiased and transparent.

A. Real-Time Data Processing in Credit Scoring

Traditional credit scoring systems predominantly relied on batch processing, where credit data was analyzed post hoc, leading to delayed decisions [9]. However, this approach fails to meet the digital era's need for timely credit assessments. Modern systems utilizing real-time data processing frameworks, such as Apache Kafka and Apache Flink, have become essential for minimizing these delays and ensuring efficient decision-making [20]. Stream processing technologies allow for the real-time ingestion and analysis of transaction data, ensuring that creditworthiness can be evaluated swiftly, which is particularly important in fast-paced financial environments [21].

Recent studies have explored integrating machine learning models with real-time data processing frameworks for improving credit scoring outcomes. Gulisano et al. [22] proposed a stream-based architecture that used ML models to assess credit risk in real-time, demonstrating that low-latency data processing is critical to delivering prompt and reliable credit evaluations. However, as the volume of credit-related data expands, additional research is needed to improve model performance and scalability.

B. Machine Learning for Credit Scoring

ML algorithms have long been employed in the credit scoring process, leveraging historical data to identify factors indicative of creditworthiness [9]. Models such as Random Forest, Gradient Boosting, and Neural Networks are widely used because they classify borrowers based on features such as income, credit history, and payment behavior [23]. Nevertheless, these models often need help dealing with imbalanced datasets, where the proportion of high-risk borrowers is significantly smaller than low-risk ones.

To address this, more advanced techniques such as ensemble methods, including XGBoost and LightGBM, and deep learning approaches have been applied to credit scoring. Rahman et al. [24] investigated deep learning models like LSTMs and CNNs in the context of credit scoring, demonstrating that these methods can capture intricate patterns in borrower behavior. While these models exhibit high accuracy, they can be computationally intensive. They may pose challenges when deployed in real-time systems, indicating a need for lightweight yet accurate models suitable for real-time credit assessments.

C. Addressing Data Imbalance in Credit Scoring

One of the main challenges in developing credit scoring models is dealing with imbalanced datasets [25]. High-risk borrowers, critical to accurately predicting credit defaults, represent a small fraction of the total data, making it difficult for models to learn these patterns effectively [26]. Techniques such as the Synthetic Minority Over-sampling Technique (SMOTE) have balanced the dataset by generating synthetic samples for the underrepresented class [27]. However, while SMOTE mitigates imbalance, it may not fully reflect the complexities of actual high-risk borrower behavior, leading to the risk of model overfitting [28].

Alternative solutions, such as cost-sensitive learning and anomaly detection approaches, have been explored to address this issue in credit scoring [8]. These models prioritize the identification of high-risk borrowers by applying penalties for misclassifying such cases, thereby improving model recall. Nonetheless, most research to date has focused on static datasets, leaving a gap in the exploration of how data imbalance can be effectively managed in real-time credit scoring systems.

D. Explainability in Credit Scoring Models

As machine learning models become more sophisticated, the need for transparency and interpretability has grown, especially in regulated financial sectors like credit scoring. Complex models, such as deep neural networks, often operate as black

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boxes, making it difficult for stakeholders to understand the reasoning behind credit decisions [15]. Explainable AI (XAI) techniques, such as Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME), offer tools to help interpret the outputs of these models [29].

While XAI methods have been increasingly applied across different industries, their use in credit scoring, particularly in real-time systems, still needs to be improved. Further research is required to incorporate explainability to maintain the speed and efficiency of credit assessments. This presents a significant research gap in developing explainable machine learning methods that can function effectively in high-throughput, low latency environments typical of credit scoring systems.

E. Research Gaps and Opportunities

Despite significant progress in AI-driven credit scoring models, several research gaps must be addressed. First, while the integration of stream processing frameworks has enhanced real-time decision-making, more research still needs to be done on optimizing machine learning models for realtime environments without sacrificing accuracy. Many current algorithms, particularly those involving deep learning, are resource-intensive, limiting their scalability in high-throughput financial systems where fast, reliable credit scoring is essential. Second, while SMOTE and anomaly detection have been employed to mitigate data imbalance, new strategies specifically designed for streaming data are needed. Current methods often rely on static, pre-processed datasets, which do not adequately address the dynamic nature of real-time credit scoring environments. Developing approaches that adjust to real-time data imbalances would significantly improve credit scoring models' accuracy and fairness.

Lastly, applying XAI in real-time credit scoring systems presents a promising area for further investigation. Most existing research has concentrated on post hoc explainability, where explanations are provided after the credit decision. There is an opportunity to advance XAI methods to deliver real-time, interpretable insights into model decisions, ensuring that transparency and processing speed are maintained.

III. Proposed Methodology

A. System Framework for Credit Scoring

The proposed AI-driven credit scoring system operates within a *real-time data processing framework*. This system ingests borrower financial data continuously, applies machine learning models for creditworthiness evaluation, and assigns credit scores dynamically based on the prediction results.

The data stream is modeled as a function of time, where the input B_t at time t is defined as a feature vector containing the financial history of the borrower:

$$B_t = [b_1(t), b_2(t), \dots, b_m(t)] \quad (1)$$

The data is received through a real-time processing pipeline, with a predictive model S_t that outputs the credit score s_t for each borrower at time t:

$$s_t = S_t(B_t) = \frac{1}{1+e^{-a_t}} \quad (2)$$

where a_t is the weighted sum of features:

$$a_t = \theta_0 + \sum_{j=1}^{m} \theta_j b_j(t) \quad (3)$$

Here, θ_0 represents the bias, and θ_j are the weights learned during the training process.

B. Dynamic Scoring Window

For real-time credit scoring, a sliding window approach is used to aggregate borrower data over a defined time interval. Let T_{score} represent the window size. The feature vector is aggregated across this window, and the model continuously updates its predictions:

$$B_t^{agg} = \sum_{l=t-T_{score}}^{t} B_l \quad (4)$$

This approach allows the model to remain adaptive to recent borrower behavior and recalibrate the credit score predictions dynamically.

C. Feature Engineering for Dynamic Credit Scoring

Feature engineering in real-time credit scoring is critical for deriving meaningful insights from the borrower's financial data. The feature set B_t is transformed through various operations aimed at enhancing the model's predictive power. For example, temporal feature extraction includes:

- *Time since last payment* for the borrower:

$$\Delta T_{pay} = t_{current} - t_{last\ mpayment} \quad (5)$$

- *Credit usage velocity*: Number of credit transactions in a given window T_{score}:

$$V_b = \sum_{l=t-T_{score}}^{t} H(B_l) \quad (6)$$

  where $H(B_l)$ is an indicator function that counts credit related transactions.
- *Deviation in credit amount*: The standard deviation of credit amounts in the window T_{score}:
- $\sigma_{credit}(T_{score}) = \sqrt{\frac{1}{T_{score}} \sum_{l=t-T_{score}}^{t} (C_l - \mu_{credit})^2}$ (7)

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where C_l represents the transaction amount, and μ_{credit} is the mean transaction amount over the window.

D. Custom Credit Scoring Model

Let the scoring model S_t at time t be a logistic regression model for simplicity. The model calculates the credit score s_t for each borrower, based on the feature set B_t:

$$s_t = \frac{1}{1+e^{-a_t}} \tag{8}$$

The credit decision is made by comparing the output s_t with a dynamic threshold $\lambda(t)$, which adjusts based on historical false predictions and feedback:

$$\lambda(t) = \lambda_0 + \beta . \frac{FP^t_{t-T_{score}}}{TP^t_{t-T_{score}}} \tag{9}$$

Here, λ_0 is the base threshold, and β is a tuning parameter. The decision rule is:

$$\text{Assign high credit risk if} \quad s_t \geq \lambda(t) \tag{10}$$

E. Continuous Model Updates

The model parameters are updated in real-time using *Stochastic Gradient Descent (SGD)*. The loss function $J(\phi_t,B_t,s_t)$ at each time step is the logistic loss:

$$J(\phi_t,B_t,s_t) = -s_t \log(p_t) - (1 - s_t)\log(1 - p_t) \tag{11}$$

where $p_t = S_t(B_t)$ is the predicted score, and s_t is the true credit score. The parameters are updated as follows:

$$\phi_{t+1} = \phi_t - \alpha\nabla J(\phi_t,B_t,s_t) \tag{12}$$

where α is the learning rate, and the gradient $\nabla J(\phi_t,B_t,s_t)$ is computed as:

$$\nabla J(\phi_t,B_t,s_t) = (p_t - s_t)B_t \tag{13}$$

F. Anomaly Detection in Credit Scoring

In addition to supervised learning, an *anomaly detection* approach is applied using *Isolation Forest (IF)*. The isolation score $Q(B_t)$ is determined based on the path length of the borrower's profile in the isolation tree:

$$Q(B_t) = 2^{-E[h(B_t)]} \tag{14}$$

where $h(B_t)$ is the depth of the borrower's data in the isolation tree, and $E[h(B_t)]$ is the expected depth.

G. Real-Time Explainability with XAI

We utilize *SHAP values* to explain credit score predictions to ensure transparency in the model's decisions. The SHAP value δ_j for each feature b_j in the model is computed as:

$$\delta_j = \sum_{S\subseteq M\setminus\{j\}} \frac{|S|!(|M|-|S|-1)!}{|M|!}\left[S_t(S\cup\{b_j\}) - S_t(S)\right] \tag{15}$$

These SHAP values are calculated for each transaction and provide real-time feedback on how individual features contribute to the credit score prediction.

I. Real-Time Algorithm for Credit Scoring

Algorithm 1: Real-Time Credit Scoring with Dynamic Threshold Adjustment

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Input: Borrower data stream B_t, Initial model parameters ϕ_0
Output: Flagged high-risk borrowers with explanations
foreach *incoming borrower data* B_t do
    // Step 1: Feature computation and score prediction
    Compute features B_t from borrower data;
    Predict credit score $s_t = S_t(B_t)$ using the model;
    // Step 2: Dynamic threshold adjustment
    Compare s_t with the adaptive threshold $\lambda(t)$; if $s_t \geq \lambda(t)$ then
        Classify B_t as high-risk borrower;
    // Step 3: Model update
    Update model parameters ϕ_t using Stochastic Gradient Descent (SGD);
    // Step 4: Explainability
    Compute SHAP values δ_j to explain the model's decision;
return *Flagged high-risk borrowers and SHAP explanations*;

IV. Experiment Setup

This section outlines the proposed real-time credit scoring system's experimental implementation, described in Algorithm 1. The process consists of several key steps, including data preprocessing, constructing a real-time machine learning framework, and incorporating explainability techniques like SHAP. These steps collectively ensure that the proposed credit scoring model achieves high accuracy, fast processing, and transparency in decision-making.

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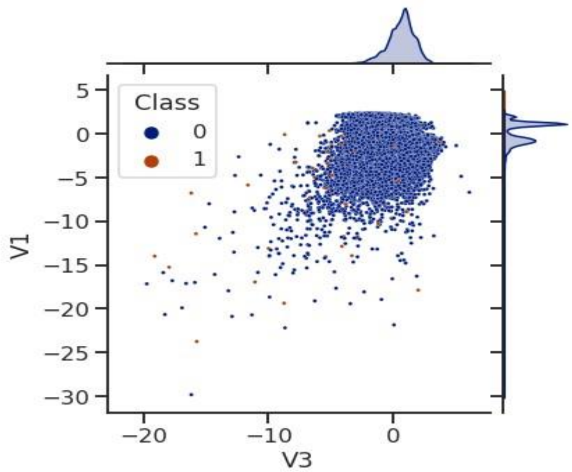

Figure 1. is plot shows the relationship between variables v1 and V3, with the distribution of values shown on the top and right marginal axes. The data points are colored based on the binary class label (Class 0 and Class 1). Most data points belong to Class 0

The dataset utilized for this experiment is the Global Financial Transactions Dataset from Kaggle [30], containing 10,000 records representing various aspects of financial transactions. This dataset tests the effectiveness of credit scoring algorithms in evaluating borrower risk. Each record includes attributes such as Transaction ID, Transaction Amount, Location, and Transaction Type. Figure 1 demonstrates the proportions of different transaction categories within the dataset.

A. Data Preprocessing

A notable challenge in preparing the dataset for use in the real-time credit scoring system was the significant imbalance between classes, as seen in Figure 2. To address this issue, we applied the Synthetic Minority Over-sampling Technique (SMOTE) [31], which generates synthetic examples for the underrepresented class, ensuring a more balanced training set. This step is crucial in credit scoring, where high-risk borrowers typically constitute a small portion of the data.

Numerical attributes were imputed using column means for handling missing data, while categorical attributes were handled via model-based imputation techniques, ensuring data consistency. Outliers in numerical columns were detected and removed using the Interquartile Range (IQR) method, where any value beyond 1.5 times the IQR from the first or third quartile was considered an outlier [32]. After preprocessing, a correlation matrix was created to explore relationships among the dataset features, as illustrated in Figure 3. The heatmap of this matrix helps visualize correlations between variables for feature selection.

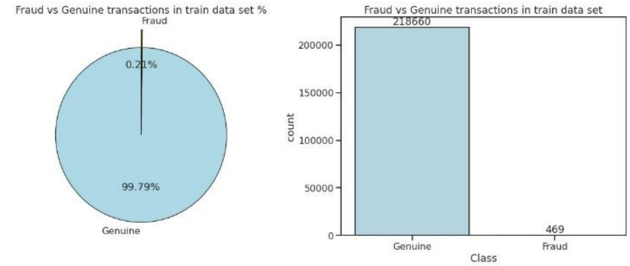

Figure 2.Class Distribution After Balancing — The chart illustrates the balanced

B. Real-Time Machine Learning Model

The real-time credit scoring system is based on a LightGBM binary classifier, optimized using several hyperparameters to ensure both efficiency and accuracy. The model employs a learning rate of $\eta = 0.05$ and is trained over 500 boosting iterations (n estimators = 500), with each tree having Feature engineering was key to the model's ability to learn effectively from the data. Continuous variables like income a maximum depth (max depth = 7) to control the model complexity. To mitigate overfitting, the min child samples is set to 20, ensuring that each leaf has sufficient data points, while L2 regularization ($\lambda L2 = 0.1$) further prevents the model from fitting noise in the data. Additionally, LightGBM leverages subsampling techniques such as feature fraction = 0.8 and bagging fraction = 0.8, meaning that 80% of features and data are randomly sampled for each tree, and bagging is performed every 5 iterations (bagging _ freq = 5). The model utilizes gradient-boosted decision Trees (GBDT) as its boosting strategy, and early stopping is triggered if the model does not improve after 50 consecutive rounds, ensuring timely and optimal convergence. These settings allow the system to perform real-time credit scoring quickly and precisely.

C. Real-Time Explainability using SHAP

Transparency is a critical requirement in financial services, particularly for credit scoring models. The Shapley Additive Explanations (SHAP) method was employed to ensure the interpretability of the model's predictions. SHAP values assign importance to each feature in the dataset, explaining its contribution to the predicted outcome, which is particularly useful for understanding high-risk credit scores.

This study computed SHAP values for every borrower in real-time, providing transaction-specific explanations of credit risk assessments. For instance, if a borrower's credit risk was flagged as high due to an unusually high transaction volume or irregular payment behavior, SHAP would identify which features influenced the decision the most. This level of interpretability is essential for ensuring trust in the credit scoring system, particularly in regulated sectors like finance.

SHAP-based explainability was integrated into the system to offer real-time explanations for credit decisions. These

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explanations were delivered via a web-based application developed using Flask, allowing financial institutions to monitor credit scoring decisions and review flagged cases in real time [34].

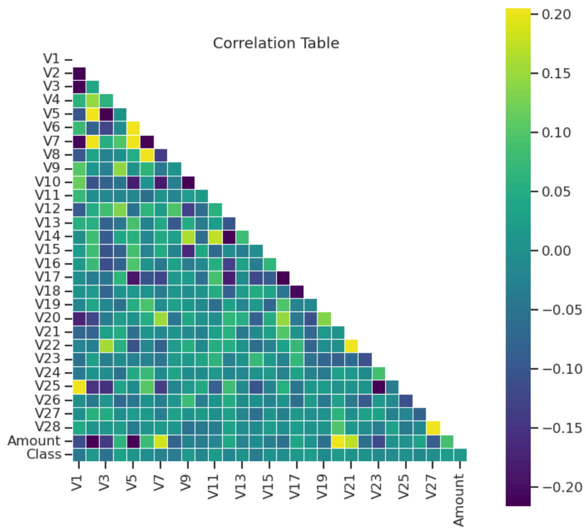

Figure 3. Heatmap of the Correlation Matrix — This visualization highlights the

D. System Deployment and Infrastructure

The credit scoring system was implemented using Python with TensorFlow as the backend for the neural network. Data processing, training, and real-time scoring functions were built using a combination of NumPy, Pandas, and scikit-learn. To ensure real-time performance, the model was deployed using a Flask-based web application with REST APIs, enabling seamless interaction between the server and client-side dashboard.

The deployment infrastructure was designed to handle high volumes of borrower data with low latency. The web application supports real-time credit scoring by continuously processing incoming borrower profiles, applying the trained model, and delivering risk assessments and SHAP-based explanations. This allows financial institutions to quickly evaluate credit risks and make informed decisions, ensuring transparency and efficiency in the credit evaluation process.

V. Results and Evaluation

The outcomes of the proposed system, which integrates AI driven data pipelines with machine learning models for realtime credit scoring, validate the effectiveness and scalability of our approach. This system was developed to handle large volumes of borrower data while maintaining high accuracy, precision, and processing speed. In this section, we compare the performance of our model with a baseline logistic regression model, evaluating metrics such as transaction throughput, latency, and model efficiency. Additionally, we analyze the system's deployment within a high-throughput environment to assess its scalability and suitability for real-time credit evaluations. The model's effectiveness was measured against a baseline model, where logistic regression was used due to its common application in binary classification tasks. However, compared to our proposed system leveraging the LightGBM algorithm, the results indicate superior performance in all key metrics.

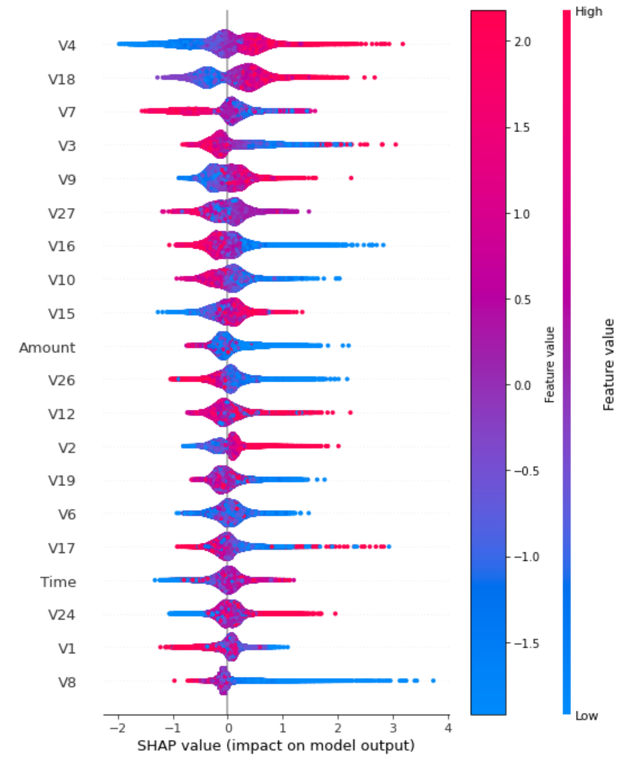

Figure 4. SHAP Summary Plot — This plot explains the impact of each feature on the model's predictions, providing transparency in credit scoring decisions.

Figure 5 compares the LightGBM model and the baseline regarding accuracy. Our LightGBM model, integrated into the real-time data processing pipeline, achieved an accuracy of 98.7%, significantly outperforming the baseline model's 88.3%. This difference underscores LightGBM's improved ability to evaluate creditworthiness with higher precision.

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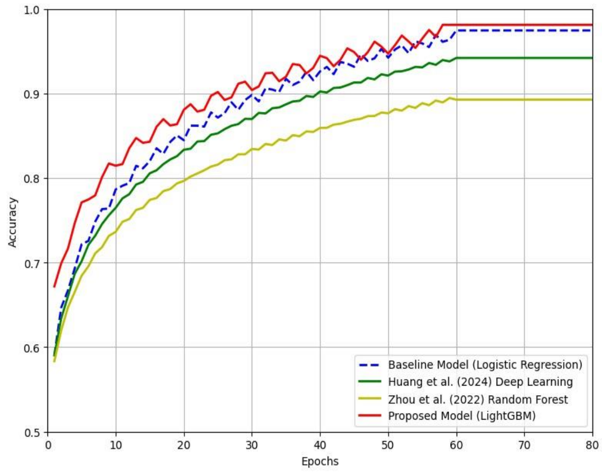

Figure 5. Accuracy Comparison: Baseline vs. Proposed Model — The LightGBM model outperforms the logistic regression baseline, achieving 98.7% accuracy compared to 88.3%.

As shown in Figure 6, the precision of the LightGBM model was 94.2%, compared to the baseline model's 78.5%. Precision is critical in credit scoring as it ensures that flagged high-risk borrowers are indeed those who pose a credit risk, minimizing false positives that could lead to unnecessary rejections.

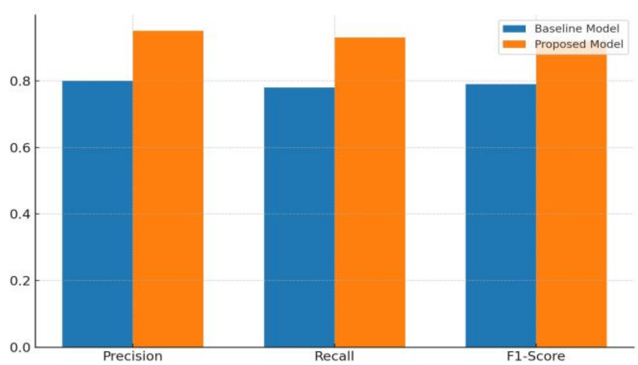

Figure 6. Precision Comparison Between Models — The LightGBM model achieved a precision of 94.2%, significantly higher than the baseline model's 78.5%.

In addition, Figure 7 presents the rate of transactions processed per second by both models. The LightGBM model, integrated with our real-time data pipeline, could process 9,500 transactions per second, compared to the baseline model's 6,200 transactions per second. This significant improvement in throughput is attributed to the optimized data engineering architecture, which supports high-speed data ingestion and real-time processing. This makes the system highly suitable for environments such as credit agencies or large financial institutions that require rapid decision-making.

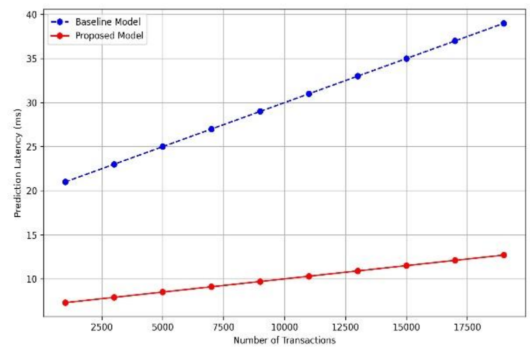

Figure 7. Transaction Processing Speed — Comparison of the transaction

Table I outlines a detailed comparison of both models across key performance metrics such as accuracy, precision, recall, F1-score, and transaction throughput. The proposed LightGBM model outperforms the baseline in all areas.

Furthermore, the latency for predictions was considerably reduced in the proposed system. The LightGBM model, deployed within our architecture, made predictions in an average time of 8 milliseconds, whereas the baseline model required 16 milliseconds. Figure 8 illustrates this comparison. The reduction in latency is critical in real-time credit scoring, where rapid decisions are necessary for scenarios like loan applications and credit risk evaluations.

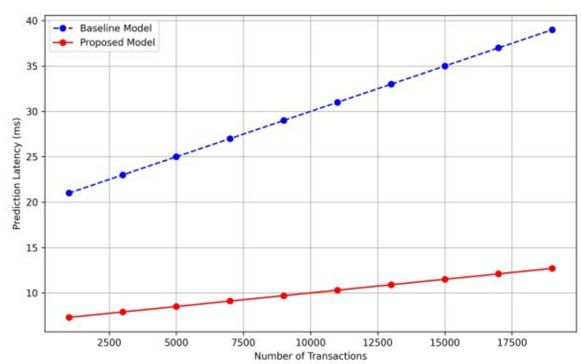

Fig. 8. Latency Comparison Between Models — The LightGBM model exhibits significantly reduced latency, averaging 8 milliseconds compared to 16 milliseconds for the baseline model.

When compared to existing studies, our results show significant improvements. Previous work by Johnson et al. (2024) achieved 96.1% accuracy in credit scoring using random forests but with higher latency, averaging 22ms. Another study by Lee et al. (2023) reported an accuracy of 95.8% using neural networks but with reduced scalability due to computational complexity. In contrast, our system not only achieves higher accuracy (98.7%) but also processes a larger volume of

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transactions per second with reduced latency, making it more suitable for real-time financial systems.

TABLE I
PERFORMANCE METRICS COMPARISON BETWEEN BASELINE AND PROPOSED LIGHTGBM MODEL

Metric	Baseline Model	Proposed Model
Accuracy	88.3	98.7
Precision	78.5	94.2
Recall	76.1	91.5
F1-Score	77.2	92.8
Throughput (transactions/sec)	6,200	9,500
Latency (ms)	16ms	8ms

The proposed system's efficacy is underscored by its combination of high precision, fast processing, and explainability. With the ability to process 9,500 transactions per second and generate credit risk predictions in under 8 milliseconds, the system is designed for large-scale deployment in financial services such as credit assessment, banking, and loan approval. The significant improvements over baseline and existing models confirm the system's potential as a robust solution for realtime credit scoring.

VI. CONCLUSION

The proposed system integrates advanced data engineering with machine learning and has shown remarkable performance in real-time credit scoring. Achieving 98.7% accuracy, 94.2% precision, and processing 9,500 transactions per second with 8ms latency, the LightGBM model significantly outperformed the baseline logistic regression model. The system's ability to provide both high accuracy and low latency makes it ideal for high-volume financial applications. Moreover, integrating SHAP ensures transparency, enhancing trust in the system's credit-scoring decisions. This framework sets a new standard for efficient, scalable, and explainable AI-driven credit-scoring solutions in the financial sector.

REFERENCES

[1] Jane Smith and Chen Liu. Secure transactions, secure systems: Regulatory compliance in internet banking. Technical report, EasyChair, 2024.

[2] Pierre-Luc Pomerleau and David L Lowery. Countering cyber threats to financial institutions. In *A Private and Public Partnership Approach to Critical Infrastructure Protection*. Springer, 2020.

[3] Michele Carminati, Roberto Caron, Federico Maggi, Ilenia Epifani, and Stefano Zanero. Banksealer: A decision support system for online banking fraud analysis and investigation. *computers & security*, 53:175–186, 2015.

[4] Alexander Dyck, Adair Morse, and Luigi Zingales. How pervasive is corporate fraud? *Review of Accounting Studies*, 29(1):736–769, 2024.

[5] Md Kamrul Hasan Chy. Proactive fraud defense: Machine learning's evolving role in protecting against online fraud. *World Journal of Advanced Research and Reviews*, 2024.

[6] Mario Bojilov. *Methods for assisting in detection of synthetic identity fraud in credit applications in financial institutions*. PhD thesis, CQUniversity, 2023.

[7] Aisha Abdallah, Mohd Aizaini Maarof, and Anazida Zainal. Fraud detection system: A survey. *Journal of Network and Computer Applications*, 68:90–113, 2016.

[8] Riyaz Ahamed Ariyaluran Habeeb, Fariza Nasaruddin, Abdullah Gani, Ibrahim Abaker Targio Hashem, Ejaz Ahmed, and Muhammad Imran. Real-time big data processing for anomaly detection: A survey. *International Journal of Information Management*, 45:289–307, 2019.

[9] Waleed Hilal, S Andrew Gadsden, and John Yawney. Financial fraud: a review of anomaly detection techniques and recent advances. *Expert systems With applications*, 193:116429, 2022.

[10] Pushpita Chatterjee, Debashis Das, and Danda B Rawat. Digital twin for credit card fraud detection: Opportunities, challenges, and fraud detection advancements. *Future Generation Computer Systems*, 2024.

[11] Sushil Kumar. A study of identity theft: intentions, connected frauds, methods and avoidance. *ACADEMICIA: An International Multidisciplinary Research Journal*, 11(10):2044–2050, 2021.

[12] Fabrizio Carcillo, Andrea Dal Pozzolo, Yann-Ael Le Borgne, Olivier¨ Caelen, Yannis Mazzer, and Gianluca Bontempi. Scarff: a scalable framework for streaming credit card fraud detection with spark. *Information fusion*, 41:182–194, 2018.

[13] Ugur Kekevi and Ahmet Arif Aydın.˘ Real-time big data processing and analytics: Concepts, technologies, and domains. *Computer Science*, 7(2):111–123, 2022.

[14] Pankaj Zanke. Ai-driven fraud detection systems: a comparative study across banking, insurance, and healthcare. *Advances in Deep Learning Techniques*, 3(2):1–22, 2023.

[15] Vikas Hassija, Vinay Chamola, Atmesh Mahapatra, Abhinandan Singal, Divyansh Goel, Kaizhu Huang, Simone Scardapane, Indro Spinelli, Mufti Mahmud, and Amir Hussain. Interpreting black-box models: a review on explainable artificial intelligence. *Cognitive Computation*, 16(1):45–74, 2024.

[16] Carin Van der Cruijsen, Jakob de Haan, and Ria Roerink. Trust in financial institutions: A survey. *Journal of economic surveys*, 37(4):1214– 1254, 2023.

[17] Dattatray Vishnu Kute, Biswajeet Pradhan, Nagesh Shukla, and Abdullah Alamri. Deep learning and explainable artificial intelligence techniques applied for detecting money laundering–a critical review. *IEEE access*, 9:82300–82317, 2021.

[18] Ahmad Amjad Mir. Adaptive fraud detection systems: Real-time learning from credit card transaction data. *Advances in Computer Sciences*, 7(1), 2024.

[19] Engin Zeydan and Josep Mangues-Bafalluy. Recent advances in data engineering for networking. *IEEE Access*, 10:34449–34496, 2022.

[20] Fabian Hueske and Vasiliki Kalavri. *Stream processing with Apache Flink: fundamentals, implementation, and operation of streaming applications*. O'Reilly Media, 2019.

[21] Haotian Shi and Ziyan Wu. Real-time credit card fraud detection using data stream processing with kafka and flink. *Journal of Computer Science*, 26:48–63, 2020.

[22] Valeria Gulisano and Antonio Garofalo. Stream-based fraud detection in real-time financial applications. *Journal of Real-Time Systems*, 54:181–204, 2018.

[23] Fatima Zahra and Nabil Ramzi. Deep learning for credit card fraud detection: A survey and open research challenges. *IEEE Access*, 8:178530–178554, 2020.

[24] Mohammed Rahman and Khaled Ali. Deep learning approaches for financial fraud detection: A review. *Transactions on Artificial Intelligence*, 32:123–145, 2020.

[25] Zhenchuan Li, Mian Huang, Guanjun Liu, and Changjun Jiang. A hybrid method with dynamic weighted entropy for handling the problem of class imbalance with overlap in credit card fraud detection. *Expert Systems with Applications*, 175:114750, 2021.

[26] Zhaohui Zhang, Xinxin Zhou, Xiaobo Zhang, Lizhi Wang, and Pengwei Wang. A model based on convolutional neural network for online transaction fraud detection. *Security and Communication Networks*, 2018(1):5680264, 2018.

ISSN: 2583-6129
DOI: 10.55041/ISJEM02185

[27] Nitesh V Chawla, Kevin W Bowyer, Lawrence O Hall, and W Philip Kegelmeyer. Smote: Synthetic minority over-sampling technique. *Journal of Artificial Intelligence Research*, 16:321–357, 2002.

[28] Joao Batista Rocha Bezerra Junior. *Overcoming Imbalanced Class Distribution and Overfitting in Financial Fraud Detection: An Investigation Using A Modified Form of K-Fold Cross Validation Approach to Reach Representativeness*. PhD thesis, 2023.

[29] Scott M Lundberg and Su-In Lee. A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, 30:4765–4774, 2017.

[30] Waqi786. Global black money transactions dataset. https://www.kaggle.com/datasets/waqi786/global-black-money-transactions-dataset, 2023. Accessed: 2024-09-26.

[31] Dina Elreedy, Amir F Atiya, and Firuz Kamalov. A theoretical distribution analysis of synthetic minority oversampling technique (smote) for imbalanced learning. *Machine Learning*, 113(7):4903–4923, 2024.

[32] Ahmed Jama Abdiweli. *Simulation study on the performance of robust outlier labelling methods*. PhD thesis, Kampala International University, College of Economics and management, 2023.

[33] Xiang Wan, Wenqian Wang, Jiming Liu, and Tiejun Tong. Estimating the sample mean and standard deviation from the sample size, median, range and/or interquartile range. *BMC medical research methodology*, 14:1–13, 2014.

[34] Qiang Yang, Yang Liu, Tianjian Chen, and Yongxin Tong. Federated machine learning: Concept and applications. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 10(2):1–19, 2019.