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Real-Time credit scoring and risk analysis: Integrating AI and data processing in loan platforms

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Abstract

Real-time credit scoring and risk analysis play a crucial role in ensuring accurate lending decisions in modern financial platforms, particularly with the growing adoption of alternative financing models like Buy Now, Pay Later (BNPL). However, traditional credit scoring models often fall short because of their reliance on static historical financial data, which limits their effectiveness for individuals with little or no credit history and reduces responsiveness to evolving borrower behaviour. To address these limitations, this manuscript proposes a deep learning-based approach, Credit Scoring and Risk Analysis utilizing Deep Processing Loan Platform (CSRA-DPLP-BSCNN). Initially, input data is collected from BNPL datasets. Then, the input data is pre-processed using the Regularized Bias-Aware Ensemble Kalman Filter (RBEKF) to manage missing values, normalize inputs, and remove noise. The cleaned data is then processed using a Binarized Simplicial Convolutional Neural Network (BSCNN), which identifies patterns related to credit scores, repayment history, income levels, and financial behaviour to predict credit risk in real-time. The proposed CSRA-DPLP-BSCNN method achieves 98% accuracy, 97% precision, 96% recall, 98% F1-score, and 1.159 seconds of computational time, with a high ROC of 0.95, compared with existing methods. For example: Using Machine Learning, Alternative Data, and Predictive Analytics to Improve Financial Scoring via Advanced AI-Driven Credit Risk Assessment for Buy Now, Pay Later (BNPL) and E-Commerce Financing (CRA-ECF-PAEFS); Increasing Financial Stability through Real-Time Credit Risk Monitoring Using Machine Learning Techniques and Advanced Data Analytics (EFS-RTCRM-MLT-ADA); and Credit Risk Evaluation in the Financial Sector Using Deep Learning (CRE-FSDL).

Keywords: Binarized simplicial convolutional neural network, Credit Risk, E-commerce, Real-time credit scoring, Risk analysis.

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Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
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1. Introduction

E-commerce financing strategies, such as Buy Now, Pay Later (BNPL), have changed customer purchasing habits by providing flexible payment options without the need for traditional credit checks [1]. These financing options allow consumers with minimal or no credit history to obtain short-term loans for purchasing products and services [2]. Lenders face credit risk concerns due to the lack of standardized financial profiles among BNPL users, making it difficult to assess repayment capacities [3]. Traditional credit scoring methods rely on banking history, credit card transactions, and loan repayments, excluding underbanked and unbanked people from the financial system [4]. BNPL allows consumers, particularly those with limited or no access to traditional credit systems, to make purchases that would otherwise be too expensive [5]. This includes underbanked or unbanked persons who may be unable to obtain credit cards or bank loans because of a lack of credit history or financial means [6]. BNPL providers frequently do not require specific banking information, allowing those who would otherwise be excluded from the financial system to participate in e-commerce and track their transactions over time [7]. This offers a more inclusive alternative to traditional financing and has the potential for increased consumer spending [8]. However, from the lender's standpoint, the lack of traditional financial profiles among BNPL users increases credit risk [9]. In contrast to traditional loans or credit cards, which employ well-established credit scoring systems to assess a borrower's potential to repay, BNPL schemes often rely on alternative data such as the consumer's purchasing behavior, internet activity, and payback history with the BNPL provider [10].

These considerations include ethical and regulatory issues related to the employment of alternative data sources, which may raise privacy concerns and necessitate rigorous adherence to data protection rules [11]. Furthermore, biases in the models might lead to biased lending decisions, disproportionately affecting underrepresented groups. These systems' complexity may also restrict transparency, making it challenging for regulators and consumers to understand the decision-making process [12]. Furthermore, the lack of interpretability in these systems may hinder their widespread implementation, as stakeholders attempt to ensure fairness and accountability in financial assessments [13]. Addressing these issues is critical to encouraging responsible lending and protecting consumer rights.

To overcome these limitations, different financial scoring models have emerged as a feasible approach. These models use modern analytical methods to assess a wider range of financial and behavioral data, including transaction history, spending trends, and internet activities [14]. Unlike traditional methods, these methodologies assess credit risk in a more dynamic manner, responding to new information and thus providing a better evaluation for individuals outside the standard credit framework. By combining non-traditional data sources, such systems can identify creditworthy persons who would otherwise be rejected. This not only encourages broader financial participation but also helps to reduce default rates through more accurate risk assessment [15].

2. Literature Survey

Numerous works previously presented in the literature have focused on credit scoring and risk analysis using machine learning. Few of these are mentioned here.

Md Rakib et al. [16] have presented improving credit risk assessments for BNPL financing through the use of alternative data sources and reinforcement learning. AI credit assessment models can increase forecast accuracy and reduce default risks by leveraging non-traditional financial indicators such as transactional data, digital footprints, and behavioral analytics. The study employs a hybrid methodology that combines supervised deep learning and reinforcement learning algorithms to enhance credit decision-making.

Stow [17] has presented the deep learning methods for assessing credit risk, specifically Long Short-Term Memory (LSTM) networks. The experiment was conducted in a Jupyter Notebook and includes two main phases: exploratory data analysis (EDA) and LSTM model training. Exploratory Data Analysis (EDA) identifies dataset features such as data imbalances, which can be corrected using oversampling approaches.

Alonge et al. [18] have presented the advanced machine learning (ML) model for credit assessment in banking that was intended to increase predictive accuracy, accelerate decision-making, and reduce loan-related risks. The intended hybrid framework integrates supervised learning approaches, such as gradient boosting and neural networks, with unsupervised anomaly detection and grouping. The model evaluates credit risk precisely by analysing structured and unstructured data such as financial records, transactions, and behavioural patterns.

Eniola and Amos [19] have presented Blockchain and AI have the potential to completely transform credit risk management in the financial sector. Credit risk methods were developed by AI's machine learning and data analytics capabilities, which provide real-time insights into borrower behavior and financial trends. Blockchain technology provides transparency, immutability, and decentralization, allowing for secure and quick verification of financial data and identification, ultimately reducing fraud and improving trust.

Adams and Owen [20] have presented the implementation of these technologies can lead to improved decision-making capabilities and a stronger competitive advantage in the market. This research emphasizes the vital significance of modernizing credit risk practices to include machine learning and current information. By doing so, financial institutions not only improve their risk assessment frameworks but also contribute to increased financial stability and resilience in a volatile economic climate.

Yadav [21] has presented the immediate pipelines that can update credit scores, monitor portfolio health, and detect credit deterioration early on. Using actual information improves model correctness and responsiveness compared to batch processing, as demonstrated by the experimental findings. The research covers difficulties such as computational scalability, data latency, and model drift, as well as solutions to address them.

Nwachukwu [22] has presented the need for verifying the accuracy of borrower financial data, as inconsistencies can result in poor lending decisions and higher credit risk. The study also examines how credit history evaluations affect procedural financing, with a particular emphasis on how precise credit history analyses aid in defining loan terms and conditions and streamline decision-making. The report also highlights how crucial procedural financing is to establishing internal controls that reduce risk throughout the lending process. Table 1 presents a summary of the literature survey.

Table 1.
Summary of literature survey.

Ref	Algorithm	Advantage	Disadvantage
Md Rakib et al. [16]	Recurrent Neural Network (RNN)	Enhances credit prediction accuracy and broadens access using alternative data.	Involves privacy issues and high implementation complexity.
Stow [17]	Long Short-Term Memory (LSTM) networks	Captures time-based credit patterns for better prediction.	Needs heavy pre-processing and is sensitive to imbalance.
Alonge et al. [18]	Artificial Neural Network (ANN)	Improves risk accuracy using hybrid ML	High complexity and data requirements.
Eniola and Amos [19]	Deep Learning (DL)	AI insights and blockchain transparency.	Complex to implement and maintain
Adams and Owen [20]	Deep Neural Network (DNN)	Enhances decision-making and stability	Requires significant investment and expertise.
Yadav [21]	Machine Learning (ML)	Real-time updates improve accuracy.	Issues with latency and model drift.
Nwachukwu [22]	Machine Learning (ML)	Ensures data accuracy and optimizes loans.	Data errors can still affect decisions.

Despite significant advancements in credit risk assessment, several critical challenges remain. It is still difficult for traditional models to determine the creditworthiness of people with little to no credit history because they mainly rely on historical financial data. Buy Now, Pay Later (BNPL) financing is becoming increasingly popular, which highlights the need for more flexible and inclusive credit evaluation methods. Current systems frequently struggle to incorporate current information, resulting in delays in decision-making and decreased responsiveness to changing borrower behaviour. Additionally, challenges such as data inconsistency, model drift, and inadequate transparency continue to impact the reliability and fairness of credit determinations. There are also insufficient robust methods to ensure the accuracy and integrity of financial data, raising the risk of bad lending outcomes. These gaps highlight the need to modernise credit risk practices by adopting innovative approaches that can improve prediction accuracy, provide timely insights, and enable more secure and transparent lending processes.

In this paper, the CSRA-DPLP-BSCNN method is proposed to address the limitations of traditional credit scoring systems in real-time credit risk assessment, particularly within BNPL-based financial loan platforms. The approach enhances credit evaluation by leveraging the RBEKF for data pre-processing, which effectively manages missing values, reduces noise, and normalizes the dataset. The cleaned data is then analyzed using a BSCNN, which accurately identifies complex financial behavior patterns such as repayment history and income dynamics. Optimized through binarization, BSCNN ensures high computational efficiency and scalability. The CSRA-DPLP-BSCNN method outperforms existing techniques, achieving superior performance with high accuracy, recall, F1-score, precision, loss, and ROC, while supporting real-time analysis with minimal false positives.

An important contribution of this research work is abridged below,

- In this research, a deep learning-based credit risk prediction model titled Credit Scoring and Risk Analysis using Deep Processing Loan Platform (CSRA-DPLP-BSCNN) is proposed.
- RBEKF handles missing values, reduces noise, and normalizes multi-source input data to ensure clean and consistent credit evaluation inputs.
- BSCNN identifies complex behavioral and financial patterns to enable accurate and real-time credit risk prediction.
- Enhances credit accessibility for users with limited or no credit history, promoting financial inclusion and fairer lending practices.
- The obtained results of the proposed CSRA-DPLP-BSCNN algorithm are compared with existing models such as CRA-ECF-PAEFS, EFS-RTCRM-MLT-ADA, and CRE-FSDL, demonstrating superior performance across all metrics.

The remaining manuscript is arranged as follows: Part 2 presents the proposed methodology, Part 3 displays the results, and Part 5 concludes the manuscript.

3. Proposed Methodology

In this sector, real-time credit scoring and risk analysis using deep learning for BNPL-based loan platforms (CSRA-DPLP-BSCNN) are discussed. The approach begins with data sourced from a BNPL dataset, which includes user demographics, repayment history, purchasing behavior, and alternative financial indicators. This raw data is pre-processed using an RBEKF to handle missing values and eliminate noise. The enhanced data is then fed into a Binarized Simplicial Convolutional Neural Network (BSCNN) for credit risk prediction. BSCNN efficiently captures complex relational patterns and topological features within the financial data while maintaining computational efficiency through binarization. This method improves the accuracy and speed of credit risk assessment, making it highly effective for real-time lending decisions in BNPL environments. Figure 1 illustrates the Block Diagram of the proposed CSRA-DPLP-BSCNN.

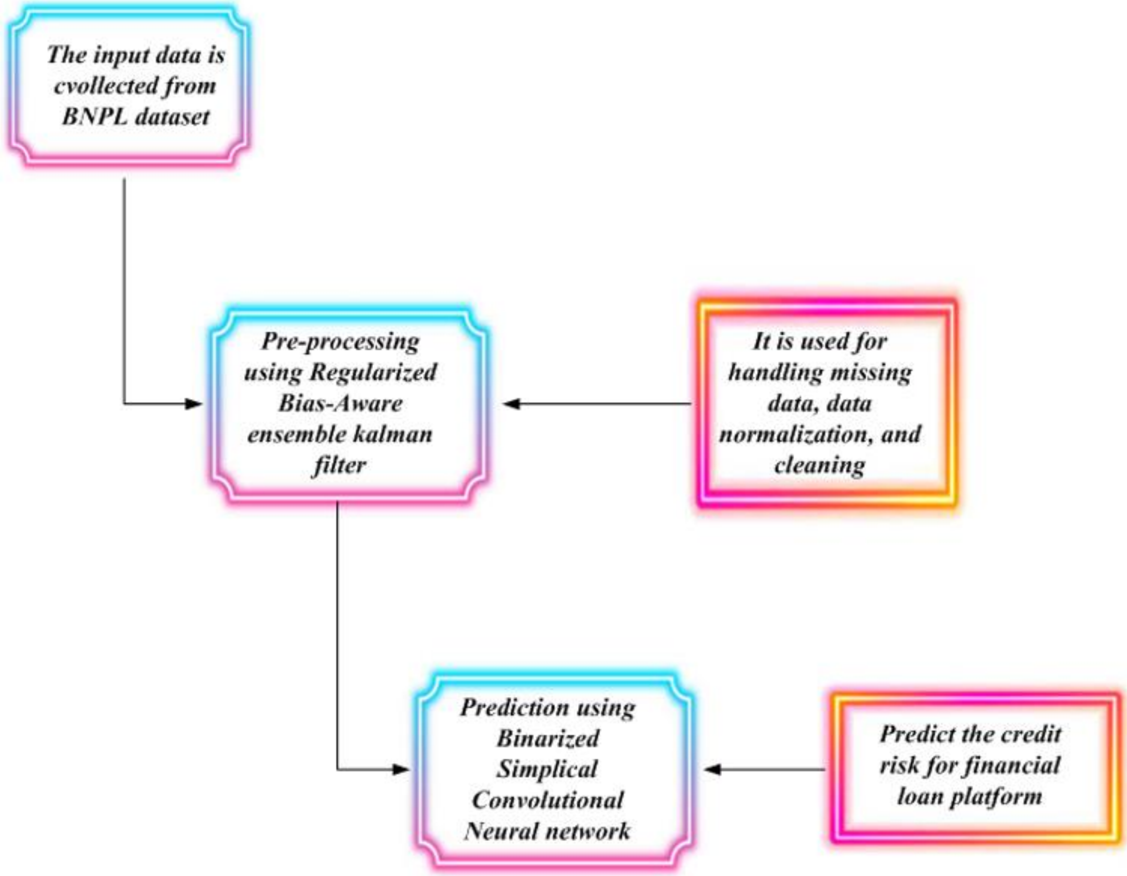

Figure 1.
Block Diagram of the proposed CSRA-DPLP- BSCNN.

3.1. Data Acquisition

The input data is initially gathered from a representative BNPL (Buy Now, Pay Later) transaction dataset, sourced from various platforms including e-commerce sites, BNPL providers, and financial applications. This dataset is commonly employed to assess the performance of real-time credit scoring and risk analysis systems powered by deep learning. It includes comprehensive, labeled data such as user demographics, purchase records, repayment patterns, and alternative financial signals like digital footprints. Originally comprising over 1.5 million records, the dataset was pre-processed to handle missing values, normalize the data, and remove duplicates and irrelevant attributes. After cleaning, the dataset was refined to 85,000 high-quality records and divided into 70% for training, 15% for testing, and 15% for validation to ensure balanced and effective model development.

3.2. Pre-Processing Utilizing Regularized Bias-Aware Ensemble Kalman Filter (RBEKF)

In this segment, pre-processing utilizing RBEKF [23] is discussed. It is used for handling missing data, data normalization, and cleaning. The RBEKF is used in credit scoring and risk analysis to enhance prediction accuracy by correcting model bias and reducing overfitting in financial data. It helps manage noise, missing values, and inconsistencies in credit-related indicators. By integrating real-time data updates and applying regularization, RBEKF ensures that the inputs to the scoring model are more stable and representative, improving the reliability and precision of credit risk classification and default prediction.

$$J(\psi_j) = \left\|\psi_j - \psi_j^f\right\|^2_{C^{f\,-1}_{\psi\psi}} + \left\|y_j - d_j\right\|^2_{C^{-1}_{dd}} + \gamma\left\|b_j\right\|^2_{C^{-1}_{bb}}, \quad for \quad j = 0,....,m-1 \tag{1}$$

Where, ψ_j denotes the estimated state variable at time , ψ_i^f represents the state at time , $C^f_{\psi\psi}$ represents error covariance matrix, y_j represents the observation vector at time, d_j denotes predicted observation corresponding to ψ_i, C_{dd} denotes the observation noise covariance matrix, γ represents regularization parameter, b_i denotes the estimated model bias, and C_{bb} represents the bias covariance matrix. RBEKF enhances data quality by effectively handling missing values, normalizing inconsistent data, and reducing noise in the dataset, although it may involve high computational cost in Equation 2.

$$\frac{1}{2}\frac{dJ}{d\psi}\bigg|_{\psi_j^n} = C_{\psi\psi}^{f-1}\left(\psi_j^a - \psi_j^f\right) + \frac{dy_j}{d\psi_j}\bigg|_{\psi_j^a}^T C_{dd}^{-1}\left(y_j^a - d_j\right) + \lambda \frac{db_j}{d\psi_j}\bigg|_{\psi_j^a}^T C_{bb}^{-1} b_j^a = 0 \tag{2}$$

Where, ψ_j represents the control variable or model state at point j, ψ_j^a and ψ_j^f denote its background and analysis values, $C_{\psi\psi}^{f-1}$ is the inverse of the background error covariance matrix, y_j^a and d_j measures the mismatch between model predictions and actual data. The matrix C_{dd}^{-1} is the inverse of the observation error covariance, $\frac{dy_j}{d\psi_j}$ represents how the observations change with respect to the control variable, b_j is the bias term that adjusts for missing or inconsistent data patterns, C_{bb}^{-1} represents the inverse bias error covariance, λ and is a tuning parameter that controls the extent of data correction. RBEKF improves credit risk analysis by handling missing data, normalizing inputs, and cleaning noise, though it requires careful tuning, as shown in Equation 3.

$$b_j^a \approx b_j^f + J^f M\left(\psi_j^a - \psi_j^f\right) \tag{3}$$

This Equation 3 expresses that the value of b_j^a is equal to the value of b_j^f plus a term involving the difference between $\psi_j^a - \psi_j^f$ scaled by the factor $J^f M$ .Finally, the RBEKF method has handled missing values, normalized inconsistent entries, and cleaned the data. The prediction model is then fed the pre-processed data.

3.3. Prediction Using Binarized Simplicial Convolutional Neural Network (BSCNN)

In this segment, prediction using a BSCNN [24] is discussed. It is used to predict credit risk for financial loan platforms by analyzing patterns in historical financial data, such as loan repayment histories, credit scores, income levels, and other relevant financial indicators. BSCNN can be applied to optimize credit risk evaluation by modeling high-order relationships among financial indicators. BSCNN captures the topological and structural dependencies within the financial data, enabling precise and efficient risk prediction. BSCNN enhances credit risk prediction for loan platforms by analyzing patterns in historical financial data, such as credit scores and repayment histories, improving accuracy and precision as shown in Equation 4.

$$L_k = U_k \Lambda_k U_k^T \tag{5}$$

Where Λ_k denotes the eigenvalue matrix, U_k is represents the eigenvector matrix, and U_k^T is represents the transpose of the eigenvector matrix. BSCNN predicts credit risk by capturing structural dependencies in financial data and is expressed in Equation 6.

$$\tilde{x}_k = U_k^T x_k \tag{6}$$

Where represents the input data, x_k represents the financial data on the nodes. BSCNN optimizes credit risk prediction by capturing complex patterns in financial data, such as credit scores and repayment histories, as shown in Equation 7.

$$y_k = U_k h(\Lambda_k)\tilde{x}_k = U_k h(\Lambda_k) U_k^T x_k \tag{7}$$

Here, y_k is denoted as the outcome of the simplicial convolution, $h(\Lambda_k)$ a function applied to a parameter Λ_k. Finally, BSCNN predicts credit risk for loan platforms by analyzing historical financial data, improving risk assessment effectiveness.

4. Result

The results of the proposed technique are discussed in this section. The proposed CSRA-DPLP-BSCNN technique is then simulated in Python and compiled using Jupyter Notebook and executed on a system with 64 GB RAM, an Intel Core i9-13900K CPU, and 500 GB SSD storage. The process begins by splitting the dataset into training (70%) and testing (15%) sets, followed by performance evaluation of various classification algorithms. The obtained results of the proposed CSRA-DPLP-BSCNN approach are analyzed in comparison with existing systems such as CRA-ECF-PAEFS, EFS-RTCRM-MLT-ADA, and CRE-FSDL, respectively.

4.1. Performance Measure

This is an important step in selecting the best classifier. Accuracy, recall, F1-score, precision, and detection rate are among the performance metrics that are evaluated. The performance metric is used to scale the performance metrics. To scale the performance metric, the True Negative (TN), True Positive (TP) False Negative (FN) and False Positive (FP) samples are needed.

4.1.1. Accuracy

The accuracy of a model evaluates its overall correctness based on the percentage of true positive and true negative predictions among all forecasts. It provides an indication of how well the method identifies instances that are positive and negative across the entire dataset.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

Where TP is denoted as true positive, FP is denoted as false positive, TN is denoted as true negative and FN is denoted as false negative.

4.1.2. Precision

One measure of a machine learning method's efficiency is precision, or how well the method creates positive forecasts. It is measured utilizing Equation 7 that follows.

$$\Pr ecision = \frac{TP}{(TP + FP)} \tag{8}$$

4.1.3. Recall

A method's recall quantifies its capacity to accurately detect every pertinent instance, with an emphasis on reducing false negatives. It is crucial in situations where capturing all true positives is more important than avoiding false positives.

$$\operatorname{Re} call = \frac{TP}{TP + FN} \tag{9}$$

4.2. Performance Analysis

Figure 2–7 displays the simulation outcomes of the proposed CSRA-DPLP-BSCNN technique. Then the proposed CSRA-DPLP-BSCNN technique is compared with the existing CRA-ECF-PAEFS, EFS-RTCRM-MLT-ADA, and CRE-FSDL methods, respectively.

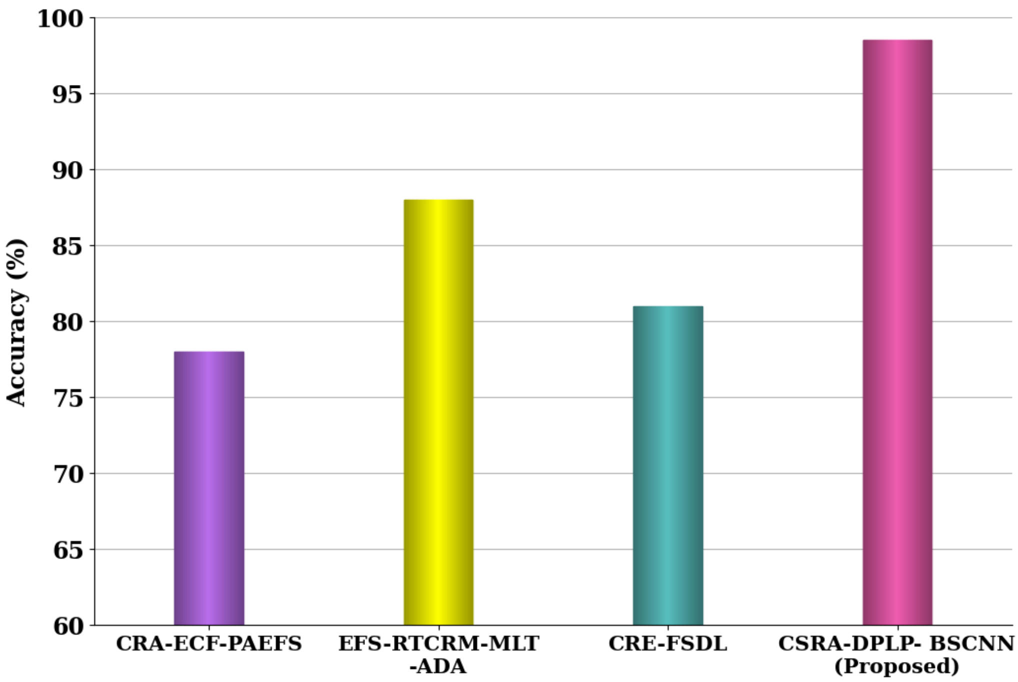

Figure 2.
Performance Analysis of Accuracy.

Figure 2 illustrates the performance analysis of accuracy in credit risk prediction across four different methods. CRA-ECF-PAEFS achieves an accuracy of 78%, EFS-RTCRM-MLT-ADA scores 88%, and CRE-FSDL reaches 81%. The proposed CSRA-DPLP-BSCNN outperforms the others with an accuracy of 98%. The proposed technique demonstrates the highest accuracy, showcasing its superior capability in credit risk analysis.

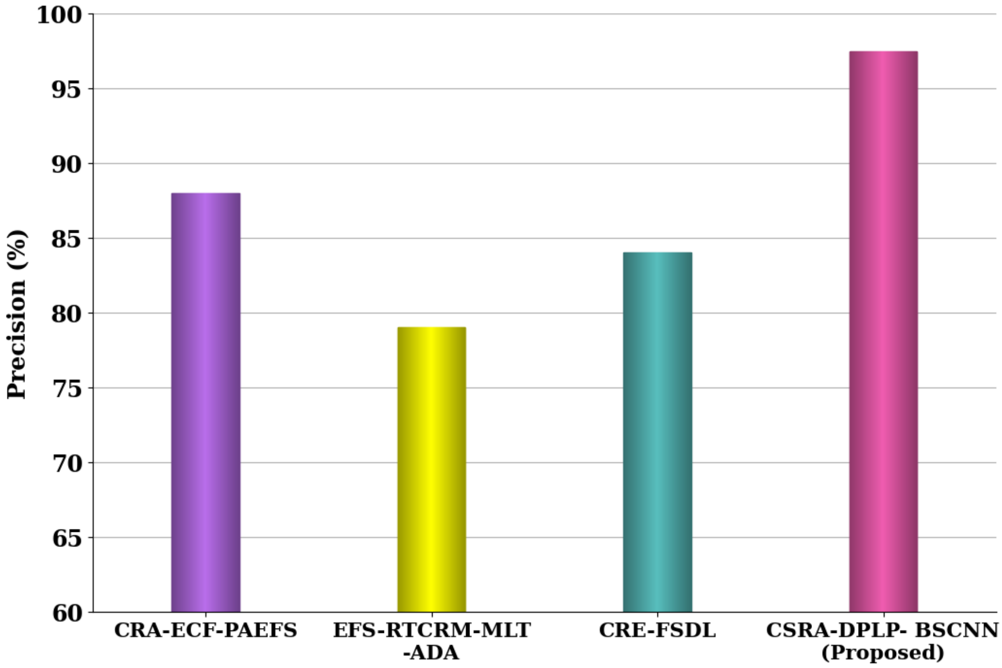

Figure 3.
Performance Analysis of Precision.

Figure 3 illustrates the performance analysis of precision in credit risk prediction, comparing the effectiveness of various methods. CRA-ECF-PAEFS achieves 88% precision, EFS-RTCRM-MLT-ADA around 79%, CRE-FSDL about 84%, and the proposed CSRA-DPLP-BSCNN significantly outperforms the others with 97%. The proposed method demonstrates the highest precision, showcasing its superior capability in accurately identifying credit risk.

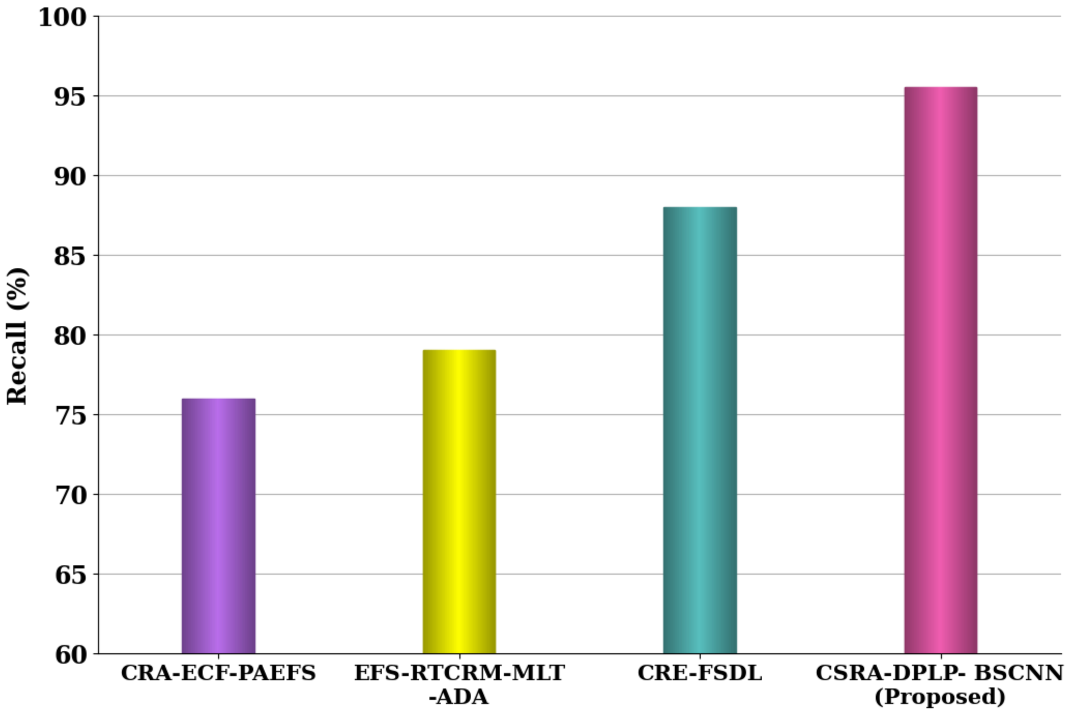

Figure 4.
Performance Analysis of Recall.

Figure 4 illustrates the performance analysis of recall in credit risk prediction, comparing the effectiveness of various methods. CRA-ECF-PAEFS achieves 76% recall, EFS-RTCRM-MLT-ADA around 79%, CRE-FSDL about 88%, and the proposed CSRA-DPLP-BSCNN significantly outperforms the others with 96%. The proposed method demonstrates the highest recall, showcasing its superior capability in accurately identifying relevant credit risk.

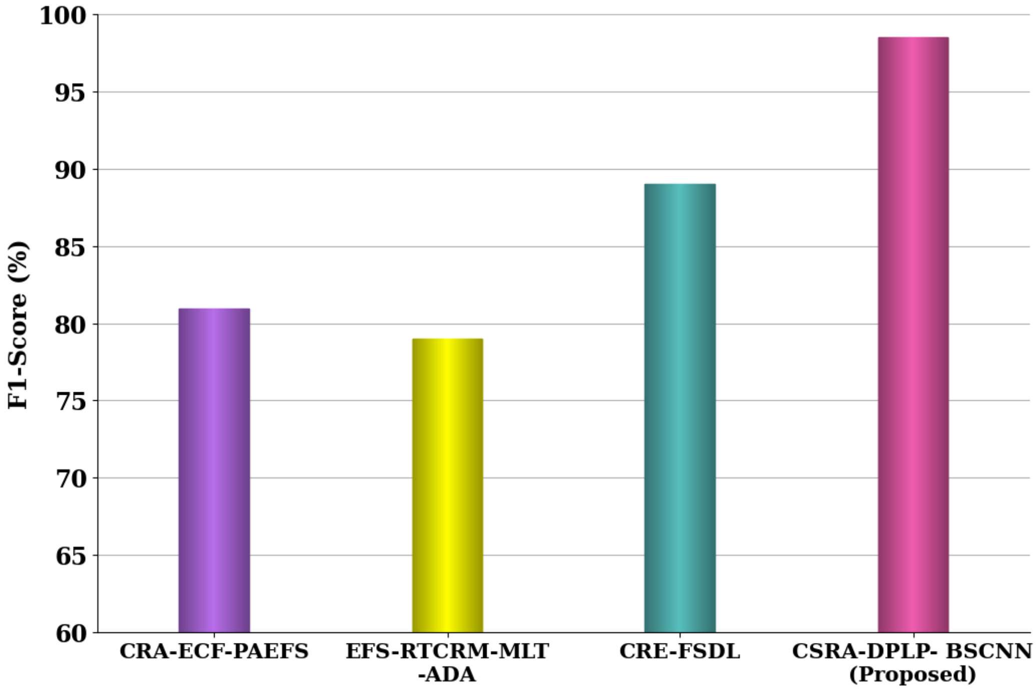

Figure 5.
Performance Analysis of F1-Score.

Figure 5 illustrates the performance analysis of the F1-score in credit risk prediction, comparing the effectiveness of various methods. CRA-ECF-PAEFS achieves an 81% F1-score, EFS-RTCRM-MLT-ADA around 79%, CRE-FSDL about 89%, and the proposed CSRA-DPLP-BSCNN significantly outperforms the others with a 98% F1-score. The proposed method demonstrates the highest F1-score, showcasing its superior capability in achieving a balanced and accurate credit risk assessment.

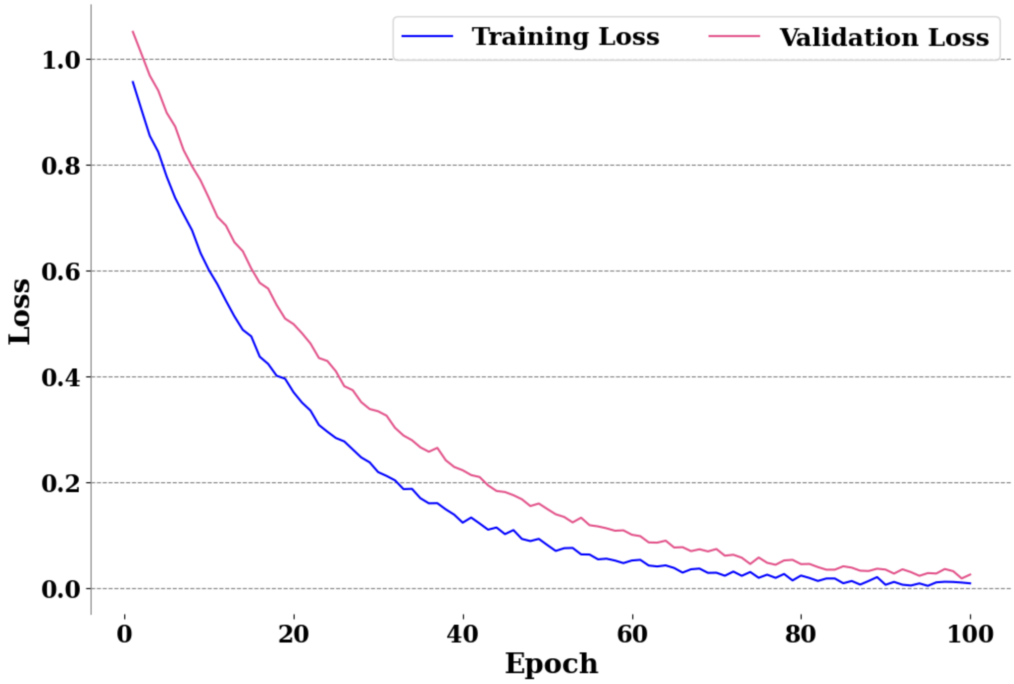

Figure 6.
Performance Analysis of Loss.

Figure 6 illustrates the performance analysis of loss over 100 training epochs, showcasing both training and validation loss trends. The training loss decreases steadily from around 0.95, reaching nearly 0.01, while the validation loss drops from 1.05 to 0.03, indicating effective learning and generalization in the initial phases. Following epoch 60, there is a slight overfitting trend as the training loss continues to decrease while the validation loss starts to plateau. The proposed method demonstrates better convergence and consistently lower loss compared with existing methods such as CRA-ECF-PAEFS, EFS-RTCRM-MLT-ADA, and CRE-FSDL, confirming superior training stability and performance.

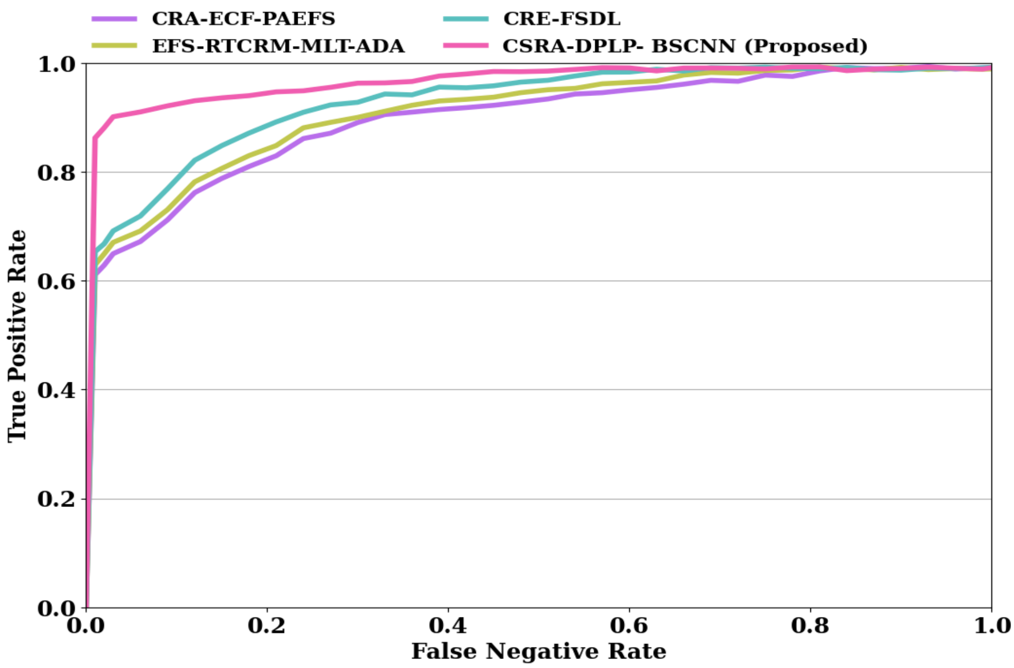

Figure 7.
Performance Analysis of ROC.

Figure 7 illustrates the performance analysis of the ROC curve for four methods in a deep learning-based model comparison. It assesses how well the model detects positive cases while reducing false negatives. The ROC curve contrasts each method's true positive rate (TPR) with its false negative rate (FNR). The proposed CSRA-DPLP-BSCNN method starts with a TPR of 0.85 at a low FNR of around 0.05 and consistently outperforms the other methods, achieving a TPR of about 0.95 while maintaining a low FNR of 0.02. In comparison, CRA-ECF-PAEFS reaches a TPR of 0.70 at an FNR of 0.10, EFS-RTCRM-MLT-ADA reaches 0.75 at an FNR of 0.08, and CRE-FSDL achieves a TPR of 0.80 at an FNR of 0.06.

The proposed method excels in identifying positive cases and minimizing false negatives across the entire range of FNR.

Table 2.
Comparison results of the performance analysis.

Methods	Specificity	Computational Time
CSRA-DPLP-BSCNN (proposed)	97.5%	1.159
CRA-ECF-PAEFS	96.2%	1.280
EFS-RTCRM-MLT-ADA	94.6%	1.165
CRE-FSDL	86.7%	1.324

Table 2 displays the comparison results of the performance analysis. In this analysis, the specificity of the methods is as follows: the proposed CSRA-DPLP-BSCNN achieved the highest specificity at 97.5%, followed by CRA-ECF-PAEFS at 96.2%, EFS-RTCRM-MLT-ADA at 94.6%, and CRE-FSDL at 86.7%. Regarding computational time, the proposed CSRA-DPLP-BSCNN had the shortest processing time of 1.159 seconds, while EFS-RTCRM-MLT-ADA required 1.165 seconds, CRA-ECF-PAEFS took 1.280 seconds, and CRE-FSDL had the longest time of 1.324 seconds.

5. Conclusion

In conclusion, the CSRA-DPLP-BSCNN method presented in this paper offers a robust framework for real-time credit scoring and risk analysis in modern financial platforms. By integrating deep learning techniques and advanced pre-processing strategies, this approach enhances prediction accuracy, ensuring efficient and reliable credit assessments. Its application in fintech improves lending decision-making while fostering trust and driving innovation in the financial services industry. The proposed method is implemented in Python. The CSRA-DPLP-BSCNN method achieves 98% accuracy, 97% precision, 96% recall, 98% F1-score, and 1.159 seconds of computational time, with a high ROC of 0.95. The framework shows significant potential in improving the accuracy and efficiency of credit risk prediction in dynamic financial environments. However, challenges such as the computational intensity of deep learning methods and the difficulty of adapting to rapidly changing financial patterns still exist. Future work could focus on optimizing the model's efficiency by developing more lightweight deep learning architectures that reduce processing time while maintaining high performance.

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