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An Ai-Based Intelligent Approach for Credit Risk Assessment

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Abstract Credit risk poses a substantial problem to the banking and financial industries, especially when borrowers fail to satisfy their repayment commitments. Conventional approaches have various challenges in effectively anticipating credit risk evaluations, including the incidence of fraudulent activity. Therefore, to avoid these problems, a new approach called the Pigeon U Net Prediction System (PUNPS) has been developed for credit risk prediction and classification. The credit card transaction dataset was collected using the Kaggle platform. The dataset was then preprocessed to remove duplicate items. The feature selection approach was used to keep only relevant variables. Credit risk prediction was successfully carried out using the fitness function of the pigeon optimization algorithm. Furthermore, the classified credit risk forecasts were processed with the U-Net framework. Finally, the model's performance was evaluated, and the findings were compared with those of standard approaches. This method offers significant advantages over conventional models, demonstrating improved performance in predicting credit risk through enhanced accuracy. The performance of this model is evaluated using various risk assessment metrics, including F1 score, Precision, recall, Accuracy, and error rate. It demonstrates an impressive accuracy of 99.8%, accompanied by precision and recall scores of 99.9% and 99.7%, respectively. An F1 score of 99.6% confirms its effective balance between Precision and recall, establishing it as a reliable and accurate tool for credit risk assessment. Additionally, it maintains a minimal error rate of 0.2%.

Keywords Credit risk assessment, classification, Pigeon optimization, Preprocessing, Feature extraction.

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1. Introduction

The credit risk assessment (CRA) process determines the likelihood of financial loss if a borrower fails on another commitment. A credit card is a means of borrowing money to purchase goods and services in the modern era. [1]. The increased purchasing of leisure products and simpler access to online financial services compound the phenomenon [2]. Compared to traditional banking institutions, the car financing business offers easier screening procedures and a more flexible credit verification process [3]. In an effort to dominate the car loan industry, corporations are attempting to attract customers with new models and advanced technology. There are indications that the car financing sector is poised for rapid growth. [4]. A general risk governance tool is a credit rating technique that banks and other credit organizations use to estimate the likelihood of future default based on data from credit card customers [5]. They assist banks and other financial organizations in determining whether providing credit cards to potential customers is suitable. Banks and other financial institutions must avoid poor or defaulting clients to prevent unnecessary expenses [6]. The relevance of various risk assessment models has grown in the credit industry due to its expansion [7]. To resolve the card and credit score issue, the customer's completed application form is a vital asset for the institution and contains valuable information [8]. Creditors will set a cutoff point for credit rating. If the applicant's score is below the threshold, the institution may decide not to lend to them;

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if not, they may be charged extra when issued a risk [9]. Credit risk evaluation is essential to managing credit risk in commercial institutions [5].

Credit risk refers to the likelihood that a borrower will default on their loan due to an inability to make monthly payments [10]. It demonstrates the potential for credit card loan issuers to fail to receive principal or interest payments on time. By accurately assessing the credit risk of its applicants, commercial banks can effectively mitigate credit risk and make more informed lending decisions [11]. An effective underwriting and loan approval process is essential to maintaining a good portfolio quality, and reducing needless risk is one of the function's primary duties [12]. As previously said, for a business to maintain a healthy credit portfolio, it is essential to comprehend its clients' financial circumstances and histories before granting them a credit facility [13]. This knowledge will extend the cardholder's life and contribute to sustaining a steady income [14]. Excessive interest rates do not affect them. Non-payers are the last thing any credit card company wants to have as clients. They apply for and use all available credit on all available credit cards, but they never pay for them [15]. This work requires a significant amount of time and resources, resulting in increased operating costs. These charges might add up, considering the price of hiring collection agencies and other resources. Our study is situated at the nexus of this important problem [16]. Banks and credit card issuers can better and more efficiently manage their credit risk using this data-driven, automated method, thereby reducing losses and ensuring a healthy cash flow [17].

The procedure is streamlined, allowing financial institutions to choose and implement credit risk classifiers, readily preprocess information about their credit customers, and accurately forecast the consumers' potential credit risk, categorizing them into "good" and "bad" groups [18]. This article primarily uses deep learning and machine learning techniques to determine which non-payers are most at risk [19]. Studies conducted with this goal in mind produced varying results, particularly for the classification method [20]. Analyzing and assessing the application of data-splitting techniques in conjunction with dimensionality reduction provides additional impetus [21]. There are several traditional approaches were implemented in the past in both deep learning and optimization models, such as Lion Optimization (Lo) [31], Antlion Optimization (ALO) [32], particle swarm Optimization (PSO) [33] and Genetic algorithm (GA) [34] are tested for the optimization approach in credit card risk prediction. Still, those optimal features are not well-suited due to the improper use of control variants. Also, the deep learning and the ensemble models like a neural network [35], AdaBoost [36], extreme gradient boost (XGBoost) [37], Catboost [38], and graph neural networks [39] were tested for this credit card risk assessment application, but due to the unique features of the credit card data, those models can't reach the desired finest accuracy. Considering this, the Unet and Pigeon models are considered for this work. The Unet has reported the best feature selection outcome among all other ensemble models [30]. In addition, the reason for considering the pigeon model is inspired by its homing features [29], which are based on environmental conditions. Here, the Pigeon homing features were updated in the Unet classification layer, which affords the proposed model the flexibility to process in various applications. The main contribution of this research work is described as follows,

- The dataset for credit card transactions was sourced from the Kaggle platform.
- Consequently, a novel Pigeon U-Net Prediction System (PUNPS) is developed for credit risk prediction and classification.
- Additionally, preprocessing was used to remove duplicate records in the collected dataset.
- A feature selection process was used to extract only relevant variables from the dataset.
- Accurate credit risk prediction was conducted using the fitness function of the pigeon optimization algorithm.
- Furthermore, the predicted credit risk was classified using the U-Net framework.
- Finally, the model's performance was evaluated, and its results were compared to those of conventional methods.

2. Related work

The following is a description of recent related works:

Rao et al. [22] provide access to the data sets on personal car loans through a deep learning-based credit risk assessment system for personal vehicle loans on the Kaggle platform. It is advised to use an integrated Smote-Tomek Link strategy to ensure balanced data collection. An enhanced Filter-Wrapper feature selection technique may be used to select credit risk assessment indices for the loans. Therefore, it is crucial to effectively manage and control credit risk associated with personal vehicle loans as automotive finance continues to expand.

Amarnath et al. [23] evaluate the reliability of individuals, companies, and other entities in forecasting the possibility of default, a process known as credit risk assessment. Financial organizations classify customers based on their creditworthiness, but there is no single, widely accepted set of characteristics or indices. Therefore, Credit risk arises from a contractual party's failure and is a crucial factor in financial organizations.

Wang et al. [24] develop new machine learning-based forecast models that use an imbalanced sampling method and financial, operational, innovation, and adverse event data as predictors. We then forecast using these algorithms to assess the credit risk of Chinese SMEs. It is a frequent yet challenging task to assess the value of integrating data from multiple sources to predict the credit risk of small and medium-sized enterprises (SMEs) in supply chain finance (SCF). As a result, the issues of imbalanced class and key variable selection must be addressed concurrently.

Wang et al. [25] Several machine learning techniques, including deep learning, are used to create a unique two-stage ensemble model for corporate credit risk early warning. The findings demonstrate that this model may improve forecast accuracy and provide a qualitative investigation into the origin of corporate credit risk from several perspectives. Since these algorithms usually overlook further qualitative data analysis, there are no well-established theoretical models for early warnings of corporate credit risk when it comes to deep learning models with higher prediction skills.

Talaat et al. [26] have developed a novel technique that integrates explainable artificial intelligence (XAI) and deep learning methods to predict credit card defaults. By incorporating these methods, the process of determining decisions used to predict credit card default becomes more interpretable. Therefore, even though machine learning and deep learning techniques have demonstrated encouraging outcomes in default prediction, the interpretability and utility of these models are frequently constrained by their opaque nature.

3. System Model with Problem

Conventional methods of evaluating credit risk primarily rely on credit rule-based systems and historical data to forecast the likelihood of a borrower's debt default. These approaches overlook the intricate and dynamic character of creditworthiness, which may result in erroneous risk evaluations, increased default rates, or lost loan opportunities. Furthermore, traditional methods are often ineffective, slow, and unable to account for unstructured data, such as social media activity, transaction histories, or external economic factors. Deep learning (DL) and artificial intelligence (AI) developments might greatly enhance the Precision and robustness of credit risk models. Nevertheless, all-inclusive AI based frameworks are specifically designed for credit risk assessment and incorporate various models, as shown in Figure 1.

4. Proposed Methodology

In this study, a new Pigeon U-Net Prediction System (PUNPS) has been developed to predict and classify credit risk. Initially, the credit card transaction dataset was obtained from the Kaggle platform. Moreover, preprocessing techniques were employed to eliminate duplicate records within the dataset. A feature selection process was implemented to identify only the relevant characters from the dataset. The prediction of credit risk was accurately performed utilizing the fitness function associated with pigeon optimization. In addition, the classified credit risk predictions were processed using the U-Net framework. Ultimately, the model's performance was evaluated, and its outcomes were compared with those of traditional methods. The Proposed architecture is shown in Figure 2.

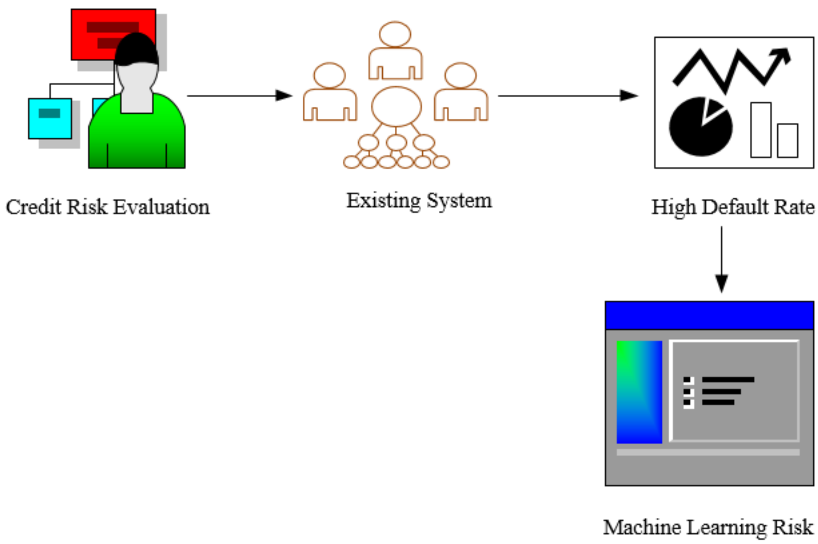

Figure 1. System model with issues

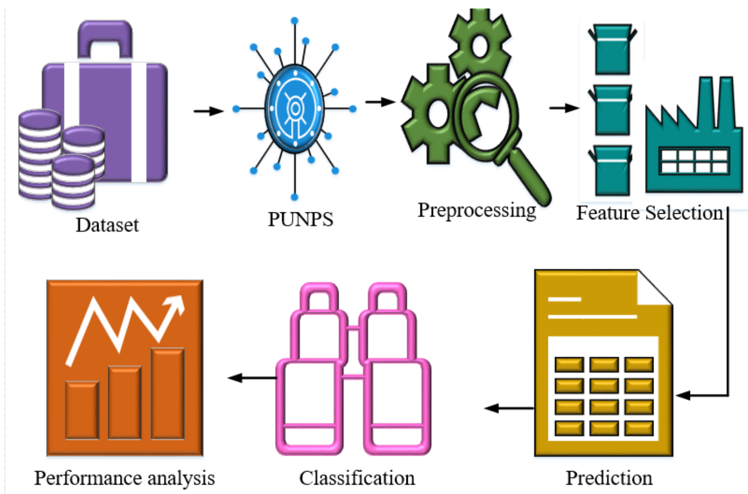

Figure 2. Proposed Methodology

4.1. Process of the developed PUNPS

This hybrid technique combines the Pigeon Optimization Algorithm (POA) with the U-Net framework, yielding optimal feature selection and classification. PUNPS is crucial in credit risk assessment to ensure accurate risk assessment. POA enhances the learning process by dynamically adjusting model parameters, thereby increasing the ability to identify risk. The U-Net network ensures accurate risk classification. PUNPS successfully identifies risk categories using optimization and deep learning, improving prediction accuracy and reducing false positives. This hybrid model outperforms existing approaches, making it reliable for assessing credit risk.

4.1.1. Data initialization The data was first collected from the static site and then integrated into the Python system for training purposes. The credit risk assessment data was then imported into the system as input. Eqn.(1) represents the data initialization process.

$$I(C_D) = \{C_1, C_2, C_3, \ldots, C_n\} \tag{1}$$

Here, I indicate the initialization process variable (C_1, C_2, C_3) indicates data in the dataset, C_D indicating the total data and $I(C_D)$ defines the data initialization function, which is processed to initialize the data. To simplify the fraud detection process in credit card applications, time series analysis has been performed using the following parameters: data preparation, model selection, parameter tuning, model evaluation, and integration of existing models for performance comparison. Here, data cleaning was performed in the preprocessing layer using the min-max scalar function for support. Moreover, the Unet approach was considered for model selection, and then, for parameter tuning, pigeon optimization was chosen, followed by tuning of the Unet parameters. The model's performance was evaluated with other traditional models in terms of accuracy, Precision, recall, F-score, and error rate. Here, the pigeon tuning mechanism has provided flexible control variants for all temporal variations in credit risk.

4.1.2. Preprocessing The preprocessing stage is crucial for removing noisy characters, including irrelevant symbols and missing values. Noise filtering approaches improve the dataset's structure and reliability for model training. This improvement in data quality ensures greater accuracy and reduces errors, resulting in more precise credit risk assessments from the PUNPS. The preprocessing of credit risk is shown in Eqn.(2).

$$S_i^{n+1} = \text{sig}\left(e^{-Vn} R_i^t + \text{rand}\left(X_{\text{due}} - X_i^t\right)\right) \tag{2}$$

While, R denotes noisy features a. X_{due} indicates the normal feature, S_i^{n+1} indicates the preprocessing variable, e^{-Vn} is the min-max scalar function, R_i^t is the normalization function, rand defines the random selection of data and X_i^t is the noise features. Here, the min-max scalar is utilized to remove noisy constraints, and the dropout regularization concept is applied to handle redundant data and missing data [28]. Following the data preprocessing phase, the feature selection process commenced.

4.1.3. Feature Extraction Feature extraction is considered a crucial technique that involves identifying key features within a dataset. This dataset contains many potential risk attributes. It is crucial to extract the necessary and relevant features from the data. The data extraction procedure is depicted in Eqn.(3).

$$FE = b_i(n) + \text{rand} \times (y_{\text{due}}(n) - a_i(n)) \tag{3}$$

Where n denotes the number of current iterations, a_j indicates the selected features. y_{due} the denote global optimal solution, b_j indicates the unwanted features, FE indicate the feature selection variable, utilized for selecting the required features that are *spatial features statistics*. Subsequently, after the feature selection phase, the risk prediction process began.

4.1.4. Prediction The evaluation of credit risk assessment involves examining the effects of feature extraction. To improve the process and enhance risk prediction analysis, the pigeon optimization algorithm is utilized. Increased credit risk is a key factor in improving the ability to differentiate between risky activities. The prediction process was described in Eqn.(4).

$$S = \frac{f(b_i(n) + \text{rand} \times a_i(n))}{FE} \tag{4}$$

While S denotes the prediction variable, FE indicates the feature selection outcomes, f indicates the fitness function of the optimization, n denotes the number of current iterations. Here, the happening of unusual features was forecasted as risk. After the risk prediction phase, the risk classification process was initiated.

4.1.5. Classification The risk assessment categorization is done using the U-Net methodology. This strategy improves the accuracy of credit risk categorization by considering potential risk outcomes. The mathematical description of this process is explained as, where $S = 0$ denotes 1-29 days past due, 1 denotes 30-59 days past due, 2 denotes 60-89 days past due, 3 denotes 90-119 days overdue, 4 denotes 120-149 days overdue, 5 denotes 150 days overdue, 6 denotes the paid of that month, 7 denote the No loan for the month is classified. Here, C denotes the classification variable. Figure 3 presents a flowchart that sequentially outlines the operational process of the proposed model. The methodology for the recommended model is elaborated in Algorithm 1, which is provided in pseudo-code format.

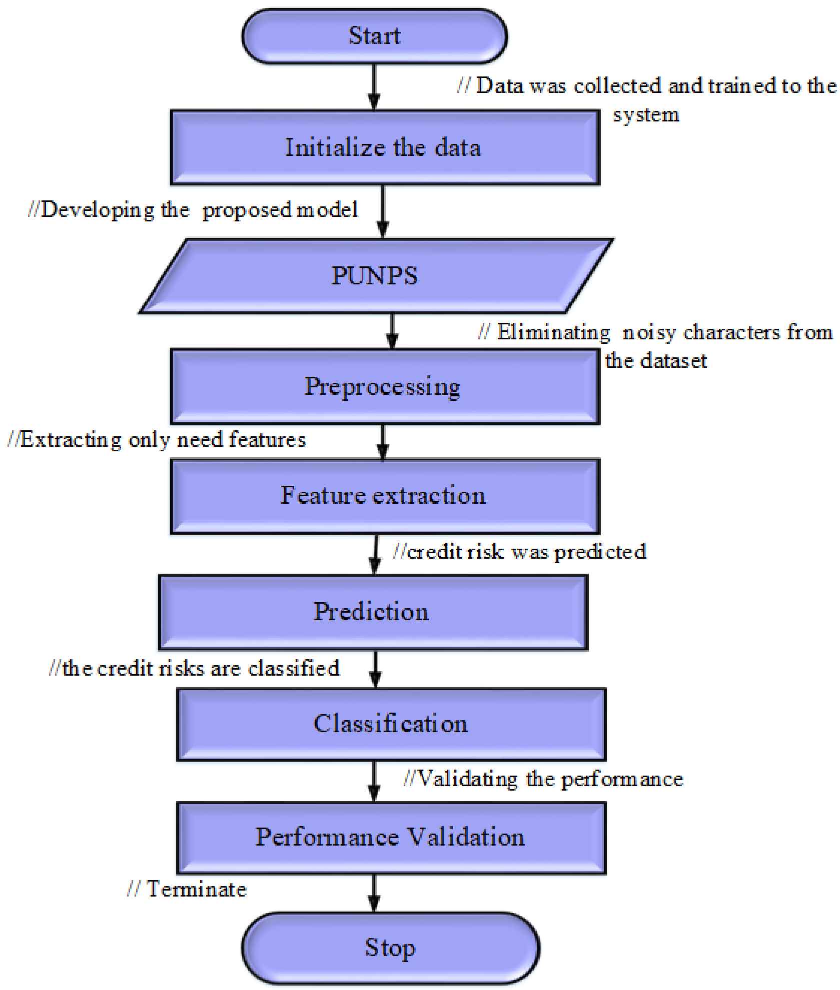

Figure 3. Flow chart for the Proposed Architecture

Equation derivation

The preprocessing equation is derived based on the pigeon search function, as shown in Eqn. (2), which is processed in the hidden layer of the Unet. The Unet hidden layer is processed with the sig mod function. Hence, in the modular function is upgraded with the pigeon search fitness, which is expressed as $\boldsymbol{sig}\left(e^{-V_n}\boldsymbol{R}_i^t + \boldsymbol{rand}\left(\boldsymbol{X}_{\boldsymbol{due}} - \boldsymbol{X}_i^t\right)\right)$. Then the best Pigeon was selection based on the good position finding. Hence, the position finding formulation is

Algorithm PUNPS

Start

Step 1

Data initialization

Data was initialized based on pigeon population

Step 2

Data preprocessing

fix $\rightarrow$ min_max scalar + regularization

// min_max scalar for removing the noise and regularization of redundancy data and miss data handling

Step 3

Feature extraction

extract $\rightarrow$ spatial features

Step 4

Prediction

def. predict_risk(y_{due}, trained_model)

prediction = trained_model.predict(x_{due})

Step 5

Classification Based on Prediction

if ($S = 0$)

1–29 days past due

if ($S = 1$)

30–59 days past due

if ($S = 2$)

60–89 days overdue

if ($S = 3$)

90–119 days overdue

if ($S = 4$)

120–149 days overdue

if ($S = 5$)

150 days overdue

if ($S = 6$)

Paid off that month

if ($S = 7$)

No loan for the month

Stop

exposed as $FE = b_i(n) + rand \times (y_{due}(n) - a_i(n))$. In the pigeon position location finding, the due features were updated from the credit card data. Here, the client data is taken into random that is mentioned as **rand**, while testing process the data. Additionally, the Unet hyperparameters for the classification logic are a learning rate of 0.001, a batch size of 32, 100 epochs, neuron weight update architecture of Pigeon, a dropout rate of 0.2, and a number of filters of 3. These outcomes were gained during the sensitivity test.

5. Result and Discussion

The parameters determined in this study are shown in Table 1. The operating system is Windows 10, which is a stable and modern system for running applications. Python was selected for the required programming environment since it is a very strong and flexible programming language. Python is primarily used in this study to facilitate seamless interaction with various libraries and frameworks that execute the algorithm. The model of use is the PUNPS, which is an extremely complex machine learning framework that leverages the Pigeon U Net optimization algorithm alongside self-supervised learning.

Table 1. Execution Parameters

Metrics	**Specification**
Operating System	Windows 10
Program platform	Python
Version	3.7.14
Optimization	Pigeon
Deep Learning	U-Net
Data count	1 048 575
Processor	Intel Core i5 CPU
RAM	8 GB
Dataset name	Credit risk detection

5.1. *Case study*

Credit cards are a risk control method in the financial industry, utilizing personal information to predict future defaults and borrowing patterns. They are based on historical data and use the logistic model for binary classification tasks. The score card multiplies the logistic regression coefficient by a certain value to simplify operations. The dataset comprises details on essential clients and their credit history for risk assessment purposes. It includes features such as ID, gender, car ownership, education level, marital status, employment duration, loan details, months balance, and status. This structured dataset enables effective credit risk analysis and classification using advanced predictive models. This dataset is obtained from the Kaggle repository (Credit Card Fraud Detection). To ensure an equal distribution, the dataset is split 80:20. Dataset details are present in the table 2

Table 2. dataset details

Credit risk Classes	**Total sample 100% 1048575**	**Training 80% (8,38,859)**	**Testing 20% (209,716)**
0	383120	3,06,496	76,624
1	11090	8,872	2,218
2	868	694	174
3	320	256	64
4	223	178	45
5	1693	1,354	339
6	442031	3,53,625	88,406
7	209230	1,67,384	41,846

The confusion matrix is proposed as the framework for predicting risk within the PUNPS framework. It is a classification based on 0 denotes 1-29 days past due 76,609 samples, 1 denotes 30-59 days past due 2,212 samples, 2 denotes 60-89 days past due 168 samples, 3 denotes 90-119 days overdue, 4 denotes 120-149 days overdue, 5

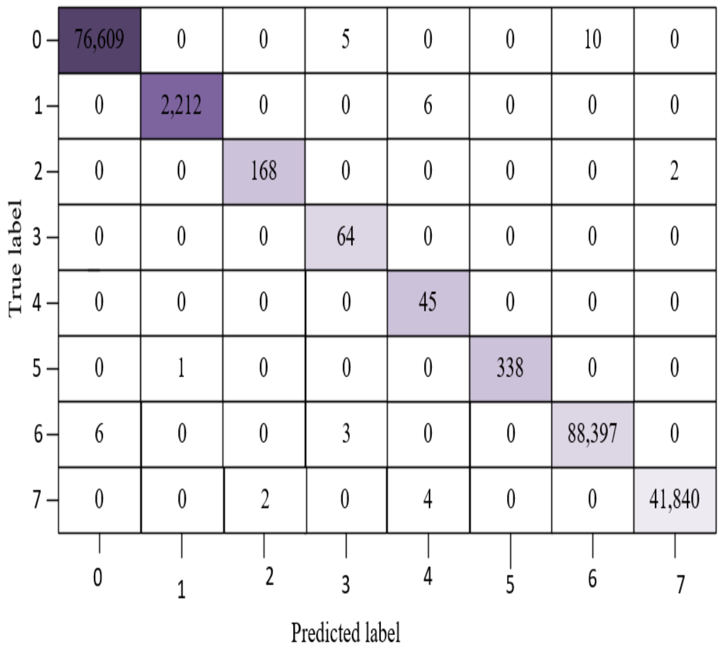

Figure 4. Confusion matrix

denotes 150 days overdue, 6 denotes the paid off that month, 7 denote the No loan for the month is 41,840 sample the respectively.

5.2. Performance Evaluation

The effective function of the developed PUNPS model for predicting credit risk assessment is demonstrated using the Credit Risk Detection Dataset. To evaluate the model's performance using measures for risk assessment, including F1 score, Accuracy, recall, Precision, and error rate. Several current approaches are compared with the proposed strategy to evaluate the effectiveness of the suggested framework. The Accuracy, Precision, Recall, and F1 scores are compared for Logistic Regression (LR), Neural Network (NN), AdaBoost, Random Forest (RF), Light Gradient Boosting Machine (LGBM), and eXtreme Gradient Boosting (XGB) [27].

5.2.1. Accuracy Accuracy is the most well-known and renowned categorization statistic for classification problems. Divide the total number of projections by the number of accurate forecasts. The false negative rate (FNR), false positive rate (FPR), true negative rate (TNR), and true positive rate (TPR) all show accuracy. The calculation of accuracy expressed in Eqn.(5).

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

The accuracy of the developed process is evaluated and compared with that of existing techniques, as shown in Figure 5. The accuracy rates of the existing techniques are as follows: LR is 84.3%, NN is 87.2%, AB is 92%, RF is 97.9%, LGBM is 99.2%, and XGB is 99.3%. Hence, the accuracy rate of 99.8% is comparatively higher than that of existing approaches, demonstrating better performance. Figure 5 illustrates the correlation of accuracy.

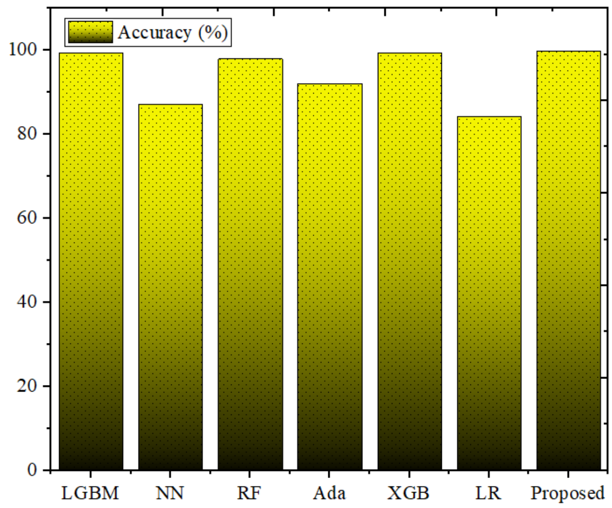

Figure 5. correlation of accuracy

5.2.2. Recall A specific class of the instance for danger in due time is called recall. Recall looks for truly correct forecasts. According to the following formula, the recall is past due among all past-due recalls. The recall calculation is expressed in Eqn.6.

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \tag{6}$$

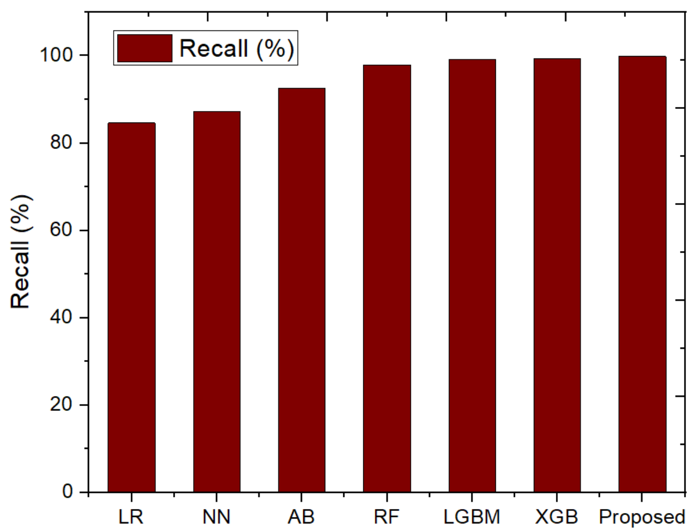

Figure 6. Recall correlation graph

The recall rates of the existing techniques are as follows: LR is 84.6%, NN is 87.2%, AB is 92.5%, RF is 97.9%, LGBM is 99.2%, and XGB is 99.3%. Hence, the recall rate of 99.9% is comparatively higher than that of existing approaches, demonstrating better performance. Figure 6 illustrates the correlation of recall.

5.2.3. Precision When an instance is past due or late, it is classified as a separate instance. Precision looks for truly correct predictions. According to the following equation, the forecast is past due compared to all the previous predictions. The mathematical calculation of Precision is expressed in Eqn.(7).

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \tag{7}$$

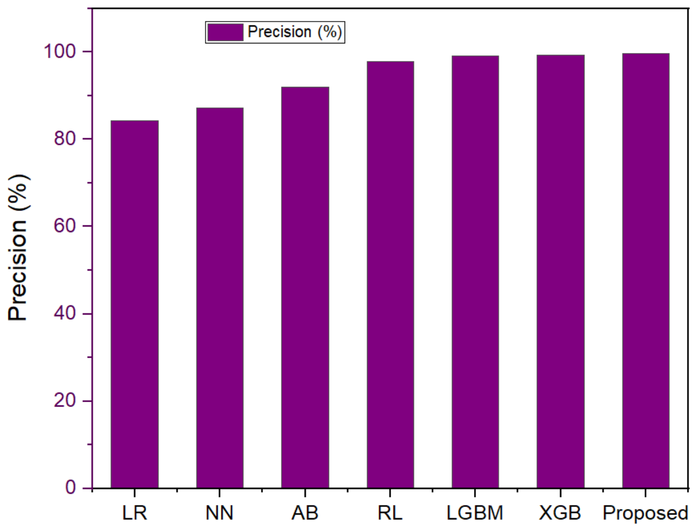

Figure 7. Comparison of Precision

The precision rates of the existing techniques are as follows: LR is 84.3%, NN is 87.2%, AB is 92%, RF is 97.9%, LGBM is 99.2%, and XGB is 99.3%. Hence, the Precision rate of 99.7% is comparatively higher than that of existing approaches, demonstrating better performance. The correlation of the Precision is shown in Figure 7.

5.2.4. F1 Score The average recall and accuracy is the F1 score, a performance statistic with a range of 0 to 1. The best measure of quality for a categorization assignment is to maximize the F1 score. The mathematical calculation of the F1-score is expressed in Eqn.(8).

$$F1_{score} = 2 * \frac{\Pr e * \text{Re}}{\Pr e + \text{Re}} \tag{8}$$

The F1 score rates of the existing techniques are as follows: LR is 84.3%, NN is 87.2%, AB is 92%, RF is 97.9%, LGBM is 99.2%, and XGB is 99.3%. Hence, the F1 score rate of 99.7% is comparatively higher than the existing approaches, demonstrating better performance. The correlation of the F1-score is shown in Figure 8.

5.2.5. Error Rate The error rate reflects the frequency with which the model makes inaccurate predictions. This rate is estimated using Eqn.(9).

$$\text{Error rate} = \frac{P_F + N_F}{P_T + N_T + P_F + N_F} \tag{9}$$

The correlation of the error rate is displayed in Figure 9. The PUNPS outperforms conventional credit risk assessment models with an error rate of 0.2%. In comparison to other approaches, such as LGBM and XGB, PUNPS performs well, with error rates of 0.8% and 0.7%. Traditional techniques, such as NN and LR, had error rates of 12.8% and 15.7%, respectively, demonstrating that the system outperforms in credit risk categorization.

Table 3 presents an overall comparison of the developed framework with the prevailing model, showing proposed values of 99.8%, 99.9%, 99.7%, and 99.6%.

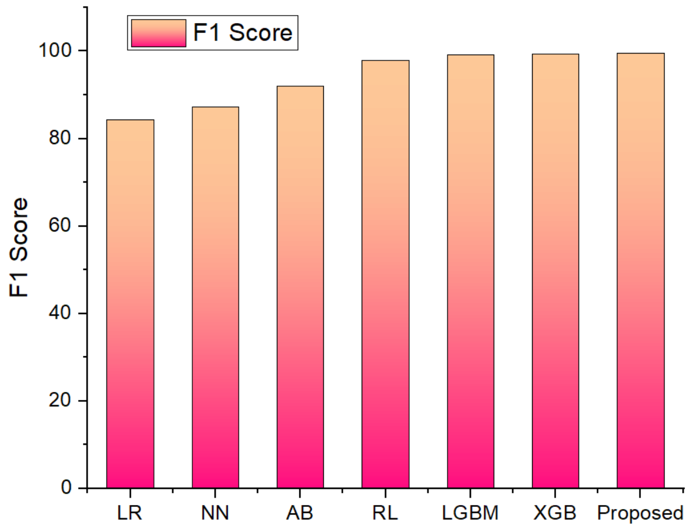

Figure 8. Comparison of F1 score

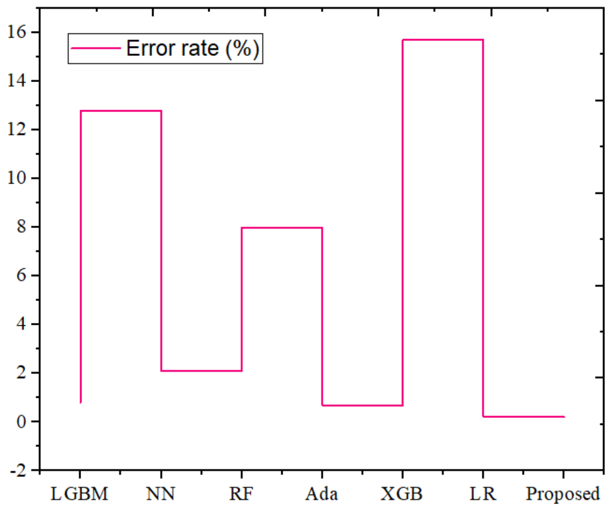

Figure 9. Correlation of Error Rat

5.3. Discussions

The PUNPS has shown superior performance in credit card risk prediction, surpassing existing models in accuracy. It employs a hybrid approach that combines deep learning and optimization techniques to minimize false positives and false negatives, thereby ensuring more precise risk classification. The POA enhances feature selection, reducing dimensionality and improving computational efficiency. PUNPS has achieved high F1 scores, recall, Accuracy, and Precision, proving its effectiveness in data-driven, intelligent credit risk predictions. The results of the full performance, along with the developed model, are presented in detail in Table 4. To measure the real-time data flexibility, mortgages and personal loans from the governance data were considered, and testing was conducted on

Table 3. Entire comparison

Methods	Recall (%)	F score (%)	Precision (%)	Accuracy (%)	Error rate (%)
LGBM	99.2	99.2	99.2	99.2	0.8
NN	87.2	87.2	87.2	87.2	12.8
RF	97.9	97.9	97.9	97.9	2.1
Ada Boost	92.5	92	92	92	8
XGB	99.3	99.3	99.3	99.3	0.7
LR	84.6	84.3	84.3	84.3	15.7
Proposed	99.9	99.6	99.7	99.8	0.2

those results, along with the Kaggle data outcome of the proposed model, which is compared in Table 4. Floating-point operations per second (FLOPS) is a metric used to quantify a computer's computational ability, particularly its capacity to carry out floating-point computations.

Table 4. Performance of the PUNPS

Metrics	Kaggle data Credit card	mortgages	Real-time data personal loans
Accuracy	99.8	99.73	99.65
Precision	99.9	99.73	99.65
Recall	99.7	99.73	99.65
F1-Score	99.6	99.73	99.65
Error rate	0.2	0.3	0.4
Latency (ms)	23	21	24
Scalability (%)	98	98.2	97.4
FLOPS	12	12	12

Cost benefits analysis was conducted for the real-time personal loan data and the outcome is exposed in table 5, and the demographic parity is defined in Figure 10.

Table 5. Cost benefits analysis of the personal load data

Concept	Credit card (%)	Debit card (%)	Credit card (€/tr)	Debit card (€/tr)	Cash (%)	Cash (€/tr)	Check (€/tr)	Check (%)
Infrastructure	-0.079	-0.112	-0.05	-0.05	0	0	0	0
Float	-0.011	-0.011	-0.007	-0.005	-0.022	-0.003	-0.044	-0.044
Bank fees	-1.5	-1.5	-0.948	-0.672	0	0	-1.5	-1.5
Operational problems	-0.004	-0.005	-0.003	-0.002	-0.554	-0.083	-0.125	-0.125
accounts cash deposit	0	0	0	0	-0.554	-0.083	-0.066	-0.066
Fraud	0	0	0	0	-0.2	-0.03	-0.5	-0.05
period of payment	-0.204	-0.288	-0.129	-0.129	-0.574	-0.086	-0.201	-0.201
other cost and services	0.15	0.15	0.095	0.067	0	0	0	0
sales increment	1.5	1.5	0.948	0.672	0	0	0	0
Total Cost	-1.798	-1.916	-1.137	-0.858	-1.904	-0.286	-1.986	-1.986
Total Income	1.65	1.65	1.043	0.739	0	0	0	0
Total Merchants	-0.148	-0.266	-0.094	-0.119	-1.904	-0.286	-1.986	-1.986

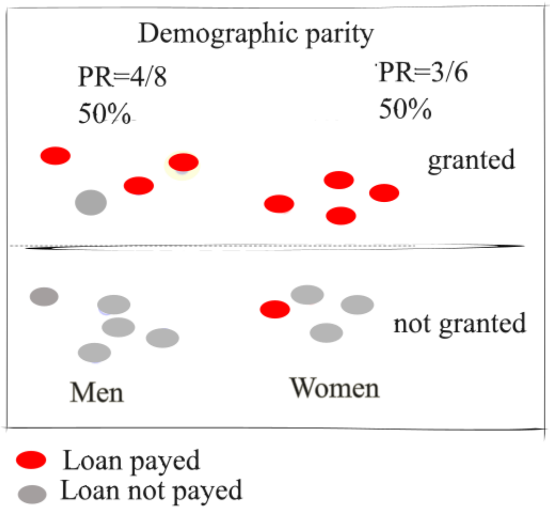

Figure 10. Demographic parity

To justify the efficiency of the proposed model, some recent traditional models were considered and executed on the same proposed platform, and their performance was compared with each other. Traditional models, such as ensemble models, graph neural networks, and optimization models, were considered. Those models were executed on the same proposed platform, and their outcomes were compared with each other, described in table 6.

Table 6. Performance of proposed with other benchmark models

Methods	**Recall (%)**	**F score (%)**	**Precision (%)**	**Accuracy (%)**	**Error rate (%)**	**Computational efficiency (ms)**	**Algorithm complexity (%)**	**Training time(ms)**	**Resource/ memory usage (%)**
Graphs neural network	86	86.2	86.2	86.2	14	34	26	71	30
Catboost	92	92.2	92.5	93	7	46	24	81	35
RF	97.9	97.9	97.9	97.9	2.1	51	11	45	19
Ada Boost	92.5	92	92	92	8	62	40	39	26
XGboost	99.3	99.3	99.3	99.3	0.7	57	14	53	20
PSO	75	74.2	73.8	74	26	43.2	19	71	47
GA	77.4	77	77	77	23	98.4	21	68	55
LO	81	81	81.2	81	19	29	17	45	62
ALO	85.6	85	84.4	86	14	71	32	97	71
SHAP-based	84.6	84.3	84.3	84.3	15.7	32	18	103	36
XGBoost Proposed	99.9	99.6	99.7	99.8	0.2	12	8	23	10

In real-time, there is a possibility of scalability issues due to the flexible distributed environment. The real-time finance data memory is unable to predict in a more accurate way, so the prediction process becomes slower due to power stability issues. Also, in some cases, poor stability causes high delay. In addition, the code sources are available in GitHub - milesial/Pytorch-UNet: PyTorch implementation of the U-Net for image semantic segmentation with high quality images, Pidgeon-Inspired optimization · Issue #107 · fcampelo/EC-Bestiary. In addition, the Application Programming Interface implementation in the credit finance system will offer the flexibility of the proposed model for detecting fraud in real-world practical environments in the future.

6. Conclusion

The Pigeon U-Net Prediction System (PUNPS) has demonstrated exceptional performance in credit risk assessment, achieving high accuracy and efficiency. The developed model enhances feature selection and reduces computational costs by integrating deep learning with the Pigeon Optimization Algorithm (POA). Accurate risk classification is ensured by the model's ability to reduce false positives and false negatives. Its advantage over current techniques is shown through comparative analysis, making it a reliable tool for managing financial risk. PUNPS provides a sophisticated, data-driven solution for accurate credit risk assessment, leveraging its strong predictive capabilities. The PUNPS effectiveness is further confirmed by comparison with current methods, which also shows that it has the potential to be a more intelligent and successful framework for credit risk assessment. After a thorough evaluation using key risk assessment measures, the model achieved 99.8% accuracy, 99.9% precision, 99.7% recall, 99.6% F1-score, and a remarkably low 0.2% error rate. Future research should focus on AI-driven multimodal learning to enhance model performance in cross-border and multi-currency financial transactions, thereby increasing the dependability and transparency of financial institutions.

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