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Leveraging Data Science Technology for Advancing Credit Risk Assessment

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Abstract

The evaluation of credit risk (CR) has become prominent in recent years, particularly among banks, as default rates are on the rise and economic insecurity remains persistent. Traditional credit scoring techniques oftentimes are inadequate and provide little means for risk estimation, necessitating the development of new models using data science methodologies. In this study, a novel Intelligent Dwarf Mongoose tuned Light Gradient Boosting Machine (IDM-LGBM) model that boosts the accuracy of CR and improves forecasting performance, is introduced. The Light Gradient Boosting Machine model's hyperparameters were optimized using the Intelligent Dwarf Mongoose technique, improving the model's predictive strength. The CR dataset was gathered from the Kaggle platform. The data is then pre-processed using Z-score normalization. To evaluate the efficiency of the suggested IDM-LGBM technique, which has been implemented employing a Python platform. Results show that the IDM-LGBM model performed significantly better than conventional methods in terms of recall (98.1%), accuracy (97.2%), F1-score (97.4%), and precision (96.5%). Subsequent studies could concentrate on addressing real-time data streams and enhancing models to respond to the changing credit environment.

Keywords

Intelligent Dwarf Mongoose tuned Light Gradient Boosting Machine (IDM-LGBM); credit risk (CR); data science; Z-score normalization

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Introduction

Accurate CR analysis is essential for those organizations intending to minimize loss and maximize profits in the changing financial environment. Derivative products and an extensive base of customers make financial relationships and, hence, CR more nuanced. The existing credit scoring methodologies based on historical performance and simplified scoring often fail to respond to the true behavior of customers and the dynamic nature of markets. Therefore, more attention is paid to utilizing data science techniques since such approaches contain valuable tools for improving systems for CR assessment (Mhlanga 2021). At its core, data science is a set of techniques for making sense of a large and complex stream of data. The subject of big data has revolutionized how organizations manage CR through the provision of unstructured data from social media, past, and other financing sources along with structured data from rating companies (Wang and Ku 2021). Advanced analytics, ML methods, and predictive modeling approaches will allow financial institutions to better know their customers, make improved lending decisions, and create more accurate risk profiles for the customers of financial institutions (Wang 2021).

Data science has several benefits when evaluating CRs, one of which is the ability of data science to detect correlations and patterns in the CRs that other traditional methods may not be able to quickly discover (Zhang et al. 2024). Lenders might adapt their risk mitigation strategies; risk management could use ML methods to analyze the past behavior of customers and emerging issues that may constitute future concerns of default. Moreover, the use of other sources of information will enable the evaluation of the credibility of a borrower comprehensively, including those with a short credit history or those who are outside the banking sector (Wu et al. 2021). The data science method also helps in real-time assessment of the various risks involved depending on the changes in the borrower's profile or even the economy. It is particularly valuable when operations take place in today's changing markets where customer risks are variable based on economic data. The ability to employ information presently available for CR assessment becomes critical as the companies seek to sustain their differential advantages (Abedin et al. 2023). Additionally, the integration of data analyses into CR assessment aids in the enhancement of regulatory compliance apart from risk estimation. Financial organizations are facing more regulatory requirements concerning maintaining risk management rules and regulations. The application of robust data-driven processes in an organization's risk management framework can significantly improve the companies' general sub-areas and allow them to meet the legal requirements of (Bello 2023).

The integration method of combining expert knowledge with soft computing approaches was proposed by Lappas and Yannacopoulos (2021). The findings demonstrated high AUC values and comparable performance to other standard techniques. A new hybrid AdaBoost algorithm and LSTM-NN ensemble categorization approach for CR ratings were introduced by Shen et al. (2021), which additionally enhanced the SMOTE approach to rebalancing credit information. According to the findings, the suggested deep learning ensemble model outperformed different approaches in general when it came to handling imbalanced CR assessment difficulties.

A DM–ACME learning technique was suggested by Song et al. (2020) to forecast default risk in P2P lending. The findings demonstrated that the suggested strategy was stronger and that some variables were crucial for predicting loan defaults. Indicator measurement, combination measurement, GBT, LightGBM, random forest, and XGBoost were used by Feng and Gu (2022) to assess the individual CR influence components. The results showed that basic loan data had the largest relative effect on individual credit default risk. The findings demonstrated the stability and accuracy of the model, as well as its ability to accurately represent the degree to which individual credit attributes affect CR. ELM was used by Tripathi et al. (2020) as a categorization tool for the CR assessment system. The findings proposed that the suggested EELM was a better fit for assessing CR. An ANN-based CR assessment method was proposed by Maruma et al. (2022) to detect customers who are likely to default. The outcomes of the research demonstrated that the suggested strategy outperformed logistic regression.

A new REMDD was proposed by Niu et al. (2020) for the evaluation of imbalanced CR in P2P lending. The findings showed that, in comparison with conventional approaches, REMDD not only had excellent forecasting efficiency for both the minority and majority classes but also significantly enhanced the comprehensive categorization efficiency for imbalanced CR evaluation in P2P lending. Utilizing the LSTM model and the AHP, Xi and Li (2022) examined individual CR using an enhanced AHP and optimized LSTM framework. In both data sets, the findings demonstrated that the approach performed better than alternative comparison techniques, particularly when dealing with unbalanced datasets. Employing hybrid ML algorithms that integrate supervised and unsupervised ML techniques, Machado and Karray (2022) forecasted the credit scores of business clients. The outcome demonstrated that combined approaches were superior to their counterparts in estimating the credit ratings of business clients. To improve prediction performance and raise the accuracy of CR evaluation, a novel IDM-LGBM approach was provided.

This research is organized into the following sections: related works, methodology, results, and conclusions.

Methodology

Initially, the CR data was obtained from the Kaggle platform. The gathered data is then preprocessed using Z-score normalization. An innovative approach called Intelligent Dwarf Mongoose tuned Light Gradient Boosting Machine (IDM-LGBM) is employed to improve the predictive performance and increase the accuracy of CR assessment.

1. Data collection

The CR dataset was obtained from the Kaggle source "https://www.kaggle.com/datasets/laotse/credit-risk-dataset". The CR dataset comprises 32,581 records and 12 features that provide information on numerous aspects influencing CR evaluation. Key attributes include age, home ownership, annual income, loan grade, loan intent, employment length, loan amount, percent income, interest rate, loan status, credit history length, and historical default. Financial institutions can use this dataset to create predictive models that assess CR and make well-informed lending decisions while efficiently handling subsequent defaults.

2. Z-score normalization

The data are rescaled using the metrics of mean and standard deviation so that the resulting characteristics have a unit variance and zero mean. In every instance, $w_{j,m}$ of the data is changed into $w'_{j,m}$ in the following manner is shown in Equation (1),

$$w'_{j,m} = \frac{w_{j,m} - \mu_j}{\sigma_j} \tag{1}$$

Where,

μ – Mean of the j^{th} feature, and

σ – Standard deviation of the j^{th} characteristic.

3. Intelligent Dwarf Mongoose tuned LightGBM (IDM-LGBM)

The IDM-LGBM is an innovative enhancement of the evaluation of CR that incorporates the advantages of the current ML algorithms and optimization. LGBM is known for how well it works on large data and for its capability to identify nonlinear interactions. The Dwarf Mongoose inspires the intelligent tuning technique, and actively cooperates in hunting behaviors to increase the efficacy of the model.

The IDM-LGBM applies a multidimensional approach to CR assessment consisting of identifying significant risk variables, selecting the best hyperparameters, and structuring financial data. The model learns the best environment, which enhances the predicted accuracy through techniques such as grid search and cross-validation. In particular, financial institutions may use the IDM-LGBM as a source of reliable risk estimation because it is particularly suitable for distinguishing between low-risk and high-risk borrowers.

Consequently, credit assessments are efficient because every participant of the model comprehends the decision-making process. The IDM-LGBM provides an effective structure for CR outcome assessment by combining the adaptable fine-tuned approach with LGBM's inherent advantages, enhancing risk supervision and decision-making capabilities in the financial sector.

3.1. LightGBM

Utilized for numerous ML applications, including categorization and position, LightGBM is a distributed, efficient gradient-boosting system based on the DT technique. LightGBM is essentially an ensemble approach that integrates the forecasts from several DTs to provide a final prediction that is well-generalized. LightGBM is notable for its additive training approach, which involves training every new tree model to forecast the residuals, or errors, of the previous models. Assuming to build a LightGBM model with S trees, the additive training procedure for a dataset containing m samples may be explained as follows in Equation (2).

$$\begin{gathered}\hat{z}_j^{(0)} = 0 \\ \hat{z}_j^{(1)} = e_1(w_j) = \hat{z}_j^{(0)} + e_1(w_j) \\ \hat{z}_j^{(2)} = e_1(w_j) + e_2(w_j) = \hat{z}_j^{(1)} + e_2(w_j) \\ \cdots \\ \hat{z}_j^{(s)} = \sum_{l=1}^{s} e_l(w_j) = \hat{z}_j^{(s-1)} + e_s(w_j)\end{gathered} \tag{2}$$

In the s^{th} iteration, $\hat{z}_j^{(s)}$ represents the prediction of the j^{th} instance, and e_s represents the learned function for the s^{th} DT. In each iteration, the previous model $\hat{z}_j$ is maintained and include a new function e (or the learned residuals) into the model, as shown by Equation (2). The following equation (3), goal can be minimized to determine es of all iterations.

$$\mathcal{L}^{(s)} = \sum_{j}^{m} k\left(z_j, z_j^{(s)}\right) + \sum_{s=1}^{S} \Omega(e_s) \tag{3}$$

The LF, which measures the variance between the target (z_j) and prediction ($z_j^{(s)}$), is the initial term. The regularization term penalizes the model's complexity.

LightGBM specifically implements GBDT. LightGBM uses two distinct techniques, leaf-wise growth, and GOSS, to train each DT (e) and divide the data. By calculating the information gain for each potential split, traditional GBDT algorithms must examine every aspect of every data point. This is the computational complexity issue that GOSS seeks to solve. Larger gradient data instances are more important for information gain calculation, according to a key finding of GOSS. GOSS thus retains data samples with randomly selected data with modest gradients and large gradients to estimate the optimal split.

This approach is efficient and quicker to implement than traditional methods. Leaf-wise growth is a productive tree-growing technique. Every time, it selects the leaf that has the most splitting gain among all of the present leaves, splits it, and repeats the procedure. Leaf-wise growth technique minimizes errors and achieves higher accuracy while maintaining the same splitting times, selecting the leaf with the highest delta loss. To achieve optimum efficiency and avoid overfitting, LightGBM hence includes a maximum depth limit leaf-wise.

3.2. Intelligent Dwarf Mongoose optimization

The DM population in the standard DMO is organized into three social groups, namely alphas, babysitters, and scouts. The family forages together as a unit, with the alpha female starting the process and choosing the route, distance, and resting mounds. Babysitters are typically comprised of female and male types who constitute a segment of the DM population. They remain around with the children until the afternoon, when the other members of the group come there.

To start foraging with the group, the babysitters initially exchanged (exploitation stage). The DM group constantly moves the resting mound in search of a fresh foraging location rather than building a nesting area for the young. The DMs have constructed a seminomadic way of living in a space large enough to satisfy the group's needs (exploration stage). Excessive utilization of a particular location is avoided by nomadic behavior. Furthermore, it ensures that the entire area is examined to make sure that no resting mounds that have already been inspected are revisited. The

DM populations of the M_{DM} individuals' candidate solutions are initially created at random in the DMO in the following manner as shown in Equation (4),

$$C_{i,c}(0) = C_{min,c} + rand(0,1).\left[C_{max,c} - C_{min,c}\right], i = 1: M_{DM}, c = 1: Dim \quad (4)$$

Whereas $C_{max,c}, and\ C_{min,c}$ indicate the maximum and minimum bounds of each control variable (c), and Dim indicates the total number of decision variables associated with the optimization task, $C_{i,c}$ indicates the position as a searching individual to each $DM(i)$ and each control variable (c).

Once the population is established, the fitness of each solution is determined. Equation (5) determines the possibility that each group will be fit, and the alpha female α is selected based on this probability.

$$\alpha = \frac{E_i}{\sum_{i=1}^{M_{DM}} E_i} \quad (5)$$

A correlation has been found between the number of DMs in the alpha category and the difference (M_{DM}) between the total number of babysitters and $Bst.\ at$ indicates how many babysitters there are. $peep$ refers to the vocalization of the alpha female, which keeps the DM family moving forward. Every DM sleep in the initial resting mound, designated as $\emptyset$. To determine a possible food position, the DMO uses the formula given in Equation (6).

$$C_{l,c}(a+1) = C_{l,c}(a) + rand(0,1) \times peep, l = 1: M_{DM} - Bst, c = 1: Dim \quad (6)$$

Where j denotes the conventional iteration. Following each iteration, the resting mound may be constructed as follows in Equation (7).

$$SM_i = \frac{E_{i+1} - E_i}{\max(|E_{i+1} - E_i|)} \quad i = 1: M_{DM} - Bst \quad (7)$$

Where i represents each DM in the scout group and is the variance between the number of babysitters (Bst) and the M_{DM}. Thus, the mean value (ψ) of the resting mound found can be obtained using Equation (8).

$$\psi_i = \frac{\sum_{i=1}^{M_{DM}} SM_i}{M_{DM}} \quad i = 1: M_{DM} - Bst \quad (8)$$

When the babysitting exchange requirement is satisfied, the DMO approach moves on to the scouting step, when a backup food supply or resting mound will be identified. Scouting takes place in DMO in combination with foraging, as the scouts seek out a different resting mound to ensure exploration. Based on the mongooses' overall performance, the movement that results is represented as an evaluation of whether or not to create a new mound. Equation (9) improves the simulation of the scout mongoose.

$$C_{l,c}(a+1) = \begin{cases} C_{l,c}(a) - CF \times rand(0,1) \times \left(C_{l,c}(a) - N\right) \ if \ \psi_{i+1} > \psi_i \\ C_{l,c}(a) + CF \times rand(0,1) \times \left(C_{l,c}(a) - N\right) \ Else \\ l = 1{:}\, M_{DM}, c = 1{:}\, Dim \end{cases} \tag{9}$$

Where Equation (10) shows that CF decreases linearly as the iterations go on, and Equation (11) shows that N represents a vector that ascertains the movement of the mongoose to the following resting mound. The CF factor is a parameter that regulates the collective-volitive motion of the mongoose category.

$$CF = \left(1 - \frac{j}{Iter_{max}}\right)^{\left(\frac{2\times j}{Iter_{max}}\right)} \tag{10}$$

$$N = \sum_{i=1}^{M_{DM}} \frac{C_i \times SM_i}{C_i} \tag{11}$$

Where $Iter_{max}$ denotes the maximum number of iterations.

This section proposes a novel IDMO with an alpha-directed LS to handle various engineering difficulties and mathematical assessment operations. To boost the searching capabilities, the innovative suggested solution incorporates an improved LS, whose modifying procedure is partially driven by the modified alpha. To improve the search performance, the alpha-directed LS is combined with Equation (6) to produce an ideal food location. As a result, the following is an update on the location of each search response within the search space,

$$C_{l,c}(a+1) = \begin{cases} BestDM_c(a) + rand(0,1) \times \left(C_{l,c}(a) - C_{Q,c}(a)\right) \ if \ rand < CP \\ C_{l,c}(a) + rand(0,1) \times peep \quad Else \\ l = 1{:}\, M_{DM} - Bst, c = 1{:}\, Dim \end{cases} \tag{12}$$

Where,
$C_{Q,c}$ - Randomly selected searching individual from the DM population;
CP - Choice probability; and
$BestDM_c$ - Position as the alpha about the searching individual with the highest fitness score.

To create a balance between the enhanced exploitation attributes provided in Equation (12), and the exploratory features provided in Equation (6), CP has been set to 50%. While utilizing the previously described structure, the exploitation attributes are significant and robust, and at the same time, the exploratory searching characteristics are maintained and achieved through the standard method.

Results and Discussion

The suggested IDM-LGBM approach is executed on a Windows 11 laptop with an Intel i5 core processor and 8GB RAM using Python 3.10. The efficiency of the proposed approach is evaluated with the existing Syncretic Cost-sensitive Random Forest (SCSRF) (Rao et al. 2020), Extreme

Gradient Boosting (XGBoost) (Coşkun and Turanli 2023), and Convolutional Neural Network - K-nearest neighbor (CNN-KNN) (Berhane et al. 2024) approaches.

A classifier's efficiency is graphically represented by the ROC curve, which plots the TPR against the FPR at different threshold values. The AUC, which represents the overall effectiveness, helps in assessing the correctness of the model. The ROC curve has the AUC value of the IDM-LGBM approach is 0.92, which is displayed in Figure 1.

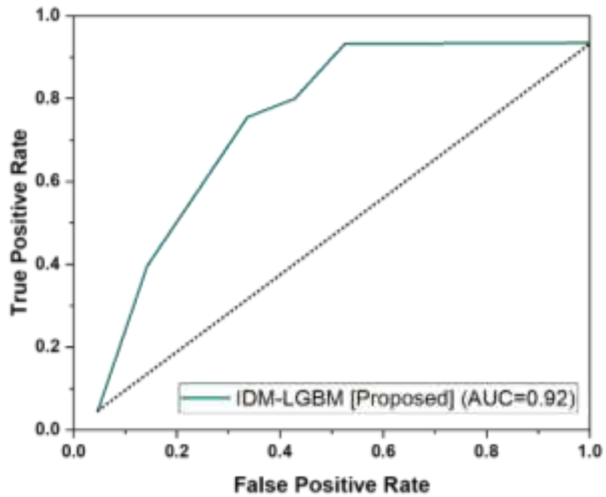

Figure 1. Output of ROC curve

Precision evaluates the accuracy of projected positive results, reflecting the percentage of actual positive forecasts among all anticipated positives, and hence assesses the model's capacity to determine creditworthy borrowers. Compared to conventional methods, the suggested IDM-LGBM produces a precision value of 96.5%, whereas the SCSRF, XGBoost, and CNN-KNN produce precision values of 61.94%, 95%, and 91.68%, respectively, as shown in Figure 2.

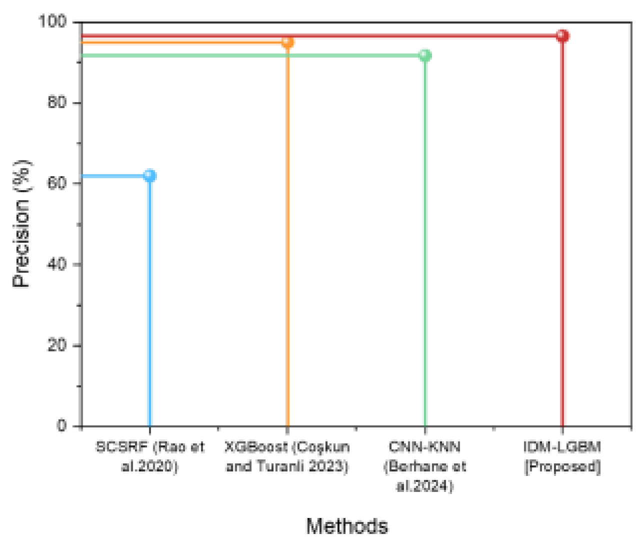

Figure 2. Result of precision

The accuracy measures how effectively the model performs by contrasting predicted and actual risk categories. It calculates the proportion of correctly anticipated instances, helping in determining the method's capacity to distinguish between creditworthy borrowers and high-risk applicants. The suggested IDM-LGBM yields an accuracy value of 97.2% when compared to traditional techniques, while the SCSRF, XGBoost, and CNN-KNN provide accuracy values of 89%, 76%, and 91.87%, which were displayed in Figure 3.

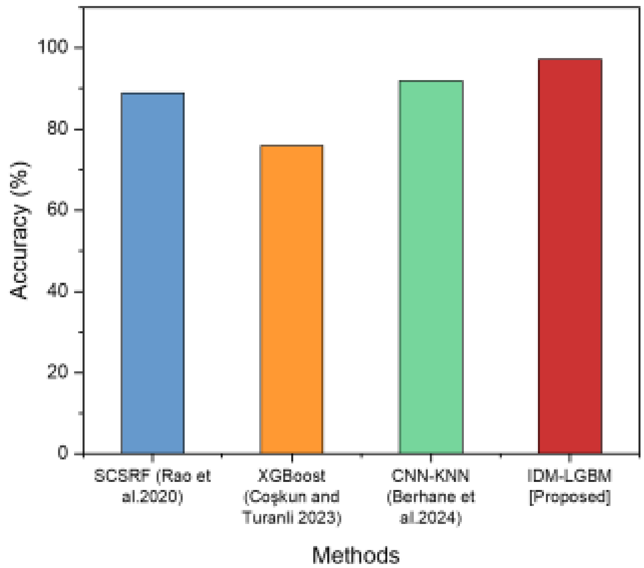

Figure 3. Output of accuracy

The F1-score measures model performance in accurately identifying creditworthy candidates while reducing false positives and negatives in forecasts. Compared with the traditional methods, which yield an F1-score of 68.88%, 85%, and 91.42% for SCSRF, XGBoost, and CNN-KNN, the proposed IDM-LGBM obtains an F1-score of 97.4% is shown in Figure 4.

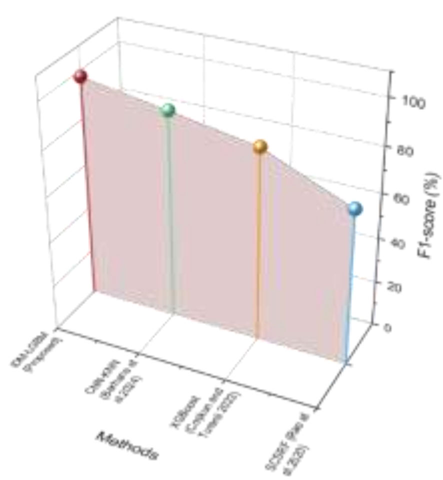

Figure 4. Result of F1-score

Recall assesses how effectively the model minimizes false negatives by measuring the capacity to correctly recognize high-risk borrowers among all actual instances of high-risk. The proposed IDM-LGBM yields a recall rate of 98.1% when compared to standard approaches, while the SCSRF, XGBoost, and CNN-KNN yield recall rates of 77.57%, 77%, and 91.16%, as displayed in Figure 5.

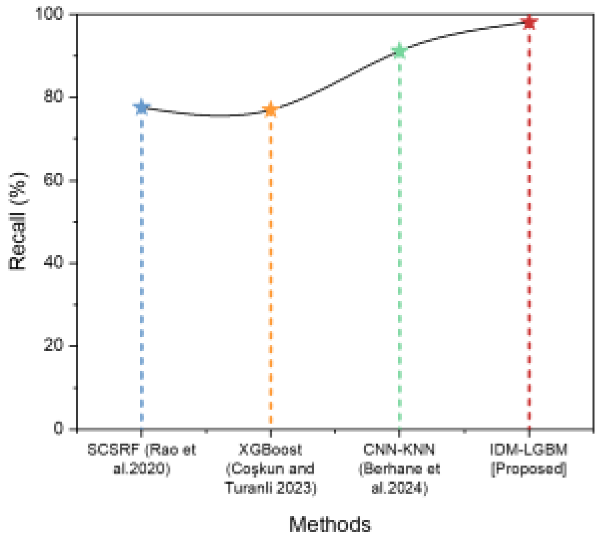

Figure 5. Output of recall

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