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A Hybrid Machine Learning Model Optimized with Reinforcement Learning Enhanced Spider Wasp Optimizer for Customer Value Prediction

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Abstract:

Having an accurate estimation of a customer's worth is one of the more important tasks performed by banks in this modern world, especially with the profound number of customers and the complex nature of transactions, along with the massive variance in transactions. In light of this need, we develop a multi-layer stacked ensemble model specifically designed to improve the predictive performance of banking customers in Iran. The first layer consists of 4 different learners (XGBoost, CatBoost, Random Forest, and Gradient Boosting). Each model has its learning capacity and learns from customer behavior and financial characteristics in complementary ways. The second layer consists of a LightGBM classifier, which fuses (by meta-model) the outputs of the first-layer learners into the final prediction. The second set of model hyperparameters were optimized using a Reinforcement Learning (RL)-based SWO to efficiently search for optimal hyperparameters across a high-dimensional space, which is typically not well-explored using classic optimization strategies. Utilizing a repeated 5-fold stratified cross-validation approach, we were able to achieve strong predictive accuracy: Accuracy = 89.70%; Precision = 92.84%; Recall = 92.46%; F-Score = 92.61%; ROC AUC = 0.9632; all of which surpass the single models. Our results provide evidence supporting the successful application of a multi-layer ensemble with metaheuristic hyperparameter optimization in building a viable and powerful customer valuation tool for banks.

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1. Introduction

Over the past few decades, the rapid growth in information technologies and the digitalization of financial processes have created increasing demands on how to use customer data to enhance CRM strategies and marketing-related decisions in banking. Among the important issues in this field is the prediction of customer lifetime value or customer churn. As one of the largest providers of financial services to thousands of customers, banks must make intensive use of data to increase financial efficiency and return on investment (Morindani et al., 2023). Knowing CLV and predicted customer churn can help banks to identify more lucrative customers and spend more on retaining them. Acquiring new customers is very expensive, but keeping the good customers costs a lot less and saves a lot of money, and the resources are better spent on retaining the good customers. Studies confirm that it is much cheaper to lose your customers than to make new customers, proving the need for an accurate prediction of customer behavior (Channa, 2018). Combining multiple (ensemble) learning models can improve prediction accuracy in ensemble learning models. Such models were used to predict customer churn and improve ROI in the banking industry. According to the study done by Deng et al. (2021), combining random forest models with gradient boosting improves the accuracy of customer churn prediction up to 90%. The combination of several machine learning models and the use of the advantages of the machines in the model, however, has made the ensemble learning models one of the most efficient models recently to predict CLV and customer churn. In using these models, through concepts like voting, random forest, gradient boosting, and other methods, one can increase the accuracy of prediction by a large margin. As discussed in Subramanian et al. (2024), applying RNN and LSTM models to predict customer churn results in an area under the ROC curve that is up to 60% higher. At the same time, there are many recent studies that show the importance of multimodal models in the framework of ensemble learning. Such models may work on such a low level of data and in a hierarchical manner, where they can analyze and predict complex behaviors more accurately. This is of fundamental importance, especially in the banking industry, where various data such as financial, behavioral, and transactional data of customers can be held (Kaukirya and Wizang, 2023).

Given the problems of the banking industry in Iran, the increasing competition between banks, the entry into the digital arena, and the complexity of customer data analysis, there is definitely a need for more advanced models to predict customer value and manage relationships with them. Optimally, one of the challenges related to Iranian banking is the limitation in analyzing customer data due to the lack of widespread use of advanced machine learning models. Iranian banks are still at the beginning of their journey in using complex data analysis. Therefore, most of the processes related to customer management are carried out in a traditional way and based on previous experience. This means that multi-layered ensemble learning models can help increase the level of accuracy of predictions, given that banks will be able to optimize their strategies. For example, if a bank has a more accurate analysis of customer behavior, it can create a customer loyalty program in a much more focused and effective way. The result of this will be improved customer experience and complete satisfaction and reduced banks' costs to attract new customers. The necessity of this research is that for the first time in Iran, a multi-layered model based on ensemble learning is comprehensively presented to estimate customer value. Since Iranian banks analyze their customer data using traditional and simple models, the findings of this study can be widely disseminated to improve the performance of customer management systems of Iranian banks. The use of these models may be due to increasing customer retention rates, improving investment return rates, or simply reducing banks' operating costs. Therefore, such models may have a very positive impact on increasing the competitiveness of Iranian banks at the international level. In addition to the rapid growth of digital banking and the need for large-scale data analysis, the use of new machine learning methods allows banks to respond faster to market changes and, accordingly, formulate appropriate customer management strategies. Ultimately, it may help to strengthen profitability and reduce customer risk in the Iranian banking system. As a result, the present study seeks to fill the gaps in this field and attempts to significantly increase the accuracy and efficiency of customer value predictions in the Iranian banking industry by presenting a multi-layered ensemble learning model. This model can be used as an efficient tool for banks to make the best use of their customer data and make significant improvements in their overall performance.

2. Theoretical Foundations

1.1. Customer Value in the Banking Sector

Customer value in the banking industry is one of the key ideas in CRM and marketing strategies. Customer value consists of the profitability that a customer is expected to provide to the bank through their relationship. One of the most useful and widely recognized indicators in tracking this value is customer lifetime value (CLV). It facilitates businesses making better decisions based on customer investment and resource allocation (Verma et al., 2024). Customer value can be divided into two main parts: i) Financial value, which consists of the actual revenue received from customer financial transactions, e.g., interest on facilities and fees, and ii) Behavioral value: in the case of behavioral value, the contributors of the account are the loyalty and long-term relationship of consumers with banks. Customer loyalty, a major contributor to increasing customer value, means that banks save expenditure on acquiring new customers and stay focused on retaining customers (Darzi and Bhat, 2018). As far as this is concerned, research has shown that banking CRM is statistically significant in improving customer satisfaction and loyalty. Thus, banking CRM supports banks in keeping customers for a longer period and in getting more from the customers through core services and customer associations.CRM is also implemented as a cost reduction to increase profitability by improving the quality of customer relationships (Nisha, 2023). Customer value measurement models provide banks with an estimate of the value of each customer throughout the relationship life cycle by analyzing a set of data inputs related to financial transactions, behavioral data, and customer interactions. Therefore, banks can direct resources towards customers with very high profitability potential based on these models (Azhari and Otari, 2023; Jafarnejad Chaghoshi et al., 2024). Research results show that customer value in the banking sector is directly related to CRM strategies and customer loyalty. By using advanced models to analyze customer data, banks can make better decisions about customer relationship management and improve profitability. Therefore, accurately recognizing and measuring customer value is a strategic imperative in modern banking.

2.2 Ensemble Learning Model

Ensemble learning models are known as one of the most effective machine learning methods in the banking field, where the most complex problems are solved using multiple integrated learning algorithms to improve accuracy and reduce prediction error. In this specific area, these models have been used to predict customer behavior, assess financial risks, or increase the accuracy of financial data analysis (Shi et al., 2022). Here, one of the main works among these studies was a cumulative ensemble learning model prediction for a bank deposit acceptance. In this research, prediction accuracy of 96.75% is achieved using algorithms like random forest, gradient boosting, and support vector machine. As can be seen, the large impact ensemble models have on the quality of financial algorithms (Wattono et al. 2024). Ensemble learning models have further been applied in financial risk management and early warnings. Here we took the RUSBoost ensemble learning model as an example, with data from the 2007-2008 global financial crisis and COVID-19, being able to achieve more accurate predictions of the financial stress for banks. Therefore, it provided early warning with the accuracy increased by 21%, and thereby banks developed and applied more appropriate programs to manage such risks (Tarkosin and Donduran, 2023). Some of the other practical applications in banking are some in the field of prediction of customer interaction. They (Morindani et al. 2023), in a study, used explainable ensemble models to improve prediction accuracy of customer interaction by a large margin. The explanatory results from the various combination models in the study revealed customer behavioral analysis. Combining different algorithms that leverage their strengths, these models are quite beneficial to improve the accuracy of predictions and thus help in better data analytics in banks. In other words, this means that with these models, banks can provide accurate predictions in areas related to financial risks, customer interactions, and marketing decisions. This promotes effective management of financial resources and customer satisfaction.

3. Research Background

Predicting customer value is one of the most important goals of the banking industry and customer relationship management. With the increasing competition in financial markets, the issue of customer retention has received special attention. In this regard, machine learning models, especially ensemble learning models, are known as one of the most effective methods in predicting customer behavior and value. These models represent a set of different prediction models, such as random forest, gradient boosting, and neural networks, together. They perform much better than any other model and may increase the accuracy of predictions. In studies related to customer value prediction, various approaches have been used to analyze customer data. In some research, special focus has been given to predicting customer lifetime value, or CLV, to help bank managers determine which customers are of high value so that managers can more accurately inform marketing and resource decisions. In other research, attention has been paid to predicting customer churn, one of the biggest problems in digital banking. The use of ensemble models in this study showed that the use of sequential models significantly improves the accuracy and performance of the model. The overall results of these studies are that hybrid models such as random forest, gradient boosting, and deep neural networks can make a very serious contribution to predicting customer behavior and value in banking. These techniques enable organizations to predict their customers' behavior more accurately and develop better strategies to maintain and increase customer loyalty. Now, for a closer look, a research background table is provided in Table 1, which shows the key results and models used in the relevant papers.

Table 1. Research Background

Authors	Article Title	Results	Model Used
Kaewkiriya and Wisaeng (2023)	Development of a Customer Prediction Model for Investment Using Ensemble Learning Technique	High Accuracy of 93.43% in Predicting Appropriate Investment Risk for Customers Based on Personal Profile	Ensemble Learning Using Neural Networks and Voting Algorithms
Murindanyi et al. (2023)	Explainable Ensemble Learning and Trustworthy Open AI for Customer Interaction Prediction in Retail Banking	Predicting Customer Interaction with High Accuracy AUC 1.0 and Using Explainable AI Techniques for Transparency and Increased Trust.	Explainable Ensemble Learning

Ejgerdi & Kazerooni (2023)	A Stacked Ensemble Learning Method for Predicting Customer Lifetime Value	Improving the Accuracy of Customer Lifetime Value Prediction Using Different Models Including Neural Network and Support Vector Machine.	Stacked Ensemble Learning Method
Nguyen et al. (2023)	A flexible framework for predicting customer behavior based on Ensemble learning	Using a Ensemble learning model to predict customer behavior with high accuracy of AUC 94.55% and F1 70.79%.	Ensemble learning based on hard voting and CNN and RF boosters
Tran et al. (2023)	Predicting customer churn in the banking sector using machine learning-based classification models	97.25% accuracy was achieved using the Random Forest model in predicting customer churn	Random Forest, Logistic Regression, Decision Tree
Murindanyi et al. (2023)	Transparent Machine Learning for Predicting Customer Attrition in Retail Banking	Random Forest Model Performed Better with 99% Accuracy and Models Were Explainable Using SHAP and LIME	Random Forest + SMOTE, Tree-Based Models
Galal et al. (2022)	Enhancing customer churn prediction in digital banking using Ensemble modeling	Using Ensemble learning algorithms to improve digital customer churn prediction with 87% accuracy.	KNN, Logistic Regression, AdaBoost, and Random Forest algorithms
Bansal et al. (2022)	Analysis of Ensemble Classifiers for Bank Attrition Prediction	Predicting Bank Customer Attrition Using Ensemble Models Including Random Forest and Gradient Boosting with High Accuracy.	Random Forest and Gradient Boosting Models
KiLiMci̇ (2022)	The effectiveness of homogeneous classifier groups on predicting customer churn in the banking, insurance and telecommunications sectors	The random forest model performed well in predicting customer churn in the banking, insurance and telecommunications sectors with an accuracy of 89.93%.	The random forest model and support vector machine
Bauer and Jannach (2021)	Improving Customer Lifetime Value Prediction with Sequence-to-Sequence Learning and Feature-Based Models	Combining Sequence-to-Sequence Neural Networks with Gradient Boosting Machines Improved Prediction Accuracy	Sequence-To-Sequence RNN + GBM
Tavassoli and Koosha (2021)	Hybrid Ensemble Learning Approaches for Customer Churn Prediction	Presenting Three New Ensemble Models Based on Bagging and Boosting Algorithms for High-Accuracy Customer Churn Prediction	Bagging and Boosting Algorithms

Dias et al. (2020)	Machine Learning for Predicting Customer Attrition in Retail Banking	Stochastic Boosting Method Showed the Best Performance in Predicting Customer Attrition	Stochastic Boosting
Channa (2018)	Customer Lifetime Value: An Ensemble Model Approach	Ensemble Learning Models for Predicting Customer Lifetime Value in Retail Banks with Improved Accuracy and Precision.	Different Marketing and Risk Models for Predicting CLV

By reviewing the research background in the field of customer value prediction and the use of ensemble learning models in the banking sector, it was found that despite extensive efforts to improve the accuracy of predictions through hybrid models such as random forests, gradient boosting, and neural networks, there are still significant gaps in this area. One of the most important gaps is the lack of sufficient attention to the use of multilayer models in the ensemble learning framework. Although some studies have used a combination of multiple models to improve results, models that examine and analyze data hierarchically and at multiple levels have received less attention. In past studies, most of the focus has been on predicting customer churn or purchasing behavior, but in this study, the main focus is on predicting customer value, which requires a deeper and multidimensional analysis. Using a multi-layered model in ensemble learning can allow us to simultaneously and more accurately examine the behavioral, financial, and interactional characteristics of customers and provide more accurate predictions of customer value. This research gap not only helps us to better understand customer behavior in the banking industry, but also can improve customer relationship management methods and marketing decisions of banks. As a result, this study attempts to fill this gap in the research literature by presenting a multi-layered ensemble learning model and help improve the accuracy of customer value prediction.

4. Research Method

The research method in this study is library-based. The statistical population of this study is 2000 customers of Tejarat Bank of Iran and their bank account information over a year. There are 14 characteristics for each customer. A brief explanation of the data set and characteristics (characteristics) will be given in Table 2. In this study, the Python programming language was used as the main tool for implementing the models. Various libraries were used to perform different stages of data analysis and build machine learning models. Pandas was used for loading and processing data, numpy for numerical calculations and array management, and scikit-learn was used to implement machine learning models such as KNN, SVM, Logistic Regression, Random Forest, and Stacking

Classifier. Also, xgboost was used to implement the XGBoost model, and matplotlib and seaborn were used to visualize data and display results.

Table 2. Information about the characteristics of the dataset

Feature Name	Description	Type
Last Late	The last number of days the customer has not had a transaction	Numerical
Maximum Late	The highest number of days the customer has not had a transaction	Numerical
Minimum Late	The lowest number of days the customer has not had a transaction	Numerical
Number of Visits	The number of times the customer has visited the bank	Numerical
Total Deposits	The total amount of customer deposits	Numerical
Total Deposits	The total number of customer deposits	Numerical
Total Withdrawals	The total amount of customer withdrawals	Numerical
Total Withdrawals	The total number of customer withdrawals	Numerical
Lowest Balance	The lowest customer account balance	Numerical
Highest Balance	The highest customer account balance	Numerical
Total Services	The total number of services the customer has used	Numerical
Total Offline Transactions	The total number of customer offline transactions	Numerical
Last Balance	The last customer account balance	Numerical
Customer Value	The customer value (1 is valuable and 0 is worthless)	Binary

A better understanding of the features can be gained by using data visualization. Figure 1 shows a numeric feature and Figure 2 shows a binary feature.

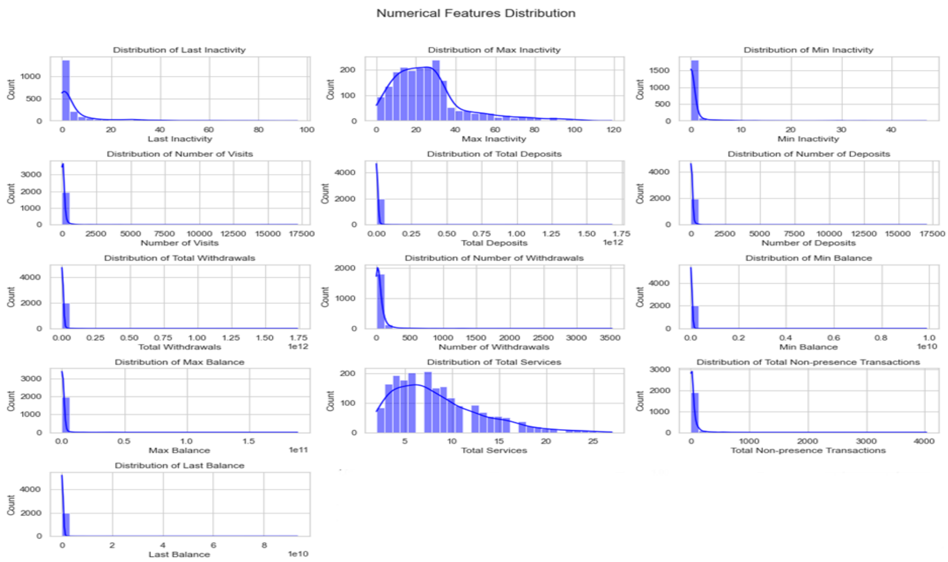

Figure 1. Distribution of number features

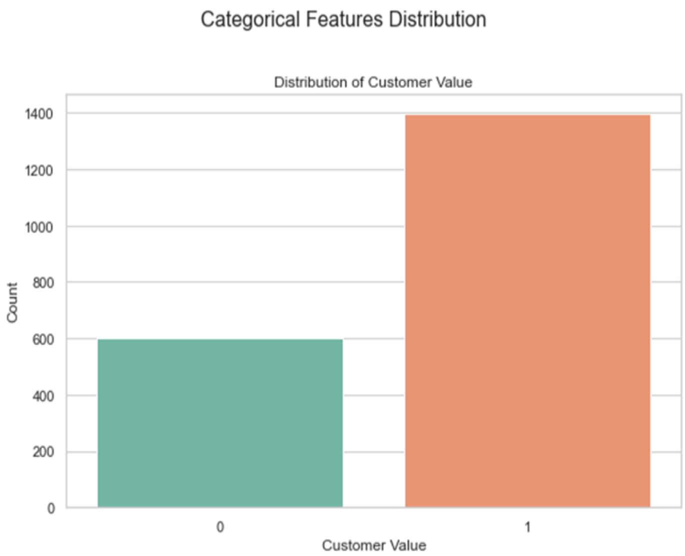

Figure 2. Distribution of categorized features

In this study, out of 2,000 bank customers, 1,397 were valuable bank customers and 603 were worthless customers.

• **Data Preprocessing**

Data preprocessing is a technical process aimed at improving data sets to make them usable. This process involves changing and sometimes removing incomplete, incorrectly formatted, irrelevant, and duplicate data. It also sometimes requires converting text data to numerical values and redesigning features (Kotsiantis et al., 2006). In the data preprocessing process, no data was lost and no duplicate data was found. The number of outliers was also very small compared to the total data and could be ignored (Hodge and Austin, 2004). Another step that is generally performed in the data preprocessing stage is data scaling. Scaling is a method used to standardize the range of independent variables or features. Among the available methods and considering the data set under study, the minimum-maximum scaling method was applied in this study. In this way, all data of a feature (independent features that are not binary) in the dataset is standardized between zero and one. The mathematical formula of MinMaxScaler is as follows:

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

In this formula:

✓ x_{scaled} is the normalized (standardized) value of the feature.

- ✓ x is the original value of the feature.
- ✓ x_{min} is the smallest feature value in the data.
- ✓ x_{max} is the largest feature value in the data.

This formula maps the values of each feature to a range between 0 and 1, so that the features are on the same scale (Jafarnejad et al., 2025).

- **Feature Selection**

Feature selection is a critical step in the process of building machine learning models, helping to improve model performance, reduce complexity, and increase interpretability. In this study, a combination of two feature selection methods, namely correlation and Chi-Square filtering, was used to select the most important features for predicting customer value.

- **Correlation method**

In this method, a linear correlation was calculated between each of the features and the target variable (customer value). Features that had a significant positive or negative correlation with the target variable were considered as selected features.

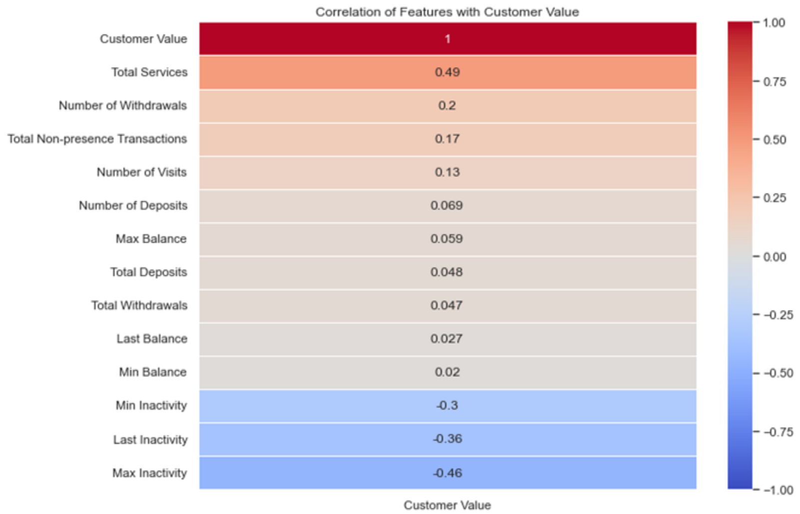

Figure 3. Correlation of features with customer value

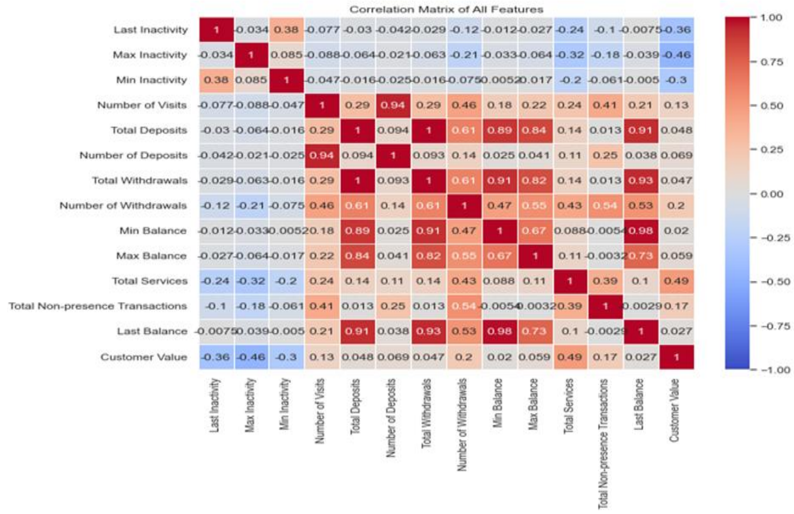

Figure 4. Correlation matrix of various characteristics of bank customers

Selected were the features with correlation coefficients above 0.1 or below -0.1 (Guyon and Eliseev 2003). In particular, it was found that the features of Total Services with a correlation coefficient within 0.49, Number of Withdrawals with a correlation coefficient of 0.20, Total Non-Presence Transactions with a correlation coefficient of 0.17, and Number of Visits with a correlation coefficient of 0.13 were positively correlated with the target value. Furthermore, significant inverse relationships with customer value were found to exist with the following features: Min Inactivity with a correlation of -0.30, Last Inactivity with -0.36, and Max Inactivity with -0.46.

- **Chi-square test method**

Another method is the filter method. In this method, all available features are examined using the Chi-square or Chi-square test based on the following formula:

$$x^2 = (\text{ObservedFrequency} - \text{ExpectedFrequency})^2 \div \text{ExpectedFrequency} \qquad (2)$$

Similarly, the Chi Square test was also used to assess the importance of each feature to the target variable. The results of this method pointed out the following features as the most important ones: Maximum Balance (4.218x1011), Total Deposits (2.482x1012), Last Balance (6.600x1010) and Total Withdrawals (2.485x1012) in ratio. The results also revealed that the customer financial transaction features, like deposits, withdrawals and the account balance are quite important for predicting the customer value.

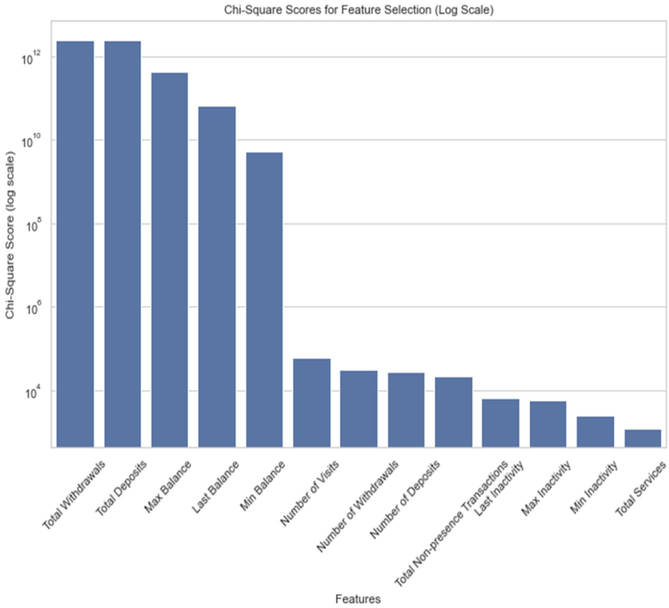

Figure 5. Results of the filter method with Chi-Square test to assess the importance of each feature

By combining these two methods, the final selected features for the model included Total Services, Total Withdrawals, Total Deposits, Max Balance, Last Balance, Max Inactivity, Last Inactivity, and Min Inactivity.

- **Multilayer Stacking Ensemble Model**

In this study, a multilayer Stacking Ensemble model was developed to predict the value of bank customers. Stacking Ensemble is an advanced ensemble learning approach that integrates multiple heterogeneous base models and leverages their combined predictions through a higher-level meta-model to improve overall predictive performance (Mehregan et al., 2025). Unlike conventional ensemble methods such as Bagging or Boosting, which rely on homogeneous learners or sequential error correction, the stacking strategy exploits the diversity of different learning algorithms to capture complementary patterns in the data (Mehregan et al., 2025). The proposed stacking framework was implemented in two distinct layers, as described below.

First layer (Base models):

In the first layer, several powerful and diverse tree-based machine learning algorithms were employed to learn distinct structural and nonlinear relationships from the input features:

- XGBoost: A highly efficient gradient boosting algorithm that incrementally improves weak learners by optimizing a differentiable loss function. XGBoost is particularly effective in modeling complex nonlinear interactions and handling structured tabular data (Rezasoltani et al., 2025).

- CatBoost: A gradient boosting model designed to address overfitting and prediction shift, offering strong generalization performance and robustness in classification tasks (Jafarnejad et al., 2025).
- Random Forest: An ensemble of decision trees built through bootstrap sampling and feature randomness, which provides stable predictions and reduces variance by aggregating multiple trees (Khani et al., 2025).
- Gradient Boosting: A boosting-based algorithm that sequentially constructs decision trees, where each tree focuses on correcting the errors of the previous ones, enabling precise modeling of complex decision boundaries (Jafarnejad et al., 2025).

Each base learner captures different aspects of the data distribution and generates independent predictions, thereby enhancing model diversity in the first layer.

Second layer (Meta-model):

The Meta Model on the 2nd Layer is Light Gradient Boosting Machine. Machine Learning (ML) has many different ways to build models; each has advantages and disadvantages. In particular, gradient boosting provides an efficient way to improve accuracy with a lower cost when using a histogram-based approach.The output of the 1st Layer Base Models is combined optimally through the use of the meta model to produce a final prediction.The Metamodel learns how to optimally integrate the strengths of the 1st-layer base learners, while overcoming any weaknesses, resulting in superior generalization and increased robustness.To achieve even greater predictive accuracy than previously achieved, the hyperparameters of both the 1st Layer Base Models and the LightGBM were optimized through the RL-Based Spider Wasp Optimizer. Through traditional methods of Hyperparameter optimization (Grid Search, Random Search), there is a limit to and rigidity within the predefined Hyperparameter regions (or boxes).Additionally, traditional Hyperparameter optimization fails to consider the experiences gained during the training and validation of individual models, and it does not adjust its search approach throughout these processes; as a result, using these traditional techniques can lead to computational inefficiency and ineffectiveness in leveraging the high-dimensional, non-linear, multi-modal relationships inherent in Hyperparameter landscapes when multiple models interact simultaneously.

The RL-SWO algorithm uses a combination (or hybrid) of two methods (or approaches) for optimizing problem data. One method is the Spider Wasp Optimizer, which is a multi-agency adaptive algorithm; the other method is reinforcement learning, which uses learning feedback to improve decision-making over time (Oueslati et al., 2026). Each potential solution (i.e., candidate solution) in RL-SWO includes all the information needed to generate the complete combined hyperparameter configuration for both the base learners (models) and the stacked ensemble (complete model). The RL-SWO algorithm will train the ensemble using cross-validation in order to rate how accurate and/or effective each individual candidate is.

An important aspect of the RL-SWO algorithm is that it is adaptable (able to change speed and direction relative to how effective it is). Unlike traditional optimization algorithms, RL-SWO uses an adaptive approach to control how it searches for potential solutions in relation to how effective it has been up to that point. By using reinforcement learning, RL-SWO¹s actions for selecting new search candidates are based on both the successes and failures already generated through exploration around previously identified promising candidate solutions and exploration into those areas of the search space that have not been explored yet. By creating an adaptive search strategy, RL-SWO is able to avoid becoming trapped within local minima and will actively increase the amount of computational resources used for directing the search toward hyperparameter combinations that yield the highest-determining lines.

Throughout the optimization process, the performance feedback obtained from repeated cross-validation plays a central role in shaping the search trajectory. Candidate solutions that lead to improved classification performance reinforce similar search actions in subsequent iterations, while suboptimal configurations discourage further exploitation of unproductive regions. This feedback-driven strategy significantly enhances search efficiency and stability, particularly in complex ensemble models where interactions between hyperparameters across different learning algorithms can strongly influence final performance.

RL-SWO brings together all of the base models and the meta-model within one optimization process, meaning that you can optimize all hyperparameters simultaneously—as a group. By optimizing the models this way, you can exploit the predictive power and synergies of all models simultaneously, which will generally result in improved generalization performance and robustness. The final hyperparameter settings are a result of balancing the trade-off between complexity of the model, bias-variance characteristics, and computational time. After 50 iterations and using a population of 20 agents, the optimum solution found by reinforcement learning was a combination of hyperparameter settings producing an F1-score of 0.9274 and an optimization cost of 0.0726 (1 - F1), which indicates that the trade-off between precision and recall is almost equal. Overall, the results show the effectiveness and stability of the RL-SWO strategy to efficiently find hyperparameters for multilayer stacking ensembles.

The optimized hyperparameter configurations achieved using RL-SWO are summarized in Table 3. These results demonstrate the effectiveness of reinforcement learning–enhanced metaheuristic optimization in constructing high-performing stacking ensembles, offering a flexible and scalable alternative to traditional hyperparameter tuning techniques for complex predictive modeling tasks.

Table 3. All parameters of the models used in the stacking layers

Model	Hyperparameter	Optimized Value
XGBoost	Number of estimators (n_estimators)	335
	Maximum tree depth (max_depth)	7
	Learning rate (lr)	0.227973
	Subsample ratio (subsample)	0.678009
	Column subsampling rate (colsample)	0.849822
CatBoost	Tree depth (depth)	3
	Learning rate (lr)	0.040130
	Number of estimators (n_estimators)	395
	L2 regularization (l2_leaf_reg)	3.690688
Random Forest	Number of trees (n_estimators)	330
	Maximum tree depth (max_depth)	12
	Maximum features (max_features)	Auto
Gradient Boosting	Number of estimators (n_estimators)	272
	Maximum tree depth (max_depth)	5
	Learning rate (lr)	0.125542
Stacking – LightGBM (Meta-model)	Number of estimators (n_estimators)	319
	Number of leaves (num_leaves)	79
	Maximum depth (max_depth)	3
	Learning rate (lr)	0.012313
	Subsample ratio (subsample)	0.831541
	Column subsampling rate (colsample)	0.819432

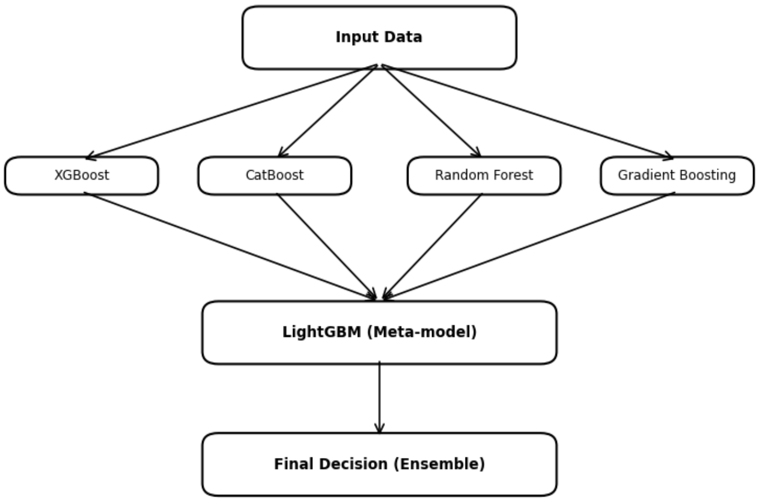

Figure 6. Multilayer model based on ensemble learning

In Table 4, five different machine learning models employed in this study are reviewed, along with their computational principles and the reasons for their selection. Each model exhibits unique characteristics and learning capabilities, making it suitable for capturing specific data patterns in customer value prediction. The selected models range from advanced gradient boosting techniques to ensemble-based tree methods, which collectively enable the proposed framework to effectively model nonlinear relationships, complex feature interactions, and heterogeneous structures in banking transaction data. By combining these complementary models within a stacking ensemble architecture, the proposed approach achieves improved predictive accuracy and robustness.

Table 4. Reasons for choosing and how to calculate machine learning models

Model	Calculation Method	Reasons for Selection
XGBoost	XGBoost incrementally trains decision trees using gradient-based optimization to minimize a loss function.	XGBoost was selected for its strong ability to model complex nonlinear relationships, handle feature interactions, and achieve high predictive accuracy on structured banking data.
CatBoost	CatBoost employs ordered boosting and symmetric trees to reduce overfitting and prediction bias.	CatBoost was chosen due to its robust generalization performance and stable learning behavior in complex classification tasks.
Random Forest	Random Forest aggregates multiple decision trees trained on bootstrap samples with random feature selection.	Random Forest was selected for its robustness, variance reduction, and reliable performance across heterogeneous data distributions.
Gradient Boosting	Gradient Boosting sequentially builds decision trees by minimizing residual errors using gradient descent.	Gradient Boosting was included for its flexibility in capturing complex decision boundaries and subtle data patterns.
LightGBM (Meta-model)	LightGBM uses histogram-based learning and leaf-wise tree growth for efficient gradient boosting.	LightGBM was selected as the meta-model due to its efficiency and strong capability to integrate predictions from multiple base learners in the stacking ensemble.

- **Data segmentation and model evaluation with Repeated Stratified K-Fold Cross-Validation**

1.Initial data split (train-test split)

In this study, the original data was divided into two sets for training and evaluating the model. It used the Train-Test Split method and the data for the train was split 80%, and the test was 20%. This is done since 80% of the data is used to train the machine learning models, and the models learn to predict accurately. Lastly, 20% of the data that the model has not seen is used to judge the accuracy of the models.100% original data (80 during training and 20 during testing) — Train Set + Test Set Without test data, you can not be sure that the model will do well when confronted with data that the model has not seen.

2. Repeated Stratified K-Fold Cross-Validation Method

To better evaluate the models and avoid the problem of Overfitting, the Repeated Stratified K-Fold Cross-Validation method was used. This method is a combination of Stratified K-Fold and Cross-Validation, which brings the advantages of both methods and leads to higher accuracy and more stable evaluation of the models (Prosti et al., 2022).

- **Stratified K-Fold Cross-Validation:**

In Stratified K-Fold Cross-Validation, the data is divided into K parts (Fold) and then the model is repeatedly trained on each of these parts. In each iteration, one part of the data is used to test the model and the remaining parts are used to train the model. The important point in this method is that Stratification is applied; That is, the proportion of samples of each class (for example, the number of valuable and worthless customers) in each section is maintained approximately the same as the proportion of the original samples.

- **Repeated Stratified K-Fold:**

In the Repeated Stratified K-Fold method, the Stratified K-Fold process is repeated several times (here 3 times). These repetitions are done so that each time the data is randomly divided into K parts, and the results from several repetitions are averaged. This process makes the final results of the model more stable and reduces random effects.

- **Steps for performing Repeated Stratified K-Fold:**
  - ✓Dividing the data into K parts (Fold): In this study, the data was divided into 5 Folds. This means that the data was divided into 5 equal parts and in each repetition, one of these parts is used as test data and the rest as training data.
  - ✓Cross-Validation: In each iteration of Cross-Validation, the model is trained on 4 parts of the data and then evaluated on the remaining part. This process is repeated for each of the 5 Folds and at the end, the average accuracy of the model is calculated.
  - ✓Repeat the process multiple times: After a full round of K-Fold Cross-Validation, this process is repeated three times and in each iteration, the data is randomly divided into different parts. This makes the evaluation of the models more stable and reduces random errors.

5. Confusion Matrix

Accuracy, Precision, Recall, F1 score and ROC-AUC were used for evaluating model performance. The metrics are obtained from TP, TN, FP and FN concepts. Correctly identified defect cases are denoted by TP and the cases that are accurately predicted without being defective are denoted by TN. FP refers to incorrect predictions of the defects while no defect exists and FN indicates that the defect cases have been missed. This is what makes up the basis for evaluating the model's accuracy and adequacy of the model. 5-fold cross validation was used to assess generalizability and stability of the model.

Table 5. Evaluation metrics for machine learning models

index	definition	Formula
Accuracy	The ratio of correct predictions (both positive and negative) to the total number of samples.	$\frac{TP+TN}{TP+FP+FN+TN}$
Precision	The ratio of correctly predicted instances of a class to the total instances predicted as that class.	$\frac{TP}{TP+FP}$
Recall	The ratio of correctly predicted instances of a class to the total actual instances of that class.	$\frac{TP}{TP+FN}$
F1 Score	The harmonic mean of Precision and Recall to balance the trade-off between them.	$\frac{2\times Precision\times Recall}{Precision+Recall}$
ROC-AUC	The area under the Receiver Operating Characteristic (ROC) curve (AUC) represents the model's ability to distinguish between classes. For this metric, the True Positive Rate (TPR = TP / (TP + FN)) and the False Positive Rate (FPR = FP / (FP + TN)) are calculated across various thresholds, and the area under their curve (ROC Curve) is computed.	$\int_0^1 \mathrm{TPR(FPR)}\ d(\mathrm{FPR})$

6. Findings

In this section, we examine the results of various machine learning models. All models were run on a system with an Intel Core i7-13700 H processor, 16 GB of RAM, and Python 12.3. The results are shown in Table 6.

Table 6. Comparison of the performance of different machine learning models based on evaluation criteria

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
Decision Tree	0.8633	0.9039	0.9003	0.9019	0.8390
KNN	0.8642	0.9058	0.8995	0.9024	0.9236
SVM	0.8785	0.9090	0.9184	0.9135	0.9449
Naive Bayes	0.5590	0.9831	0.3751	0.5420	0.9196
Logistic Regression	0.8605	0.8687	0.9432	0.9043	0.9332
Stacking	0.8970	0.9284	0.9246	0.9261	0.9632

The comparative results in Table 6 show that the proposed Stacking ensemble clearly outperforms all individual baseline models across all five evaluation metrics. With an Accuracy of 0.8970, Precision of 0.9284, Recall of 0.9246, F1-

score of 0.9261, and ROC-AUC of 0.9632, the ensemble achieves both high correctness and excellent class discrimination. In other words, it not only classifies a larger proportion of customers correctly overall, but it is also very effective at separating valuable and non-valuable customers across different decision thresholds. This confirms that combining heterogeneous learners through a LightGBM meta-model successfully exploits the complementary strengths of the base models. Among the single models, SVM is the strongest competitor, with Accuracy = 0.8785, F1-score = 0.9135, and ROC-AUC = 0.9449. These values indicate that SVM is highly capable of capturing complex, possibly non-linear decision boundaries in the feature space. However, the stacking model still improves upon SVM by about 1.85 percentage points in Accuracy (0.8970 vs. 0.8785) and about 1.26 percentage points in F1-score (0.9261 vs. 0.9135), while also increasing ROC-AUC by roughly 1.84 percentage points (0.9632 vs. 0.9449). This gain, despite already strong SVM performance, highlights that the meta-learner is indeed extracting additional predictive information from the ensemble of base models rather than simply reproducing the behavior of the best single classifier. Logistic Regression, KNN, and Decision Tree show very similar and reasonably strong performance but remain behind SVM and the stacking model. Logistic Regression achieves Accuracy = 0.8605 and F1-score = 0.9043, with a relatively high Recall (0.9432) but slightly lower Precision (0.8687). This pattern suggests that Logistic Regression tends to label more customers as high-value (fewer false negatives, more false positives), which can be beneficial if missing a valuable customer is considered more costly than occasionally misclassifying a low-value customer. KNN and Decision Tree exhibit very close Accuracy and F1-scores (around 0.86 and 0.90, respectively), but their ROC-AUC values differ: KNN (0.9236) is clearly better than Decision Tree (0.8390), meaning that KNN is more robust to changes in the decision threshold and provides a more reliable ranking of customers by risk/value. The Naive Bayes model behaves quite differently from the others. While it obtains an extremely high Precision of 0.9831, its Recall is only 0.3751, resulting in a low F1-score of 0.5420 and modest Accuracy of 0.5590. This indicates that Naive Bayes is very conservative in labeling customers as high-value: almost every customer it labels as valuable truly is valuable (few false positives), but it misses a large proportion of valuable customers (many false negatives). In applications such as bank customer valuation, this behavior is typically undesirable, because failing to identify a large fraction of profitable customers can lead to substantial opportunity costs. The stacking model, by contrast, achieves both high Precision and high Recall simultaneously, offering a much better balance between exploiting valuable customers and avoiding misclassification errors. Overall, the analysis shows a consistent ranking: Stacking > SVM > (Logistic Regression, KNN, Decision Tree) >> Naive Bayes. The stacking ensemble not only improves on the best individual model but also stabilizes performance across all metrics, which is critical for real-world decision-making in banking. These findings justify using the RL-SWO–tuned stacking architecture as the final model for predicting bank customer value.

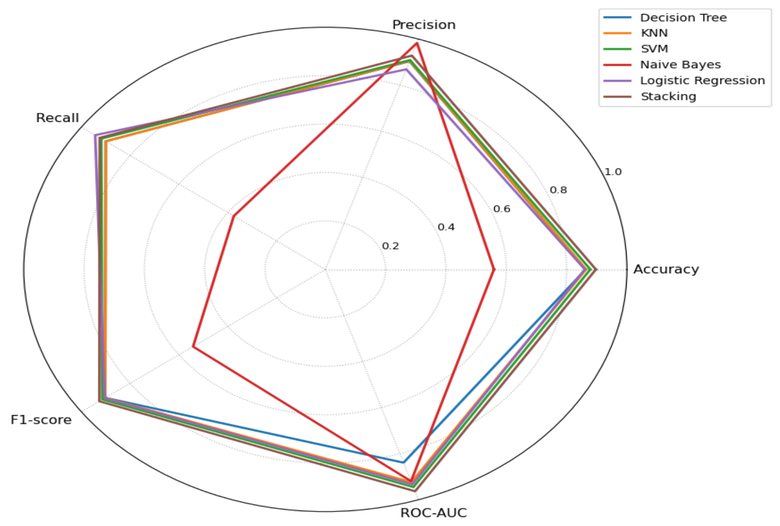

Figure 7. Comparison of machine learning models based on different evaluation criteria

Figure 7 clearly indicates that the proposed Stacking model exhibits superior and more balanced performance compared to all baseline classifiers. The polygon corresponding to the stacking ensemble covers the largest area across all evaluation metrics, including Accuracy, Precision, Recall, F1-score, and ROC-AUC. This dominance reflects the model's strong overall predictive capability as well as its ability to maintain a desirable balance between correctly identifying valuable customers and minimizing misclassification errors. The effectiveness of the LightGBM meta-model in integrating the complementary strengths of the base learners is directly evident from the consistently high values across all axes.
Among the individual models, Support Vector Machine (SVM) demonstrates the closest performance to the stacking approach, achieving high values across most metrics. However, its radar profile remains noticeably smaller than that of the stacking ensemble, particularly in terms of F1-score and ROC-AUC. This difference suggests that while SVM is effective in learning complex decision boundaries, it lacks the robustness and holistic performance achieved through model aggregation. The Logistic Regression, KNN, and Decision Tree models present moderately balanced shapes but with reduced coverage, indicating less stability in simultaneously optimizing all evaluation criteria. The Naive Bayes model exhibits a highly imbalanced performance profile on the spider chart.

Despite achieving very high Precision and relatively strong ROC-AUC, its extremely low Recall leads to a significantly contracted polygon in other dimensions. This pattern confirms that the model is overly conservative and fails to identify a substantial proportion of positive cases. Overall, the visual analysis provided by the spider chart reinforces that the stacking ensemble not only improves individual performance metrics but also delivers a more stable and reliable classification behavior, making it the most suitable model for bank customer value prediction.

7. Discussion and Conclusion

In this study, to predict bank customers' value, a two-layer stacking ensemble learning framework was developed. The experimental results clearly demonstrate that the proposed ensemble strategy significantly improves predictive performance compared to individual machine learning models. The evaluation metrics obtained through cross-validation indicate that combining multiple heterogeneous learners leads to higher classification accuracy and more stable results than relying on any single classifier alone. In particular, the stacking ensemble consistently outperformed classical models such as Decision Tree, KNN, Support Vector Machine, Naive Bayes, and Logistic Regression across all evaluation criteria.

The proposed architecture employs a diverse set of tree-based and gradient-based learners in the first layer, including XGBoost, CatBoost, Random Forest, and Gradient Boosting, each of which captures different aspects of nonlinear and complex relationships in transactional banking data. In the second layer, LightGBM is used as a meta-model to aggregate the predictions of the base learners and generate the final output. This hierarchical learning structure enables the model to simultaneously exploit the strengths of ensemble-based learning, boosting techniques, and decision tree diversity, while compensating for the weaknesses of individual models. As a result, the stacking ensemble achieves superior predictive performance, exemplified by an accuracy of 89.70%, a precision of 92.84%, a recall of 92.46%, an F1-score of 92.61%, and a ROC-AUC of 96.32%, indicating strong discriminative capability and a balanced trade-off between precision and recall.

Compared with individual classifiers, the stacking model shows noticeable improvements. Although SVM achieved strong results among the standalone models, the ensemble framework further enhanced performance, particularly in terms of F1-score and ROC-AUC, reflecting better robustness and generalization. Models such as Logistic Regression, KNN, and Decision Tree demonstrated reasonable but comparatively limited performance, while Naive Bayes exhibited a highly imbalanced behavior with very high precision but low recall. These findings confirm that the stacking ensemble more effectively integrates linear and nonlinear learning mechanisms, resulting in a more reliable and comprehensive predictive model.

To further strengthen model performance, the hyperparameters of both base learners and the meta-model were optimized using a Reinforcement Learning–based Spider Wasp Optimizer (RL-SWO). Unlike traditional tuning approaches, RL-SWO adaptively explores the hyperparameter space by dynamically balancing exploration and exploitation based on performance feedback. This optimization process played a crucial role in improving model accuracy and stability, particularly in the context of complex and potentially imbalanced banking data. The effectiveness of automated hyperparameter optimization aligns with prior studies emphasizing the importance of systematic tuning for ensemble models and boosting algorithms.

The results of this study reinforce the growing body of evidence indicating that ensemble learning models outperform individual classifiers in customer value prediction and related banking applications. Similar conclusions have been reported in the literature, such as in the studies of Kaukriya and Wisang (2023) and Morindani (2023), which demonstrated the effectiveness of ensemble approaches in predicting investment risk, customer interaction, and behavioral outcomes. Furthermore, this study employs feature selection techniques, including correlation analysis, to identify the most influential variables, which is consistent with earlier research such as Azhgerdi and Kazerooni (2023) that emphasized the role of systematic feature selection in enhancing predictive accuracy.

An important strength of the present research is the use of real-world transactional data from Tejarat Bank, consisting of customer financial behavior attributes, which significantly enhances the practical relevance and credibility of the results. The use of real banking data, similar to the approach adopted by Galal et al. (2022) in digital customer churn prediction, demonstrates the applicability of advanced machine learning models in operational banking environments. Moreover, the high performance achieved using such data highlights the potential of stacking ensemble models for deployment in real decision-support systems.

Overall, the findings confirm that the proposed stacking ensemble, combined with advanced feature selection and reinforcement learning–based hyperparameter optimization, provides a powerful and reliable approach for customer value prediction. The results are consistent with and extend existing research in the domain, demonstrating that integrating diverse models within a structured ensemble can substantially improve predictive accuracy and robustness. For future research, further improvements may be achieved by incorporating additional advanced learners, expanding dataset size, or applying the proposed framework to other application domains such as fraud detection, credit risk assessment, and recommender systems.

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یک مدل ترکیبی یادگیری ماشین بهینه‌سازی‌شده با الگوریتم زنبور عنکبوت‌گیر تقویت‌شده با یادگیری تقویتی برای پیش‌بینی ارزش مشتری

چکیده

با توجه به چالش‌های موجود در تحلیل داده‌های پیچیده تراکنش‌های بانکی و اهمیت شناسایی مشتریان ارزشمند در صنعت بانکداری، این پژوهش یک الگوریتم یادگیری ماشین هیبریدی مبتنی بر یک مدل پشته‌ای چندلایه ارائه می‌دهد که با بهره‌گیری از بهینه‌سازی هایپرپارامترها توسط الگوریتم فراابتکاری زنبور عنکبوت‌گیر تقویت‌شده با یادگیری تقویتی طراحی شده است. در لایه نخست، چهار مدل قدرتمند شامل XGBoost، CatBoost، Random Forest و Gradient Boosting برای استخراج الگوهای خطی و غیرخطی از داده‌ها به‌کار گرفته شدند. در لایه دوم، مدل LightGBM به‌عنوان فرامدل با هدف ترکیب خروجی مدل‌های پایه و افزایش توان پیش‌بینی استفاده شد. برای افزایش کیفیت داده‌ها و بهبود عملکرد مدل، از روش‌های انتخاب ویژگی و مقیاس‌بندی Min-Max نیز بهره گرفته شد. نتایج حاصل از اعتبارسنجی متقابل تکرارشونده نشان داد که مدل پیشنهادی عملکردی به‌مراتب بهتر از مدل‌های منفرد دارد و به امتیاز F1 بیش از ۹۲ درصد و دقت بسیار بالا در طبقه‌بندی مشتریان باارزش دست یافته است. همچنین معیارهای صحت، دقت، بازخوانی و ROC-AUC مؤید توانایی بالای مدل در تبیین‌پذیری و تشخیص صحیح مشتریان کلیدی هستند. این نتایج نشان می‌دهد که مدل هیبریدی پیشنهادی، به‌ویژه با استفاده از الگوریتم فراابتکاری زنبور عنکبوت‌گیر تقویت‌شده با یادگیری تقویتی برای جستجوی بهینه فضای هایپرپارامترها، می‌تواند ابزار قدرتمندی برای بهبود مدیریت ارتباط با مشتری، افزایش سودآوری، و پشتیبانی از تصمیم‌گیری داده‌محور در بانک‌های ایرانی باشد.

واژگان کلیدی: یادگیری تجمیعی، پیش‌بینی ارزش مشتری، مدل پشته‌ای، یادگیری ماشین در بانکداری، مدل‌های طبقه‌بندی چندلایه