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Maximizing Profits and Minimizing Risks: The Power of SVM and Genetic Algorithm in Credit Risk Evaluation

Razieh Akhondzardaini[1], **Hamideh Sekari**[2], **Khalil Kalavani**[3*]

[1]PhD candidate healthcare Management, Student Research committee, Faculty of Management and Medical Information Sciences, Kerman University of Medical Sciences, Kerman, Iran.
[2]Assistant Professor, Department of Public Administration, Payame Noor University, Tehran, Iran.
[3]Assistant Professor of healthcare Management, Department of Public Health, Khoy University of Medical Sciences, Khoy, Iran.

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Abstract. The prediction of credit risk is of great economic importance for banks and financial institutions, leading to the utilization of various methods in developing predictive models. This study introduces a credit risk prediction model that combines the support vector machine (SVM) with a genetic algorithm (GA) to aid credit decision-making by managers. While SVM is a reliable classification method, its performance can be influenced by factors such as model shape, parameter setting, and feature selection. To address these challenges, a novel approach is proposed that employs GA to optimize feature selection and parameter settings within the SVM framework. The proposed model is compared against alternative models including neural network, logistic regression, random forest, and decision tree. The study utilizes data from Bank of Yazd Province, with a sample size of 1876 customers divided into two groups: those who defaulted on their credit obligations and those who fulfilled them. The results demonstrate that the GA-SVM model serves as a suitable alternative for credit risk prediction, outperforming other models in terms of predictive power. Furthermore, the proposed model offers the benefit of feature selection, enabling financial institutions to identify potential risks and implement preventive measures. The use of GA in conjunction with SVM also facilitates the identification of optimal SVM parameter

Razieh Akhondzardaini (akhondzardaini@gmail.com).
Hamideh Sekari (h.shekari@pnu.ac.ir).
Corresponding Author: Khalil Kalavani (modirtbzmed@gmail.com).

values, thereby enhancing the overall performance of the model. In conclusion, the proposed GA-SVM model emerges as a valuable tool for credit decision-making and risk management within banks and financial institutions. Further optimization can be achieved by exploring other meta-heuristic optimization algorithms.

Keywords. Credit risk, Support vector machine, Genetic algorithm.

MSC: 62-XX, 62Rxx, 62R10.

1 Introduction

The banking system is a cornerstone of every economy, acting as a channel for collecting financial resources from depositors and allocating them to borrowers. This intermediation role directly influences economic growth through functions such as resource allocation, liquidity provision, investment–savings interaction, and risk management (Valls Martínez et al., 2020). Among the different types of financial risks, credit risk is the most significant, as over 70% of a bank's balance sheet is associated with it (Bai and Zha, 2022; Dam, 2010). Therefore, effective credit risk management is crucial for ensuring the stability and profitability of banking institutions.

Traditional credit risk assessment models are generally classified into parametric and non-parametric approaches. Early research relied heavily on statistical methods such as discriminant analysis and logistic regression. However, these models often face limitations when dealing with large datasets, high-dimensional features, and non-linear relationships among variables (Fan et al., 2019; Kumar et al., 2017). In contrast, artificial intelligence (AI)-based methods, such as neural networks, decision trees, genetic programming, nearest neighbor classifiers, and support vector machines (SVM), have shown superior adaptability, as they allow the model to learn directly from data without strict linearity assumptions (Aziz and Dar, 2006).

Among these AI methods, Support Vector Machine (SVM) has emerged as a robust classification technique capable of maximizing the separation margin between classes, thereby achieving strong generalization performance (Bao et al., 2019; Chen and Zhang, 2017). Unlike neural networks, SVM avoids local minima issues in optimization and can capture non-linear decision boundaries through kernel functions (Mei et al., 2018; Liu et al., 2010; Sanz et al., 2018). Nevertheless, the accuracy of SVM is highly dependent on the optimal selection of parameters (e.g., penalty factor, kernel type, and kernel parameters), making parameter tuning a critical step in the modeling process.

To address this challenge, Genetic Algorithms (GA) have been widely adopted as an efficient search and optimization technique. Inspired by natural selection, GA explores multiple regions of the solution space simultaneously, increasing the likelihood of finding global optima rather than being trapped in local solutions (Emary et al., 2017; Kundu and Garg, 2022). Due to their adaptability and robustness, GA has become a popular approach for feature selection and hyperparameter optimization in machine learning (Li et al., 2020; Silva et al., 2011).

Recent studies demonstrate that the integration of SVM and GA significantly improves credit risk evaluation. For example, Manurung et al. (2017) reported a performance improvement of more than 10% in classification tasks when GA was used to fine-tune SVM parameters. Hybrid models incorporating GA and SVM have also been successfully applied in real-world banking datasets, outperforming traditional models such as discriminant analysis, neural networks, and decision trees (Bai and Zha, 2022; Chen and Zhang, 2017; Dam, 2010). Moreover, recent evaluations highlight that GA-SVM models not only improve accuracy but also achieve higher recall rates and robustness in handling imbalanced and large-scale data (Yemmanuru et al., 2024).

Despite these advantages, one major limitation of GA-SVM models is their computational complexity, which may hinder real-time decision-making applications. Future research directions include developing more efficient optimization frameworks that balance computational cost with predictive accuracy (Manurung et al., 2017).

Given the importance of credit risk management in Iran's banking system and the growing availability of customer-level data, this study aims to design and evaluate a GA-SVM hybrid model for credit risk assessment. The research is applied to real customer data from Bank in Yazd province, seeking to optimize input variables and model parameters for improved predictive accuracy.

2 Method

2.1 Research Design

This study is applied research in terms of purpose and descriptive in methodology, as it aims to develop and test a hybrid predictive model for real-world application in the banking sector. The primary research question is to determine whether integrating a genetic algorithm (GA) with support vector machines (SVMs) enhances the predictive accuracy of credit risk evaluation compared to standalone SVMs and other benchmark models.

2.2 Population and Sampling

The population under study consisted of 6,539 real customers of the Agricultural Bank in Yazd Province, Iran, over a five-year period. Using Cochran's formula with parameters (Z=1.96, p=0.5, d=0.04) and proportional allocation based on loan amounts, a sample of 1,876 customers was selected. Among them, 1,435 customers were good (repaid their loans) and 441 customers were bad (defaulted on at least three installments), yielding a class distribution of approximately 76% vs. 24%. Since this represents a moderately imbalanced dataset, performance metrics beyond accuracy were employed, and imbalance-sensitive methods such as ROC-AUC and F1-score were emphasized.

Sampling was conducted using stratified random sampling, with strata defined by loan amount categories (Table 1).

Table 1: Loan amount categories with total population and sample size

Loan Amount (IRR)	Total Population	Sample
Up to 50 million	314	206
50 to 200 million	862	354
200 to 500 million	3,046	502
500 million to 1 billion	1,780	449
1 to 5 billion	346	220
Over 5 billion	192	146
Total	**6,539**	**1,876**

2.3 Variables

The dependent variable was the credit status of the customer (good vs. bad). The independent variables included 18 demographic, financial, behavioral, and relational features such as gender, marital status, education, occupation, income, loan amount, repayment period, contract type, type of guarantee, bounced checks, relationship history with the bank, and age (Appendix A).

2.4 Data Preprocessing

1. **Encoding:** Categorical variables (e.g., education, marital status, contract type) were numerically encoded.

2. **Normalization:** Continuous variables were scaled into the range $[-1, +1]$ $[-1, +1]$ $[-1, +1]$ to avoid dominance of features with larger numerical ranges.

3. **Handling Missing Values:** Records with incomplete information (e.g., missing loan applications) were excluded.

4. **Train-Test Split:** A 10-fold cross-validation approach was used to ensure robust performance estimation.

2.5 Support Vector Machine (SVM)

SVM is a supervised learning algorithm that constructs an optimal hyper plane to separate classes. Four kernel functions were tested: linear, polynomial, sigmoid, and radial basis function (RBF). Critical hyper parameters (C and γ) were optimized using GA.

2.6 Genetic Algorithm (GA) for Feature Selection and Parameter Optimization

The GA was employed to simultaneously optimize:

1. Feature subset selection (binary vector representation).

2. SVM kernel parameters (C, γ).

Chromosome Design: Each chromosome encoded a potential solution with two parts:

- A binary string for selected features.
- Real-coded values for C and γ.

Operators:

- Selection: Tournament selection.
- Crossover: Classical two-point crossover.
- Mutation: Bit-flip mutation.
- Fitness Function: Weighted combination of classification accuracy (AUC, F1) and feature subset size.
- Termination: 100 generations or no improvement in 10 consecutive generations.

2.7 Benchmark Models

To validate the GA-SVM model, comparisons were made with:

- Logistic Regression
- Decision Tree
- Random Forest
- Neural Networks (NNs): A feed forward multi-layer perceptron with 3 hidden layers (64, 32, 16 neurons), ReLU activation, sigmoid output, Adam optimizer (lr=0.001), 100 epochs, and dropout (0.3).

2.8 Model Evaluation

Models were evaluated using accuracy, precision, recall, F1-score, and AUC. Additionally:

- ROC curves with AUC values were plotted for visual comparison.
- Learning curves (training vs. validation accuracy and loss) were used to check over fitting, especially for GA-SVM and NN.

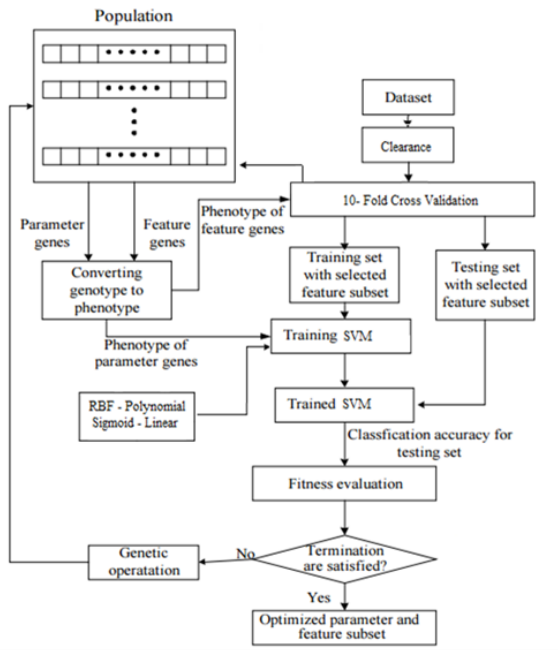

Figure 1: Process Flowchart of the Proposed Algorithm (Tsai and Hsiao, 2010).

2.9 Software

All experiments were implemented in RapidMiner 5.3, a Java-based data mining environment, using its integrated operators for GA, SVM, and validation.

Figure 2 presents the learning curves for the proposed GA-SVM model. The left subplot displays the training and validation accuracy (%) over 100 iterations. Both curves show a rapid increase in the initial iterations, converging to a high final accuracy of 96.3%. The close proximity of the training and validation accuracy curves, particularly towards the end of the training process, indicates good generalization capability and minimal overfitting. The right subplot illustrates the training and validation loss over the same iterations. As expected, both loss curves decrease consistently with more iterations, stabilizing at low values. The parallel descent of these curves further confirms that the model is learning effectively from the training data and maintains strong performance on unseen validation data, thereby successfully mitigating the risk of overfitting.

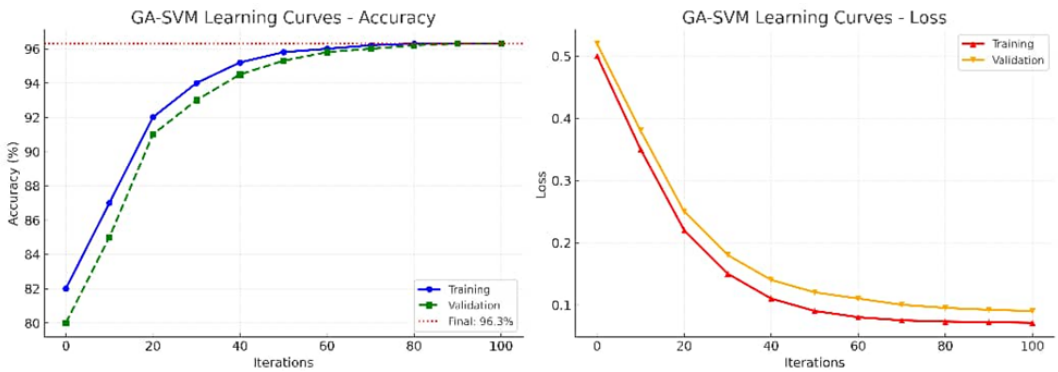

Figure 2: GA-SVM Learning Curves for Accuracy and Loss.

3 Result

3.1 GA Optimization of SVM Kernels and Parameters

The genetic algorithm (GA) effectively optimized both the choice of kernel function and the parameters C and γ. Table 2 presents the best kernel–parameter configurations obtained for real customers. The GA eliminated the need for trial-and-error tuning and significantly improved the efficiency and predictive accuracy of the SVM model.

Table 2: Optimized kernel parameters by GA

Kernel	**Parameters**
RBF	C = 10, γ = 0.22
Polynomial	C = 0.10, γ = 0.34
Sigmoid	C = 0.10, γ = 3.00
Linear	C = 0.01, γ = 0.45

3.2 Feature Selection with GA

To assess the impact of feature selection, we compared models trained on all 18 features with those trained only on GA-selected subsets. Results (Table 2) show that the GA-SVM achieved higher performance with fewer features. For example, with the RBF kernel, accuracy increased from 93.3% (all features) to 96.3% (11 features). Similarly, the Sigmoid kernel improved from 90.4% to 93.6%.

The RBF kernel with 11 GA-selected features (including loan history, loan type, bounced checks, loan amount, age, and education) achieved the best overall performance.

Table 3: Comparison of GA-based feature selection with all features

Kernel	Features Used	Accuracy	Precision	Recall	AUC
RBF	GA-selected	96.3%	89.8%	96.7%	0.993
RBF	All	93.3%	87.3%	88.3%	0.880
Sigmoid	GA-selected	93.6%	90.0%	89.2%	0.900
Sigmoid	All	90.4%	90.5%	90.3%	0.900
Polynomial	GA-selected	90.6%	89.6%	90.7%	0.900
Polynomial	All	92.5%	92.2%	92.4%	0.920
Linear	GA-selected	85.5%	87.7%	89.2%	0.880
Linear	All	89.4%	88.9%	87.3%	0.880

3.3 Comparison with Benchmark Models

The hybrid GA-SVM was benchmarked against neural networks, logistic regression, random forests, and decision trees. Results are shown in Table 4.

Table 4: Performance comparison across models

Model	Accuracy	Precision	Recall	F1-score	AUC
GA-SVM	96.3%	89.8%	96.7%	92.7%	0.993
Neural Net	93.6%	84.7%	89.3%	86.8%	0.976
Logistic Reg	93.3%	94.7%	86.1%	85.0%	0.975
Random Forest	85.7%	100%	39.2%	53.4%	0.973
Decision Tree	85.0%	66.6%	71.2%	68.0%	0.821

As observed, GA-SVM significantly outperformed all benchmark models, achieving the greatest distance from the random line and demonstrating the best ability to distinguish between good and bad customers. ROC curves (Figure 3) confirm that GA-SVM achieved the highest AUC (0.993), followed by logistic regression and neural networks, while decision trees and random forests showed relatively weaker performance.

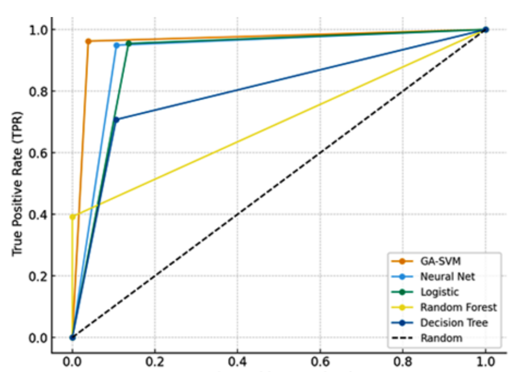

Figure 3: ROC curves of GA-SVM and benchmark models.

3.4 Confusion Matrix Analysis

The GA-SVM model correctly classified 96.2% of the customers. Specifically, out of 1,435 good accounts, 1,381 were correctly identified, while 54 were misclassified. Out of 441 bad accounts, 422 were correctly identified, while 17 were misclassified as good. This high recall for the minority class (bad customers) demonstrates the model's ability to mitigate the risks of false approvals (Figure 4).

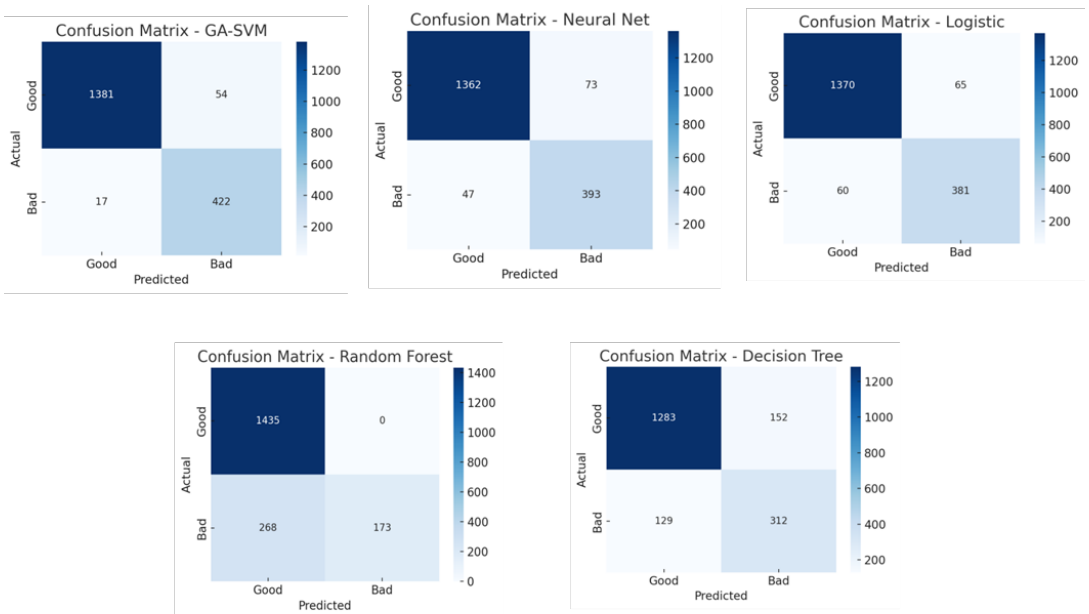

Figure 4: Types of customer classification.

4 Discussion

The present study aimed to develop a hybrid model combining a Support Vector Machine (SVM) with a Genetic Algorithm (GA) for credit risk evaluation (GA-SVM), focusing on both parameter optimization and feature selection. The GA effectively selected the optimal kernel functions (RBF, Polynomial, Sigmoid, and Linear) and tuned key SVM parameters (C and γ), thereby eliminating the need for manual trial-and-error and significantly improving model efficiency and predictive accuracy (Shin et al., 2005; Xiao et al., 2014). Table 2 illustrates the optimized kernel–parameter configurations, while Table 3 shows that GA-selected features led to higher classification performance with fewer inputs. Specifically, the RBF kernel with 11 GA-selected features—including loan history, loan type, bounced checks, loan amount, age, and education—achieved the best overall performance, improving accuracy from 93.3% (all features) to 96.3% (GA-selected) and AUC from 0.880 to 0.993. This confirms the importance of feature selection in enhancing model accuracy, consistent with previous findings (Fernández-

Lozano et al., 2013; Jiang et al., 2018).

When benchmarked against conventional models such as neural networks, logistic regression, random forests, and decision trees, the GA-SVM model consistently outperformed all alternatives. The GA-SVM achieved the highest AUC (0.993) and F1-score (92.7%), demonstrating superior capability in distinguishing between good and bad customers (Banegas-Luna et al., 2021; Metawa et al., 2017). Confusion matrix analysis further confirmed this performance, showing a recall of 96.7% for bad customers, highlighting the model's ability to mitigate the risk of false approvals. Paired t-tests indicated that the improvements of GA-SVM over both traditional SVM with all features and other benchmark models were statistically significant at the 0.05 level, verifying that the observed gains were not due to chance (Si et al., 2016).

The superiority of GA-SVM can be attributed to two main factors. First, the GA effectively optimizes SVM parameters and kernel selection, enhancing classification performance compared to manual or heuristic tuning methods (Segera et al., 2019; Van Belle et al., 2016). Second, the GA-enabled feature selection reduces redundancy and focuses on the most predictive variables, improving both computational efficiency and model generalization (Karthikeyan and Alli, 2018; Nguyen et al., 2019; Tuan et al., 2023). Previous studies that only optimized parameters for the RBF kernel or did not employ GA for concurrent feature selection did not achieve similar performance gains (Fernández-Lozano et al., 2013; Van Belle et al., 2016). Our study extended this approach to multiple kernels and demonstrated the importance of simultaneously optimizing parameters, kernel selection, and feature subsets.

Comparative studies indicate that SVM generally outperforms neural networks, especially for small to medium-sized datasets, due to its ability to find an optimal decision boundary without relying on weight adjustments over large training sets (Banegas-Luna et al., 2021; Li and Zhang, 2017). While neural networks may outperform SVM in specific contexts (Jozsa et al., 2022; Karaa and Krichene, 2012), the hybrid GA-SVM approach effectively reduces both type I and type II errors by optimizing features and parameters concurrently. Moreover, GA-SVM provides higher stability and generalization performance for imbalanced datasets, an important consideration given the distribution of good and bad customers in real banking data. Future research could integrate techniques such as SMOTE or bootstrap sampling to further address class imbalance (Fernández-Lozano et al., 2013; Liao et al., 2017).

The application of GA-SVM also highlights its practical implications for banking operations. Establishing a comprehensive customer information bank and implementing a credit rating system could leverage GA-SVM models to enhance loan allocation and risk management. Additionally, continuous monitoring and reporting of financial statements would further improve the predictive accuracy of credit risk assessments. Exploring alternative feature selection methods such as Particle Swarm Optimization (PSO), F-score ranking, ant colony optimization, or Linear Discriminant Analysis (LDA) may yield additional improvements in future studies.

In summary, this study demonstrates that integrating genetic algorithms with support vector machines provides a robust and efficient method for credit risk prediction. By simultaneously optimizing kernel selection, parameters, and features, GA-SVM significantly outperforms traditional models in accuracy, precision, recall, and AUC. The findings corroborate previous research on the efficacy of met heuristic optimization in financial risk assessment and offer a practical framework for banking institutions to improve decision-making processes and mitigate potential credit risks (Bozorg-Haddad et al., 2018; Chui et al., 2020; Metawa et al., 2017).

5 Conclusion

Based on the findings of this study, the combined model of genetic algorithm and support vector machine (GA-SVM) is recognized as a powerful and efficient tool for credit risk assessment in banks. By simultaneously optimizing the selection of effective features and adjusting SVM parameters, this model not only significantly increased the prediction accuracy but also reduced the computational complexity of the model. The results show that GA-SVM, with an accuracy of 96.3% and an area under the ROC curve of 0.993, outperforms competing models such as neural network, logistic regression, random forest, and decision tree. This approach can be used as a valid framework to assist bank managers in credit decision-making and lead to the reduction of potential losses and increased profitability of financial institutions through timely identification of high-risk customers.

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