Optimization Strategy of Credit Scoring System based on Support Vector Machine

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Abstract. This article proposes a novel optimization strategy for credit scoring systems that exploits the capabilities of SVM. Focusing on the importance of personal credit scoring in today's credit dynamics, the article explores SVM's versatility in various domains through a literature review. The theoretical background underscores the unique approach and computational efficiency of SVM. The optimization strategy encompasses four critical aspects: debt solvency, earning potential, operational prowess, and growth capability using metrics such as asset-liability ratios. Experimental validation with credit card datasets from Australia and Germany illustrates the nuanced relationship between different K-values and performance metrics, and demonstrates the adaptability of SVM in improving credit scoring. In short, the article presents an original, comprehensive approach to credit risk management that integrates theoretical foundations, literature findings, and empirical experiments to improve the accuracy of credit scoring in the dynamic economic landscaper.

Keywords: Support Vector Machine; Optimization Strategy; Credit Scoring System; Data Mining.

1. Introduction

The credit economy transcends its role as a mere manifestation within the realm of social economy; it stands as an inexorable trajectory in the development of society and the economy. The relentless surge in credit consumption, coupled with the extensive deployment of diverse credit instruments and derivatives, has led to the proliferation of transactional scales and methods among credit entities, giving rise to a nuanced, multi-tiered credit system. Across sovereign, industry, and personal credit domains, credit entities find an urgent need for effective tools in credit risk management to navigate the intricacies of credit exchange and consumption, mitigating potential credit risks. Personal credit scoring, positioned as the most potent tool for managing individual credit risk, ensures precision in lending and optimizes the allocation of credit resources. Its prowess lies in the comprehensive evaluation of creditworthiness and risk prediction during loan origination and management processes, directly impacting the development of personal credit. Empirical evidence from developed countries attests that sophisticated risk management significantly stimulates the dynamism of the credit economy.

Within a robust social credit system, equitable and authoritative credit products and services have permeated, establishing credit transactions as the predominant issue in the market economy. Enterprises and individuals, attuned to market dynamics, place heightened emphasis on credit maintenance, elucidating a discernible market demand for credit. The maturation of the credit system has induced a rationalized approach among market participants, fostering standardized behavior and substantially elevating market efficiency. The credit scoring system, a pivotal component of the broader credit framework, assumes a crucial role in advancing the overall credit scoring infrastructure. The pervasive adoption of big data technology has propelled credit scoring applications into the limelight, emerging as a foreseeable developmental trajectory. This paradigm shift is poised to furnish the requisite technological underpinning for the sustained flourishing of the credit economy, thereby laying a resilient foundation for enduring social and the economic development. In the Figure 1, the credit score basic components are demonstrated.

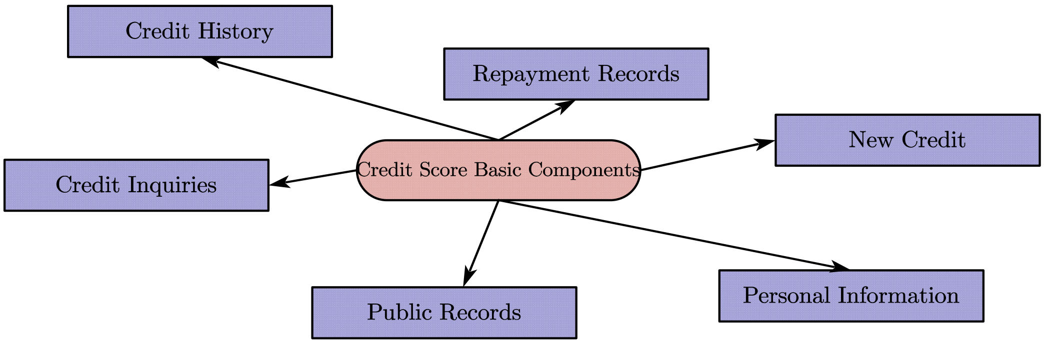

Figure 1. The Credit Score Basic Components

In the real scenarios, after modelling the credit score system, the evaluation methods are also essential, the creation of a credit scoring model necessitates a meticulous evaluation of the rating process and strategy to ensure its reasonability, effectiveness, legality, and compliance. This scrutiny encompasses diverse facets, such as explicitly defined metrics for the model's observation period, goal establishment, performance duration, sample curation, feature selection, loan default characterization, quantification of bad debt, and delineation of loan loss. Initially, there is a need to scrutinize whether the delineations of default concepts, bad debt quantification, and loan loss quantification adhere to the sensible confines of the capital management regulations for commercial banks in our country. Furthermore, the inquiry extends to the objectivity of default definitions and the rationality of identification standards. Subsequently, for retail credit scoring models opting for the master scale definition, it is imperative to verify the rationality and intuitiveness of rating levels and standards. Additionally, a meticulous review of the methodology for calculating the prolonged central default trend is warranted to ascertain its fidelity in portraying the historical default scenario of the commercial banks. This involves checking if the most conservative weighting method is employed for estimating the long-term default trend. Lastly, an assessment is required to determine the appropriateness and operationality of the definition of the economic recession period. It is essential to confirm whether it genuinely encapsulates the features of loss given default during economic downturns and whether the relationship with the stress test scenario is rational. The validation process for the scoring model also demands benchmarking, instating challenge models, and gauging the influence of diverse rating methodologies on the precision and stability of risk evaluations. Widely accepted methodologies comprise internal rating systems, methods for quantifying risk parameters, and comparative analyses with alternative approaches. The validation endeavors should rigorously test the model's adaptability across various time-frames and datasets, both internal and external. In cases where in-line data limitations hinder this, the model's performance can be evaluated through continuous monitoring post its online deployment or validation following its production roll-out. In the subsequent sections of this manuscript, leveraging insights gained from the literature review, we delve into the exploration of optimization strategies for a credit scoring system grounded in the support vector machine paradigm.

2. Literature Review

2.1 State-of-the-art Studies Regarding Support Vector Machine

In the agricultural domain, the integration of profound attributes and SVM for identifying diseases in rice leaves is paramount [1]. The investigation not only unveils an extensive data-set of images captured in real-field conditions but also scrutinizes the comparative performance of different CNN models, emphasizing the superior efficacy of the SVM-embedded deep feature methodology. The study's revelations provide valuable insights into refining disease recognition processes, critical for promoting sustainable agricultural practices.

The proposed mixed-load prediction model for power systems is notably pertinent in the era of intelligent grids [2]. By assimilating real-time pricing and incorporating intelligent mechanisms for the culling of features and the optimization of parameters, the research tackles the evolving complexities associated with precise load forecasting. The model's effectiveness in terms of precision, stability, and efficacy positions it as a notable stride forward in the methodologies of power load prediction.

For extensive supervised categorization tasks, the Local-to-Global Support Vector Machine (LGSVM) method emerges as a notable tool [3]. Capitalizing on regional SVM contributions, the LGSVM streamlines the computational intricacies linked with SVMs. The theoretical scrutiny and comprehensive numerical tests lay the groundwork for understanding and deploying this approach in scenarios involving myriad instances.

The prognosis and diagnosis of energy consumption in public structures are crucial for attaining energy efficiency objectives [4]. The SVM-rooted model presented in the study, which factors in aspects like historical consumption and meteorological conditions, underscores the practical application of SVM in refining the operations of buildings. The implications of the research extend to informing policies and methodologies for promoting sustainable energy practices in public infrastructure.

Ensuring the precise anticipation of photovoltaic power is essential for amplifying the efficiency of grid-connected PV systems [5]. The study's exploration into data pre-processing and the introduction of an SVM model with enhanced ant colony optimization highlights the ongoing efforts to enhance the ultra-short-term PV power forecasting. The revelations contribute to advancements in harnessing renewable energy and optimizing grid management.

In the realm of medical image scrutiny, the research on classifying Synovial Sarcoma using SVM highlights the potential of advanced techniques in cancer diagnosis [6]. By fusing discrete wavelet transformation and structural attributes, the proposed framework demonstrates the synergy between machine learning and digital histopathology. The study unveils prospects for more accurate and intelligent cancer prognosis within the medical field.

The advanced two-stage fault diagnosis methodology for rotating machinery introduces a fresh approach to counteract the imbalance between regular and faulty samples [7]. Integrating optimized SVDD and SVM, alongside multi-scale entropy for characteristic extraction, the methodology proves effective in fault detection and identification. The research contributes to fortifying the reliability and practicality of fault diagnosis in rotating machinery.

2.2 State-of-the-art Studies Regarding Credit Scoring System

The meticulous assessment of the creditworthiness of borrowers holds paramount importance in the decision-making processes of financial institutions. Scholars have undertaken a quest to refine credit scoring models, employing an array of methodologies ranging from statistical techniques to artificial intelligence (AI) strategies. A notable surge in interest has been observed in the exploration of ensemble or multi-classifier systems, which have demonstrated heightened accuracy when compared to solitary classifier models.

In the work by Ala'raj and Abbod (2016) [8], the authors address the imperative for more accurate credit scoring models, proposing an innovative amalgamation methodology grounded in a consensus-driven classifier approach. By deploying six widely recognized foundational classifiers, including logistic regression, neural networks, support vector machines, random forests, decision trees, and Naïve Bayes, the study showcases the newfound capacity of the proposed approach to enhance predictive efficacy, surpassing conventional combination methodologies.

Continuing this exploration, Ala'raj and Abbod (2016) [9] introduce a hybrid ensemble model for evaluating creditworthiness. This model amalgamates data pre-processing techniques and a classifier consensus approach. Comparative assessments against individual foundational classifiers, traditional combination methods, and contemporary literature highlight the model's ascendancy in average accuracy, AUC, H-measure, and Brier score across diverse real-world credit datasets.

In the study by Harris (2015) [10], the introduction of the Clustered Support Vector Machine (CSVM) for credit scorecards addresses computational quandaries associated with traditional nonlinear SVM methods. Comparative analysis pits the CSVM against its nonlinear SVM counterparts, spotlighting its commensurate classification performance while preserving computational frugality.

Lessmann and colleagues (2015) [11] reinvigorate a bench-marking scrutiny of classification techniques in the creditworthiness domain. Novel methodologies are juxtaposed against established benchmarks, exploring alternative gauges of predictive accuracy and appraising the managerial pertinence of more accurate classifiers, offering salient insights to practitioners and scholars alike.

He, Zhang, and Zhang (2018) [12] conceive a groundbreaking ensemble model tailored for creditworthiness evaluation, adept at accommodating disparate imbalanced ratio datasets. The model intertwines data pre-processing, adjustable balanced subsets, and a tripartite ensemble mechanism employing random forest and extreme gradient boosting. Outcomes demonstrate superior performance and robustness of the other algorithmic frameworks.

Kozeny (2015) [13] scrutinizes the predictive efficacy of diverse fitness functions employed by genetic algorithms in the domain of creditworthiness assessment. Propounding an alternative fitness function grounded in a variable bit-mask, the study attests to its superiority in both accuracy and sensitivity over alternative methodologies.

In the work by Xia et al. (2017) [14], a sequential ensemble model for creditworthiness assessment is advocated, founded on the tenets of extreme gradient boosting and enriched through Bayesian hyper-parameter optimization. Placing emphasis on the hyper-parameter calibration, model-driven feature selection, and interpretability, the study reveals the ascendancy of Bayesian hyper-parameter optimization and the proposed model over foundational models.

3. The Proposed Model

3.1 The Theoretical Background of Support Vector Machine

The operating mechanism of a SVM can be viewed as finding an optimal hyperplane to satisfy the corresponding classification conditions. This hyperplane not only needs to accurately distinguish samples with different labels, but also ensures that the distance to the nearest sample point is maximized, that is, the interval between the sample and the hyperplane is maximized. For a linearly separable two-classification problem, the design goal of the optimal classification line is to minimize the empirical risk while maximizing the classification interval distance between positive and negative classes, thereby effectively reducing the uncertainty of classification and forming an optimal classification line. optimal classification decision boundary. The core idea is to introduce a kernel function to transform a complex nonlinear classification problem into a relatively simple linear classification problem by mapping it to another high-dimensional space. The uniqueness of this method is that it avoids the specific solution of nonlinear mapping forms and high-dimensional space dimensions, thereby reducing the complexity and computational difficulty of the problem. The inner product operation of nonlinear mapping through kernel functions does not significantly increase the computational complexity of the algorithm. This means that although we have performed dimensionality enhancement on the data, this has not resulted in a significant increase in computational burden in the actual calculations. Therefore, the nonlinear mapping implemented through the kernel function shows good computational efficiency and practicality when dealing with complex problems. This provides a feasible and effective solution for support vector machines to process large-scale, high-dimensional data in practical applications.

Maximum margin classification hyperplane is the key issue for the SVM, suppose a certain observation sample set as:

$$S = \{(x_1, y_1), (x_2, y_2), (x_3, y_3), \ldots, (x_l, y_l)\} \tag{1}$$

Where the x_n is the n-th training sample, the variable y represents the category type of the sample. The objective of interval surface classification is to identify a high-dimensional hyperplane capable of effectively segregating positive and negative samples. Assume that the hyperplane is:

$$H_0 : \overline{w}^T x + \overline{b} = 0 \tag{2}$$

This hyper-plane divides the sample set S into:

$$\begin{cases} \overline{w}^T x_i + \overline{b} > 0, & y_i = 1 \\ \overline{w}^T x_i + \overline{b} < 0, & others \end{cases} \tag{3}$$

Then, 2 hyper-planes are defined and the distance is defined as:

$$\Delta = \frac{2}{\|w\|} = d^+ + d^- \tag{4}$$

In the Figure 2, the hyper-plane for SVM is presented.

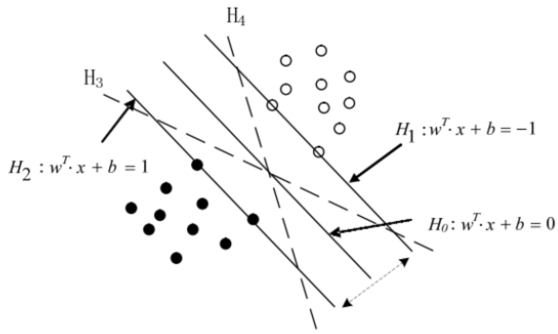

Figure 2. The Hyper-plane for SVM

3.2 The Optimization Strategy of Credit Scoring System based on Support Vector Machine

For the credit scoring model, the 4 aspects are considered in this section and regarded as the input for the SVM model:

(1) Debt solvency denotes an enterprise's capacity to fulfill its debt obligations, encompassing both principal and interest repayments. This metric serves as a pivotal gauge reflecting the financial health of a company. A meticulous examination of solvency not only facilitates an understanding of the company's prevailing operational status and associated business risks but also furnishes a foundation for prognosticating its future trajectory. Solvency indicators assume a crucial role in the assessment of corporate credit risk. Conventional evaluative measures comprise the asset-liability ratio, quick ratio, cash flow-to-liability ratio, long-term debt ratio, and quick ratio. The asset-liability ratio and long-term debt ratio predominantly appraise a company's proclivity for long-term solvency. By contrasting total debt against total assets and scrutinizing the proportion between long-term liabilities and shareholders' equity, insights into the company's adeptness in managing debt over an extended temporal horizon are gleaned. Conversely, current ratios, cash-to-liability ratios, and quick ratios pivot towards the assessment of short-term solvency. The current ratio juxtaposes current assets against current liabilities, whereas the quick ratio sidesteps inventories, deemed less liquid, yielding a more circumspect estimation of short-term solvency. The cash flow liability ratio hones in on the nexus between a company's cash flow generated from routine operational activities and its short-term debt, delineating the financial robustness of the company in the face of imminent short-term debt obligations. These solvency indicators not only furnish investors with pivotal insights into the financial well-being of the company but also proffer managerial guidance and strategic direction to other stakeholders. This aids in making judicious decisions, fostering a nuanced understanding of the company's trajectory, and enhancing the precision of future performance predictions.

(2) Earning potential characterizes an organization's adeptness in acquiring profits, encompassing its capacity to fulfill financial obligations and serving as an indicator of the likelihood of achieving sustained and steady long-term growth. It forms the bedrock for maintaining equilibrium in financial indebtedness and stands as a pivotal element in the scrutiny of corporate credit vulnerabilities. Among the commonly employed gauges for assessing corporate earning potential are six metrics, including coverage ratio for interest, yield on total assets, net asset return, profit margin on sales, gross profit margin from operations, and the proportion of primary business activities.

(3) Operating prowess pertains to an enterprise's efficacy in resourcefully leveraging assets, manifesting the adeptness in capital utilization and managerial acumen. Elevated operational proficiency within a company signifies heightened operational efficacy and a more judicious utilization of resources, thereby augmenting the company's capability to meet debt obligations and enhance profitability. Frequently utilized benchmarks for gauging corporate operational capabilities encompass turnover rates for accounts receivable, inventory, and accounts payable, along with asset turnover and the turnover of working capital. These benchmarks not only facilitate an understanding of the efficiency of asset management within the enterprise but also offer guidance for the formulation of efficacious business strategies.

(4) Growth and development capability. Metrics gauging an enterprise's ability to expand and progress appraise alterations in its fiscal information relative to preceding years. These gauges can depict the course of modifications within a company and foreshadow potential developmental scenarios. Frequently employed gauges for assessing a company's capability to grow and advance involve the analysis of variations in financial data over time, delivering insights into changing trends, and establishing a foundation for forecasting forthcoming developments. This facet is critical for grasping the financial evolution of an enterprise, facilitating proactive decision-making, and refining strategic planning to foster sustained expansion.

4. Experiment

We perform intricate numerical experiments utilizing credit card datasets from Australia and Germany, which are sourced from the UCI KDD [15]-[18] Archive. Within the Australian credit card data-set, a comprehensive set of 700 samples is encompassed, with 310 identified as "favorable credit" and 390 as "unfavorable credit" samples. Each individual sample incorporates 14 distinctive characteristics, comprising 6 nominal variables and 8 continuous variables. Regarding the German credit card data-set, a total of 1,000 samples are present, with 800 falling into the affirmative category. Each sample instance is composed of 13 nominal variables and 7 continuous variables. To enhance the treatment of nominal variables, we convert n categorical attributes' nominal variables into n-dimensional vectors. Concurrently, continuous variables undergo normalization, confining them within the range of [0, 1]. The categorization labels assigned to each data point, denoted as "favorable credit" and "unfavorable credit," are respectively encoded as 1 and -1, aligning with the categories of "positive class points" and "negative class points."

In the ensuing experimental phase, we will employ the SVM to train the pre-processed data, culminating in the creation of the robust classifier. This methodology enables a more precise differentiation between instances of "favorable credit" and "unfavorable credit," furnishing robust backing for the process of credit assessment. In the Table 1, the basic information of the data-set is introduced.

Table 1. The Basic Information of the Data-set

Data name	Number of nominal variables	Number of continuous variables	Number of positive points	Number of negative points
Australia	6	8	310	800
Germany	13	7	390	200

For the Australia data sets, the test result is demonstrated in the Figure 3 and the Germany’s data simulation result is demonstrated in the Figure 4.

For the Australia data sets, experimental results derived from manipulating different K values shed light on the performance metrics of Precision, Recall, and F1 Score. As K fluctuates across different settings, Precision shows a dynamic pattern reflecting the accuracy of positive predictions with values ranging from 82.78% to 81.33%. At the same time, Recall shows the evolving ability of the system to identify actual positive instances, with percentages fluctuating between 77.48% and 69.21%. The

F1 Score, which harmonizes Precision and Recall, provides a comprehensive assessment of performance, with values ranging from 80.04% to 74.78%. These results provide nuanced insights into the trade-offs involved in selecting an optimal K-value, facilitating a balanced approach to credit scoring or similar classification tasks.

For the Germany data sets, it is presented in the re-plotted graphs with red lines, provides a detailed depiction of the interplay between varying K values and key performance metrics—Precision, Recall, and F1 Score. Notably, the Precision plot reveals a nuanced trend, capturing the accuracy of positive predictions as K values fluctuate. Concurrently, the Recall plot illustrates the evolving ability of the system to identify true positive instances across the range of K values. The F1 Score plot, harmonizing Precision and Recall, offers a comprehensive evaluation, showcasing the delicate balance achieved under different K settings.

Specifically, the experiment demonstrates that precision percentages range between 82.78% and 81.33%, highlighting the model's ability to make accurate positive predictions. Meanwhile, recall percentages exhibit fluctuations from 77.48% to 69.21%, indicating variations in the system's capacity to identify actual positive instances. The F1 Score, representing the harmonic mean of Precision and Recall, ranges from 80.04% to 74.78%, reflecting the overall effectiveness of the classification model across different K values.

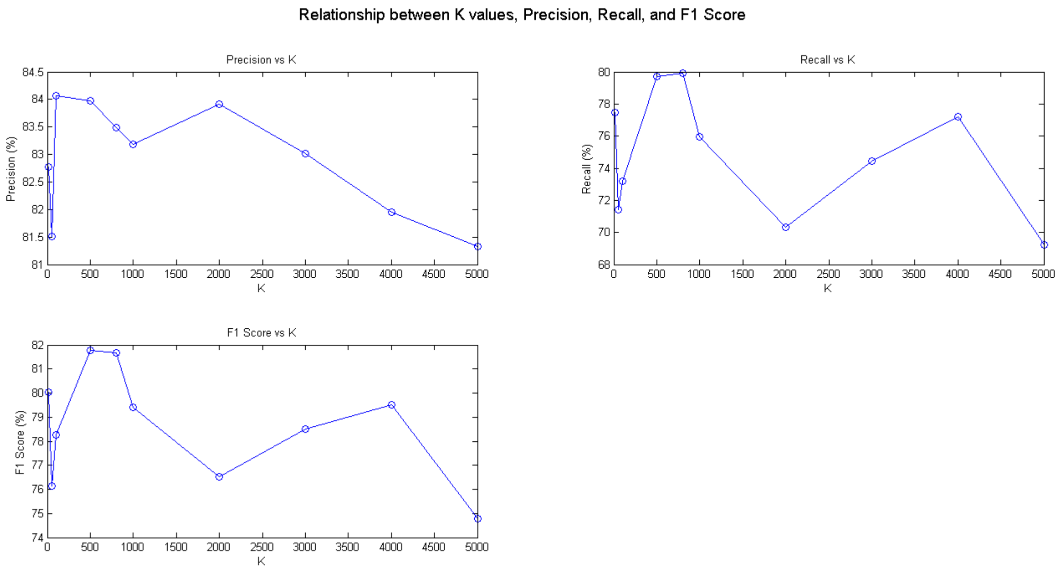

Figure 3. Australia Data Set Simulation Result

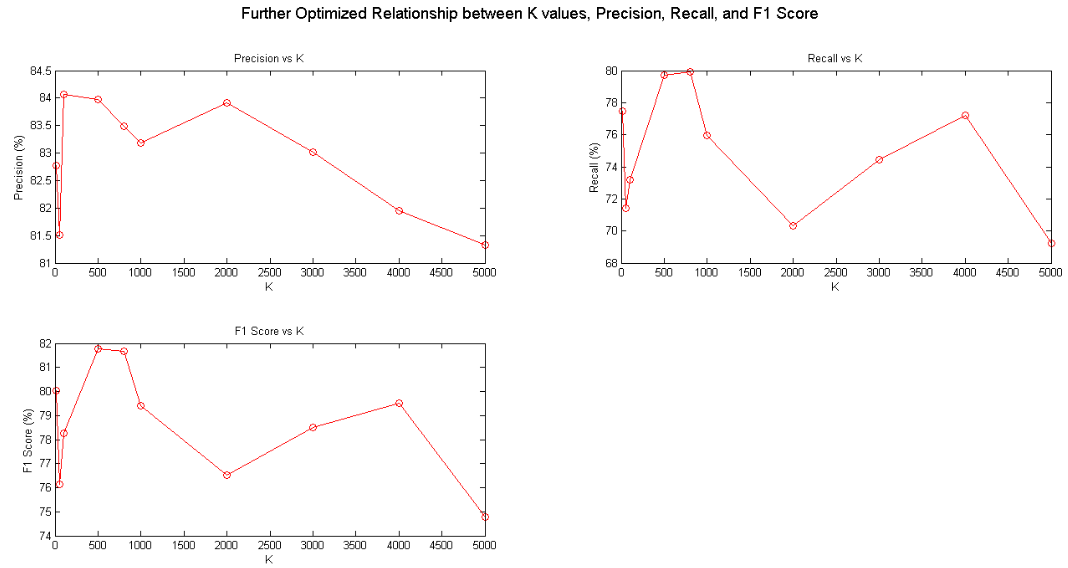

Figure 4. Germany Data Set Simulation Result

5. Conclusion

This paper discusses an optimization strategy for credit scoring using SVM. It addresses debt solvency, earning potential, operational capability, and growth capability. The theoretical background of SVM emphasizes its efficiency in handling high-dimensional data. The literature highlights SVM's versatility in various applications such as disease identification and fault diagnosis. The experiments, using credit card data from Australia and Germany, use SVM to create a robust classifier. The results, presented in graphs, emphasize the importance of choosing an optimal K-value to balance precision and recall in credit scoring. In summary, the article provides a comprehensive approach to credit risk management that integrates theory, literature findings, and empirical experiments for effective credit scoring in a dynamic economic landscape.

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