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Comparative Temporal Analysis of SVM-Based Machine Learning Techniques for Bank Risk Assessment

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Abstract: This paper introduces an innovative approach that utilizes support vector machines (SVMs) to predict the bankruptcy of financial institutions within the United States. The study aims to identify influential factors that contributed to bankruptcy during two significant periods: the 2008 financial crisis and post-2013. The goal is to highlight both shared and distinctive characteristics between these time frames. The proposed method incorporates a meticulous feature selection procedure to identify the most critical variables for assessing a bank's financial stability. Subsequently, the SVM model is fed with data containing these key variables from various banks, initiating both the training and testing phases. Specifically, two SVM models were trained: one utilizing a linear kernel, and the other employing a non-linear kernel. The objective was to assess their effectiveness in distinguishing between solvent and insolvent banks. Moreover, a neural network model was developed and subjected to a comparative analysis alongside the aforementioned SVM models, all with the aim of identifying the optimal method for bankruptcy prediction. The training dataset comprised data from the ten quarters preceding bank failures post-2013, as well as the eight quarters leading up to bank failures in 2010, during 2008 financial crisis. The SVM models were implemented using Scikit-Learn, while the neural network model was trained using PyTorch. Through this comprehensive approach, the paper contributes to the advancement of predictive methodologies for identifying potential financial institution bankruptcies.

Keywords: Machine learning; Support Vector Machine; Bank failures; Stress testing; Forecasting

1. Introduction

American banks, particularly some commercial banks, have undergone a prolonged period of restructuring and consolidation. This transformative process dates back to the 19th century(or earlier). The exceptional and unparalleled consolidation process of the American banking system has garnered significant research attention. According to the study conducted by Ahn and Choi (2009), it was demonstrated that banks play an exceedingly vital role because of their central position within the financial system [1].

However, American banks often confront various risks in their daily operations, particularly during times of extreme volatility, fragile risk management can potentially endanger a bank's stability. A bank is considered as a bank failure when it is unable to fulfill its financial commitments to creditors or depositors, leading to its closure under the oversight of federal or state regulators [2]. In addition, as the number of bankruptcy increases, the expenses associated with post-failure resolution also surge [3].

In line with recent analysis by Greg and Carey (2023), the FDIC could have saved $13.6 billion had regulators previously adhered to the total loss-absorbing capacity standard. In this research, the data was selected from 527 banks during the period of 2007-2010 [4]. Additionally, figures from 804 banks post-2013 were concurrently chosen for comparison, encompassing 44 insolvent banks and 760 solvent banks. All data were derived from the American market, primarily consisting of commercial banks with minimal government involvement.

Predicting bank failures is a crucial aspect of financial supervision and regulatory oversight. It enables authorities to step in early, maintain financial stability, safeguard depositor funds, and mitigate broader economic risks. In 2009, Boyacioglu, Kara, and Baykan originally introduced a classification approach to categorize banks as solvent or insolvent [5]. However, this paper proposes a more precise outcome in the form of a 4-level risk model.

Some notable research approaches have been proposed recently. For instance, discriminant analysis primarily aims to identify financial variables that differentiate between solvent and insolvent banks [6]. According to GARP, stress testing estimates how a portfolio or financial institution would fare under extreme market conditions,which means it can determine whether a bank possesses sufficient capital and liquid assets to endure various scenarios. When combined with VaR/ES analyses, a more comprehensive risk assessment can be presented [7]. Furthermore, as demonstrated by Awaworyi Churchill's (2019) experimentation, Panel Data Analysis can effectively process data across multiple periods for different banks, a methodology also applied in this research [8]. This approach enables the capture of trends and changes over time that could serve as potential indicators of impending failures.

Machine Learning, a subset of artificial intelligence, grants computers the ability to learn without explicit programming (Katsafados et al., 2023), which is employed in this research, combining multiple models to enhance prediction accuracy by capitalizing on their individual strengths [9]. Besides, this work also conduct Artificial Neural Networks (ANN), seeking to emulate the information processing capabilities of the human brain.

In conclusion, this study advances the comprehension of bank failure prediction. It yields insights into model effectiveness, crisis implications, stress testing, and the provision of improvement suggestions for bank managers. Additionally, some limitations and prospects are also addressed.

2. Methodology

2.1. Support Vector Machine

In this study, a range of methodologies will be employed to construct models intended for stress testing and predicting bank failures. Subsequent to this, a comparison and contrast of their respective outcomes will be carried out. While exploring various approaches, the primary emphasis will be placed on the SVM (Support Vector Machine) model. This selection is based on its notable proficiency in scenarios involving limited training data, as evident in the case with only 51 recorded instances of bank failures post-2013. The forthcoming sections will provide a concise overview of the SVM model.

In 1995, Corinna Cortes and Vladimir Vapnik introduced Support Vector Machines (SVM), which have since become a prevalent supervised machine learning technique primarily used for binary classification tasks [10].The fundamental concept behind SVM learning is to identify a hyperplane that effectively partitions the data while maximizing the margin between the two classes within the feature space.

As depicted in Figure 1, the hyperplane $\mathbf{w} \cdot \mathbf{x} + b = 0$ serves as a separator. While there are infinitely many possible separators for a given dataset, but the one with the maximum margin from both classes is unique.

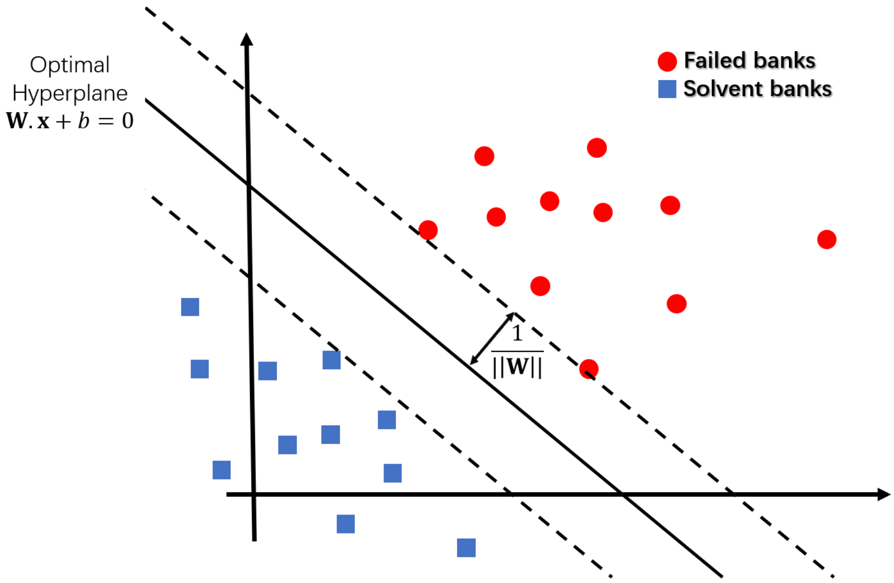

Figure 1: The optimal hyperplane and the maximized margin $\frac{1}{\|\mathbf{w}\|}$.

Before proceeding with the derivation, define the training dataset:

$$T = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), ..., (\mathbf{x}_m, y_m)\}$$

Where:

$$\mathbf{x}_i \in \mathbb{R}^n, y_i \in \{-1, 1\}\ \forall i = 1, 2, ..., m,$$

$\mathbf{x}_i$ represents the i^{th} feature vector, which encompassing all n variables of the i^{th} bank

y_i indicates whether the bank fails. ($y_i = 1$ signifies the bank's solvency, while $y_i = -1$ indicates otherwise.)

2.1.1. SVM in linearly separable case

To begin, the initial assumption is that the dataset can be linearly separated.

Hence, a separator can be represented as:

$$\mathbf{w} \cdot \mathbf{x} + b = 0\ (1)$$

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satisfying:

$$y_i(\mathbf{w} \cdot \mathbf{x}_i + b) > 0 \text{ for } i = 1, 2, ..., m$$

The distance between the data point $(\mathbf{x}_i, y_i)$ and the separator is given by:

$$y_i(\frac{\mathbf{w}}{\|\mathbf{w}\|} \cdot \mathbf{x}_i + \frac{b}{\|\mathbf{w}\|})$$

Therefore, the objective of maximizing the SVM margin can be expressed as:

$$\max_{\mathbf{w},b} \min_{i=1,2,..,m} y_i(\frac{\mathbf{w}}{\|\mathbf{w}\|} \cdot \mathbf{x}_i + \frac{b}{\|\mathbf{w}\|})$$

Upon reparameterization, the Lagrangian for this specific problem can be formulated as follows:

$$L(\mathbf{w}, b, \lambda_1, \lambda_2, ..., \lambda_m) = \frac{1}{2}\|\mathbf{w}\|^2 - \sum_{i=1}^{m} \lambda_i(y_i(\mathbf{w} \cdot \mathbf{x}_i + b) - 1),$$

In this equation, $\lambda_1, ..., \lambda_m$ represent Lagrange multipliers, satisfying $\lambda_i \geq 0$ for $i = 1, ..., m$.

Given the convexity of this optimization problem and its satisfaction of the Karush-Kuhn-Tucker (KKT) conditions, strong duality is established. Thus, it becomes advantageous to tackle its dual counterpart, which is defined as follows:

$$\min_{\lambda_1,...\lambda_m} \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} \lambda_i \lambda_j y_i y_j (\mathbf{x}_i \cdot \mathbf{x}_j) - \sum_{k=1}^{m} \lambda_i$$

$$s.t. \sum_{i=1}^{m} \lambda_i y_i = 0 \text{ and } \lambda_i \geq 0 \text{ for } i = 1, ..., m$$

After obtaining the solution for the dual problem, denoted as $\lambda_1^*, \lambda_2^*, ..., \lambda_m^*$, the solution for the primal problem is as follows:

$$\mathbf{w}^* = \sum_{i=1}^{m} \lambda_i^* y_i \mathbf{x}_i \text{ (2)}$$

$$b^* = y_j - \sum_{i=1}^{m} \lambda_i^* y_i (\mathbf{x}_i \cdot \mathbf{x}_j) \text{ for some } \lambda_j > 0$$

2.1.2. SVM in linearly inseparable case

In reality, the majority of datasets exhibit linear inseparability, as illustrated in Figure 1.

One approach to address this challenge involves improving SVM by introducing the concept of soft margins. This concept permits a systematic approach to learning from training set errors [10].

In other words, this work permit certain points to satisfy $y_i(\mathbf{w} \cdot \mathbf{x}_i + b) < 1$, and a penalty parameter C will be introduced along with non-negative slack variables ξ_i. This allows the primal optimization problem be reformulate as follows:

$$\min_{\mathbf{w},b,\xi_i} \frac{1}{2}\|\mathbf{w}\|^2 + C \sum_{i=1}^{m} \xi_i$$

$$\text{s.t. } y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1 - \xi_i$$

$$\text{Here, } \xi_i = \max\{0, 1 - y_i(\mathbf{w} \cdot \mathbf{x}_i + b)\}$$

Likewise, through the application of Lagrangian and its dual formulation, the result can be derived:

$$\mathbf{w}^* = \sum_{i=1}^{m} \lambda_i^* y_i \mathbf{x}_i \text{ (3)}$$

$$b^* = y_j - \sum_{i=1}^{m} \lambda_i^* y_i (\mathbf{x}_i \cdot \mathbf{x}_j) \text{ for some } 0 < \lambda_j^* < C$$

$$f(\mathbf{x}) = \sum_{i=1}^{m} \lambda_i^* y_i (\mathbf{x}_i \cdot \mathbf{x}) + b^* \text{ (4)}$$

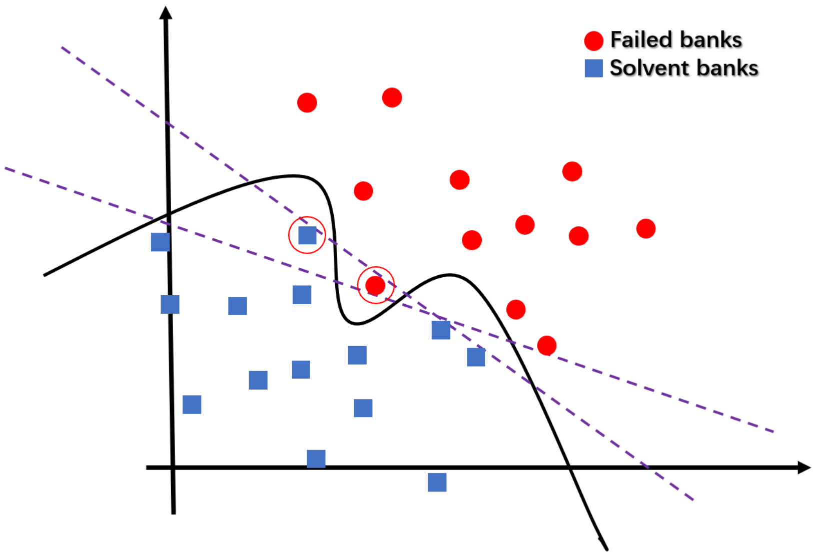

Figure 2: The linearly inseparable dataset. As evident from the graph, none of the straight lines can effectively segregate failed banks from solvent banks.

The value of $f(\mathbf{x})$ predicts the probability of a bank failure to some extent.

In addition to the "soft margin" approach, linear inseparability can also be tackled using the "Kernel Trick." As the required outcomes are solely based on the dot product, there is no necessity to explicitly define the nonlinear transformation. By replacing the dot product with various Kernel functions, the dataset can be mapped into a higher-dimensional space, achieving linear separability and enabling the establishment of a non-linear SVM model without a substantial escalation in computational expenses.

In summary, the results in non-linear SVM model with soft margin should be:

$$b^* = y_j - \sum_{i=1}^{m} \lambda_i^* y_i K(\mathbf{x}_i, \mathbf{x}_j) \text{ for some } 0 < \lambda_j^* < C$$

$$f(\mathbf{x}) = \sum_{i=1}^{m} \lambda_i^* y_i K(\mathbf{x}_i, \mathbf{x}) + b^* \text{ (5)}$$

In this study, the SVM model will undergo training using the following three distinct kernels:

(1) The inhomogeneous degree-1 polynomial kernel (Linear):

$$K(\mathbf{x}, \mathbf{x}') = (\mathbf{x} \cdot \mathbf{x}' + c)$$

(2) The Gaussian kernel:

$$K(\mathbf{x}, \mathbf{x}') = exp(-\frac{\|\mathbf{x}-\mathbf{x}'\|^2}{2\sigma^2})$$

(3) The inhomogeneous degree-4 Polynomial kernel:

$$K(\mathbf{x}, \mathbf{x}') = (\mathbf{x} \cdot \mathbf{x}' + c)^4$$

(The choice of a degree-4 polynomial kernel is driven by the observation that both degree-2 and degree-3 polynomial kernels yield results that are approximately linear.)

2.1.3. Class weight

The collected bank dataset exhibits a substantial class imbalance, with the number of solvent banks being approximately fifteen times greater than that of failed banks. Given this scenario, it becomes imperative to assign class weights that are approximately fifteen times higher to the failed banks. The approach known as MetaCost prompts the model to attribute roughly 15 times higher values to the penalty parameter 'C' for the failed banks. Consequently, the cost associated with misclassifying failed banks is amplified, effectively heightening the penalty for any misclassification errors related to this minority class [11]. Through this process, the machine learning algorithm places heightened significance on the underrepresented failed banks in contrast to the solvent banks. This strategic weighting fosters a more equitable learning process, thereby enhancing the model's ability to generalize effectively.

2.2. Tenfold cross-validation method

As evident from the kernels above, the parameters c and σ are present. These parameters are commonly referred to as hyperparameters. Hyperparameters play a pivotal role in determining the structure of the SVM model, and their optimization during the learning process is of paramount importance to ensure both effective performance and prevention of overfitting.

Overfitting, a prevalent occurrence in machine learning and statistical modeling, denotes a situation where the model achieves very high accuracy on the training data but fails to generalize effectively on new, unseen data. When overfitting occurs, the model exhibits poor performance on test data, demonstrates unwarranted complexity, and produces predictions that lack coherence and appear excessively irrational. Hence, preventing overfitting of training an SVM model is crucial. One effective approach is to employ cross-validation during model training, as this method provides enhanced insights into its performance on previously unseen data.

In this study, a cross-validation technique termed tenfold cross-validation is employed. A brief overview of this approach is provided follows below. Tenfold cross-validation stands as an established and conventional methodology in practical applications, with thorough testing revealing that 10 is about the right number of folds to get the best estimate of error [12].

In the tenfold cross-validation method, data is divided into ten equal partitions. In each iteration, one partition serves as the test set while the others constitute the training set. This process is repeated ten times, and the mean-squared-error (MSE) is computed by averaging the MSE across iterations. The hyperparameter and factor selection associated with the lowest average MSE are ultimately chosen.

2.3. Feature Selection

To reduce the risk of overfitting of the SVM model, it is necessary to simplify its complexity. One effective strategy involves conducting feature selection prior to model training. Thus, this section provides a concise introduction to the functioning of the feature selection method. The technique employed in this work is known as ElasticNet [13]. This technique amalgamates both Ridge regression by Hoerl, A. E. and Kennard, R. W. in 1970 and LASSO regression by Robert Tibshirani 1996 methods [14,15]. This is achieved by modifying $Q(\beta)$ to:

$$Q(\beta) = \|\mathbf{y} - \mathbf{X}\beta\|^2 + \alpha(1 - L_1 Ratio)\|\beta\|^2 + \alpha(L_1 Ratio)\sum_{i=1}^{p}|\beta| \quad (6)$$

Here, both α and $L_1 Ratio$ are hyperparameter that need to be specified at the outset.

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In this scenario, $L_1Ratio = 0$ corresponds to Ridge regression, and $L_1Ratio = 1$ corresponds to LASSO regression.

Since $Q(\beta)$ incorporates an absolute value term, rendering it non-differentiable. Thus, employing subgradient descent or coordinate descent methods becomes necessary to attain the optimal value of β.

3. Experiments

3.1. Data

The dataset of this research comprises 44 banks that encountered failure after 2013 and possessed over 10 consecutive quarters of accessible data before their collapse. For each failed bank, it is matched with approximately 17 solvent banks, and data over the 10 quarters preceding the collapse of the failed bank were collected for all banks in this group. This approach resulted in the final dataset comprising data from 44 failed banks and 760 solvent banks across a span of 10 quarters.

Throughout this timeframe, this research gathered 42 factors (as detailed in Table 1) for each bank. (Data from Assets and Liabilities are expressed as a ratio to total assets, while data from Income and Expense are expressed as a ratio to total interest income.)

Furthermore, this research extended the analysis to banks that failed during the 2008 financial crisis to enable a comparative study. For this purpose, data with same factors was collected from 47 randomly chosen failed banks and 480 solvent banks within that timeframe.

Table 1: 42 factors collected for each bank

Source	Category	Name	Detail
A&L	Assets	CDDI	Cash and due from depository institutions
A&L	Assets	LLA	Loan loss allowance
A&L	Assets	GOI	Goodwill and other intangibles
A&L	Liabilities	TD	Total Deposits
A&L	Liabilities	IBD	Interest-bearing deposits
A&L	Liabilities	SD	Subordinated debt
A&L	Memoranda	AAY	Average Assets, year-to-date
A&L	Memoranda	VL	Volatile liabilities
A&L	Memoranda	ULC	Unused loan commitments
A&L	Memoranda	T1RC	Tier 1 (core) risk-based capital
A&L	Memoranda	T2RC	Tier 2 risk-based capital
A&L	Memoranda	TUC	Total unused commitments
I&E	Interest Expense	TIE	Total interest expense
I&E	Other Expense	TNE	Total noninterest expense
I&E	Other Expense	SEB	Salaries and employee benefits
I&E	Other Expense	PLLL	Provision for loan and lease losses
I&E	Other Income	TNI	Total noninterest income
I&E	Other Income	TAGF	Trading account gains and fees
I&E	Other Income	ANI	Additional Noninterest Income
I&E	Other Income	PNOI	Pre-tax net operating income

Source	Category	Name	Detail
I&E	Other Income	SGL	Securities gains (losses)
I&E	Other Income	NIBM	Net income of bank and minority interests.
I&E	Other Income	CD	Cash dividends
I&E	Other Income	NOI	Net operating income
P&C	Performance Ratios	YEA	Yield on earning assets
P&C	Performance Ratios	CFEA	Cost of funding earning assets
P&C	Performance Ratios	NIM	Net interest margin
P&C	Performance Ratios	ROA	Return on assets (ROA)
P&C	Performance Ratios	ROE	Return on Equity (ROE)
P&C	Performance Ratios	NCL	Net charge-offs to loans
P&C	Performance Ratios	CLPNC	Credit loss provision to net charge-offs
P&C	Performance Ratios	ER	Efficiency ratio
P&C	Performance Ratios	APE	Assets per employee ($millions)
P&C	Condition Ratios	LAL	Loss allowance to loans
P&C	Condition Ratios	LLANL	Loan loss allowance to noncurrent loans
P&C	Condition Ratios	NLL	Noncurrent loans to loans
P&C	Condition Ratios	NLLD	Net loans and leases to deposits
P&C	Condition Ratios	NLLTA	Net loans and leases to total assets
P&C	Condition Ratios	ECA	Equity capital to assets
P&C	Condition Ratios	CCR	Core capital (leverage) ratio
P&C	Condition Ratios	T1RCR	Tier 1 risk-based capital ratio
P&C	Condition Ratios	TRCR	Total risk-based capital ratio

(A&L: Assets and Liabilities, I&E: Income and Expense. P&C: performance and condition ratios. Variables from A&L are expressed as ratios to total assets, while variables from I&E are expressed as ratios to total interest income.)

3.2. Feature selection

To enhance the efficiency of the SVM model, the identification of relevant, useful, and uncorrelated features before training is crucial. In this study, the feature selection process will be conducted using the ElasticNet Regression Algorithm, as introduced in the methodology part. Acknowledging the potential variation in the influence of specific factors across different time periods, once relevance indices are acquired for 420 variables, these indices will be combined for each factor over ten quarters to do the feature selection. Hence, for banks that experienced failure after the year 2013, the ten most significant factors ranked by relevance have been determined. These factors are presented in Table 2.

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Table 2: Results of feature selection for data of bank failures after 2013

Name	Detail
NLL	Noncurrent loans to loans
NCL	Net charge-offs to loans
TRCR	Total risk-based capital ratio
ECA	Equity capital to assets
T1RC	Tier 1 (core) risk-based capital to total assets
LAL	Loss allowance to loans
TD	Total Deposits to total assets
GOI	Goodwill and other intangibles to total assets
NLLTA	Net loans and leases to total assets

Similarly, in the case of bank failures during the 2008 financial crisis, the ten most relevant factors are also identified. These factors are presented in Table 3.

Table 3: Results of feature selection for data on bank failures during the 2008 financial crisis

Name	Detail
T1RC	Tier 1 (core) risk-based capital to total assets
CCR	Core capital (leverage) ratio
TD	Total Deposits to total assets
VL	Volatile liabilities to total assets
ECA	Equity capital to assets
NLL	Noncurrent loans to loans
LAL	Loss allowance to loans
TIE	Total interest expense to total interest income
NCL	Net charge-offs to loans

3.3. Training SVM model

Following the completion of the feature selection process, the remaining variables are input into the SVM model. A linear SVM model and two non-linear SVM models (with Gaussian Kernel, 4-degree Polynomial Kernel) were constructed. Through utilization of the hyperplane equation, accuracy of the SVM models can be deduced by assessing each vector against the separator. Table 4 outlines details of the three distinct SVM models. (Given that selecting 20 variables might introduce a greater amount of noise, this research use a more comprehensive approach by not only employing cross-validation but also partitioning 20% of banks into a separate testing set. Furthermore, the table includes a so-called CV score, which represents the evaluated accuracy obtained through cross-validation.)

Table 4: The accuracy of 20-dimensional SVM models based on data from post-2013

Model	Solvent Accuracy	Insolvent Accuracy	General Accuracy	CV Score	Factor employed
Linear SVM	100%	86.364%	99.254%	99.536%	ECA, TRCR
Gaussian SVM	99.474%	90.909%	99.005%	98.288%	ECA, NLL
Degree-4 Poly. SVM	95.921%	95.455%	95.896%	94.553%	NLLTA, TRCR

Based on Table 4, all three trained SVM models exhibit remarkable accuracy in predicting bank failures. The Linear SVM model stands out, boasting 100% accuracy in solvent accuracy, 86.364% accuracy in insolvent accuracy, and an general accuracy of 99.254%. The Gaussian SVM also performs well, achieving 99.474% solvent accuracy, 90.909% insolvent accuracy, and an general accuracy of 99.005%. As for the Degree-4 Poly SVM, although its solvent accuracy of 95.921% and general accuracy of 95.896% are comparatively lower, it excels with the highest insolvent accuracy, reaching 95.455%.

For the linear SVM model, it assigns an importance index to each variable and establishes a hyperplane based on a subset of these variables. In the post-2013 SVM model, which refers to the model covering the period after 2013, its hyperplane equation involves 20 variables, encompassing 2 factors over a span of 10 quarters. The hyperplane equation is as follows:

$$-5.544 \times ECAQ1 - 3.329 \times ECAQ2 - 2.720 \times ECAQ3 - 1.893 \times ECAQ4 - 1.681 \times ECAQ5$$

$$-0.910 \times ECAQ6 - 0.721 \times ECAQ7 - 0.515 \times ECAQ8 - 0.511 \times ECAQ9 - 0.347 \times ECAQ10$$

$$-6.281 \times TRCRQ1 - 2.891 \times TRCRQ2 - 1.884 \times TRCRQ3 - 1.021 \times TRCRQ4 - 0.346 \times TRCRQ5$$

$$+0.632 \times TRCRQ6 + 0.693 \times TRCRQ7 + 0.715 \times TRCRQ8 + 0.438 \times TRCRQ9 + 0.496 \times TRCRQ10 + 2.078 = 0$$

(Values are retained to three decimal places)

Among the factors, "ECA" (Equity capital to assets) and "TRCR" (Total risk-based capital ratio) emerge as the two most relevant variables to bank failures during the overall 10-quarter period. The quarters are denoted as Q1 for the final quarter preceding bank failures, Q2 for the penultimate quarter, and so forth.

Based on the above results, as time distances itself from the bankruptcy event, the absolute coefficients linked to ECA (Equity capital to assets) remain negative and tend to decrease. This indicates that the equity capital of a poorly managed bank usually constitutes a smaller ratio of its total assets compared to other normal banks. In addition, more recent data holds a stronger influence on predictive outcomes.

Similarly, the coefficients of TRCR (total risk-based capital ratio) increase as time moves further away from the collapse event. This suggests that the total risk-based capital ratio of a failed bank consistently declines as it approaches its failure.

In addition to the straightforward trend, both data sets display a distribution closely resembling a logarithmic curve in relation to the quarters.

3.3.1. A linear SVM model with only two variables

Visualizing a hyperplane in a 20-dimensional space, however, is intricate and unfeasible through a graph. To present more comprehensible results and reduce the complexity of the model, a model selecting only 2 variables from a pool of 100 variables was trained. (As using only 2 variables contain significantly less noise, cross-validation alone is sufficient to tackle overfitting.) This model demonstrates inferior performance compared to the 20-variable model, achieving a prediction accuracy of 98.756%, and the hyperplane equation of this model is:

$$-10.117 \times T1RCQ1 - 11.741 \times ECAQ1 + 1.362 = 0$$

The key variables that hold substantial predictive significance in anticipating instances of bank failures comprise T1RCQ1 (Tier 1 (core) risk-based capital to total assets in Quarter 1) and ECAQ1

(Equity capital to assets in Quarter 1). Remarkably, the variable T1RCQ1 does not emerge as a selection within the scope of the 20-dimensional linear SVM model. This observed disparity could be attributed to the overarching influence wielded by the TRCR factor throughout the complete ten-quarter period leading up to occurrences of bank failures, whereas T1RC demonstrates a more pronounced influence as a constituent variable within specific quarters. Moreover, these two factors exhibit a significant degree of interrelation, thus the identification of a variable change subsequent to an alteration in the count of selected variables is a coherent outcome.

Figure 3 visually presents the hyperplane and dataset within a 2-dimensional context.

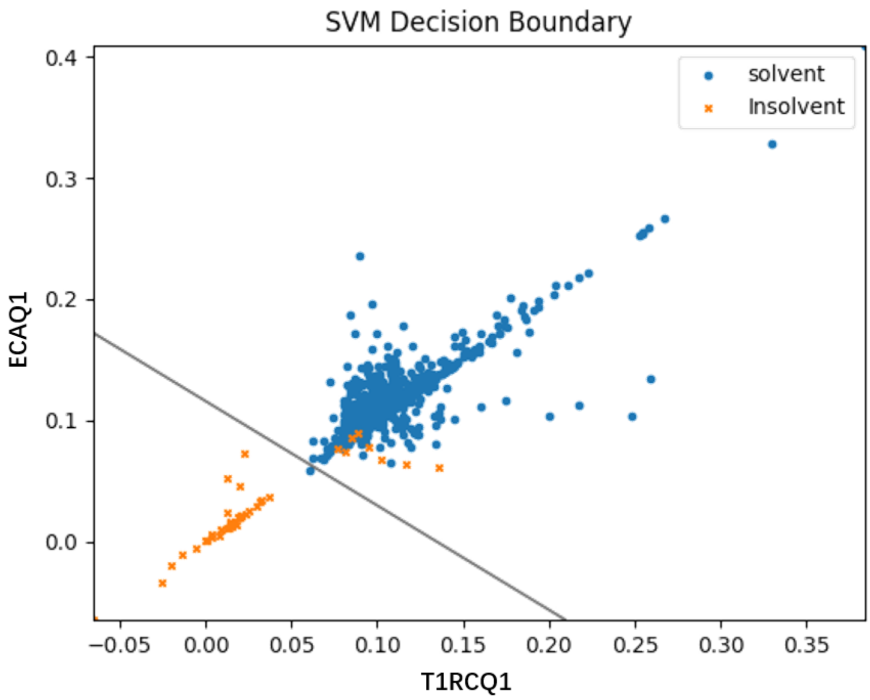

Figure 3: The bank dataset along with the 2D hyperplane

3.3.2. Classify the risk level

As evident from the analysis, a noteworthy portion of failed banks continues to be categorized as solvent under the linear SVM model. To address this limitation, a refinement in this approach is introduced, whereby banks are separated into four distinct level of risk (L1 for highest risk, L4 for lowest risk and so on). In the subsequent sections of this paper, this model is referred to the ’4-level model’ to prevent any confusion with the linear SVM model.

In the following, separators for these risk levels will be abbreviated, e.g. "Sep12" representing the separator between L1 and L2. The hyperplane generated earlier shows a remarkable accuracy in classifying the solvent banks, so it can effectively act as Sep12.

To establish the boundaries for the remaining three risk levels, a multi-classification approach is required for the SVM . Thus, a manual manipulation similar to the one-against-all method by Hsu and Lin in 2002 is executed on the penalty parameter ’C’. Through an increase in penalties associated with the erroneous classification of failed banks, and with a reduction in penalties for the misclassification

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of solvent banks, this research purposefully modify the class weighting scheme [16]. This adjustment culminates in the formulation that substantially advances the precision of failed bank classification. Consequently, through a calibration of the penalty parameter 'C', the other two separators are able to derived, which distinguish L2, L3 and L4. It's worth noting that while this process utilizes an approach similar to multi-classification, the dataset exclusively provides information regarding the occurrence of bank failures, rather than offering explicit insight into their distinct risk levels. Consequently, the 4-level model does not strictly qualify as a genuine multi-class SVM.

Given that increasing the penalty parameter 'C' for a relatively small class (failed banks) can potentially lead to overfitting, it becomes evident that reducing the complexity of the machine learning approach is essential.Thus, the new model is designed to operate in a two-dimensional space, as described above, instead of utilizing all 20 variables. The accuracy, along with the corresponding equations for each separator, have been presented in Table 5, and the graphical representation of the separators can be observed in Figure 4.

Table 5: The accuracy and equation of three separators for post-2013 4-level model.

Separator	Solvent Accuracy	Insolvent Accuracy	General Accuracy	CV Score	Equation
Sep12	99.868%	81.818%	98.881%	98.877%	-10.117×T1RCQ1-11.741×ECAQ1=-1.362
Sep23	97.368%	88.636%	96.891%	96.765%	-8.026×T1RCQ1-16.820×ECAQ1=-1.979
Sep34	95.132%	95.455%	95.149%	91.935%	-6.068×T1RCQ1-17.950×ECAQ1=-2.013

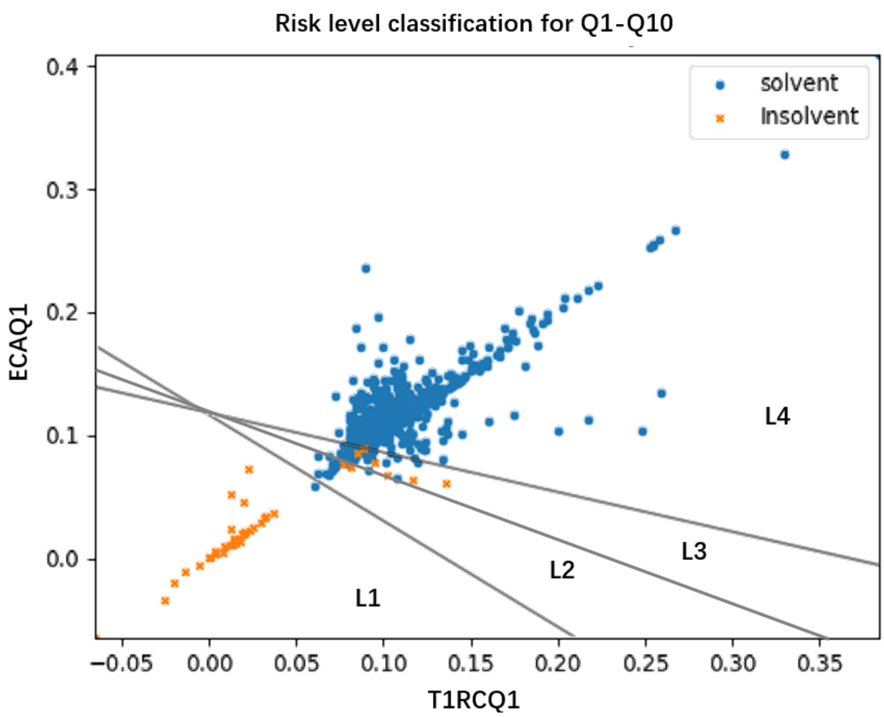

Figure 4: Graph of separators for post-2013 4-level model

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3.3.3. Long-term forecasting

In previous experiments, a forecasting model using the dataset is formulated, enabling an evaluation of risk levels for individual banks. Managers input historical data spanning the past 10 quarters, and the model generates a risk assessment for the bank in the upcoming month. Consequently, this forecasting model can only offer risk assessments for the immediate future. This limitation might not fully satisfy the needs of managers and regulators seeking to evaluate bank risks over a more extended period. To address this limitation, a long-term risk assessing model was developed by adapting this 4-level model in the following manner:

Select two most influential factors within "Q1-Q10" (20 variables) to build a 4-level model, as previously done.

Likewise, in the case of "Q2-Q10" (comprising 18 variables), after two quarters, identify the two most relevant variables. These chosen variables will then be input into the 4-level model to derive the updated separator equations. It is worth noting that the resulting separator equations are likely to differ from those of the initial model.

Repeat this process for "Q3-Q10" (16 variables) and "Q4-Q10" (14 variables) to create two additional models. These models enable predictions of the bank's risk level after 3 and 4 quarters, respectively.

Combine these four linear SVM models and establish a forecasting model that predicts bank failures 4-quarter in advance.

In practice, with managers inputting a bank's data from the past 10 quarters, data from 9, 8, and 7 moset recent quarters can be selected. This selected data can then be utilized as input for the risk level classification model, resulting in the bank's risk level prediction for the following 2, 3, and 4 quarters, respectively.

In this experimental setup, four 4-level models (Q1-Q10, Q2-Q10, Q3-Q10, and Q4-Q10) were developed, and evaluations were conducted for each model. The separator equations, their corresponding accuracy, and the accompanying graphs have been derived and are presented below. (Results for Q1-Q10 have already been derived above, so the following (Table 6 to Table 8 and Figure 5 to Figure 7) contains results for the remaining three models):

Table 6: The accuracy and equation of separators for post-2013 Q2-Q10 4-level model

Separator	Solvent Accuracy	Insolvent Accuracy	General Accuracy	CV Score	Equation
Sep12	99.079%	81.818%	98.134%	98.136%	-9.763×ECAQ3-12.688×ECAQ2=-1.619
Sep23	95.921%	90.909%	95.647%	96.148%	-12.753×ECAQ3-15.086×ECAQ2=-2.295
Sep34	84.605%	97.727%	85.323%	84.468%	-14.542×ECAQ3-15.234×ECAQ2=-2.762

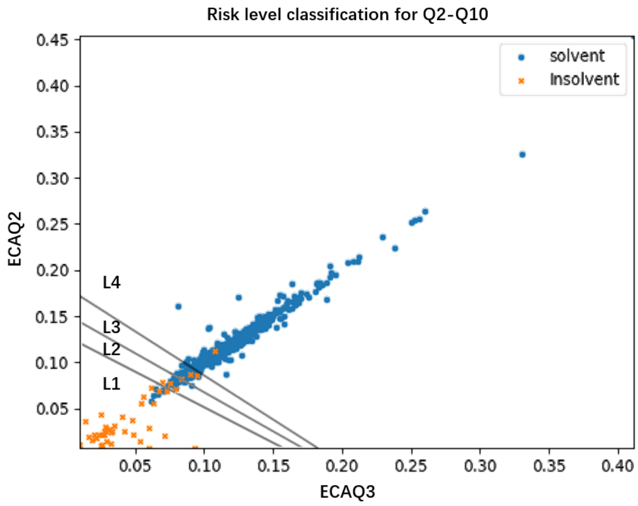

Figure 5: Graph of separators for post-2013 Q2-Q10 4-level model

Table 7: The accuracy and equation of separators for post-2013 Q3-Q10 4-level model

Separator	Solvent Accuracy	Insolvent Accuracy	General Accuracy	CV Score	Equation
Sep12	99.737%	75%	98.383%	98.383%	-11.199×ECAQ4-10.488×TRCRQ3=-1.911
Sep23	90.395%	86.363%	90.174%	88.815%	-14.895×ECAQ4-11.271×TRCRQ3=-2.675
Sep34	77.5%	97.727%	78.607%	79.002%	-15.137×ECAQ4-10.099×TRCRQ3=-2.731

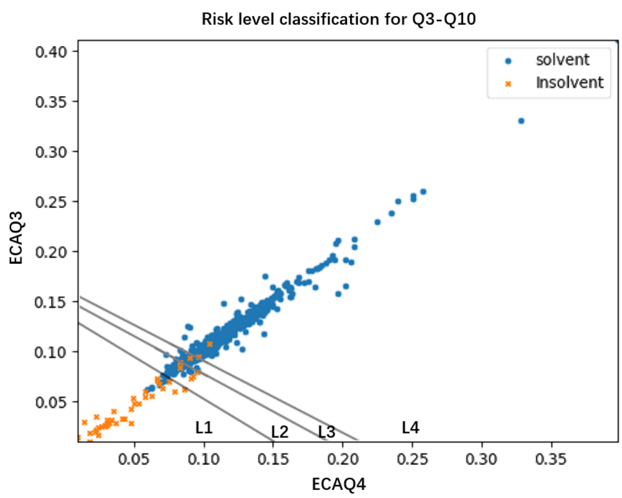

Figure 6: Graph of separators for post-2013 Q3-Q10 4-level model

Table 8: The accuracy and equation of separators for post-2013 Q4-Q10 4-level model

Separator	Solvent Accuracy	Insolvent Accuracy	General Accuracy	CV Score	Equation
Sep12	97.895%	77.273%	96.766%	96.523%	-9.806×ECAQ5-11.933×ECAQ4=-1.642
Sep23	87.763%	88.636%	87.811%	87.942%	-12.325×ECAQ5-15.274×ECAQ4=-2.416
Sep34	60.789%	95.455%	62.686%	63.211%	-12.229×ECAQ5-15.201×ECAQ4=-2.777

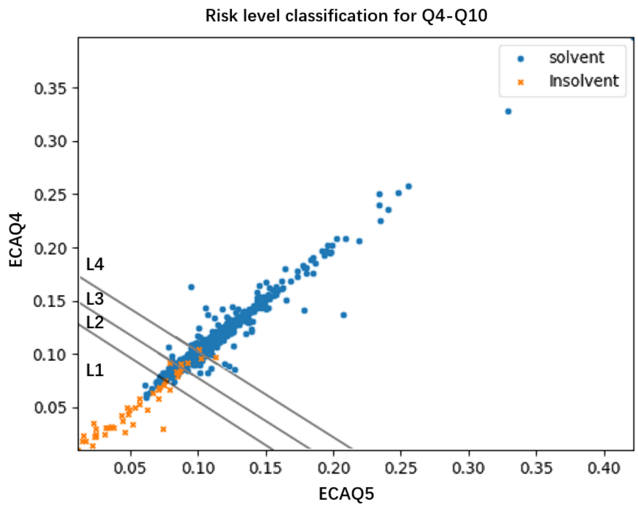

Figure 7: Graph of separators for post-2013 Q4-Q10 4-level model

Based on the results above, the accuracy trends of the 4-level model align with the expected pattern, where the general accuracy predicting for bankruptcies that are more distant in the future tends to decrease. For instance, the general accuracy of the Sep12 prediction trained by Q1-Q10 reduces from 98.881% to 96.766% when trained by Q4-Q10. In other words, as the model is trained with data from time points further removed, its overall accuracy tends to decline.

However, a slight fluctuation in insolvent accuracy persists. For instance, the general accuracy of the Sep12 prediction trained by Q3-Q10 data, which stands at 98.383%, is slightly higher than the 98.134% achieved when trained by Q2-Q10 data. This slight fluctuation is primarily can be attributed mainly to the constrained size of the failed banks dataset. In summary, despite the accuracy decline, the 4-level model maintains a relatively high overall accuracy even trained with quarters Q4-Q10. This suggests that the model retains its ability to effectively forecast the prospective risk level of a bank in the next year, thereby offering valuable insights to bank managers for enhancing their institutions.

4. Discussion

4.1. Application

In previous experiments, feature selection methods and SVM theory were used to construct two different models. The linear SVM models give a prediction whether a specific bank will fail while the 4-level model derive its risk level. However, in practice, merely forecasting failure or risk level is not enough for managers and regulators. In this part, several practical application of these two models are introduced:

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4.1.1. Stress testing model

Instead of solely inputting data exclusively from the bank under examination into the models, bank managers also have the option to input a combination of their bank's data along with data from failed banks or data from specific severe economic scenarios. This approach enables them to evaluate, under these rigorous conditions, whether the bank might potentially fail based on the prediction of the linear SVM model or whether the bank could maintain its present risk level based on the result of the 4-level model.

Additionally, beyond directly altering the data, managers can consider adverse economic events as a vector, denoted as $\mathbf{v}$, within the context of a two-dimensional scenario depicted in Figure 8.

Importantly, the utilization of a two-dimensional graph is intended to enhance the comprehensiveness and clarity of this approach. It is crucial to note that this methodology is not limited to two dimensions. Rather, it is applicable across all dimensions and is effective for both the linear SVM model and the 4-level model. This event exerts a negative impact on the bank, causing it to shift towards the lower-left side of the graph. A new separator can be defined by displacing the original separator $\mathbf{w} \cdot \mathbf{x} + b$ in the opposite direction of $\mathbf{v}$ with a magnitude of $\|\mathbf{v}\|$ (illustrated as the dashed line in Figure 8). This new separator is parallel to the initial one, and its equation is:

$$\mathbf{w} \cdot (\mathbf{x} + \mathbf{v}) + b = 0$$

In financial terms, this hyperplane determines whether the bank will transition into the insolvency class (or a higher risk level) as a result of the impact of the event $\mathbf{v}$.

Now, let's consider two banks, namely Bank A and Bank B, with their respective positions illustrated in Figure 8. Notably, Bank A is positioned farther from the original separator ($\mathbf{w} \cdot \mathbf{x} + b$) in comparison to Bank B. This positioning implies that Bank A often demonstrates a greater resilience against adverse economic conditions or systemic shocks. Furthermore, upon introducing the new separator ($\mathbf{w} \cdot (\mathbf{x} + \mathbf{v}) + b$), despite both institutions are classified as solvent in the linear SVM model (or categorized as Li in the 4-level model, where $i = 2, 3, 4$, thereby making $\mathbf{w} \cdot \mathbf{x} + b$ represent Separator of Li and $L(i-1)$), there remains a notably high potential risk for Bank B under the influence of this event. (Bank B is anticipated to transition into the insolvency class or a higher risk level.)

Consequently, both of the methods mentioned above provide a practical application for utilizing this linear SVM models as well as the 4-level model in stress testing. These methods aid bank managers in evaluating their bank's capacity to withstand adverse conditions and the potential impact of economic downturns on their institutions.

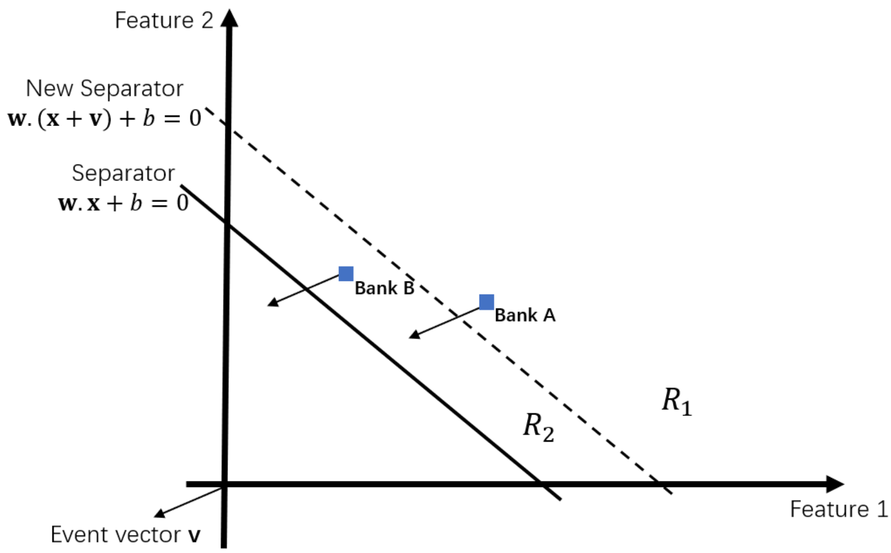

Figure 8: Graph of two separators, Bank A, Bank B, and the event vector v

4.1.2. Improvement strategy

In addition to negative influences, certain events can also positively impact a bank's operations. However, it is important to note that bank managers cannot rely solely on the occurrence of these events to enhance their bank's operations. Instead, they must proactively make improvements to the bank's operations through strategic actions. In the following, the paper will introduce how to use the linear SVM model or a 4-level model mentioned in the previous part to enhance bank operations.

Figure 9 illustrates a simplified 2-dimensional scenario. However, it is important to emphasize that our methodology is applicable across all dimensions. Within this context, point C represents a particular bank (referred to as bank C) and is characterized by its position vector $\mathbf{x}_c$. According to the 4-level model, this bank is classified as L1 which means it has very high risk of potential failure. (or predicted to fail in a near future in linear SVM model) To shift it into L2, the high-risk category, (or solvency class in linear SVM model) various strategies are viable for bank C. This can be accomplished by elevating either feature 1, feature 2, or both, until the bank's position lies above the separator.

For bank managers aiming to enhance their institution's operations, the primary objective is to identify the improvement strategy that incurs the minimal opportunity cost. Initially, let us consider a loss function denoted by $f(\mathbf{x})$, which quantifies the impact of altering the bank's state by a vector $\mathbf{x}$. The manager's objective is to reduce the bank to a lower risk level by adjusting its position through a vector $\mathbf{x}$, where the equation of the separator is:

$$\mathbf{w}\cdot\mathbf{x}+b=0$$

This problem can be formalized as follows:

$$\min_{\mathbf{x}} f(\mathbf{x}) \text{ s.t. } \mathbf{w}\cdot(\mathbf{x}_c+\mathbf{x})+b>0$$

By employing the Lagrangian approach, the problem can be written as:

$$\min_{\mathbf{x}} f(\mathbf{x})-\lambda(\mathbf{w}\cdot(\mathbf{x}_c+\mathbf{x})+b-z)$$

Here, λ represents the Lagrange multipliers and z acts as a slack variable, with the conditions $\lambda > 0$ and $z > 0$

As a result, the optimal strategy for improvement, denoted as $\widehat{\mathbf{x}}$, can be derived by differentiating the equation with respect to $\mathbf{x}$ and subsequently satisfying the equation:

$$\nabla f(\widehat{\mathbf{x}}) = \lambda \mathbf{w}$$

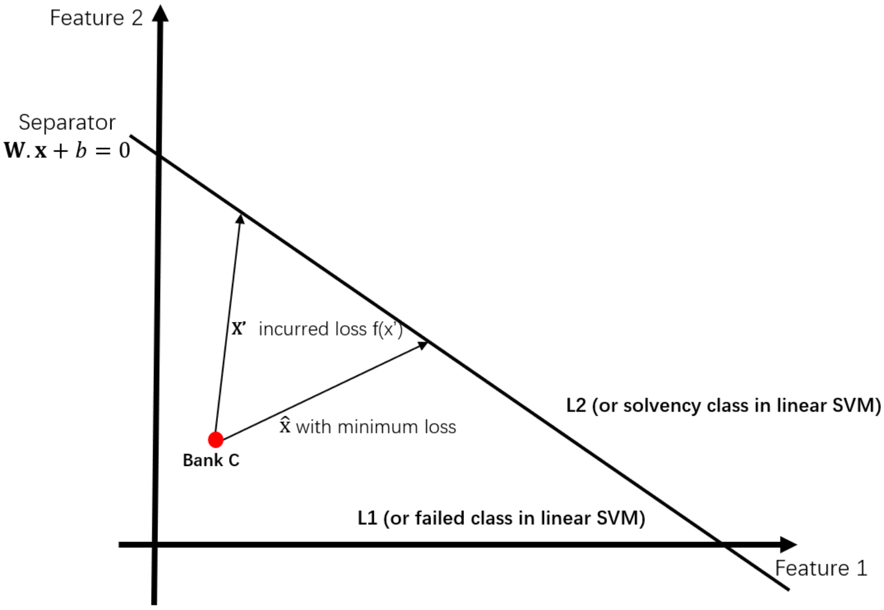

Figure 9: A simplified 2-dimensional scenario for improving strategy of the bank

4.2. Comparison

In the preceding sections, this research developed a long-term forecasting model to assess the risk of bank failure, and the SVM model has exhibited a high accuracy. In this section, several distinct types of comparisons will be undertaken.

4.2.1. Comparison between SVM and Neural Networks

The study conducted by Iturriaga and Sanz (2015) gave a comparative analysis of the Artificial Neural Networks and Support Vector Machines (SVM) in the context of predicting U.S. bank failures from 2002 to 2012 [17]. Their investigation indicated that Neural Network methodologies are more accurate in a short period, specifically in the immediate year prior to a bank's failure, whereas the SVM approach outperforms over long durations (2 to 3 years preceding a bank's failure).

In this study, two distinct models were formulated: a linear Support Vector Machine (SVM) model and an Artificial Neural Networks (ANN) model. Both model are trained with ten-fold crsoss validation to avoid the overfitting happens. These models were trained using data from different time intervals to evaluate the accuracy of predictions in both the short term and long term. The outcomes of the analysis are comprehensively outlined in Table 9. Notably, the ANN model demonstrates several distinctive characteristics:

(a) The first phenomenon is similar to the long-term SVM model which has been developed in the preceding section. The predictive accuracy of the ANN model also demonstrates a decline for bankruptcies projected further into the future. In other word, as the model incorporates data from more distant time points during training, its overall accuracy tends to diminish. This trend aligns precisely with our expectations. For instance, the general accuracy of the prediction results obtained from the ANN model exhibits a decrease from 82.090% to 79.104%. Moreover, owing to the restricted dataset size, a certain degree of fluctuation remains evident. For instance, the general accuracy of the ANN model trained using Q4-Q10 data is marginally higher than that achieved using Q3-Q10 and Q2-Q10 data.

(b) Despite the relatively poor overall accuracy demonstrated by the ANN model, it is noteworthy that the accuracy pertaining to insolvent cases is higher in the ANN model compared to the SVM model across all four training phases. However, through the strategic manipulation of the penalty parameter, the SVM model can also achieve a heightened level of accuracy in predicting insolvent cases. A comparative analysis of the Sep23 (Separator of L2 and L3) accuracy between the SVM and Neural Network models is presented in Table 9. Evidently, all three accuracy types of Sep23 are higher than those of the neural network, thereby indicating that when confronted with a limited dataset, the performance of the neural network are inferior than that of the SVM model across all evaluated dimensions.

(c) Furthermore, the ANN model operates with a notably intricate algorithm. While it outperforms in accomplishing precise classifications, the decision boundary is often not as transparent. This presents two challenges. First, upon categorizing a bank as insolvent, the ANN model does not offer the proximity of this classification to the solvent region, nor does it quantify the associated risk level. Second, the ANN model falls short in delivering feasible recommendations to specific banks, rendering it less effective in assisting bank managers with practical solutions. In contrast, the application of the Linear SVM model yields distinct advantages. The model establishes a hyperplane with precision, furnishing a clear separation between categories. This distinct boundary empowers us to provide concrete recommendations to bank managers, enhancing the model's utility in offering feasible solutions.

Table 9: The accuracy of Sep23 and Artificial Neural network in short and long term

Train Phases	Linear SVM model (Sep23)			Neural Network		
	Solvent Accuracy	Insolvent Accuracy	General	Solvent Accuracy	Insolvent Accuracy	General
Q1-Q10	97.368%	88.636%	96.891%	81.711%	88.636%	82.090%
Q2-Q10	95.921%	90.909%	95.647%	77.895%	86.364%	78.358%
Q3-Q10	90.395%	86.363%	90.174%	77.763%	86.364%	78.234%
Q4-Q10	87.763%	88.636%	87.811%	78.816%	84.091%	79.104%

4.2.2. Comparison between feature selection results in two periods

For training the SVM models in the two distinct periods, it was necessary to perform feature selection separately. The outcomes of this process hold valuable insights for analysis as well. The results of feature selection for the two timeframes are presented in Table 2 and Table 3 in the earlier section.

Although the result of feature selection are relatively similar in two periods, this experiment indicates there is still several remarkable difference between results of two periods:

(1) GOI (Goodwill and other intangibles to total assets) and TRCR (Total risk-based capital ratio) plays a more important role recently;

(2) The importance of CCR (Core capital (leverage) ratio) and VL (Volatile liabilities to total assets) drops significantly.

Although both ratios provide valuable insights,there is a trend that the importance of TRCR over CCR.Here is the breakdown of their differences and potential reasons:

(a) The Total Risk-Based Capital Ratio takes into account a broader range of risks that a bank might face, including credit risk, market risk, and operational risk. This makes it a more comprehensive measure of a bank's overall financial strength and ability to withstand various types of economic and financial shocks.

(b) The Total Risk-Based Capital Ratio adjusts the capital requirement based on the risk profile of a bank's assets and activities. This means that banks with riskier portfolios will be required to hold more capital to cover potential losses. This sensitivity to risk makes the Total Risk-Based Capital Ratio more reflective of a bank's actual risk exposure.

(c) The Total Risk-Based Capital Ratio is designed to assess a bank's ability to weather economic downturns and financial crises. By incorporating various risk factors, it provides a more realistic assessment of a bank's resilience in adverse scenarios.

To sum up, the Total Risk-Based Capital Ratio is often considered more comprehensive and reflective of a bank's risk exposure. It takes into account a wider range of risks, aligns with international standards, and is used as a regulatory compliance measure.

In addition, GOI also plays an essential role among these correlative factors.Goodwill and other intangibles generally represent non-physical assets such as brand value, intellectual property, customer relationships, and patents.The ratio of Goodwill and other intangibles to total assets is a financial metric that provides insights into a bank's financial structure and the extent to which intangible assets, like goodwill, contribute to its overall asset base.The reasons why this ratio can be important and what it signifies are:

(a) The ratio helps assess the significance of intangible assets on a bank's balance sheet. It provides an indication of how much of the bank's value is tied up in assets that do not have a physical presence.

(b) Goodwill is often recorded when a bank acquires another bank for a price that exceeds the fair value of its identifiable tangible and intangible assets. This excess is recorded as goodwill. Banks need to periodically assess whether their recorded goodwill has become impaired due to changes in economic conditions. A higher ratio of goodwill to total assets might indicate a higher risk of goodwill impairment, which could impact a bank's financial health.

(c) The presence of a significant amount of goodwill and intangibles can impact financial ratios, such as return on assets (ROA) and return on equity (ROE). Since these intangibles typically do not generate immediate cash flows, their inclusion in the asset base might lead to lower returns on these metrics, potentially affecting how depositors and funder perceive the bank's profitability and efficiency.

(d) Banks with a high ratio of goodwill and other intangibles to total assets might experience greater volatility in their financial performance. Intangibles are often more difficult to value and can be subject to changes in market sentiment. This can lead to fluctuations in reported assets and potentially impact a bank's stability during economic downturns or changes in economy dynamics.

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4.2.3. Comparison between SVM model

During 2008 financial crisis, numerous banks succumbed to bankruptcy. However, after 2013, instances of bank failures experienced a marked reduction. This transformation can be attributed to enhancements in the risk management framework and the steady economic progress in the United States. In this study, a comparative analysis of bank failures occurring in 2010 and those failed after 2013 was conducted. The objective of this work was to discern similarities or differences in the contributing factors for bankruptcy during these two distinct periods. Consequently, this research constructed two types of SVM models: the first utilizing a dataset of insolvent and solvent banks in 2010, while the second model was founded upon data after 2013.

At first, feature selection methods were utilized and the result was in Table 2. Then this work established a hyperplane in 16 dimensions (2 factors in 8 quarters), the equation shows below:

$$3.924 \times NLLQ1 + 2.194 \times NLLQ2 + 1.865 \times NLLQ3 + 2.160 \times NLLQ4$$
$$+1.515 \times NLLQ5 + 1.102 \times NLLQ6 + 1.032 \times NLLQ7 + 0.260 \times NLLQ8$$
$$-3.440 \times ECAQ1 - 3.046 \times ECAQ2 - 2.057 \times ECAQ3 - 1.113 \times ECAQ4$$
$$-1.129 \times ECAQ5 - 0.652 \times ECAQ6 - 0.179 \times ECAQ7 - 2.228 \times ECAQ8 - 0.088 = 0$$

Additionally, a 4-level model is also trained which demonstrated four different risk levels. The evaluation of two models in different periods are presented in Table 10. and the equations and the graph of three separators show below:

Sep12:

$$10.799ECAQ2 + 10.317TIEQ1 - 1.246 = 0$$

Sep23:

$$12.817ECAQ2 + 10.564TIEQ1 - 1.637 = 0$$

Sep34:

$$12.237ECAQ2 + 7.651TIEQ1 - 1.684 = 0$$

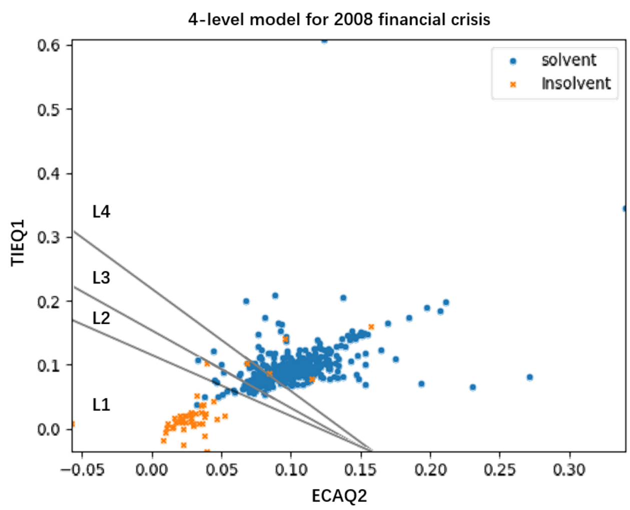

Figure 10: graph of 4-level model for 2008 financial crisis

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Table 10: The comparison between rank of factors from linear SVM model

Post-2013	2008 financial crisis
ECA (Equity capital to assets)	NLL (Noncurrent loans to loans)
TRCR (Total risk-based capital ratio)	ECA (Equity capital to assets)
TD (Total Deposits to total assets)	CCR (Core capital (leverage) ratio)
NLLTA (Net loans and leases to total assets)	TD (Total Deposits to total assets)
NLL (Noncurrent loans to loans)	NCL (Net charge-offs to loans)
T1RC (Tier 1 (core) risk-based capital to total assets)	TIE (Total interest expense to total interest income)
LAL (Loss allowance to loans)	T1RC (Tier 1 (core) risk-based capital to total assets)
NCL (Net charge-offs to loans)	VL (Volatile liabilities to total assets)
GOI (Goodwill and other intangibles to total assets)	LAL (Loss allowance to loans)

Based on the results of two models, this research present an analysis of temporal changes in the factors of SVM model:

The 2007–2008 financial crisis is commonly viewed as the worst financial crisis since the Great Depression of the 1930s [18].

According to the definition given by Ross and Shibut (2021) , the non-current loans to loans ratio (NLL) is a financial metric that measures the percentage of non-current loans (loans that are past due by 90 days or more) to the total amount of loans held by a bank or financial institution [19]. It is also known as the non-performing loan (NPL) ratio, an important indicator of the health of a bank's loan portfolio, as it reflects the percentage of loans that are at risk of default. This research result infers that NLL ratio is particularly significant during a financial crisis, the possible reasons are:

First of all, during a financial crisis, economic conditions are likely to deteriorate, leading to reduced income, business closures, and job losses. This can result in borrowers struggling to make timely loan payments, which will increase the NLL ratio. And a high NLL ratio indicates that a significant portion of a bank's loans are at risk of not being repaid (the quality of the bank's loan portfolio decreases). Thus, NLL ratio can reveal the credit risk exposure of a bank, affecting the bank's capital adequacy, profitability, and overall financial health.

Non-current loans to loans ratio ties up a bank's resources and capital, limiting its ability to lend and invest. If the NLL ratio is high, the bank's capital may be eroded due to provisions set aside to cover its potential loan losses. This may impact the bank's ability to absorb further losses and maintain stability. Moreover, non-current loans can reduce a bank's cash flow as loan repayments are delayed or not received. This will impact the bank's liquidity position to some extent, making it harder to meet obligations and respond to deposit withdrawals during times of stress.

A widespread increase in NLL ratios across multiple banks will contribute to systemic risk, where the health of the entire financial system is compromised. A crisis-induced surge in non-current loans can lead to a credit crunch, making it harder for businesses and consumers to access credit. As a result, investor confidence in a bank's financial health and management may be eroded. This will further lead to decreased stock prices, increased borrowing costs, and reduced access to capital markets.

Regulatory authorities closely monitor NLL ratios as a measure of a bank's risk exposure. During a crisis, regulators may require banks to maintain higher capital buffers to withstand potential loan losses, ensuring the stability of the financial system.

ECA becomes especially important during financial crises and after regulatory changes, such as those introduced after 2013 with the implementation of Basel III banking regulations. The following are the possible reasons why ECA is vital:

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During the period of financial crisis, banks may face unexpected losses due to economic downturns, credit defaults, and market turmoil. A higher equity capital to assets ratio provides a buffer that enables the bank to absorb losses without jeopardizing its financial stability.

Moreover, in bad times, banks might be hesitant to lend because of increased credit risk. A strong capital base can enhance a bank's confidence to continue lending, helping to maintain the flow of credit to individuals and businesses, which is crucial for economic recovery.

Regulators normally require banks to maintain a minimum capital adequacy ratio to ensure their stability. In a drastic situation, regulatory authorities might impose stricter capital requirements to enhance the resilience of the financial system.

Stricter capital requirements for banks were implemented by the Basel III framework after 2013 to increase their resilience to financial crises. To reduce risks and guard against potential losses, banks must maintain stronger equity capital to assets ratios. Risk-based capital requirements, which relate the necessary capital to the riskiness of a bank's assets, were also introduced by Basel III. As a result, banks holding riskier assets must maintain greater levels of equity capital, underscoring the significance of the equity capital to assets ratio for risk management.

4.3. Limitations and Solution

4.3.1. Limitations:

The previous experiments have established a linear SVM model and 4-level model regarding bank failures. Nevertheless, this research has some limitations and inadequacies, which can be outlined as follows:

1. Limited data volume: Owing to regulation improvements, the number of bank failures in the United States decreased significantly after 2013. Consequently, only 44 banks possess complete data for the ten quarters preceding their collapse. As a result, the dataset used in this study is relatively limited in size. The relatively small size of the dataset has posed difficulties in generalization and contributed to overfitting in the two models.

2. The authenticity of the data: The dataset, sourced from FDIC via U.S. bank quarterly call reports, contains a significant number of non-listed banks. This raises concerns about data reliability due to their lack of transparency and regulatory oversight. Non-listed banks may submit inaccurate or fabricated reports to conceal financial risks or engage in improper activities. Even without deliberate manipulation, data from these banks may be unreliable due to less rigorous internal reporting and record-keeping. Consequently, models trained on such data may be influenced by false information, potentially distorting the accuracy of the resulting 4-level or linear SVM model.

3. Regional Scope: In this study, the period of the models extends from 2013 and this research is specifically centered on domestic banks within the United States. In fact, different countries exhibit unique economic conditions and national policies, leading to diverse reasons for bank failures and a wide range of risks encountered by banks. Therefore, both the linear SVM model and the 4-level model are exclusively applicable to banks operating within the United States.

4.3.2. Potential solution for the limitation:

1. Limited Data Volume: To address the limitations arising from the dataset's limited size, integrating relevant datasets from other countries that share similar economic conditions and national policies with the United States may help. Alternatively, extending the time period covered by the dataset can also provide supplementary data. These adjustments have the potential to enhance the models'

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performance and alleviate the challenges mentioned earlier. Moreover, an Artificial Neural Network can be trained using this expanded dataset, which is likely to yield improved results.

2. Authenticity of the Data: Addressing concerns about data authenticity and reliability can be approached as follows:

(a) Implement more rigorous procedures for data validation and cleaning. Instead of relying solely on FDIC data, expand the scope to incorporate additional data sources. This will enable cross-referencing of data from diverse sources to identify inconsistencies and erroneous entries more effectively.

(b) Assess the models' robustness by conducting simulations to evaluate the impact of potential data inaccuracies. This can be achieved by introducing synthetic errors into the dataset and observing the effects on the models' results.

3. Regional Scope: To address the issue of regional scope and generalizability:

(a) Extend these modeling techniques to other regions or countries with distinct economic conditions and policies compared to the United States. This expansion would provide a comprehensive perspective on bank failure prediction across diverse contexts.

(b) Conducting a comparative analysis of the models' performance across various regions offers valuable insights into potential variations when applied beyond the United States.

(c) If certain factors used in the SVM model or 4-level model are specific to the United States, modify the models to incorporate context-specific variables that align with the characteristics of each respective region.

4.4. Prospects

The knowledge of human analysts can be supplemented with machine learning. Analysts can concentrate on higher-level decision-making and scenario refinement by using it to generate insights, uncover hidden patterns, and automate repetitive processes.While there is a lot of potential for employing machine learning for stress tests, there are also issues that need to be resolved in the future, including data quality, model interpretability, regulatory approval, and potential algorithmic biases. Domain experts, data scientists, and regulators must work together to make sure that ML-driven stress testing becomes a dependable and widely used procedure in the banking sector.

5. Conclusion

This paper discusses the importance of ensuring the healthy operations of banks to prevent failures, especially in challenging economic conditions. It presents a forecasting model that can be used by bank managers and governments for this purpose. The model can also function as a stress testing tool by incorporating data from banks under extreme scenarios to assess their resilience.

The research used a dataset that included data from failed U.S. banks from 2014 to 2023, matched with solvent banks for analysis. A total of 42 variables were collected for each bank over ten consecutive quarters before a bank's failure. A feature selection process was used to identify the most relevant variables for prediction and classification.

The retained 10 factors from the dataset were used to train a Support Vector Machine (SVM) model with a tenfold cross-validation approach to fine-tune hyperparameters. The optimized hyperplane accurately distinguished between solvent and insolvent banks with an impressive accuracy rate of 99.341%. The model also assessed the risk level of potential bank failures, providing a more nuanced view.

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The paper compares the SVM model with a Neural Network algorithm, finding comparable accuracy but noting the SVM's advantage in risk assessment due to its transparency. Additionally, it compares highly correlated factors in two different time intervals, revealing changes in the importance of specific variables.

The findings and details of these comparisons are discussed in the paper.

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