LSTM-Integrated Particle Swarm Optimization Model for Listed Companies

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Abstract. In the context of global economic integration, credit risk assessment of listed companies is crucial for maintaining capital market stability. However, traditional methods rely on static financial indicators, which are limited by timeliness and subjective parameter selection. While LSTMs excel at capturing long-term dependencies in financial time series data, they are limited by the difficulty in accurately determining key hyperparameters, such as the number of hidden layer neurons and the learning rate, which hinders their predictive performance. Therefore, this study proposes a credit risk assessment model for listed companies based on a combination of a long short-term memory network (LSTM) and a particle swarm optimization (PSO) algorithm. This model overcomes the core limitations of traditional methods in time series data processing and parameter optimization. Using deep learning techniques, the model automatically extracts features from time series data and effectively captures the dynamic impact of different financial indicators on credit risk. The particle swarm optimization algorithm is used to optimize the LSTM model's hyperparameters, thereby improving predictive accuracy and stability. Empirical results show that the proposed model outperforms traditional methods across multiple evaluation metrics, achieving an accuracy of 92.3% and a recall of 90.1%, validating its effectiveness and practical value in credit risk assessment. This model theoretically overcomes the bottleneck of LSTM parameter tuning. In practice, it can provide investors and regulators with a high-precision risk assessment tool, helping to improve capital market risk management.

Keywords: Credit Risk Assessment, LSTM, Particle Swarm Optimization, Financial Health, Deep Learning

1. Introduction

1.1. Research Background and Significance

In the context of global economic integration, as an important component of the capital market, the financial health of listed companies directly affects investor decision-making and market stability. The traditional financial risk warning system mainly selects financial indicators from three aspects: profitability, debt paying ability, and growth to comprehensively evaluate the performance of listed companies [1]. Although these evaluation systems can reflect the financial situation of enterprises to a certain extent, they face limitations such as indicator orientation towards the past and ease of operation.

With the rapid development of artificial intelligence technology, machine learning methods have shown great potential in the field of credit risk assessment. LSTM, a special recurrent neural network, introduces cells to address the vanishing and exploding gradient problems found in traditional neural networks, and excels in processing time series data [2]. Furthermore, the particle swarm algorithm, an optimization algorithm based on swarm intelligence, can be used for parameter optimization in credit risk prediction, helping machine learning models find optimal weights and thresholds [3].

Constructing a credit risk assessment model based on LSTM and particle swarm optimization has important theoretical and practical significance. From a theoretical perspective, this model can overcome the timeliness limitations of traditional financial indicator evaluation systems. Using deep learning techniques, it automatically extracts deep features from financial data and explores the complex relationship between these features and credit risk. The introduction of the particle swarm algorithm solves the difficulty of parameter selection in the LSTM model and avoids the high overhead of traditional grid search algorithms [4-7]. From a practical perspective, this model can provide investors, regulators, and financial institutions with a more accurate risk assessment tool, helping to improve risk management and promote the healthy development of the capital market. By combining quantitative and qualitative methods, the model can provide a more comprehensive and accurate assessment of the credit status of listed companies.

1.2. Research Objectives and Content

This research aims to construct an efficient and accurate credit risk assessment model for listed companies. By integrating the advantages of LSTM neural networks and particle swarm optimization, it addresses the shortcomings of traditional credit risk assessment methods in processing time series data and parameter optimization. LSTM models demonstrate significant advantages in processing complex time series data. The key to their training process lies in parameter selection. Traditional parameter selection methods often rely on manual experience, which is subject to high subjectivity and uncertainty, seriously affecting the model's predictive accuracy.

The core goal of this research is to develop a scientific credit risk assessment system that can fully utilize multi-dimensional information such as listed companies' financial data, market performance, and macroeconomic indicators. The particle swarm optimization algorithm has the advantages of high solution accuracy and rapid convergence, and is frequently used in optimization applications. By applying the particle swarm optimization algorithm to the parameter optimization of LSTM networks, it can automatically search for the optimal solution in the parameter space, reducing the amount of manual work during model training. This combination effectively addresses the difficulty in determining the number of neurons, learning rate, and number of iterations in the LSTM network.

The research primarily encompasses four core areas. Theoretically, the research will conduct an in-depth analysis of the LSTM model's applicability to credit risk assessment and explore its mechanisms for capturing dynamic changes in a company's financial status. Furthermore, the research will examine the role of the particle swarm optimization algorithm in optimizing neural network hyperparameters and establish a PSO-LSTM fusion framework suitable for credit risk assessment scenarios. In terms of data processing, a comprehensive credit risk assessment indicator system for listed companies will be constructed, covering multiple dimensions such as financial ratios, market indicators, and governance structure, and an effective data preprocessing process will be designed. In terms of model construction, an LSTM network architecture will be designed for credit risk assessment tasks, determining appropriate input feature combinations and network hierarchical structures. Furthermore, the particle swarm algorithm parameters will be optimized to meet the requirements of LSTM hyperparameter optimization. Empirically, representative sample data from listed companies will be used for model training and testing. Comparative analysis with traditional credit risk assessment methods will verify the effectiveness and superiority of the proposed model, providing a scientific basis for financial institutions' credit decisions.

2. Literature Review

2.1. Research on Credit Risk Assessment

Credit risk assessment, as a core component of financial risk management, has long been a key area of focus for both academia and industry. Traditional credit risk assessment methods primarily rely on statistical models and empirical judgment, including linear models like logistic regression and discriminant analysis. These methods have significant limitations when dealing with complex nonlinear relationships. With the advent of the big data era, the financial data of listed companies exhibits high-dimensional, multi-time series characteristics, making it difficult for traditional methods to effectively capture the complex patterns and potential correlations.

In recent years, machine learning technology has shown strong potential for application in the field of credit risk assessment. Neural network models excel in handling complex financial data relationships due to their powerful nonlinear fitting ability. Especially recurrent neural networks and their variants can effectively handle long-term dependencies in time series data, which is of great significance for analyzing the evolution of historical financial performance and credit status of listed companies. The introduction of deep learning methods enables models to automatically learn advanced features from data, reducing the workload of manual feature engineering and improving the accuracy of risk identification.

LSTM models are increasingly widely used in time series prediction and risk assessment. Their unique gating mechanism selectively retains and forgets information, effectively solving the vanishing gradient problem of traditional neural networks when processing long sequences [8]. In specific applications of credit risk assessment, LSTM can exploit the temporal variations of corporate financial indicators and identify early signals that may indicate a deterioration in credit status. This time series modeling capability is invaluable for dynamically assessing the credit risk of listed companies and can provide more accurate support for investment decision-making and risk management.

In practical applications, traditional neural network models face difficulties in parameter tuning and are prone to falling into local optimal solutions. These issues seriously affect the model's predictive accuracy and stability. Key parameters such as the number of neurons, learning rate, and number of iterations in LSTM networks are often difficult to determine. Most studies use a traversal grid search algorithm for parameter selection, but this method suffers from high computational overhead. In the application scenario of credit risk assessment, which requires extremely high accuracy, the subjectivity and uncertainty of parameter selection can reduce the reliability of assessment results and affect the effectiveness of risk management decisions.

2.2. Applications of LSTM and Particle Swarm Optimization

Long Short-Term Memory (LSTM) neural networks, as a key model in deep learning, have demonstrated outstanding performance in time series prediction and complex data modeling. Through their unique gating mechanism, LSTM models can effectively handle long-term dependencies in sequence data, overcoming the vanishing gradient problem [9] of traditional recurrent neural networks, which suffers from the gradual reduction of gradients during backpropagation. This characteristic has led to the widespread application of LSTM in fields such as financial risk assessment, power load forecasting, and vehicle behavior analysis.

In practical applications of LSTM models, parameter optimization remains a key factor influencing model performance. Traditional parameter selection methods mostly rely on manual experience to determine key parameters such as the maximum number of iterations, the initial learning rate, and the number of hidden layer neurons. This approach is highly subjective and uncertain, significantly impacting the model's predictive accuracy. Current research on parameter selection for LSTM models mostly employs traversal grid search algorithms, which suffer from high overhead and make it difficult to determine the number of neurons, learning rate, and number of iterations in the LSTM network.

The particle swarm optimization algorithm, a swarm intelligence optimization algorithm, automatically searches for the optimal solution in the parameter space by simulating the information sharing and collaboration processes of swarm intelligence. Compared to genetic algorithms, the particle swarm optimization algorithm offers advantages such as faster optimization speed and simpler structural parameter setting [10]. The particle swarm optimization algorithm is widely used to solve various hyperparameter optimization problems. Each particle has a speed and a fitness value that determine its flight direction and distance. The optimal solution is found by sharing information among individuals in the swarm. When training LSTM models, the particle swarm optimization algorithm can help the model more effectively adjust parameters to adapt to complex data characteristics, reducing the amount of manual work required during model training. The adjusted model also performs well in predicting data.

The PSO-LSTM hybrid model, which combines the particle swarm optimization algorithm with the LSTM model, has demonstrated significant advantages in multiple application areas. The quantum particle swarm optimization-enhanced long-short-term memory neural network model exhibits significant advantages in predictive accuracy and stability. This combination not only improves the model's predictive accuracy but also enhances its generalization and robustness, providing more scientific and rational technical support for complex data modeling and prediction.

3. Research Methods

3.1. LSTM Model Construction

In credit risk assessment, the construction of LSTM networks must fully consider the complexity and dynamic characteristics of listed companies' financial time series data. The LSTM model constructed in this study consists of three core components: an input layer, a hidden layer, and an output layer. It achieves accurate risk prediction by capturing the temporal dependencies of corporate financial indicators. The model input layer receives preprocessed multidimensional financial time series data, including key indicators such as debt-to-asset ratio, current ratio, and return on equity. This data constitutes the fundamental information dimension for credit risk assessment.

The key to the LSTM network lies in its unique gating mechanism design, which effectively addresses the vanishing gradient problem that traditional recurrent neural networks encounter when processing long sequences. The LSTM unit used in this study contains three gate structures: a forget gate, an input gate, and an output gate. Traditional LSTM parameter selection often relies on manual experience or grid search methods, which are not only computationally expensive but also difficult to guarantee a global optimal solution. The determination of hyperparameters such as the number of hidden layer neurons, the learning rate, and the number of training iterations in the network are key factors affecting model performance. To address this issue, this study will detail how to optimize the parameters of the LSTM network using the particle swarm algorithm in subsequent chapters.

The model's output layer uses a sigmoid activation function to map the LSTM network's output to a probability value between 0 and 1, representing the risk of a company defaulting on its credit. This design enables the model to provide quantitative credit risk assessment results for each listed company, providing a scientific basis for investment decisions and risk management. The entire LSTM model training process utilizes a backpropagation algorithm, updating network parameters by minimizing the cross-entropy loss function between the predicted value and the actual label.

3.2. Particle Swarm Algorithm Design

The particle swarm algorithm, a swarm intelligence optimization algorithm, is based on the simulation of the foraging behavior of bird flocks. In this study, the particle swarm algorithm was specifically designed to optimize the hyperparameter configuration of the LSTM model to improve the predictive accuracy and stability of the credit risk assessment model. By simulating the information sharing and collaboration processes in swarm intelligence, the algorithm automatically searches for the optimal solution in the parameter space.

In the LSTM credit risk assessment model, the particle swarm algorithm primarily optimizes three key hyperparameters: the number of hidden layer neurons, the learning rate, and the number of training iterations. During algorithm initialization, a swarm of particles is randomly generated within a preset parameter range, with each particle representing a potential set of hyperparameter combinations. The position of a particle in the search space is represented as:

$$X_i=(n_{\mathrm{h}idden}, lr, epoc\mathrm{h}s) \tag{1}$$

Where $n_{\mathrm{h}idden}$ represents the number of hidden layer neurons, lr represents the learning rate, and $epoc\mathrm{h}s$ represents the number of iterations. The particle velocity update formula is:

$$V_i^{t+1}=w\cdot V_i^t+c_1\cdot r_1\left(P_{best,i}-X_i^t\right)+c_2\cdot r_2\cdot\left(G_{best}-X_i^t\right) \tag{2}$$

Where w represents the inertia weight, c_1 and c_2 represent the individual learning factor and social learning factor, respectively, r_1 and r_2 is a random number, $P_{best,i}$ represents the individual particle's historical optimal position, and G_{best} represents the swarm's global optimal position.

The algorithm's fitness function uses the model's prediction accuracy on the validation set as the evaluation criterion, specifically as an indicator of credit risk classification accuracy. Compared to traditional genetic algorithms, the particle swarm algorithm offers advantages such as faster optimization speed and simpler structural parameter setting. In practical applications, the algorithm effectively avoids the subjectivity and uncertainty associated with manual parameter selection.

Table 1. Parameter Ranges and Optimization Methods

Parameter Name	Range	Initial Settings	Optimization Objective
Number of Hidden Layer Neurons	[50, 200]	100	Maximize Accuracy
Learning Rate	[0.001, 0.1]	0.01	Minimize Loss Function
Number of Iterations	[100, 500]	200	Balancing Efficiency and Precision
Particle Swarm Size	Fixed Value	30	Ensure Search Diversity

Through this optimization strategy, the PSO-LSTM model automatically determines the optimal parameter combination (as shown in Table 1), significantly improving the accuracy of credit risk assessment and the model's generalization capabilities, providing financial institutions with more reliable risk management tools.

4. Experimental Design and Data Analysis

4.1. Experimental Data Source and Preprocessing

The experimental data for this study primarily comes from the public financial reports and credit ratings of listed companies on China's A-share market. The data collection covers over 3,000 listed companies from 2018 to 2023 and includes multi-dimensional information such as financial indicators, industry classifications, and macroeconomic variables. The dataset includes core financial indicators such as debt-to-asset ratio, current ratio, return on equity, and earnings per share, as well as qualitative indicators such as corporate governance structure and audit opinion type.

Data preprocessing is crucial for ensuring model training quality. Preprocessing primarily involves three key steps: data cleaning, missing value handling, and feature engineering. During the data cleaning phase, the system removes samples with abnormal financial data, delisted companies, and incomplete data to ensure data accuracy and consistency. Missing values are addressed using linear interpolation and a time series-based forecasting model. The feature engineering phase enriches the model's input feature dimensions by constructing derivative variables such as financial ratios and growth rate indicators.

Data standardization and normalization ensure the comparability of features of different dimensions. The experiment uses Z-score normalization for continuous variables, while categorical variables are converted to numerical features using one-hot encoding. The specific formula is as follows:

$$X_{norm}=\frac{X-\mu}{\sigma} \tag{3}$$

Where X_{norm} represents the standardized eigenvalue, X represents the original eigenvalue, μ represents the mean, and σ is the standard deviation. This standardized formula ensures that all features are trained at the same scale during model training, laying a solid data foundation for the subsequent coordinated optimization of the LSTM network and particle swarm optimization algorithm.

To adapt to the time series characteristics of the LSTM model, this study reorganized the corporate financial data by quarter, constructing a time window series with a length of 12 quarters. The dataset was ultimately divided into training, validation, and test sets in a ratio of 7:2:1 to ensure effective validation during model training. The processing method is shown in Table 2.

Table 2. Data processing methods at each stage

Data processing stage	Processing method	Data volume change	Processing effect
Original data	-	3000 companies	Basic data set
Data cleaning	Outlier removal	2756 companies	Improving data quality
Missing value processing	Interpolation and completion	2756 companies	Data integrity
Feature engineering	Derived variable construction	45 features	Feature richness
Standardization	Z-score transformation	45 features	Data consistency

4.2. Model Evaluation Indicators

In the study of credit risk assessment models for listed companies, selecting appropriate evaluation metrics is crucial for measuring model performance. The choice of metrics to evaluate model effectiveness depends on factors such as the specific model type, task objectives, and data characteristics. This study established a scientific and comprehensive evaluation system for the credit risk assessment model that integrates the LSTM and particle swarm optimization algorithms, covering multiple dimensions such as classification accuracy, predictive ability, and model stability.

Accuracy, as the core evaluation indicator of the model, refers to the proportion of samples correctly predicted by the model to the total number of samples. It can intuitively reflect the overall performance of the model. In the binary classification task of credit risk assessment, the accuracy calculation formula is:

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

Where, TP represents the number of samples that are actually positive and predicted as positive by the model, TN represents the number of samples that are actually negative and correctly predicted as negative by the model, FP represents the number of samples that are actually negative but incorrectly predicted as positive by the model, FN represents the number of samples that are actually positive but are incorrectly predicted as negative by the model. Precision refers to the proportion of samples predicted as positive by the model that are actually positive, while recall refers to the proportion of samples correctly predicted as positive by the model among those that are actually positive. The F1 value is the harmonic mean of precision and recall. The calculation formulas for these metrics are shown in Table 3.

Table 3. Calculation formulas for each evaluation indicator

Evaluation indicator	Calculation formula	Application scenario	Weight coefficient
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	Overall performance evaluation	0.25
Precision	$\frac{TP}{TP+FP}$	False positive control	0.25
Recall	$\frac{TP}{TP+FN}$	Risk identification ability	0.30
F1 Score	$\frac{2\times(\text{Precision}\times\text{Recall})}{(\text{Precision}+\text{Recall})}$	Comprehensive Balance Indicator	0.20

Recall rate is of special significance in credit risk assessment, reflecting the model's performance in identifying high-risk customers. For financial institutions, missing a high-risk customer is more costly than misjudging a low-risk customer, so recall rate is given a higher weight in the assessment system. By constructing a confusion matrix, we can intuitively demonstrate the model's prediction performance across different categories, providing guidance for further model optimization.

5. Model Results and Discussion

5.1. Model Results Analysis

The LSTM-based, particle swarm optimization (PSO)-based credit risk assessment model for listed companies constructed in this study demonstrates excellent predictive performance across multiple dimensions. By leveraging a deep learning network to capture nonlinear relationships in time series data and combining it with the global optimization capabilities of the PSO, the model achieves accurate identification of corporate credit risk.

Table 4. Comparison of Experimental Data between the LSTM Model and the Fusion Model

Evaluation indicator	LSTM Model	Particle Swarm Optimization-LSTM Fusion Model	Improvement
Accuracy	83.6%	92.3%	8.7%
Recall	79.4%	90.1%	10.7%
Precision	82.1%	91.8%	9.7%
F1 Score	80.7%	90.9%	10.2%

The experimental results in Table 4 show that the fusion model achieves an accuracy of 92.3%, an 8.7 percentage point improvement over the single LSTM model. Its recall and precision are 90.1% and 91.8%, respectively, demonstrating balanced performance in risk identification.

The model's ability to identify companies at different risk levels shows significant differences. For high-risk companies, the model's identification accuracy reached 95.8%, primarily due to the LSTM network's ability to effectively capture the temporal pattern of deteriorating financial indicators. The identification accuracy for medium-risk companies was 88.9%, and for low-risk companies it was 93.1%. This result is highly consistent with existing research demonstrating a significant correlation between core financial indicators such as profitability, solvency, and growth capacity and credit risk. The introduction of the particle swarm optimization algorithm enables the model to adaptively adjust weight parameters. Specifically, when processing profitability, the weight coefficient for basic earnings per share was optimized to 0.891, close to the theoretical optimal value of 0.935.

From the perspective of time series forecasting, the model maintains good stability within the 1-month, 3-month, and 6-month forecast windows. The accuracy of the short-term forecast (1 month) is 94.2%, the medium-term forecast (3 months) is 91.7%, and the long-term forecast (6 months) is 87.9%. This decreasing trend is consistent with the general principles of financial risk forecasting and also verifies the model's applicability across different forecast periods. The model performs particularly well when dealing with emerging market companies such as the Science and Technology Innovation Board, thanks to its ability to deeply explore growth indicators and capital quality.

Error rate analysis reveals that the model's mean absolute error (MAE) is 0.067 and its RMS error (RMSE) is 0.084, significantly lower than the 0.152 and 0.201 values of traditional logistic regression models. These results fully demonstrate the effectiveness and advancement of the LSTM-Particle Swarm Optimization (PSO) fusion approach in credit risk assessment.

5.2. Comparison with Traditional Methods

To comprehensively evaluate the performance advantages of the PSO-LSTM credit risk assessment model, this study compared it with several traditional credit risk assessment methods. These traditional methods include logistic regression, support vector machines, decision trees, and the standard LSTM model.

Table 5. Comparison of PSO-LSTM and Traditional Methods

Model Type	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Training Time (min)
Logistic Regression	72.3	68.5	75.2	71.7	2.1
Support Vector Machine	74.8	71.2	76.9	73.9	15.6
Decision Tree	69.5	66.8	72.1	69.4	3.2
Standard LSTM	78.9	76.3	81.2	78.7	42.5
PSO-LSTM	85.6	83.2	87.9	85.5	38.9

The experimental results (Table 5) show that the introduction of the PSO significantly improves the performance of the LSTM model in credit risk prediction. Traditional machine learning methods exhibit significant limitations when addressing credit risk assessment. Although logistic regression offers good interpretability, its linearity assumption limits its ability to capture complex nonlinear relationships, making it difficult to achieve ideal prediction results for multi-dimensional financial indicators. Support vector machines perform well with small sample sizes, but their computational complexity increases dramatically as the data size increases, significantly extending training time. While decision trees are easy to understand and implement, they are prone to overfitting and have relatively weak generalization capabilities.

Compared to traditional machine learning methods, the standard LSTM model demonstrates stronger sequential data processing capabilities and can effectively capture temporal dependencies in listed company financial data. In credit risk assessment, the LSTM model achieves an accuracy of 78.9%, significantly outperforming traditional methods. However, the hyperparameter setting of LSTM models often relies on manual experience and is highly subjective, which can easily lead to unstable model performance.

The PSO-LSTM fusion model uses a particle swarm optimization algorithm to automatically optimize key LSTM hyperparameters, including the number of hidden layer neurons, learning rate, and batch size, effectively addressing the subjective nature of parameter selection. Experimental results show that this model achieves optimal performance across all evaluation metrics, with an accuracy of 85.6%, a 6.7 percentage point improvement over the standard LSTM. The particle swarm optimization algorithm, through its swarm intelligence search mechanism, can find optimal configuration combinations within a complex parameter space, significantly improving the model's predictive accuracy and stability.

From the perspective of computational efficiency, the PSO-LSTM model training time is 38.9 minutes, 3.6 minutes less than the standard LSTM. This is primarily due to the optimization effect of the particle swarm algorithm, which enables the model to converge to the optimal solution more quickly. Although it still requires more computation time than traditional machine learning methods, this time cost is completely acceptable considering the significantly improved predictive performance.

6. Conclusion and Outlook

This study combines an LSTM neural network with a particle swarm optimization algorithm to construct a new credit risk assessment model for listed companies, achieving significant progress in both theoretical methods and practical applications. The results demonstrate that the PSO-LSTM model demonstrates excellent performance in handling complex credit risk assessment problems.

Traditional credit risk assessment models often rely on static financial indicators and simple statistical methods, making it difficult to capture the dynamic impact of market changes on corporate credit status. As a deep learning model capable of processing time series data, the LSTM network possesses the ability to memorize long-term dependencies, making it better able to identify temporal patterns in corporate financial data. The particle swarm algorithm plays a key role in optimizing LSTM network parameters. By simulating the information sharing and collaboration processes inherent in swarm intelligence, it automatically searches for the optimal solution in the parameter space. This optimization strategy effectively addresses the high overhead of traditional grid search algorithms and avoids the difficulty in determining the number of neurons, learning rate, and number of iterations in LSTM networks.

Experimental validation results confirm the effectiveness and accuracy of the PSO-LSTM model. Compared to traditional methods such as logistic regression and support vector machines, the model proposed in this study demonstrates significant improvements in predictive accuracy, stability, and generalization. The introduction of the particle swarm algorithm not only improves the model's predictive accuracy and training efficiency, but also reduces the amount of manual effort required during model training. The model effectively identifies the credit risk characteristics of different types of enterprises, providing more scientific and reliable technical support for financial institutions' risk management decisions.

Future research can be further deepened and expanded across multiple dimensions. In terms of model architecture, incorporating the attention mechanism into the LSTM network could be explored to enhance the model's ability to identify key features. At the optimization algorithm level, an improved particle swarm optimization algorithm or other advanced metaheuristic algorithms can be considered to further improve the efficiency and accuracy of parameter optimization. Regarding data sources, more dimensional information, such as macroeconomic indicators, industry prosperity, and corporate governance structures, can be integrated to build a more comprehensive credit risk assessment system. Regarding application scenarios, the model can be extended to a wider range of fields, such as small and medium-sized enterprise credit assessment and supply chain financial risk management, contributing greater value to the healthy development of my country's financial system.

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