International Journal of Advanced Engineering Research and Science (IJAERS)
Peer-Reviewed Journal
ISSN: 2349-6495(P) | 2456-1908(O)
Vol-11, Issue-12; Dec, 2024
Journal Home Page Available: https://ijaers.com/
Article DOI: https://dx.doi.org/10.22161/ijaers.1112.12

Credit Risk Assessment of Listed Companies Based on Long Short-Term Memory Neural Networks

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Received: 21 Nov 2024,

Receive in revised form: 18 Dec 2024,

Accepted: 23 Dec 2024,

Available online: 30 Dec 2024

***Keywords*— Credit Risk Assessment, Listed Companies, Long Short-Term Memory, Factor Analysis, Financial Indicators**

***Abstract*— *Listed companies are vital to capital markets, but issues like information opacity and poor governance elevate credit risks, impacting economic stability. This study proposes a Long Short-Term Memory (LSTM) neural network model to assess credit risk by analyzing time-series financial indicators. Factor analysis reduces dimensionality of indicators, followed by LSTM training on sequential data to predict risk levels. Using CSI 300 firms' data, the model achieves 87.5% accuracy, outperforming traditional methods like logistic regression (80.2%). The approach captures temporal dependencies, offering dynamic risk forecasts. Limitations include data quality reliance and computational complexity. Results support regulators and investors in enhancing risk management.*

I. INTRODUCTION

1.1 Research Background and Significance

Publicly listed firms are pivotal to capital markets, channeling resources that fuel economic progress. Yet, their exposure to risks—stemming from inconsistent financial reporting, governance lapses, or market fluctuations—can destabilize broader systems[1]. Events like the 2008 Lehman Brothers collapse or China's 2015 stock market crash highlight how a single firm's failure can ripple, eroding investor confidence and tightening credit. Regulators face mounting pressure to monitor such vulnerabilities, while investors seek reliable tools to protect assets[2]. Conventional risk assessment, often based on snapshot metrics, struggles to track evolving financial patterns in turbulent markets. This study employs Long Short-Term Memory (LSTM) neural networks to analyze sequential financial data, offering precise, forward-looking risk predictions[3]. By modeling time-varying trends, LSTM empowers policymakers to strengthen oversight and helps investors make informed choices, fostering resilience in complex economic landscapes.

1.2 Literature Review

Efforts to evaluate credit risk span several methodologies, each with distinct strengths and shortcomings[4-6]. Early approaches leaned on statistical techniques, such as logistic regression and discriminant analysis, which assess financial ratios like leverage or profitability to gauge default likelihood[7]. These methods, foundational in works from the late 20th century, falter when faced with fluctuating market conditions, as they rely on fixed data points[8]. More recently, machine learning techniques—random forests and support vector machines—have gained traction for their ability to handle complex patterns[9]. Studies from the early 2000s showed these models outperforming older techniques, yet their static frameworks limit effectiveness with time-series data, often demanding extensive feature curation. Emerging deep learning methods, particularly recurrent neural networks like LSTM, offer promise by capturing sequential relationships. While applications in areas like stock prediction have grown, credit risk studies remain sparse, hindered by data inconsistencies and computational hurdles[10-14]. This research combines factor analysis with LSTM to deliver a precise, adaptable model, addressing gaps in dynamic risk evaluation for listed firms.

1.3 Research Methods

This study employs a structured approach to evaluate credit risk, harnessing the strengths of LSTM neural networks[15]. The methodology unfolds in three phases. First, financial indicators—covering profitability, liquidity, and leverage—are selected and refined using factor analysis to eliminate redundancy and enhance interpretability, ensuring a compact yet meaningful dataset. Second, an LSTM model is designed to process these indicators as time-series sequences, capturing patterns across quarters to forecast risk categories (low, medium, high)[16-19]. The model's architecture leverages memory cells to retain critical trends, optimizing predictive accuracy[20-24]. Third, the framework is tested on financial data from CSI 300 companies, with performance benchmarked against established methods like logistic regression and support vector machines. Data standardization and sequence formation ensure robustness, while rigorous validation confirms reliability[25]. This approach integrates statistical rigor with deep learning's flexibility, tailored to the complexities of corporate finance.

1.4 Innovations

This research introduces a novel framework for credit risk assessment, distinguished by three contributions. First, it employs LSTM neural networks to model financial sequences, offering a time-sensitive lens that captures subtle shifts in company performance, unlike static alternatives. Second, factor analysis streamlines indicator selection, yielding a clear, interpretable set of metrics that resonate with financial theory and practice. Third, the model achieves superior accuracy on real-world data, validated through CSI 300 firms, providing a reliable tool for decision-makers. These advancements enable real-time risk monitoring for regulators and precise portfolio adjustments for investors, bridging theoretical insights with practical needs. By addressing gaps in dynamic modeling, this work redefines risk assessment standards, paving the way for adaptive strategies in volatile markets.

II. LONG SHORT-TERM MEMORY MODEL FOR CREDIT RISK ASSESSMENT

2.1 Model Framework

Long Short-Term Memory (LSTM) neural networks, a specialized form of recurrent neural networks, are designed to process sequential data by preserving long-term dependencies, overcoming the limitations of traditional models that struggle with vanishing gradients[26]. In the context of credit risk assessment, LSTM analyzes sequences of financial indicators—such as profitability and leverage metrics—over multiple quarters to forecast risk categories (low, medium, high)[27]. This sequential approach is particularly suited to financial data, where patterns evolve gradually, reflecting underlying economic shifts or firm-specific developments.

2.1.1 LSTM Architecture

The proposed model is structured to balance complexity and interpretability, tailored to the nuances of corporate financial data. Its components include:

- **Input Layer**: The model ingests sequences spanning T=8 quarters, with each time step comprising m financial indicators derived from factor analysis[28]. These indicators, representing dimensions like liquidity and efficiency, are preprocessed to ensure consistency across firms and periods[29]. The sequence length of eight quarters balances historical context with computational feasibility, capturing trends without excessive noise.
- **LSTM Layers**: The core consists of two LSTM layers, each with 64 units, to extract sequential patterns. Each unit operates through a series of gates that regulate information flow:
    - **Forget Gate**: Determines which past information to discard, calculated as：

$$f_t = \sigma(W_f * [h_{t-1}, x_t] + b_f)$$

where W_f is the weight matrix, $[h_{t-1}$ is the previous hidden state, x_t is the current input,

b_f is the bias, and σ is the sigmoid function ensuring outputs between 0 and 1[30].

- **Input Gate**: Decides which new information to store, defined by:

$$i_t = \sigma(W_i * [h_{t-1}, x_t] + b_i)$$

- paired with a candidate cell state:

$$\widehat{C_t} = tanh(W_C * [h_{t-1}, x_t] + b_C)$$

- **Cell State Update**: Combines old and new information:

$$C_t = f_t * C_{t-1} + i_t * \widehat{C_t}$$

preserving relevant trends across quarters.

- **Output Gate**: Generates the hidden state for predictions:

$$o_t = \sigma(W_o * [h_{t-1}, x_t] + b_o), \quad h_t = o_t * tanh(C_t)$$

The dual-layer design enhances the model's ability to capture both short-term fluctuations and longer-term financial trajectories, critical for identifying risk signals like declining solvency.

- **Dense Layer**: The final layer transforms the LSTM's output into probabilities across k=3 risk classes (low, medium, high) using a softmax activation[31]:

$$p(y_t) = \text{softmax}(W_d * h_t + b_d)$$

where W_d and b_d are learned parameters. This setup ensures probabilistic outputs interpretable as risk likelihoods, aiding decision-makers in prioritizing interventions.

To explore robustness, alternative architectures were considered, such as single-layer LSTMs (faster but less expressive) and three-layer models (more powerful but prone to overfitting on smaller datasets). The two-layer, 64-unit configuration was selected for its balance of predictive power and generalization, validated through preliminary experiments. Dropout layers (rate 0.2) were incorporated to mitigate overfitting, ensuring the model adapts to diverse firm profiles within the CSI 300 index.

2.1.2 Loss Function

The model minimizes categorical cross-entropy:

$$L = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{k} y_{ij}\log(\widehat{y_{ij}})$$

where N is the number of samples, y_{ij} is the true label (1 if class j applies, 0 otherwise), and $\widehat{y_{ij}}$ is the predicted probability for class j. This loss penalizes misclassifications, guiding the model to refine its weights via backpropagation[32]. The Adam optimizer, with a learning rate of 0.001, accelerates convergence while maintaining stability, chosen over alternatives like SGD for its adaptive step sizes. Early stopping was implemented to halt training if validation loss plateaued, preserving generalizability.

The loss function's design aligns with the imbalanced nature of credit risk data, where high-risk cases are rarer[33]. Techniques like weighted loss were evaluated but deemed unnecessary, as the model's performance remained strong across classes, as detailed in Section 3.4.

2.2 Model Validation

To establish the LSTM's reliability before applying it to financial data, a preliminary validation was conducted using the Iris dataset, a standard benchmark with 150 samples, four features, and three classes. The dataset was reformatted into pseudo-sequences to simulate time-series inputs, testing the model's ability to handle structured patterns[34]. After 50 epochs with a batch size of 16, the LSTM achieved a classification accuracy of 90.0%, surpassing logistic regression's 73.6% and a basic neural network's 82.4%. This gap highlights LSTM's strength in modeling complex relationships, even in non-financial contexts.

Beyond Iris, the model was tested on a synthetic financial dataset mimicking corporate metrics (e.g., simulated ROE, debt ratios). Generated with controlled noise, this dataset included 200 firms over 10 quarters, labeled by hypothetical default thresholds. The LSTM correctly classified 88.2% of cases, compared to 79.5% for a gradient-boosting model, reinforcing its suitability for sequential tasks. These experiments underscore the model's robustness across domains, justifying its use for CSI 300 data.

Validation also considered practical constraints, such as computational cost and scalability. Training on Iris took ~2 minutes on a standard GPU, while the synthetic dataset required ~10 minutes, indicating feasibility for larger financial datasets. Sensitivity analyses—varying sequence lengths (T=4, 12) and units (32, 128)—confirmed the chosen configuration (T=8, 64 units) as optimal, balancing accuracy and efficiency. These rigorous checks ensure the model's readiness for real-world credit risk assessment, where data variability and class imbalance pose significant challenges.

III. EMPIRICAL STUDY

3.1 Data Sources

The study draws on quarterly financial statements from 300 companies listed in the CSI 300 index, covering the period 2019–2021. Sourced from the China Stock Market & Accounting Research (CSMAR) database, the dataset includes metrics across four dimensions: profitability (e.g., return on equity, net profit margin), liquidity (e.g., current ratio, quick ratio), leverage (e.g., debt-to-equity, interest coverage), and efficiency (e.g., asset turnover, inventory turnover). This timeframe captures a volatile economic landscape, including China's post-COVID recovery and global trade disruptions, providing a rich context for risk analysis.

The CSI 300 spans diverse sectors—finance, manufacturing, technology, and energy—ensuring representativeness. Data quality was verified by cross-referencing with annual reports and regulatory filings, addressing gaps (e.g., missing quarters) via interpolation for <5% of entries. The dataset's granularity (quarterly intervals) aligns with LSTM's sequential requirements, enabling the model to detect trends like deteriorating cash flows or rising debt burdens, critical for risk forecasting.

3.2 Indicator Selection

Initial analysis identified 15 financial indicators, selected for their relevance to credit risk based on financial theory and prior studies. These included return on assets, operating margin, current ratio, quick ratio, debt-to-equity, interest coverage, total debt ratio, asset turnover, inventory turnover, accounts receivable turnover, earnings per share, book value per share, cash flow per share, revenue growth, and net income growth. However, correlations among indicators (e.g., current and quick ratios) suggested multicollinearity, risking model instability.

Factor analysis was employed to distill these into five independent factors, reducing dimensionality while preserving explanatory power. The Kaiser-Meyer-Olkin (KMO) measure yielded 0.72 (>0.5), confirming suitability for factor analysis, and Bartlett's test of sphericity returned p<0.01, verifying indicator interdependence. Principal component analysis with varimax rotation extracted factors explaining 82.03% of variance:

Table 1: Total Variance Explained (Rotated)

Component	Eigenvalue	Variance (%)	Cumulative (%)
1	4.302	28.680	28.680
2	2.683	17.887	46.567
3	2.263	15.087	61.654
4	1.885	12.565	74.219
5	1.171	7.810	82.029

The factors were interpreted as:

1. **Profitability**: High loadings for ROE, ROA, and net profit margin.
2. **Liquidity**: Dominated by current and quick ratios.
3. **Leverage**: Driven by debt-to-equity and interest coverage.
4. **Efficiency**: Linked to asset and inventory turnover.
5. **Growth**: Captured by revenue and net income growth.

Rotated loadings (Table 5, not shown due to space constraints) clarified each indicator's contribution, ensuring interpretability. This process eliminated redundant metrics, producing a streamlined input set for LSTM training, robust against overfitting and aligned with financial decision-making needs.

3.3 Data Processing

To prepare data for LSTM modeling, indicators underwent standardization to normalize scales across firms and metrics:

$$x'_{id} = \frac{x_{id} - \mu_d}{\sigma_d}$$

where x_{id}^{i} is indicator d for firm i, μ_d and σ_d are mean and standard deviation. Sequences of T=8 quarters were formed, with labels (low, medium, high risk) based on historical defaults.

Data were then structured into sequences of T=8 quarters, forming inputs of shape (N, T, m), where N is the number of firms and $m=5$ (post-factor analysis). Risk labels (low, medium, high) were assigned based on historical default records and financial distress thresholds (e.g., Altman's Z-score variants), cross-validated with market data. Missing values, affecting <3% of sequences, were imputed using linear interpolation to preserve temporal continuity. Outliers, identified via interquartile range checks, were capped to avoid skewing predictions.

The dataset was split into 80% training and 20% testing sets, with stratification to maintain class balance. A validation subset (20% of training) monitored performance during training, preventing overfitting. This preprocessing ensured the LSTM could focus on meaningful patterns, such as gradual liquidity declines, rather than noise or scale artifacts.

3.4 Empirical Results

The LSTM model was trained with the following hyperparameters:

- **Optimizer**: Adam, learning rate 0.001, for efficient convergence.
- **Epochs**: 50, with early stopping if validation loss stagnated for 10 epochs.
- **Batch Size**: 32, balancing memory use and gradient stability.
- **Dropout**: 0.2, applied to LSTM layers to enhance generalization.

Training occurred on a GPU-enabled system, taking ~20 minutes for convergence, feasible for academic and practical settings. The model's performance was evaluated on the test set, yielding:

- **Accuracy**: 87.5%, compared to 80.2% for logistic regression and 83.1% for SVM, highlighting LSTM's superiority in sequential modeling.
- **Confusion Matrix**:

Table 2 Credit risk matrix

Type	No. of Firms	Scores	Credit risk class
1	7	0.891	low
2	22	0.073	medium
3	2	-0.112	high

  - Low risk: 90% precision, reflecting strong identification of stable firms.
  - Medium risk: 88% precision, capturing firms with moderate vulnerabilities.
  - High risk: 82% precision, slightly lower due to fewer high-risk samples (10% of data), but still reliable for flagging critical cases.
- **F1-Scores**: 0.89 (low), 0.87 (medium), 0.80 (high), confirming balanced performance across classes.
- **Loss Convergence**: Training loss dropped to 0.25 by epoch 40, with validation loss stabilizing at 0.27, indicating robust learning without overfitting.

Detailed analysis revealed LSTM's strength in detecting temporal signals, such as a firm's declining ROE over three quarters predicting medium risk, missed by static models. Sector-specific trends—e.g., manufacturing firms' leverage spikes in 2020—were accurately flagged, showcasing the model's adaptability. Comparison models struggled with such dynamics; logistic regression overemphasized single-quarter metrics, while SVM missed gradual shifts.

Robustness checks varied hyperparameters (e.g., learning rate 0.0005, units 128), with minimal accuracy gains (<1%), affirming the chosen setup. Data perturbations (e.g., 5% noise injection) reduced accuracy to 85.2%, underscoring the need for clean inputs, a limitation noted in Section 4. These results position the LSTM model as a powerful tool for stakeholders, enabling proactive risk management in volatile markets.

IV. CONCLUSIONS

The LSTM-based model effectively predicts credit risk for listed companies, achieving 87.5% accuracy by leveraging sequential financial data. Factor analysis ensures interpretable inputs, while LSTM captures dynamic patterns, surpassing traditional models like logistic regression. Applications include real-time risk monitoring for regulators and portfolio optimization for investors. Limitations include reliance on data quality and high computational costs, requiring robust infrastructure. Future work could integrate macroeconomic variables or hybrid models (e.g., LSTM+CNN) to enhance prediction. This approach strengthens financial risk management, supporting economic stability.

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