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An Improved Neural Manufacturing Corporate Credit Rating Model Based on LSTM

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Abstract: This paper proposes an improved neural manufacturing corporate credit rating model based on Multi-head Self-attention (MSA) mechanism and Long Short-Term Memory (LSTM) network. The proposed model leverages MSA to simulate the marketdynamics and generate dynamic weights for each indicator based on the financial dataof all manufacturing companies. Meanwhile, LSTM is utilized to extract sequential features from long-term financial and operational data to capture the long-term financialstatus and reduce the risk of deviation. The experimental results show that the proposedmodel provides more objective and reliable credit ratings for manufacturing companies.In the comparison experiment with the baseline model, it was proven that the model proposed in this paper outperforms other baseline models. In the comparison experiment with SMAGRU, it was proven that the proposed model has better predictionability than SMAGRU on both datasets, and it also demonstrates that the GRU simplifies the internal computation of LSTM. The ablation experiment verified the feasibility of the two modules of the proposed model separately, which further proved the effectiveness of the proposed model.

Keywords: *Manufacturing, Corporate Credit Rating, Multi-head Self-attention, Long Short-Term Memory, Neural Network*

1. Introduction

The key factor for corporate development is the funding chain. The primary sources of public funding are stocks or bonds, where issuing bonds is more primary. Prior to a company's IPO or bond issuance, in order to evaluate the company's ability and willingness to repay debt, it is necessary to conduct a corporate credit rating, also known as a credit evaluation or assessment. Corporate Credit Rating is one of the mainindicators that reflect the risk and reliability level of a company in fulfilling its financial obligations. At the same time, corporate credit rating is also a key indicator that investors pay close attention to. However, traditional, human-based credit rating processes are often the manpower-intensive.

The Manufacturing industry is made up of businesses that are involved in converting raw materials, substances, or parts into brand new products through mechanical, physical, or chemical processes. These businesses are generally referred to as plants, factories, or mills, and commonly utilize powered machinery and material-handling equipment. Manufacturing businesses may either process materials themselves or outsource processing to other businesses, and both types of enterprises are considered to be part of the manufacturing industry. As the cornerstone of economic development, manufacturing is an economic entity with the relatively clear capital structure.

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Manufacturing enterprises tend to reduce the manufacturing cost per unit product through mass production, hence they are highly sensitive to capital flow and capital chain.

The economic cycle of manufacturing industry is commonly considered to be long. Most manufacturing enterprises are in the middle of the industrial chain. The manufacturing industry is constrained by the production scale and raw material supplyof energy, electricity and non-ferrous metals in the upstream, while is constrained by the changes in supply and demand and carrying capacity of real estate, automobile, railway, highway, power transmission and distribution enterprises, and the end consumer market in the downstream. The bargaining power of manufacturing thereforeis limited by multiple factors. In this context, in order to avoid more risks and enhance the industrial structure of the enterprise, manufacturing enterprises have basically ended the large-scale aimless production mode and turned to the order-based productionmode. Whereas, unappropriated order-based production mode may possibly lead to excessive inventory and inventory management costs, and a large number of inventory backlog issues hence have to be tackled. This will cause operating capital constraints and increase of borrowing and financing needs. Therefore, in addition to working capital loans, there is an increasing demand for bank fixed asset loans, financing lease products, and merger and acquisition financing, investment banking products such as industry funds, non-standard investments, and corporate bonds is also increasing.

Manufacturing companies have many difficulties in gaining market trust to raise public funds. Externally, there are some reasons such as the financial management of manufacturing enterprises is not suitable for the transformation of macro-environment, the unreasonable capital structure of enterprises and the improper guidance of income distribution. Internally, there are some problems, such as weak understanding of financial risks, imperfect management methods of inventory and accounts receivable, and imperfect internal control system of financial management. Therefore, an objective, scientific credit risk evaluation method for manufacturing industry is crucial for gainingpublic trust.

The Corporate has undergone various stages such as purely manual rating, rating based on statistical methods, machine learning assisted rating and deep learning neural network assisted rating. In the manual rating stage, 5C’s, 5P’s, and LAPP methods are successfully applied. In the stage of rating based on statistical methods, Multiple Discriminant Analysis (MDA), Logit regression (LM), and Probit model (PM) technologies are the most representative. In the stage of machine learning assisted rating,Support Vector Machine (SVM) and Decision Tree (DT) came out and were utilized inthe credit rating. In the stage of neural network assisted rating, Multilayer Perceptron (MLP), Backpropagation Neural Network (BPNN), Recurrent Neural Network (RNN), and Attention technologies gained more achievements. However, most of the previous models are universal methods for corporate credit evaluation, and there are few specialized corporate credit rating models designed for the manufacturing industry according to the industry characteristics.

Therefore, this study focuses on constructing a corporate credit rating model for specific purpose, i.e., manufacturing corporate credit rating. Inspired by SMAGRU[1],we have constructed a improved end-to-end approach based on Multi-head Self- attention (MSA)[2] mechanism with Long Short-Term Memory (LSTM)[3], namely Multi-Head Self-Attention Long Short-Term Memory (MSA-LSTM), to automatically evaluate manufacturing corporate credit rating.

The main contributions of this study areas follows:

1. Based on the real financial and operational data of the manufacturing industry,we propose an improved neural manufacturing corporate credit rating model. In this paper, we leverage the Multi-head Self-attention mechanism and the financial data of all manufacturing companies to simulate the operation of the entire manufacturing industry market. The dynamic adjusting weight for each indicator is further generated, which replaces the manually-set weight used in previous works.

Considering the high inherent financing risk of manufacturing industry, the traditional credit evaluation method based on short-term financial condition is liable to lead to the deviation from the actual situation and further the loss of investors. To address the issue of poor ability of previous models to capture long-term dependencies,we use LSTM's ability to extract features from long-term financial and operational data to model large-scale manufacturing financial data. Experimental results show that the MSALSTM model proposed in this paper provides more objective and reliable corporate credit ratings for manufacturing companies.

2. Related Works

2.1 Corporate Credit Rating

In the late 19th century, the American capital market developed rapidly. However, due to incomplete information, it was difficult for investors to accurately assess the credit value of bonds. Corporate credit rating emerged to address this issue.

In the early stage, corporate credit rating was achieved through a combination of subjective assessments and statistical models, including evaluation methods based on qualitative and quantitative approaches, such as the 5C's [4], 5P's [5], LAPP [6], financial ratio analysis [7], and factor analysis [8], which are still widely used today. However, subjective assessment can have a significant impact on the rating results. Different experts may make drastically different judgments on the same company, and this evaluation method is relatively inefficient. Additionally, the impact of different ratios on the model's credit rating for a company varies.

The application of corporate credit rating methods based on statistical models hasessentially solved the problems of subjective factors and low efficiency in traditional corporate credit rating work. Widely used methods include Analytic Hierarchy Process(AHP), MDA [9], LM [10], PM [11, 12], Univariate Analysis (UA), etc. These methodshave high evaluation accuracy and robustness, especially in the prediction ofbankruptcy in companies or banks. However, these methods have high requirements forthe distribution of sample data and cannot handle high-dimensional and complex data. Compared to corporate methods based on statistical models, artificial intelligence technology does not require the assumption of data distribution, and is good at handlinghigh-dimensional and non-linear data, and performs well in classification tasks. Odom& Sharda[13] initially proposed a simple neural network for predicting corporatebankruptcy. Since then, simple neural networks, including MLP and BPNN, have beenwidely used in bankruptcy prediction [14], debt risk assessment, securities market applications, and financial forecasting [15, 16]. However, these methods are difficult toobtain good results due to problems such as difficulty of setting appropriate learning rate during training, easy falling into local optimal, overfitting, and long training times.

Moreover, they barely achieve satisfactory accuracy in classification tasks that beyond two categories [17].

Cluster analysis (CA), K-nearest neighbor (KNN), and SVM are machine learningmethods that are widely used in credit scoring [18-27]. Research has shown that SVM perform better than simple neural networks in corporate credit rating [28, 29]. DT are also commonly used in corporate credit rating due to their white-box nature and fast implementation [30, 31]. However, DT performs poorly in handling high-dimensional, sparse, and highly correlated feature data [32]. Although these machine learning methods have greatly improved the previous rating works and improved efficiency andaccuracy, they still have limitations in seeking time series and high-dimensional, multi-class characteristics of data.

Credit rating of manufacturing enterprises

In the field of corporate credit rating research, many scholars have extensively explored manufacturing enterprises and their financial conditions. Tisshaw [33] used the Z-score model to analyze unlisted private manufacturing companies in the UK, while Lincoln [34] studied the role of accounting ratios in describing bankruptcy risk levels in four industries, including manufacturing, retail, real estate, and finance. Altman et al. [35] introduced a rating system called EMS model in the field of emergingmarket corporate bonds The model is an enhanced version of the Z-score model designed for US corporations, with broader applicability to both manufacturing and non-manufacturing companies, whether private or listed [36]. Becchetti and Sierra [37] investigated the determinants of bankruptcy of Italian companies and studied representative manufacturing enterprises of three periods: 1989-1991, 1992-1994, and 1995-1997. They found that the impact of financial indicators on companies varied overtime and suggested that banks should not limit their monitoring activities to balance sheet variables only. Tomczak [38] analyzed bankrupt and operating firms in the manufacturing industry from 2007 to 2012 and found that due to the diversity of the manufacturing industry, the choice of indicators for analyzing the industry exhibits high volatility. Additionally, Tomczak and Radosiński [39] analyzed the financial condition of manufacturing enterprises and used 33 bankruptcy prediction models, finding that only five models had sufficient predictive capability in the five years prior to bankruptcy of the firms. They argued that there was no unique, accurate, and optimal model that can efficiently evaluate companies then. Tongli et al. [40] analyzed the financial performance of manufacturing companies in cement subsector of the basic industry and chemicals sector listed on Indonesia Stock Exchange, involving multiple financial ratios such as liquidity, leverage, profitability, and activity ratios, and also used Altman Z-Score ratio to predict bankruptcy likelihood. Furthermore. Sebastian Tomczak [41] constructed two models to determine different states of financial condition of manufacturing enterprises. The objective of these models was to identify the deteriorating financial condition of manufacturing firms prior to the announcementof bankruptcy by several years. In the study, the conventional discriminant model and the Bayesian model were constructed, and the Cluster Analysis was used to select categories of financial condition of companies for analysis. The findings show that theconventional discriminant model is more suitable for categorizing firms compared to the Bayesian model. Regarding the evaluation of credit risk of small and medium-sizedmanufacturing enterprises on the Chinese stock market. Yu [42] conducted relevant research. He used algorithms such as SVM, LR, RF, and MLP to evaluate manufacturing supply chain between 2015 and 2020. The results showed that the random forest algorithm was more accurate in evaluating the credit risk of manufacturing supply chain. Different indicators had a significant impact on the evaluation results.

Overall, the current corporate credit rating method for the manufacturing industry

still adopts the statistical-based approached. A minority of machine learning-based methods remains in research level not into implement due to the substandard accuracy.

3. Methodology

3.1 Task definition and notation

The MSALSTM proposed in this study consists of a Time Series Feature-based Corporate Credit Rating Classifier based on LSTM and a Dynamic Weight Calculation Module based on MSA. The Time Series Feature-based Credit Rating Classifier captures the long-term serial operations and financial characteristics of manufacturing enterprises, while the Dynamic Weight Calculation Module adjusts the corresponding financial indicators of individual enterprises based on the overall market operating conditions. The structure diagram of MSALSTM is as follows:

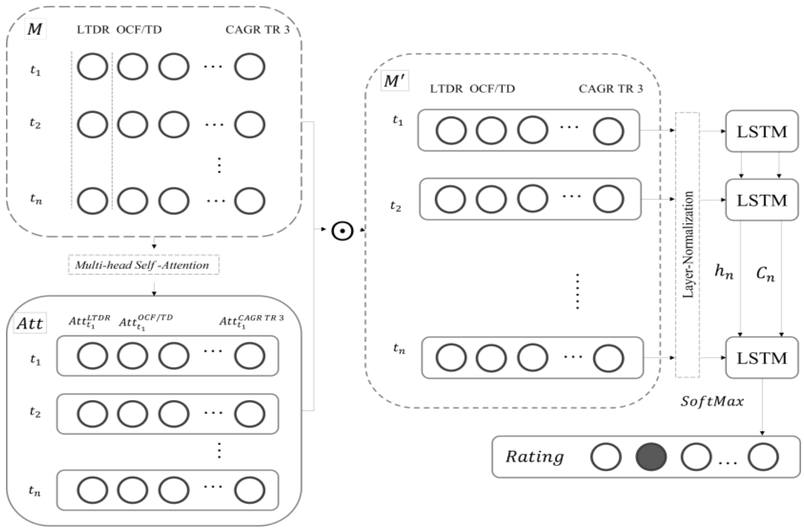

Fig 1. The architecture of multi-head self-attentive long short-term memory - MSALSTM.

To allow the LSTM model to capture long-term sequence features during the input of data into the corporate classification model, it is necessary to present the data in a time series format. Thus, we encapsulate the values for 30 financial indicators for a single company into a time vector containing 30 financial data values, segmented by time step (quarterly).

Given matrix M, which contains the values of 30 financial indicators for a certaincompany over 35 financial quarters (time steps), it represents the company's dynamic operating conditions across these 35 quarters.

$\{LTDR$, OCF/TD, $\cdots$ CAGR TR 3$\}$ represent the values of financial indicators (as shown in Tab. 1), where t represents different time steps, i.e., different quarters of financial statement data in this study:

$$Time\ \ steps\ =\ \{t_1, t_2 \cdots t_n\}\ \ (n \leq 35, n \in \mathbb{N}^*) \quad (1)$$

The long-term financial indicator representation obtained by LSTM objectively reflects the company's operating conditions. By dividing the 35 periods into quarters, we construct the vector V^F of financial data for all companies according to the corresponding time periods and financial indicators. Within each quarter, we perform multi-head self-

attention calculations between a certain financial indicator vector and its financial indicator vectors (including itself), calculating the impact of that indicator on the overall market operations in that quarter, that is, its market weight. By repeating this process, this study can calculate the weights of a total of 30 financial indicators across all quarters, composing the vector Att^F.

Subsequently, this study performs a dot product operation between the market- weighted financial indicators vector Att^F and the corresponding financial indicator values in matrix M for each company in their respective time periods, resulting in a new matrix M'. This process aims to adjust the rating impact of individual company's financial indicators and avoid the bias of manually setting weights. The computation ofthe above process is shown as follows:

$$M' = \begin{bmatrix} [\ Att_{t_1}^{LTDR} \odot LTDR_{t_1} & \cdots & Att_{t_n}^{LTDR} \odot LTDR_{t_n}\ ]^T \\ \vdots & \ddots & \vdots \\ [Att_{t_1}^{\text{CAGR TR 3}} \odot \text{CAGR TR } 3_{t_1} & \cdots & Att_{t_n}^{\text{CAGR TR 3}} \odot \text{CAGR TR } 3_{t_n}] \end{bmatrix} \quad (2)$$

From the above, vector M is transformed into vector M^'. Then, the time series vector M^' is transmitted to the corporate model to obtain the credit rating R, according to the time sequence $[Att^{LTDR} \odot LTDR_t \cdots tt^{LTDR} \odot LTDR_t]$ (any row of M').

The credit rating standards for the two datasets in this study are different, namely R_1 and R_2.

$R_1\ =\ \{AA, A, BBB, BB, B, CCC, CC, C, D, ST\}$

$R_2\ =\ \{AAA, AA, A, BBB, BB, B, CCC, CC, C, D\}$

R_1 are the rating scales in the Ds_1 dataset, which includes 10 rating levels, while

R_2 is the rating scales in the Ds_2 dataset, which includes 10 rating levels. This meansthat this study performs a classification task with different numbers of categories in different datasets.

In order to reflect the operating capacity of the above-mentioned companies and predict the credit rating of manufacturing companies more objectively based on the model, this study selected 30 secondary financial indicators as input for the model, as shown in the Tab. 1.

No.	Type of ratios	Raw financial indicators.	Abbr.
$X1$	Solvency	Long-term debt ratio	LTDR
$X2$		Operating cash flow/total debt	OCF/TD
$X3$		Cash and cash equivalents/short-term debt	CCE/STD
$X4$		EBITDA /interest expense	EBITDA/IE
$X5$		Operating cash flow/interest-bearing debt	OCF/IBD
$X6$	Cash flow	Net cash flow from investing activities (NCFIA) as a percentage of total cash flow	NCFIA/TCF
$X7$		Net cash flow from operating activities (NCFOA) as a percentage of total cash flow	NCFOA/TCF
$X8$		NCFOA /total revenue	NCFOA/TR
$X9$		NCFIA /total revenue	NCFIA/TR
$X10$	Profitability	Operating profit margin	OPM
$X11$		EBITDA margin	EBITDA M
$X12$		Operating cash flow/profit before tax	OCF/PBT
$X13$		Net profit margin	NPM
$X14$		Selling expenses/total revenue	SE/TR
$X15$		Growth rate of return on net assets	GRNA
$X16$	Operating efficiency	Accounts receivable turnover ratio	ART
$X17$		Current asset turnover ratio	CAT
$X18$		Inventory turnover in days	ITID
$X19$		Total asset turnover ratio	TAT
$X20$	Capital structure	Long-term capital debt ratio	LTCDR
$X21$		Debt-to-asset ratio	DTAR
$X22$		Interest-bearing debt/total invested capital	IBD/TIC
$X23$		Current liabilities/total liabilities	CL/TL
$X24$	Growth rate	YoY growth rate of operating profit	YoY OPG
$X25$		YoY growth rate of profit before tax	YoY PBT
$X26$		YoY growth rate of net profit	YoY NP
$X27$		YoY growth rate of total revenue	YoY TR
$X28$		YoY growth rate of net assets	YoY NA
$X29$		Compound annual growth rate (CAGR) of net profit over 2 years	CAGR NPA 2
$X30$		Three-year CAGR of total revenue	CAGR TR 3

Table 1. Financial indicators

3.2 Dynamic Weight Calculation Module

The attention mechanism is a method used in deep learning to process correlative relations. It can assign different weights to different inputs when processing data, making the network more focused on important information. However, the attention mechanism requires external information to provide weight allocation. For example, in machine translation tasks, the Attention mechanism adjusts the vector of each word in the target language generation sentence based on the importance of each word in the source language sentence[43]. The formula is as follows:

$$Attention = Simlarity/Relevance(Source, Target) \quad (3)$$

The self-attention mechanism is an Attention mechanism used in the Transformer[2], it can learn the relationships between different inputs, thereby better capturing the information of sequence inputs. Compared with regular attention, self-attention does not require external information (such as another sequence) to assign weights. Instead,it allows the model to determine the weight of each input according to its relative importance. In this study, the goal is to obtain the financial weight of a specific financial indicator in the entire market. This weight is considered as the degree of influence of this indicator on the company's operating conditions and is used as the weight of financial indicators to help credit rating classification, in order to address the impact ofmanually set weights. Moreover, since self-attention supports parallel computation - MSA, this will greatly improve the computational efficiency of the model [2, 44]. The calculating diagram is as follows:

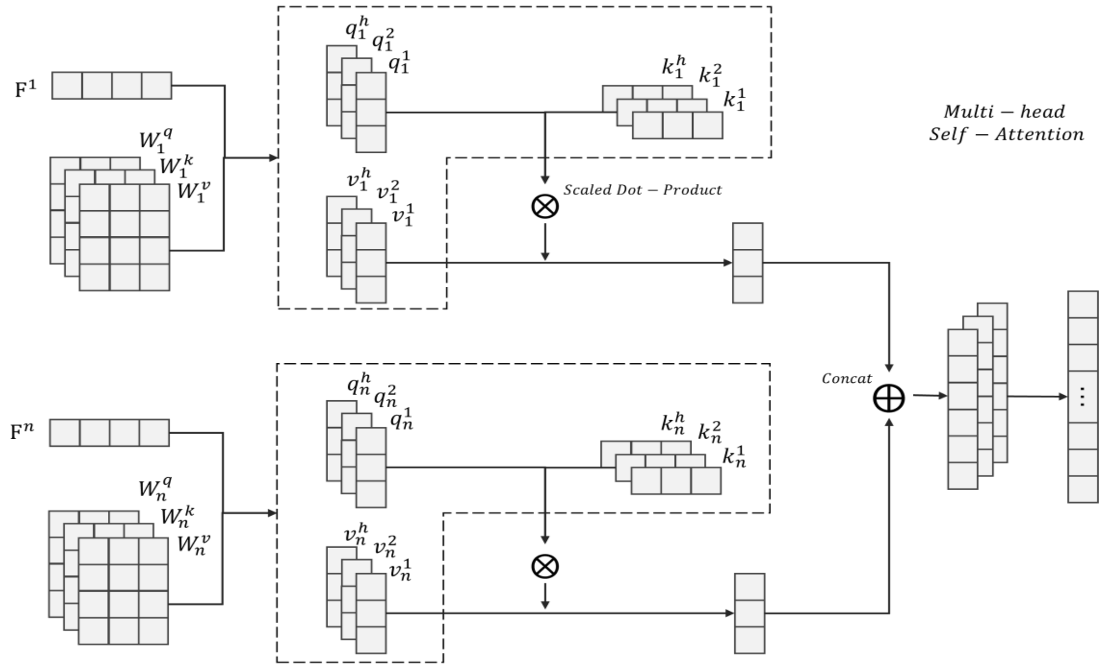

Fig 2. Multi-head Self-Attention

This article believes that the impact of financial indicators on the market situationis dynamic. Therefore, in order to calculate the importance of a financial indicator in the market, that is, its relative importance, it is necessary to take into account the dynamic nature of this impact.

In this module, the input is the vector of financial data in a certain quarter of all companies, encapsulated according to financial indicators, denoted as

F^n $(n = number\ of\ financial\ indicators)$.

This article uses the dynamic weight calculation module based on multi-head self-attention (MSA) to calculate the representation of F^n,which is the weight of a specific financial statement indicator in the entire market at a specific time. The equations are as follows:

$$head\,_1^h = Attention\left(QW_h^Q, KW_h^K, VW_h^V\right) \quad (4)$$

$$Att_{t_1}^{TR} = \text{Msa}\ of\ F^1 = Concat(head\,_1^1, \dots, head\,_1^h)w^O \quad (5)$$

Where $\boldsymbol{W}_h^Q \in \mathbb{R}^{d_{model}\times d_k}$, $\boldsymbol{W}_h^K \in \mathbb{R}^{d_{model}\times d_k}$, $\boldsymbol{W}_h^V \in \mathbb{R}^{d_{model}\times d_v}$ and $\boldsymbol{W}^O \in \mathbb{R}^{\mathrm{h}d_v\times d_{model}}$. For each of these, we use $d_k = d_v = d_{model}/h$.

We repeat the above process to capture the relative weights between different financial indicators in different quarters. Different $MSAs$ for different times can represent the benchmark for the corresponding financial indicators in the entire marketat that time and serve as the weight for adjusting the financial statement values input tothe next module.

3.3 Time Series Feature-based Credit Rating Classifier

In previous studies, SMAGRU achieved good rating results because the Gated Recurrent Units (GRU) [1, 45] have small volume structures and fast processing speed. However, compared with LSTM, the problem with GRU is that it has fewer gate mechanisms and insufficient ability to process long-term dependent sequential data. Therefore, it is necessary to make appropriate improvements to SMAGRU to achieve better credit rating ability on long-term sequential data. In this article, we choose LSTMas the basis for the credit rating classifier.

Recurrent Neural Networks (RNNs) have advantages in dealing with sequence problems, especially time series problems[46]. Such problems describe that results of specific things or phenomena change due to the time fluctuation. Overall, these types of problems share a feature that their independent variable data contains the temporal correlation, whether it is temporal correlation or causal correlation. The formula for computing RNNs is as follows:

$$o_t = g(Vs_t) \quad (6)$$

$$s_t = f(Ux_t + Ws_{t-1}) \quad (7)$$

Although RNNs have a working memory-like mechanism, the problem of vanishing gradients leads to poor long-term memory effects, resulting in the "long-term dependency" problem in RNNs. If the sequence is too long, it will be difficult to transmit information from earlier time steps to later time steps. Compared with RNNs, GRU perform better when dealing with long sequences as a simplified version of LSTM,because GRUs introduce gating mechanisms: the Update gate and Reset gate. The Update gate controls how much information from the previous state can be carried over to the current state, and the Reset gate controls how much information from the previous state can be written into the current state[45]. The formula for computing GRUs is as follows:

$$z_t = \sigma(W_z x_t + U_z h_{t-1}) \quad (8)$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1}) \quad (9)$$

$$\widetilde{h_t} = \tanh(\mathrm{Wx_t} + \mathrm{r_t} \odot \mathrm{Uh_{t-1}}) \quad (10)$$

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \widetilde{h_t} \quad (11)$$

Comparatively, LSTM has three gates: the forget gate f_t, the input gate i_t, and the output gate o_t. The functions of the three gates are as follows: the f_t controls which parts of the long-term state c_{t-1} should be discarded, i.e., which parts of the long-term state should be deleted; the i_t controls how much information from the candidate state c_t at the current time t will be saved to the long-term hidden state c_t at the current time; and the o_t controls how much information from the current internalstate c_t should be output to the external state and passed to the $t + 1$ time step. The following is the structure diagram of LSTM:

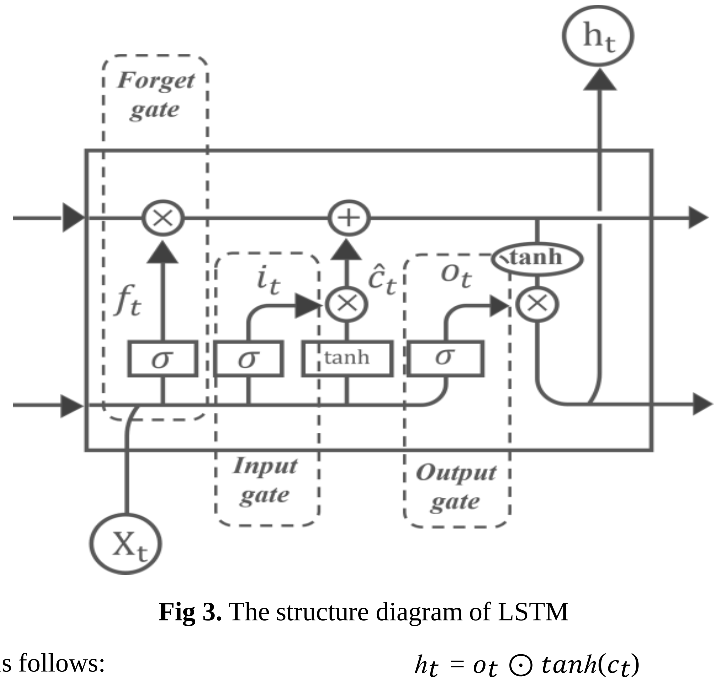

Fig 3. The structure diagram of LSTM

The calculation formula is as follows:

$$f_t = sigmoid(W_f \cdot (x_t + h_{t-1})) \quad (12)$$

$$i_t = sigmoid(W_i \cdot (x_t + h_{t-1})) \quad (13)$$

$$o_t = sigmoid(W_o \cdot (x_t + h_{t-1})) \quad (14)$$

$$\hat{c_t} = \tanh(W_C \cdot (x_t + h_{t-1})) \quad (15)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \hat{c_t} \quad (16)$$

$$h_t = o_t \odot tanh(c_t) \quad (17)$$

There are three gates activated by $sigmoid$, which generate vectors with elementsranging from 0 to 1. The values of the gates can be regarded as retention probabilities. The candidate vector is activated by tanh, which generate vectors with elements rangingfrom -1 to 1.

4. Database and Corporate Credit Rating

4.1 Credit rating scales for manufacturing enterprises

The corporate credit rating acales used by Chinese rating agencies is mainly developed in accordance with the unified requirements specified in the “Credit Rating Business Regulations for the Credit Market and Interbank Bond Market Part 2: Credit Rating Business Regulations” issued by the People’s Bank of China in 2010 [47] (as shown in the Tab. 2). The three most famous rating agencies internationally are STANDARD & POOR'S, Moody's, and Fitch,

which use credit rating symbols and their corresponding meanings (as shown in the Tab. 3).

People's Bank of China	Credit worthiness
AAA	the highest debt repayment ability, positive operating recurring state.
AA	very good debt repayment ability, positive operating recurring state.
A	good debt repayment ability, positive operating recurring state.
BBB	average debt repayment ability, positive operating recurring state.
BB	low debt repayment ability, poor operating recurring state, a certain degree of risk.
B	poor debt repayment ability, troubled operating recurring state, high risk.
CCC	very poor debt repayment ability, troubled operating recurring state, very high risk.
CC	severe inability to repay debt, troubled operating recurring state, extremely high risk.
C	extremely poor debt repayment ability, negative operating recurring state, on the verge of bankruptcy.
	specially refers enterprises in stock market, on the verge of ST.
	operating loss for two consecutive years, warning of exiting the stock market.

Table 2. Credit ratings and worthiness of the People'sBank of China

S&P's	MOOSY'S	Fitch Ratings	Credit worthiness
AAA	Aaa	AAA	An extremely high level of creditworthiness and very low credit risk.
AA+	Aa1	AA+	A high level of creditworthiness and low credit risk.
AA	Aa2	AA	
AA−	Aa3	AA−	
A+	A1	A+	A good level of creditworthiness and low credit risk.
A	A2	A	
A−	A3	A−	
BBB+	Baa1	BBB+	Adequate creditworthiness and moderate credit risk.
BBB	Baa2	BBB	
BBB−	Baa3	BBB−	
BB+	Ba1	BB+	A very high level of credit risk.

BB	Ba2	BB	
BB−	Ba3	BB−	
B+	B1	B+	
B	B2	B	A very high level of credit risk and extremely high default risk.
B−	B3	B−	
CCC+	Caa1	CCC+	
CCC	Caa2	CCC	An extremely high level of credit risk and extremely high default risk.
CCC−	Caa3	CCC−	
CC	Ca	CC	Extremely speculative
C		C	Default imminent
RD	C	RD	
SD	/	D	In default
D	/	/	

Tab. 3. Credit ratings and worthiness of S&P, Moody's and Fitch

Manufacturing enterprise dataset

Based on the credit rating reports of various rating agencies in 2022, we create twodatasets that consist of disclosed corporate financial statements along with corresponding credit rating labels.

The credit labels for Ds1 dataset are provided by a Chinese credit rating agency, Ji'an Ratings. This agency rates all listed manufacturing companies in China, with a wide range of ratings from ST to AAA, and a relatively even risk distribution. This diverse range of ratings covers more company entities, which helps the model capture the characteristics of enterprises with a higher risk of default. However, the more ratinglevels there are, the higher the demands on the model's classification ability. The Ds1 dataset contains 35 quarterly financial reports from March 2014 to December 2022, with 2142 companies distributed across 10 credit rating levels. The distribution of the number of companies for each credit rating is shown in Tab. 4.

The credit rating labels for Ds2 dataset are sourced from the three major credit rating agencies in the United States - Standard & Poor's, Moody's, and Fitch, and their enterprise credit ratings cover all listed manufacturing companies in the United States.These credit ratings are also often referenced by many issuers in the global corporate bond market. The Ds2 dataset contains 35 quarterly financial reports from March 2014to December 2022, with 648 companies distributed across 10 credit rating levels. The distribution of the number of companies for each credit rating is shown in Tab. 4.

Ds1		Ds2	
Rating	Number of companies	Rating	Number of companies
AA	76	AAA	14
A	198	AA	3
BBB	268	A	58
BB	487	BBB	198
B	397	BB	168
CCC	162	B	174
CC	223	CCC	27
C	143	CC	2
D	24	C	3
ST	164	D	1

SUM	2142	648

Table 4. Corporate credit rating distribution in datasets.

5. Experiments and Discussions

5.1 Comparison with Baseline Models

In order to evaluate the performance of our proposed model in this study, we conducted experiments on two datasets, Ds1 and Ds2, using the proposed model and other baseline models. Accuracy is used to measure the performance of MSA-LSTM and the baseline models. The experimental hyperparameters setting for MSA-LSTM is in Tab. 5. The parameter settings for other baseline models are shown in the Tab. 6. Thecomparative experimental results between the proposed model and the baseline modelare presented in Tab. 7. When training and validating MSALSTM, the accuracy and loss function values of the model varied as shown in Fig. 4.

Hyperparameters	value
Batch size	32
Epoch	100
learning rate	0.01
dropout rate	0.2
Network layer	4
Cell number of network	200

Table 5. The experimental hyperparameters setting for neural networks.

Model	Parameter
LR	The default settings of Scikit-Learn 1.2.2 in Python 3.9 were used. To perform the classification task, LR was set with L1 regularization.
KNN	The default settings of Scikit-Learn 1.2.2 in Python 3.9 were used.
SVM	One of the strategies of SVM for multiclass problems is OVR SVMs, and its parameter settings were set to the default settings of Scikit-Learn 1.2.2 in Python 3.9.
DT	The ID 3.0 algorithm was used as the basic strategy for implementing DT, and its parameter settings were set to the default settings of Scikit-Learn 1.2.2 in Python 3.9.
GBDT	The ID 3.0 algorithm was used as the basic strategy for implementing Gradient Boosted Decision Trees (GBDT).
BPNN	The same parameters as MSA-LSTM were used.
MSALSTM	Multi-head Self-Attention + Long Short-Term Memory

Table 6. The parameter settings for models

Model	Accuracy	
	Ds1	Ds2
LR	0.4387	0.4756
KNN	0.7465	0.7543
SVM	0.6874	0.6952
DT	0.7451	0.7652
GBDT	0.7245	0.7652
BPNN	0.2764	0.2561

MSALSTM	0.9134	0.9041

Table 7. Credit rating classification accuracies of our model and baseline models.

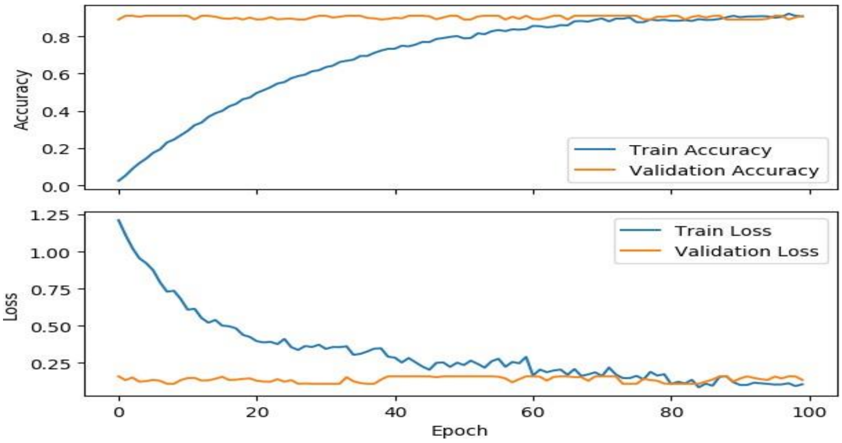

Fig 4. Accuracy and Loss curve of MSALSTM models during training and validation on theDs1 dataset.

From Tab. 7, it can be seen that the MSALSTM model has the best classification performance. In the baseline model, non-parametric algorithms such as KNN, DT, and GBDT achieved excellent classification results. However, among these three models, itcan be observed that GBDT, as an improved version of DT, has a lower accuracy than DT on two datasets. In the classification experiments of this paper, the classification performance of the unoptimized BPNN model was significantly lower than other models, which confirms the idea proposed in previous work [28, 29, 48].

5.2 Comparison with SMAGRU

In order to demonstrate the effectiveness of the proposed model compared to the SMAGRU model before improvement, the accuracy of the two models is calculated onthe manufacturing enterprise dataset in this article. The experimental results are shownbelow:

Model	Ds1	Ds2
SMAGRU	0.8523	0.8249
MSA-LSTM	0.9134	0.9041

Table. 8. Credit rating classification accuracies of our model and SMAGRU.

From the experimental results, it can be seen that due to the larger data size of theDs1 dataset than the Ds2 dataset, MSA-LSTM performs better than SMAGRU on both datasets, proving that GRU simplifies the internal computation of LSTM and does reduce the ability of GRU to extract long-term temporal features. Additionally, SMAGRU performed 0.0274 lower on the Ds2 dataset than on the Ds1 dataset. Meanwhile, the difference in the performance of MSA-LSTM on the two datasets wassmaller than that of SMAGRU, indicating that MSA-LSTM is more robust.

5.3 Ablation Experiments

In order to evaluate the influence of time sequence features and attention mechanisms on the proposed model, this article conducted ablation experiments on the proposed model in the two datasets. The models compared in the ablation experiments include MSA-LSTM, MSA-BiLSTM (MSA Bi-directional LSTM), MSA-BPNN, andLSTM (LSTM without attention). The hyperparameters for each model can be found inTab. 5. The experimental results are shown in Tab. 9:

Model	Modules	D1	D2
LSTM	Ø - uni – LSTM	0.7181	0.7044
MSA-BPNN	MSA - uni - BPNN	0.3284	0.2948
MSA-BiLSTM	MSA - bi – LSTM	0.8046	0.7981

MSA-LSTM	MSA - uni – LSTM	0.9134	0.9041

Table 9. Ablation Experiments

From the Tab. 9, it can be seen that the score of MSA-LSTM in Ds1 is 0.5850 higher than that of MSA-BPNN, proving that the LSTM-based model has an advantagein capturing long-term dependencies. Additionally, it is not shown in Tab. 9, but MSA-BPNN took more time to converge compared to MSA-LSTM.

Furthermore, models with multi-head self-attention mechanisms, including MSA-BPNN, MSA-BiLSTM, and MSA-LSTM, all showed significantly higher classification accuracy than the LSTM, indicating the benefit of the dynamic weight calculation module for credit rating. Furthermore, MSA-LSTM outperforms MSA-BiLSTM by 0.1088 in Ds1, indicating that MSA-BiLSTM is almost incapable of capturing temporal sequence features when dealing with sparse short-term data.

6. Conclusion

In this paper, we constructed a credit rating model named MSALSTM, which combines a dynamic weight calculation module based on multi-head self-attention and a time series feature-based credit rating classifier based on LSTM. The experimental results suggested that the dynamic weight calculation module in the evaluation process is able to well obtain the dynamic weights of financial indicators from the entire market data, eliminating human factors with the help of Multi-head Self-attention. The time series feature-based credit rating classifier can extract long-term financial statement features from a large amount of financial data, improving the credit rating ability of themodel by utilizing LSTM. The comparison experiment demonstrated that the time-series feature extraction ability of LSTM is superior than that of GRU with simplified internal calculations. Through ablation experiments, the effectiveness of the dynamic weight calculation module and the time-series feature credit rating classifier is demonstrated to significantly improve the accuracy of credit rating.

This study focuses on the disclosed financial statement data and its correspondingprocessing architecture, rather than factors beyond the statements. In future research, natural language techniques can be integrated with numeric data into corporate credit rating works to further improve the accuracy and reliability, such as corporate news andannual reports.

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