A Starfish Optimization Algorithm-Based Federated Learning Approach for Financial Risk Prediction in Manufacturing Enterprises

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***Abstract*—During digital transformation, manufacturing enterprises encounter challenges such as the high cost of smart devices, operational interruptions, and increased technology expenses, raising their financial risks. Addressing the digital transformation challenges confronting manufacturing enterprises necessitates developing an intelligent financial risk prediction system leveraging AI technologies like big data and deep learning, enabling enterprises to mitigate financial exposure. In addition, some data of some manufacturing enterprises cannot be disclosed and shared due to the involvement of trade secrets and shareholder interests. To address these challenges, this study proposes a federated learning (FL)-based framework for predicting financial risk in manufacturing enterprises. Without sharing data, each client (manufacturing enterprise) in the FL framework uses deep learning models to train financial risk prediction models through a central server federation. In this study, the proposed FL framework employs a deep learning model based on a neural Turing machine (NTM) with a long short-term memory (LSTM) controller. In addition, in order to improve the prediction accuracy of the hybrid NTM-FL model, an improved starfish optimization algorithm (ISFOA) was used to optimize the structure of the NTM model. Finally, the experimental results showed that the ISFOA-based NTM-FL (ISFOA-NTM-FL) model improved the prediction accuracy by 26.32% compared to the other three financial risk prediction models.**

***Keywords*—Deep learning; neural Turing machine; prediction; starfish optimization algorithm; federated learning**

I. Introduction

The intelligent financial risk management system is of great significance to manufacturing enterprises by enabling accurate risk prediction and optimized fund allocation. However, their digital transformation introduces critical financial risk challenges. These include high costs of smart devices, investment risks brought by technological iterations, and substantial capital expenditures that can constrain cash flow [1]. In addition, the massive capital expenditures during the digital transformation of manufacturing enterprises may also lead to cash flow constraints. Furthermore, the pace of technological change can quickly render previous investments ineffective, failing to meet profit expectations. Traditional financial risk prediction models struggle to accurately quantify these specific manufacturing risks [2]. To address this challenge, manufacturers are actively pursuing the development of AI-based intelligent financial risk management systems to more effectively manage financial risks throughout their transformation and ongoing operations.

Recurrent neural network (RNN), as a fundamental architecture in the field of deep learning, focuses on feature extraction and complex pattern recognition through multi-layer nonlinear transformations [3]. However, traditional RNN models have significant limitations in handling sequence dependent tasks, with one of the biggest challenges being long-term memory decay. Indicative examples include long short-term memory (LSTM) networks and gate recurrent units (GRU) [4]. The neural Turing machine (NTM), as a typical model under the deep learning architecture, introduces external memory on the basis of the deep learning infrastructure and constructs a hybrid computing system with active memory read and write capabilities. Compared with LSTM and GRU models, the introduction of external memory enables the NTM model to have memory function and achieve information reuse across time steps. Therefore, another typical application of NTM is time series prediction that considers causal relationships. For example, when processing quarterly financial reports of manufacturing enterprises, NTM can autonomously associate the causal relationship between equipment investment and current profitability of manufacturing enterprises, while traditional RNNs can only indirectly capture such relationships through fixed window time series feature engineering. Therefore, in the field of financial risk prediction, NTM has disruptive potential.

In addition, the development of financial risk prediction models for manufacturing enterprises faces severe data privacy challenges. The operational data of manufacturing enterprises involves a large amount of core business data such as inventory costs and supply chain costs, so the financial risk prediction of manufacturing enterprises has the characteristics of strong data sensitivity and large data volume [5]. At the same time, when manufacturing enterprises complete digital transformation, the above data will be scattered in independent systems such as manufacturing management systems and supply chain management systems, making integration difficult. The traditional RNN framework requires manufacturing enterprises to upload a large amount of raw data to third-party platforms

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during model training, which poses a risk of privacy data leakage for the enterprise. These risks may lead to market share losses and cost structure leaks for manufacturing companies. In summary, intelligent manufacturing enterprises often hold multiple private data that cannot be shared, which has led to a decrease in the accuracy of financial risk prediction in traditional models.

Federated learning (FL) technology has the potential to protect data privacy in financial risk prediction for manufacturing enterprises through distributed computing frameworks. Specifically, FL adopts a multi-layer federated encryption protocol, which can isolate the financial data of various manufacturing enterprises in a local encryption domain. Sensitive fields such as research investment cost, equipment investment cost, and supply chain cost of manufacturing enterprises are encrypted and trained locally with relevant model parameters, which are then uploaded to the global model of the alliance. Therefore, this study focuses on the financial risk prediction problem of manufacturing enterprises, considering the complexity and privacy constraints of manufacturing enterprise data. Based on the NTM model and FL framework, a hybrid NTM-FL framework is designed, which uses the NTM model with an LSTM controller to predict the financial risk of manufacturing enterprises. At the same time, the improved starfish optimization algorithm (ISFOA) was used for the parameter of NTM optimization. Overall, this study designed an intelligent decision-making system with privacy protection, temporal modeling, and adaptive optimization features. The main contributions of this study are summarized as follows:

- This study develops an FL-based distributed framework where a central server coordinates local deep learning model training across manufacturing enterprise clients, achieving accurate financial risk prediction without raw data disclosure.
- An improved starfish optimization algorithm (SFOA) has been designed, which incorporates the reconnaissance and foraging strategies of artificial bee colony (ABC) algorithm into the search strategy of the improved SFOA (ISFOA), aiming to improve the convergence accuracy of SFOA and optimize the hyperparameters of deep learning models.
- A hybrid ISFOA-NTM model was constructed as a local deep learning model for the FL framework. Optimizing the hyperparameter combination of NTM model with LSTM controller using ISFOA algorithm, including learning rate, regularization coefficient, and number of neurons, aims to improve the prediction accuracy of local deep learning model.
- The ISFOA-based NTM-FL (ISFOA-NTM-FL) framework has improved the accuracy and generalization ability of financial risk prediction models. On the test set corresponding to 10 epochs, the performance of ISFOA-NTM-FL was validated. Compared with the baseline NTM-FL model and LSTM model, the prediction accuracy of ISFOA-NTM-FL model increased by 13% and 23%, respectively.

The remaining parts of this study are arranged as follows: Section II focuses on reviewing work related to deep learning and federated learning. Section III introduces the methodology and ISFOA-NTM-FL framework of this study. In Section IV, the proposed framework's test results on two test sets are presented. Finally, Section V provides a conclusion of this study.

II. Literature Review

A. Deep Learning and Neural Turing Machine

Deep learning frameworks can model the complex relationships of a system, accurately capturing causal relationships between inputs and outputs. Due to the above advantages of deep learning frameworks, there have been numerous studies using deep learning frameworks in prediction problems at present. The author in [6] proposed a Bayesian-based deep learning model for complex signal processing problems, which significantly improved the performance of deep learning models. Jawed et al. developed a real-time learner learning style recognition model based on deep learning in the context of animation education [7]. This study utilized learners' raw EEG data for evaluation and successfully achieved accurate recognition of learners' learning styles in the context of animation education by constructing an efficient deep learning architecture, providing new tools and methods for the development of personalized education technology. Kim et al. studied the application of deep learning models in predicting the risk behavior of retail investors [8]. The results indicate that this study demonstrates the potential of deep learning models in identifying high-risk investors, providing an effective risk management tool for financial institutions.

The author in [9] proposed a deep learning-based image processing method for quantifying financial audit risks in the healthcare field. This study aims to develop a system that can automatically identify and quantify risks by combining deep learning techniques with financial audit requirements, while providing intelligent solutions for financial management in the healthcare industry. In response to the real-time pedestrian detection, pose estimation, and tracking problems based on visual sensors, a unified deep learning framework integrating multiple deep learning techniques was designed in [10], aiming to improve the accuracy and efficiency of object detection tasks based on deep learning, and provide technical support for intelligent transportation systems and security monitoring fields. Park et al. proposed an investment portfolio management method based on uncertainty perception, which optimized the decision-making process of the investment portfolio by introducing uncertainty factors and combining them with a risk-sensitive multiagent network [11]. Sattar et al. developed a deep reinforcement learning model that combines reinforcement learning with investment strategies to optimize portfolio management in stock trading [12]. The results showed that the proposed deep learning model can significantly improve the returns and stability of investment portfolios. Biswas et al. developed a dual-output time convolutional network with an attention mechanism for stock price prediction and risk assessment, aiming to enhance the model's ability to capture key information [13]. This study improved the accuracy of financial market forecasting and risk prediction by introducing attention mechanisms.

NTM is an advanced architecture in deep learning models that integrates DNN with classical computational theory. By introducing external memory mechanisms, it extends the capabilities of traditional neural networks to handle more complex sequential tasks, thereby improving the interpretability of DNN. The author in [14] developed an NTM architecture that can process time series data and generate interpretable predictive results by combining data from physician-pharmacist collaborative clinics. Stogin et al. proposed an NTM model that can be proven stable under finite accuracy and time conditions, demonstrating its robustness and reliability under limited computing resources, providing a foundation for the deployment of neural Turing machines in practical applications [15]. The author in [16] designed an NTM model based on differentiable decision trees and introduced the finite time difference method into NTM, aiming to solve electromagnetic problems. Wu et al. revealed the emergence mechanism of machine thinking in complex systems through theoretical modeling and experimental analysis [17]. Postlethwaite et al. extended the computational power of traditional Turing machines by introducing continuous time dynamics theory, providing a new framework for modeling and optimizing complex systems [18].

B. Federated Learning

Federated learning has the advantage of protecting data privacy. How to train the dataset on local devices and upload the model parameters generated during the training process to the central server is a key issue. Therefore, federal learning is widely used in a large number of financial, pharmaceutical and Internet enterprises. Mistry et al. designed a federated learning framework for privacy-preserving screen activity tracking and classification problems [19]. This study uses a federated learning framework based on an electronic learning background to track and classify screen activity in real-time. The results show that the federated learning framework effectively avoids centralized storage of sensitive data through local data processing and model aggregation. Orlandi et al. explored the problem of federated learning in processing independent data in edge intelligence environments [20]. This study proposes an entropy-based approach that improves the performance of federated learning on edge devices by optimizing data distribution. Xie et al. designed a federated learning framework based on the problem of multi-target recognition that combines differential privacy technology, which can achieve accurate recognition of multiple task targets while protecting data privacy [21].

Kalapaaking et al. combined blockchain technology with federated learning and proposed a secure aggregation framework based on a trusted execution environment, suitable for internet of things (IoT) scenarios [22]. This study ensures data security and traceability through blockchain while utilizing federated learning for distributed model training. The author in [23] provided a comprehensive review of privacy inference attacks and defenses in centralized and federated learning, while also introducing the potential applications of federated learning in privacy-sensitive fields. In [24], the author proposed a federated learning framework that combines server learning and effectively alleviates the challenges posed by non-independent and identically distributed data through global model optimization on the server side. Sun et al. introduced federated learning based on the background of machine fault diagnosis tasks, gradually training the model to learn data features from simple to complex, effectively reducing the impact of noisy labels on model performance [25].

III. Materials and Methods

In order to improve the accuracy of predicting financial risks in manufacturing enterprises and enhance the intelligence level of financial risk management, this study designed a hybrid NTM-FL framework based on FL architecture and NTM model for financial risk prediction. This hybrid framework uses a distributed architecture to protect the privacy data of enterprises, while the NTM model with LSTM controller is trained on each local device. In the financial risk prediction model for manufacturing enterprises based on the NTM-FL framework, the client (participant) is a local device that collects core data of the manufacturing enterprise. The local device uses a deep learning model to train the parameters of the risk prediction system. The central server is responsible for coordinating the training of financial risk prediction models and aggregating updates of local models. During the FL framework training process, data from distributed local devices is always stored on the local devices, and only model parameters are shared. In the FL model prediction process, each local device is trained using NTM models based on data from different manufacturing companies. Fig. 1 shows the designed hybrid NTM-FL framework.

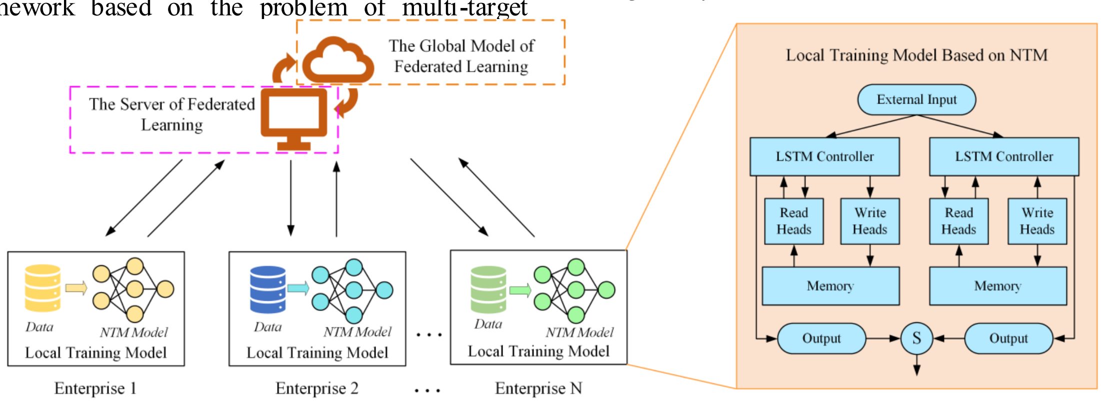

Fig. 1. The hybrid NTM-FL framework for financial risk management in manufacturing enterprises.

A. The Hybrid NTM-FL Approach

In this study, a federated learning framework was used to predict the financial risks of manufacturing companies, aiming to train a global financial risk prediction model for manufacturing companies using time-series data from multiple local devices. Fig. 2 shows the flowchart of the FL framework. Each local device is trained using NTM. Algorithm 1 demonstrates the pseudocode of NTM. In Algorithm 1, $T_{\max}$ is the maximum number of training iterations and k is the current number of training iterations.

Algorithm 1: Neural Turing Machine (NTM)

```
Initialize: Input layer size, hidden layer size, memory size, number of heads.
NTM.Controller ← LSTM
NTM.Memory ← zeros (memory size)
Training frequency ← T_max
Compute:  Output layer status.
While (k < Training frequency) do
|  Forward propagation
|      |  NTM.Controller processes input.
|      |  NTM.Memory reads memory.
|      |  NTM.Memory writes into memory.
|      |  Generate predictions.
|      |  k ← k+1
|  End
Return (Output layer status).
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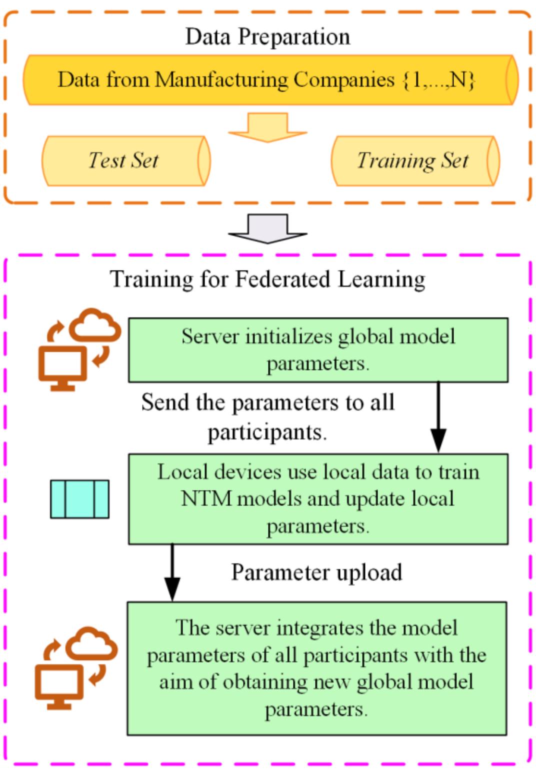

Fig. 2. The flowchart of the FL model.

B. Improved Starfish Optimization Algorithm

This study uses a federated learning architecture to design financial risk management systems for manufacturing companies, aiming to protect their data privacy. At the local device layer, the differential controller of NTM automatically encodes various heterogeneous data, such as financial reports and supply chain logistics costs of manufacturing companies, into temporal feature vectors, and performs causal inference based on the training set in memory. Therefore, in order to further improve the prediction accuracy of the NTM algorithm at the local device layer, this study uses metaheuristic algorithms to optimize hyperparameters such as scaling factors, interpolation weights for new and old content addressing, learning rates, and gradient clipping thresholds. Specifically, in this study, an improved SFOA (ISFOA) algorithm was designed based on the Artificial Bee Colony (ABC) algorithm [26] and the Starfish Optimization Algorithm (SFOA) algorithm [27]. The optimization process of the ISFOA algorithm is shown below.

Step 1. Initialize the population and parameters of the ISFOA algorithm. Generate L solutions based on the maximum and minimum range of hyperparameters in NTM, where each solution $SF\_l=[S_l^1,S_l^2,\cdots S_l^X]$ is an X-dimensional vector. Therefore, the population matrix of the ISFOA algorithm is as follows:

$$SF=\begin{bmatrix} SF\_1 \\ SF\_2 \\ \cdots \\ SF\_L \end{bmatrix} \tag{1}$$

Step 2. The exploration stage is based on the starfish optimization mechanism. Generate a random number P_{sa} on the interval [0,1], and for the $x-th$ individual in each solution, if $P_{sa}>0.5$, execute an exploration strategy based on the starfish optimization mechanism. When implementing the exploration strategy in the starfish optimization mechanism, generate a random number $Rand1$ in the interval [-1,1]. If $Rand1>0.5$, update based on the starfish exploration environment strategy, which is defined in (2); Otherwise, update based on the starfish predation strategy, which is defined in (3).

$$S_l^x\_new=\begin{cases} S_l^x+(2\times Rand2-1)\pi\times(S_{best}^x-S_l^x)\times\cos\theta, & Rand2<0.5 \\ S_l^x-(2\times Rand2-1)\pi\times(S_{best}^x-S_l^x)\times\sin\theta, & Rand2\geq 0.5 \end{cases} \tag{2}$$

where, $S_l^x\_new$ is the parameter of the updated solution vector. S_{best}^x is the solution vector of the currently searched optimal solution. $Rand2$ is a random number on the [0,1] interval.

$$S_l^x\_new=S_l^x+Rand3\times(S_{best}^x-S_{rands1}^x)+Rand4\times(S_{best}^x-S_{rands2}^x) \tag{3}$$

where $Rand3$ and $Rand4$ are random numbers on the [0,1] interval, respectively. S^x_{rands1} and S^x_{rands2} are two randomly selected solution vectors from all current solution vectors.

θ is the angle variable for search, which is defined in (4).

$$\theta = \frac{\pi}{2} \times \left(\alpha / \alpha_{\max}\right) \tag{4}$$

where α is the current iteration count of the ISFOA algorithm, and $\alpha_{\max}$ is the maximum iteration count of the ISFOA algorithm.

In addition, Fig. 3 illustrates the process of the starfish predation strategy.

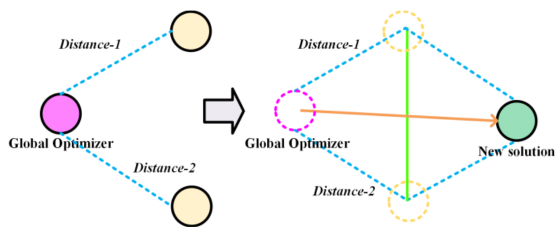

Fig. 3. The predation strategy of ISFOA

Step 3. The development stage is based on the foraging mechanism of bees. If $P_{sa} \leq 0.5$, the development phase based on the bee foraging mechanism will be executed. The definition of development strategy based on bee foraging mechanism is as follows:

$$S^x_l\_new = \begin{cases} S^x_l + \phi_{lx} \times (S^x_l - S^x_{rands1}), & Rand5 < 0.5 \\ S^x_{\min} + \phi_{lx} \times (S^x_{best} - S^x_{\min}), & Rand5 \geq 0.5 \end{cases} \tag{5}$$

where, $Rand5$ is a random number on the interval [0,1]. $S^x_{\min}$ is the $x-th$ vector of the worst solution so far.

Step 4. Update the global optimal solution. Calculate the fitness function of the current solution of the ISFOA algorithm based on the objective function $f(\hat{y}, y)$, while updating the fitness function of the optimal solution. The definition of $f(\hat{y}, y)$ is as follows:

$$f(\hat{y}, y) = \frac{\sum|\hat{y} - y|}{N} \tag{6}$$

where $\hat{y}$ is the predicted value of financial risk. y is the true value of financial risk. N is the size of the test set.

Step 5. Output the optimal solution. Determine whether the maximum number of iterations has been reached, and if so, output the global optimal solution vector.

IV. Results

This study designed a hybrid NTM-FL framework aimed at predicting financial risks in manufacturing enterprises using both NTM and FL architectures. In addition, to further improve the accuracy of the hybrid NTM-FL prediction framework in financial risk prediction problems, we optimized the hyperparameters of NTM using the ISFOA algorithm. To evaluate the application effectiveness of the ISFOA-NTM-FL model in financial risk prediction problems. Validate based on a dataset consisting of interim and annual reports disclosed by 263 manufacturing companies listed on the Hong Kong Stock Exchange (HKEX) and the New York Stock Exchange (NYSE) from 2015 to 2024. Therefore, when conducting time series forecasting of financial risks, a prediction is made every 6 months, with 20 samples corresponding to each enterprise in the dataset. The sample size of the financial risk prediction dataset is 5260. The dataset includes financial expenditures and profit margins of manufacturing enterprises. Based on the above data, we trained the ISFOA-NTM-FL model for 10 epochs. Therefore, in each epoch experiment, data from 100 samples in the dataset were used to test the ISFOA-NTM-FL model. Before conducting the experiment, the scores, levels, and classifications of financial risks are defined in Table I. The indicators for evaluating the application effectiveness of ISFOA-NTM-FL in 10 epochs are defined in Table II [28]-[30].

TABLE I. THE CLASSIFICATIONS OF FINANCIAL RISKS

Risk Score	Risk Level	Risk Classification
0. ≤ Score <2	Low Risk	Class 1
2 ≤ Score <4	Low to Medium Risk	Class 2
4 ≤ Score <6	Medium Risk	Class 3
6 ≤ Score <8	Medium to High Risk	Class 4
8 ≤ Score <10	High Risk	Class 5

TABLE II. EVALUATION INDICATORS FOR RISK PREDICTION MODELS

Index	Definition
Macro-Precision	$Macro-Precision = \frac{1}{M}\sum_{m=1}^{M}\frac{TP_m}{TP_m + FP_m}$
Macro-Recall	$Macro-Recall = \frac{1}{M}\sum_{m=1}^{M}\frac{TP_m}{TP_m + FN_m}$
Macro-F1 Score	$Macro-F1\ Score = \frac{2 \times Macro-Precision \times Macro-Recall}{Macro-Precision + Macro-Recall}$

TP_m represents the number of samples in the financial risk prediction test set whose true value is class m and were predicted as class m. FP_m represents the number of samples in the financial risk prediction test set whose true value is not class m but were predicted as class m. FN_m represents the number of samples in the financial risk prediction test set whose true value is class m but were predicted incorrectly.

In addition, the ABC-NTM-FL model, classic NTM-FL model, and classic LSTM model were used to compare with the proposed ISFOA-NTM-FL model, aiming to demonstrate the potential of the proposed ISFOA-NTM-FL model in predicting financial risks in manufacturing enterprises. Fig. 4 shows the financial risk prediction results of the ISFOA-NTM-FL model for two manufacturing companies. As previously mentioned, this study developed hyperparameters for ISFOA optimized NTM model with LSTM controller. In Fig. 5, the loss function curves of ISFOA and ABC algorithm optimized

NTM model with LSTM controller during 15 training processes in epoch 1 are shown.

TABLE III. THE RESULTS OF FOUR LOCAL DEEP LEARNING MODELS

Algorithm	The Parameters of the Optimization Algorithm		Hyperparameters of NTM		Loss Function		
	Population Size	*Number of Iterations*	*Learning Rate*	*Number of Neurons*	*Average Value*	*The Upper Bound of 95% C.I.*	*The Lower Bound of 95% C.I.*
ISFOA-NTM	80	100	0.0093	118	0.0843	0.1301	0.0384
ABC-NTM	80	100	0.0087	124	0.2651	0.3344	0.1958
NTM	-	-	0.0010	124	0.4978	0.5745	0.4212
LSTM	-	-	0.0010	124	0.5139	0.5975	0.4658

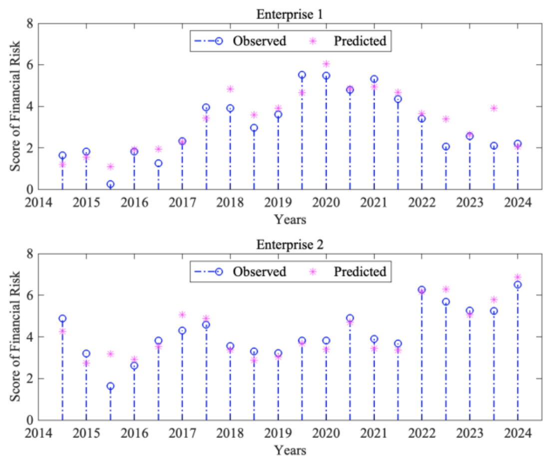

Fig. 4. The ISFOA-NTM-FL model predicts the financial risks of two manufacturing enterprises.

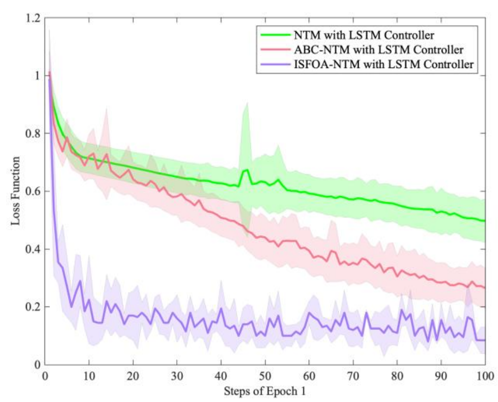

Fig. 5. The loss function curves of ISFOA and ABC algorithm optimized NTM model with LSTM controller.

Table III shows the results of 15 training sessions for four local deep learning models in epoch 1, including ISFOA-NTM, ABC-NTM, NTM, and LSTM. From Table III and Fig. 5, it can be concluded that when optimizing the NTM model with LSTM controller for financial risk prediction, the average loss function value of the ISFOA-NTM model in 15 training sessions is 0.0843, which is lower than other algorithms. Specifically, the average loss functions corresponding to the ABC-NTM, NTM, and LSTM models are 0.2651, 0.4978, and 0.5139, respectively. Compared with the ABC-NTM, NTM, and LSTM models, ISFOA-NTM has reduced losses by approximately 68.19%, 83.07%, and 83.60%, respectively. This result demonstrates the effectiveness of the ISFOA algorithm in NTM hyperparameters, which can effectively improve the accuracy of financial risk prediction models used for manufacturing enterprises.

In addition, the 95% C.I. of ISFOA-NTM is [0.0384, 0.1301], with a width of 0.0917. Compared with the other three models, ISFOA-NTM has the narrowest confidence interval width, indicating that the ISFOA-NTM-FL model has high stability. In addition, the confidence interval of the ISFOA-NTM model has no overlap with other algorithms, and the upper bound of the confidence interval of the ISFOA-NTM model is 0.1301, which is lower than the lower bound of ABC-NTM and significantly lower than the lower bounds of NTM and LSTM. Although the confidence interval of ABC-NTM is better than the benchmark NTM model and benchmark STM model, the confidence interval width is 0.1386, which further reflects that the ISFOA optimization strategy has more advantages in stability. Therefore, ISFOA-NTM achieves a significant reduction in loss function and synchronous improvement in stability through hyperparameter optimization.

When testing the ISFOA-NTM-FL model, ABC-NTM-FL model, NTM-FL model, and LSTM model in Epoch 1, the four indicators of macro-F1 score, macro-precision, macro-recall, and accuracy were used to evaluate the financial risk prediction results. Fig. 6 shows the confusion matrix of the financial risk prediction results of the ISFOA-NTM-FL model in Epoch 1 on a test set consisting of 100 samples. Table IV shows the indicators of the ISFOA-NTM-FL model's financial risk prediction results for five categories in Epoch 1, including the F1 score, precision, recall, and accuracy indicators corresponding to each risk category.

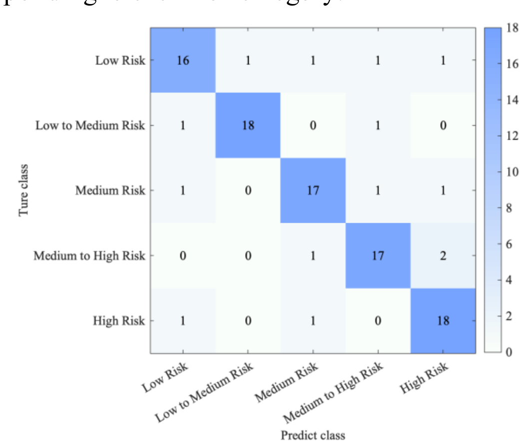

Fig. 6. The confusion matrix of the financial risk prediction results of the ISFOA-NTM-FL model in Epoch 1.

TABLE IV. THE INDICATORS OF ISFOA-NTM-FL MODEL'S FINANCIAL RISK PREDICTION RESULTS FOR FIVE CATEGORIES IN EPOCH 1

Index	Class 1	Class 2	Class 3	Class 4	Class 5
F1 Score	0.8205	0.9231	0.8500	0.8500	0.8571
Precision	0.8421	0.9474	0.8500	0.8500	0.8182
Recall	0.8000	0.9000	0.8500	0.8500	0.9000
Accuracy	0.8000	0.9000	0.8500	0.8500	0.9000

From the data in Table IV, it can be seen that the ISFOA-NTM-FL model has a high overall accuracy in predicting five types of financial risks, with an accuracy of over 80% for each type of financial risk prediction. Among them, the F1 score corresponding to Class 2 is 0.9231, the precision is 0.9474, and the recall rate is 0.9, indicating that the accuracy of risk prediction for this class (Class 2) is the highest. The F1 score for Class 1 is 0.8205, with a recall rate of 0.8000, indicating a 20% real risk of missed detections in Class 1. Overall, the ISFOA-NTM-FL model performs robustly in multiple categories.

Table V shows the training results of four models (ISFOA-NTM-FL model, ABC-NTM-FL model, NTM-FL model, and LSTM model) based on Epoch 1 dataset. Fig. 7 shows the results of the four models corresponding to the four indicators of macro-F1 score, macro-precision, macro-recall, and accuracy. The ISFOA-NTM-FL model achieved optimal performance in three aspects: accuracy, recall, and generalization ability in financial risk prediction tasks. The macro-precision of ISFOA-NTM-FL is 0.8615, and the macro-precision of ABC-NTM-FL is 0.7959. Compared with ABC-NTM-FL, the ISFOA-NTM-FL model has improved macro-precision by 8.24%. The macro-precision of classic NTM-FL and LSTM are 0.7300 and 0.6327, respectively. The ISFOA-NTM-FL model has the highest macro-precision. Compared with the ABC-NTM-FL model, the ISFOA-NTM-FL model can reduce seven prediction errors for every 100 financial risk warnings. The macro-recall of the ISFOA-NTM-FL model is 0.8600, which is an 8.86% increase compared to the ABC-NTM-FL model. The macro-F1 score of the ISFOA-NTM-FL model is 0.8601.

Fig. 8 shows the loss function values of the ISFOA-NTM-FL model over 10 epochs. Fig. 9 shows the corresponding macro-F1 score, macro-prediction, and macro-recall for the financial risk prediction results of the ISFOA-NTM-FL model over 10 epochs. Table VI shows the financial risk prediction results of the ISFOA-NTM-FL model over 10 epochs.

The ISFOA-NTM-FL model exhibits strong generalization ability in 10 epochs. In Epoch 1, the macro accuracy of the ISFOA-NTM-FL model is 0.8615, and the validation loss is 0.0843. In Epoch 10, all metrics of the ISFOA-NTM-FL model achieved the best results, with a macro-precision of 0.9200 and a validation loss of 0.0529. Compared with the results in Epoch 1, the macro-precision in Epoch 10 increased by 6.79%, the macro-recall increased by 5.81%, the validation loss decreased by 37.3%, and the training loss decreased by 47.3%.

The prediction accuracy of the ISFOA-NTM-FL model in handling financial risk prediction problems has improved from 86% in Epoch 1 to 91% in Epoch 10. The average accuracy of the ISFOA-NTM-FL model throughout the entire cycle is 88.5%, which is 2.91% higher than the initial value in Epoch 1. The ISFOA-NTM-FL model maintains high stability with an accuracy of nearly 89% throughout the entire training process.

TABLE V. THE TRAINING RESULTS OF FOUR MODELS BASED ON DATASET OF EPOCH 1

Index	ISFOA-NTM-FL	ABC-NTM-FL	NTM-FL	LSTM
Macro-Precision	0.8615	0.7959	0.7302	0.6327
Macro-Recall	0.8600	0.7900	0.7300	0.6300
Macro-F1 Score	0.8601	0.7901	0.7295	0.6296
Accuracy	0.8600	0.7900	0.7300	0.6300

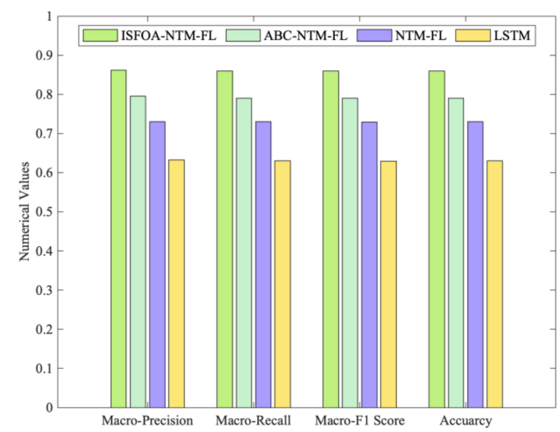

Fig. 7. The results of the four models correspond to the four indicators of macro-F1 score, macro-precision, macro-recall, and accuracy.

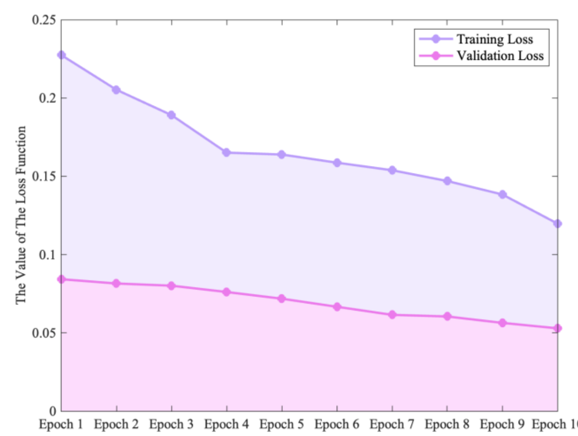

Fig. 8. The loss function of training the ISFOA-NTM-FL model in 10 epochs.

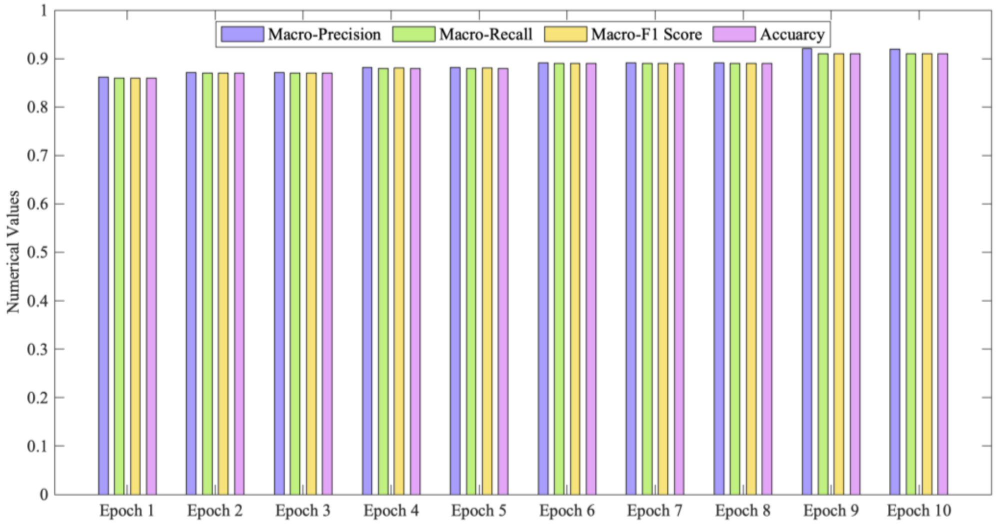

Fig. 9. The results of the ISFOA-NTM-FL correspond to the four indicators of macro-F1 score, macro-precision, macro-recall, and accuracy.

TABLE VI. THE RESULTS OF TRAINING THE ISFOA-NTM-FL MODEL IN 10 EPOCHS

Index	Epoch 1	Epoch 2	Epoch 3	Epoch 4	Epoch 5	Epoch 6	Epoch 7	Epoch 8	Epoch 9	Epoch 10
Training Loss	0.2274	0.2053	0.1891	0.1651	0.1639	0.1587	0.1539	0.1470	0.1384	0.1198
Validation Loss	0.0843	0.0815	0.0801	0.0761	0.0718	0.0667	0.0615	0.0605	0.0564	0.0529
Macro-Precision	0.8615	0.8709	0.8708	0.8812	0.8817	0.8916	0.8915	0.8909	0.9202	0.9200
Macro-Recall	0.8600	0.8700	0.8700	0.8800	0.8800	0.8900	0.8900	0.8900	0.9100	0.9100
Macro-F1 Score	0.8608	0.8705	0.8704	0.8806	0.8808	0.8908	0.8907	0.8904	0.9151	0.9150
Accuracy	0.8600	0.8700	0.8700	0.8800	0.8800	0.8900	0.8900	0.8900	0.9100	0.9100

V. CONCLUSION

In response to the challenges in the accuracy of financial risk prediction for manufacturing enterprises, this study designed a hybrid NTM-FL based intelligent prediction system based on the FL framework and NTM model. On this basis, an ISFOA algorithm is proposed to optimize the hyperparameters of the NTM model with LSTM controller, aiming to improve the prediction accuracy of the NTM model. Overall, the proposed financial risk intelligent prediction system achieves cross enterprise collaborative modeling without sharing raw data through FL architecture. Meanwhile, the system combines the memory enhancement capability of NTM with the temporal modeling advantage of LSTM. The results showed that compared to the ABC-NTM-FL, NTM-FL, and LSTM models, the proposed model improved the accuracy of financial risk prediction by 26.315%. At the end of training in ISFOA-NTM-FL, a prediction accuracy of 91% was achieved. In future research, the application of multimodal data in financial risk prediction models, such as fusion modeling techniques that consider market public opinion, will be further explored.

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