Application of Residual Graph Attention Networks Algorithm in Credit Evaluation for Financial Enterprises

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***Abstract*—In the context of digital transformation of enterprises, credit evaluation of financial enterprises faces new challenges and opportunities. Digital transformation introduces a large amount of data and advanced analytical tools, providing richer information and methods for credit evaluation. In this paper, we propose a credit evaluation model based on improved quantum genetic algorithm and residual graph attention network (DRQGA-ResGAT), which aims to utilize the complex correlation data and multi-dimensional information among enterprises for enterprise credit evaluation. The credit evaluation model based on DRQGA-ResGAT performs well in dealing with large-scale and high-dimensional data and can significantly improve the accuracy of credit evaluation. The experimental results show that the ResGAT model combined with the improved quantum genetic algorithm performs even better, and the proposed model has a high precision rate in the credit evaluation of financial enterprises, which has a greater application value. Compared with the traditional ResGAT model, the model improves about 17.06% in precision rate.**

***Keywords*—Quantum genetic algorithm; residual networks; attention mechanisms; graph neural networks; credit evaluation**

I. Introduction

In the context of enterprise digital transformation, financial enterprise credit evaluation faces new challenges and opportunities. Digital transformation not only changes the operation mode of enterprises, but also introduces a large amount of data and advanced analytical tools, providing richer information and methods for credit evaluation [1]. With the development of big data and artificial intelligence technology, deep learning algorithms are more and more widely used in the financial field. In particular, Residual Graph Attention Network (ResGAT), which is based on graph neural network, is excellent in processing graph-structured data and has been widely used in credit evaluation of financial enterprises [2].

Digital transformation refers to the optimization of business processes and the enhancement of operational efficiency and service capabilities by enterprises through the application of information technology [3-5]. In the financial industry, digital transformation not only includes the automation of traditional business, but also involves the in-depth integration of emerging technologies such as big data, cloud computing, and artificial intelligence [6]. The application of these technologies enables financial firms to process huge data sets more efficiently, thus realizing more accurate credit evaluation [7]. Deep learning, as an important branch of artificial intelligence, is able to automatically extract and learn complex features in data by simulating the neural network structure of the human brain. In financial enterprise credit evaluation, deep learning algorithms can effectively handle heterogeneous data, such as financial statements, transaction records, social media data, etc., so as to improve the precision and reliability of credit evaluation [8].

Shi et al. formulated a hybrid kNN-GNN model, investigated the integration of multiple graphs and the introduction of edge weights, and verified the feasibility and validity of the integrated model [9]. Zhang used a convolutional neural network (CNN) and a long short-term memory (LSTM) network to build a model that utilizes soft attention, and the gradient is propagated back to the rest of the model through the Attention Mechanism module [10]. The problem of recurrent neural network (RNN), which suffers from severe gradient vanishing under long sequence training, was solved. Gao et al. proposed a credit scoring model based on contrast-enhanced and tree-enhanced embedding mechanisms, which automatically constructs interpretable cross-features by using a tree-based model to learn decision rules from the data [11]. Currently, multiple improvement methods of graph neural networks shine in the aspect of credit risk evaluation for enterprises, especially after verifying the excellent effect of the attention mechanism, the practical effect of the graph attention model becomes more and more significant. Zhang et al. used a multimodal learning strategy to fuse two different data sources, and the cascade vectors derived from the data fusion were used as inputs to the feed-forward neural network to predict the credit risk of SMEs [12]. Sang et al. developed a graph attention network called DialogueGAT for predicting financial risk by simultaneously modeling the speakers and their words in a conversation during a teleconference [13].

However, GAT usually falls into overfitting or model degradation occurs when training a large amount of data, so residual networks were incorporated into GAT. Huang et al. proposed a residual-based graph attention network (ResGAT), which solves the over smoothing problem of the traditional graph convolutional networks (GCNs) when dealing with graph data by introducing the residual connectivity and attention mechanism, making it able to capture important features in the data and complex relationships between nodes [14]. Zhang et al. proposed two graph-based algorithms, E-ResSAGE and E-ResGAT algorithms, which build on the established GraphSAGE and GAT algorithms, respectively, to integrate residual learning into GNNs using available graph information [15]. Adding residual ties as a strategy to cope with high class imbalances aims to preserve the original information and improve the performance of a few classes. Fan et al. proposed a multi-headed residual graphical attention network model using graph neural networks to extract interaction features from compiled graphical data, and designed the SDAE-GPC model for assembly condition classification to derive graphical data inputs for the ResGAT regression model [16].

In credit evaluation, ResGAT can utilize the complex correlation data and multidimensional information among enterprises to predict their future credit risk. It is shown that the credit evaluation model based on ResGAT performs well when dealing with large-scale and high-dimensional data, and can significantly improve the precision of credit scoring. Zhou et al. proposed a credit default risk prediction model based on graphic attention network, which considers the potential relationship between users by constructing a multi-view graph [17]. The experimental results on a real dataset verified the model's validity. Song et al. proposed a multi-structured cascading graph neural network framework for ECR evaluation, which enhances the learning of enterprise representations based on enterprise graph structures with different granularities [18]. These studies show that deep learning algorithms such as ResGAT have significant advantages and potentials in dealing with complex data in financial enterprise credit evaluation.

However, the hyperparameters of the network in deep learning are usually difficult to set to the optimal combinations and often require repeated human experiments, so optimization algorithms were developed to be combined with deep learning models to accomplish hyperparameter tuning of the algorithms through automatic optimization search. Nebojsa et al. proposed an improved version of the population intelligence and monarch butterfly optimization algorithms for training feed-forward artificial neural networks to enhance the exploration capabilities and the intensification-diversification balance [19]. Stefan et al. proposed a new hybrid meta-heuristic approach to optimize network neuron parameters by using the hybrid bat algorithm for feed-forward neural network training [20]. Nebojsa et al. explored the application of population intelligence techniques for tuning hyper-parameters in convolutional neural networks by proposing an augmented meta-heuristic algorithm through the implementation of the automated method for hyperparameter optimization and structural design [21].

In summary, enterprise digital transformation provides new data sources and technical means for financial enterprise credit evaluation [22]. Deep learning algorithms, especially ResGAT, significantly improve the precision and reliability of credit evaluation by effectively processing graph-structured data. The development and application of these technologies not only promote the digitalization process of financial enterprises, but also provide strong support for enterprise risk management. By combining the research results of several literatures, it can be seen that the application of ResGAT in the credit evaluation of financial enterprises has a broad prospect and is worthy of further in-depth research and practice.

This article is organized as follows. Section II presents related research work. Section III presents the details of the credit evaluation model, including the problem description and the evaluation indicators used in the analysis. Section IV introduces the Quantum Genetic Algorithm (QGA) and its application in optimizing the ResGAT network. Section V presents the integration of QGA with ResGAT for financial enterprise credit evaluation and discusses the proposed enhancements. Finally, Section VI shows the experimental results, including dataset preparation, performance metrics, and a comparison of the DRQGA-ResGAT model with other optimization algorithms, discussion is given in Section VII followed by conclusions and future work in Section VIII.

II. Related Work

A. Graph Neural Networks in Credit Risk Prediction

Recent advancements in credit risk assessment (CRA) have shifted from traditional methods, which primarily rely on individual borrower or loan-level predictors, to more complex models that incorporate relational and network-based data. One significant approach combines graph-based models with machine learning techniques to better capture the interactions between different entities, such as borrowers and financial institutions. For example, the use of Relational Graph Convolutional Networks (RGCN) has proven effective in assessing the creditworthiness of Micro, Small, and Medium-sized Enterprises (MSMEs). By leveraging the topological structures of business relationships, RGCN helps identify key factors that influence credit risk, significantly improving the accuracy of predictions compared to conventional credit scoring models. This approach is further enhanced by integrating Random Forest (RF) classifiers, which categorize enterprises based on the embeddings generated by the graph model, achieving a balanced accuracy of 92% in the case of MSMEs in India [23]. Additionally, the dynamic nature of borrower relationships has been recognized as a crucial factor in predicting default risk. Recent work has incorporated Graph Neural Networks (GNNs) and Recurrent Neural Networks (RNNs) to model these evolving connections. By constructing a multilayer network where each layer reflects different sources of connection—such as geographical location or mortgage provider—these models offer a more nuanced understanding of how defaults propagate through networks over time. The use of custom attention mechanisms further refines these models, enabling them to weigh the importance of different time snapshots, which enhances their predictive power in behavioral credit scoring tasks [24]. Moreover, combining Graph Attention Networks (GAT) with Long Short-Term Memory (LSTM) networks has shown promise in capturing both the spatial and temporal dynamics of borrower interactions. Empirical results have demonstrated that such hybrid models not only outperform traditional methods in predicting default probabilities but also provide novel insights into the critical role of borrower relationships and time-sensitive data in credit risk assessment [25].

B. Graph Attention Networks and Residual Networks

Recent advances in deep learning have led to the development of residual graph attention networks (ResGAT) for a wide range of applications, showcasing the model's versatility across different domains. In molecular property prediction, ResGAT has been applied to quantitative structure-activity relationship (QSAR) modeling, significantly improving the prediction of molecular properties by utilizing graph-structured data. The model effectively extracts key features from molecular graphs, addressing both regression and classification tasks. When tested on benchmark datasets, ResGAT demonstrated competitive performance and stability, outperforming state-of-the-art methods in terms of accuracy and generalizability [26]. In the field of software vulnerability detection, ResGAT has been integrated with a custom local feature extraction module and a dynamic loss function to handle imbalanced data, enabling the model to learn more effective node features from control flow graphs and achieve state-of-the-art results in detecting vulnerabilities [27]. In hyperspectral image (HSI) classification, a spectral-spatial variant of ResGAT (S^2RGANet) has been proposed to address the limitations of conventional convolutional networks by combining spectral residual modules with graph attention for adaptive aggregation of spatial information. This method significantly improves classification accuracy, especially when the number of training samples is limited [28]. Lastly, in visual grounding tasks, ResGAT has been employed to model complex relationships between objects in images and their corresponding textual descriptions. A language-guided residual graph attention network (LRGAT-VG) is introduced to better handle long and complex expressions, incorporating language-guided data augmentation (LGDA) to enhance training data diversity. The model has achieved competitive performance on multiple visual grounding benchmarks, demonstrating its effectiveness in handling complex cross-modal tasks [29].

C. Hyperparameter Optimization

Hyperparameter optimization is a critical yet challenging task in machine learning, especially when models involve a large number of hyperparameters. Recent studies have proposed various methods to address this challenge. One approach focuses on modifying gradient-based methods to optimize multiple hyperparameters simultaneously, using two model selection criteria—cross-validation and evidence lower bound. The results show that models optimized using the evidence lower bound exhibit greater stability, particularly in noisy data scenarios, though they may yield slightly higher error rates than those selected via cross-validation. This method is particularly useful when dealing with overfitting or when cross-validation is computationally expensive [30]. Another study proposes a genetic algorithm-based approach, named HESGA (Hierarchical Evaluation Strategy Genetic Algorithm), to optimize hyperparameters of Graph Neural Networks (GNNs). By combining a full evaluation with a fast evaluation strategy, HESGA reduces the computational cost while maintaining the quality of the model. The method demonstrated its effectiveness in optimizing GNNs, showing superior performance over traditional Bayesian hyperparameter optimization methods on benchmark datasets [31]. A third approach, HyperBRKGA, introduces a population-based method for hyperparameter optimization that combines the Biased Random Key Genetic Algorithm (BRKGA) with an exploitation method. HyperBRKGA improves search efficiency by incorporating strategies like Random Walk and Bayesian Walk for better hyperparameter space exploration. The method outperformed traditional optimization algorithms, such as Grid Search and Random Search, on multiple datasets, demonstrating significant improvements in predictive performance [32].

III. Credit Evaluation Model

A. Description of the Problem

The application of enterprise digital transformation in credit evaluation of financial enterprises is one of the key topics in the current financial industry. With the rapid development of information technology, financial enterprises are constantly exploring and adopting new technological tools to enhance the precision and efficiency of their credit evaluation. The digital transformation of enterprises has provided financial institutions with rich data sources and advanced analytical tools, enabling them to assess the credit risk of borrowers or customers more comprehensively. This transformation is not limited to traditional financial data analysis, but also includes the integration and analysis of unstructured data (e.g., social media behaviors, spending habits, etc.) to more accurately portray a customer's credit profile. By applying algorithms like DRQGA-ResGAT, financial institutions are able to handle complex data patterns more efficiently and improve the predictive power and precision of credit evaluations within the framework of digital transformation, thereby optimizing lending decisions and risk management strategies.

B. Evaluation Indicators

In accordance with the basic principles of combining qualitative and quantitative indicators and combining potential and actual capabilities, the following enterprise credit rating indicator system structure was established. In addition, we divided the enterprise credit evaluation model into 9 first-level indicators and 25 second-level indicators, and each second-level indicator corresponds to a measurement content, as shown in Table I.

C. Model Data Normalization

The data depicted in Table I are discretely distributed and each level 1 indicator is independent of each other, so normalization can speed up the learning of the data. Define a set of input data $X = [x_1, x_1, \cdots, x_n]$ for the second-level indicators, and the maximum value of this set of data is $max(X)$ and the minimum value is $min(X)$. The normalized data is shown in Eq. (1).

$$x_i' = \frac{x_i - min(X)}{max(X) - min(X)}, i = 1, 2, \cdots, n \tag{1}$$

TABLE I. EVALUATION INDEX SYSTEM

Level 1 Indicators	Level 2 indicators	Measuring Content
The quality of the enterprise itself	Information Disclosure Assessment Results for Listed Companies	character
Solvency indicators	Long-term debt-to-equity ratio	capacity
	Long-term borrowings to total assets	capacity
	Gearing	capacity
	Current ratio	capacity
	Long-term debt to working capital ratio	capacity
	Total EBITDA/Liability	capacity
	Equity multiplier	capacity
Indicators of operational capacity	Current asset turnover ratio	capacity
	Total asset turnover	capacity
Profitability indicators	Return on net assets	capacity
	Return on investment (ROI)	capacity
	Net profit margin on current assets	capacity
	R&D expense ratio	capacity
	Non-recurring gains and losses	capacity
	Cash to total profit ratio	capacity
Cash flow indicators	Net cash flow per share	capacity
Capacity development indicators	Growth rate of selling expenses	capacity
	Total asset growth rate	capacity
	Revenue growth rate	capacity
	Rate of capital accumulation	capacity
Shareholder profitability	Earnings per share	capital
	Net asset per share	capital
Long term assets	Net fixed assets of enterprises	collateral
Supply Chain Status	Supply chain concentration	condition

IV. QUANTUM GENETIC ALGORITHM BASED ON DYNAMIC REVOLVING DOORS

Quantum Genetic Algorithm (QGA) is an optimization algorithm that combines quantum computing and traditional genetic algorithms. It takes advantage of the superposition of quantum bits and the parallel computing property of quantum gates to make the search space wider and thus improve the optimization performance. Individuals in QGA are usually represented in the form of quantum bits, and their states are described by probability magnitude, and population evolution is carried out through quantum gate operations. QGA can effectively search for the global optimal solution, and it performs well in dealing with the complex optimization problems of multi-peak functions.

A. Quantum Encoding

According to the principle of quantum superposition states, in two mutually independent quantum states $|0\rangle$ and $|1\rangle$, their arbitrary linear superposition forms a quantum state:

$$|\varphi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{2}$$

where the squares of α and β denote the probability that the system is at $|0\rangle$ and $|1\rangle$, respectively, and $\alpha^2 + \beta^2 = 1$. The mathematical model of (2) can also be referred to as the probability amplitude, which is denoted as:

$$|\varphi\rangle = \alpha\begin{bmatrix}0\\1\end{bmatrix} + \beta\begin{bmatrix}1\\0\end{bmatrix} = \begin{bmatrix}\alpha\\\beta\end{bmatrix} \tag{3}$$

B. Quantum Chromosomes

Traditional genetic algorithms usually use the problem parameter variable itself as an individual for optimization calculations and are computed through binary coding to form chromosomes that serve as information carriers so that they can convert the solution space into a search space that can be processed, thus completing the construction of the genetic structure of the individual.

While the quantum chromosome does not contain the problem solution directly, it constructs the quantum chromosome through the encoding method of quantum bits and expresses the state information through the form of probability amplitude shown in Eq. (3). According to Eq. (3), the Bth quantum chromosome of generation t with m quantum bits and m observation angles i is:

$$X_i^t = \begin{bmatrix} \alpha_{i1}^t, \alpha_{i2}^t, \cdots, \alpha_{im}^t \\ \beta_{i1}^t, \beta_{i2}^t, \cdots, \beta_{im}^t \end{bmatrix} \tag{4}$$

C. Dynamic Quantum Revolving Door

In quantum theory, transitions between individual quantum states are realized using quantum gates. The quantum gate rotates the probability amplitude angle of the quantum bits, taking into account the most individual information, which always makes the population converge to the optimal solution. The expression for a quantum rotating gate is:

$$U(\Delta\theta) = \begin{bmatrix} cos(\Delta\theta), -sin(\Delta\theta) \\ sin(\Delta\theta), cos(\Delta\theta) \end{bmatrix} \tag{5}$$

where $\Delta\theta$ denotes the rotation angle of the individual. The quantum rotating gate does not change the mode length of the quantum bit, but only changes the phase of the quantum bit, which is shown schematically in Fig. 1.

When the rotation angle is too large, the QGA is easy to fall into the local optimal solution, and the angle is too small will lead to too slow convergence and consume a lot of computational resources. Numerous improved versions of QGA use a fixed rotation angle as shown in Eq. (5), in order to minimize the impact of the rotation angle on the final computational precision, this paper proposes a dynamic rotation strategy, which is calculated as follows:

$$\Delta\theta_i^t = \frac{\Delta\theta_i^{t+c} - \Delta\theta_i^{t-c}}{2c} + \theta_{max} - \frac{t}{T}(\theta_{max} - \theta_{min}) \tag{6}$$

where c denotes the sequence scale from the current state, t is the current iteration number, T is the maximum iteration number, θ_{max} is the maximum rotation angle, and θ_{min} is the minimum rotation angle.

According to Eq. (6), it can be seen that the size of the rotation angle is determined by the number of iterations and the amount of accumulated angle change. From the first half of (6), it can be seen that the rotation angle is related to the difference of the previous rotation angle, which enables the rotation angle to be associated with the past and future states, and a larger rotation angle is used in the pre-evolutionary stage to expand the search range, and a smaller rotation angle is used in the later stage of the evolution for accurate search. DRQGA is able to change the angle dynamically according to the characteristics of the problem and the performance of the individual constantly, correlating the previous step and future state information, thus adjusting the current angle. The dynamic rotation angles for 2D coding are shown in Table II. The flowchart of the DRQGA algorithm is shown in Fig. 2.

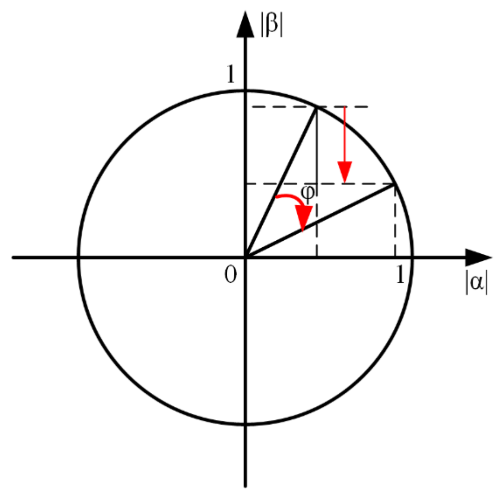

Fig. 1. Schematic diagram of a quantum revolving door.

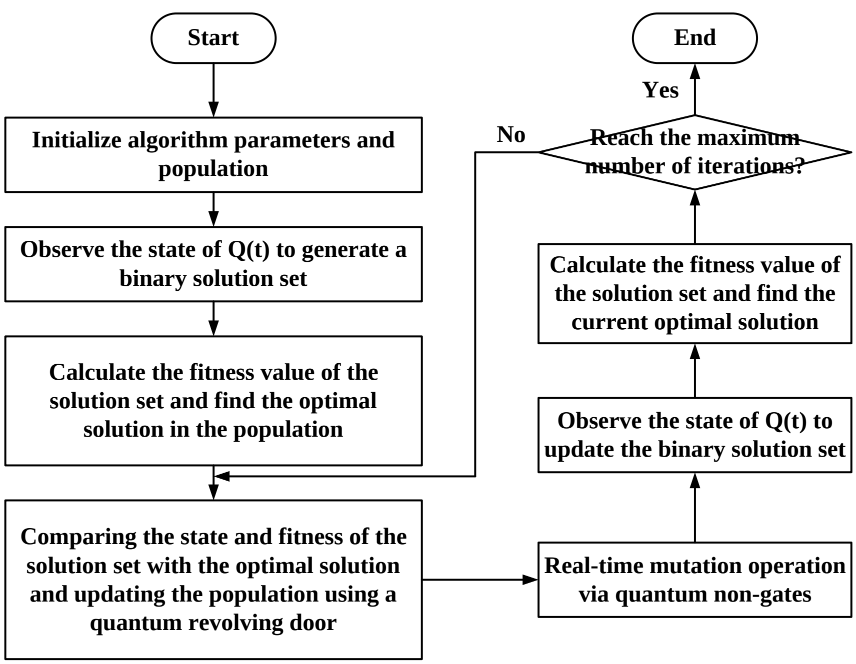

Fig. 2. Flowchart of DRQGA algorithm.

TABLE II. DYNAMIC ROTATION ANGLE LOOKUP TABLE FOR 2D CODING

x_i	x_i^{best}	$f(X) \geq f(X^{best})$	$\Delta\theta_i$	**Rotary Angle Symbol**			
				$\alpha_i\beta_i > 0$	$\alpha_i\beta_i < 0$	$\alpha_i = 0$	$\beta_i = 0$
0	0	false	$\Delta\theta_i^t$	0	0	0	0
0	0	ture	$\Delta\theta_i^t$	0	0	0	0
0	1	false	$\Delta\theta_i^t$	0	0	0	0
0	1	ture	$\Delta\theta_i^t$	-1	+1	±1	0
1	0	false	$\Delta\theta_i^t$	-1	+1	±1	0
1	0	ture	$\Delta\theta_i^t$	-1	+1	0	±1
1	1	false	$\Delta\theta_i^t$	-1	+1	0	±1
1	1	ture	$\Delta\theta_i^t$	-1	+1	0	±1

V. CORPORATE CREDIT EVALUATION MODEL BASED ON DRQGA-RESGAT

A. *Financial Enterprise Credit Evaluation Mapping Data*

In the process of credit evaluation of financial companies, we observe a significant effect of the financial leverage ratio on the overall credit score due to interactions between different credit evaluation indicators. The strength of these interactions varies with the particular combination of indicators, as determined by ANOVA. Considering these variables and their potential confounders in the modeling process, we propose to utilize the correlation information between the indicators as inputs to the model. To this end, we introduce a new data structure to accurately capture the effects of indicator interactions and improve predictive performance. We adopt the graph data structure approach proposed by Kipf and Welling [33], which proves to be very beneficial in analyzing the credit evaluation process. The graph data structure is able to efficiently encode information in a structured and meaningful way, representing both the attributes of each metric and the relationships between them. Fig. 3 illustrates an attribute-relationship graph describing the interrelationships of some of the credit evaluation metrics, where changes in the metric interactions can be interpreted as changes in the relationships between the nodes in the graph, utilizing $x_i, i = 1,2,\cdots,25$ to denote the second-level metrics we have defined and e_{ij} to denote the edges that are related, where $i, j = 1,2,\cdots,25, i \neq j$.

B. *ResGAT Evaluation Model*

In the process of credit evaluation of financial enterprises, GAT (Graph Attention Network) processes graph data, extracts attributes and relational features of nodes through a hidden masked self-attention layer, and uses an attention mechanism to process input variables, focusing on the most relevant parts. Credit evaluation metrics graph data can be processed through the graph attention network architecture to obtain higher-level feature representations. To cope with the overfitting problem under small sample conditions, we introduce a residual network architecture in the computation of the attention coefficients and the forward propagation of the model, which enhances the attention mechanism by introducing jump connections. As shown in Fig. 4, the ResGAT network consists of a residual feature extraction module and a graph attention module. The basic attribute features of credit evaluation metrics are represented by layers with residual connections, while the attention module provides learning focus based on the interaction information between metrics so that nodes can pay attention to the features in their neighborhood.

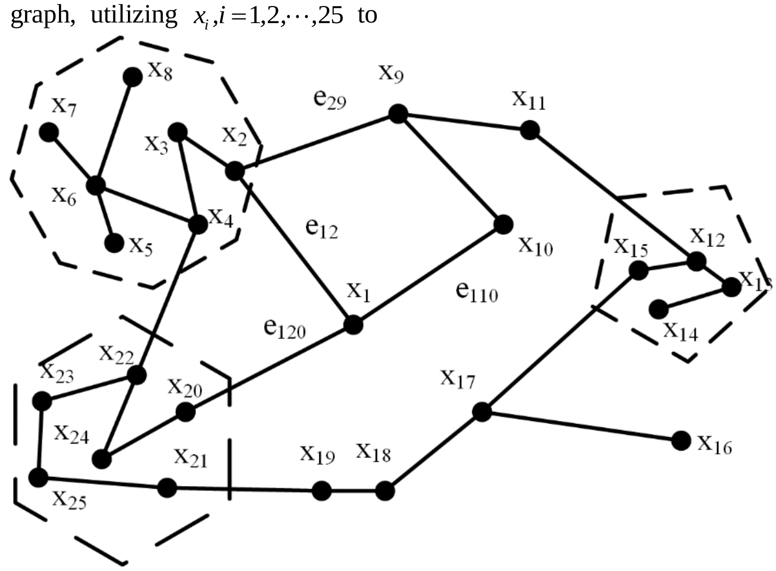

Fig. 3. Schematic diagram of indicator mapping.

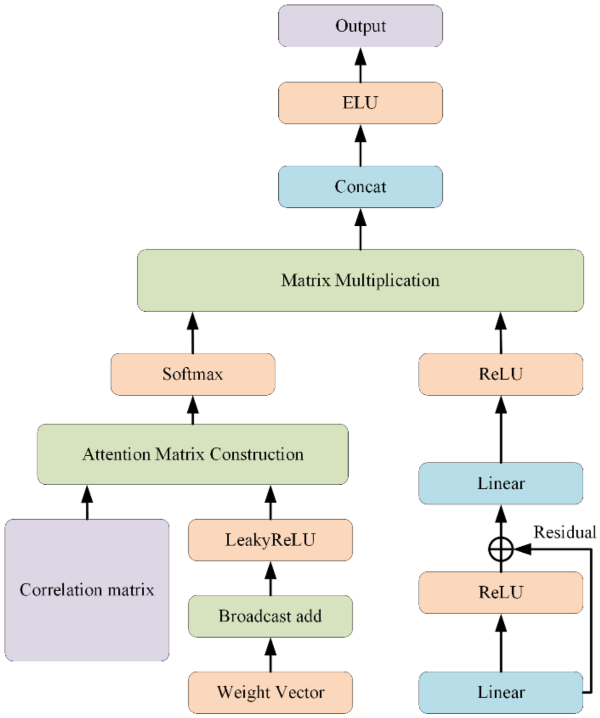

Fig. 4. Structure of the ResGAT network.

The input of the model is the evaluation index data after our normalization, and in the attention module, the attention coefficient e is calculated using the set of parameters to control the weight of the model, as shown in Eq. (7).

$$e = LeakyReLU((x \times a) + (x \times a)^T) \tag{7}$$

where x is the indicator parameter input, a is the trainable attention weights, and $LeakyReLU$ is the activation function as shown in Eq. (8). The plus sign in $(x \times a) + (x \times a)^T$ denotes the broadcast addition of the matrix.

$$y = max(0, x) + leak \cdot min(0, x) \tag{8}$$

Further, we use the adjacency matrix to represent the interaction between the parameters. Element A_{ij} indicates the existence of a significant interaction. When $A_{ij} = 1$, the interaction of indicator parameters X_i and X_j has a greater effect on the counterweight. An attention matrix Att is constructed using the attention coefficients e and 0 as shown in Eq. (10) and Eq. (11).

$$\hat{A} = \begin{bmatrix} 1 & A_{12} & A_{13} & \cdots & A_{1n} \\ A_{21} & 1 & A_{23} & \cdots & A_{2n} \\ A_{31} & A_{32} & 1 & \cdots & A_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_{n1} & A_{n2} & A_{n3} & \cdots & 1 \end{bmatrix} \tag{9}$$

$$\varepsilon_{ij} = \begin{cases} e, a_{ij} = 1 \\ 0, a_{ij} = 0 \end{cases} \tag{10}$$

$$Att_{ij} = Softmax(\varepsilon_{ij}) = \frac{exp(\varepsilon_{ij})}{\sum_{k \in N_i} exp(e_{ik})} \tag{11}$$

where ε_{ij} is an element of the adjacency matrix A, Att_{ij} is an element of the attention matrix Att, and N_i is the neighborhood quantity of node i in the graph. In order to avoid falling into degradation during the training of the network model, a residual connection is introduced in the propagation part of the right side, where the attention matrix of the left branch is multiplied with the result of the right branch after a nonlinear change, and w_1 and w_2 are assigned as weights thus obtaining the final result.

$$h = Att \times ReLU(x + ReLU(x \times w_1)) \times w_2 \tag{12}$$

C. DRQGA-ResGAT

In the credit evaluation process of financial enterprises, quantum genetic algorithm can significantly improve and enhance the performance of ResGAT network. The global optimization of ResGAT network using quantum genetic algorithm is as follows: the initial weights and attention coefficients of ResGAT network are optimized using quantum genetic algorithm. Then, the gradient descent algorithm is applied to adjust the parameters of the ResGAT network according to the negative gradient direction to train the network. The overall algorithm structure is schematically shown in Fig. 5.

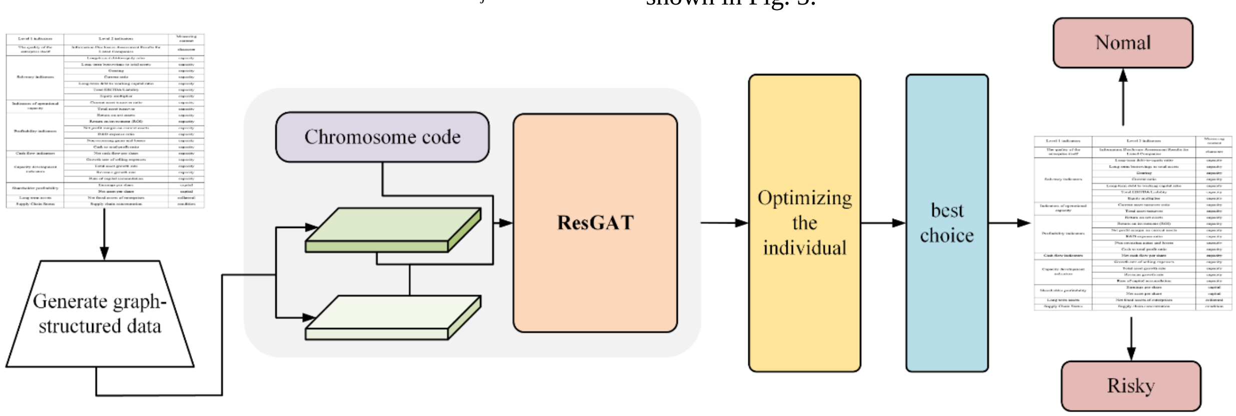

Fig. 5. The overall structure of the algorithm at a glance.

The main reasons for adopting this method to improve and enhance the ResGAT network are as follows:

- The quantum genetic algorithm utilizes quantum superposition and quantum gate operations to make the search space more extensive, effectively avoiding the shortcoming of the search range falling into a local minimum.
- The quantum genetic algorithm can converge quickly, thus reducing the number of training times of the weights and the attention coefficients.
- The parallel computing characteristics of the quantum genetic algorithm can significantly accelerate the convergence speed of the model.

The operation of the ResGAT network optimized by quantum genetic algorithm is divided into the following two steps:

1) Initialize the network parameters using quantum genetic algorithm: This step takes advantage of the superposition of quantum bits and the quantum revolving door operation to generate a variety of possible initial solutions, and obtain the optimal solution through quantum measurements, thus providing a better starting point for the network. Specifically, quantum genetic algorithms are used to determine the initial attention coefficients and weights of the ResGAT network, giving it a better performance from the start [34].

2) Chromosome coding: Since the quantum bit and quantum gate operations of the quantum genetic algorithm are able to represent continuous parameters, and the coding method of quantum states is characterized by continuous parameter optimization, the traditional steps of coding and decoding are omitted. To a certain extent, the computing speed and the precision of feasible solutions of quantum genetic algorithm are improved. Therefore, in this paper, the quantum state coding method is chosen to encode the chromosome. The quantum states are cascaded to the hidden layer nodes according to the input layer nodes and then cascaded from the hidden layer nodes to the output layer nodes. It should be noted that the chromosomes in the population are represented as a cascaded output array of quantum states.

3) Fitness function: The value of the fitness function determines the result of the quantum genetic algorithm's evaluation of the chromosome's survivability. The larger the value of the fitness function of a chromosome, the more likely it is to be selected for genetic manipulation and the smaller the sum of squares of the errors between the actual output value and the desired output value of the ResGAT network. The results show that the optimized ResGAT network has higher precision. In this paper, the logarithmic loss function is chosen as the adaptation evaluation function as shown in Eq. (13) to measure the performance of ResGAT network.

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i log(p_i) + (1-y_i) log(1-p_i)\right] \tag{13}$$

VI. Model Experiment

A. Dataset

Dataset In this paper, 253 SMEs were selected from the CSMAR database in 2020 for the empirical study, and after the data preprocessing ticks, except for the enterprises with serious missing information, the missing information of the remaining enterprises was replaced by the mean value. Finally, 210 SMEs were selected. Among them, there are 137 normal enterprises and 73 risky enterprises.

B. Results

In this paper, precision rate and recall rate are selected as the key evaluation indexes, and six hyperparameters such as learning rate, batch size, number of hidden layers, number of hidden units per layer, weight initialization method, Dropout rate are optimized, and the precision rate is used as the objective function of the quantum genetic algorithm, and the GPU used in the training is the NVIDIA GeForce RTX 2080 Ti. The number of iterations of the quantum genetic algorithm $T=100$, the population size $Pop=100$, the number of quantum bits $nq=10$, and the mutation probability $mr=0.01$. The quantum genetic algorithm is compared with the classical simulated annealing algorithm, genetic algorithm, particle swarm algorithm, and whale optimization algorithm, and the algorithm comparison results obtained are shown in Fig. 6. A comparison of the results of DRQGA-ResGAT with other algorithms is shown in Table III.

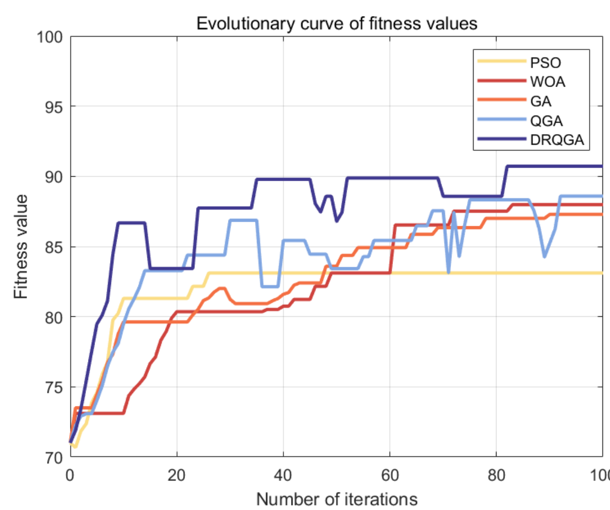

Fig. 6. Comparison of results of the optimization algorithm.

TABLE III. Performance of ResGAT Network Under Different Optimization Algorithms

Model	Precision	F1 score	AUC
PSO-ResGAT	0.8311	0.7939	0.9121
WOA-ResGAT	0.8798	0.8305	0.9476
GA-ResGAT	0.8728	0.7877	0.9298
QGA-ResGAT	0.8858	0.8439	0.9213
DRQGA-ResGAT	0.9071	0.8602	0.9647

The precision iteration curve of DRQGA-ResGAT under optimal hyperparameters is shown in Fig. 7. The training loss iteration curve is shown in Fig. 8. The validation loss iteration curve is shown in Fig. 9.

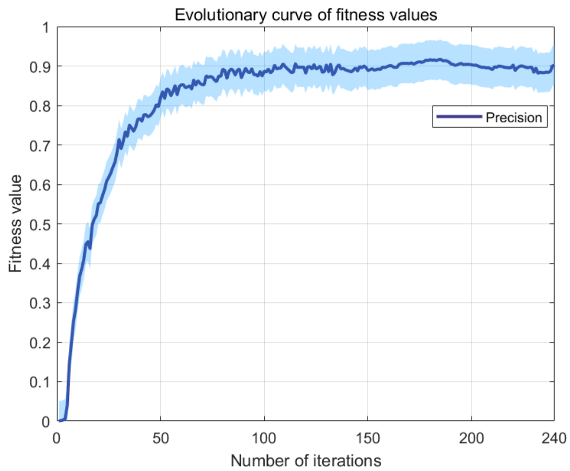

Fig. 7. Evolutionary curve of fitness values.

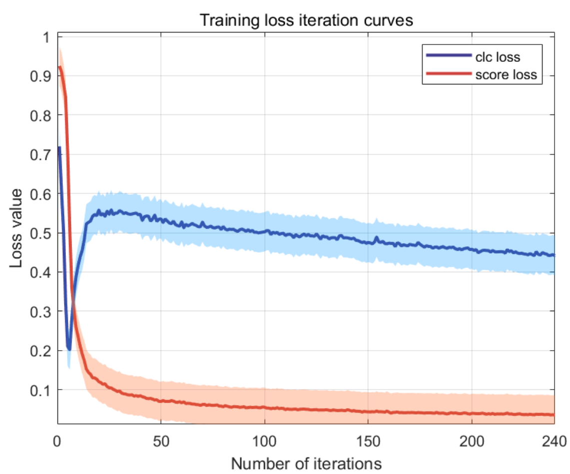

Fig. 8. Iteration curve of loss function for training set.

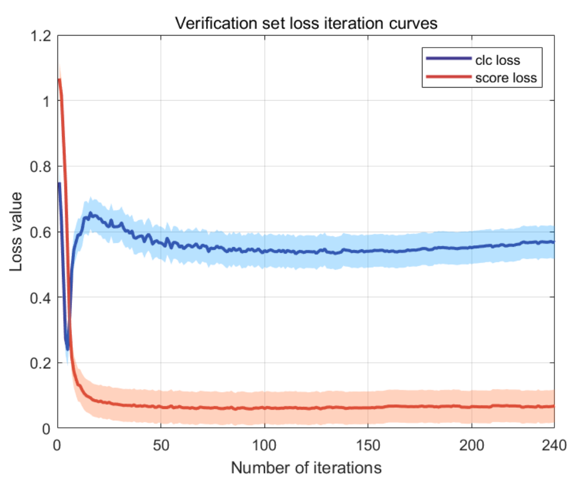

Fig. 9. Verification set loss function iteration curve.

TABLE IV. RESULTS OF ABLATION EXPERIMENTS

Model	Precision	F1 score	AUC
GAT	0.7310	0.7386	0.8431
ResGAT	0.7749	0.7795	0.8758
QGA-GAT	0.7705	0.7695	0.8812
QGA-ResGAT	0.8728	0.7877	0.9421
DRQGA-GAT	0.8001	0.7619	0.9257
DRQGA-ResGAT	0.9071	0.8602	0.9647

In order to explore the contribution of each improvement component, we conducted ablation experiments and the comparison results of the six different algorithms obtained are as follows. As can be seen in Table IV, DRQGA-ResGAT improves the precision by 24.09% compared to the most basic GAT, and the F1 score improves from 0.7386 to 0.8602. Compared to ResGAT, it improves by 17.06%. 3.92% compared to QGA-ResGAT and 13.37% compared to DRQGA-GAT. It can be seen that the precision of the models optimized with hyperparameters using DRQGA for GAT or ResGAT is significantly improved. Meanwhile, based on the GAT model, the ResGAT model with the introduction of the residual mechanism is able to achieve higher precision and more performance improvement with DRQGA optimization.

VII. DISCUSSION

Compared with the classical ResGAT model, DRQGA-ResGAT improves the evaluation precision by 17.06%, which is 3.92% higher compared with QGA-ResGAT. Compared with the classical optimization algorithm, the dynamic revolving door-based quantum genetic algorithm is able to explore the global optimal solution on a larger scale [35], and its ability to cope with mutant data makes the algorithm less susceptible to be interfered by special data. interference, thus ensuring the overall individual quality [36]. In future research, we will consider introducing the optimization strategy of the population intelligence optimization algorithm into the dynamic internal adjustment of the network model [37], and further exploring the combination of the optimization algorithm and deep learning network on the basis of hyperparameter tuning. In addition, on top of the existing datasets, larger datasets should be considered to enhance the scope of enterprises into the risk evaluation of enterprises in various industries.

VIII. CONCLUSION

Under the digital transformation of enterprises, in order to be able to evaluate the credit of financial enterprises more comprehensively and objectively, this paper adopts a quantum genetic algorithm based on dynamic revolving door for hyper-parameter tuning of residual map attention network. On this basis, a financial enterprise credit evaluation model is established. Specifically, the introduction of quantum genetic algorithm effectively enhances the optimization ability of the model and makes it perform well in the hyperparameter optimization search process. In addition, the excellent performance of the residual graph attention network in dealing with graph-structured data enables the model to better capture the complex associations among enterprises, thus enhancing the precision of credit evaluation. The experimental results show that the DRQGA-ResGAT algorithm outperforms other algorithms in key metrics such as precision rate, F1 value and AUC value. Especially when compared with the classical simulated annealing algorithm, genetic algorithm, particle swarm algorithm and whale optimization algorithm, DRQGA-ResGAT shows obvious advantages, which verifies its potential for application in the credit evaluation of financial enterprises.

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