Deep Learning-Based Attention Mechanism Algorithm for Blockchain Credit Default Prediction

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***Abstract*—With the rise of internet finance and the increasing demand for personal credit risk management, accurate credit default prediction has become essential for financial institutions. Traditional models face limitations in handling complex and large-scale data, especially in the blockchain domain, which has emerged as a crucial technology for securing and processing financial transactions. This paper aims to improve the accuracy and generalization of blockchain-based credit default prediction models by optimizing deep learning algorithms with the Special Forces Algorithm (SFA) and attention mechanism (AM) networks. The study introduces a hybrid approach combining SFA with AM to optimize hyperparameters of the credit default prediction model. The model preprocesses blockchain credit data, extracts critical features such as user and loan information, and applies the SFA-AM algorithm to improve classification accuracy. Comparative analysis is conducted using other machine learning algorithms like XGBoost, LightGBM, and LSTM. Results: The SFA-AM model outperforms traditional models in key metrics, achieving higher precision (0.8289), recall (0.8075), F1 score (0.8180), and AUC value (0.9407). The model demonstrated better performance in identifying both default and non-default cases compared to other algorithms, with significant improvements in reducing misclassifications. The proposed SFA-AM model significantly enhances blockchain credit default prediction accuracy and generalization. While effective, the study acknowledges limitations in dataset diversity and model interpretability, suggesting future research could expand on these areas for more robust applications across different financial sectors.**

Keywords*—Deep learning; attention mechanism; blockchain credit default prediction; special forces algorithm

I. Introduction

The rapid development of international Internet finance, more and more third-party lending institutions, Internet finance companies continue to emerge and appear [1]. At the same time, people's living standards are getting better, consumption level rises, consumption demand increases, the number of people borrowing and consuming is also increasing, and credit institutions are paying more and more attention to personal credit risk management [2]. Credit risk management focuses on the measurement of default risk, and when a borrower applies for a loan, the lending institution needs to evaluate the risk of the borrower with the help of certain methods to decide whether to borrow or not [3]. Credit default prediction as one of the core of credit risk management, the accurate identification and assessment of default customers, not only can avoid the loss of credit default customers to the counterparty, but also can be based on the credit risk assessment model to provide customers with more accurate, more personalised, better quality products and services [4].

With the arrival of the era of big data, the use of a large amount of information data to establish an effective credit default prediction model helps financial institutions to analyse the user's consumption, capital, and creditworthiness in a certain period of time, and then predict whether there is a user's default to reduce the risk of loss [5]. Therefore, researching scientific and accurate blockchain credit default prediction methods is very significant for financial institutions to make decisions. Analysing a large number of previous studies, scholars around the world and beyond have launched a large number of research works on credit default prediction [6].

Artificial intelligence technology is updated and iterative, machine learning and deep learning algorithms are gradually applied to credit default prediction [7]. Han et al [8] applied the decision tree model to the field of credit risk assessment. Oliver [9] used the personal loan data of LC company and built KNN, SVM, Logistic and RF models, and found that the RF model performed the best. Liu et al [10] compared the performance of different classification models such as RF, ANN, and LR based on different sampling strategies according to different evaluation indexes, and the results showed that the oversampling strategy has obvious advantages in dealing with unbalanced data. Ragab and Saleh [11] constructed a credit assessment model of Lasso-LR, and the results showed that it can effectively screen out features. Kriebel and Stitz [12] proposed to build an XGBoost-RF credit assessment model, and the results show that XGBoost can improve the accuracy of RF model after filtering the features. Lin and Liu [13] used a hybrid whale bat optimization algorithm to optimize the hyper-parameters of the machine learning model, and constructed a credit default prediction model for users, and the results show that the proposed prediction model not only has higher classification accuracy, but also has higher accuracy. model not only has higher classification accuracy, but also has strong interpretability.

Based on previous research, this paper uses intelligent optimisation algorithm and deep learning algorithm to optimise and improve the personal credit default prediction model, which improves the model classification accuracy and makes the model more explanatory. In this paper, the research will be carried out through the following architectures:

- The personal credit default prediction problem is analysed, relevant features are extracted, and data preprocessing is carried out;

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- The SFA algorithm [14] is used to optimise the hyper-parameters of the Attention Mechanism Model [15], and the personal credit default prediction model based on the SFA-AM is constructed; and
- The proposed method is validated and analysed using credit default data.

Based on the research objectives, the remainder of this paper is structured as follows: Section II provides an overview of blockchain technology and the key issues in credit default prediction. Section III describes the problem-solving approach, including feature analysis, data preprocessing, model construction, hyperparameter optimization, and model evaluation. Section IV introduces the improved SFA algorithm and the attention mechanism network, presenting the SFA-AM hybrid model. Section V details the experimental design, dataset description, parameter settings, and evaluation metrics, followed by a comparative analysis of model performance. Section VI summarizes the key findings, highlights the limitations, and proposes future research directions.

II. Blockchain Credit Default Analysis

A. Blockchain Technology

1) Overview: Blockchain technology is an innovative distributed ledger technology originally proposed by Satoshi Nakamoto, the anonymous creator of Bitcoin, to create a decentralised digital currency system [16-18]. The blockchain is maintained and updated by multiple nodes in the network, with each "block" containing a batch of transaction records that are cryptographically linked to the previous block to form a tamper-proof chain. This structure ensures data transparency and security, and any attempt to modify existing information will be detected and rejected by nodes in other parts of the network, as shown in Fig. 1.

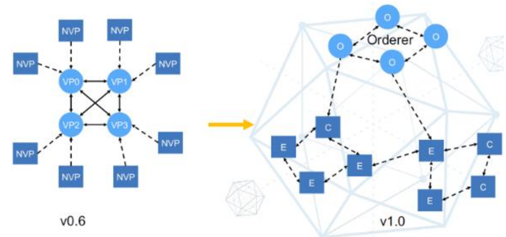

Fig. 1. Blockchain technology.

2) Blockchain characteristics: According to the principles of blockchain technology, blockchain has the following characteristics [19] (Fig. 2): 1) decentralisation; 2) immutability; 3) transparency; and 4) cryptographic security.

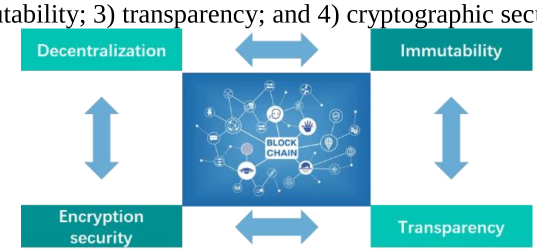

Fig. 2. Blockchain characteristics.

3) Blockchain applications: The application of blockchain technology has been extended to a number of fields, including financial services, supply chain management, healthcare, real estate, and voting systems [20], as shown in Fig. 3.

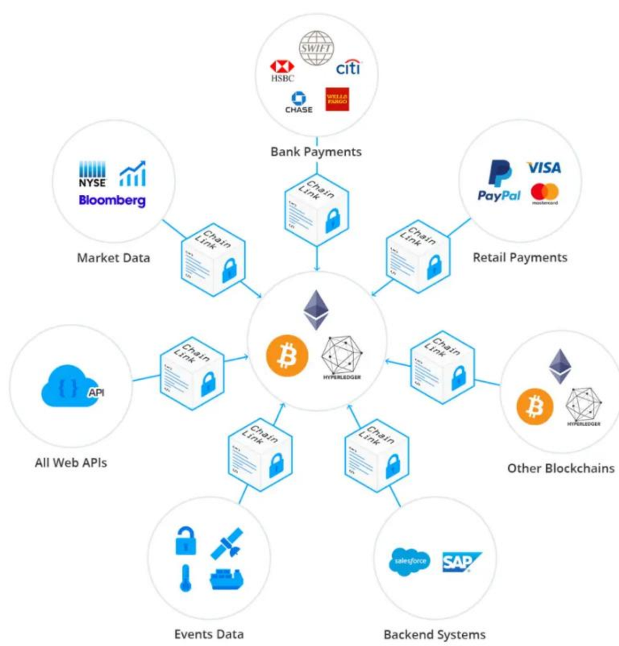

Fig. 3. Blockchain applications.

B. Credit Default Prediction Issues

1) Credit rating: Credit rating is an important indicator for financial institutions in assessing the credit risk of users. There are seven grades of loan users, which are A, B, C, D, E, F, and G, and their credit ratings decrease in order [21]. The percentage of users in each grade is given in Fig. 4. From Fig. 4, it can be seen that users of grades A, B, and C in the dataset occupy 73.12%, and the remaining grades occupy 26.88%, in which users of grades A, B, and C are higher credit rating users, which indicates that most of the users have fewer defaults.

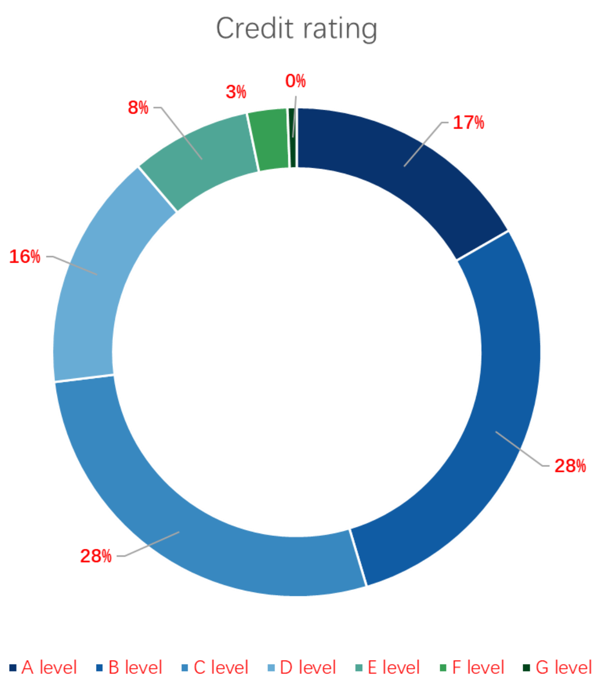

Fig. 4. Distribution of credit ratings.

2) Characterisation: The features that need to be analysed in the user credit default prediction problem mainly include basic information about the user, basic information about the borrowing project, and historical information about the borrowing project [22].

a) Basic information of loan users: In addition to the user's credit rating, the basic profile of the loan user includes the user's years of employment (Fig. 5), the user's home ownership (Fig. 6), the distribution of the user's annual income (Fig. 7), and the distribution of the loan user's loan amount (Fig. 8).

As can be seen from Fig. 5, 34.64% of the users have worked for more than 10 years, 26.05% have worked for 0 to 3 years, and the rest have worked for 3 to 10 years. The number of years of working experience reflects whether the user has the ability to make repayments, and usually the higher the number of years of working experience, the lower the possibility of their default.

Fig. 6 gives the distribution of home ownership among users. It can be seen from Fig. 6 that 50 % of the users are in home ownership and 40.13 per cent of the users are still renting their homes.

Fig. 7 shows that more than 90 % of the users have an annual income of less than $500,000, and very few users have more than $500,000 per year.

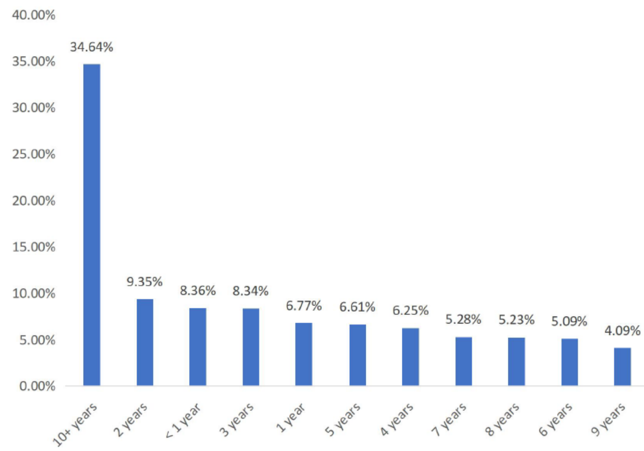

Fig. 5. Distribution of users' years of working experience.

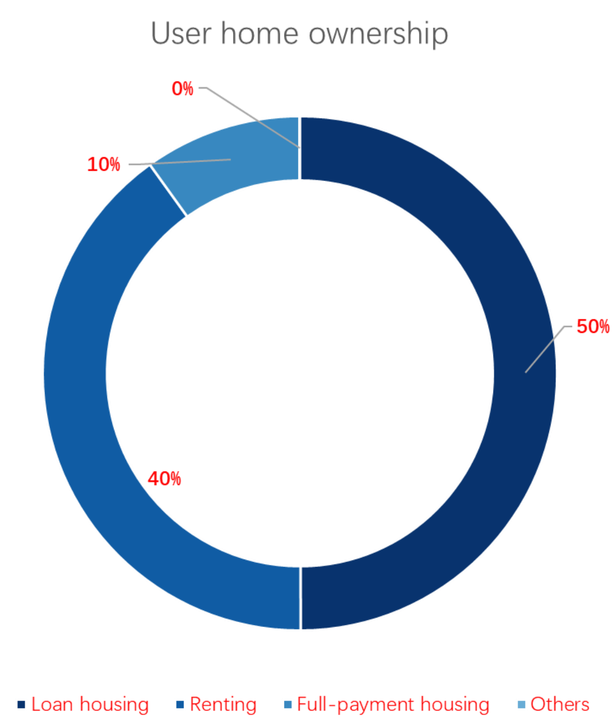

Fig. 6. Distribution of users' home ownership.

Fig. 8 gives the distribution of users' loan amounts. Most of the loans are between 5,000 and 20,000 yuan, with 10,000 yuan having the highest number of loans, and relatively few users having loans of more than 20,000 yuan.

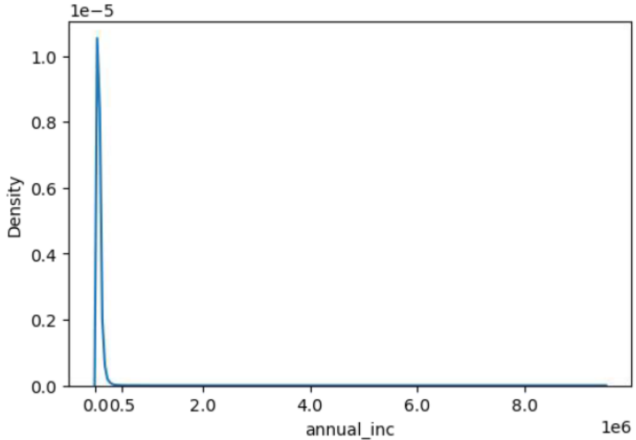

Fig. 7. Distribution of annual income of users.

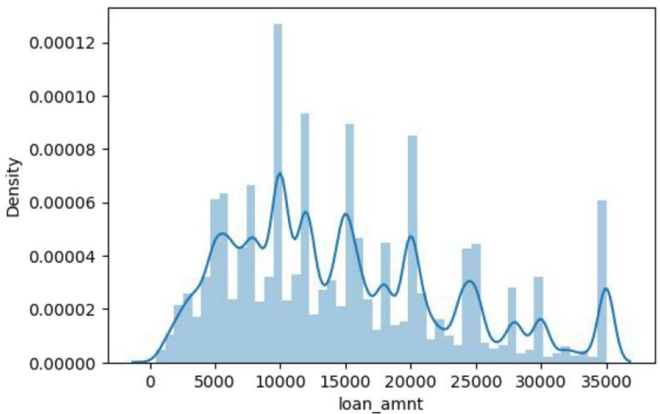

Fig. 8. Distribution of users' loan amount.

b) Basic information of the borrowing project: The basic information about the borrowing item mainly includes information such as the amount of the loan requested by the customer, the term of the loan, the interest rate of the loan, the income status verified by the bank, and the current total balance of all accounts.

c) Borrowing project history information: Borrowing item history information mainly includes information such as the number of enquiry cases in the past six months, the number of months since the last default, the number of months since the public record, the number of open lines in the credit line, and the total collection amount ever owed.

d) Description of the credit default prediction problem: The credit default prediction problem is essentially a classification and identification problem, where the inputs are user credit default characteristic variables and the outputs are user defaults, i.e., non-defaults versus defaults, as shown in Fig. 9.

Fig. 9. Description of the user default prediction problem.

C. Problem Solving Ideas and Design

In order to solve the blockchain credit default prediction problem, this paper adopts hybrid machine learning algorithm to construct blockchain credit default prediction model and design blockchain credit default prediction method based on hybrid machine learning algorithm. The design idea of this method mainly solves the blockchain credit default prediction problem from the aspects of feature analysis, data preprocessing, feature selection, credit default prediction model building, model optimisation, model evaluation, etc., as shown in Fig. 10.

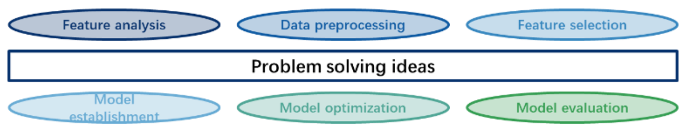

Fig. 10. Problem solving ideas.

III. Improving the SFA Algorithm to Optimise Networks of Attention Mechanisms

A. Network of Deep Attention Mechanisms

A class of deep learning models known as attention mechanism networks (AMNs) [23] enable neural networks to concentrate on pertinent components of the input data during the processing process, thereby emulating the human visual and cognitive systems. The performance and generalization of the model are enhanced by the Attention mechanism, which enables neural networks to automatically learn and selectively concentrate on the critical information in the input. The structure of the Attention mechanism network is illustrated in Fig. 11. In order to focus on the most relevant portions of each sequence element when processing it, the attention mechanism is often applied to the processing of sequential data, such as text, speech, or image sequences. This allows the model to assign various weights to different positions in the input sequence.

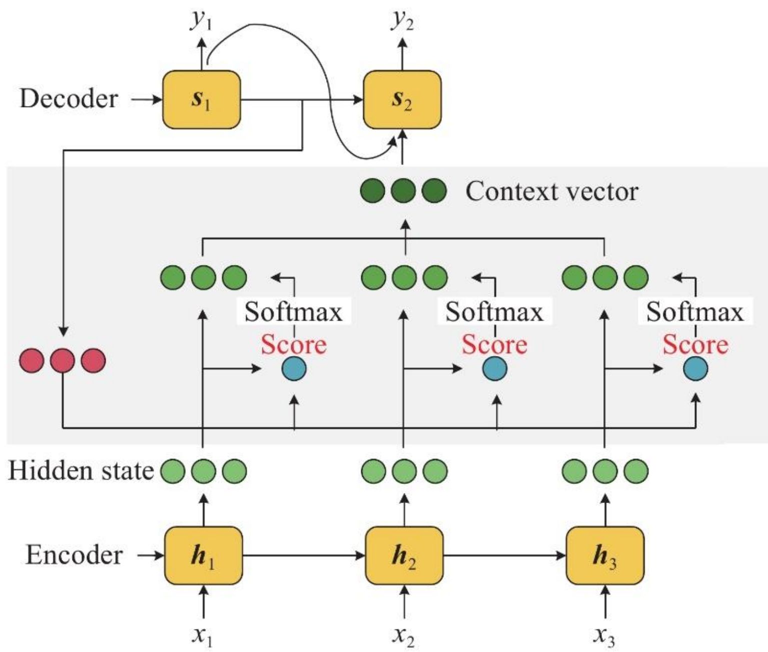

Fig. 11. Structure of the network model of the deep attention mechanism.

The core architecture of the attention mechanism consists of three main components, Query, Key and Value. Query represents the element currently being processed or the target to be attended to, Key represents the identity or characteristic of each element in the input sequence, and Value contains the specifics or information about each element in the input sequence. In attention computation, Key is used to determine how well each element matches the Query, while Value provides the actual information related to the Query.

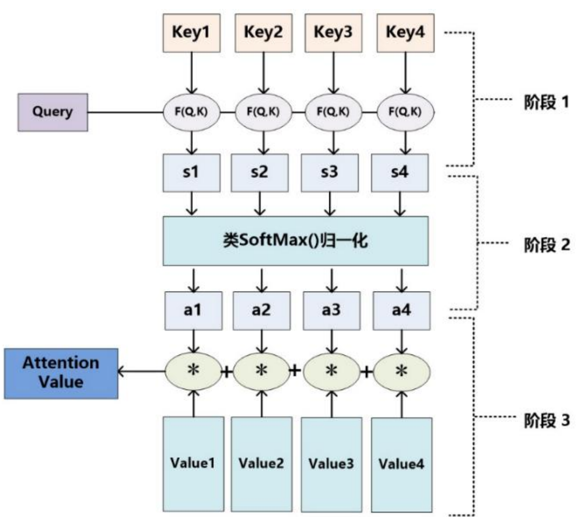

Fig. 12. Principles of attention mechanisms.

B. SFA Algorithm

Based on the strategies and behaviors of Special Forces engaged in counter-terrorism combat operations, the Special Forces Algorithm (SFA) [14] is a swarm intelligence algorithm. In order to satisfy the optimization requirements, SFA can simulate genuine dynamic behaviors by integrating a variety of strategies and incorporating unique mechanisms into the algorithm. According to the common characteristics of MAs, the process of SFA is divided into three phases: exploration phase, transition phase, and development phase (shown in Fig. 13).

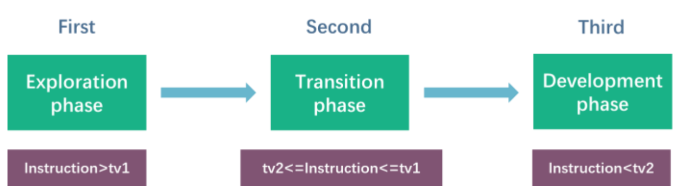

Fig. 13. Analysis of optimisation strategies for the special forces algorithm.

A "directive" is a feature of SFA that serves as an identifier to direct all team members in the completion of the mission. The directive and the threshold value, which is represented as follows, will alter in accordance with the number of iterations, allowing for the identification of the specific task type:

$$Instruction(t) = (1 - 0.15rand)\left(1 - \frac{t}{T}\right) \tag{1}$$

Where t is the current iteration number, T is the maximum iteration number, and $rand$ is a random number between 0 and 1.

2 thresholds tv_1 and tv_2 are set in SFA to clarify the phase transition as follows:

$$\begin{cases} \text{Exploration phase} & Instruction > tv_1 \\ \text{Transition phase} & tv_2 \le Instruction \le tv_1 \\ \text{Development phase} & Instruction < tv_2 \end{cases} \tag{2}$$

During the execution of mission engineering, team members can access the location information of their colleagues; however, there is a possibility that communication terminals may be lost by any team member throughout the algorithm's process, resulting in the potential loss of some team members' information:

$$p(t+1) = p_0 \cos\left(\frac{\pi t}{2T}\right) \tag{3}$$

Where, p is the lost connection probability at the current iteration t, and p_0 is the initial lost connection probability, the specific trend is shown in Fig. 14.

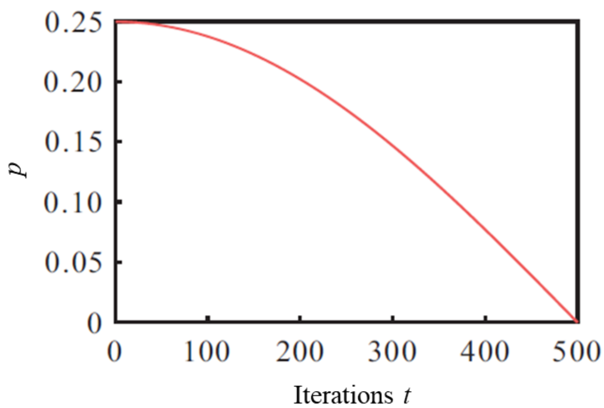

Fig. 14. Trends in probability of missing a connection.

1) Exploratory phase: Following the algorithm's initialization, the investigation phase commences. Two strategies, assault search and mass search, comprise the exploration aspect of SFA.

a) Large-scale search: Mass search missions are the primary responsibility of special forces during the exploration phase. The team members' activity area will be quite vast during mass search, and they are free to look for any possible target anywhere within the practical range at any time. Given that there are two types of jobs that team members may complete during the exploration phase, this study adds a random number to provide the team members with the ability to divide the work and conduct a random search. In other words, the location is updated based on the following equation:

$$X(t+1) = r_1\left(X_{best} - X(t)\right) \pm (1-r_1)\,range \qquad r_1 \geq 0.5 \tag{4}$$

Where, $X(t+1)$ is the position vector of the player in the next iteration, $X(t)$ is the position vector of the current player, X_{best} is the optimal position of the previous population, r_1 is a uniformly distributed random number, and $range$ is the solution space range.

b) Raids and searches: The Special Forces occasionally conduct raids on potential locations during large-scale search missions, as they already possess some information about hostages or miscreants. The known direction of the closest and most skilled team member affects the location of every maneuver. When the random number r_1 decides to perform a surprise raid, the team members perform a position update according to the following equation:

$$X_i(t+1) = X_i(t) + w(t)A_i(t), r_1 < 0.5 \tag{5}$$

where $X_i(t)$ is the search and capture vector of player i for the tth iteration. For any player, the search vector is:

$$A_i(t) = \frac{f_i(t)}{f_i(t) + f_{aim}(t)}\left(X_{aim}(t) + X_i(t)\right) \tag{6}$$

Among them, $X_{aim}(t)$ is the position of player aim No. i, i.e., the optimal position known to player i, and $f_i(t)$ and $f_{aim}(t)$ are the values of their positional adaptations respectively.

The search coefficient w decreases until 0 depending on the number of iterations:

$$w(t+1) = w_0 - 0.55\arctan\left(\left(\frac{t}{T}\right)^{2\pi}\right) \tag{7}$$

Among them, this paper sets $w_0 = 0.75$, and the specific trend is shown in Fig. 15.

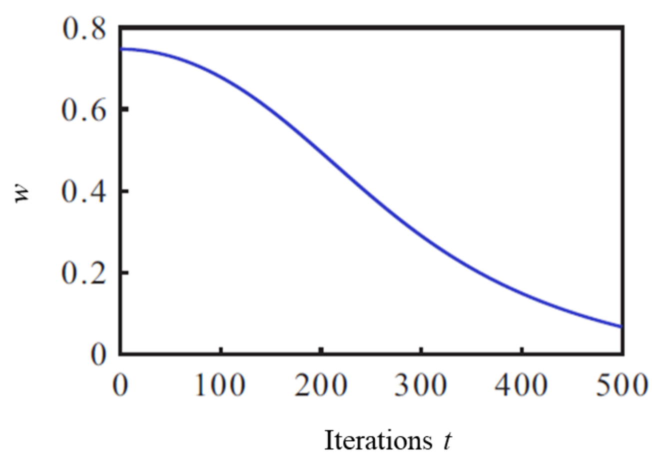

Fig. 15. Schematic diagram of search coefficient.

2) Transition phase: A buffer between the Exploration and Exploitation phases is the Transition Phase. In this period, the team will progressively transition to the exploitation phase while continuing to accomplish the previous tasks. The details are shown below:

$$X(t+1)=\begin{cases} X(t)+w(t)A(t) & r_2 \geq 0.5 \\ Instruction(t)\cdot\left(X_{best}-X(t)\right)+0.1\cdot X(t) & r_2 < 0.5 \end{cases} \quad (8)$$

where r_2 is a random number satisfying a uniform distribution.

3) Development phase: A significant amount of information on the location of the criminals or hostages has been gathered by the special forces throughout the development phase, and they have now officially started the "capture" phase of the activity. The term "capture and rescue" refers to their mission of apprehending the offenders or freeing the captives.

The special operations team members in the development phase decisively approach and take a concentrated approach to surround and attack the hostage or robber based on the most likely point known to the entire team (i.e., the location of the hostage or robber). At this point, the team members use the positional updates shown below:

$$X(t+1)=X_{best}+r\cdot\left|X_{best}-X_{ave}(t)\right| \quad (9)$$

Where r is a uniformly distributed random number and X_{ave} is the current average position, calculated as follows:

$$X_{ave}(t)=\frac{1}{N}\sum_{i=1}^{N}X_i(t) \quad (10)$$

where $X_i(t)$ is the position of each player for the tth iteration and N is the total number of the whole team.

According to the SFA optimisation strategy, the SFA pseudo-code is shown in Table I.

TABLE I. SFA ALGORITHM PSEUDO-CODE

```
Algorithm 1: SFA algorithm pseudo-code
Initialise the parameters tv1, tv2, p0, w0, and the population size N with the maximum number of iterations T;
Initialise population X;
While t<=T do
    Calculate the fitness value;
    Update the optimal fitness value and the optimal value;
    Calculate the instructions;
    If command >= tv1 do
        If r1>=0.5 do Execute the mass search strategy;
        Else if r1<0.5 do Execute the raid and search strategy;
    Else if tv2< instruction<=tv1 do
        Implementation of the transition phase;
    Else if instruction <= tv2 do
        Implementation development phase;
    End if
    Update p and w;
    t=t+1;
End while
Return the optimal solution
```

The initialization, adaptation value calculation, missing information screening, and position update processes comprise the majority of the SFA computational volume. Let N represent the number of players in the SFA algorithm, T denote the maximum number of iterations, and D signify the number of issue dimensions. The computational complexity of the initialisation is $O(N)$, the computational complexity of the adaptation value update calculation is $O(N\times T)$, the computational complexity of the lost information screening is $O(N\times T)$, the computational complexity of the location updating is $O(N\times T\times D)$, and the total computational complexity is $O\left(N\times\left(1+2T+T\times D\right)\right)$.

C. SFA Improved Attention Mechanism Network

In order to improve the credit default prediction accuracy of the attention mechanism network, this paper adopts the SFA algorithm to optimise the parameters of the attention mechanism network, with the RMSE value as the adaptation value and the SFA algorithm optimisation strategy as the optimisation iteration process, and the specific improvement principle is shown in Fig. 16.

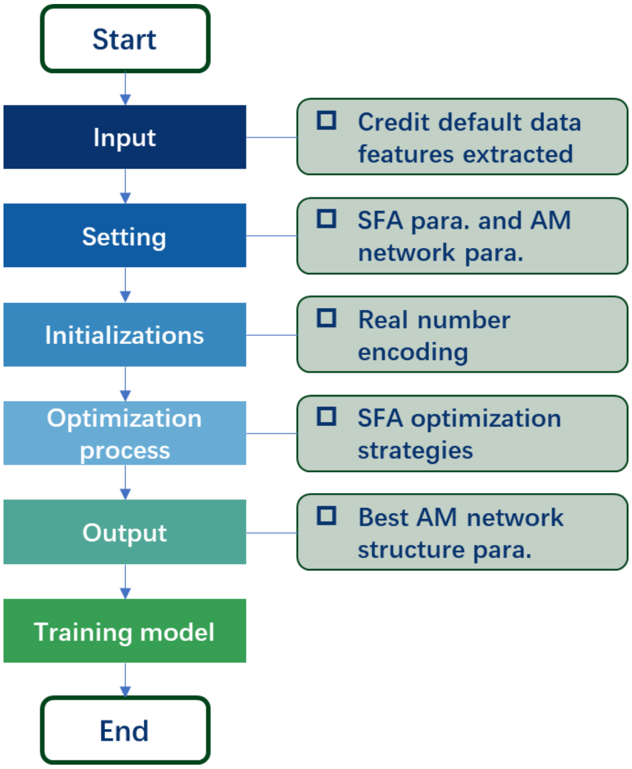

Fig. 16. Schematic diagram of improvement principle.

IV. Algorithmic Applications

In order to solve the blockchain credit default prediction problem, this paper proposes a blockchain credit default prediction method based on SFA-AM network structure. The method analyzes the blockchain credit default prediction problem, extracts the blockchain credit default feature vectors, preprocesses the data in terms of missing value processing, category variable processing, continuous variable processing, etc., constructs the blockchain credit default prediction model by using the Attention Mechanism Network, combines with the SFA Search Optimization Algorithm to optimize the blockchain credit default prediction model based on the AM network, and adopts the blockchain Bank loan dataset as the research object, the performance of the constructed blockchain credit default prediction model is verified, and the specific algorithm application idea is shown in Fig. 17.

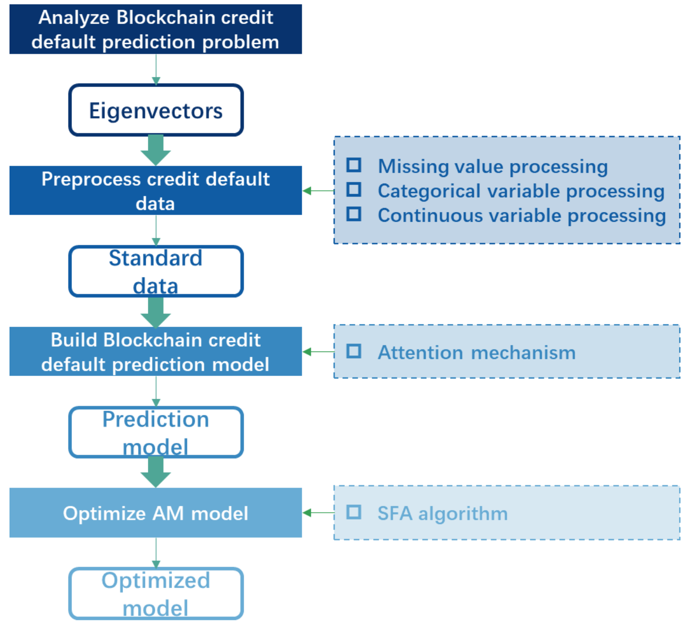

Fig. 17. SFA-AM network model application idea.

V. Results and Discussion

A. Environmental Settings

In this paper, we take Bank load data based on blockchain framework as the research object, firstly, we analyse the basic situation of the dataset, including the size of the data volume, the number of features, and the basic situation of the users; and then, we complete the work of data cleansing for the data, including irrelevant feature deletion, missing value processing, and category coding.

In order to verify the effectiveness and superiority of the blockchain credit default prediction problem based on SFA-AM network, this paper uses XGBoost, CatBoost, LightGBM, LSTM, AMnet and SFA-AM for comparative analysis, as presented in Table II.

In this paper, we use the credit dataset bank loan from kaggle website. The dataset contains information about more than 500,000 different users of Indesa bank in September 2016, out of which there are 406,601 honest customers and 125,827 defaulted customers. The percentage of honest users versus defaulted users is given in Fig. 18.

TABLE II. Parameter Settings of different Credit Default Prediction Comparison Algorithms

serial number	arithmetic	Algorithm setup
1	XGBoost	Booster= gbtree, max_depth=6, learning_rate=0.3, n_estimators=100
2	CatBoost	Iterations=1000, learning_rate=0.11, depth=6, l2_leaf_reg=3
3	LightGBM	max_depth=-1, learning_rate=0.1, n_estimators=100, min_child_weight0.003, min_child_samples=20
4	LSTM	The optimiser is Adam, the hidden layer nodes are 50 and the activation function is ReLu
5	AMnet	The optimiser is Adam, the hidden layer nodes are 100 and the activation function is tanh
6	SFA-AM	SFA population size 100, maximum number of iterations 1000, AM parameters set as in AMnet

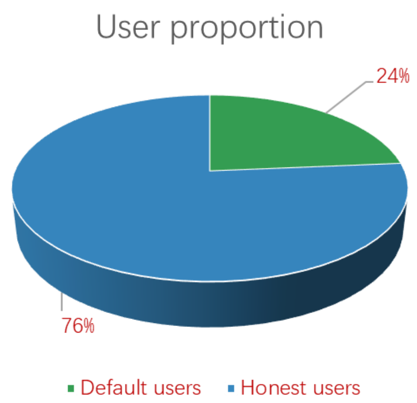

Fig. 18. Schematic representation of users.

The algorithm validation in this paper is carried out in Win11 system, the programming software is Matlab2023a, and the visualisation software includes Pycharm, PPT and Excel.

B. Comparative Analysis of Results

1) Analysis of data preprocessing results: Firstly, the missing values of the data are processed to plot the true scale of the features as shown in Fig. 19. From Fig. 19, it can be seen that, there are 16 features with missing values. In this paper, we take 50% as the limit, and the features with missing rate more than 50% are deleted. mths_since_last_recor, mths_since_last_major_derog, mths_since_last_delinq have more serious missing values, and their missing rate is already more than 50%, so these three features are deleted.

The most significant data gaps are found in "mths_since_last_record" and "mths_since_last_major_derog," which may influence model accuracy if not properly handled (e.g., through imputation or feature elimination). The features with fewer missing values, such as "tot_cur_bal" and "tot_coll_amt," are more reliable for modeling.

A 50% missing rate for "mths_since_last_delinq" means this feature could still be usable but requires careful imputation strategies. Features with more than 50% missing data might need to be dropped, depending on the importance of the feature and the model being used.

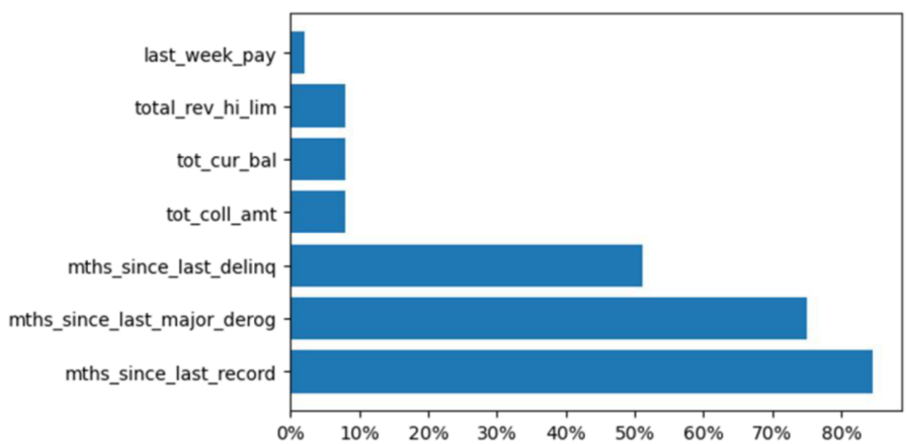

Fig. 19. Mapping the rate of absence of special diagnosis.

2) SFA optimisation of AMnet network processes: The SFA-AM optimisation iteration process is given in Fig. 20. From Fig. 20, it can be seen that the AUC value of the validation set stabilises after the number of iterations reaches 5, and reaches a maximum value of 0.951432 after the number of iterations is at 8. The AUC score starts at around 0.9495 and rapidly increases during the first few iterations, reaching approximately 0.9510 after 2 iterations. This indicates that the model performance improves significantly at the early stages of training or optimization. After about 5 iterations, the AUC reaches a peak of 0.9515, and the curve flattens, indicating that further iterations do not significantly improve the model's performance.

The model reaches a near-optimal performance (AUC of 0.9515) within a small number of iterations (around 5). Beyond that, the improvement is minimal, suggesting that the model has converged. The plateau in AUC after 5 iterations indicates that the model maintains consistent performance and does not suffer from overfitting or performance degradation, which is a good sign of stability.

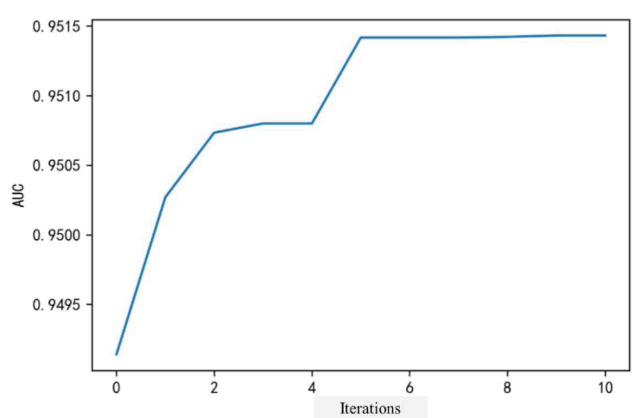

Fig. 20. Iterative process of SFA optimisation.

3) Algorithm comparison results: The model results were evaluated using the test dataset and the results of XGBoost, CatBoost, LightGBM, LSTM, AMnet and SFA-AM comparison were obtained as shown in Table III. From Table III, it can be seen that the SFA-AM model has the highest Precision, the highest Recall, the highest F1 value, and the highest AUC value, which are 0.8289, 0.8075, 0.8180, and 0.9407, respectively, which indicates that the model has a better ability to identify the defaults and non-defaults, and the model's generalisation ability is also better. The SFA-AM model demonstrates the best overall performance across all metrics, especially in Precision, Recall, and AUC, indicating that the optimization of the attention mechanism with the Special Forces Algorithm (SFA) significantly improves the predictive accuracy. CatBoost is a close second and might be a viable alternative when considering slightly lower computational complexity.

TABLE III. COMPARISON OF RESULTS

Serial number	Arithmetic	Precision	Recall	F1-score	AUC
1	XGBoost	0.7973	0.7901	0.7937	0.9324
2	CatBoost	0.8188	0.8074	0.8130	0.9400
3	LightGBM	0.7865	0.7225	0.7531	0.9156
4	LSTM	0.8166	0.7936	0.8050	0.9353
5	AMnet	0.8065	0.7309	0.7668	0.9188
6	SFA-AM	0.8289	0.8075	0.8180	0.9407

Table IV gives the blockchain credit default prediction results for AMnet and SFA-AM. As can be seen from Table IV, the ability of AM to identify defaulted customers has been improved, 27236 defaulted users can be identified before SFA is used, 27551 defaulted users can be identified after SFA is used, while identifying defaulted users as non-defaulted users has been reduced from 10460 to 10145. The SFA-AM model correctly classifies 115,423 non-default cases, which is 785 more than the AMnet model. Additionally, the number of misclassified defaults (mistakenly predicted as non-defaults) drops from 7,395 in AMnet to 6,610 in SFA-AM, showing an improvement in identifying true default cases.

SFA-AM also correctly identifies 27,551 default cases, slightly better than AMnet's 27,236. Furthermore, it reduces the number of non-defaults incorrectly predicted as defaults from 10,460 in AMnet to 10,145, reducing false positives.

The SFA-AM model consistently performs better than the AMnet model in both the identification of non-default and default cases. The reduction in misclassifications (both false negatives and false positives) indicates that the SFA-AM model has superior classification accuracy and a better ability to handle both default and non-default scenarios in credit risk prediction

TABLE IV. COMPARISON OF RESULTS BETWEEN AMNET AND SFA-AM MODELS

Real value	Projected value	Non-default	Default (on a loan or contract)
AMnet	non-default	114638	7395
	default (on a loan or contract)	10460	27236
SFA-AM	non-default	115423	6610
	default (on a loan or contract)	10145	27551

VI. CONCLUSION AND FUTURE WORK

In order to improve the accuracy of blockchain credit default prediction, this paper adopts SFA algorithm and attention mechanism model to construct blockchain credit default prediction optimisation model. It proposes a credit default prediction model based on the Attention Mechanism Network (AM) optimized by the Special Forces Algorithm (SFA). The key contributions include: (1) analyzing the credit default prediction problem, extracting relevant features, and performing data preprocessing; (2) constructing the credit default prediction model by optimizing the hyperparameters of the AM network using SFA; (3) validating the proposed model using blockchain credit default data. The experimental results demonstrate that the SFA-optimized model improves classification accuracy and generalization, achieving an AUC value of 0.9407.

We also recognise the following three areas of weakness: First, the blockchain credit default data used comes from a single bank, lacking diverse datasets from multiple industries or regions, which may limit the model’s generalizability. Then, while the paper compares several common algorithms (e.g., XGBoost, CatBoost, LSTM), it does not explore other emerging deep learning models or hybrid models in depth. Finally, although the model shows high prediction accuracy, there is insufficient analysis of the model's interpretability, particularly for the deep learning model.

Future research could incorporate more diverse datasets from different industries and regions to test the model's robustness and applicability in various scenarios. Investigating other deep learning or reinforcement learning algorithms and comparing their performance with the current model could further enhance prediction accuracy. As the complexity of models increases, focusing on the interpretability of the model—

especially the role of the attention mechanism in credit default prediction—would help financial institutions better understand and trust the model's decisions.

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