Financial risk assessment to improve the accuracy of financial prediction in the internet financial industry using data analytics models

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Abstract
A sound credit assessment mechanism has been explored for many years and is the key to internet finance development, and scholars divide credit assessment mechanisms into linear assessment and nonlinear assessment. The purpose is to explore the role of two important data analytics models including machine learning and deep learning in internet credit risk assessment and improve the accuracy of financial prediction. First, the problems in the current internet financial risk assessment are understood, and data of MSE (Micro small Enterprises) are chosen for analysis. Then, a feature extraction method based on machine learning is proposed to solve data redundancy and interference in enterprise credit risk assessment. Finally, to solve the data imbalance problem in the credit risk assessment system, a credit risk assessment system based on the deep learning DL algorithm is introduced, and the proposed credit risk assessment system is verified through a fusion algorithm in different models with specific enterprise data. The results show that the credit risk assessment model based on the machine learning algorithm optimizes the standard algorithm through the global optimal solution. The credit risk assessment model based on deep learning can effectively solve imbalanced data. The algorithm generalization is improved through layer-by-layer learning. Comparison analysis shows that the accuracy of the proposed fusion algorithm is 25% higher than that of the latest CNN (Convolutional Neural Network) algorithm. The results can provide a new research idea for the assessment of internet financial risk, which has important reference value for preventing financial systemic risk.

Keywords Machine learning · Deep learning · Internet finance · Risk assessment management · Credit risk assessment

1 Introduction
In recent years, Internet finance, as a novel financing method, has mushroomed. It provides financing, payment, and information platforms through Internet technology (IT) and Big Data Analytics (BDA) algorithms (Akhter et al. 2022). Compared with the traditional financial industry, the Internet financing industry has a systematic structure and real-time response characteristics, such as real-time capital arrival and multi-dimensional offline payment (Talal et al. 2019). Unlike direct financing in the capital market, Internet Finance enables Micro and Small Enterprises (MSEs) to borrow from various platforms. Thus, it breaks the monopoly of commercial banks and brings a massive impact to the traditional financial industry (Luo et al. 2018). Especially in the era of informatization and globalization, Internet finance is booming. According to China's National Bureau of Statistics (NBS), the domestic transaction volume of Internet finance increased from 195 billion RMB in 2014 to 9153 billion RMB in 2019, an increase of 370% (Sui and Geng 2021). At the same time, a variety of non-governmental loans, such as campus loans, naked loans, and capital loans, come into being, stimulating the domestic consumer market through instant loans and high-value loans. Many of them have become non-performing loans. Probably, it is due to the barbaric and unregulated development of Internet finance and the lack of a healthy and sustainable development vision. This has
resulted in a failure to maximize the benefits of people’s lives and production (Khumaini et al. 2022). Additionally, substantial numbers of capital have entered the capital market without proper pre-assessment of solvency, which constitutes an overall systemic risk and undermines the stability of the financial market (Chen et al. 2017). Therefore, studying Internet financial risks has important reference value for promoting the healthy development of China’s financial industry.

Nowadays, China embraces a much more open attitude towards the financial industry and provides a favorable Internet financial and developmental environment. All social strata, such as Small and Medium-sized Enterprises (SMEs), MSEs, and self-employed households, need more capital to expand operations. People are more willing to take greater risks for higher returns (Yang et al. 2018). In this context, Internet finance can effectively meet the needs of debtors and creditors and get popular in the lending market where demand exceeds supply. However, an industry-standard has not been formatted in China for Internet finance. Hence, many problems have been found, such as the transformation of unqualified financial enterprises, illegal fund-raising, and malicious fraud (Yang et al. 2019). Therefore, it is of great significance to systematically evaluate the Internet financing risks of enterprises. In particular, Machine Learning (ML) technology can significantly improve the ability of financial processing and Decision Making (DM). Deep learning (DL) technology can analyze and model financial data to help enterprises and regulators make decisions (Nguyen et al. 2020; Kim et al. 2020). ML and DL methods can measure enterprise performance indexes and have strong data analysis and processing capabilities. They provide solutions for the risk assessment of the Internet financial industry (Zhang and Mahadevan 2019). To sum up, the current social demand for high-risk financial products is increasing. Nevertheless, the social control mechanism for high-risk financial products is not perfect. Thus, more research is needed to provide technical support for developing high-risk financial fields. As a relatively advanced technology, DL can provide a better calculation model for Internet credit analysis to contribute to the development of social control of high-risk financial fields.

Thereupon, this work first discusses the problems in the current Internet financial risk assessment. Then, a feature extraction model based on ML is proposed. Finally, it analyzes the performance of the proposed model in Credit Risk Assessment (CRA), reveals the problems in the Internet financial industry, and implements the proposed model through DL, ML, and the fusion algorithms. The research content provides a reference for the healthy development of the Internet financial industry and a certain direction for the development of the financial industry.

2 Related works

2.1 CRA methods

With continuous social progress, all industries are seeing rapid development. As the basic driving force of social development, the financial industry provides a broad platform for society to obtain benefits under high risks. However, social benefits have not been multiplied as expected, and some negative impact of Internet finance has been discovered. Scholars in related fields have been exploring a perfect CRA mechanism to promote the development of Internet finance development. At present, the CRA mechanism is divided into the linear evaluation and nonlinear evaluation. Among them, linear CRA is the most widely used and has long-term and in-depth research. Habib (2019) believed that information technology innovation gave birth to Internet finance and played an important role in financial innovation. Internet CRA system originated from the traditional financial CRA system and had some unique characteristics. Driven by big data, Artificial Intelligence (AI) continued to deepen in the research of risk identification (Habib 2019). Ouyang and Lai (2021) proposed a novel heterogeneous set CRA model by introducing Bstacking and successfully improving CRA efficiency (Ouyang and Lai 2021). Cao et al. (2022) implemented a new fuzzy distance measurement analysis model to effectively evaluate the existing credit data (Cao et al. 2022). On the other hand, nonlinear CRA can solve the correlation and multicollinearity between assessment indexes and rely on Artificial neural networks (ANN) and DL. Shen et al. (2019) proposed a fusion model based on integrated minority oversampling and classifier optimization technology, which showed more effective CRA performance than other classification models (Shen et al. 2019). Liu (2020) adopted BDA and clustering algorithm in Internet finance to improve the accuracy of CRA (Liu 2020). Du et al. (2021) built the CRA model of Internet finance Based on Backpropagation Neural Network (BNN) and genetic algorithm (GA). The analysis and verification of specific enterprise data proved that BPNN could accurately and effectively assess and pre-alarm the credit risk of Internet finance (Du et al. 2021). To sum up, there is extensive research on CRA, most of which use DL or ML. Therefore, it is reasonable and scientific for this work to predict the credit risk of the financial industry through DL methods.

2.2 Research on Financial Risk Management (FRM)

The major development defects of Internet finance have brought many negative effects to the lives of the public.
In order to predict the development prospects of the financial industry, many scholars have studied FRM, mostly using a single model. For example, Duan et al. (2022) implemented the FRM model through traditional regression analysis methods and enterprise financial indexes and achieved excellent performance (Duan et al. 2022). Xu and Gao (2019) analyzed the causality of financial risks based on the nonlinear causality test and dynamic copula method. They effectively analyzed the changes in financial market risks (Xu and Gao 2019). Li et al. (2021a) introduced new comprehensive analysis indexes into the traditional financial index system based on Hidden Markov Model (HMM), integrated economic statistical structure data, and Internet information. They significantly improved the risk prediction ability of the model (Li et al. 2021a). Cui et al. (2021) proposed a general data-driven framework, which achieved high accuracy in the pricing and risk management of multiple financial contracts (Cui et al. 2021). Thus, a single model may perform well in a specific field. However, with the continuous maturity and complexity of the financial market, the fusion model of several independent algorithms has begun to receive close attention from more researchers and financial enterprises. Research examples include Wang et al. (2021a, b) integrating different classifiers through model aggregation to improve the generalization ability of the entire financial industry and promote credit risk modeling (Wang et al. 2021a, b). Li et al. (2021b) enhanced the predictability of fusion learning technology through a new model of high entropy and fusion learning technology based on information gain (Li et al. 2021b). Therefore, in terms of FRM, the current research mainly focuses on the index analysis method, and the learning efficiency is relatively low. The fusion model is gaining popularity in risk assessment to improve financial risk predictability and management ability and has become a new research hotspot. Therefore, this work employs a fusion model based on DL technology and a financial index evaluation system to predict Internet finance credit. It hopes to effectively promote the development of the Internet financial industry and promote the financial industry’s progress.

3 Model system construction and performance assessment

3.1 CRA based on ML

ML centers around feature recognition and extraction. Strong correlation subsets in financial products can be effectively classified through data acquisition and processing, thereby simplifying the computational process (Raschka 2018). Currently, a typical feature recognition method is based on encapsulation: feature importance is calculated through statistics, and features are ranked accordingly (Choong and Islam 2020). This kind of feature recognition can improve learning performance, computational efficiency, and model generalization ability while reducing memory storage (Wang et al. 2021a, b). Consequently, this paper chooses the encapsulation-based feature recognition method to collect and analyze CRA data, and the specific structure is shown in Fig. 1.

As shown in Fig. 1, redundancy or noise in financial data increases with enterprise-scale and operation length (Abdel-Basset et al., 2020). In particular, the Grey Wolf Optimizer (GWO) algorithm is a new swarm random optimization method. It can simulate wolves’ intelligent behavior, such as searching, calling, and sieging. GWO is simple in structure and easy to operate, so it is selected to analyze Internet finance credit data. Figure 2 illustrates the four-layer social structured GWO algorithm.

Based on the management mechanism of wolves, the hunting process is described through a mathematical model to find the GOS. The movement of grey wolves can be expressed by Eqs. (1) and (2).

\[
D = |C \cdot X_p(t) - X(t)|
\]

(1)

\[
X(t + 1) = X_p(t) - A \cdot D
\]

(2)

![Feature recognition flowchart of CRA data](image-url)
In Eqs. (1) and (2), $D$ represents the distance between the gray wolf and the prey, $X(t)$ denotes the position vector of the gray wolf, $A$, $C$ stands for the coefficient vector, and $t$ is the current iteration number. $X_p(t)$ represents the position vector of prey (Parast 2021). The grey wolf can be moved to any position near the prey through adjustment of the coefficient vector $A$, $C$. The adjustment process can be expressed as follows.

$$A = 2ar_1 - \alpha$$  \hspace{1cm} (3)  

$$C = 2r_2$$  \hspace{1cm} (4)  

$$\alpha = 2 - \frac{2t}{t_{\text{max}}}$$  \hspace{1cm} (5)  

In Eqs. (3), (4), and (5), $r_1, r_2$ represents the random number vector in [0,1], and $\alpha$ is a linear decreasing coefficient from 2 to 0. In the hunting process, the optimal prey position is updated at each iteration by the DC wolf group. The next positions of other wolves are updated according to the average position vector calculated through their current positions and the current position of $\alpha, \beta, \delta$ wolves in the DC group. The position updating process is expressed below.

$$D_a = |C_1X_a(t) - X(t)|$$  \hspace{1cm} (6)  

$$D_\beta = |C_2X_\beta(t) - X(t)|$$  \hspace{1cm} (7)  

$$D_\sigma = |C_3X_\sigma(t) - X(t)|$$  \hspace{1cm} (8)  

$$X_1 = X_a(t) - A_1 \cdot D_a$$  \hspace{1cm} (9)  

$$X_2 = X_\beta(t) - A_2 \cdot D_\beta$$  \hspace{1cm} (10)  

$$X_3 = X_\sigma(t) - A_3 \cdot D_\sigma$$  \hspace{1cm} (11)  

$$X(t + 1) = (X_1 + X_2 + X_3)/3$$  \hspace{1cm} (12)  

In Eqs. (6)–(12), $X_a, X_\beta, X_\sigma$ represent the current position vector of three grey wolves in the DC group, respectively. $X(t)$ stands for the current position vector of the grey wolf, and the next position of the grey wolf can be calculated accordingly. Figure 3 depicts the flow of GWO-based specific analysis.

As given in Fig. 3, the GWO algorithm can predict the Internet fiancé credit risk, and the model learning can improve the computing efficiency by improving the learning rate. For higher computational efficiency, the GWO algorithm is improved through training.

### 3.2 Credit risk assessment based on DL algorithm

DL has attracted many scholars’ attention with its strong data processing ability, significant analysis ability, and high scalability. The convolution kernel can extract data features from Convolutional Neural Network (CNN) and pass them to different network nodes. Then, data are represented and learned layer-by-layer; this way, the learning efficiency is guaranteed. The DL algorithm is introduced into the CRA system because the algorithm can achieve the same training results as Deep Neural Network (DNN) in different fields, and it is more efficient. Further, the RF (Random Forest) algorithm is introduced to improve the data processing ability of the DL algorithm or to achieve high accuracy and process large data sets (Huang et al. 2018).

Figure 4 combines CNN with the RF algorithm, in which each CNN layer contains two RFs and two complete forests.
Different sampling methods are chosen for RF and complete forest to reduce redundant extractions and improve model generalization. Then, a hierarchical data scanning process is employed to process imbalanced data in the current CRA system. In Fig. 5, the multi-granularity scanning method scans the original input features through a sliding window with a specified step size. The feature vectors of different training samples fall into different categories. Afterward, the probability vectors of forests are clustered through RF and complete forest to form new feature vectors (Zhao et al. 2020).

Subsequently, the Deep Rotation Forest (DRF) model is trained by the balanced data to learn to process imbalanced data. Thus, the imbalanced data in the MSE-oriented CRA system can be processed through the DRF model, and the model recognition efficiency can be enhanced. Accordingly, the CRA model can be implemented. Firstly, the MSE data are randomly divided into training samples and test samples. Secondly, the training samples are balanced to train the DRF model. Thirdly, the trained model is verified using the test sets. Finally, the DL-based CRA model is implemented, as demonstrated in Fig. 6.

As manifested in Fig. 6, the DL-based CRA model first evaluates the risk levels. Then, following data input, it classifies the data set according to the risk level through balance treatment, then calculates the average and maximum, respectively, and finally assesses specific risks. The combination of deep learning and neural network technology can have more advantages in data analysis. The first is the FE of data. The calculation formula is as follows:
In Eq. (13), $P_n$ represents the eigenvalue extraction of input data in the hidden layer, $n$ denotes the dimension of input data, and $a$ denotes the weight of input data. Then, the data are normalized. That is, the weight and offset of the data in the output layer are adjusted. Meanwhile, it is necessary to analyze the dimension of the input data, that is, to determine the composition of the input data. Finally, the fitting degree of the DL curve is analyzed. That is, the gap between the output result and the ideal result is analyzed. Thereby, the actual error is determined, as calculated by Eq. (14):

$$J(\theta) = \frac{1}{m} \sum_{j=1}^{m} \frac{1}{2} (h_\theta(x^{(i)}) - y^{(i)})^2$$

(14)

In Eq. (14), $h_\theta$ represents the prediction of DL calculation, and $m$ indicates the dimension of the data label. The DL algorithm can be trained continuously through the fitting degree of the curve, so the DL algorithm can be regarded as the process of continuous adjustment and fitting of the learning curve. The adjustment range corresponding to the learning curve is the Learning Rate (LR). The adjustment of the learning curve depends on the change of the learning gradient vector. The calculation of the gradient vector reads:

$$\nabla_\theta J = \left[ \frac{\partial}{\partial \theta_1} J, \ldots, \frac{\partial}{\partial \theta_n} J \right]$$

(15)

In Eq. (15), $\nabla_\theta$ represents the gradient vector, and $J$ indicates the error between the prediction and the ideal result. The fitting degree of the general learning curve is divided into overfitting, underfitting, and normal fitting, the first two of which should be adjusted and transformed into the normal fitting.

3.3 Credit risk assessment model based on fusion algorithm

The ML-based and DL-based CRA models are very practical in data collection and data processing. Thereupon, an MSE-oriented CRA model based on the fusion algorithm is implemented. The traditional CRA system only gives the Default Probability (DP) but lacks a comprehensive assessment for enterprises. By comparison, the overall conversion method can calculate the specific credit score of each MSE via the DP, as displayed in Eq. (16).

$$Credit_{Score} = \ln \left( \frac{P}{1 - P} \right) \times factor + offset$$

(16)
In Eq. (16), $P$ represents the prediction probability of honest enterprises, and $1 - P$ denotes the prediction probability of dishonest enterprises. \textit{factor} stands for the coefficient of a linear transformation, and \textit{offset} is a constant.

Consequently, the MSE-oriented CRA system is proposed based on the fusion algorithm, as evinced in Fig. 7. Concretely, the ML in the proposed system can collect features of CRA data. Then, the GWO algorithm can preprocess feature data. Afterward, the output data is input into the DL model, and different data are processed through layer-by-layer recursive learning. All data sets are divided into test sets and training sets. The evaluation results of test sets are obtained from MSE data.

### 3.4 Data source and performance assessment

1. **Data set and parameter setting:** The ML algorithm is verified through public data sets, including an MSE data set from Paper Data and three data sets from risk assessment public data in the University of California Irvine (UCI) (Hou et al. 2020). The RF and K-Nearest Neighbor (KNN) classifier can extract data features. The specific data sets are presented in Table 1. The five-fold cross-validation method can assess fitness function. Then, algorithm parameters are set uniformly: the number of iterations is 30, the number of individuals is 20, and the number of algorithm execution is 10.

The unbalanced data from eight public data sets are chosen to verify the DL algorithm, including German,

![Fig. 7 MSE-oriented fusion-algorithm-based CRA model](image-url)

| Datasets       | Sample numbers | Dimensions | Number of positive samples | Number of negative samples |
|----------------|----------------|------------|---------------------------|---------------------------|
| Japan          | 690            | 15         | 307                       | 383                       |
| German         | 1,000          | 20         | 700                       | 300                       |
| Australian     | 690            | 14         | 307                       | 383                       |
| Paper Data     | 20,250         | 132        | 19,882                    | 368                       |

Irvine (UCI) (Hou et al. 2020). The RF and K-Nearest Neighbor (KNN) classifier can extract data features. The specific data sets are presented in Table 1. The five-fold cross-validation method can assess fitness function. Then, algorithm parameters are set uniformly: the number of iterations is 30, the number of individuals is 20, and the number of algorithm execution is 10.

The unbalanced data from eight public data sets are chosen to verify the DL algorithm, including German,
Satimage, Mammography, Solar Flare M0, Wine Quality, Yeast_ML8, Abalone_19, and Spectrometer, and the ratio of the test set and training set is 2:8 (Cai and Zhang 2020). More precisely, the German data set is used to predict the loan DP according to the personal bank loan information and the overdue situation of the customer’s loan application; the data set contains 1,000 groups of data in 24 dimensions; meanwhile, the data set classifies relevant personnel as high or low credit risk through a set of attributes. Satimage dataset contains 36 features, which is the MSE-oriented research data. The mammography dataset is a very classic dataset through which the risk level of medical enterprises can be evaluated. The rest are data sets related to Internet finance of various enterprises (see Table 2).

2. Experimental environment and performance assessment: Python is used for programming. The experiment is simulated through the Intel Core i7 CPU with the main frequency of 3.2 GHz, 8 G Random Access Memory (RAM), and the Windows10 64-bit Operating System (OS). The Pycharm is chosen for the software environment, and the results are analyzed through comparison. Assessment indexes, such as precision, recall, and comprehensive assessment, can analyze ML algorithms. The number of positive and negative

| Datasets        | Number of samples | Unbalanced ratio | Feature number |
|-----------------|-------------------|------------------|----------------|
| German          | 1,000             | 2.3:1            | 20             |
| Satimage        | 6,435             | 9.3:1            | 36             |
| Mammography     | 11,113            | 42:1             | 6              |
| Solar Flare M0  | 1,389             | 19:1             | 32             |
| Wine Quality    | 4,898             | 26:1             | 11             |
| Yeast_ML8       | 2,417             | 13:1             | 103            |
| Abalone_19      | 4,177             | 130:1            | 10             |
| Spectrometer    | 531               | 11:1             | 93             |

Fig. 8 Performance of ML algorithm
samples should be counted for each prediction algorithm and be compared with the actual results. The calculation process is shown in Eqs. (17) - (22).

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{17}
\]

\[
\text{Precision} = \frac{TP}{TP + FP} \tag{18}
\]

\[
\text{Recall} = \frac{TP}{TP + FN} \tag{19}
\]

\[
\text{TNR} = \frac{TN}{TN + FP} \tag{20}
\]

\[
F - \text{measure} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{21}
\]

\[
G - \text{mean} = \sqrt{\text{Sensitivity} + \text{Specificity}} \tag{22}
\]

In Eqs. (17) - (22), \(TP\) represents the number of positive samples in true prediction, \(FN\) denotes the number of negative samples in false prediction, \(FP\) is the number of positive samples in false prediction, and \(TN\) is the number of negative samples in true prediction. The Area Under Curve (AUC) is the area enclosed by the Receiver Operating Characteristic (ROC) curve and the abscissa, and the maximum value is 1. The greater the value is, the higher the model identification efficiency is.

Fig. 9 Model performance on different datasets
4 Results and analysis

4.1 Performance analysis of ML algorithm

Figures 8A and B corroborate the verification results of the ML algorithm on the RF sub-data set, and Figs. 8C and D prove the verification results of the ML algorithm on the KNN sub-data set. Then, the ML algorithm is optimized ten times on feature subsets, and the optimization results are counted. The FE-based GWO algorithm is more stable than a single GWO algorithm. In terms of feature fusion optimization, the feature subsets acquired through the ML algorithm can improve the assessment index of the model.

Figures 9A-D reveals the comparison results of the two algorithms on the four total data sets of Japan, German, Australian, and Paper Data. Basic Grey Wolf Optimizer-K Nearest Neighbors (BGWO-KNN) is the BGWO model on the KNN sub-data set. Basic Change Grey Wolf Optimizer-K Nearest Neighbors (BCGWO-KNN) is the GWO algorithm model after FE on the KNN sub-data set. BCGWO algorithm has the best overall convergence effect in 30 iterations. It can obtain the fitness value better than the basic BGWO in searching the feature subset.

4.2 DL performance analysis

Figs. 10A-D plots the result of different indexes on German, Satimage, Mammography, and Solar Flare M0 datasets. The results suggest that DL effectively improves the performance of each index, especially the accuracy of the model. These datasets are unbalanced data, proving that DL can well process unbalanced data. In all data sets, the sampling effect of the SSNSMOTE algorithm is better than that of others.

Figures 11A-D draws the results of different indexes on the data sets of WineQuality, Yeast_ML8, Abalone_19, and Spectrometer. The results imply that the DL-based RF algorithm effectively improves the performance of each index, especially the accuracy of the model. Thus, the proposed DL-based RF algorithm is advantageous for Internet data processing.

In Fig. 12, A shows the test set results of the model without balance treatment, and B unveils the model's results after balance treatment. Apparently, the precision of the minority class and the overall accuracy are greatly improved compared with the DLRF. The model presents a significant improvement in the recall of MSE-oriented CRA.
with Semantic Robot Description Format (SRDF), it has a greater improvement in recall of minority class. Although the model identification accuracy is reduced, the average of all indexes has improved.

In Fig. 13, A shows the model performance under RF, fixed forest, and consensus algorithm, and B demonstrates the model performance under fusion algorithm, rotating forest, DRF, and Decision Tree (DT) algorithm. The results corroborate that under different classification thresholds, the rotating transformation strategy and feature enhancement strategy can improve the recognition ability of the rotating forest in model prediction. Without overall prediction accuracy reduction, the recognition of minority and majority classes can achieve a good balance, implying that deep representation learning has a good effect on risk assessment.

4.3 Performance comparison of different models

Figures 13D and 14A shows the results of precision, recall, comprehensive assessment, and AUC index performance of different models, respectively. Thus, the model's overall performance improves with the increase in the number of data
sets. The performance of the DL algorithm is higher than other algorithms. CNN and Deep & Cross Network (DCN) is significantly improved compared with Analytic Hierarchy Process (AHP) and RF. The accuracy of the proposed fusion algorithm model is 25% higher than that of the latest CNN algorithm, and the proposed fusion algorithm has obvious advantages in all indexes.

### 4.4 Enterprise credit risk assessment

In Fig. 15, A refers to the assessment results of the first batch of MSE (No. 4537–4548), and B indicates the assessment results of the second batch of MSE (No. 2243–2254). Thus, the CRA system gives the comprehensive score and the DP according to the actual enterprise data. The higher the DP is, the higher the credit risk is. Analysis shows that the results are consistent with actual enterprise assessment results, and the final accuracy of risk assessment is as high as 100%. Thus, the proposed fusion algorithm has strong predictability for MSE-oriented Internet credit risk.

### 4.5 Discussion

The rapidly developing Internet technology and the financial industry provide an economic impetus for social development. At the same time, the emergence of high-risk financial products with high-yield effects has quickly attracted the favor of many people. However, its high-risk nature will still have a certain impact on the financial industry. Therefore, to reduce the harm caused by its high risk and optimize the
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Internet financing environment, it is urgent to analyze the credit risk of Internet financing. This work has contributed to the optimization of the Internet finance credit environment and social development. In the performance comparison of the proposed DL-based CRA model, the BCGWO algorithm has the best overall convergence effect at the 30th iteration. It can get higher fitness than the basic BGWO in searching the feature subset. Introducing the random forest method has gained a better Internet finance data processing. Secondly, the model has significantly improved recall in the credit evaluation of MSEs. Compared with the Semantic Robot Description Format (SRDF) of Zaki et al. (2021), the proposed model has greatly improved the recall of a few categories (Zaki et al. 2021). Although the model recognition accuracy has been reduced, the overall index performance of the proposed model has been improved. It is also found that under different classification thresholds. The rotation transformation strategy and feature enhancement strategy can improve the prediction and recognition ability of the deep forest model. Under the condition that the overall prediction accuracy does not decrease, the recognition of minority and majority classes can reach a better balance. It also indirectly shows that the DL has a better effect on risk assessment. Finally, after evaluation, it is found that the accuracy of the proposed fusion algorithm model is improved by 25% compared with the latest CNN. The research of Chen and Lai (2021) implies that the proposed DL-based model has good advantages in Internet finance risk prediction, and the model

Fig. 14 Performance comparison of different algorithms. Note: MMF, CNN, RF, BP, AHP, and DCN is the proposed fusion algorithm, the convolutional neural network algorithm, random forest algorithm, BPNN algorithm, analytical algorithm, and the deep belief network algorithm, respectively
performance is better than theirs. Therefore, this work provides strong technical support for Internet finance CRA and contributes to the sustainable development of the financial industry (Chen and Lai 2021).

5 Conclusion

With the development of society, credit risk has become a major obstacle to the development of various industries, especially in the financial field. Therefore, studying and optimizing Internet credit evaluation methods are essential. To this end, this work first analyzes the existing CRA mechanism. Then, ML and DL are introduced to collect, process, and analyze data. The single CRA model and fusion CRA model are implemented, respectively. Then, the performance of the fusion CRA model is verified by MSE public dataset. Finally, experiments are designed to verify the ML algorithm in the proposed CRA model. The results are used to improve its processing accuracy and solve the data feature redundancy and noise interference. The results show that the proposed Internet finance CRA model based on DL technology has some defects. Future research will optimize the algorithm at a deeper level and in more detail to comprehensively improve the learning ability, the efficiency, and comprehensive effect in Internet finance credit prediction. It is expected to promote the financial industry’s far-reaching development through research.

Implications of theory.

The theoretical significance of this work lies in that through DL technology, the accuracy of Internet finance credit detection and prediction is improved. The security environment of the financial field is improved. Additionally, this work integrates various DL algorithms in the model design and optimizes the algorithm. Improving the algorithm's learning ability improves the computing efficiency. It provides a reference for the comprehensive application of DL technology in the financial field.

5.2 Implications of practice

The practical significance of this work is to improve the reliability of Internet finance by detecting and predicting Internet finance credit risks. It provides users with clear risk prediction results. It helps them deeply understand the risks in Internet finance to help users effectively avoid risks. Therefore, it can provide technical support for the financial industry development and safeguard enterprise financing transactions. Ultimately, it comprehensively promotes the development of the financial field.

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Fig. 15 Predicted comprehensive credit risk score and DP of MSE
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Declarations

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent Informed consent was obtained from all individual participants included in the study.

Human and animal rights This article does not contain any studies with human participants or animals performed by any of the authors.

Conflict of interest All Authors declare that they have no conflict of interest.

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