A Kepler Optimization Algorithm-Based Convolutional Neural Network Model for Risk Management of Internet Enterprises

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***Abstract*—Internet enterprises, as the representative enterprises of technology-based enterprises, contribute more and more to the growth of the world economy. To ensure the sustainable development of enterprises, it is necessary to predict the risks in the operation of Internet enterprises. An accurate risk prediction model can not only safeguard the interests of enterprises but also provide certain references for investors. Therefore, this study designed a Convolutional Neural Network (CNN) model based on the Kepler optimization algorithm (KOA) for risk prediction of Internet enterprises, aiming to maximize the accuracy of the prediction model, and to help Internet enterprises carry out risk management. Firstly, we select the indicators related to the financial risk of Internet enterprises, and predict the risk based on the traditional statistical analysis of Logistic regression model. On this basis, KOA was improved based on evolutionary strategies and fish foraging strategies, and the improved algorithm was applied to optimize CNN. Based on improved KOA and CNN algorithms, an IKOA-CNN risk prediction model is proposed. Finally, by comparing traditional statistical analysis-based models and other learning-based models, the results show that the IKOA-CNN algorithm proposed in this study has the highest prediction accuracy.**

Keywords*—Risk management; Kepler optimization algorithm; Convolutional Neural Network; Internet enterprises

I. Introduction

Internet enterprises are facing diversified risks while developing rapidly. These risks mainly come from internal operations, technical implementation, and data management. The main content of Internet enterprise risk management includes risk identification, risk assessment, risk control and risk monitoring [1]. Effective risk management can not only help enterprises develop steadily in uncertain market environments but also enhance their market competitiveness and improve the quality of their decision-making. For Internet enterprises, risk management is not only a necessary defense mechanism, but also an important tool to enhance enterprise value and competitiveness [2]. Therefore, Internet enterprises urgently need a risk management system, which can not only accurately identify the business risks of enterprises, but also accurately assess the risk level.

Improving the accuracy of Internet enterprise business risk prediction has always been the focus of relevant researchers. For the risk management system of interconnected enterprises, business risk identification and business risk assessment have always been two widely discussed topics. Risk management of Internet enterprises is a continuous process, which requires enterprises to constantly identify and evaluate new risks, and use cutting-edge technologies to improve the efficiency and effect of risk management [3]. In the process of risk identification and assessment, Internet enterprises often use big data analysis and artificial intelligence technology. Among them, big data analysis means that Internet enterprises use big data tools to analyze user behaviour, market trends and other content, to accurately predict potential risks. The disadvantage of this method is that it requires extracting massive amounts of user data and internal enterprise data. Due to some privacy issues, the data is unavailable, making risk prediction impossible or inaccurate [4]. Therefore, a large number of researchers use artificial intelligence technology to predict the operational risks of enterprises. The risk prediction model based on artificial intelligence technology refers to the use of AI models, such as machine learning and deep learning models, to identify and predict risk patterns in enterprises [5]. Compared to risk prediction models based on big data, learning based models do not require massive amounts of data. In addition, with the development of technology, blockchain technology and cloud computing technology have also been used to enhance data security and prevent tampering, especially in the fields of financial transactions and data storage.

Risk prediction of Internet enterprises is a complex and changeable process. The factors related to risk prediction of Internet enterprises mainly include technological change, market competition, laws and regulations, user behavior, economic environment and corporate governance. The accuracy of risk prediction of Internet enterprises is mainly affected by data and prediction technology [6]. The data aspect mainly includes data quality and availability, and the breadth, depth, and accuracy of data collection directly affect the reliability of prediction results. The technical aspect mainly includes the prediction technology used, such as the applicability and progressiveness of statistical models and machine learning algorithms. In addition, the integration between systems may also affect the accuracy of prediction results. The degree of integration between the risk management system and other management systems in the enterprise affects

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data flow and information sharing, thereby affecting the comprehensiveness and timeliness of predictions [7].

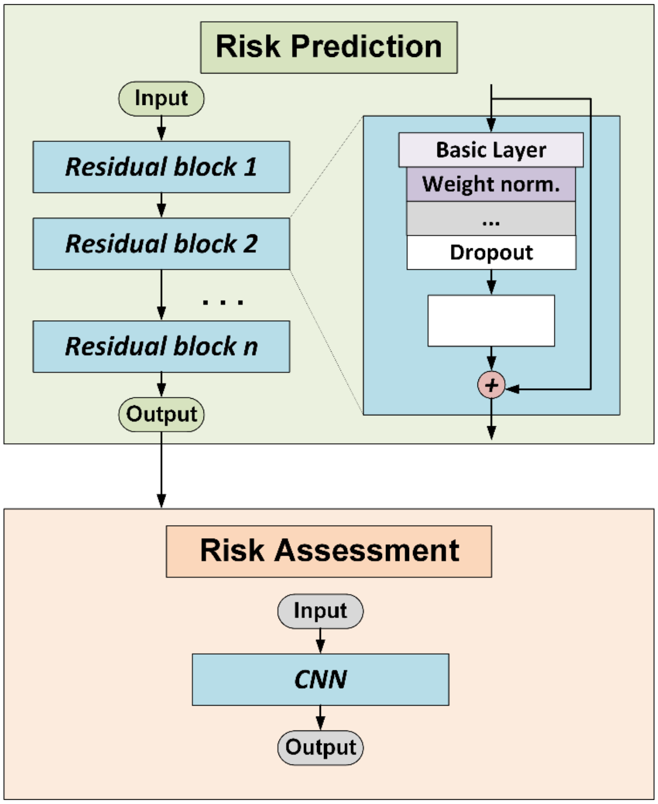

Fig. 1. The framework of Internet enterprise risk management system.

Deep learning models have shown great potential in the field of enterprise risk management. Deep learning technology can process and analyze a large amount of unstructured data, which is particularly important for predicting business risks. In enterprise risk management systems, deep learning is mainly applied in three aspects: enterprise credit risk prediction, enterprise market risk prediction, and enterprise financial risk prediction [8]. CNN, as a deep learning architecture, is particularly suitable for processing data with grid like topological structures. Due to this characteristic, CNN has been widely used in fields such as image recognition, healthcare, autonomous driving, and natural language processing. At present, there is relatively little research on the application of CNN to predict business risks. Li et al. proposed a model for predicting loan credit risk based on CNN and conducted preliminary exploration of CNN based prediction models [9]. The risk prediction model based on CNN mainly includes three steps: data collection and preprocessing, network design and training of CNN algorithm, and validation and testing of CNN algorithm. Therefore, based on the work [9], this study introduces intelligent optimization algorithms in the design process of CNN to improve the accuracy of prediction. Further, for the risk prediction of Internet enterprises, a risk management system is designed. Fig. 1 shows the operational risk management system designed in this paper for Internet enterprises.

Aiming at the problems of inaccurate prediction results and unsatisfactory evaluation results in the risk prediction and evaluation of Internet enterprises at this stage, this study designed a system for Internet enterprise risk management, aiming to improve the accuracy of risk prediction and risk evaluation. The main contributions of this study are summarized as follows:

- In this study, a model for Internet enterprise risk management was established, and the model was tested through a dataset of 100 Internet companies, which verified the effectiveness of the model.
- This study developed an IKOA-CNN algorithm based on KOA and CNN algorithms. Firstly, the classic KOA algorithm was improved by designing improvement strategies, and the CNN model was optimized using the improved KOA algorithm. The results indicate that the IKOA-CNN algorithm can effectively improve the prediction accuracy of CNN.
- A two-stage prediction risk management model was developed. In the first stage, the operational risk of Internet enterprises was predicted based on the data of Internet enterprises. The second stage is to assess the level of operational risk according to the prediction results, to provide a basis for risk management of Internet enterprises.

The rest of this article is organized as follows. Section II reviews the work related to risk prediction and machine learning algorithms. Section III designs an improved CNN model. Section IV is the result display of the organized dataset to validate the developed algorithm. Finally, the entire article was summarized in the Section V.

II. Literature Review

A. Operational Risks of Internet Enterprises

Internet enterprises face a wide range of risks, which can be analyzed from technology, market, law, operation and other dimensions. Technical risks mainly include two aspects: data security and privacy leakage. Internet enterprises will collect and store a large amount of user data in the operation process, and the security of these data has become the main concern of enterprises. At present, the technologies mainly used to prevent technological risks include blockchain technology [10]. The operational risks of Internet enterprises mainly include supply chain interruption risk, brain drain risk, financial risk, credit risk and currency fluctuation risk [11]. Financial and credit risks are crucial for the development of enterprises. Therefore, this research focuses on the financial risk and credit risk of Internet enterprises. In addition, although the supply chain disruption of Internet enterprises can also lead to serious operational problems, the risk of supply chain disruption can be solved by designing flexible supply chains and introducing other advanced transportation equipment [12]. Therefore, Lee et al. explored how to establish a resilient supply chain to reduce the risk of supply chain disruptions [13].

B. Financial Risk Prediction

The traditional financial ratio analysis method is a commonly used method by early scholars in the process of enterprise financial risk analysis. Delen et al. used financial ratio analysis methods and knowledge graph techniques to predict a company's financial risk by analyzing its financial ratios [14]. The financial ratio analysis method is simple and does not require a large amount of data, but it also has certain limitations, such as ignoring non-financial information, etc. These limitations often lead to unsatisfactory predictive performance of this method. In response to this issue, researchers have started using more complex statistical models to predict financial risk. For example, logistic regression and multiple regression analysis methods [15]. In recent years, with the development of artificial intelligence technology, machine learning and deep learning techniques have also been applied to financial risk prediction. For example, machine learning algorithms such as artificial neural networks, support vector machines, and random forests are used to process large amounts of financial and non-financial data to improve prediction accuracy. These methods can capture nonlinear relationships in data and process high-dimensional data [16]. In addition, some researchers use text analysis and unstructured data to predict financial risks. For example, by analyzing text information such as annual reports, news reports, and social media of enterprises, natural language processing techniques are used to extract relevant information, thereby helping to improve the accuracy of financial risk prediction [17].

C. *Credit Risk Prediction*

The credit prediction of Internet enterprises is also an important research direction in the field of Internet business risk assessment, especially in the assessment of credit risk. In recent years, with the development of artificial intelligence technology, credit prediction methods and applications have made significant progress. Similar to financial risk prediction, the credit risk assessment of Internet enterprises also includes the traditional scoring model and the prediction model based on artificial intelligence technology. Linear statistical models, as representatives of traditional models, mainly include two types: logistic regression and discriminant analysis. The linear statistical model relies on the historical financial data and credit history of the enterprise to predict credit risk [18]. The credit risk prediction model based on artificial intelligence technology mainly uses machine learning and deep learning techniques. Zhang et al. provided an in-depth description of credit risk prediction methods for small and medium-sized enterprises. The deep learning model proposed by him can effectively integrate various types of data, thereby improving the accuracy of prediction [19]. Liu et al. also designed a two-stage prediction algorithm based on deep learning models to predict the credit risk of enterprises [20]. Yao et al. designed a support vector machine model for risk prediction in supply chain enterprises, which can effectively integrate multiple types of data [21]. It can be said that the credit prediction of Internet enterprises is changing from traditional statistical methods to the use of artificial intelligence technology. These modern methods can handle more complex and dynamic data sets, provide more accurate and personalized credit evaluation, and thus help Internet enterprises more effectively manage credit risk [22]-[23].

D. *Convolutional Neural Network*

Convolutional Neural Networks (CNNs) have the advantages of automatically extracting data features, a concise hierarchical structure, and the ability to share parameters. Therefore, they are gradually being applied in the financial risk assessment process of enterprises [24]. However, CNN also has drawbacks such as a large demand for training data and unsatisfactory performance in handling non visual tasks. Therefore, when applying CNN to the process of enterprise risk prediction, it is necessary to improve it [25]. In recent research, the application of CNN has been extended to multiple cutting-edge technological fields, and relevant researchers have made improvements to it from different perspectives. Deepak Khatri et al. developed an intelligent framework based on serverless computing in their research, aiming to improve service efficiency through the use of artificial intelligence and machine learning [26]. Qin developed a financial risk prediction model for listed companies using CNN, which preliminarily demonstrated the potential of CNN in processing non-traditional image datasets [27]. In the study of network systems, Lou et al. (2023) proposed using a CNN algorithm to predict the robustness of networks, which utilizes CNN's powerful feature extraction ability to analyze the complex interactions of network structures [28]. In addition, de la Cruz et al. used an improved CNN model to detect eye flicker integrity in their study, which not only demonstrated the effectiveness of CNN in time series data processing, but also emphasized the importance of combining recurrent neural networks [29]. These studies collectively demonstrate the breadth and depth of CNN applications in multiple fields, from traditional image processing to complex time series analysis and 3D data processing, demonstrating its sustained development and innovation as a powerful machine learning tool [30]-[31].

III. ALGORITHM DESIGN

In this section, we designed an IKOA-CNN algorithm aimed at optimizing the learning rate in CNN using IKOA [32]. In CNN-based prediction models, learning rate has a significant impact on prediction performance. We first introduced the improved KOA algorithm. Fig. 2 shows the flowchart of the IKOA algorithm.

A. *The Improved Kepler Optimization Algorithm*

We improved the KOA algorithm by utilizing the evolutionary strategy of the genetic algorithm (GA) and the foraging strategy of the artificial fish swarm algorithm (AFSA). The main steps of the improvement are as follows:

Step 1: Initialize the parameters of the KOA algorithm based on Eq. (1) and Eq. (2).

$$\rho_k = Rand(0,1), k \in \{0,1,\cdots,k_{max}\} \tag{1}$$

$$Ha_i = |R\_n|, k \in \{0,1,\cdots,k_{max}\} \tag{2}$$

where, ρ_k is the eccentricity of the planet's orbit. Ha_i is the period of the planet's orbit, and R_n is a random number that follows a normal distribution pattern. $\{0,1,\cdots,k_{max}\}$ is a set of the number of planets.

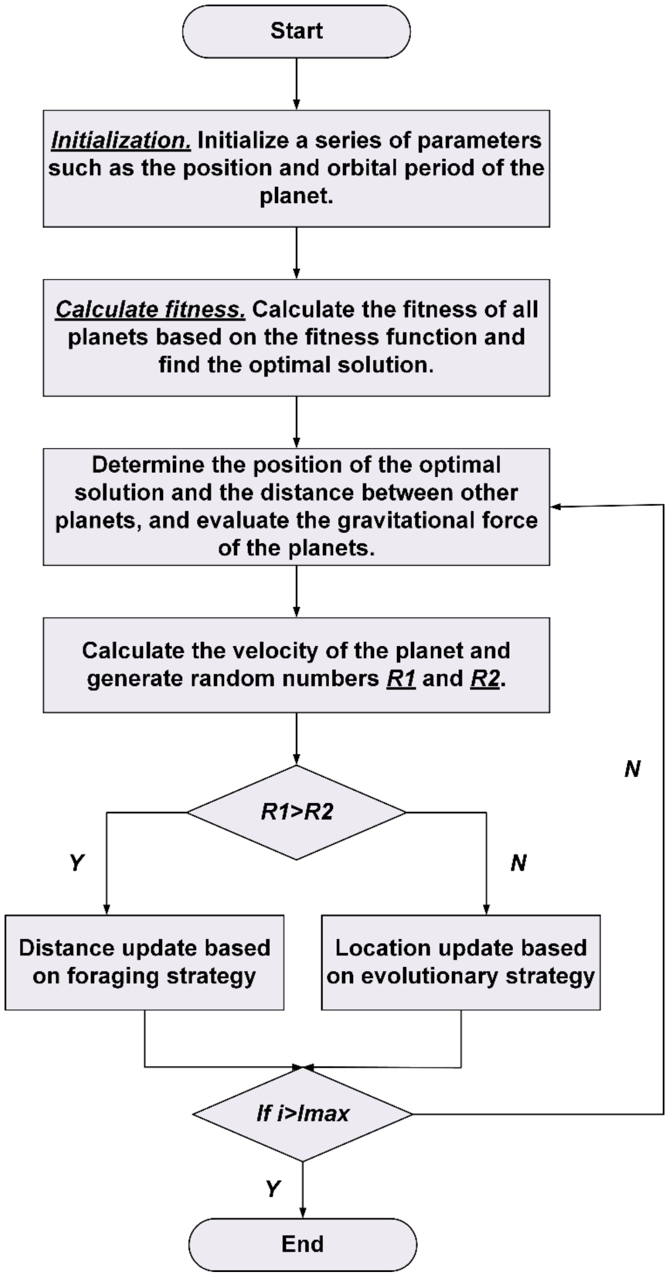

Fig. 2. The flowchart of the improved Kepler optimization algorithm.

Step 2: Update celestial body velocity $V_k(i)$ based on the formula for updating celestial body velocity in work [32].

Step 3: Inspired by the rotation of planets around the sun, the KOA algorithm's planets rotate around the sun. During each iteration, the planet updates its position based on the optimal solution. Unlike the classic KOA algorithm, we introduce the evolutionary strategy of GA algorithm into the update strategy of planetary position, as shown in Eq. (3).

$$S_k(i+1) = S_k(i) + \chi \times V_k(i) + \delta + \vec{S}_k(i) \quad (3)$$

where, $S_k(i+1)$ is the position of planet k in the $i+1$ st iteration process. χ and δ are two small variables.

Step 4: Introducing the foraging strategy of AFSA algorithm into the planetary distance update strategy, the update process of distance $\vec{S}_k(i)$ is shown in Eq. (4).

$$\vec{S}_k(i+1) = \frac{\vec{S}_k(i) + \vec{S}_a(i) + \vec{S}_b(i)}{3} \quad (4)$$

where, $\vec{S}_a(i)$ and $\vec{S}_b(i)$ are two randomly selected distances.

Step 5: Update Determine if the maximum number of iterations has been reached, and if so, output the result. If not, restart the loop.

B. Risk Management Based on CNN

Before conducting calculations, it is necessary to first rate all influencing factors based on expert experience, and weight and accumulate the obtained random probability of risk to obtain the comprehensive random probability P_n of risk factors.

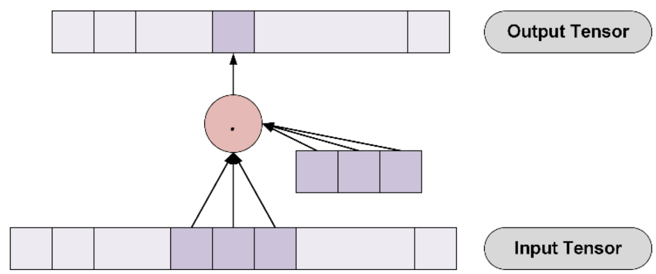

Fig. 3. The process of calculating the elements of the output tensor.

Fig. 3 shows the calculation process of CNN at each level, and the convolution $C(j)^l$ calculation formula is as follows:

$$C(j)^l = \delta \times \left(\sum C(j)^{l-1} \times K(j)^l + a(j)^l \right) \quad (4)$$

where l represents hierarchy. $C(j)^{l-1}$ is the j th feature of the input layer. $K(j)^l$ is a convolutional kernel. δ is the activation function.

IV. Result Display

This study selects a dataset of 100 Internet enterprises to verify the algorithm. The data of 40 Internet companies are used as the training set, and the data of 60 companies are used as the test set. We compared five algorithms: BP neural network, CNN, AFSA-CNN, KOA-CNN, and IKOA-CNN. The comparison results are reflected through the following four indicators: root mean square error (MSE), mean pure square error (MSPE), mean absolute error (MAE), and mean absolute percentage error (MAPE). In this study, risks were categorized into five levels: low risk, medium low risk, medium risk, medium high risk, and high risk. For the purposes of statistical analysis, the numerical ranges assigned to these risk categories were 0 to 5, 5 to 10, 10 to 15, 15 to 20, and 20 to 25, respectively.

A. Financial Risk Prediction Results of Internet Enterprises

Fig. 4 and Fig. 5 show the financial risk prediction results of the IKOA-CNN algorithm and CNN algorithm, respectively.

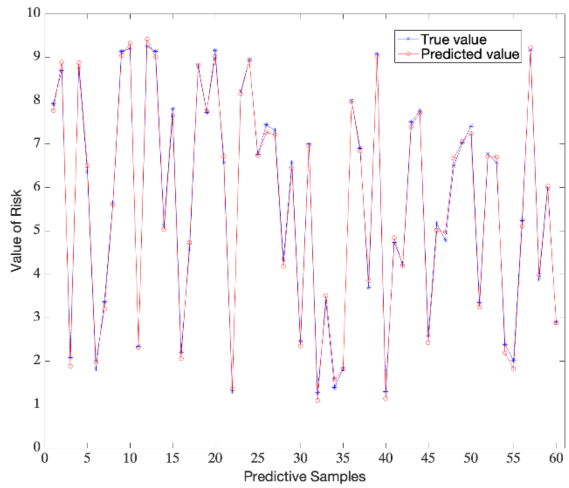

Fig. 4. Financial risk prediction results of IKOA-CNN algorithm.

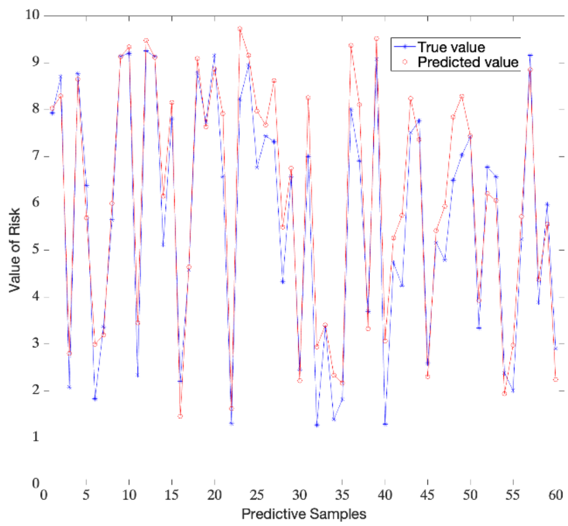

Fig. 5. Financial risk prediction results of CNN algorithm

TABLE I. ERROR ANALYSIS OF FINANCIAL RISK PREDICTION RESULTS

Algorithm	Index			
	MSE	**MSPE**	**MAE**	**MAPE**
BP	0.5962	9.86*10^(-15)	0.3265	0.4953
CNN	0.2189	8.22*10^(-15)	0.3189	0.4762
KOA-CNN	0.1195	3.67*10^(-15)	0.1014	0.1852
AFSA-CNN	0.1906	6.98*10^(-15)	0.2159	0.2478
Ours	0.0072	2.17*10^(-15)	0.0124	0.0875

B. Results of Credit Risk Prediction of Internet Enterprises

Fig. 6 and Fig. 7 show the credit risk prediction results of the IKOA-CNN algorithm and CNN algorithm, respectively.

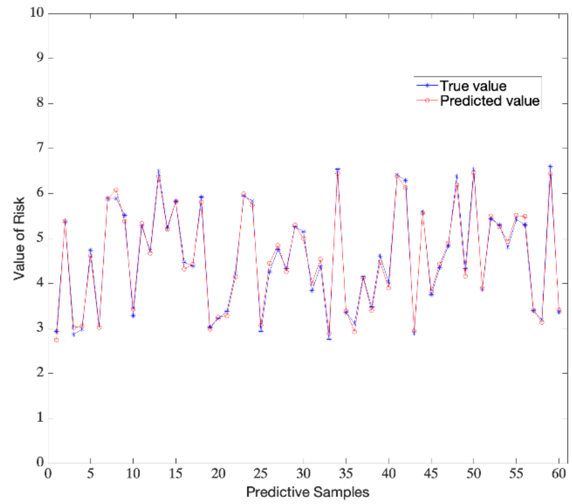

Fig. 6. The credit risk prediction results of IKOA-CNN algorithm.

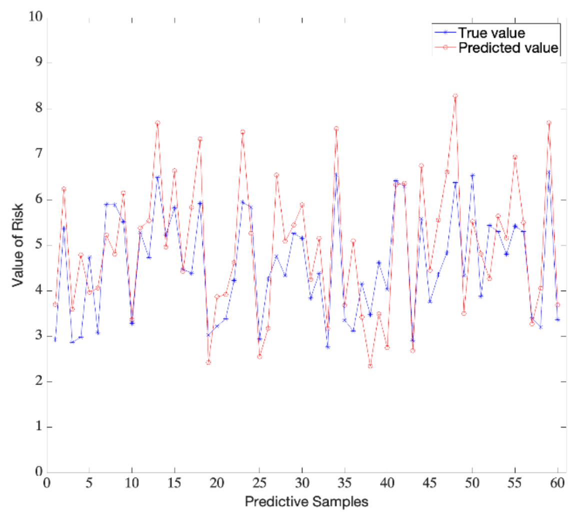

Fig. 7. The credit risk prediction results of CNN algorithm.

TABLE II. ERROR ANALYSIS OF CREDIT RISK PREDICTION RESULTS

Algorithm	Index			
	MSE	**MSPE**	**MAE**	**MAPE**
BP	0.6784	5.57*10^(-15)	0.4324	0.4707
CNN	0.4579	9.26 *10^(-16)	0.3501	0.4186
KOA-CNN	0.2375	8.79*10^(-16)	0.2728	0.3966
AFSA-CNN	0.2286	7.65*10^(-16)	0.2688	0.3038
Ours	0.0092	6.86*10^(-16)	0.0154	0.0629

C. Management Risk Assessment of Internet Enterprises

Fig. 8 and Fig. 9 show the business risk prediction results of the IKOA-CNN algorithm and CNN algorithm, respectively.

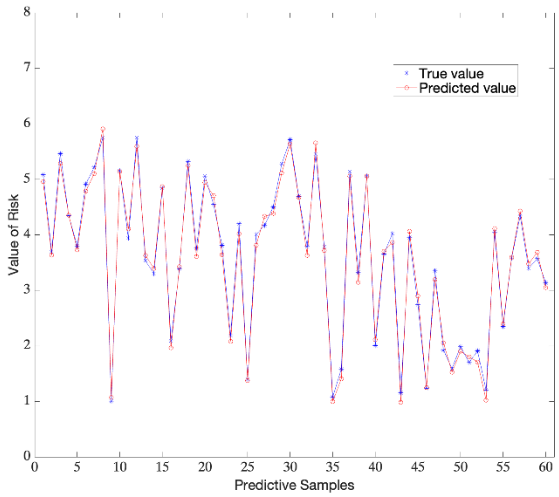

Fig. 8. The business risk prediction results of IKOA-CNN algorithm.

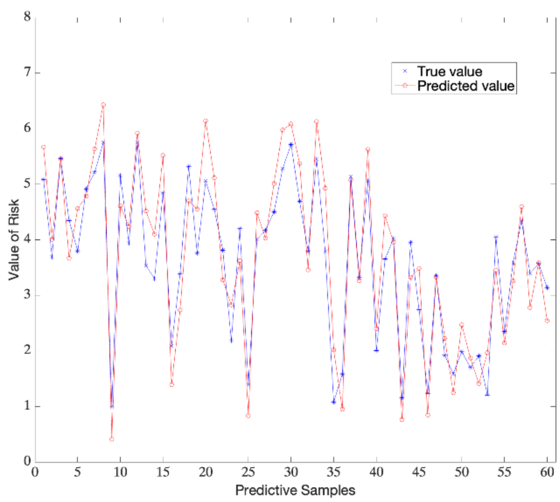

Fig. 9. The business risk prediction results of IKOA-CNN algorithm.

TABLE III. ERROR ANALYSIS OF BUSINESS RISK PREDICTION RESULTS

Algorithm	Index			
	MSE	MSPE	MAE	MAPE
BP	0.6908	9. 80*10^(-15)	0.5570	0.4239
CNN	0.3896	8.68*10^(-15)	0.3527	0.4961
KOA-CNN	0.3570	4.66*10^(-15)	0.2914	0.2826
AFSA-CNN	0.2411	4.28*10^(-15)	0.1646	0.1957
Ours	0.0093	2.17*10^(-15)	0.0358	0.0763

Tables I, II, and III respectively show the results of applying BP, CNN, KOA-CNN, AFSA-CNN and IKOA-CNN algorithms in financial risk prediction, credit risk prediction, and business risk prediction. The results show that compared with BP, CNN, KOA-CNN and AFSA-CNN algorithms, algorithm IKOA-CNN consistently exhibits the lowest MSE and MSPE values, indicating higher prediction accuracy compared to other algorithms. In addition, the MAE and MAPE values of IKOA-CNN algorithm are also the lowest, indicating its robustness in maintaining lower average deviations. The output results of BP and CNN algorithms differ significantly from the true values. The output results of AFSA-CNN and KOA-CNN algorithms also have certain deviations from the true values. In contrast, the overall risk prediction performance of the IKOA-CNN model is the best, and the difference between its trend and the true value is smaller. The prediction results show that IKOA-CNN model has a high performance in financial risk, credit risk and operational risk prediction, and this model can be effectively applied to the financial management process of Internet enterprises.

V. CONCLUSION

To foster the sustainable development of Internet enterprises, this study developed a risk prediction model utilizing the CNN algorithm. The architecture of the deep neural network model was optimized using an enhanced KOA, which is defined as IKOA-CNN. The research employed a dataset comprising data from 100 Internet enterprises. Comparative analysis with other learning-based risk prediction models demonstrates that the IKOA-CNN algorithm, as proposed in this study, achieves the highest prediction accuracy. Although IKOA-CNN algorithm in this study can accurately predict the financial risk, credit risk and business risk of Internet enterprises, the accuracy of this model for the prediction of business risk of other industries has not yet been explored. Therefore, in the next stage, we will further improve the generalization ability of the model.

REFERENCES

[1] Hossam Hassan, Manal A. Abdel-Fattah and Amr Ghoneim, "Risk Prediction Applied to Global Software Development using Machine Learning Methods" International Journal of Advanced Computer Science and Applications (IJACSA), 13(9), 2022.

[2] Zhao, Yuting. "Risk Prediction for Internet Financial Enterprises by Deep Learning Algorithm and Sustainable Development of Business Transformation." Journal of Global Information Management, 30(7), 2022, 1–16.

[3] Yao, Gang, Xiaojian Hu, and Guanxiong Wang. "A Novel Ensemble Feature Selection Method by Integrating Multiple Ranking Information Combined with an SVM Ensemble Model for Enterprise Credit Risk Prediction in the Supply Chain." Expert Systems With Applications, 200, 2022, 117002.

[4] Xianjuan Li, "Study on Early Warning on the Financial Risk of Project Venture Capital through a Neural Network Model" International Journal of Advanced Computer Science and Applications (IJACSA), 13(9), 2022.

[5] Sun, Xiaojun, and Yalin Lei. "Research on Financial Early Warning of Mining Listed Companies Based on BP Neural Network Model." Resources Policy, 73, 2021, 102223.

[6] Wang, Qi et al. "The Application of Big Data and Artificial Intelligence Technology in Enterprise Information Security Management and Risk Assessment." Journal of Organizational and End User Computing, 35(1), 2023, 1–15.

[7] Stevenson, Matthew, Christophe Mues, and Cristián Bravo. "The Value of Text for Small Business Default Prediction: A Deep Learning Approach." European Journal of Operational Research, 295(2), 2021, 758–771.

[8] Du, Guansan, and Frank Elston. "Financial Risk Assessment to Improve the Accuracy of Financial Prediction in the Internet Financial Industry Using Data Analytics Models." Operations Management Research, 15(3–4), 2022, 925–940.

[9] Li, Meixuan, Chun Yan, and Wei Liu. "The Network Loan Risk Prediction Model Based on Convolutional Neural Network and Stacking Fusion Model." Applied Soft Computing, 113, 2021,107961.

[10] Singh, Sushil Kumar, and Jong Hyuk Park. "TaLWaR: Blockchain-Based Trust Management Scheme for Smart Enterprises With Augmented Intelligence." IEEE Transactions on Industrial Informatics, 19(1), 2023, 626–634.

[11] Hou, Liangliang, Ke Lu, and Gongbing Bi. "Predicting the Credit Risk of Small and Medium - sized Enterprises in Supply Chain Finance Using Machine Learning Algorithms." Managerial and Decision Economics, 45(4), 2024, 2393‑2414.

[12] Liu, Haishi, Y.P Tsang, and C.K.M Lee. "A Cyber-Physical Social System for Autonomous Drone Trajectory Planning in Last-Mile Superchilling Delivery." Transportation Research. Part C, Emerging Technologies, 158, 2024, 104448.

[13] Lee, Eunji, and Stefan Minner. "How Power Structure and Markup Schemes Impact Supply Chain Channel Efficiency under Price-Dependent Stochastic Demand." European Journal of Operational Research, 318(1), 2024, 297–309.

[14] Delen, Dursun, Cemil Kuzey, and Ali Uyar. "Measuring Firm Performance Using Financial Ratios: A Decision Tree Approach." Expert Systems With Applications, 40(10), 2013,3970–3983.

[15] Wu, Ning et al. "Do Liquidity and Capital Structure Predict Firms' Financial Sustainability? A Panel Data Analysis on Quoted Non-Financial Establishments in Ghana." Sustainability, 15(3),2023, 2240.

[16] Allemar Jhone P. Delima, Ariel M. Sison and Ruji P. Medina, "Variable Reduction-based Prediction through Modified Genetic Algorithm" International Journal of Advanced Computer Science and Applications (IJACSA), 10(5), 2019.

[17] Amountzias, Chrysovalantis. "Income Disparities and Financial Development: Evidence from a Panel Firm-Level Analysis." Empirical Economics, 66(1), 2024, 175–206.

[18] Liu, Jiaming et al. "Enhancing Credit Risk Prediction Based on Ensemble Tree - based Feature Transformation and Logistic Regression." Journal of Forecasting, 43(2), 2024, 429‑455.

[19] Zhang, Wen et al. "Credit Risk Prediction of SMEs in Supply Chain Finance by Fusing Demographic and Behavioral Data." Transportation Research. Part E, Logistics and Transportation Review, 158, 2022, 102611.

[20] Liu, Jiaming, Sicheng Zhang, and Haoyue Fan. "A Two-Stage Hybrid Credit Risk Prediction Model Based on XGBoost and Graph-Based Deep Neural Network." Expert Systems With Applications,195, 2022, 116624.

[21] Yao, Gang, Xiaojian Hu, and Guanxiong Wang. "A Novel Ensemble Feature Selection Method by Integrating Multiple Ranking Information Combined with an SVM Ensemble Model for Enterprise Credit Risk Prediction in the Supply Chain." Expert Systems With Applications, 200, 2022, 117002.

[22] Li, Meiyan, and Yingjun Fu. "Prediction of Supply Chain Financial Credit Risk Based on PCA-GA-SVM Model." Sustainability, 14(24), 2022, 16376.

[23] Chi, Guotai et al. "Long-Horizon Predictions of Credit Default with Inconsistent Customers." Technological Forecasting & Social Change, 198, 2024, 123008.

[24] Li, Zhe, Zhenhao Jiang, and Xianyou Pan. "Default Risk Prediction of Enterprises Based on Convolutional Neural Network in the Age of Big Data: Analysis from the Viewpoint of Different Balance Ratios." Complexity, 2022, 2022, 1–18.

[25] Pavitha N and Shounak Sugave, "Explainable Multistage Ensemble 1D Convolutional Neural Network for Trust Worthy Credit Decision" International Journal of Advanced Computer Science and Applications (IJACSA), 15(2), 2024.

[26] Deepak Khatri, Sunil Kumar Khatri and Deepti Mishra, "Intelligent Framework in a Serverless Computing for Serving using Artificial Intelligence and Machine Learning" International Journal of Advanced Computer Science and Applications (IJACSA), 15(5), 2024.

[27] Qin, Weina. "Research on Financial Risk Forecast Model of Listed Companies Based on Convolutional Neural Network." Scientific Programming, 2022, 2022, 1–10.

[28] Lou, Yang et al. "A Learning Convolutional Neural Network Approach for Network Robustness Prediction." IEEE Transactions on Cybernetics, 53(7), 2023, 4531–4544.

[29] de la Cruz, Gonzalo et al. "Eye-LRCN: A Long-Term Recurrent Convolutional Network for Eye Blink Completeness Detection." IEEE Transaction on Neural Networks and Learning Systems, 35(4), 2024, 5130–5140.

[30] Rahayu, Endang Sri et al. "A Combination Model of Shifting Joint Angle Changes with 3D-Deep Convolutional Neural Network to Recognize Human Activity." IEEE Transactions on Neural Systems and Rehabilitation Engineering, 32, 2024, 1078-1089.

[31] Rong Wu, Yong Yang, Xiaotong Yao and Nannan Lu, "Optimal Trajectory Planning for Robotic Arm Based on Improved Dynamic Multi-Population Particle Swarm Optimization Algorithm" International Journal of Advanced Computer Science and Applications (IJACSA), 15(5), 2024.

[32] Mohamed, Reda et al. "Novel Hybrid Kepler Optimization Algorithm for Parameter Estimation of Photovoltaic Modules." Scientific Reports, 14(1), 2024, 3453–3453.