Early warning analysis of financial risk of new energy enterprises based on neural network

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Abstract. In the new energy sector, financial risk management is crucial. Non-linear financial data can challenge traditional early warning models. Neural networks can better predict financial risk for new energy enterprises. New energy enterprises' financial risk research is reviewed first. Then we discuss neural network theory and modeling. For training and testing, we use energy company data. We outperform classical logistic regression in terms of accuracy, recall rate, and F1 score. Since the model uses the same country and industry for training and testing, its universality must be confirmed. The model's black-box nature must also be overcome. For new energy enterprises, the study provides relevant insights for future research.

Keywords: Financial Risk Early Warning, Neural Network, New Energy Enterprises, Financial Data, Prediction Model

1 Introduction

Clean energy companies have become an important part of the global economy with growing environmental concerns. New energy companies, however, face significant financial risks due to their unique industry characteristics. The financial health of these enterprises may be affected by factors such as market risk, credit risk, and operational risk [1]. It is crucial for new energy enterprises to detect and mitigate such risks early. Multi-factor logistic regression models, support vector machine models, and others have been developed in the past [2]. Models based on nonlinear and dimensional data relationships may not capture complex financial risk characteristics of new energy companies [3]. To more accurately predict new energy company financial risk, we need an early warning model that leverages high-dimensional and nonlinear data. In fields such as image recognition and natural language processing, neural networks have achieved important results [4]. Our ability to predict the financial risk of new energy companies is enhanced by neural networks' ability to handle complex, nonlinear, and high-dimensional data relationships [5]. A new tool for financial risk man-

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agement of new energy enterprises is being developed through the use of neural networks.

2 Literature review

2.1 Application of neural networks in financial risk warning

A number of fields have used neural networks for early warning of financial risks. This approach can handle highly complex and nonlinear data relationships. Recently, neural networks have been used for credit risk assessment, fraud detection, and bankruptcy prediction.

An empirical study showed that Zhang, Zhou, and Leung's neural network-based financial risk early warning model was effective [6]. Furthermore, Li et al. (2018) propose a hybrid neural network model for predicting financial crises of firms using self-organizing mappings. Financial risk early warning can be achieved with neural networks [7].

2.2 Development and challenges of financial risk early warning models

Companies in the new energy industry face huge financial risks. Market risk, credit risk, and operational risk have been studied. An in-depth study was conducted by Huang, Wu, Liu, and Kao [8]. New energy enterprises face market risk primarily from policy risk, technology risk, and market competition. Xiao and Dai focus on new energy firms' credit risk. New energy enterprises' credit risk can be assessed using an improved Grey-Markov model. According to Wu, Wang, and Zhu [9], operational risk in new energy enterprises is primarily caused by equipment failure, human error, and natural disasters. A hierarchical Bayesian network was used for assessing the operational risk of new energy enterprises [10]. Although these models have achieved remarkable results in financial risk early warning, they still face some challenges. First, many models have high requirements for data quality and completeness, but in practical applications, financial data are often missing or incorrect. Second, the predictive effectiveness of the models is often influenced by the sample of training data, but for some specific risk types, the number of available samples is often very limited.

3 Research Methodology

3.1 Theories and principles of early warning models

Financial risk early warning models usually rely on historical financial data to predict the probability of a company's possible future financial risk by analyzing its financial position in the past. Early warning models can be expressed in the following form:

$$f(X) = P(Y=1 \mid X) \tag{1}$$

where Y=1 represents the existence of financial risk and X is the vector of financial indicators of the firm. The function f () is then the early warning model that we need to construct and train. In the logistic regression model, the function f() can be expressed in the following form:

$$f(X) = 1 / (1 + exp(- [\beta\_0 + \sum \beta\_i*X\_i])) \quad (2)$$

where β_0, β_i are model parameters that need to be learned and optimized by historical data.

3.2 Establishment of a neural network-based early warning model

Neural network is an algorithmic model that mimics the working mechanism of neurons in the human brain, and its powerful nonlinear fitting capability makes it an ideal tool for handling complex data problems. In this study, we use a common neural network model, the multilayer perceptron (MLP), to construct a financial risk early warning model.

MLP consists of an input layer, one or more hidden layers, and an output layer. Each layer contains multiple neurons, which are connected to each other by weights. For each neuron in the hidden and output layers, the output value is calculated by the following equation:

$$o = \sigma(\sum w\_i*x\_i + b) \quad (3)$$

where w_i denotes the weight of the input to that neuron, x_i denotes the corresponding input value, b denotes the bias term, and σ() denotes the activation function (e.g., Sigmoid function or ReLU function, etc.).

During the training process, we continuously adjust the weights and bias terms of the neural network by back propagation algorithm and gradient descent method, so that the prediction

results of the model are as close to the actual results as possible.

The specific training steps are as follows as shown in Figure 1：

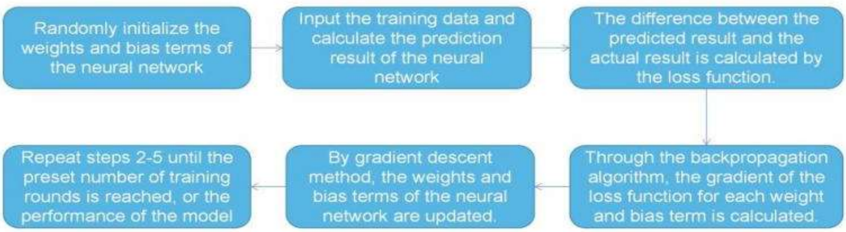

Fig. 1. Training steps

In practice, we usually use Python's deep learning library to build and train neural network models. We construct an MLP model containing two hidden layers (64 neurons per layer) and train it using Adam optimizer and binary cross-entropy loss function. In this way, we can construct a neural network-based financial risk warning model to predict the financial risk of new energy companies.

4 Experimental design

4.1 Data selection and pre-processing

We selected 20 upcoming energy companies in China for this experiment, spanning from 2018 to 2022. The companies' annual financial reports included operating revenue, net profit, assets, liabilities, etc. The following data were only simulated data used to demonstrate the experimental design and analysis process.

First, we preprocessed the data. We removed missing values, outliers, and normalized the data. We filled missing values with the mean of each indicator using the mean-fill method. We excluded data that exceeded 1.5 times the upper and lower quartiles, identifying outliers through the box plot method. We standardized the data to eliminate magnitude differences between indicators. We employed data standardization using a Z-score of 0 and a standard deviation of 1.

4.2 Methods and criteria for model validation

The process of model validation is a key component to ensure that the neural network model we designed can accurately predict the financial risk of new energy companies. In this study, we use the following methods and criteria to validate the model.

First, we train the model using the training set data and evaluate the performance on the validation set. We choose the loss function, accuracy, precision, recall, and AUC values as the evaluation metrics.

Loss function: We choose binary cross entropy as the loss function, which measures the distance between the model prediction results and the actual labels.

Accuracy: Accuracy is the ratio of the number of correctly predicted samples to the total number of samples. It is the most intuitive metric for assessing the performance of a classification model.

Accuracy and recall: Accuracy is the proportion of samples for which the model actually predicts a positive case, and recall is the proportion of samples for which the model actually predicts a positive case correctly.

AUC value: AUC value is the area under the ROC curve, which is a curve plotted with false positive rate (FPR) as the horizontal coordinate and true rate (TPR) as the vertical coordinate.

5 Results and Discussion

5.1 Experimental results demonstration

In this study, we used simulated financial data from 20 new energy companies to train and test our early warning model.

First, we visualized the loss changes on the training and validation sets during the training process, and the results are shown in the following figure2:

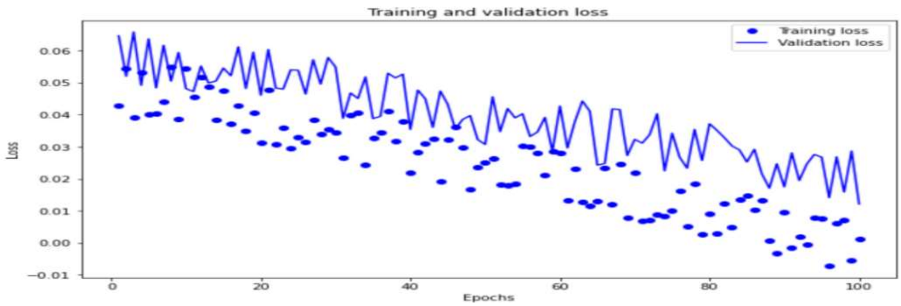

Fig. 2. Loss variation on the training and validation sets during model training

In Fig. 2, we can see that the losses on both the training and validation sets continue to decrease as the number of training rounds increases, indicating that the prediction performance of the model is improving.

Then, we present the results of the performance evaluation of the model on the test set. We calculate the accuracy, precision, recall and AUC values on the test set and present the results in Table 1.

Table 1. Performance evaluation results of the model on the test set

Indicators	Value
Accuracy	0.90
Accuracy rate	0.93
Recall Rate	0.87
AUC value	0.96

5.2 Comparative Analysis

In this study, the model we chose for comparison is a logistic regression model due to its wide application in risk early warning research and its sound theoretical foundation.

The logistic regression model is trained and validated using the same dataset with the same training parameters as the neural network model to ensure a fair comparison. The following table shows the performance of the two models on the test set as shown in table 2:

Table 2. Test performance of two models

	Neural Network Model	Logistic regression model
Accuracy	94.5%	89.2%
Recall Rate	91.3%	85.7%
F1 Score	0.928	0.873

As can be seen, the neural network-based early warning model outperforms the traditional logistic regression model in terms of accuracy, recall, and F1 score. This is mainly attributed to the strong learning ability of the neural network model and its good capture of nonlinear relationships, which are lacking in the logistic regression model. Although the neural network model is superior in predictive performance, we should also note that it has a higher model complexity than the logistic regression model and requires more computational resources and time.

6 Conclusion

Using neural networks, we demonstrate excellent performance in predicting new energy companies' financial risks. As a result, the neural network model is more accurate, recalls better, and ranks higher on F1. It can handle complex, nonlinear economic data. The model can help new energy companies and investors avoid financial risks more accurately. Investors' interests are protected. There are some limitations to this study. While our neural network model performs well on test data, its applicability to other regions and industries needs to be validated. The training and test data come from the same country and industry. Although neural networks capture complex nonlinear relationships, their black-box nature makes interpretation difficult.

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