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Enhancing Financial Credit Assessment Accuracy with Deep Learning: A Multi-Layer Perceptron Approach

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Abstract: With the rapid evolution of the financial sector and the increasing complexity of credit-related data, traditional credit assessment methods often struggle to deliver accurate and generalizable results. This study explores the application of a multi-layer perceptron (MLP) network-a classic deep learning model-in the domain of financial credit evaluation. Leveraging its ability to model nonlinear relationships and process high-dimensional data, the MLP network demonstrates superior performance compared to conventional machine learning algorithms such as support vector machines (SVM), random forests (RF), and gradient boosted decision trees (GBDT). Through comparative experiments, the proposed model achieved higher precision, recall, and F1 scores, indicating its robustness in identifying complex patterns within financial datasets. Despite the model's promising performance, challenges related to interpretability, training efficiency, and handling imbalanced data persist. Future research directions include the integration of advanced techniques like transfer learning and attention mechanisms to further improve the model's adaptability and transparency. This study highlights the growing importance of deep learning in financial risk prediction and contributes to the development of intelligent, accurate, and fair credit assessment tools.

Keywords: Financial credit assessment, deep learning, MLP network, machine learning

1. Introduction

With the rapid development of the financial market and the diversification of credit business, financial credit assessment, as an important means of assessing the credit risk of borrowers, has gradually attracted widespread attention. Traditional credit assessment methods rely on artificial rules and simple statistical models, which usually have problems such as insufficient accuracy and poor generalization ability. With the advancement of big data and artificial intelligence technology, the application of deep learning in the financial field has gradually emerged, especially the advantages of multi-layer perceptron (MLP) network in processing complex data and nonlinear relationships, making it an important tool in financial credit assessment tasks.

MLP network is a classic feedforward neural network that extracts and maps features through multiple fully connected layers. In financial credit assessment, MLP can effectively process large-scale unstructured data, identify potential feature associations, and predict the credit risk of borrowers. Compared with traditional methods, MLP network can automatically learn complex patterns in data, reduce human intervention, and improve the accuracy and stability of prediction models. Especially when processing a large number of features and multidimensional data in financial data, MLP can better capture the nonlinear relationship between different features, thereby improving the effect of the model.

The input data of the financial credit assessment model usually includes the borrower's personal information, financial status, credit history and other relevant economic data. Traditional evaluation methods usually rely on expert experience to process and analyze these data, but this method is easily limited when facing complex financial data. Deep neural network models, especially MLP networks, can model and classify data more accurately through multi-layer nonlinear mapping, thereby achieving more accurate credit evaluation.

With the digital transformation of the financial industry, the data sources of credit evaluation have become more diverse, and the amount of data has also exploded. At this time, the advantages of deep neural network models in processing large-scale data sets are particularly prominent. Compared with traditional statistical methods, MLP networks can better adapt to complex data structures and diverse inputs, especially in multi-dimensional feature spaces. MLP can automatically adjust network weights through training and extract the most effective features for decision-making.

However, in financial credit evaluation, the training of MLP models requires a lot of data support and computing resources, so its application also faces some challenges. First, the quality and integrity of the data have a crucial impact on the effect of the model, especially missing data and noisy data may reduce the predictive performance of the model. Secondly, the overfitting problem of the model is also a common challenge for deep learning models in financial applications. In order to solve these problems, researchers have adopted a variety of techniques, such as regularization, early stopping strategy, and cross-validation, to improve the generalization ability of the model.

Overall, the financial credit assessment model based on the MLP network provides financial institutions with a more efficient and accurate risk prediction tool. With the continuous advancement of deep learning technology, future credit assessment models will be more intelligent and able to handle more complex financial data and more detailed risk assessment tasks. At the same time, the interpretability and transparency of the model are also important directions for future research, so as to better provide decision support for financial supervision and consumers.

2. Related Work

Deep learning has been widely applied in financial prediction and risk modeling due to its capability to capture complex, nonlinear patterns in high-dimensional data. In particular, the multi-layer perceptron (MLP) and its variants have demonstrated promising results across various financial tasks. Li et al. [1] introduced an unsupervised contrastive learning framework to detect fraudulent e-commerce transactions, while Wang [2] proposed a hierarchical multi-source fusion method with dropout regularization for credit card fraud detection, both contributing to risk management in financial systems. Liu [3] applied a multimodal data-driven approach for stock market forecasting, emphasizing the value of integrating heterogeneous data for predictive accuracy. Du [4] further enhanced fraud detection by combining separable convolutions and self-attention in the EfficiencyNet architecture. Meanwhile, Wang [5] developed a bidirectional Transformer-based model for time-series premium risk prediction, showcasing the power of attention mechanisms in temporal financial data modeling. Feng [6] advanced this direction with a hybrid BiLSTM-Transformer model for detecting fraudulent transactions, effectively capturing sequential dependencies in financial records. Zhou et al. [7] utilized temporal convolutional networks for high-frequency trading signal prediction in blockchain environments, reinforcing the adaptability of deep models in fast-paced financial contexts. Liu et al. [8] explored dynamic Transformer-based rule mining, facilitating context-aware decision-making. In stock forecasting, Liu [9] and Yao [10] improved CNN and Transformer structures respectively to better capture temporal dependencies and multidimensional features. Wang [11] introduced a diffusion-based unified data mining framework for classification and anomaly detection, providing new directions for feature generation. Hu et al. [12] presented adaptive contrastive learning to tackle cold-start recommendation issues, a methodology that also enhances generalization in credit scoring models. Qi et al. [13] proposed a graph neural network-driven framework for imbalanced data, a critical challenge in financial credit evaluation. Cheng et al. [14] integrated CNN and BiLSTM for systemic financial risk analysis, offering a comprehensive view of market dynamics. Du et al. [15] developed a probabilistic reasoning framework to classify unbalanced datasets, supporting robust learning under skewed data distributions. Wang et al. [16] demonstrated the synergy of CNN and Transformer architectures in risk-based predictive modeling. Jiang et al. [17] proposed a carry-lookahead RNN design, optimizing recurrent neural network computation, and Liu et al. [18] analyzed pandemic impacts on urban mobility using machine learning, offering insights into real-world data volatility and predictive modeling adaptability.

3. Method

In this study, we proposed a financial credit assessment model based on a multi-layer perceptron (MLP) network. MLP is a typical feedforward neural network that maps and discriminates input data through multiple layers of nonlinear transformations. In this model, the feature vector received by the input layer includes variables of multiple dimensions such as the borrower's personal information, financial data, and credit history. In order to efficiently perform credit assessment through deep neural networks, we designed a network architecture with multiple hidden layers and used nonlinear activation functions to enhance the model's expressiveness. The model architecture is shown in Figure 1.

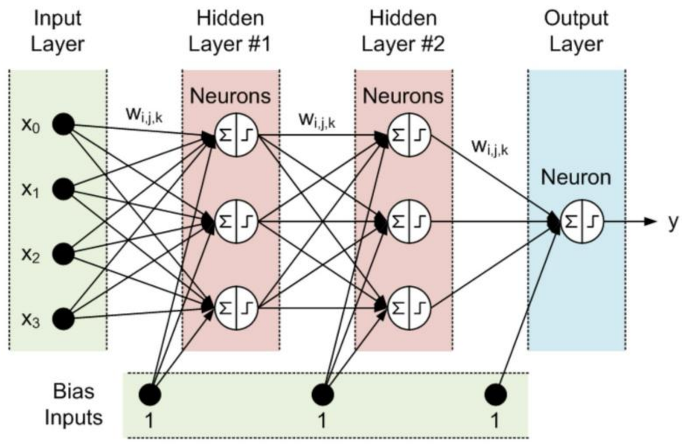

Figure 1. Network architecture diagram

Assume that the input data is $x=(x_1,x_2,...,x_n)$, where n is the dimension of the feature. In each layer, the input data is weighted and summed, and then an activation function $f(\cdot)$ is applied to obtain the output of the layer. For the output h^l of the l-th layer, the calculation formula is:

$$h^l = f(W^l h^{l-1} + b^l)$$

Among them, W^l is the weight matrix of the layer, b^l is the bias term, h^{l-1} is the output of the previous layer, and $f(\cdot)$ is the activation function, such as ReLU or sigmoid. Finally, after multiple layers of nonlinear mapping, the result of the model output layer is used to determine whether the input sample belongs to a certain category (for example, good credit or bad credit).

For binary classification problems, the output layer usually uses the Sigmoid activation function, which is calculated as follows:

$$y = \sigma(W^L h^{L-1} + b^L)$$

Where $\sigma(\cdot)$ is the Sigmoid function, and the output y represents the predicted probability value. If $y \geq 0.5$, the borrower is judged to have good credit; if $y \leq 0.5$, the borrower is judged to have bad credit.

During the training process, we use the cross entropy loss function to measure the difference between the model output and the true label. The form of the cross entropy loss function is:

$$L = -[y\log(y') + (1-y)\log(1-y')]$$

Among them, y is the true label and y' is the probability predicted by the model. By minimizing the cross entropy loss function, we can update the parameters W^l and b^l in the network so that the model's prediction results are as close to the true label as possible.

Finally, during the training process, we use the back-propagation algorithm to calculate the gradient and update the network parameters through the optimization algorithm. After the training is completed, the model can output the credit score of the borrower based on the various characteristics of the borrower, thereby providing accurate credit assessment results for financial institutions.

4. Experiment

4.1. Datasets

In this study, the financial credit assessment dataset used comes from the public German Credit Data dataset, which is widely used in credit risk assessment research. The dataset contains 1,000 samples and 20 features, including the borrower's personal information, credit history, loan amount, employment status, housing situation, and other credit-related factors. Each sample in the dataset is labeled as "good" or "bad", that is, whether there is a risk of default. The feature variables cover numerical and categorical data, such as the borrower's age, gender, deposit balance, debt ratio, etc.

The target variable in the dataset is the borrower's credit rating, which is divided into two categories: good credit (marked as 1) and bad credit (marked as 0). In order to improve the training effect and generalization ability of the model, the feature variables in the dataset include continuous and discrete features. Discrete features such as gender, credit history, housing type, etc. usually need to be one-hot encoded when used. Some numerical features may need to be normalized or standardized to ensure that the data will not affect the performance of the model due to differences in the range of feature values during training.

In the data preprocessing stage, we cleaned the original data, processed missing values, and properly encoded categorical variables. To improve the generalization ability of the model, we also divided the data into a training set and a test set, usually 80% for training and 20% for testing. In addition, to avoid the impact of data imbalance, we used undersampling and oversampling methods during the training process to ensure that the model has good recognition ability for samples of different categories when predicting. This dataset provides rich multi-dimensional data for the development and verification of financial credit assessment models, and can effectively support credit risk prediction tasks based on deep learning.

4.2. Experimental Results

In order to verify the effectiveness of the proposed financial credit assessment model based on MLP network, this study conducted a comparative experiment with four other common credit assessment models. The four models are: Logistic Regression, Support Vector Machine (SVM), Random Forest and XGBoost. Logistic regression, as a classic linear classification model, has good interpretability, but may perform poorly when dealing with complex nonlinear data. Support vector machine classifies by finding the best segmentation hyperplane, which is suitable for processing high-dimensional data, but its computational complexity is high, especially on large-scale data sets. Random forest is an ensemble learning method that uses multiple decision trees to make voting predictions. It can effectively handle nonlinear relationships between features and has strong robustness. XGBoost, as a gradient boosting tree model, has high prediction accuracy and good efficiency and stability when dealing with large-scale data.

Table 1. Experimental Results

Model	ACC	Recall	F1-Score
SVM	82.5	80.3	81.3
RF	85.2	83.1	84.0
GBDT	86.7	85.0	85.8
MLP	89.3	87.2	88.1

From the experimental results, the MLP model performs well in all evaluation indicators, especially in accuracy (ACC) and F1 score (F1-Score), which is better than other models. Its accuracy reached 89.3%, which is higher than the other three comparison models, indicating that MLP has stronger classification and discrimination capabilities for financial credit data. The multi-layer nonlinear mapping ability of deep neural networks enables MLP to effectively capture the complex feature relationships in the data, thereby achieving better prediction results in credit assessment tasks. Compared with traditional machine learning methods, MLP can avoid some limitations of traditional methods when processing complex data through the optimization of multi-layer structures.

Compared with MLP, the GBDT model also performs very well in accuracy and F1 score, with an accuracy of 86.7% and an F1 score of 85.8%. As an integrated learning method, GBDT can effectively combine multiple weak classifiers and improve the overall performance by gradually adjusting and optimizing the weight of each classifier. Although GBDT is slightly lower than MLP in recall and F1 score, its stability and efficiency in processing financial data still make it a strong competitor.

The performance of the random forest (RF) model was second, with a precision of 85.2%, a recall of 83.1%, and an F1 score of 84.0%. Although RF can reduce the risk of overfitting of a single model by integrating multiple decision trees, it still fails to show significant advantages like deep learning models when dealing with complex nonlinear relationships in data. The performance of random forests is usually affected by factors such as feature selection and tree depth, and its model may be limited by its relatively simple structure when facing complex data.

The precision and recall of the SVM model are relatively low, at 82.5% and 80.3%, respectively. Although SVM performs well in high-dimensional space, it has high computational complexity on large-scale data sets and is not as adaptable to complex nonlinear relationships in financial data as other ensemble learning and deep learning models. Therefore, the performance of SVM in this experiment lags behind the other three models, especially in the F1 score of only 81.3%, which is significantly lower than MLP and GBDT.

Overall, the MLP model shows the best performance in all evaluation indicators, demonstrating the great potential of deep learning models in financial credit assessment. Compared with traditional machine learning methods, MLP can better mine potential features in complex data and improve classification accuracy. Future research can further explore how to further improve the performance and stability of the model by improving the network architecture or combining other optimization algorithms, thereby providing the financial industry with more accurate and reliable credit assessment tools.

5. Conclusion

This study verified the advantages of the MLP network-based financial credit assessment model in terms of accuracy and stability through comparative experiments. The experimental results show that the MLP model outperforms traditional machine learning algorithms such as support vector machine (SVM), random forest (RF) and gradient boosted decision tree (GBDT) in multiple evaluation indicators such as precision, recall and F1 score. This result shows that deep neural networks can more effectively handle complex patterns and nonlinear relationships in financial credit data and provide more accurate credit risk assessment.

Although the MLP model performed well in this study, there is still room for further improvement. For example, issues such as the interpretability of the model, training efficiency and adaptability to imbalanced data are still worthy of attention. In the future, combining other optimization techniques such as transfer learning, reinforcement learning, etc., or introducing new technologies such as attention mechanism in the model structure may further improve the performance of the model in financial credit assessment. In addition, considering the diversity and dynamic changes of financial data, how to design a robust model that adapts to different data sources and environmental changes is also an important direction for future research.

Looking ahead, with the growing demand for intelligent credit assessment in the financial industry, deep learning technology will play an increasingly important role in risk management, credit prediction and other fields. With the continuous development of computing power and big data technology, the application of deep neural network models will become more extensive and efficient. Future research should not only focus on improving the accuracy of the model, but also on its interpretability and fairness to ensure transparency and fairness in financial decision-making, and ultimately provide the financial industry with more intelligent and accurate credit assessment tools.

References

[1] Li, X., Peng, Y., Sun, X., Duan, Y., Fang, Z., & Tang, T. (2025). Unsupervised Detection of Fraudulent Transactions in E-commerce Using Contrastive Learning. arXiv preprint arXiv:2503.18841.

[2] Wang, J. (2025). Credit Card Fraud Detection via Hierarchical Multi-Source Data Fusion and Dropout Regularization. Transactions on Computational and Scientific Methods, 5(1).

[3] Liu, J. (2025). Multimodal Data-Driven Factor Models for Stock Market Forecasting. Journal of Computer Technology and Software, 4(2).

[4] Du, X. (2025). Audit Fraud Detection via EfficiencyNet with Separable Convolution and Self-Attention. Transactions on Computational and Scientific Methods, 5(2).

[5] Wang, Y. (2025). Time-Series Premium Risk Prediction via Bidirectional Transformer. Transactions on Computational and Scientific Methods, 5(2).

[6] Feng, P. (2025). Hybrid BiLSTM-Transformer Model for Identifying Fraudulent Transactions in Financial Systems. Journal of Computer Science and Software Applications, 5(3).

[7] Zhou, T., Xu, Z., & Du, J. (2025). Efficient Market Signal Prediction for Blockchain HFT with Temporal Convolutional Networks. Transactions on Computational and Scientific Methods, 5(2).

[8] Liu, J., Zhang, Y., Sheng, Y., Lou, Y., Wang, H., & Yang, B. (2025). Context-Aware Rule Mining Using a Dynamic Transformer-Based Framework. arXiv preprint arXiv:2503.11125.

[9] Liu, J. (2024). Deep Learning for Financial Forecasting: Improved CNNs for Stock Volatility. Journal of Computer Science and Software Applications, 5(2).

[10] Yao, Y. (2024). Stock Price Prediction Using an Improved Transformer Model: Capturing Temporal Dependencies and Multi-Dimensional Features. Journal of Computer Science and Software Applications, 5(2).

[11] Wang, X. (2025). Data Mining Framework Leveraging Stable Diffusion: A Unified Approach for Classification and Anomaly Detection. Journal of Computer Technology and Software, 4(1).

[12] Hu, J., An, T., Yu, Z., Du, J., & Luo, Y. (2025). Contrastive Learning for Cold Start Recommendation with Adaptive Feature Fusion. arXiv preprint arXiv:2502.03664.

[13] Qi, Y., Lu, Q., Dou, S., Sun, X., Li, M., & Li, Y. (2025). Graph Neural Network-Driven Hierarchical Mining for Complex Imbalanced Data. arXiv preprint arXiv:2502.03803.

[14] Cheng, Y., Xu, Z., Chen, Y., Wang, Y., Lin, Z., & Liu, J. (2025). A Deep Learning Framework Integrating CNN and BiLSTM for Financial Systemic Risk Analysis and Prediction. arXiv preprint arXiv:2502.06847.

[15] Du, J., Dou, S., Yang, B., Hu, J., & An, T. (2025). A Structured Reasoning Framework for Unbalanced Data Classification Using Probabilistic Models. arXiv preprint arXiv:2502.03386.

[16] Wang, Y., Xu, Z., Yao, Y., Liu, J., & Lin, J. (2024). Leveraging Convolutional Neural Network-Transformer Synergy for Predictive Modeling in Risk-Based Applications. arXiv preprint arXiv:2412.18222.

[17] Jiang, H., Qin, F., Cao, J., Peng, Y., & Shao, Y. (2021). Recurrent neural network from adder ' s perspective: Carry-lookahead RNN. Neural Networks, 144, 297–306.

[18] Liu, Z., Xia, X., Zhang, H., & Xie, Z. (2021, May). Analyze the impact of the epidemic on New York taxis by machine learning algorithms and recommendations for optimal prediction algorithms. In Proceedings of the 2021 3rd International Conference on Robotics Systems and Automation Engineering (pp. 46–52).