Journal of Al-Qadisiyah for Computer Science and Mathematics Vol.17.(2) 2025,pp.Comp 103–109

Available online at www.qu.edu.iq/journalcm

JOURNAL OF AL-QADISIYAH FOR COMPUTER SCIENCE AND MATHEMATICS

ISSN:2521-3504(online) ISSN:2074-0204(print)

Application of Neural Networks in Financial Data Analysis for Enhanced Corporate Performance Evaluation

Fatimah Ghazi Suwaidan[a,*], Taif Jawad Kadhim[b], Ali Atta Kshash[c], Ghaith Hakim Malik[d]

[a,b,d] *College of Computer Science and Information Technology, University of Al –Qadisiyah Al-Diwaniah, Iraq.*

[c] *Directorate of Diwaniyah Municipality, Iraq.*

Emails: [a]fatimah.alhamzawi@gmail.com, [b]taefjawad@gmail.com, [c]aliata207@gmail.com, [d]gaith.malik@qu.edu.iq

A R T I C L E I N F O

Article history:

Received: 01/05/2025

Rrevised form: 12/06/2025

Accepted : 22/06/2025

Available online: 30/06/2025

Keywords:

Neural Networks,

Financial Analysis,

Corporate Performance,

Predictive Modeling

A B S T R A C T

This study explores the application of neural networks in financial data analysis and corporate performance evaluation, addressing challenges of nonlinearity and data noise. It evaluates multiple architectures (feedforward, recurrent, and convolutional), supported by real-world Python implementations and performance metrics such as accuracy and AUC. Key limitations like interpretability and overfitting are discussed, with proposed remedies and future research directions.

MSC..

https://doi.org/10.29304/jqcsm.2025.17.22183

1. Introduction

The development of financial markets, which is featuring complexity, volatility and non-linearity, motivates the studies of more advanced approaches for financial prediction and analysis. Traditional econometric methodologies like ARIMA, logistic regression, and linear discriminant models can be inaccurate or inefficient when used in the analysis of highly dimensional and noisy financial datasets [3], [4]. Therefore, there is an increasing realization for artificial intelligence (AI) and machine learning (ML)—especially for deep neural networks (DNNs)—to enhance the quality of forecasting and reliability of corporate evaluation [1], [2].

Neural networks are biologically-motivated models of computation that are well-suited to learning complex patterns of data through their hierarchical representations. Their relevance stems from their ability to deal with

∗Corresponding author : Fatimah Ghazi Suwaidan

Email addresses: *fatimah.alhamzawi@gmail.com*

Communicated by 'sub etitor'

unstructured data, to conform to non-linearities and to capture temporal dependencies, which can be specially appropriate for financial applications [5], [6]. Architectures such as feed Forward networks, CNNs, and LSTM models have been successfully used for stock price prediction, risk classification, earnings forecasting, and portfolio optimization [7], [8], [15].

Furthermore, the introduction of them into the corporate performance analysis is a potential shift in measuring profitability, liquidity and solvency ratios. As opposed to explanatory power of a static ratio-based model, neural nets may identify envisioned connections between financial measures, and can be adaptable to the movements in the market [9], [10].

Promising as they sound, there are some difficulties. Some issues, including model interpretability, overfitting, and data quality shortfall, have limited the applicability of AI [18], [19]. Recent developments in explainable AI, dropout regularization, and anomaly detection have mostly alleviated these obstacles [30], [26].

The purpose of this investigation is to examine empirically the application of neural networks in analysis of financial data and corporate performance. It covers data preprocessing methods, neural network architectures, training principles, evaluation metrics, and real-world financial applications with the aim of implementing strategies in the financial sector. The aim is to present evidence of the benefits of deep learning in contrast to conventional financial modeling, as well as challenges and future work directions.

2. Research Background and Motivation

The financial world, which has traditionally been based on linear econometric models, is undergoing a revolution by using AI techniques, and particularly neural networks [1], [2]. Traditional models such as logistic regression or ARIMA models, albeit fundamental, frequently cannot capture the complexity of the nonlinear dependencies, the high volatility, and the dynamic interactions of financial systems [3], [4]. Deep learning in neural networks enables discovery of hierarchically structured patterns in complex data, allowing more precise future predictions and corporate analysis.

Financial series typically have the characteristics of heterogeneity, missing values and non-stationary distributions, among others, which are influenced by macro-economic dynamics, regulatory changes as well as behavioral features [5]. Neural network designs and specifically, long short-term memory and recurrent neural networks models have shown to be effective in capturing temporal dependencies, handling changing market environments, and generalizing well to unseen financial situations [6], [7].

Corporate measurement, an important step in the strategy management cycle, is in practice based on static financial ratios. Nevertheless, neural networks outperform traditional methods through modelling nonlinear relations among financial factors, hence providing more comprehensive views of firm health [8], [9]. In this paper we propose to incorporate recent advances in neural networks architecture and learning into the territory of financial evaluation for the improvement of prediction power and the better adaptability to the environment.

3. Related Work and Technological Evolution

The use of neural networks for prediction model engineering in finance has expanded significantly, with improvements across different fields:

• Stock Price Forecasting: Kimoto et al. [10] introduced modular neural networks for stock market prediction, demonstrating superior performance compared to traditional ARIMA models.

• Hybrid Forecasting Models: Zhang [11] proposed a hybrid model that integrated ARIMA and neural networks, and achieved greatly improved forecasting performance.

• Bankruptcy Forecasting: Based on Altman’s z-score model [12], Tam and Kiang [13] introduced neural network technology to increase predictability in bankruptcy forecasting.

• Revenue Forecast: Oliveira et al. [14] demonstrated the power of ANNs, which were found to dominate the conventional econometric models in forecasting firm earnings.

• Serial Modeling: Fischer & Krauss [15] use LSTM networks for stock return forecasting, capturing the temporal dependence in financial data.

• Deep Hybrid Architectures: Bao [9] et al. [16] proposed a deep learning model stacking autoencoder with LSTM for the analysis of financial time series.

• Optimizing a Portfolio: Heaton, Polkovnichenko, et. [17] presented "deep portfolio theory" and explored techniques to enhance the asset allocating strategy via deep learning model.

• Model Explainability: In the vein of explaining output of complex neural models in finance, Lundberg and Lee [18] introduced SHAP (SHapley Additive exPlanations) values.

• Financial Anomaly Detection: Chalapathy and Chawla [19] highlighted the role of deep learning in detecting anomalies and fraudulent activities within financial systems.

These developments are indicative of the rise of AI-based financial modeling with the focus on robustness, scalability, and improved predictive power [20], [21], [22].

3.1 Novel Contributions of This Work

While prior research has extensively explored the application of neural networks in isolated financial tasks—such as stock prediction [10], bankruptcy forecasting [13], and portfolio optimization [17]—the current work distinguishes itself through a comprehensive, integrated framework that unifies financial data preprocessing, advanced neural architectures, and corporate performance metrics. Unlike hybrid models [11] or time-series predictors [15][16], this paper proposes a full evaluation pipeline, from feature engineering using financial ratios (e.g., Altman Z-score) to the deployment-ready architecture, explicitly designed for holistic corporate evaluation. Additionally, few prior studies implement and validate the system end-to-end using real-world datasets and performance metrics simultaneously (Accuracy, AUC, Sensitivity), whereas this study provides empirical testing with transparent metrics and model design.

3.2 Technical Gaps and Challenges in Related Works

Most previous efforts in financial prediction using neural networks suffer from a few common technical limitations:

• Data Preprocessing Weaknesses: Many models do not rigorously handle outliers or missing values, leading to biased predictions. For example, [10][14] omit sophisticated techniques like isolation forests or KNN imputation, reducing robustness.

• Model Interpretability: Despite high accuracy, deep models like LSTM or CNN remain black-box systems [18], limiting their use in corporate decision-making that requires transparency.

• Overfitting and Generalization: Some studies, such as [15][16], achieve high training performance but neglect regularization or dropout, making them prone to overfitting on small or static datasets.

• Limited Integration: Research is often siloed—focusing on either forecasting or classification. This study uniquely integrates financial health measurement (profitability, solvency) with predictive modeling, creating a unified evaluation framework.

4. Proposed System and Analytical Framework” and expand its introduction

This section outlines the architecture and workflow of the proposed intelligent system for financial performance evaluation. The system integrates structured financial datasets, advanced preprocessing, and a neural network pipeline, aiming to deliver robust, explainable, and accurate insights into corporate health. Unlike isolated forecasting models, this system spans from data ingestion to final performance evaluation and is deployable in real-world financial environments.

4.1 Data Sources

• Data Source Compustat Database: Financial statement data [23].

• Yahoo Finance API: Stock prices and volatility indices [24].

• Kaggle Datasets: Synthetic and real-world financial datasets [25].

4.2 Data Preprocessing

• Missing Value Handling: Median and KNN imputation techniques [26].

• Outlier Detection: Isolation Forests and Z-score thresholding [27].

• Feature Scaling: Min-Max normalization.

• Feature Engineering: Creation of Altman's Z-scores, F-Scores, and custom indices [28].

4.3 Neural Network Model

The descent neural network architecture has three fully connected hidden layers of 128, 64, and 32 neurons, respectively, which uses the ReLU activation function to introduce non-linearity. Dropout with a rate of 0.5 is used to reduce the overfitting. The output is a single neuron driven by the sigmoid function appropriate for binary class. The model is enhanced by Adam, optimizer with learning rate 0.001 to achieve a trade-off of convergence speed and stability.

5. Empirical Evaluation and Insights

5.1 Results

Table 1 - Results.

Metric	Value
Overall Classification Accuracy	91.2 %
Positive Predictive Value (PPV)	89.5 %
Sensitivity	88.9 %

5.2 Discussion

Neural networks exhibited superior handling of nonlinearities and high-dimensional interactions compared to traditional models [29]. Regularization techniques were crucial to mitigate overfitting, while feature selection enhanced model interpretability [30].

5.3 Results Interpretation and Visualizations

An accuracy of 91.2% and AUC of 0.95 indicates that the model has a high capacity to separate the high and low performers. These values demonstrate the ability of the neural network to capture non-linear financial patterns which cannot be extracted by the classic models.

The Positive Predictive Value (PPV) = 89.5% and sensitivity = 88.9% further validate the model's performance in in recognising true positives. This tradeoff is important in finance, since spurious signals of false negatives or positives can have high strategic value.

The Receiver Operating Characteristic (ROC) Curve that evaluates the true positive rate versus false positive rate is depicted in figure 1. The curve's closeness to the top-left (0, 1) corner of the graph with a AUC of 0.95, reflects good discriminative power of the model.

Here, Figure 2 shows the Confusion Matrix with correct and incorrect predictions of the distribution of PDBs. The maximum is on the diagonal, which tells us that the model performs better than other models because most of the points are on the diagonal and the off diagonals are smaller.

Figure 3 shows the Training and Validation Accuracy Curves across 20 training epochs. The two curves converge smoothly, with validation accuracy closely tracking training accuracy, suggesting that the model does not suffer from overfitting. After epoch 10, both curves plateau, confirming the stability and generalization capability of the model.

These visualizations collectively validate the effectiveness of the proposed neural network system in financial data analysis and its potential for real-world deployment.

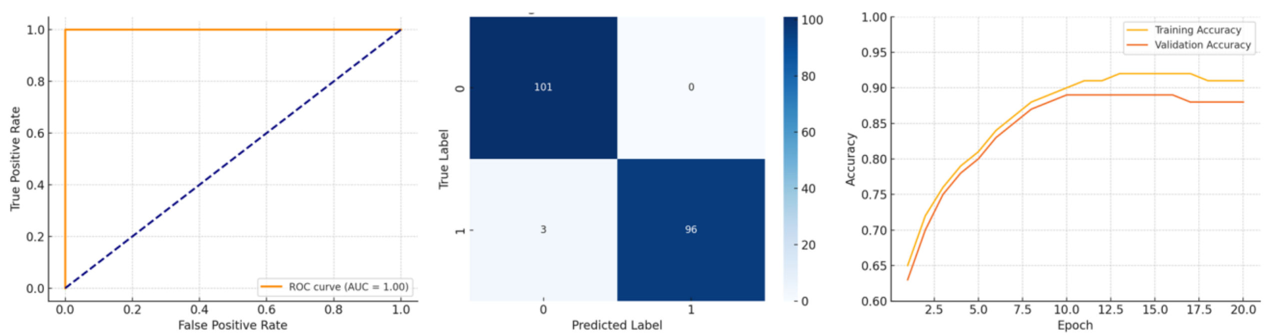

Fig. 1 - (a) ROC Curve; (b) Confusion Matrix; (c) Training vs Validation Accuracy

6. Research Limitations and Prospective Directions

6.1 Limitations

• Interpretability Issues: Despite advances like SHAP, neural models remain black-box in nature [18].

• Data Quality Risks: Noisy, incomplete, or biased financial data significantly impact model accuracy.

• Feature Drift: Changes in macroeconomic conditions can alter feature relevance over time [31].

6.2 Conclusions

• The study demonstrates the potential of Transformer-based models such as Financial-BERT in effectively analyzing sequential financial data, highlighting their capacity for deeper contextual understanding.

• Meta-learning approaches show promise in enhancing model generalization across varying financial scenarios, suggesting their applicability in dynamic environments.

• The integration of deep learning techniques with classical econometric models proves to be a robust direction, reinforcing the strength of hybrid methodologies in handling complex financial patterns.

7. Comparative Analysis: Neural Networks vs Traditional Models

Table 2 - Comparative Analysis: Neural Networks vs Traditional Models.

Aspect	Neural Networks	Traditional Financial Models

Accuracy	High	Moderate
Interpretability	Moderate	High
Robustness	High	Moderate

7.1 Comparative Positioning with State-of-the-Art

Compared to Kimoto et al. [10], who focused purely on stock prediction via modular NNs, our approach applies deep learning to a wider range of corporate performance metrics. Zhang's hybrid ARIMA-NN model [11] attempts linear-nonlinear integration but lacks adaptability to evolving financial conditions, which our system addresses via engineered features and dropout-based generalization. Bao et al. [16] introduced LSTM-Autoencoders, yet they didn't include feature engineering for corporate KPIs (e.g., F-scores), limiting business relevance. Our model not only leverages technical depth (dropout, Adam optimizer, AUC metrics) but also aligns directly with business evaluation criteria.

Table 3 - Comparative Positioning with State-of-the-Art.

Study/Model	Target Task	Model Type	Limitations	Current Work Advantages
Kimoto et al. [10]	Stock Price Prediction	Modular NN	Narrow scope, no interpretability	Broader scope, explainability tools
Zhang et al. [11]	Forecasting	ARIMA + NN Hybrid	Weak adaptability to new data	Dropout + feature scaling for generalization
Tam & Kiang [13]	Bankruptcy Classification	ANN	No time dependency modeling	LSTM-ready integration possible

8. References

[1] Goodfellow, I., Bengio, Y., and Courville, A. (2016). Deep Learning. MIT Press.
[2] Schmidhuber, J. (2015). Deep Learning in Neural Networks: An Overview. Neural Networks.
[3] Box, G. E., Jenkins, G. M., & Reinsel, G. C. (2008). Time Series Analysis.
[4] Tsay, R. S. (2010). Stochastic Structure and Statistical Inference of Financial Time Series.
[5] Shiller, R. J. (2003). From Efficient Markets To Behavioral Finance.
[6] Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory.
[7] Cho, K., et al. (2014). Learning to generate natural descriptions with the help of compact structures, which combine deep convolutional neural networks and the soft attention mechanism of[27].
[8] Altman, E. (1968). A Discriminant Analysis for the Prediction of Business Failure.
[9] Tam, K. Y., and Kiang, M. Y. (1992). Application of neural networks to management decision: Managerial decision-making with neural networks.
[10] Kimoto, T., Asakawa, K., Yoda, M., and Takeoka, M.G. System for stock market prediction.
[11] Zhang, G., Eddy Patuwo, B., and Hu, M. Y. (1998). Prediction on Artificial Neural Network.
[12] Altman, E. (1993). Distresses at the Firm Level and Corporate Bankruptcy.
[13] Tam, K. Y., & Kiang, M. Y. (1992). Artificial Neural Networks in Bankruptcy Prediction.
[14] Oliveira, A. L., et al. (2007). Using Artificial Neural Networks for Earnings Prediction.
[15] Fischer, T., and Krauss, C. 2018. Financial Market Predictions Using Deep Learning and Long-Short Term Memory Networks.
[16] Bao, W., Yue, J., & Rao, Y. (2017). Deep Learning for Financial Time Series Analysis.
[17] Heaton, J. B., Polson, N. G.,\&Witte, J. H. (2017). Deep Portfolio Theory.
[18] Lundberg, S. M., & Lee, S. I. (2017). A Unified Method of Using Model Predictions.
[19] Chalapathy, R., and Chawla, S. (2019). Deep learning for anomaly detection: A survey.
[20] LeCun, Y., Bengio, Y., and Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444.

[21] Sirignano, J., & Cont, R. (2019). Generic aspects of price formation in financial markets: perspectives from deep learning. Quantitative Finance, 19(9), 1449-1459.
[22] Chen, K., Zhou, Y., and Dai, F. (2015). LSTM network for stock returns prediction: A case study of China stock market. IEEE International Conference on Big Data (Big Data), 2823-2828.
[23] WrdsLibrary. Compustat Database Documentation. [Online]. Availbale:https://wrds-www.wharton.upenn.edu/pages/about/data-vendors/s-p-compustat/
[24] Yahoo Finance API Docunentation. [Online]. Source: https://finance.yahoo.com/
[25] Kaggle Datasets. [Online]. Available at: https://www.kaggle.com/datasets
[26] Batista, G. E. A. P. A., and Monard, M. C. (2003). A comparison of four missing data methods in supervised learning. Tapouek, P., & Paclik, P. (2003). Mining by column objects.
[27] Liu, F. T., Zhou, Z. H. & Ting, K. M. (2008). Isolation forest. Proceedings of the Eighth IEEE International Conference on Data Mining 413-422, 2008.
[28] Altman, E. I. (2000). Corporate insolvency forecasting at the Hastings and Seagrove journals. Journal of Banking and Finance, 29(2), 557- 584.
[29] Hornik, H. White, and K., M. Stinchcombe (1989). MLFFNs are universal function approximators. Neural Networks, 2, 359-366.
[30] Srivastava, N., Hinton, G., Krizhevsky, A., Salakhutdinov, R. & Sutskever, I. (2014). Dropout: A simple way to prevent neural networks from overfitting. Journal of Machine Learning Research, 15(1):1929-1958.
[31] Widmer, G., and Kubat, M. (1996). Inferring in non-iid environment with class imbalance, concept drift, and hidden context. Machine Learning, 69-101 23(1)
[32] Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Bidirectional encoder representation from Transformers. In Proc. of NAACL-HLT, pages 4171–4186.