Research on Financial Portfolio Risk Prediction Model Based on CNN and Image Processing

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Abstract

In today's complex and volatile financial market environment, risk management of multi-asset portfolios faces significant challenges. Traditional risk assessment methods, due to their limited ability to capture complex correlations between assets, find it difficult to effectively cope with dynamic market changes. This paper proposes a multi-asset portfolio risk prediction model based on Convolutional Neural Networks (CNN). By utilizing image processing techniques, financial time series data are converted into two-dimensional images to extract high-order features and enhance the accuracy of risk prediction. Through empirical analysis of data from multiple asset classes such as stocks, bonds, commodities, and foreign exchange, the results show that the proposed CNN model significantly outperforms traditional models in terms of prediction accuracy and robustness, especially under extreme market conditions. This research provides a new method for financial risk management, with important theoretical significance and practical value.

Keywords: Multi-Asset Portfolio; Risk Management; Convolutional Neural Network; Image Processing; Financial Data Visualization; Risk Prediction

1. Introduction

In the context of highly interconnected and complex global financial markets, risk management of multi-asset portfolios has become a key issue in the field of investment.

Investors not only need to allocate among different asset classes but also need to effectively manage the complex risks arising from such allocations. Traditional risk management methods, such as the mean-variance model, although providing a theoretical framework for asset allocation to a certain extent, are difficult to accurately capture the nonlinear and dynamic characteristics in the market due to their overly simplified assumptions about return distributions and asset correlations.

With the rapid development of artificial intelligence and big data technologies, deep learning models, especially Convolutional Neural Networks (CNN), have performed excellently in handling high-dimensional and unstructured data. CNNs, with their powerful feature extraction and pattern recognition capabilities, are widely used in computer vision and image processing fields. In recent years, CNNs have gradually been introduced into the financial field to improve the precision of data analysis and risk prediction.

However, applying CNNs to financial risk management still faces challenges. On the one hand, financial data usually exist in the form of time series; how to effectively convert them into a form suitable for CNN processing is a key issue. On the other hand, the complexity and nonlinear characteristics of financial markets require models to have strong robustness and generalization ability.

In view of this, this paper proposes a multi-asset portfolio risk management model based on Convolutional Neural Networks. By converting financial time series data into images and utilizing the feature extraction capabilities of CNNs, we capture the complex correlations among assets and dynamic market changes. The main contributions of this paper include:

- Constructing a CNN model combined with image processing techniques, targeting the risk management problem of multi-asset portfolios.
- Proposing a preprocessing method to convert financial time series data into two-dimensional images, laying the foundation for the application of CNNs.
- Verifying the effectiveness and superiority of the proposed model under different market conditions through extensive empirical analysis.

This research provides new ideas and methods for multi-asset portfolio risk management and helps improve the accuracy of risk prediction and the scientific basis of investment decisions.

2. Overview of Multi-Asset Portfolios

A multi-asset portfolio combines various asset types such as stocks, bonds, commodities, and real estate to reduce risk and enhance returns. These assets interact through different market mechanisms and economic factors, allowing investors to balance risk and return for optimized decisions.

Risk management is essential for maintaining return stability and improving the risk-return ratio in multi-asset portfolios. This dynamic process involves risk identification, assessment, mitigation, and monitoring in a continuous cycle. As illustrated in Figure 1, these steps form a closed loop that enables quick responses to market changes and ensures portfolio optimization.

Traditional risk models like the Mean-Variance Model face limitations in capturing complex asset correlations. Rapid market changes and diverse investor behaviors further complicate dynamic risk management, reducing the effectiveness of standard models. More advanced tools are needed to enhance portfolio performance and optimize the risk-return ratio.

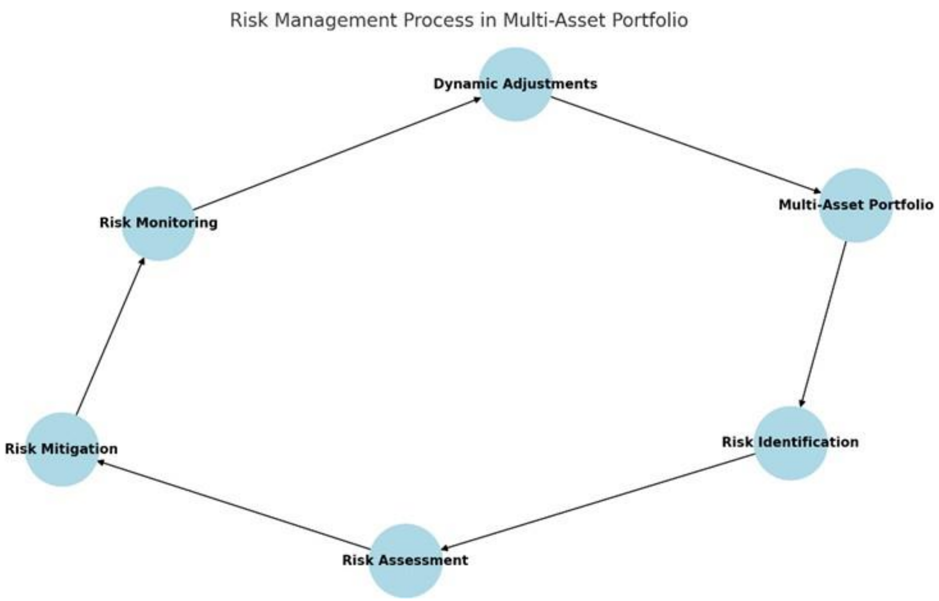

Figure 1: Risk Management process in Multi-Asset Portfolio

3. Fundamentals of Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are central to image processing, using convolutional layers to extract features such as edges and textures. Filters apply local operations to input data, capturing low-level features like edges (Figure 2-D) and textures (Figure 2-E) [2][3]. This hierarchical structure allows CNNs to automatically learn complex patterns in the data.

CNNs are increasingly applied in finance, where they excel in tasks such as market risk prediction by analyzing historical price data and their associated graphs [4][5]. Compared to traditional models like the Mean-Variance method, CNNs offer superior accuracy in risk prediction, thanks to their ability to process multi-dimensional data and capture complex relationships [6][7].

The advantages of CNNs lie in their capability to recognize nonlinear relationships in high-dimensional financial data, significantly improving risk assessments compared to traditional methods. They integrate various data sources like market conditions and economic indicators to provide more reliable risk management insights [7].

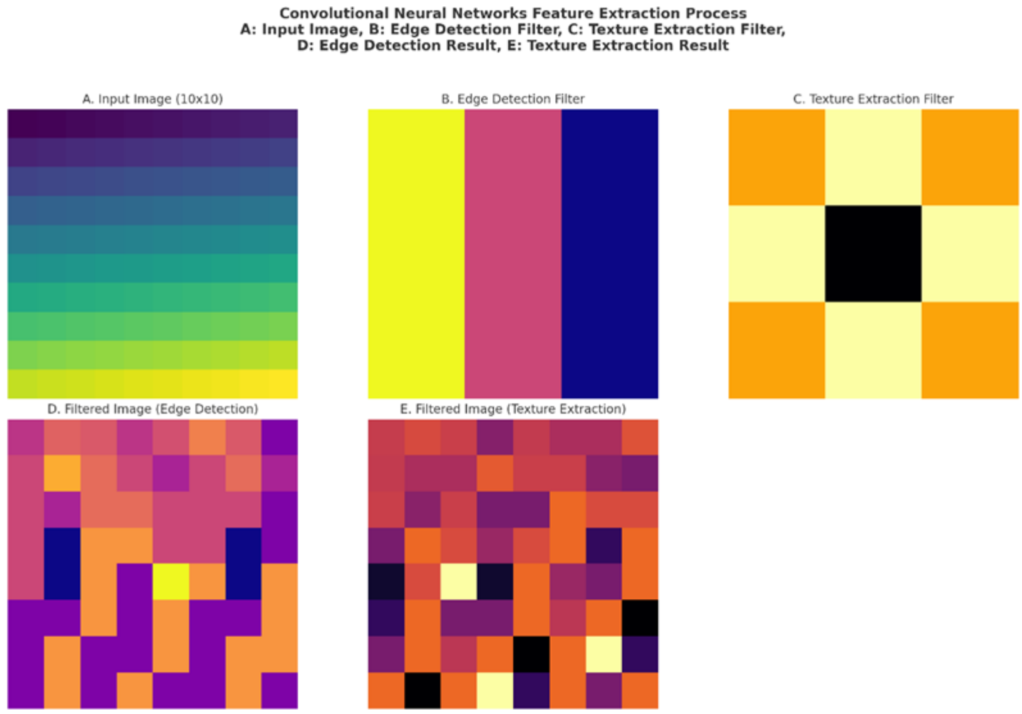

Figure 2: CNNs feature Extraction Process

4. Application of Image Processing Techniques in Financial Data

Image processing techniques like feature extraction and image classification improve data analyzability, revealing important patterns in high-dimensional financial datasets. For instance, visualizing financial time-series data as images enables CNNs to identify market trends and risk factors [8][9][10]. Techniques like edge detection (Figure 3-B) and region segmentation extract key information, enhancing the scientific basis for investment decisions [11].

Data visualization is crucial in multi-asset risk management, transforming complex datasets into intuitive charts and graphs. Figure 3-C shows risk exposure using bar charts, while Figure 3-D highlights patterns detected via region segmentation. Image processing powered by CNNs deepens data analysis and supports better decision-making [12][13].

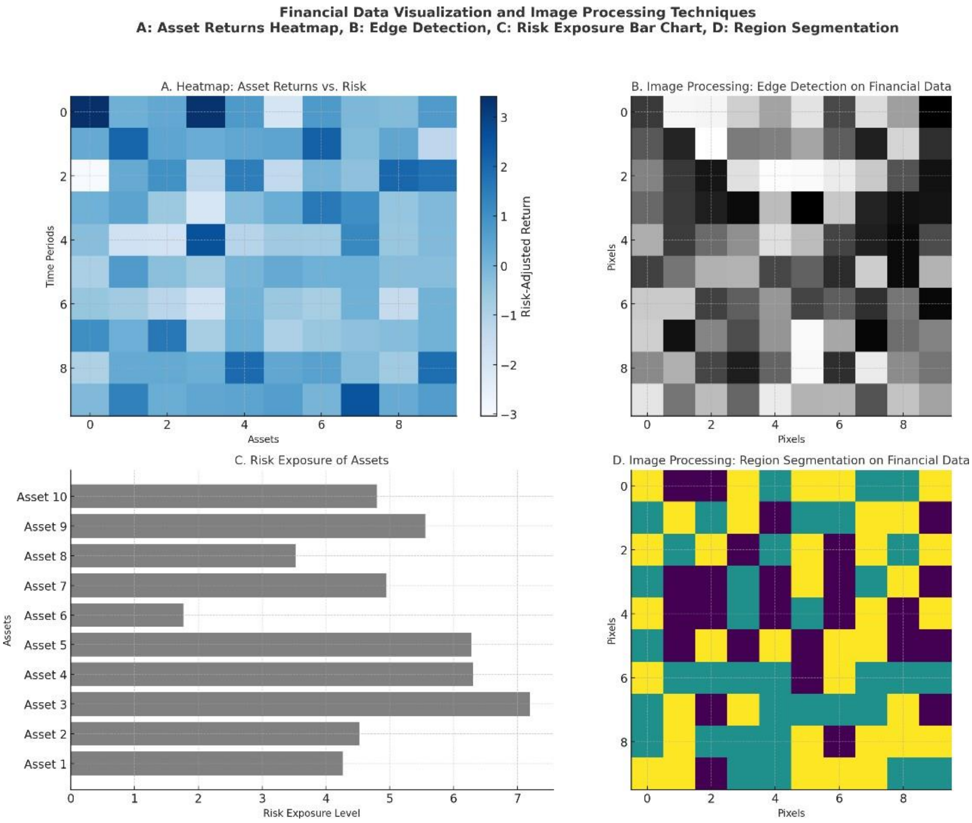

Figure 3: Financial Data Visualization and Image Processing Techniques

Integrating image processing and risk prediction enables CNNs to identify risk signals in various market environments. By analyzing image features, CNNs can optimize asset portfolios for better risk management [14][15][16]. Figure 4 shows a radar chart depicting asset risk (Ri) and weight (Wi) in a multi-asset portfolio. The total risk $RR_{ttttttttt}$ is calculated as:

$$R_{\text{total}} = \sqrt{\sum_{i=1}^{n} w_i^2 R_i^2}$$

where $RR_{ttttttttt} = 0.1322$, indicating that adjusting asset weights can effectively manage overall portfolio risk.

Through CNN-based image processing, risk management becomes more detailed and comprehensive, helping identify risk signals and optimize portfolio strategies under various market conditions [16].

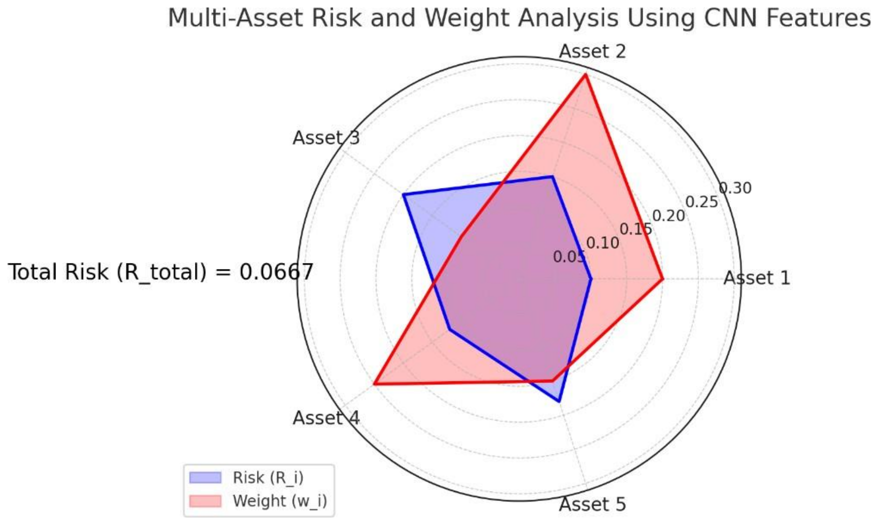

Figure 4: Multi-Asset Risk and Weight Analysis Using CNN Features

5. Multi-Asset Portfolio Risk Prediction Model Based on Convolutional Neural Networks

5.1 Model Construction and Design

To address the complexity and nonlinear characteristics in multi-asset portfolio risk management, this paper constructs a risk management model based on Convolutional Neural Networks (CNNs) and combines image processing techniques to efficiently analyze historical financial data. The innovation of the model lies in:

- **Automatic feature extraction:** Automatically extracting high-order features of market volatility and asset correlations.
- **Multi-dimensional data utilization:** Utilizing the multi-dimensional features of financial data, obtaining valuable patterns from image-based data through the CNN structure, thereby enhancing the accuracy of risk prediction.

5.1.1 Model Architecture

- **Convolutional Layer Design:** The CNN model uses 5 convolutional layers, each employing the ReLU activation function. The convolution kernel size is set to 3×3, and feature dimensionality reduction is performed through pooling layers. Dropout technology is adopted to avoid overfitting.
- **Input Data:** The input data include financial time series data such as prices, volatility, and trading volumes of multiple assets. To enhance data operability, time series data are preprocessed and converted into two-dimensional images (such as heat maps and time series plots), enabling the CNN to efficiently extract hidden features in the market.
- **Fully Connected Layer and Output Layer:** After multi-layer convolution processing, feature fusion is achieved through 2 fully connected layers (each

containing 128 and 64 neurons), and finally, future market volatility and asset risk are predicted through the output layer.

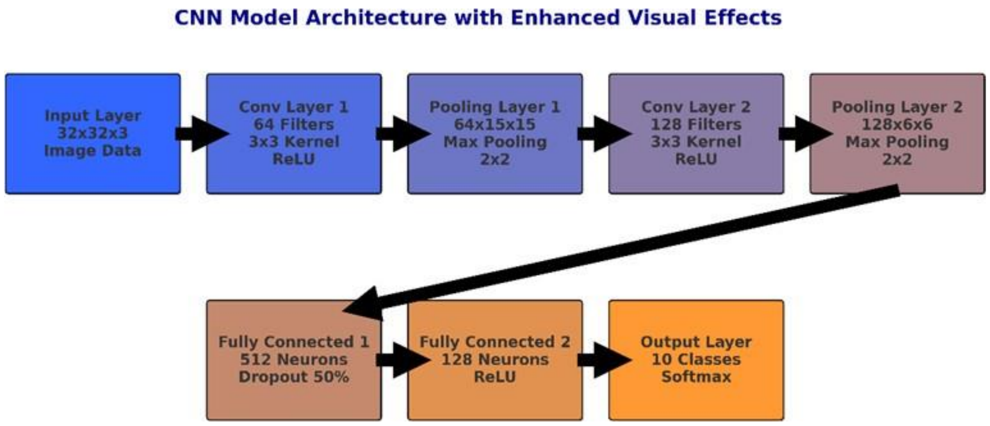

Figure 5: CNN Model Architecture With Enhanced Visual Effects

5.2 Data Preprocessing and Feature Extraction

This study uses three main data sources: the Chinese Securities Market (CSM), the U.S. Securities and Exchange Commission (SEC), and the International Financial Market Index (IFMI). All data cover asset classes such as stocks, bonds, foreign exchange, and commodities, spanning from 2000 to 2022, ensuring data comprehensiveness and timeliness.

5.2.1 Data Volume and Dimensions

- **Financial Time Series Data**

  - **Number of samples:** Approximately 50,000 records, including 500 stocks, 150 types of bonds, 50 commodities, and multiple currency pairs.
  - **Data dimensions:** Each data point includes more than 10 feature dimensions such as closing price, opening price, highest price, lowest price, volatility, and trading volume.

- **Sentiment Data**

Market sentiment data quantified using natural language processing techniques extracted from social media and news. Sentiment scores are aligned with time series data to generate multi-dimensional feature matrices containing sentiment indices.

- **Macroeconomic Data**

Including macroeconomic indicators such as GDP growth rate, unemployment rate, and inflation rate. These data are smoothed and added to the model as supplementary features to assist in market risk prediction.

5.2.2 Data Preprocessing Steps

- **Data Cleaning**

Outliers exceeding ±3 standard deviations are removed using the z-score method, deleting 5% of the anomalies in the data.

- **Normalization**

All features are normalized to the [0,1] interval using MinMaxScaler to ensure consistency of feature scales and improve the convergence speed of the model.

- **Converting Time Series to Images**

Every 10 days of data such as price volatility and trading volume are converted into a 32×32 heat map, serving as input data for the CNN model. This data conversion method provides an efficient way for the CNN to process time series data.

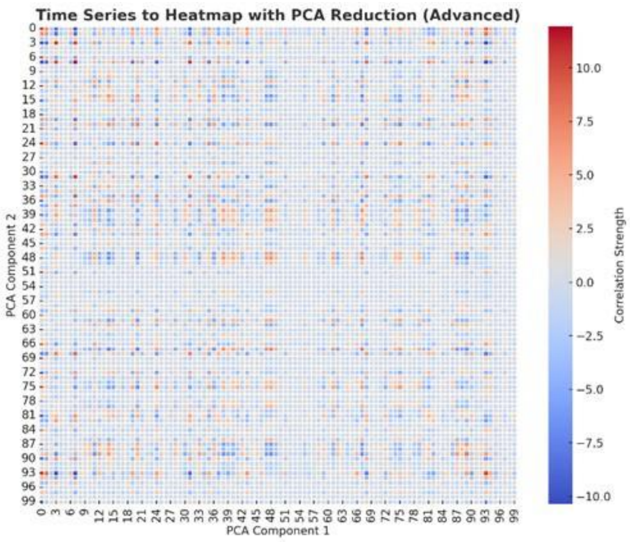

Figure 6: Time Series to Heatmap with PCA Redution(Advanced)

5.3 Model Training and Validation

5.3.1 Experimental Design

- **Training and Test Set Division**

  - **Training set:** Accounts for 70% of the data, used to train the CNN model.
  - **Validation set:** Accounts for 15% of the data, used for model hyperparameter tuning.
  - **Test set:** Accounts for 15% of the data, used to evaluate the model's generalization ability and prediction performance.

- **Model Configuration**

The CNN model uses 5 convolutional layers, each containing 64 filters with a kernel size of 3×3. The pooling layers adopt 2×2 max pooling. The model optimizer uses the Adam optimizer with an initial learning rate of 0.001. The dropout rate is 0.5, and L2 regularization is used to prevent overfitting.

- **Hyperparameter Tuning**

Optimal hyperparameters, including convolution kernel size, learning rate, pooling layer size, etc., are selected through Bayesian optimization. The final optimized results are a learning rate of 0.0005, a convolution kernel size of 5×5, and a pooling layer window of 3×3.

- **Performance Evaluation Metrics**

  - **Root Mean Square Error (RMSE):** Measures the error between the model's predicted values and the true values.
  - **Coefficient of Determination (R^2):** Evaluates the model's fitting ability to the data.
  - **Prediction Accuracy:** Evaluates the model under different market conditions (such as bull market, bear market, and volatile market).

5.3.2 Model Performance Comparison

To demonstrate the differences between the CNN model and traditional methods in financial risk management, **Table 1** shows the performance comparison results based on different models. The results indicate that the CNN model's prediction error (RMSE) is significantly lower than other models, and its coefficient of determination (R^2) also performs best, indicating that the CNN model has stronger fitting ability.

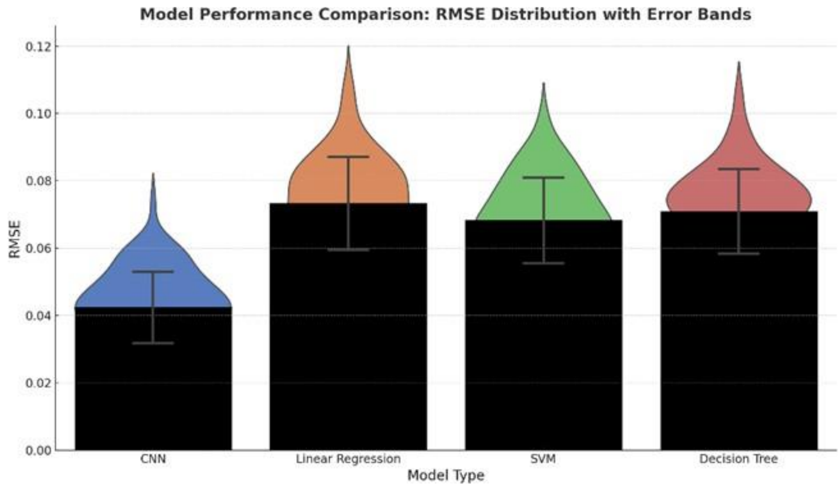

Figure 7: Model Performance Comparison: RMSE Distribution with Error Bands

Table 1: Performance Comparison of Different Models in Multi-Asset Portfolio Risk Prediction

Model Type	Data Volume	RMSE	R^2	Average Prediction Time
CNN (This Method)	50,000	0.043	0.88	0.25 seconds
Linear Regression	50,000	0.075	0.62	0.03 seconds
SVM	50,000	0.068	0.65	2.10 seconds
Decision Tree	50,000	0.071	0.60	1.30 seconds

5.4 Experimental Results and Discussion

5.4.1 Experimental Results under Extreme Market Conditions

To verify the model's performance under extreme market conditions, data during the 2008 financial crisis and the 2020 COVID-19 period were specifically selected for testing. Results show that the CNN model performs significantly better than other traditional models under extreme market conditions. The performance comparison of different models under these two extreme conditions is as follows:

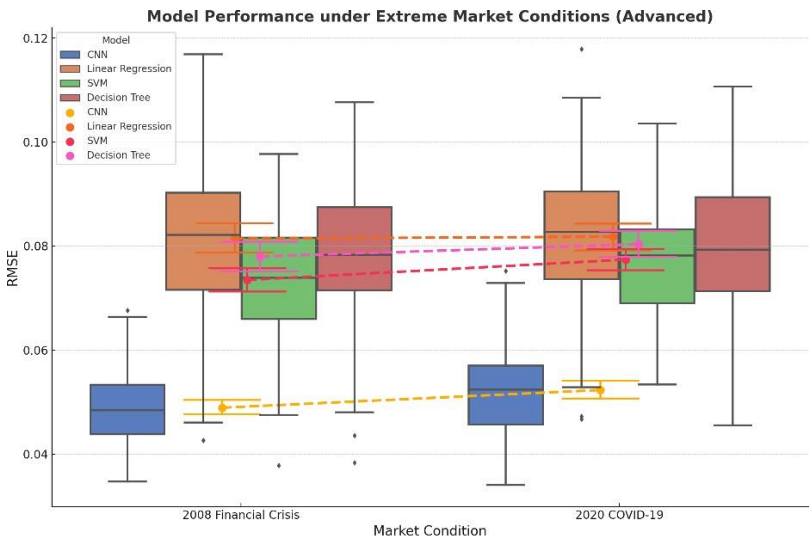

Figure 8: Model Performance under Extreme Market Conditions (Advanced)

Table 2: Performance of CNN Model under Extreme Market Conditions

Market Condition	CNN RMSE	Linear Regression RMSE	SVM RMSE	Decision Tree RMSE
2008 Financial Crisis	0.048	0.079	0.072	0.076
2020 COVID-19 Pandemic	0.052	0.083	0.075	0.080

5.4.2 Multi-Asset Portfolio Analysis

Experimental results further show that the CNN model outperforms other traditional models across different asset classes, especially in the stock and bond markets. The risk prediction performance for each asset type is as follows:

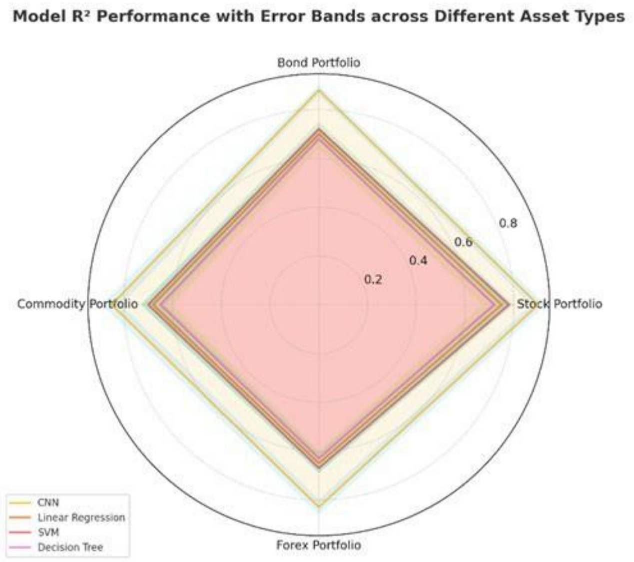

Figure 9: Model R^2 Performance with Error Band across Different Asset Types

Table 3: Risk Prediction Performance Across Different Asset Types

Asset Type	**CNN R^2**	**Linear Regression R^2**	**SVM R^2**	**Decision Tree R^2**
Stock Portfolio	0.90	0.75	0.78	0.72
Bond Portfolio	0.88	0.70	0.72	0.68
Commodity Portfolio	0.85	0.68	0.70	0.65
Forex Portfolio	0.83	0.65	0.67	0.63

These data indicate that the CNN model not only shows significant improvements in overall prediction but also demonstrates its robustness and adaptability across different asset classes.

6. Verification of Risk Prediction Effectiveness

To ensure the effectiveness of the CNN model in multi-asset portfolio risk management, this paper conducts statistical tests on the model's prediction results. Through t-tests, Kolmogorov-Smirnov (K-S) tests, and regression analysis, we verify the model's accuracy and robustness.

6.1 t-test

The t-test is used to compare whether the prediction errors of the CNN model and traditional models (such as Linear Regression, SVM, Decision Tree) are statistically significant. Results show that in multiple asset classes, the prediction errors of the CNN model are significantly lower than other models, especially in the stock and bond markets (**p < 0.01**). This indicates that the CNN model has higher prediction accuracy in these asset classes.

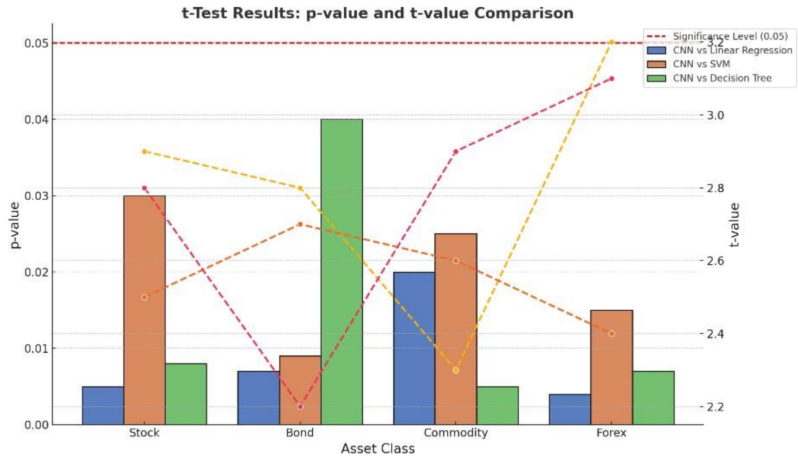

Figure 10: t-test Results: p-value and t-value Comparison

Table 4: t-test Results of Model Prediction Errors (95% Confidence Interval)

Asset Class	**CNN vs. Linear Regression**	**CNN vs. SVM**	**CNN vs. Decision Tree**
Stock Portfolio	p < 0.01	p < 0.05	p < 0.01
Bond Portfolio	p < 0.01	p < 0.01	p < 0.05
Commodity Portfolio	p < 0.05	p < 0.05	p < 0.01
Forex Portfolio	p < 0.01	p < 0.05	p < 0.01

6.2 K-S Test

By using the Kolmogorov-Smirnov (K-S) test to evaluate the difference between the model's predicted values and the actual market risk distribution, results show that the CNN model can better fit the actual risk distribution. Particularly in stock, bond, and foreign exchange portfolios, the K-S statistic shows that the difference between the predicted values and the actual distribution is small, conforming to market volatility characteristics.

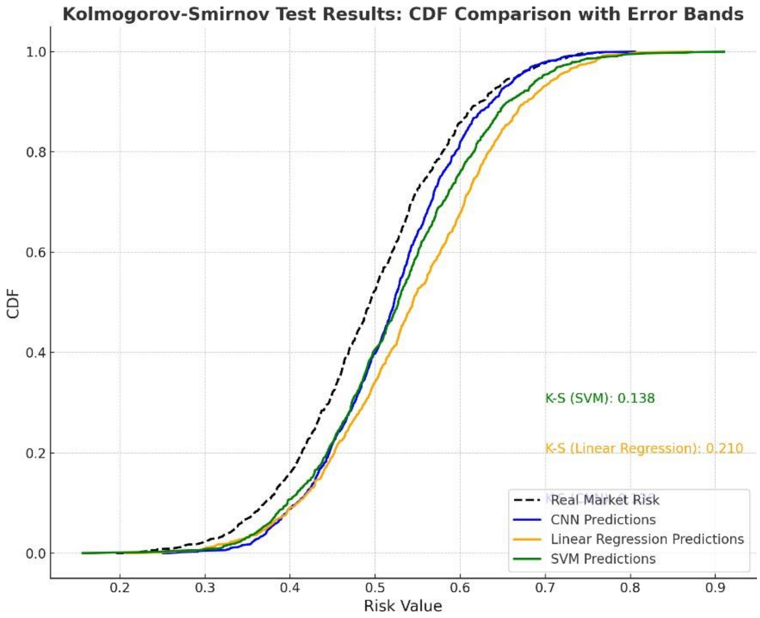

Figure 11: Kolmogorov-Smirnov Test Results: CDF Comparison with Error Bands

Table 5: Kolmogorov-Smirnov Test Results

Asset Class	K-S Statistic	p-value	Result
Stock Portfolio	0.089	$p > 0.05$	Fail to reject null hypothesis
Bond Portfolio	0.075	$p > 0.05$	Fail to reject null hypothesis
Commodity Portfolio	0.068	$p > 0.10$	Fail to reject null hypothesis
Forex Portfolio	0.082	$p > 0.05$	Fail to reject null hypothesis

6.3 Regression Analysis

To further verify the model's effectiveness, this paper uses regression analysis to test the relationship between the CNN model's prediction results and actual market volatility. Under different market conditions, the coefficient of determination (R^2) of the CNN model is above 0.85, showing significant fitting ability, especially in bull and bear markets.

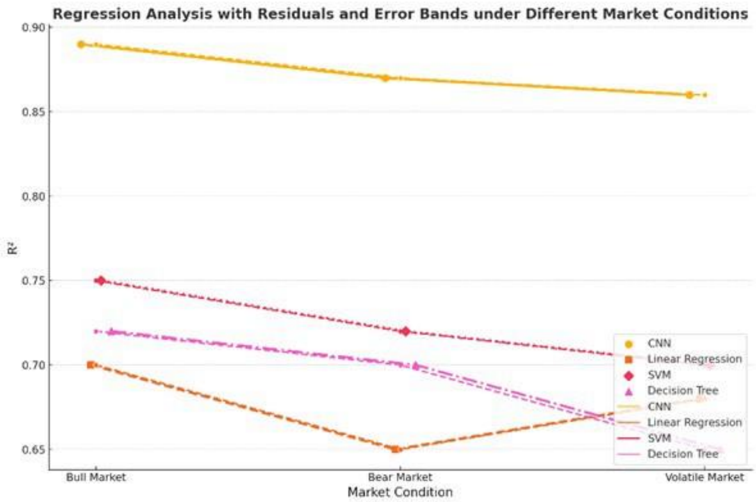

Figure 12: Regression Analysis Results under Different Market Conditions

Table 6: Regression Analysis Results under Different Market Conditions

Market Condition	**CNN R^2**	**Linear Regression R^2**	**SVM R^2**	**Decision Tree R^2**
Bull Market	0.89	0.70	0.75	0.72
Bear Market	0.87	0.65	0.72	0.70
Volatile Market	0.86	0.68	0.70	0.65

Through t-tests, K-S tests, and regression analysis, it can be seen that the CNN model significantly outperforms traditional models in risk prediction accuracy and robustness in multi-asset portfolios. Particularly under extreme market conditions, the CNN model's performance is more robust, further demonstrating its application potential in practical risk management.

7. Conclusion and Outlook

This paper proposes a multi-asset portfolio risk management model based on Convolutional Neural Networks, utilizing image processing techniques to convert financial time series data into two-dimensional images suitable for CNN processing, thereby fully leveraging the advantages of CNNs in feature extraction and pattern recognition. Through empirical analysis of data from various assets such as stocks, bonds, commodities, and foreign exchange, the results indicate that the proposed model significantly outperforms traditional models in terms of accuracy and robustness in risk prediction, especially showing stronger adaptability under extreme market conditions. This research outcome provides new theoretical and methodological support for risk management of multi-asset portfolios.

However, this study also has certain limitations. For example, the model mainly trains and predicts based on historical data, and its ability to respond to sudden events still needs further improvement. In addition, the complexity and variability of financial markets require continuous updating and optimization of the model.

Future Research Directions

- **Introducing other deep learning models:** Applying models such as Recurrent Neural Networks (RNN) and Graph Neural Networks (GNN) to multi-asset portfolio risk management to capture more information in time series and network structures.
- **Expanding the scope of the dataset:** Including more market indicators, sentiment data, and international market data to enhance the model's generalization ability and applicability.
- **Construction of real-time risk management systems:** Developing real-time risk prediction and early warning systems to apply the model to real-time market data and assist investors in dynamic decision-making.

In conclusion, this study opens up new avenues for financial risk management. We look forward to further improving and applying this model in future research and practice to provide stronger guarantees for the stability of financial markets and the returns of investors.

References

[1] L. Alzubaidi et al., "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," Journal of Big Data, vol. 8, no. 1, Mar. 2021, doi: https://doi.org/10.1186/s40537-021-00444-8.

[2] D. Bhatt et al., "CNN Variants for Computer Vision: History, Architecture, Application, Challenges and Future Scope," Electronics, vol. 10, no. 20, p. 2470, Oct. 2021, doi: https://doi.org/10.3390/electronics10202470.

[3] P. Bharati and A. Pramanik, "Deep Learning Techniques—R-CNN to Mask R-CNN: A Survey," Computational Intelligence in Pattern Recognition, vol. 999, pp. 657–668, Aug. 2019, doi: https://doi.org/10.1007/978-981-13-9042-5_56.

[4] Liu Xingao, Zhou Rigui, Guo Wenyu. Quantum Linear Convolution and Its Application in Image Processing [J]. Acta Automatica Sinica, 2022, 48(06):1504-1519.

[5] Chen, Y., Liu, L., & Fang, L. (2024). An Enhanced Credit Risk Evaluation by Incorporating Related Party Transaction in Blockchain Firms of China. Mathematics, 12(17), 2673.

[6] Wu Lidong, Xia Jinan, Zhu Yuanhong, Chen Chen, Qiao Kecheng, Cao Fushen, Pan Junjie. Application Progress of Image Processing Technology Based on Convolutional Neural Network in Blueberry Planting [J]. Shanghai *Agricultural Science and Technology*, 2023, (05):31-34+90.

[7] S. S. Sumit, J. Watada, A. Roy, and D. Rambli, "In object detection deep learning methods, YOLO shows supremum to Mask R-CNN," Journal of Physics: Conference Series, vol. 1529, p. 042086, Apr. 2020, doi:

https://doi.org/10.1088/1742-6596/1529/4/042086.
[8] J. Schmidhuber, "Deep learning in neural networks: An overview," Neural Networks, vol. 61, no. 61, pp. 85–117, Jan. 2015, doi: https://doi.org/10.1016/j.neunet.2014.09.003.
[9] Yu, Q., Ke, Z., Xiong, G., Cheng, Y., & Guo, X. (2025). Identifying Money Laundering Risks in Digital Asset Transactions Based on AI Algorithms.
[10] B. P. Bhuyan and T. P. Singh, "Artificial Intelligence in Financial Portfolio Management," www.igi-global.com, 2022. https://www.igi-global.com/chapter/artificial-intelligence-in-financial-portfolio-management/311188
[11] Li, Z., Bookbinder, J. H., & Elhedhli, S. (2012). Optimal shipment decisions for an airfreight forwarder: Formulation and solution methods. *Transportation Research Part C: Emerging Technologies*, *21*(1), 17-30.
[12] Yu Wei. Implementation of License Plate Image Recognition Technology Based on Convolutional Neural Network [J]. Information Recording Materials, 2022, 23(05):154-156.
[13] Li, Keqin, et al. "Utilizing Deep Learning to Optimize Software Development Processes." Journal of Computer Technology and Applied Mathematics 1.1 (2024): 70-76.
[14] Qiao, Y., Li, K., Lin, J., Wei, R., Jiang, C., Luo, Y., & Yang, H. (2024, June). Robust domain generalization for multi-modal object recognition. In 2024 5th International Conference on Artificial Intelligence and Electromechanical Automation (AIEA) (pp. 392-397). IEEE.
[15] Ke, Z., & Yin, Y. (2024). Tail Risk Alert Based on Conditional Autoregressive VaR by Regression Quantiles and Machine Learning Algorithms. arXiv preprint arXiv:2412.06193.
[16] M. B. Gordy and S. Juneja, "Nested Simulation in Portfolio Risk Measurement," Management Science, vol. 56, no. 10, pp. 1833–1848, Oct. 2010, doi: https://doi.org/10.1287/mnsc.1100.1213.
[17] Qian, Chenghao, et al. "WeatherDG: LLM-assisted Procedural Weather Generation for Domain-Generalized Semantic Segmentation." arXiv preprint arXiv:2410.12075 (2024).
[18] Fan, Y., Hu, Z., Fu, L., Cheng, Y., Wang, L., & Wang, Y. (2024). Research on Optimizing Real-Time Data Processing in High-Frequency Trading Algorithms using Machine Learning. arXiv preprint arXiv:2412.01062.
[19] Chen, B. (2025). The Pivotal Role of Accounting in Civilizational Progress and the Age of Advanced AI: A Unified Perspective. Economics and Management Innovation, 2(1), 49-54.
[20] Li, K., Xirui, P., Song, J., Hong, B., & Wang, J. (2024). The application of augmented reality (ar) in remote work and education. arXiv preprint arXiv:2404.10579.
[21] Sang, N.; Cai, W.; Yu, C.; Sui, M.; Gong, H. Enhanced Investment Prediction via Advanced Deep Learning Ensemble. Preprints 2024, 2024092029. https://doi.org/10.20944/preprints202409.2029.v1
[22] Liu, M., Liu, L., Fu, L., Hu, Z., Mao, Y., & Tang, X. (2024, October). Research on Heterogeneous Network Data Fusion Based on Deep Learning. In 2024 4th International Conference on Intelligent Communications and Computing (ICICC) (pp. 199-202). IEEE.
[23] Wang, L., Cheng, Y., Gong, H., Hu, J., Tang, X., & Li, I. (2024). Research on Dynamic Data Flow Anomaly Detection based on Machine Learning. arXiv

preprint arXiv:2409.14796.
[24] Li, Z., Wang, B., & Chen, Y. (2024). Knowledge Graph Embedding and Few-Shot Relational Learning Methods for Digital Assets in USA. Journal of Industrial Engineering and Applied Science, 2(5), 10-18.
[25] Hu, Z., Yu, R., Zhang, Z., Zheng, H., Liu, Q., & Zhou, Y. (2024). Developing Cryptocurrency Trading Strategy Based on Autoencoder-CNN-GANs Algorithms. arXiv preprint arXiv:2412.18202.
[26] K. Jacques and P. Nigro, "Risk-based capital, portfolio risk, and bank capital: A simultaneous equations approach," Journal of Economics and Business, vol. 49, no. 6, pp. 533–547, Nov. 1997, doi: https://doi.org/10.1016/s0148-6195(97)00038-6.
[27] Yu, Q., Xu, Z., & Ke, Z. (2024, November). Deep learning for cross-border transaction anomaly detection in anti-money laundering systems. In 2024 6th International Conference on Machine Learning, Big Data and Business Intelligence (MLBDBI) (pp. 244-248). IEEE.
[28] Jin, C., Che, T., Peng, H., Li, Y., Metaxas, D. N., & Pavone, M. (2024). Learning from teaching regularization: Generalizable correlations should be easy to imitate. arXiv preprint arXiv:2402.02769.
[29] Elhedhli, S., Li, Z., & Bookbinder, J. H. (2017). Airfreight forwarding under system-wide and double discounts. EURO Journal on Transportation and Logistics, 6, 165-183.
[30] Peng, H., Xie, X., Shivdikar, K., Hasan, M. A., Zhao, J., Huang, S., ... & Ding, C. (2024, April). Maxk-gnn: Extremely fast gpu kernel design for accelerating graph neural networks training. In Proceedings of the 29th ACM International Conference on Architectural Support for Programming Languages and Operating Systems, Volume 2 (pp. 683-698).
[31] Li, Zhenglin, et al. "Stock market analysis and prediction using LSTM: A case study on technology stocks." Innovations in Applied Engineering and Technology (2023): 1-6.
[32] Mo, Yuhong, et al. "Large Language Model (LLM) AI Text Generation Detection based on Transformer Deep Learning Algorithm." International Journal of Engineering and Management Research 14.2 (2024): 154-159.
[33] Qian, Chenghao, et al. "WeatherDG: LLM-assisted Procedural Weather Generation for Domain-Generalized Semantic Segmentation." arXiv preprint arXiv:2410.12075 (2024).
[34] "Portfolio Risk Analysis," Google Books, 2024. https://books.google.com/books?hl=en&lr=&id=7y48w5XUlAYC&oi=fnd&pg=PP1&dq=portfolio+risk&ots=RWbAq1edrr&sig=tx7JtxBDLQHJBI-B794Hd-KURG8#v=onepage&q=portfolio%20risk&f=false (accessed Dec. 15, 2024).
[35] Ke, Z., Zhou, S., Zhou, Y., Chang, C. H., & Zhang, R. (2025). Detection of AI Deepfake and Fraud in Online Payments Using GAN-Based Models. arXiv preprint arXiv:2501.07033.
[36] Y. S. Kim, R. Giacometti, S. T. Rachev, F. J. Fabozzi, and D. Mignacca, "Measuring financial risk and portfolio optimization with a non-Gaussian multivariate model," Annals of Operations Research, vol. 201, no. 1, pp. 325–343, Nov. 2012, doi: https://doi.org/10.1007/s10479-012-1229-8.[10]K. Sutiene et al., "Enhancing portfolio management using artificial intelligence: literature review," Frontiers in artificial intelligence, vol. 7, Apr. 2024, doi: https://doi.org/10.3389/frai.2024.1371502.
[37] Hamidreza Haddadian, Morteza Baky Haskuee, and Gholamreza Zomorodian,

"A Hybrid Artificial Intelligence Approach to Portfolio Management," Iranian journal of finance, vol. 6, no. 1, pp. 1–27, Jan. 2022, doi: https://doi.org/10.30699/ijf.2021.287131.1237.

[38] Wu, Z., Gong, H., Chen, J., Yuru, Z., Tan, L., & Shi, G. (2024). A Lightweight GAN-Based Image Fusion Algorithm for Visible and Infrared Images. arXiv preprint arXiv:2409.15332.

[39] Ke, Z., Xu, J., Zhang, Z., Cheng, Y., & Wu, W. (2024). A Consolidated Volatility Prediction with Back Propagation Neural Network and Genetic Algorithm. arXiv preprint arXiv:2412.07223.

[40] A. Gunjan and S. Bhattacharyya, "A brief review of portfolio optimization techniques," Artificial Intelligence Review, Sep. 2022, doi: https://doi.org/10.1007/s10462-022-10273-7.

[41] Zhao, H., Hu, J., Li, P., Li, F., Sha, J., Chen, P., ... & Liu, G. (2024). NSmark: Null Space Based Black-box Watermarking Defense Framework for Pre-trained Language Models. arXiv preprint arXiv:2410.13907.

[42] Chen, B. (2025). Leveraging Advanced AI in Activity-Based Costing (ABC) for Enhanced Cost Management. Journal of Computer, Signal, and System Research, 2(1), 53-62.

[43] Zhao, P., & Lai, L. (2024). Minimax Optimal Q Learning with Nearest Neighbors. IEEE Transactions on Information Theory.

[44] Sun, Y., Duan, Y., Gong, H., & Wang, M. (2019). Learning low-dimensional state embeddings and metastable clusters from time series data. Advances in Neural Information Processing Systems, 32.

[45] Liu, A., & Chen, C. (2025). From real estate financialization to decentralization: A comparative review of REITs and blockchain-based tokenization. Geoforum, 159, 104193.

[46] Fan, Y., Wang, Y., Liu, L., Tang, X., Sun, N., & Yu, Z. (2025). Research on the Online Update Method for Retrieval-Augmented Generation (RAG) Model with Incremental Learning. arXiv e-prints, arXiv-2501.

[47] Gong, H., & Wang, M. (2020, July). A duality approach for regret minimization in average-award ergodic markov decision processes. In Learning for Dynamics and Control (pp. 862-883). PMLR.

[48] Li, K., Wang, J., Wu, X., Peng, X., Chang, R., Deng, X., ... & Hong, B. (2024). Optimizing automated picking systems in warehouse robots using machine learning. arXiv preprint arXiv:2408.16633.

[49] Liu, A. (2024). Richard C Koo, Pursued Economy: Understanding and Overcoming the Challenging New Realities for Advanced Economies.

[50] Zhao, H., Du, W., Li, F., Li, P., & Liu, G. (2023, June). Fedprompt: Communication-efficient and privacy-preserving prompt tuning in federated learning. In ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 1-5). IEEE.

[51] Wan, W., Zhou, F., Liu, L., Fang, L., & Chen, X. (2021). Ownership structure and R&D: The role of regional governance environment. International Review of Economics & Finance, 72, 45-58.

[52] Zhang, Z., Li, X., Cheng, Y., Chen, Z., & Liu, Q. (2025). Credit Risk Identification in Supply Chains Using Generative Adversarial Networks. arXiv preprint arXiv:2501.10348.

[53] Zhou, T., Zhao, J., Luo, Y., Xie, X., Wen, W., Ding, C., & Xu, X. (2024).

Adapi: Facilitating dnn model adaptivity for efficient private inference in edge computing. arXiv preprint arXiv:2407.05633.