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# Research on Financial Multi-Asset Portfolio Risk Prediction Model Based on Convolutional Neural Networks 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

## I. 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.

## II. 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.

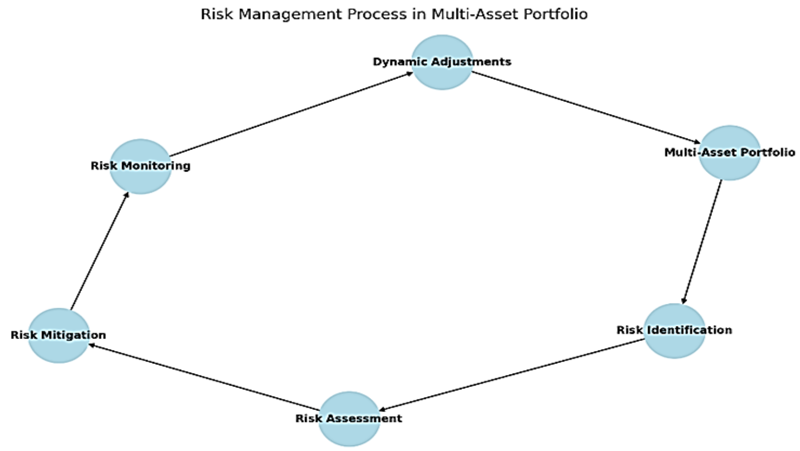


Figure 1: Risk Management process in Multi-Asset Portfolio

## III. 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].

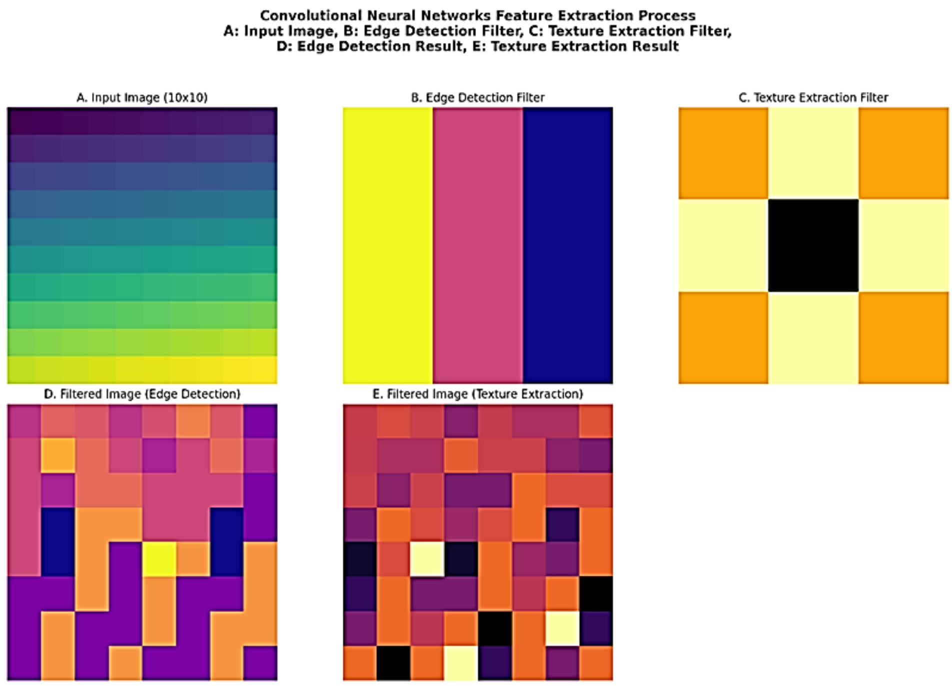


Figure 2: CNNs feature Extraction Process

## IV. 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].

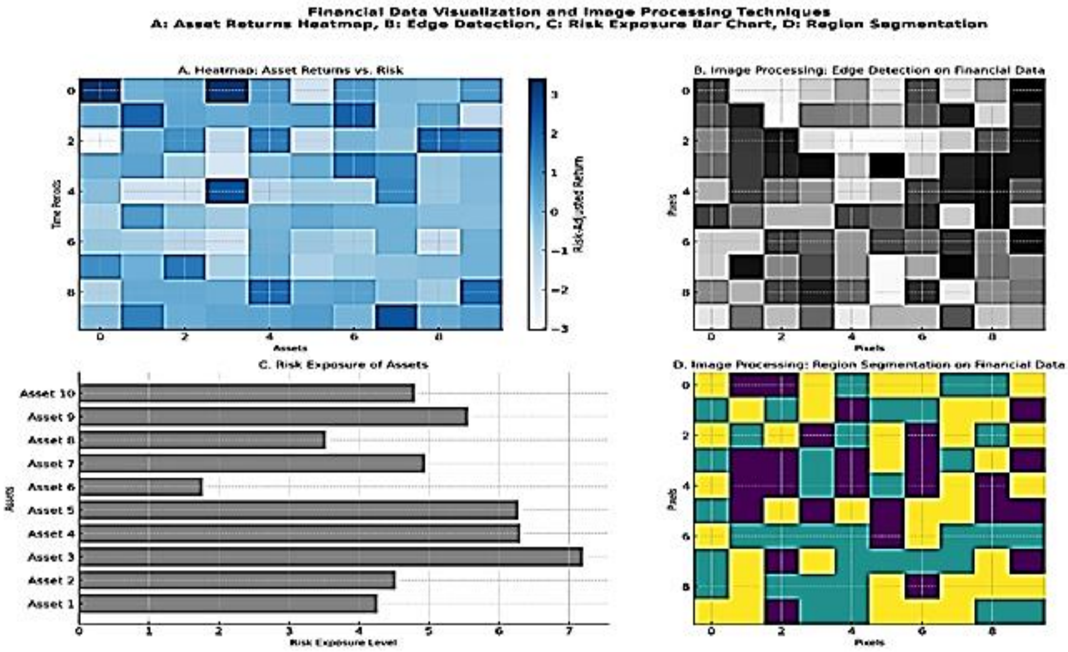


Figure 3: Financial Data Visualization and Image Processing Techniques

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 $R_{total}$ is calculated as:

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

where $R_{total} = 0.1322$, 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 [17].

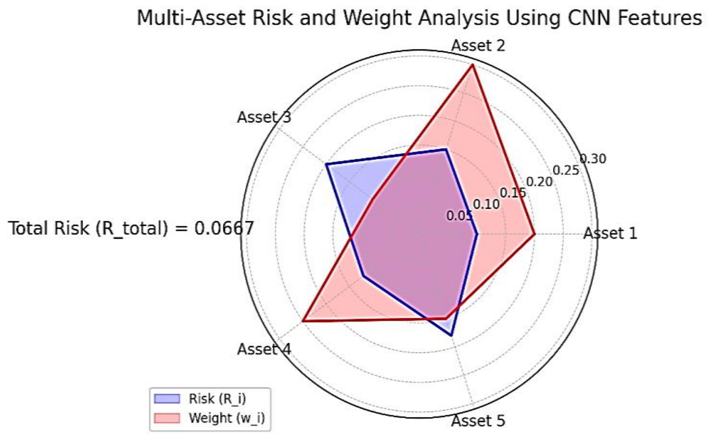


Figure 4: Multi-Asset Risk and Weight Analysis Using CNN Features

## V. MULTI-ASSET PORTFOLIO RISK PREDICTION MODEL BASED ON CONVOLUTIONAL NEURAL NETWORKS

### *A. 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.[18]
- **Model Architecture**
- **Convolutional Layer Design:** The CNN model uses 5 convolutional layers, each employing the ReLU activation function[19]. 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[20].
- **Input Data:** The input data include financial time series data such as prices, volatility, and trading volumes of multiple assets[21]. 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[22].
- **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[23]. Figure 5 illustrates the overall CNN architecture designed for multi-asset portfolio risk prediction The input two-dimensional financial data representations pass through multiple convolutional and pooling layers, extracting hierarchical patterns. The fully connected layers integrate these extracted features, and the final output layer provides risk predictions. The enhanced visual effects highlight the step-by-step information flow, emphasizing the models feature extraction capability.

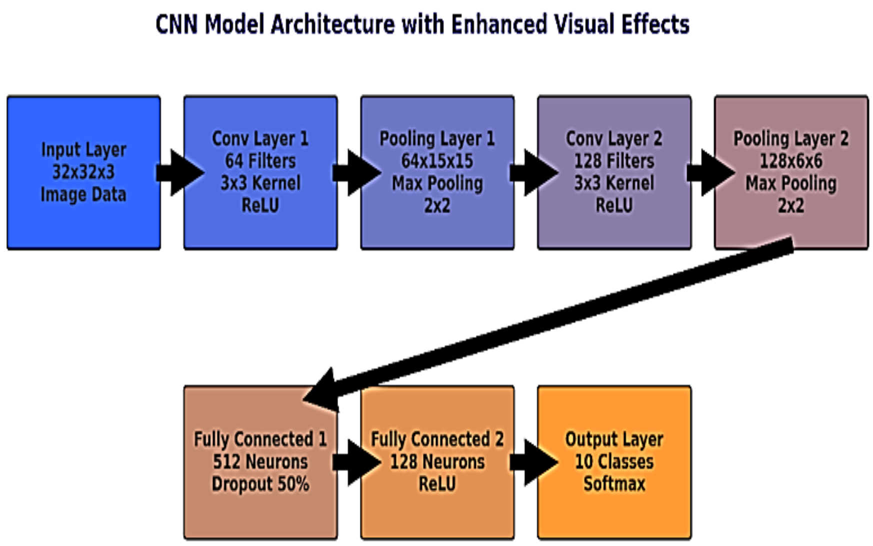


Figure 5: CNN Model Architecture With Enhanced Visual Effects

### *B. 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)[24]. All data cover asset classes such as stocks, bonds, foreign exchange, and commodities, spanning from 2000 to 2022, ensuring data comprehensiveness and timeliness[25].

- **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[26].
- **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[27].
- **Sentiment Data**

Market sentiment data quantified using natural language processing techniques extracted from social media and news[28]. Sentiment scores are aligned with time series data to generate multi-dimensional feature matrices containing sentiment indices[29].

- **Macroeconomic Data**

Including macroeconomic indicators such as GDP growth rate, unemployment rate, and inflation rate[30]. These data are smoothed and added to the model as supplementary features to assist in market risk prediction[31].

- **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[32].

- **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[33].

- **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.[34] This data conversion method provides an efficient way for the CNN to process time series data.[35]

Figure 6 demonstrates the data transformation pipeline where raw financial time series are normalized, dimensionally reduced (via PCA), and converted into heat maps[36]. This graphical transformation facilitates the CNN's image-based feature extraction and enables a more robust detection of underlying market dynamics[37].

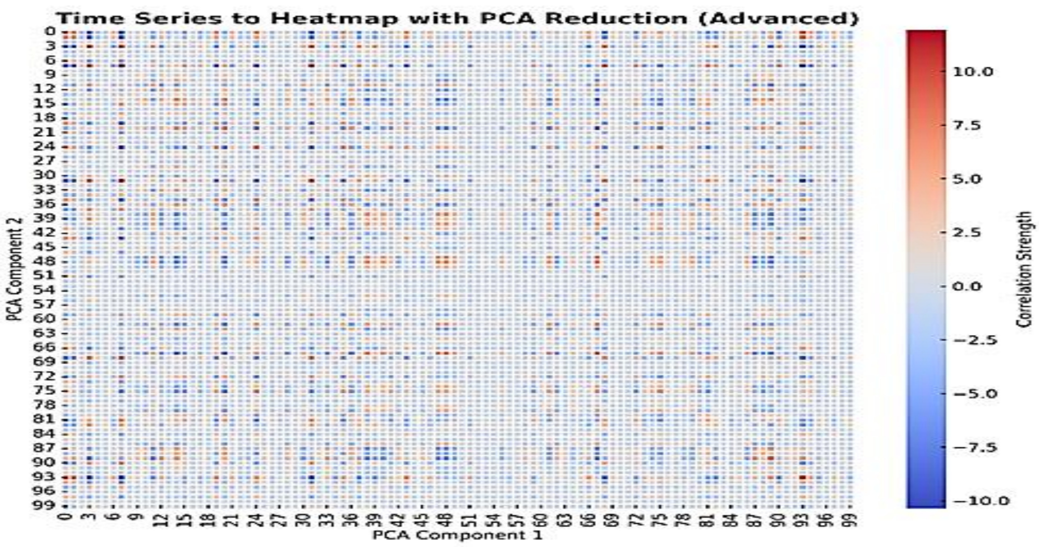


Figure 6: Time Series to Heatmap with PCA Redution(Advanced)

*C. Model Training and Validation*

- **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[38].
- **Test set:** Accounts for 15% of the data, used to evaluate the model's generalization ability and prediction performance[39].

➢ **Model Configuration**

The CNN model uses 5 convolutional layers, each containing 64 filters with a kernel size of 3×3[40]. 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[41].

➢ **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[42].

➢ **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).

- **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 visualizes the RMSE distributions of different models across the test set. The error bands highlight variations in prediction accuracy. The CNN model consistently exhibits lower RMSE values, reflecting a tighter error distribution and improved prediction stability compared to baseline models.[43]

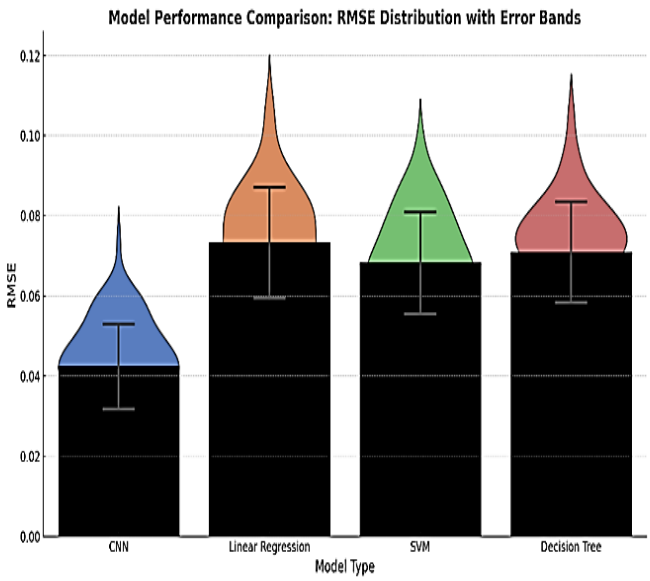


Figure 7: Model Performance Comparison: RMSE Distribution with Error Bands

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 econds |

### *D. Experimental Results and Discussion*

- **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 illustrates the model's resilience when confronted with periods of high volatility (e.g., the 2008 crisis and 2020 pandemic)[44]. The figure shows that the CNN model's predictions remain comparatively stable and accurate, highlighting its robustness during market shocks. Table 2 compares the CNN model's RMSE against traditional methods under extreme conditions. The CNN model consistently shows lower RMSE values, reflecting better predictive performance during highly volatile and uncertain market phases.

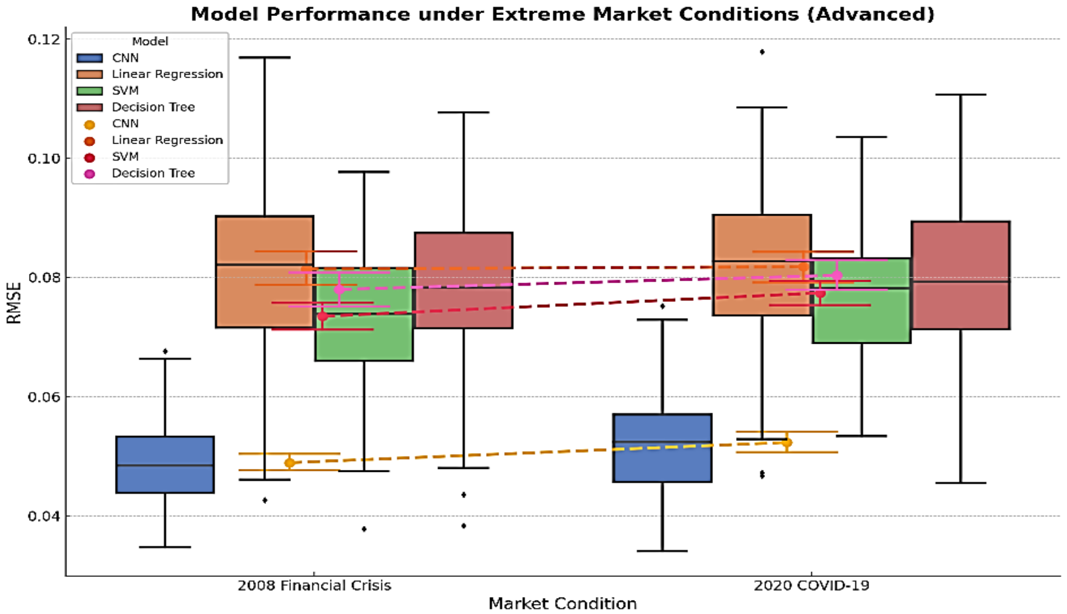


Figure 8: Model Performance under Extreme Market Conditions (Advanced)

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 |

- **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 visualizes the $R^2$ performance for the CNN model and baseline models across various asset categories[45]. The displayed error bands represent confidence intervals, confirming that the CNN model provides a more reliable and better fit in all tested asset classes. Table 3 summarizes the $R^2$ values for the CNN model and other methods across multiple asset classes. The CNN model's consistently higher $R^2$ confirms its superior capability in capturing asset-specific risk patterns.

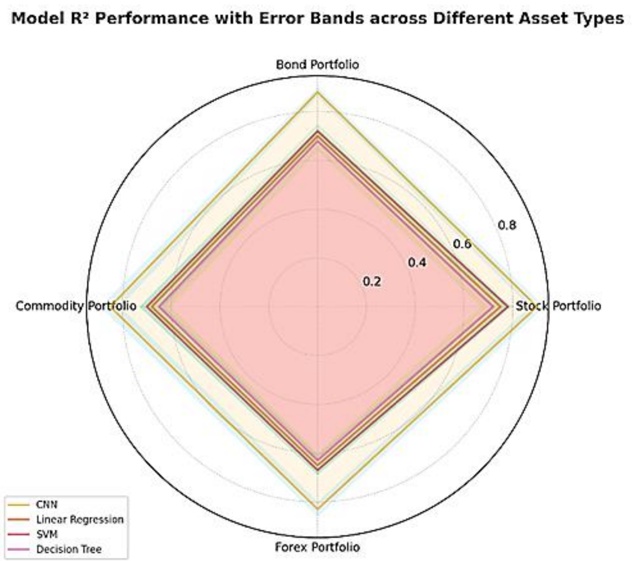


Figure 9: Model $R^2$ Performance with Error Band across Different Asset Types

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.

## VI. 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.

### *A. 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 displays p-values and t-values from t-tests comparing the CNN model's errors against baseline methods. Lower p-values for CNN vs. others indicate statistically significant superiority of the CNN approach. Table 4 presents t-test results showing the statistical significance of the CNN model's lower prediction errors. For multiple asset classes, the CNN outperforms traditional models with a high level of statistical confidence.

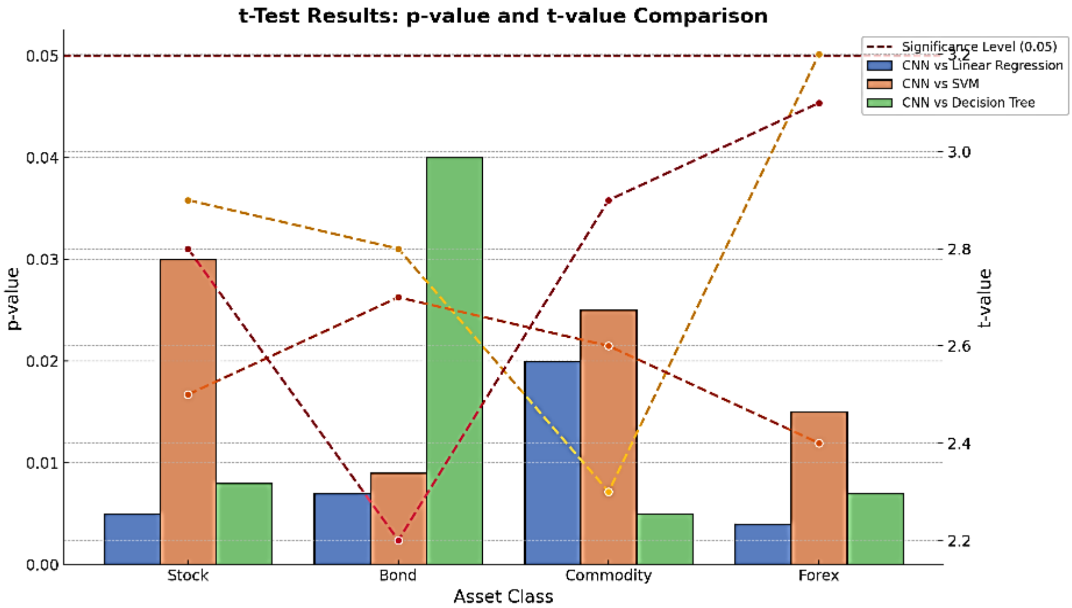


Figure 10: T-Test Results: P-Value and T-Value Comparison

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 | $p < 0.01$ | $p < 0.05$ | $p < 0.01$ |

### *B. 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 compares the cumulative distribution functions (CDF) of predicted vs. actual risks. Smaller K-S statistics for the CNN model imply that its predictions are statistically similar to the actual market risk distributions. Table 5 shows that the K-S statistics for the CNN model are low, and the corresponding p-values are high enough that we fail to reject the null hypothesis. This implies that the distribution of the model's predictions is not significantly different from the actual market risk distribution.

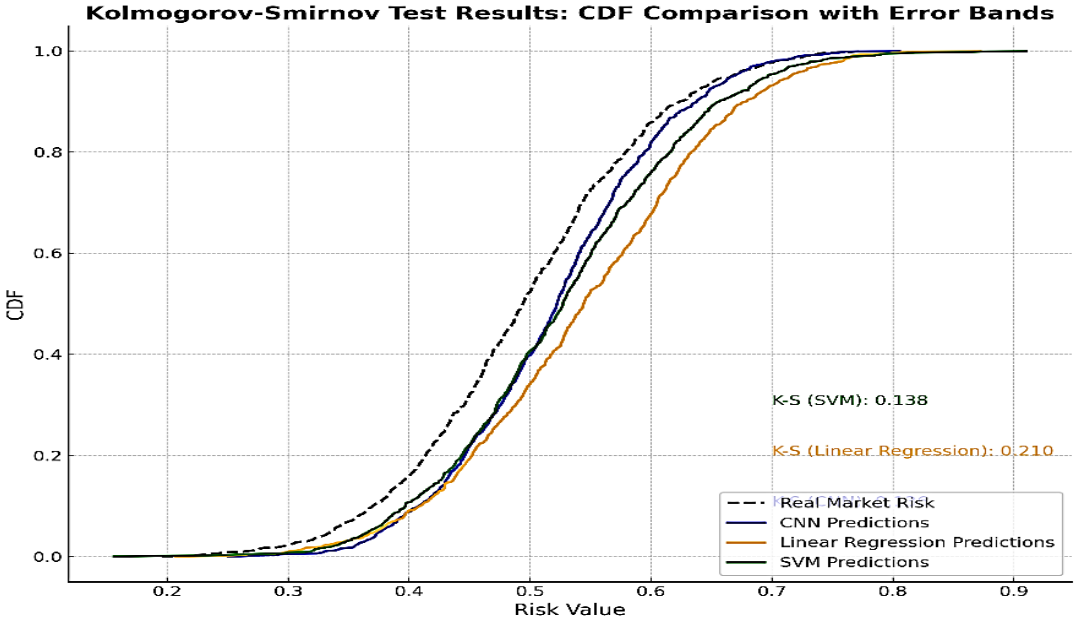


Figure 11: Kolmogorov-Smirnov Test Results: CDF Comparison with Error Bands

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 |

### *C. 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 displays scatter plots and fitted regression lines comparing CNN predictions and actual volatility across varying market states. The strong linear fit (high $R^2$ values) indicates that the CNN model effectively tracks real market fluctuations. Table 6 contrasts $R^2$ values under different market regimes. The CNN model consistently achieves higher $R^2$, indicating robust predictive performance regardless of market direction or volatility levels.

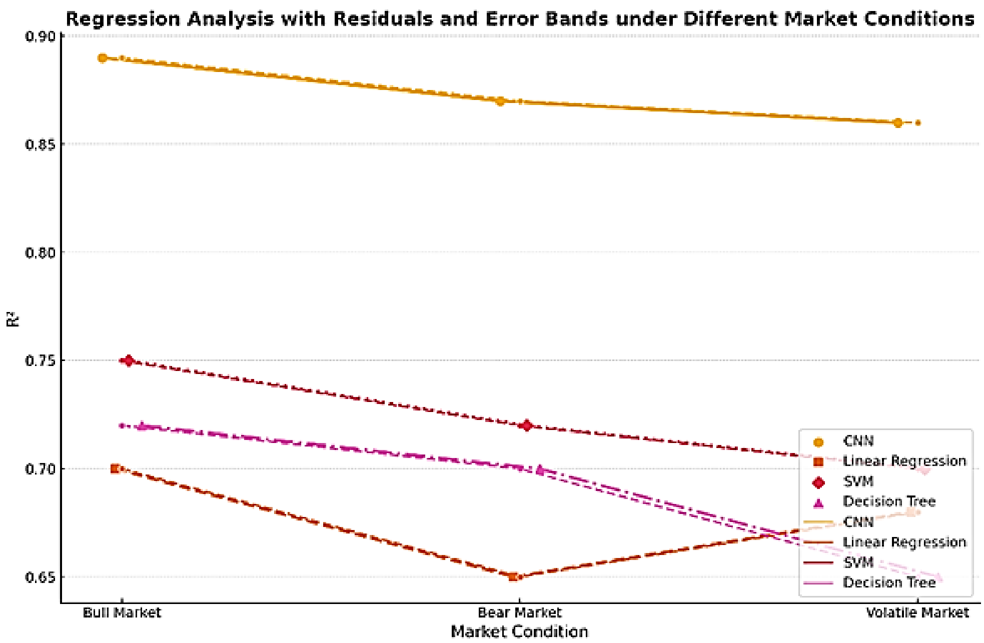


Figure 12: Regression Analysis Results under Different Market Conditions

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.

## VII. 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.

### *A. 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.

## CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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