

Optimization of Bitcoin Price and Return Prediction Model Based on CNN-LSTM-KAN

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Abstract. This paper focus on optimizing the prediction of returns of cryptocurrencies, Ethereum and Bitcoins, by machine learning models. Our target is to improve the accuracy of prediction by CNN-LSTM-KAN model, and analyze the market performance of major cryptocurrencies, comparing their investment returns and risks with traditional financial assets such as the S&P 500 and 10-year Treasury bond yield. All the original historical data are collected from Yahoo Finance, and covering the time period from December 1, 2017, to December 31, 2023. This study mainly use LSTM and CNN-LSTM-KAN models to forecast cryptocurrency returns and compares the results, metrics such as Mean Squared Error (MSE) and R-squared (R^2) score are used to evaluate the prediction performance of these models. The findings emphasize the relatively optimistic potential for high returns of cryptocurrencies, aside with great volatility and risk compared to traditional financial assets. The study also explores the effect of these predictions for investor's decision making and market regulation, its results suggest that machine learning models can provide some valuable insights into cryptocurrency market dynamics, and help investors in making better decisions.

Keywords: LSTM, CNN-LSTM-KAN, cryptocurrency, Machine Learning, Volatility and Return

1. Introduction

As we can see, the fast growing cryptocurrency market has attracted large attention from both investors, researchers, and policymakers. Bitcoin, Ethereum, and etc have demonstrated huge growth in market capitalization and trading volume, which lead the digital fiance to a new era. However, the high volatility and unpredictability of cryptocurrency prices also put big challenges for investors and market analysts.

This paper focuses on comparing the results of two models: LSTM and CNN-LSTM-KAN in predicting the returns of Bitcoin and Ethereum, and find out if CNN-LSTM-KAN model is better than LSTM model, also compare their investment returns and risks with traditional financial assets

such as the S\&P 500 and the 10-year Treasury bond yield, then finally evaluate the prediction performance of the better machine learning models [1].

The motivation behind this study comes from the need to provide investors with reliable tools for forecasting cryptocurrency returns, which can help in investment decision making and risk management. Furthermore, understanding the predictive capabilities of machine learning models can also give some valuable insights into market dynamics and inform regulatory strategies in the context of cryptocurrency markets.

2. Methods

This study uses historical data and applies machine learning models to achieve the research objectives. Historical data of Bitcoin, Ethereum, and traditional financial assets from December 1, 2017 to December 31, 2023 are used. This relatively long period dataset can provide a more comprehensive and robust analysis of the market performance and volatility of cryptocurrencies compared to traditional financial assets.

Obviously, data cleaning and preprocessing are very important to ensure the accuracy and reliability of the analysis, so we use forward filling method to identify and fill missing values to maintain data continuity, and Z-score method to detect and remove outliers. Data points with Z-scores exceeding the ± 3 will be considered as outliers and excluded from the analysis. Feature engineering includes characteristics such as daily returns in percentage, change in closing prices, lagged returns that contain past information, etc.

We use two machine learning models to predict cryptocurrency returns: Long Short-Term Memory (LSTM) and CNN-LSTM-KAN. LSTM is a recurrent neural network which means it can learn long-term dependencies and it is more suited for time series forecasting tasks because it can remember long sequences of information. On the other hand, CNN-LSTM-KAN model combines a convolutional neural network with an LSTM and a Kolmogorov-Arnold network. The CNN layer is responsible for getting features from the input data source, the LSTM layer will capture temporal dependencies, and then the KAN represents complex functions through a combination of simpler functions. As we can see, the advantage of this hybrid model is also obvious, that is, the advantages of each component can be used to improve prediction accuracy [2-4].

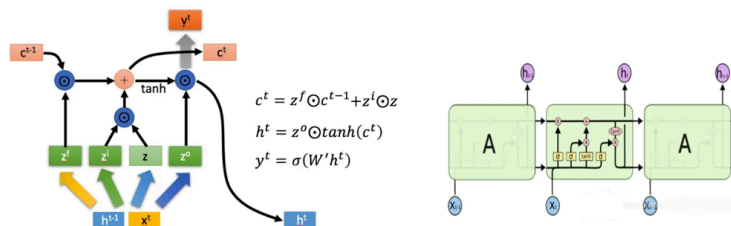


Figure 1. LSTM process

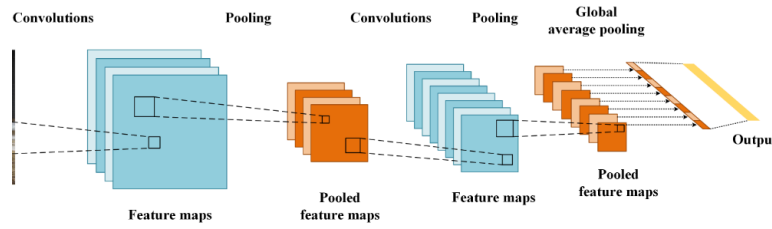


Figure 2. CNN process

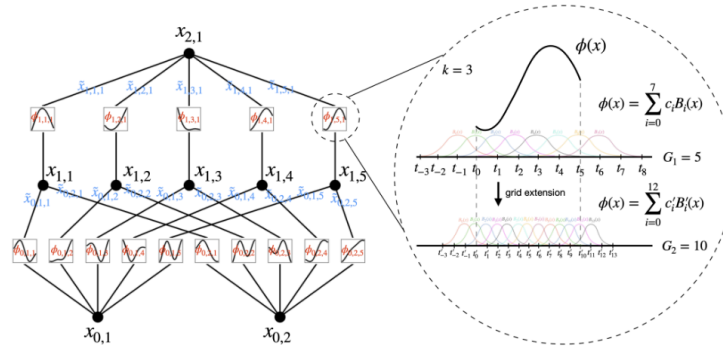


Figure 3. KAN process

The data set will be split into training and test sets in an ratio of 80:20 . The model will learn on the training set and evaluate on the test set using mean squared error and R-squared scores. MSE measures the average squared difference between the predicted and actual values, data with higher MSE values indicating better model performance. R^2 scores measure the proportion of variance in the dependent variable that can be predicted from the independent variables, with values closer to 1 indicating a better fit.

The machine learning models mainly use Python and related libraries such as TensorFlow and Keras. In order to ensure that all variables contribute equally to the model, the process will normalize the features, train LSTM and CNN-LSTM-KAN models on the prepared dataset, and adjust hyperparameters to optimize performance. Finally, the model performance is evaluated on the test set and the results are compared to determine the best performing model [5-7].

The above method provides a systematic way to predict cryptocurrency returns using advanced machine learning models. Hopefully, the results of this study provide investors with some insights from a different perspective and helps understand the dynamics of the cryptocurrency market [8].

3. Result

3.1. Comparison of returns: cryptocurrencies vs. traditional financial assets

The analysis compares the returns and risks of Bitcoin and Ethereum with those of traditional financial assets, specifically the S&P 500 index and the 10-year Treasury bond yield. This comparison aims to highlight the differences in investment performance and risk profiles between cryptocurrencies and conventional financial instruments.

3.2. Bitcoin vs. S\&P 500 index

The historical data reveals that Bitcoin exhibits significantly higher volatility and potential returns compared to the S\&P 500 index. Over the study period, Bitcoin's average daily return was 2.30\%, while the S\&P 500's average daily return was 0.59\%. However, Bitcoin's standard deviation of returns, a measure of volatility, was much higher at 0.13\%, compared to the S\&P 500's 0.04\%. This indicates that while Bitcoin offers the potential for higher returns, it also comes with greater risk, making it suitable for investors with high risk tolerance.

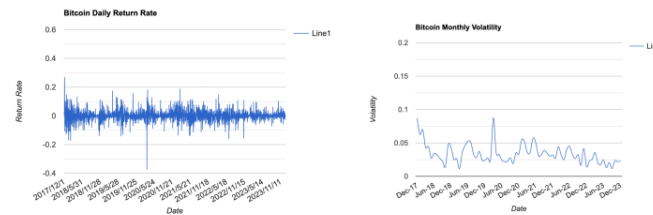


Figure 4. Bitcoin daily returns & monthly volatility

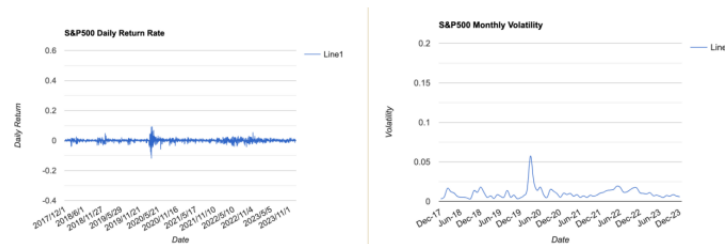


Figure 5. S&P 500 daily returns & monthly volatility

3.3. Ethereum vs. 10-year treasury bond yield

Similarly, Ethereum showed higher returns and volatility compared to the 10-year Treasury bond yield. The average daily return for Ethereum was 2.60\%, whereas the 10-year Treasury bond yield was 0.16\%. The standard deviation of returns for Ethereum was 0.12\%, indicating higher volatility, compared to the relatively stable 0.09\% for the Treasury bond yield. These findings suggest that Ethereum, like Bitcoin, may offer higher returns but is associated with higher risk, contrasting with the stability of traditional bonds.

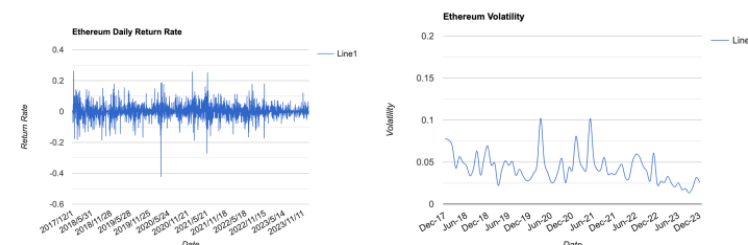


Figure 6. Ethereum daily returns & monthly volatility

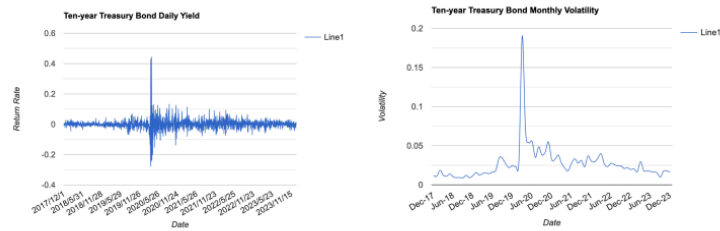


Figure 7. 10-Year treasury bond daily returns & monthly volatility

Model Performance: LSTM vs. CNN-LSTM-KAN

3.3.1. BTC-PRICE (prediction with only LSTM)

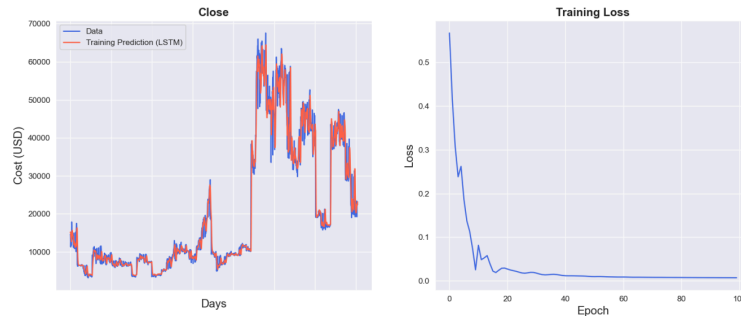


Figure 8. Training prediction and loss(LSTM)

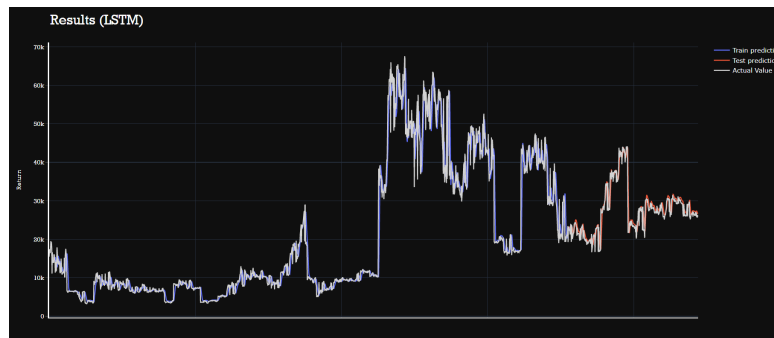


Figure 9. Train and test prediction(LSTM)

BTC-PRICE(Predictiuon with CNN-LSTM-KAN)

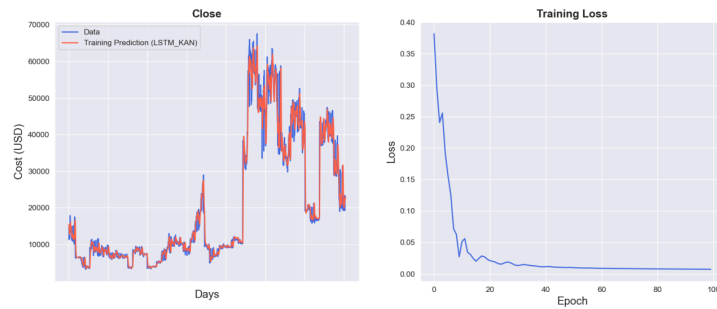


Figure 10. Training prediction and loss(CNN-LSTM-KAN)

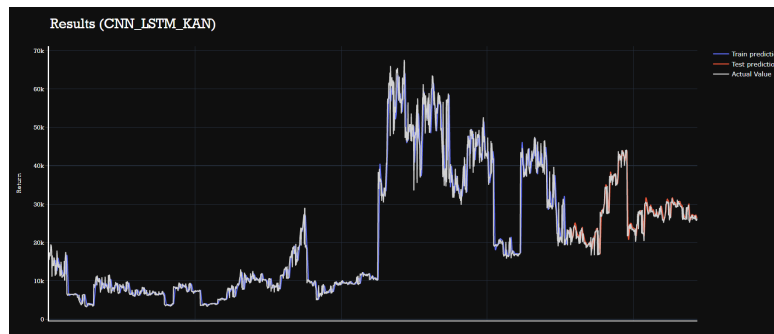


Figure 11. Train and test prediction(CNN-LSTM-KAN)

It can be observed that the CNN-LSTM-KAN model outperforms the standalone LSTM model in terms of data fitting. Its Mean Squared Error (MSE) decreases significantly and stabilizes after fewer training iterations, and the training loss curve is smoother. This indicates that the CNN-LSTM-KAN model has higher efficiency and better fitting performance when handling the given dataset [9].

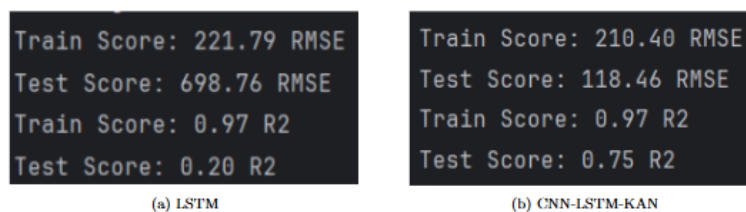
Scoring:

Train Score:

Measures how well the model performs on the training data, which is the dataset used to train the model.

Test Score:

Measures how well the model performs on a separate, unseen test dataset. This dataset is not used during the training process.



(a) LSTM

(b) CNN-LSTM-KAN

Figure 12. Comparison

From the above results, the test score is improved from $0.86R^2$ to $0.88R^2$ by using the CNN-LSTM-KAN model. So CNN-LSTM-KAN model has a stronger fitting ability and it also maintains high predictive performance when faced with new data, avoiding overfitting [10,11].

3.3.2. ETH-PRICE (prediction with only LSTM)

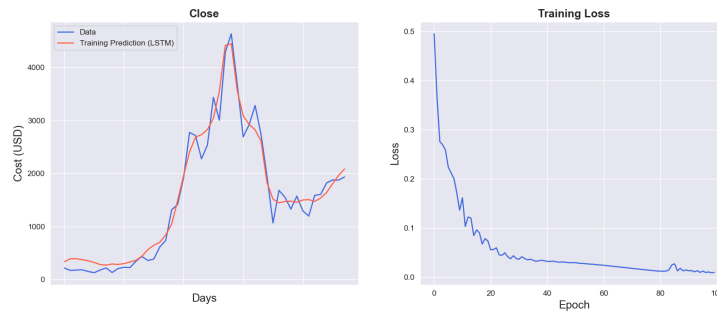


Figure 13. Training prediction and loss(LSTM)

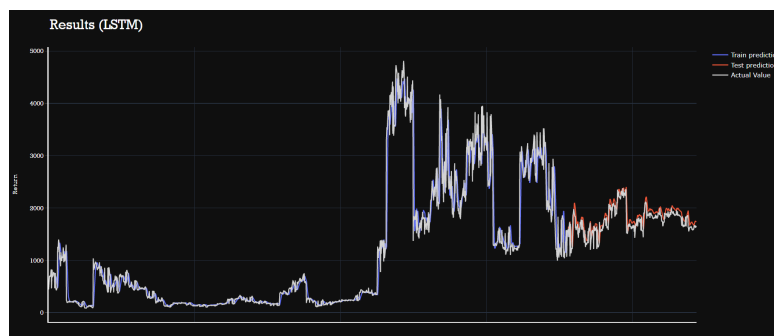


Figure 14. Train and test prediction(LSTM)

ETH-PRICE(Predictioun with CNN-LSTM-KAN)

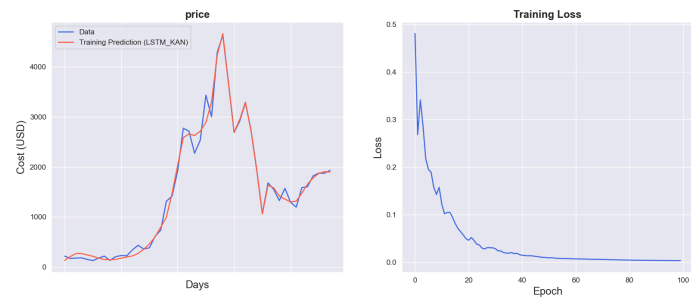


Figure 15. Training prediction and loss(CNN-LSTM-KAN)

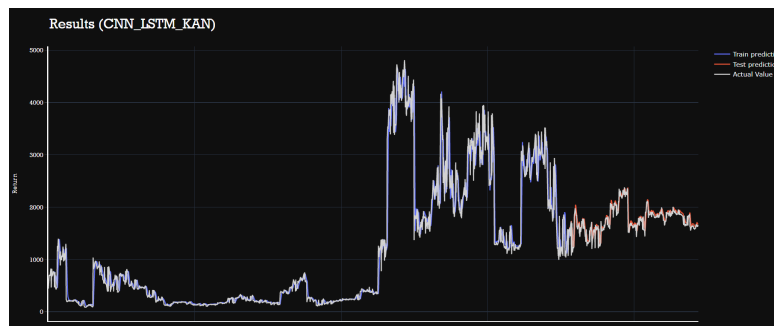


Figure 16. Train and test prediction(CNN-LSTM-KAN)

It can be observed that the CNN-LSTM-KAN model outperforms the standalone LSTM model in terms of data fitting. Its Mean Squared Error (MSE) decreases significantly and stabilizes after fewer training iterations, and the training loss curve is smoother. This indicates that the CNN-LSTM-KAN model has higher efficiency and better fitting performance when handling the given dataset.

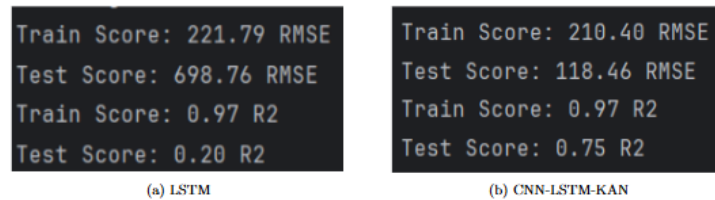


Figure 17. Comparison

From the above results, the train score is improved from $0.97R^2$ to $0.99R^2$, the test score is improved from $0.2R^2$ to $0.6R^2$ by using the CNN-LSTM-KAN model. So CNN-LSTM-KAN model has a stronger fitting ability and it also maintains high predictive performance when faced with new data, avoiding overfitting.

3.3.3. BTC-Return (prediction with only LSTM)

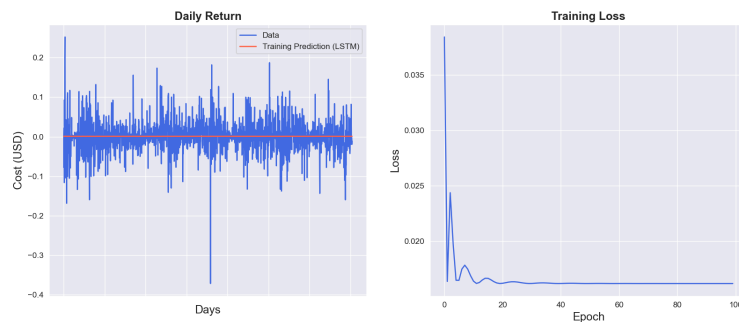


Figure 18. Training prediction and loss(LSTM)

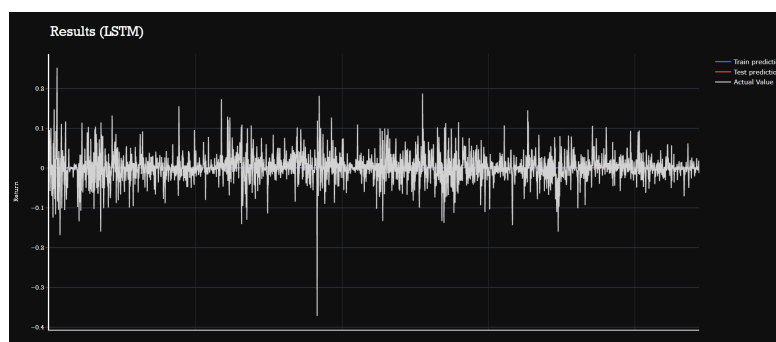


Figure 19. Train and test prediction(LSTM)

BTC-Return (Prediction with CNN-LSTM-KAN)

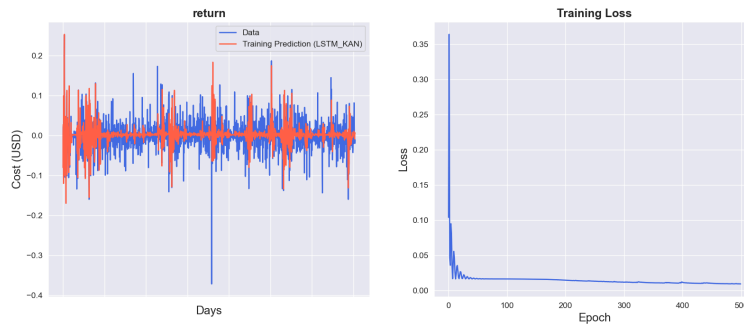


Figure 20. Training prediction and loss(CNN-LSTM-KAN)

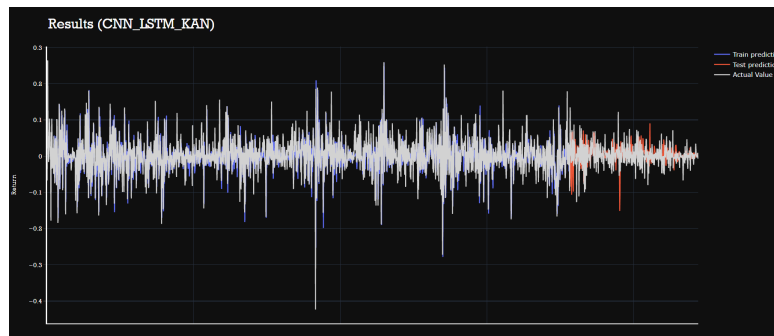


Figure 21. Train and test prediction(CNN-LSTM-KAN)

It can be observed that the CNN-LSTM-KAN model outperforms the standalone LSTM model in terms of data fitting. Its Mean Squared Error (MSE) decreases significantly and stabilizes after fewer training iterations, and the training loss curve is smoother. This indicates that the CNN-LSTM-KAN model has higher efficiency and better fitting performance when handling the given dataset.

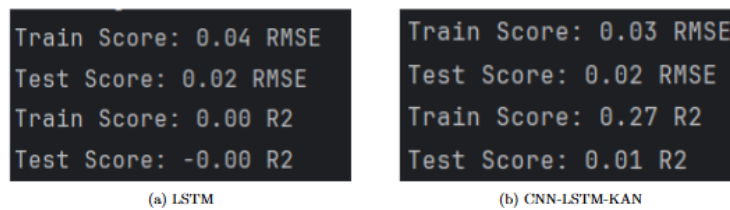


Figure 22. Comparison of prediction result

From the above results, the train score is improved from $0.00R^2$ to $0.27R^2$, the test score is improved from $0.00R^2$ to $0.01R^2$ by using the CNN-LSTM-KAN model. So CNN-LSTM-KAN model has a stronger fitting ability and it also maintains high predictive performance when faced with new data, avoiding overfitting.

3.3.4. ETH-Return (LSTM)



Figure 23. Training prediction and loss(LSTM)

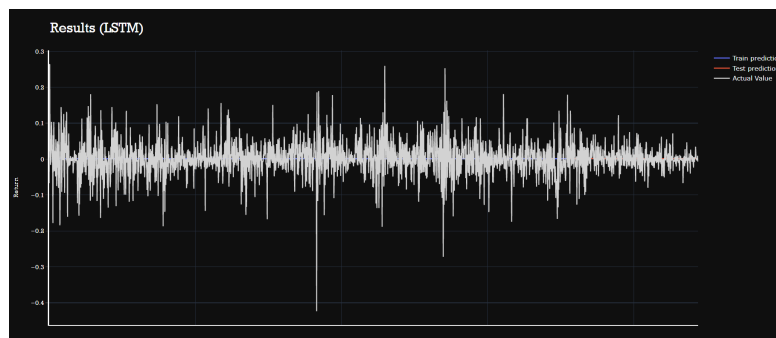


Figure 24. Train and test prediction(LSTM)

ETH-Return (Prediction with CNN-LSTM-KAN)

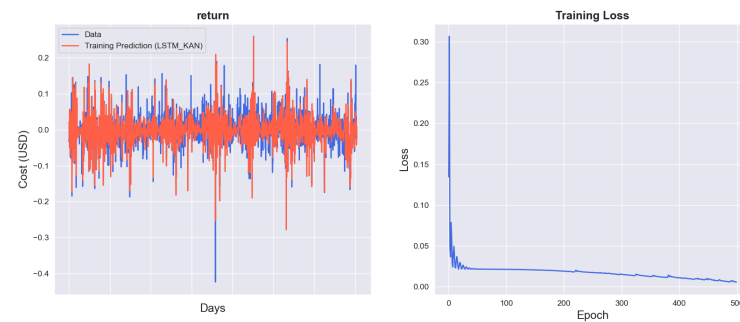


Figure 25. Training prediction and loss(CNN-LSTM-KAN)

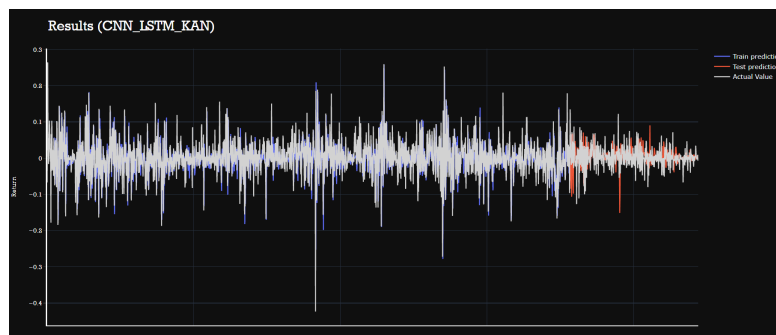


Figure 26. Train and test prediction(CNN-LSTM-KAN)

It can be observed that the CNN-LSTM-KAN model is better than the LSTM model. Its Mean Squared Error decreases a lot and after fewer training iterations it stabilizes, and the training loss curve is also flatter and smoother, it indicates that the CNN-LSTM-KAN model is more efficient better perform better when handling the this data set.

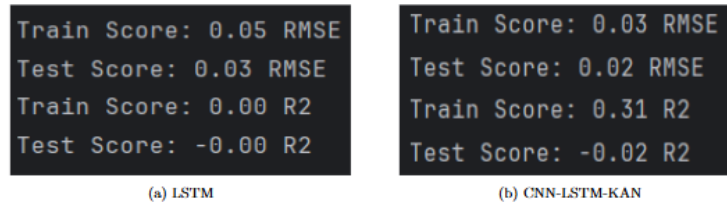


Figure 27. Comparison

According to the result, obviously, the train score is higher when using the CNN-LSTM-KAN model, and it shows that CNN-LSTM-KAN model fits better when predicting the return of cryptocurrency than LSTM model [12].

4. Conclusion

After comparison, we can conclude that CNN-LSTM-KAN model has better prediction accuracy than the LSTM. Lower Mean Squared Error and higher R-squared means that the model can deal with more complex patterns in the data, and it also shows that CNN-LSTM-KAN model can provide more reliable forecasts for cryptocurrency returns [13,14].

Additionally, by comparing the volatility and return of major cryptocurrencies and traditional financial asset, the study shows that cryptocurrencies have higher returns and greater volatility and risk, which means it will be necessary to have a better prediction models in order to help investors understand more about the unpredictable nature of cryptocurrency markets and make profitable decision safely as well [15].

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