Prediction of Euro to US Dollar Exchange Rate Using CNN Method with Grid Optimization

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ABSTRACT

This research compares the performance of Convolutional Neural Network (CNN) models without optimization and CNN with Grid Search optimization in predicting the Euro exchange rate against the United States Dollar. Data obtained from Yahoo Finance for the period 2018-2023. The results showed that the CNN model with Grid Search optimization provided better performance with an RMSE value of 0.01, MAE of 0.01, MAPE of 0.61%, and R^2 of 0.8586 on test data, and prediction accuracy reached 99.39%. Grid Search optimization successfully found the best parameters with batch_size 32, dense_units 50, filters 64, kernel_size 3, and learning_rate 0.001. This research proves that hyperparameter optimization can improve the performance of CNN models in predicting currency exchange rates, which can be a decision support tool for foreign exchange market players.

1. INTRODUCTION

Currency exchange rates are one of the most important economic indicators and have a significant impact on the global economy. Fluctuations in the Euro to US Dollar (EUR/USD) exchange rate are of major concern to investors, international business people and monetary policy makers as the two currencies represent the two largest economies in the world[1] . Accurate forecasts of currency exchange rates are necessary to support strategic decision-making in foreign exchange transactions, risk management, and international financial planning.

The complexity of currency exchange rate movements is influenced by various factors such as monetary policy, economic conditions, geopolitics, market sentiment, and other external factors[2] . The non-linear and non-stationary nature of exchange rate data makes exchange rate prediction a challenge in econometrics and finance. Traditional approaches such as linear time series models have long been used in predicting exchange rates, but often fail to capture the complex patterns of financial data .[3]

In recent years, deep learning methods have shown excellence in analyzing and predicting time series data, especially in financial data[4] . Convolutional Neural Network (CNN), originally developed for image processing, has been adapted for time series prediction and shown promising results in predicting price movements of financial assets including currency exchange rates[5] . CNN's capabilities in local feature extraction and temporal pattern recognition make it a potential choice for currency exchange rate prediction.

Although deep learning methods such as CNNs have proven to be effective, optimal hyperparameter selection remains a key challenge that affects model performance[6] . Hyperparameter optimization using techniques such as Grid Search can help find the best parameter configuration, thereby improving the accuracy and reliability of the prediction model .[7]

Several previous studies have applied CNN for currency exchange rate prediction. Livieris et al. (2020)[4] conducted a comparison of various deep learning architectures for exchange rate prediction and found that CNN has an advantage in capturing temporal patterns in financial data. Meanwhile, Abedinet al. (2021)[8] developed a CNN model to predict currency exchange rates with promising results compared to traditional methods. However, these studies have not specifically compared the performance of CNN without optimization and CNN with Grid Search optimization in the context of EUR/USD exchange rate prediction.

This research aims to: (1) develop a CNN model for predicting the Euro to US Dollar exchange rate using historical data from 2018 to 2023; (2) optimize CNN architecture and hyperparameters using Grid Search technique; and (3) compare the performance of CNN models without optimization and CNN with Grid Search optimization based on RMSE, MAE, MAPE, R^2, and accuracy evaluation metrics. The results of this research are expected to provide new insights into the benefits of hyperparameter optimization in improving the performance of deep learning models for currency exchange rate prediction, as well as a foundation for the development of more reliable prediction systems in the future.

2. METHOD

2.1. Data and Data Sources

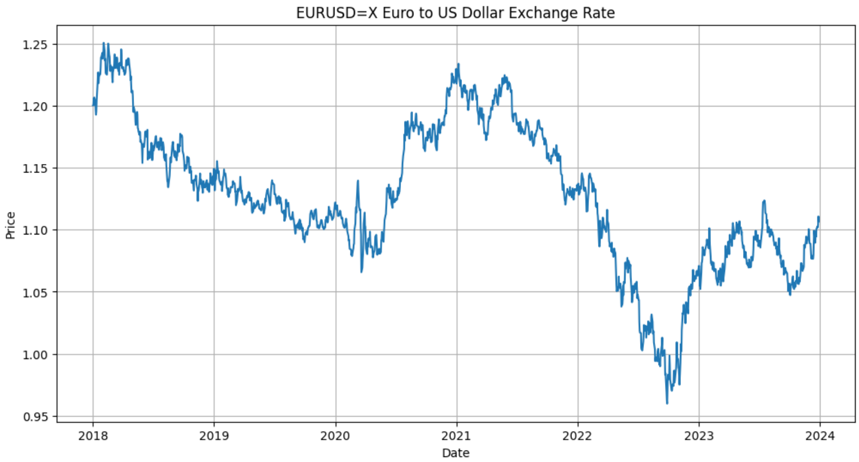

Figure 1. Historical data chart of Euro to USD exchange rate

This study uses historical data of the Euro to US Dollar (EUR/USD) exchange rate obtained from Yahoo Finance for the period 2018 to 2023. The data consists of daily closing price values that reflect the EUR/USD exchange rate at the end of each trading day. The selection of a five-year time span aims to capture a range of market conditions, including periods of normalcy, high volatility, as well as significant economic events affecting both currencies.

The data obtained is then divided into two parts: training data and testing data with a proportion of 80% for training data and 20% for testing data. This division follows the standard approach in machine learning and deep learning model evaluation[1] . Testing the model with data that has not been seen during the training process helps evaluate the generalization ability of the model and avoid overfitting.

2.2. Data Pre-processing

Data pre-processing is an important step in the preparation of a dataset before it is used for CNN model training. This process goes through several stages, each of which has a specific purpose to improve the quality and reliability of the data used.

First, handling missing data is a crucial first step. In time series studies, missing data often occurs which can cause bias and reduce the accuracy of the model. One effective method to handle missing data is linear interpolation; this method was chosen because it is able to maintain data continuity and integrity. Properly handling missing data not only improves the quality of the dataset, but also ensures that the analysis performed is not compromised by data gaps that may be detrimental.

Furthermore, data normalization is an equally important stage. The Min-Max Scaling technique, which transforms data values into a range[9] , is often used in data processing. This normalization contributes to improving model performance, especially when features that have different scales or different units will be integrated in the CNN model. Several references show that normalization using this technique has proven successful in various time series analysis applications[10]–[12] . By transforming all features into the same scale, the model can learn more efficiently without being affected by significant scale differences among different features.

Next, sequence formation is the stage where the time series data is converted into a sequence format. For CNN model training, data samples are formed such that each sample consists of 60 days of previous observation data as the input feature (X) and the exchange rate on the next day as the target (y). The selection of the 60-day window size refers to previous research which shows that the pattern of exchange rate movements over a period of about three months provides a significant predictive signal in decision-making, although it is important to note that variations within this timeframe can affect the prediction results.[13] . Here, the importance of sequence formation is that it supports the model in understanding the temporal patterns present in the data, which is critical in predictive analysis.

The last process is reshaping the data to fit the needs of the input layer in the CNN architecture. Dimensioning the data into a 3D format (samples, time steps, features) is necessary to ensure that the input model conforms to the expected structure. This is vital to ensure that the CNN model can process the data in an optimal and effective manner. This reshaping process is discussed in depth in various works focusing on data processing techniques for deep learning models .[14], [15]

Through these steps, the processed time series data will be ready for CNN model training, supporting the expected modeling goals with more accurate and reliable results.

2.3. CNN Model Architecture

This research developed two CNN models: a basic model without optimization and a model with Grid Search optimization. The basic architecture of the CNN model used can be seen in Table 1:

Table 1. Basic CNN Model Architecture

Layer (Type)	Configuration	Function	Output Shape
Input	-	Input time series data	(60, 1)
Conv1D	filters=128, kernel_size=5, padding="causal", activation="relu"	Temporal feature extraction by preserving time dependency	(60, 128)
MaxPooling1D	pool_size=1	Reduction of feature dimensions while maintaining temporal structure	(60, 128)
Flatten	-	Transform the output to vector form	(7680)
Dense	units=50, activation='relu'	Non-linear representation learning	(50)
Dense (Output)	units=1	Final grade prediction	(1)

This architecture consists of the following main components:

1. 1D Convolution Layer
   - Using 128 filters with a kernel size of 5
   - Applying "causal" *padding* that ensures the model only uses information from previous time points
   - ReLU (*Rectified Linear Unit*) activation function to capture non-linear patterns in the data
   - Receive inputs of the form (60, 1) which represents 60 *time steps* with univariate features.
2. MaxPooling1D Layer
   - Using pool_size=1 to preserve the temporal dimension
   - Serves to extract the most significant features
3. Flatten Layer
   - Transform multidimensional outputs into one-dimensional vectors
   - Enables connection to the *fully connected* layer
4. Dense Layer
   - The first layer consists of 50 units with ReLU activation
   - Serves as a *hidden layer* for high-level representation learning
   - The output layer consists of 1 unit for final score prediction

This architecture is specifically designed to handle the unique characteristics of financial time series data, taking into account temporal dependencies and the need for effective pattern extraction. The use of "causal" *padding* is a critical feature that differentiates this implementation from conventional CNN models, as it maintains the temporal integrity of the data during the training process.

2.3. Hyperparameter Optimization with Grid

For the CNN model with optimization, the Grid Search technique is applied to find the optimal hyperparameter combination. The optimized parameters include:

Table 2. CNN Model basic hyperparameters

Parameters	Description	Search Space
Batch Size	Number of samples processed before model parameter update	[16, 32, 64]
Dense Units	Number of neurons in the hidden dense layer	[30, 50, 70]
Filters	Number of filters in the convolution layer	[32, 64, 128]
Kernel Size	Convolution kernel size	[3, 5, 7]
Learning Rate	Learning rate for Adam optimizer	[0.001, 0.0005, 0.0001]

The Grid Search process performs an exhaustive search on the predefined parameter space to find the combination that yields the best performance based on validation loss. A 3-fold cross-validation is used to ensure the reliability of model evaluation during the optimization process.

2.4. Training

Both models (CNN without optimization and CNN with Grid Search optimization) were trained using:

1. Optimizer: Adam optimizer was chosen for its ability to adaptively adjust the learning rate for each parameter .[16]
2. Loss Function: Mean Squared Error (MSE) is used as a suitable loss function for regression problems such as exchange rate prediction.
3. Early Stopping: This technique is applied with patience=10 to stop training when there is no improvement in validation loss for 10 consecutive epochs, helping to prevent overfitting.
4. Epochs: Maximum 100 epochs with monitoring validation loss to identify the optimal convergence point.

2.5. Model Evaluation

The performance of both models was evaluated using several metrics to provide a comprehensive perspective:

1. Root Mean Square Error (RMSE): Measures the square root of the average square of the difference between the predicted value and the actual value .[17]
2. Mean Absolute Error (MAE): Measures the average absolute value of the difference between the predicted value and the true value .[18]
3. Mean Absolute Percentage Error (MAPE): Measures the average percentage absolute error relative to the true value.
4. Coefficient of Determination (R^2): Measures the proportion of variation in the dependent variable that can be explained by the independent variable.
5. Accuracy: Calculated as 100% - MAPE, shows the level of model accuracy in percentage form.

Evaluations were conducted on training and test data to analyze the model's ability to learn data patterns (in-sample) and its ability to generalize to new data (out-of-sample).

3. RESULTS AND DISCUSSION

3.1. CNN Model Performance Without Optimization

The CNN model without optimization performed well in predicting the EUR/USD exchange rate. The model evaluation results on training and test data are shown in Table 2.

Table 3. CNN Evaluation Results without Optimization

Metrics	Training Data	Test Data
RMSE	0,01	0,01
MAE	0,01	0,01
MAPE	0,60%	0,63%
R^2	0,9754	0,8407
Accuracy	99,40%	99,37%

The results show that the CNN model without optimization achieves good performance with RMSE and MAE of 0.01 on both training and test data. The low MAPE values (0.60% in training data and 0.63% in test data) indicate a minimal percentage error rate, resulting in very high prediction accuracy (99.40% in training data and 99.37% in test data).

The R^2 value of 0.9754 on the training data indicates that the model can explain 97.54% of the variation in the training data. The decrease in the R^2 value to 0.8407 on the test data indicates a difference between the model's ability to model the training data and its ability to generalize to new data, however, this value still shows good performance.

3.2. Grid Search Optimization Results

The Grid Search process successfully identified the optimal hyperparameter combination for the CNN model. The best parameters found are:

Table 4. Hyperparameter Search Results with Grid Search

Parameters	Value
Batch Size	32
Dense Units	50
Filters	64
Kernel Size	3
Learning Rate	0.001

With this combination of parameters, the CNN model with Grid Search optimization achieves the best validation loss of 0.000820, which shows an improvement in performance compared to the model without optimization.

3.3. CNN Model Performance with Grid Search Optimization

The evaluation results of the CNN model with Grid Search optimization on training data and test data are shown in Table 4.

Table 5. CNN Evaluation Results with Grid Search Optimization

Metrics	Training Data	Test Data
RMSE	0,01	0,01
MAE	0,00	0,01
MAPE	0,39%	0,61%
R^2	0,9889	0,8586
Accuracy	99,61%	99,39%

The CNN model with Grid Search optimization shows improved performance compared to the model without optimization. Although the RMSE value on the test data remains 0.01, there are improvements in other metrics. MAE on the training data reached 0.00 (with rounding), indicating a very low absolute error rate. The MAPE on the training data decreased from 0.60% to 0.39%, and the MAPE on the test data improved slightly from 0.63% to 0.61%.

A significant improvement was seen in the R^2 value of the training data which increased from 0.9754 to 0.9889, and in the test data from 0.8407 to 0.8586. This shows that the optimized model can better explain the variation in the data. The prediction accuracy also increased to 99.61% on the training data and 99.39% on the test data.

3.4. Comparison of CNN Models Without Optimization and CNN with Grid Search Optimization

The performance comparison of the two models on the test data is visualized in Figure 1 and summarized in Table 5.

Table 6. Comparison of Model Performance on Test Data

Metrics	CNN Without Optimization	CNN with Optimization	Difference
RMSE	0,01	0,01	0,00
MAE	0,01	0,01	0,00
MAPE	0,63%	0,61%	-0,02%
R^2	0,8407	0,8586	+0,0179
Accuracy	99,37%	99,39%	+0,02%

From the comparison, it can be seen that the CNN model with Grid Search optimization generally shows better performance compared to the CNN model without optimization. Although the difference in some metrics such as RMSE and MAE does not look significant due to rounding, the improvement is especially visible in the R^2 value which increases by 0.0179 or 1.79%. This increase in the R^2 value indicates that the model with optimization has a better ability to explain variations in the EUR/USD exchange rate.

This performance improvement is consistent with previous research findings by Wu et al. (2019)[7] and Zhao et al. (2021)[6] that emphasize the importance of hyperparameter optimization in improving the performance of deep learning models for financial data prediction.

3.5. Analysis of Prediction Results

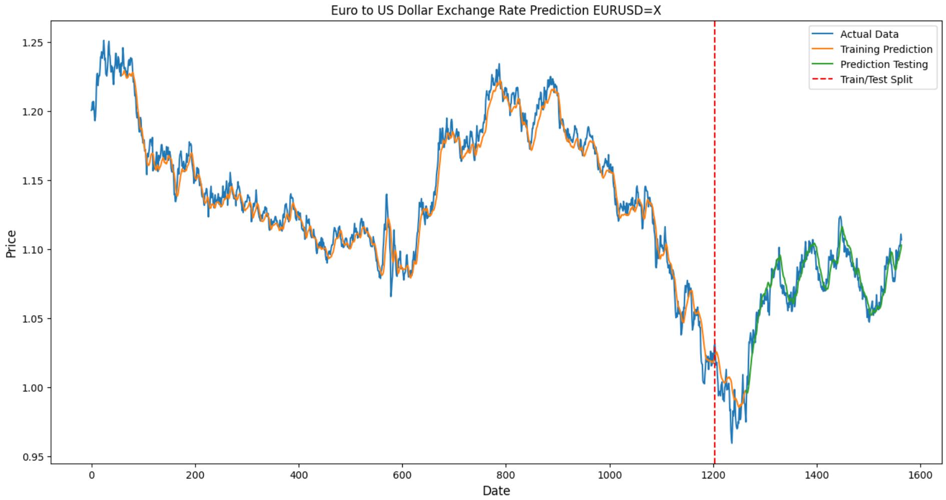

Figure 2. Comparison graph of train and test data CNN model without hyperparameter optimization

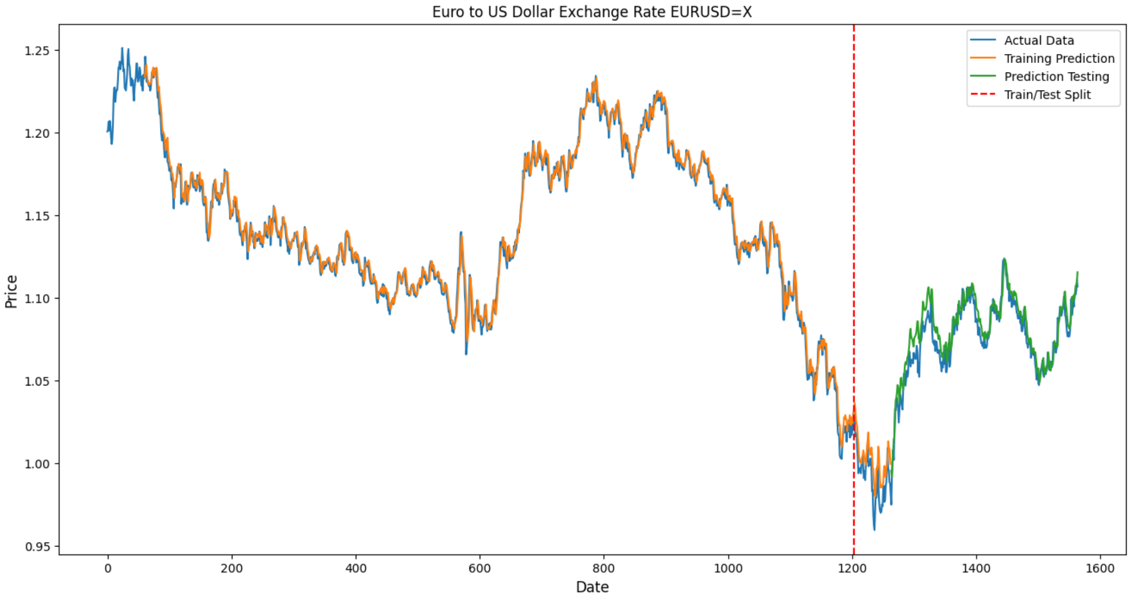

Figure 3. Comparison graph of train and test data of CNN model with Grid Search hyperparameter optimization.

Further analysis of the prediction results of both models shows that they can follow the general trend of EUR/USD exchange rate movement well. The CNN model with Grid Search optimization shows a better ability to capture exchange rate fluctuations, especially in periods of high volatility.

The prediction results show that both models tend to make more accurate predictions in periods with low to medium volatility, while in periods of high volatility, there is a slight decrease in accuracy. This is in line with research by Livieris et al. (2020)[4] which shows that deep learning models, although superior to traditional methods, still face challenges in predicting extreme movements in financial data.

3.6. Practical and Theoretical Implications

The results of this study have several important implications, both practically and theoretically:

1. Practical Implications: The CNN model with Grid Search optimization can be a valuable tool for traders, investors, and policy makers in predicting the movement of the EUR/USD exchange rate. With a prediction accuracy of 99.39% on the test datathis model can help in strategic decision-making related to foreign exchange transactions, hedging, and international financial planning.
2. Theoretical Implications: This study strengthens the empirical evidence of the superiority of deep learning methods, particularly CNN, in the prediction of financial time series data. In addition, the results also confirm the importance of hyperparameter optimization in improving the performance of deep learning models, in line with the findings of .[1], [19], [20]

4. CONCLUSION

This research has successfully developed and compared the effectiveness of two CNN models for predicting the exchange rate of the Euro against the US Dollar, namely the basic CNN model and the model optimized using Grid Search. The results showed that the CNN model with Grid Search optimization achieved superior performance compared to the basic model, with an increase in R^2 value of 1.79% and prediction accuracy of 0.02% on test data. The optimization process successfully identified the optimal parameter combination consisting of batch size 32, dense units 50, filters 64, kernel size 3, and learning rate 0.001, which significantly contributed to the improved model performance.

An important finding of this research is that both models exhibit very high prediction accuracy (>99%), confirming the CNN's ability to capture complex temporal patterns in currency exchange rate data. Although the performance difference between the base model and the optimized model is not very large, this result still confirms the importance of the hyperparameter optimization process in the development of robust and accurate deep learning models for financial applications.

Overall, this research contributes significantly to the development of a more accurate deep learning-based exchange rate prediction model. The findings have valuable practical implications for various stakeholders in the finance and international trade sectors, particularly in decision-making that requires reliable exchange rate predictions. Future research could explore more complex network architectures or alternative optimization techniques to further improve prediction accuracy.

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