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Prediction of Currency Exchange Rate Based on Transformers

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Abstract: The currency exchange rate is a crucial link between all countries related to economic and trade activities. With increasing volatility, exchange rate fluctuations have become frequent under the combined effects of global economic uncertainty and political risks. Consequently, accurate exchange rate prediction is significant in managing financial risks and economic instability. In recent years, the Transformer models have attracted attention in the field of time series analysis. Transformer models, such as Informer and TFT (Temporal Fusion Transformer), have also been extensively studied. In this paper, we evaluate the performance of the Transformer, Informer, and TFT models based on four exchange rate datasets: NZD/USD, NZD/CNY, NZD/GBP, and NZD/AUD. The results indicate that the TFT model has achieved the highest accuracy in exchange rate prediction, with an R^2 value of up to 0.94 and the lowest RMSE and MAE errors. However, the Informer model offers faster training and convergence speeds than the TFT and Transformer, making it more efficient. Furthermore, our experiments on the TFT model demonstrate that integrating the VIX index can enhance the accuracy of exchange rate predictions.

Keywords: Transformer, Informer, TFT, Currency exchange rate

1. Introduction

The exchange rate is a fundamental economic factor, significantly impacting domestic and international economic relations. The exchange rate acts as a bridge for financial communication between various countries (Pradeepkumar & Ravi 2018). Its instabilities will not only affect the country's international trade and capital flows but also directly impact the international investment of enterprises, foreign trade and individual investment. Forecasting exchange rate trend is an essential basis for judging the timing of exchange rate transactions.

The exchange rate market is a nonlinear dynamic market characterized by complexity, diversity and uncertainty (Niu & Zhang 2017). This makes exchange rate forecasting more challenging. With the advent of artificial intelligence, the existing research work in financial time series forecasting has also obtained more and more attention. In contrast to traditional time series methods, they can manage the nonlinear, chaotic, noisy and complex data of exchange rate markets, allowing for more effective forecasts (Rout, Dash, Dash, and Bisoi 2017). The dataset is crucial in exchange rate forecasting, mainly including exchange rate prices, volatility, etc. However, if the selected time series is long and has high dimensions, it is tough to achieve the expected results by using the existing models for exchange rate prediction (Lai et al. 2018). Afterwards, with the rapid growth of artificial intelligence (AI), the usage of deep learning models to process time series-related tasks became the recent mainstream, and a series of neural network models for time series tasks appeared. Early proposed models such as Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are considered suitable for processing time series tasks (Pirani, Thakkar, Jivrani, Bohara, and Garg 2022).

As the most popular mainstream architecture of deep learning in recent years, the Transformer models are widely adopted in typical tasks such as text classification,

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sentiment analysis, target detection, speech recognition, etc. However, there are few related works in the field of time series analysis, and multiple financial time series analysis research work still is use of traditional sequence prediction methods. Therefore, this paper proposes the research questions as follows:

- **Question 1:** How does the Transformer model perform in predicting the exchange rate?
- **Question 2:** By comparing the Transformer, Informer and Temporal Fusion Transformer, which algorithm performs best in predicting the exchange rate?

This paper aims to achieve exchange rate predictions based on NZD and discover the most advanced algorithms fitting for exchange rate predictions through deep learning. Based on Transformers, we have studied two recent algorithms, Informer and TFT. During our experiments on Google Colab, we trained the model, adjust parameters, and obtain results established on four processed datasets. Subsequently, the performance of the three algorithms was compared and analyzed to determine the optimal forecast exchange rate model. Eventually, this paper explored the pros and cons of the model, summarized the experimental results, and provided references for other related research work.

The structure of this paper is outlined as follows: Section 2 presents the related works and elaborates on the methodologies of the three models. Section 3 displays the results through experiments in the three models. Section 4 contains the conclusion by comparing the performance of the three models and analyzing them in conjunction with their own characteristics.

2. Materials and Methods

This section consists of related work based on traditional time series models and proposed models: Transformer, Informer, and TFT. Besides that, it illustrates the corresponding methodologies. Subsequently, the experimental processes are presented, and the measures for model evaluation are clarified.

2.1. Related Work Based on Traditional Time Series Models

Since the exchange rate is non-stationary in mean and variance, its relationship with other data series changes dynamically due to nonlinear and dynamic changes in the exchange rate over time (Xu, Han, Wan, & Yin 2019). As international trade continues to grow at an increasing rate, it is becoming more and more common, and the factors affecting exchange rates gradually increase (Eichengreen 2007).

2.1.1. ARIMA

ARIMA is one of the most universal linear methods for forecasting time series, and its research has achieved great success in academic and industrial applications (Khashei & Bijari 2011). In the study of the USD/TRY exchange rate forecast, Yıldıran and Fettahoğlu (2017) generated long-term and short-term models based on the ARIMA framework. Through comparison, it was found that ARIMA is more fitting for short-term forecasts. Similarly, Yamak, Yujian, and Gadosey (2019) used a data set of Bitcoin prices and applied with ARIMA, LSTM and GRU models for prediction analysis. The results showed that ARIMA delivered the best results among these models, with MAPE and RMSE of 2.76% and 302.53, respectively.

2.1.2. RNN

RNN is one of the neural networks specifically designed to handle time series problems (Hu, Zhao, & Khushi, 2021). It can extract information from a time series, allow the information to persist, and use previous knowledge to infer subsequent patterns.

Traditional neural networks such as the Backpropagation Neural Network (BPNN) are also used for time series modelling, while the time series information of such models is usually less than RNN.

2.1.3. LSTM

Although RNN has outstanding advantages in dealing with time series problems, as the training time rises and the number of network layers increases after the nodes of the neural network have been calculated in many stages, the features of the previous relatively long time slice have been covered, so problems such as vanishing gradient or exploding gradient are prone to occur, which leads to the incapability to learn the relationship between information, thereby losing the ability to process long-term series data (Li, Li, Cook, Zhu, & Gao, 2018).

2.2. Related Work Based on Transformer, Informer, and TFT

2.2.1. Transformer

Transformer was initially explored by Vaswani et al.(2017), no longer stuck to the framework of RNN and CNN, and attention is applied to the seq-to-seq structure to form the Transformer model and applied to process natural language tasks. Since then, the Transformer model has generated outstanding results in fields such as computer vision (Han et al. 2022). Besides, the research work on Transformer in time series has also aroused great interests (Wen et al. 2023). Through experimental research on 12 public datasets with time series, it was found that Transformer can capture long-term dependencies and obtain the best accurate prediction results in five of the dataset training (Lara-Benítez, Gallego-Ledesma, Carranza-García, and Luna-Romera 2021). However, its calculation is more complex than CNN, so the training process is relatively slow.

Despite of in-depth research outcomes on the Transformer, it is evident from the literature that most studies primarily focus on reducing the computational requirements of the Transformer model (Tay, Dehghani, Bahri, and Metzler 2022). However, they overlook the importance of capturing the dependencies among neighbouring elements, addressing the heterogeneity between the values of time series data, the temporal information corresponding to the time series, and the positional information of each dimension within the time series.

2.2.2. Informer

To solve the heterogeneity of time information, position information and numbers, a model based on Transformer architecture and attention mechanism was offered (Zhou et al. 2021). For the first time, time coding, position coding and scalar were introduced in the embedding layer to crack the long sequence input problem. ProbSparse self-attention captures long-distance dependencies and lessens the time complexity in the computation process. Using the distillation mechanism can effectively decrease the time dimension of the feature map and lower memory consumption. Although Informer outperforms LSTM in time series forecasting tasks, its inability to capture dependencies among neighboring elements with the multihead attention mechanism leads to insufficient capture of the time-series local information. This results in lower prediction accuracy and higher memory consumption, which could be more conducive to large-scale deployment. A relative coding algorithm (Gong et al., 2022) was based on the Informer framework to predict the heating load. The experimental results indicate that the improved Informer model is more robust. Besides, based on Informer and the proposed Autoformer (Wu, Xu, Wang, and Long, 2021), a new decomposition architecture was designed with an autocorrelation mechanism. The model breaks the preprocessing convention of sequence decomposition and updates it into the fundamental internal blocks of the deep model. This design enables Autoformer to progressively decompose complex time series. Moreover, inspired by the random process theory, Autoformer designed an autocorrelation mechanism based on sequence periodicity, replacing the Self-Attention module in Transformer with autocorrelation mode. In long-term forecasting, Autoformer achieves outstanding accuracy.

2.2.3. TFT

Transformer model has demonstrated its outstanding performance in both natural language processing and computer vision (Bi, Zhu, and Meng 2021). Applying this model to capture long-term dependencies and data interaction in time series has become the focus. The general method for processing time series data is to treat data in all dimensions with equal weight. This may cause the model to ignore critical input information or be interfered with by noise, which is also a shortcoming of traditional processing methods. Temporal Fusion Transformer (TFT) is a Transformer model for multistep prediction tasks, which is developed to effectively process different types of input information (i.e., static, known or observed inputs) and construct feature representations to achieve high predictive performance (Lim, Arık, Loeff, and Pfister 2021). The TFT model (Zhang, Zou, Yang, and Yang, 2022) was proposed to predict short-term highway speed by collecting Minnesota traffic data and applying it to the training and testing of the model. Compared with traditional models, the TFT model performs best when the prediction range exceeds 30 minutes.

2.3. Methods Based on Transformer, Informer, and TFT

2.3.1. Transformer

In Transformers, the self-attention mechanism has received more recognition rate compared to other neural network models that utilize the attention mechanism. The attention mechanism in Transformers excels at capturing the internal correlation within data and features, and more effectively solves the problem of long-distance dependence (Wang, Pi, Zhang, Liu, and Guo 2022).

Contrary to other models that only take use of a single attention module, the Transformer employs multihead attention modules to operate in parallel (Sridhar and Sanagavarapu 2021). In this step, the original queries, keys, and values of dimension D_m are each mapped into spaces of dimensions D_k , D_m , and D_v using H different learned vectors. The model computes each of these mapped queries, keys, and values according to eq. (1), outputting attention weights for each. Then, it concatenates all these outputs and converts them back into an D_m dimensional representation.

$$MultiHeadAttn(Q,K,V) = Concat(head_1, \cdots, head_H)W^O,$$
$$where \quad head_i = Attention\left(QW_i^Q, KW_i^K, VW_i^V\right) \tag{1}$$

where $head_i$ is computed by applying the attention function to the transformed inputs. W^O represents the weight matrix applied after concatenating the outputs of all attention heads.

2.3.2. Informer

Informer model has been proposed to address the long-sequence forecasting issues in the Transformer. This model provides an improved self-attention module to reduce time complexity (Sun, Hou, Lv, and Peng 2022).

In the Informer network, probabilistic sparse self-attention replaces traditional self-attention. Each input vector is utilised to calculate query, key, and value vectors in the self-attention mechanism. Then, attention weights are calculated by computing the dot product of query vectors and key vectors. The attention weights represent the similarity between each and all input vectors. In the probabilistic sparse self-attention mechanism, query vectors compute the similarity with each key vector, generating an attention distribution. The probabilistic sparse self-attention calculation is shown in the eq. (2).

$$ProbAttn(\hat{Q}^l, K^i, V^i) = softmax(\frac{\hat{Q}^l {K^i}^T}{\sqrt{d}})V^i \tag{2}$$

where $\hat{Q}^l$ represents the distance calculated using KL divergence among the attention distribution and the uniform distribution to determine the value of each query point, thus specifying which queries should be allocated computational resources, it selects the active query with the most significant distance.

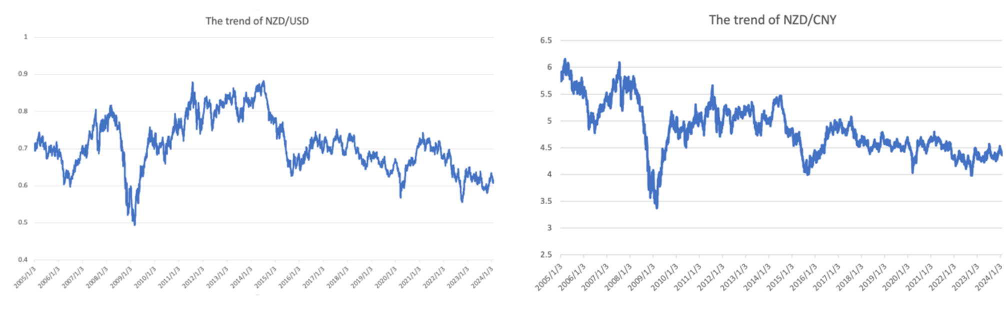
In general, in probabilistic sparse self-attention calculation, attention is only given to the far-active queries. In contrast, the dot products for other queries are substituted with the mean of the value vectors, thus reducing the computational task.

2.3.3. TFT

Temporal Fusion Transformer (TFT) is a time series prediction model based on the Transformer architecture, aiming to solve the limitations of traditional time series prediction models (Lim et al. 2021). TFT introduces a novel to capture features and nonlinear relationships across multiple time scales (Fayer et al. 2023). TFT employs recurrent layers for localized processing and interpretable attention layers to manage long-term dependencies. The algorithm also leverages specialized components for feature selection and a sequence of gating layers to filter out unnecessary elements, thereby maintaining the optimal performance of this model across various scenarios. The main components of this TFT model are: Gating mechanism and variable selection network, Static covariate encoder, and Temporal fusion decoder.

2.4. Data Collection and Preprocessing

Due to the changes in the exchange rate being impacted by multiple aspects, they display diverse characteristics of change. We selected four representative currencies, USD, GBP, CNY, and AUD, as training and test samples because of their significant impact on the global economy, widespread usage in international trade, and substantial influence on foreign exchange markets. These currencies are representative of major economic regions, providing a comprehensive and diverse dataset for robust predictive modelling. The datasets of NZD against these four currencies are all from Yahoo! Finance (https://nz.finance.yahoo.com) and Investing website (www.investing.com). To enhance the learning ability of our proposed model for unexpected fluctuations, each sample includes daily data from January 3, 2005, to February 2, 2024, totalling 4,980 entries. The primary variables of the dataset include closing, opening, highest, lowest, and floating prices of the day. We select the closing price as the experimental objective.



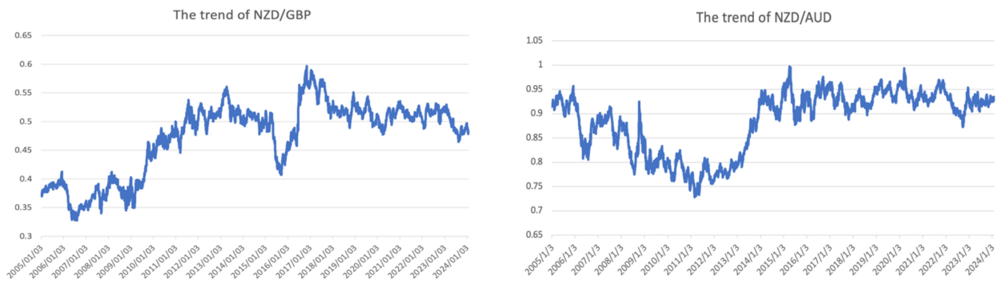


Figure 1. The trend of NZD against the four selected currencies.

We adopt eq. (4) for imputing missing values.

$$X_i = \frac{X_{i-1} + X_{i+1}}{2} \tag{3}$$

where X_i defines the data to be imputed, X_{i-1} represents the data from the day before the missing data, and X_{i+1} illustrates the data from the day after the missing data.

The most common method, min-max standardization, is also utilized in data preprocessing. The calculation process is

$$X^* = \frac{X - X_{min}}{X_{max} - X_{min}}. \tag{4}$$

Among them, X^*represents the dimensionless data after normalization, X means the observation value, X_{min} denotes the minimum value, and X_{max} tells the maximum value. Denormalization is restoring normalized data to facilitate subsequent data analysis and other operations.

2.5. Data Description

After preprocessing the four datasets, the total number of samples for each is 4,980. To better understand the data's characteristics and distribution features and utilize the relevant data for modelling, it is essential to conduct a descriptive statistical analysis before modelling. Table 1 provides the descriptive statistics for the four datasets.

Table 1. The descriptive statistics of NZD against four currency exchange rates

Currency	Mean	Min	Max	Median	Standard Deviation	Kurtosis	Skewness
USD	0.709	0.494	0.882	0.703	0.073	-0.369	0.118
CNY	4.827	3.371	6.163	4.79	0.484	-0.148	0.258
GBP	0.473	0.328	0.597	0.497	0.063	-0.726	-0.693
AUD	0.884	0.728	0.997	0.91	0.064	-0.886	-0.686

Table 1 shows that the standard deviation for NZD/USD is 0.073, indicating that the exchange rate fluctuates within a narrow range. A kurtosis value of -0.369 and a skewness value of 0.118 suggest that the distribution of NZD/USD deviates slightly from a normal distribution, showing slight flatness and right skewness. Still, overall, it is close to symmetry. Compared to NZD/CNY, there is a significant difference between its minimum and maximum values, which are 3.371 and 6.163, respectively. The median of 4.79 is slightly lower than the average, implying a skewed distribution to the right. The standard deviation is 0.484, indicating the volatility is higher than the other three currency pairs. The kurtosis and skewness are -0.148 and 0.258, respectively, indicating a relatively flat and slightly right-skewed distribution. The statistical results for NZD/GBP show that the average exchange rate for NZD/GBP is 0.473, with a minimum of 0.328 and a maximum of 0.597, revealing a smaller fluctuation range and, hence, a relatively stable exchange rate. The median of 0.497 is very close to the mean, reflecting the central tendency of the data. Its standard deviation of 0.063 is the smallest among the four currency pairs, showing the lowest volatility. The average exchange rate for NZD/AUD is 0.884, with a fluctuation range from 0.728 to 0.997, which is relatively moderate. The median of 0.91 is higher than the average, exhibiting more data points in the higher value range. A standard deviation of 0.064 indicates lower volatility. The kurtosis of -0.886 and skewness of -0.686 present a skewed and peaked distribution, suggesting a frequent occurrence of lower values.

Throughout this detailed analysis, we summarize that these four datasets demonstrate diverse levels of volatility and distribution characteristics. NZD/GBP and NZD/AUD show relatively lower volatility, while NZD/USD and NZD/CNY exhibit higher volatility. In the experiment, we divided the dataset into two parts for the training process of the three models: 80% for training and 20% for testing.

2.6. Experiment Implementation

2.6.1. The Experimental Implementation of Transformer

In the training process of the Transformer model, it is vital to set essential parameters, which are continuously adjusted and optimized. Due to the complexity of the Transformer, we employ a lower learning rate parameter of 0.0005. Although this means that the model learns more slowly, it can help the model adapt more finely to the training data, leading to better stable and accurate predictions. The value of input_window is set to 7, which allows for more suitable capturing of weekly patterns or trends in the data for time series data like exchange rates, a typical setting in financial sequences. We experimented with the multiple training epochs, setting them at 50, 100, 150, and 200, and finally found that 150 is the best, avoiding the risk of overfitting.

Table 2. The parameters setting of Transformer

Parameters	Settings
input_window	7
batch_size	100
learning_rate	0.0005
epochs	150

2.6.2. The Experimental Implementation of Informer

Unlike the parameter settings of the Transformer, through multiple attempts, we have set the number of epochs to 60. Since the Informer optimizes computational complexity, reducing unnecessary computations and parameter usage, it achieves better results in a shorter training time. The table below details the model parameters of the Informer.

Table 3. The parameters setting of Informer

Parameters	Settings
sequence_length	64

predict_length	5
batch_size	128
learning_rate	5e-5
epochs	60

2.6.3. The Experimental Implementation of TFT

The model training of TFT is conducted within a PyTorch-lightning framework. In this environment, it is possible to adjust the model's hyperparameters promptly during the data training process. This setup integrates with the Early-Stopping mechanism to obtain an outstanding combination of parameters. For the TFT model, a learning rate of 0.001 is a moderate value that supports balanced training speed and convergence quality. Setting the hidden layer's size to 32 means the TFT model is relatively simple and computationally efficient. Since no overly complex recognition tasks exist, we set the number of attention heads to 1.

Table 4. The parameters setting of TFT

Parameters	Settings
learning_rate	0.001
hidden_size	32
attention_head_size	1
output_size	8
batch_size	128
epochs	150

2.7. Evaluation Methods

In our experiment of exchange rate prediction, to reflect the reliability of the predictive performance accurately and objectively, we utilize four evaluation metrics, including root mean square error (RMSE), mean absolute error (MAE), coefficient of determination (R^2), mean absolute percentage error (MAPE). The smaller the RMSE and MAE, the closer the predictions are to the actual values. A larger R^2 indicates a better fit of the model. MAPE provides a comprehensive indication of the model's overall predictive effectiveness.

3. Results

3.1. Experimental Results of Transformer

In this experiment, the initial model we trained on Google Colab for the four exchange rate datasets was Transformer model. By considering both the training on the training set and the predictions on the test set, the Transformer has achieved satisfactory results. Figure 2 displays the actual and predictive results on the test set.

NZD/USD NZD/CNY

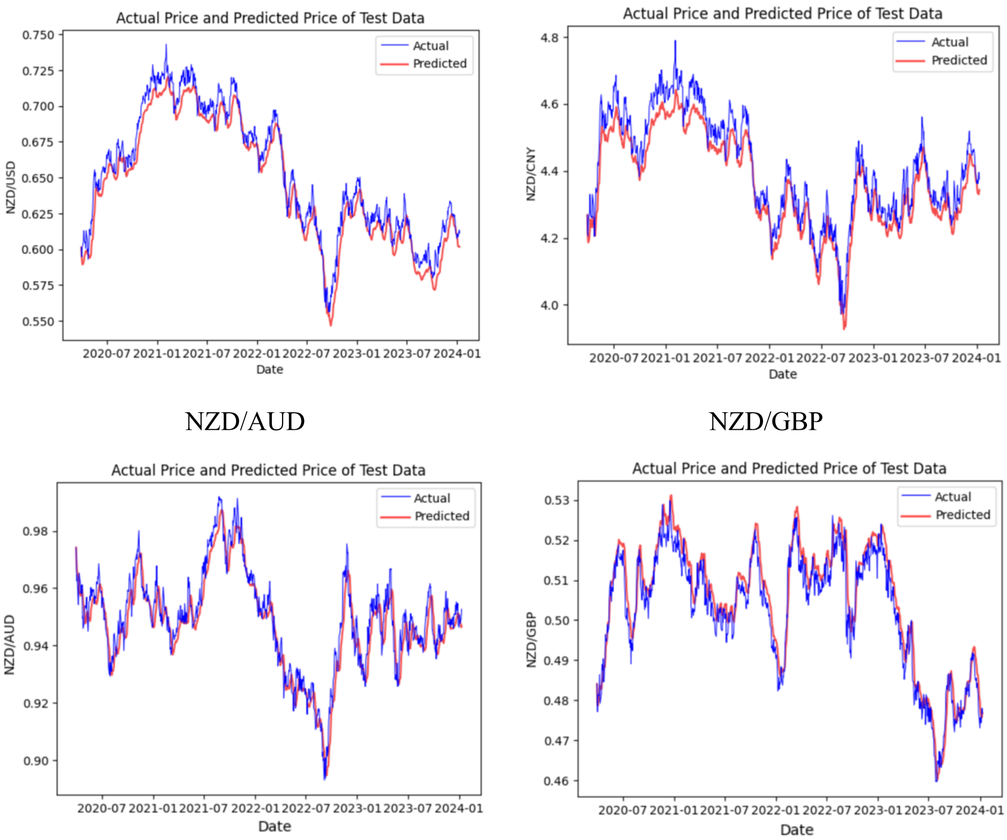


Figure 2. The predictive result of each dataset by using Transformer.

From the prediction results related to the four test sets, the trend of NZD/USD is very close to the actual result, reaching highs and lows at almost the same time, and the high degree of overlap between the two lines indicates that the Transformer can effectively capture the trends and seasonal changes of the exchange rate. However, from the NZD/CNY prediction graph, we discover the deviations during periods of high volatility, and the Transformer model has yet to capture the peaks and troughs of the exchange rate perfectly. Despite of this, the overall prediction trend still tracks the real exchange rate well. Similar to NZD/AUD, though the figure shows a strong correlation between prediction and reality, the Transformer still underestimates or overestimates the peaks in some intervals. Regarding the NZD/GBP trend, the prediction accuracy is high for most of the timeline, showing that the Transformer is robust. Table 1 shows more details of the experimental evaluation results of Transformer.

By evaluating the model with four different indicators, we notice that in the training and prediction of the Transformer model based on the four datasets, NZD/USD exhibits remarkably high precision and reliability. The very low RMSE and MAE values show that the forecast values are extraordinarily close to the actual values. Furthermore, the low MAPE value 0.0141 verifies that the error percentage is minor, representing an ideal outcome in currency prediction. In comparison, an R^2 value closes to 0.94 indicates that the model has strong predictive power and a high degree of explanatory capability regarding the fluctuating exchange rate trends.

Table 5. The experimental results with four datasets using Transformer.

Currency	**RMSE**	**MAPE**	**MAE**	$\mathbf{R^2}$
NZD/USD	0.011	0.0141	0.0092	0.9369
NZD/CNY	0.0585	0.0113	0.0502	0.8589

NZD/AUD	0.0571	0.0048	0.0046	0.8891
NZD/GBP	0.0051	0.0084	0.0042	0.8841

Although the MAPE values are relatively low in the NZD/CNY and NZD/AUD predictions, at 0.0113 and 0.0048, respectively, the increased RMSE and MAE indicate that the model faces more significant challenges in forecasting these currency pairs. Possible reasons may include higher market volatility, differences in trading volume, or the characteristics of these datasets. Nevertheless, the R^2 values for both currency pairs exceed 0.85, reflecting the Transformer's powerful capability to capture essential information and trends.

Compared to other results, NZD/GBP has the lowest RMSE and MAE, implying that the model is able to generate highly accurate predictions with minimal error for this currency pair. An R^2 value 0.8841 demonstrates a satisfactory model fit, and though slightly lower than NZD/USD, it is still an excellent result, given the complexity of the currency market.

The strong performance of Transformer model partly derives from its self-attention mechanism, which allows it to fully consider the influence of other points in time when predicting the exchange rate at any given moment.

In summary, the Transformer performs outstandingly across all four datasets, especially in NZD/USD predictions, where it achieves a very high level of accuracy.

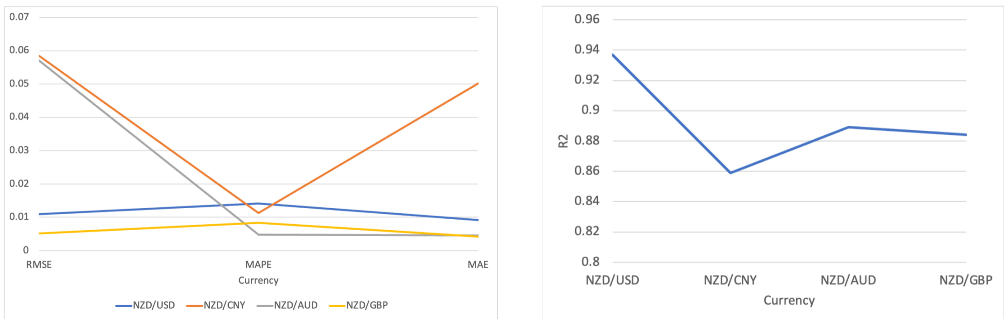
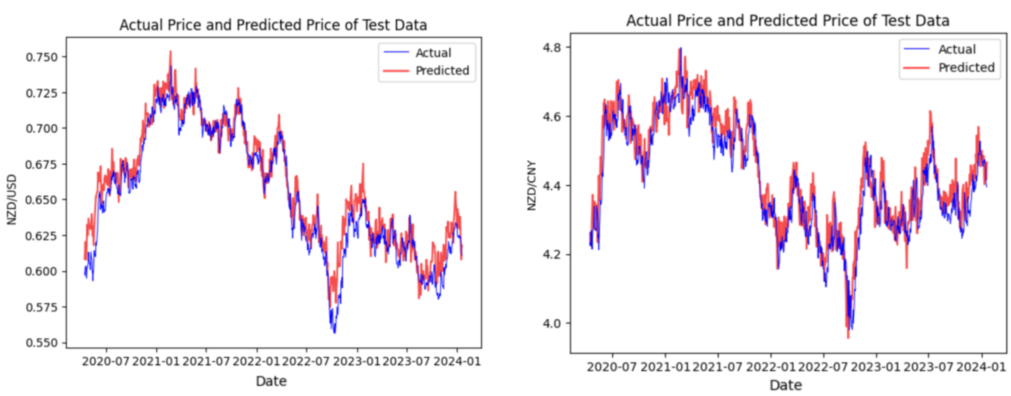


Figure 3. Visualisation of the experiment result on Transformer.

3.2. Experimental Results of Informer

The second model we conducted in this experiment was the Informer, an advancement based on the Transformer framework. The prediction trend charts are as follows through the training and prediction of four datasets.

NZD/USD NZD/CNY



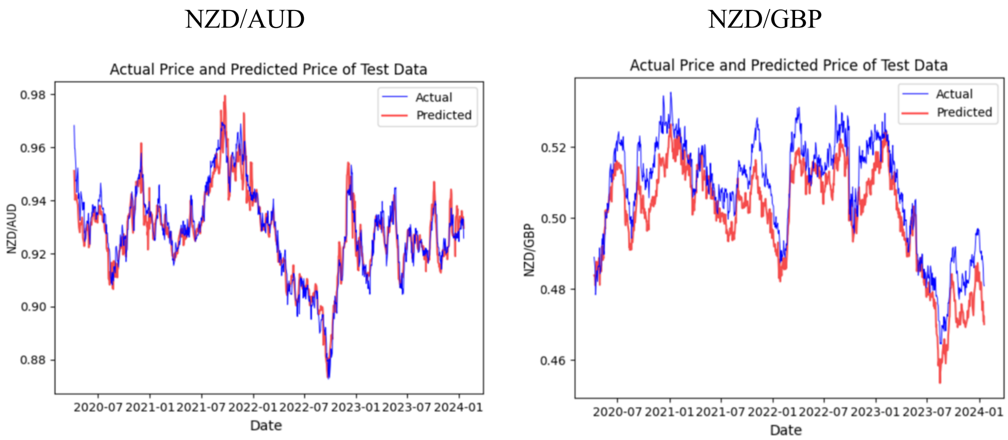


Figure 4. The predictive result of each dataset performed by using Informer.

From the prediction trend charts, the actual and predicted values of NZD/USD are roughly similar, especially at the peaks and troughs. However, between July 2022 and January 2023, there is a relatively large gap between the predicted and actual lines. As for NZD/CNY, the overall prediction for this currency pair also maintained synchronicity, but the deviation at the beginning of 2023 was more extensive than that of NZD/USD. Similar to NZD/USD and NZD/AUD, where the prediction curve of this currency pair closely matches the actual price curve most of the time. Likewise, in a number of intervals, the prediction failed to capture the rapid changes in the exact exchange rate. Slightly different from the trend results of the other three, the trend of NZD/GBP did not match as well as others, but it also captured the trend of the exchange rate. Table 2 illustrates the results based on the four evaluation metrics.

Table 6. The experimental results with four datasets by using Informer.

Currency	RMSE	MAPE	MAE	R^2
NZD/USD	0.011	0.0141	0.0092	0.9369
NZD/CNY	0.0585	0.0113	0.0502	0.8589
NZD/AUD	0.0571	0.0048	0.0046	0.8891
NZD/GBP	0.0051	0.0084	0.0042	0.8841

In the NZD/USD results, the Informer model achieved a high level of precision, specifically reflected in the low RMSE value 0.012. At the same time, the low MAPE and MAE values 0.0144 and 0.0092, respectively, also demonstrate that the forecast errors are relatively minor. An R^2 value 0.925 further indicates that the Informer can broadly explain fluctuations in the exchange rate.

In the NZD/CNY results, despite the low MAPE value 0.0105, which explains a certain degree of accuracy, the higher RMSE and MAE values reveal the challenges faced by the Informer in predicting this currency pair. Nevertheless, an R^2 value exceeding 0.85 means that the Informer can still fit the data reasonably well despite the difficulties.

Regarding NZD/AUD and NZD/GBP, the Informer performed exceptionally well, especially in NZD/AUD, where the very low RMSE and MAE values reflect the superior performance of Informer model in terms of prediction accuracy. The MAPE value is nearly zero, almost achieving a perfect prediction effect. This shows that the Informer can accurately predict the exchange rate movements of these two currency pairs, even in the face of fluctuations in exchange rates.

Overall, the Informer model demonstrates adaptability and accuracy under different market conditions in handling the exchange rate predictions of these four datasets.

Particularly in predicting NZD/AUD and NZD/USD, it illustrates the advantages of being an improved model based on the Transformer. Although there are challenges in the NZD/CNY predictions, the model can still effectively capture and predict the dynamics of exchange rate changes.

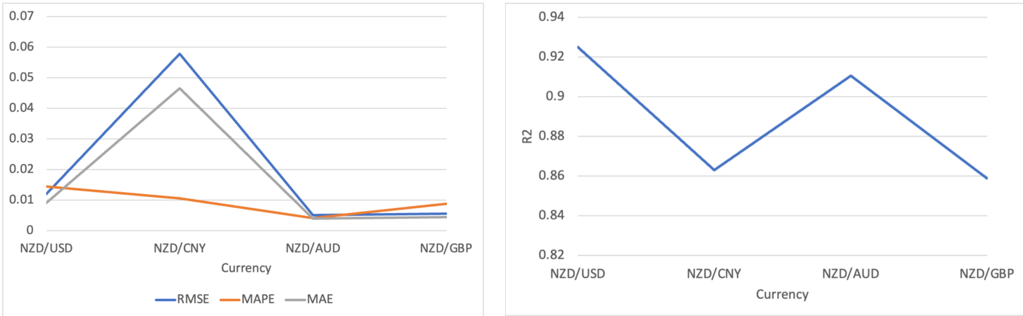


Figure 5. Visualisation of the experiment result on Informer.

3.3. Experimental Results of TFT

Our third trained model is the TFT, an enhancement of the Transformer model that specializes in processing time-series data. Figure 4 exhibits the TFT's prediction trends for the four test sets.

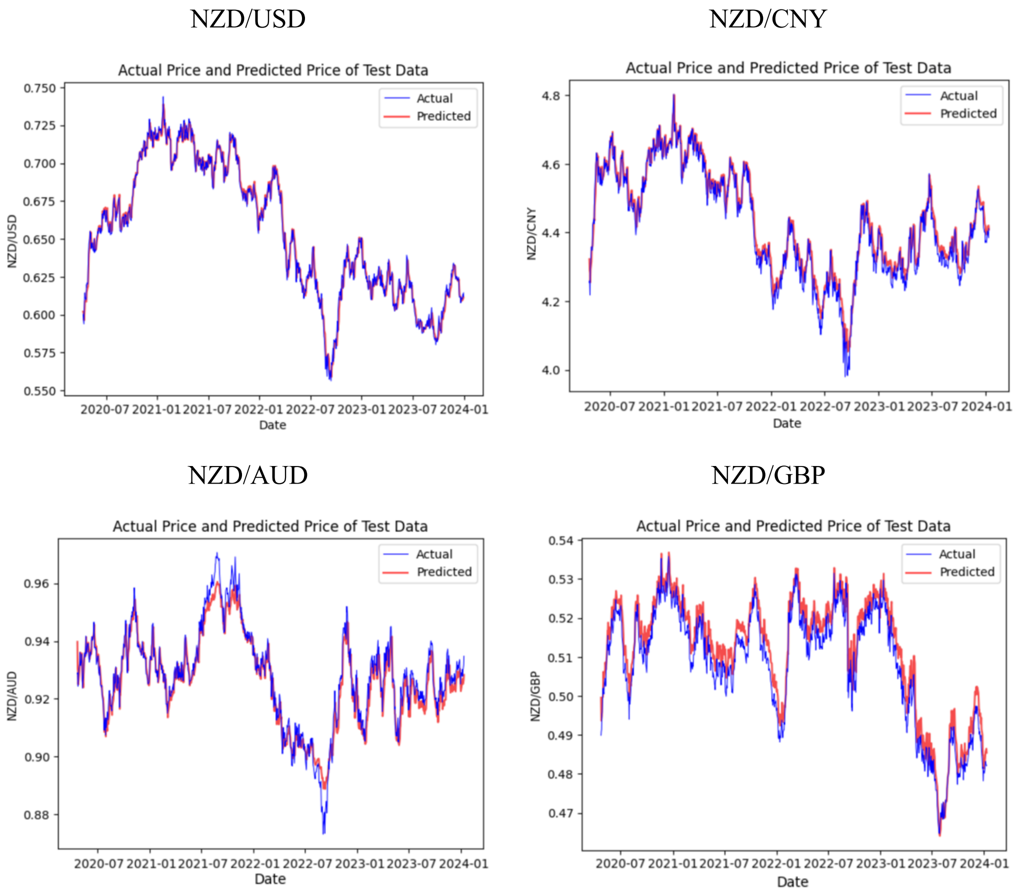


Figure 6. The predictive result of each dataset performed on TFT.

From the trend chart of NZD/USD, the prediction curve closely follows the actual price curve most of the time, demonstrating the solid predictive capability of the TFT model for this currency pair, particularly in adapting quickly during significant trend changes. As for the trend charts of the other three currency pairs, we observe that the lag or deviation at critical turning points. Nevertheless, the TFT model generally follows the actual trends well. Table 3 shows the result by using evaluation metrics.

Table 7. The TFT experiment results with four datasets.

Currency	RMSE	MAPE	MAE	R^2
NZD/USD	0.0045	0.0055	0.0035	0.9892
NZD/CNY	0.0312	0.0056	0.0041	0.96
NZD/AUD	0.0041	0.0035	0.0032	0.9381
NZD/GBP	0.0044	0.0075	0.0062	0.9122

The assessment results in Table 3 show that the predictions for NZD/USD are the best, with shallow RMSE, MAPE, and MAE values 0.0045, 0.0055, and 0.0035, respectively, revealing that the predicted values are very close to the actual values. The high R^2 value additionally confirms the nearness between the predicted and actual trends of exchange rate fluctuations for this currency pair.

As for the results of NZD/CNY, though the MAPE remains at a low level 0.0056, a relatively higher RMSE suggests significant deviations between the predicted and actual values at specific time points. However, the high R^2 value 0.96 indicates that the TFT model can still capture most exchange rate changes.

In the predictions for NZD/AUD, even though the R^2 value is slightly lower than that of NZD/USD, the remarkably low errors indicate the high accuracy of the TFT on this test set.

Although NZD/GBP has the highest MAE among all the currency pairs at 0.0075, this does not mean that the overall performance of this model is poor. An R^2 value 0.9122 points that the model successfully captures most of the dynamics of the pound's exchange rate changes, with a slight decrease in predictive accuracy, possibly due to the complexity of market fluctuations during specific periods.

The TFT model performs reasonably well across all four test sets, especially in predicting NZD/USD and NZD/AUD, showing high accuracy and reliability. Despite the drop in predictive precision for NZD/CNY and NZD/GBP, the R^2 values still demonstrate that the model's predictions are pretty reliable for these currency pairs.

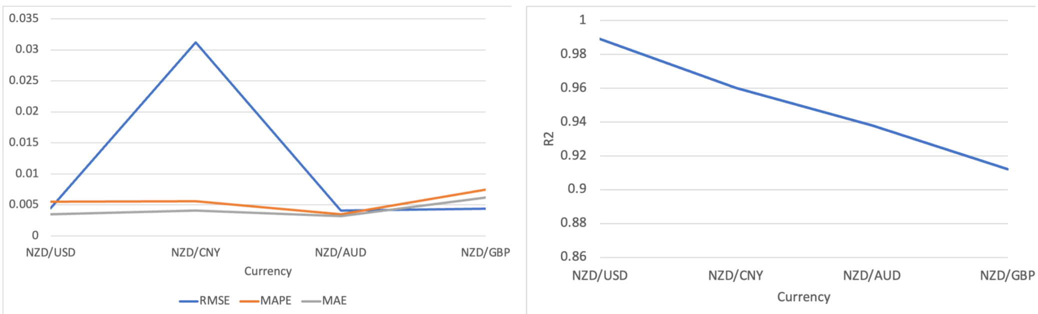


Figure 7. Visualisation of the experiment result on TFT.

4. Analysis and Discussion

To compare the performance of these three models more thoroughly—Transformer, Informer, and TFT, we summarized the evaluation results of each model for the four test sets, taking the average for each evaluation criterion. The results are presented in Table 4.

Table 8. The evaluation result of each model based on the test set.

Model	RMSE	MAPE	MAE	R^2
Transformer	0.0329	0.0097	0.0171	0.8922
Informer	0.0201	0.0095	0.016	0.8893
TFT	0.0111	0.0055	0.0043	0.9499

In Table 4, it is evident that the Transformer model has relatively high RMSE and MAE values. Nevertheless, an R^2 value 0.8922 indicates a reasonable correlation between the predictions and actual values. Its explanatory power is slightly weaker compared to the other two models. As an improved version of the Transformer, the Informer has lower RMSE and MAE values, at 0.0201 and 0.016, respectively, while its MAPE is 0.0095 and R^2 is 0.8893. This suggests that the Informer performs better than the original Transformer, especially when dealing with time series data with high volatility. Lastly, the TFT exhibits the best performance among all the models, with an RMSE of only 0.0111, a MAPE 0.0055, an MAE 0.0043, and the highest R^2 value 0.9499. The TFT model integrates various methods for time series forecasting, including time attention mechanisms and interpretable features, enabling it to excel across all evaluation metrics.

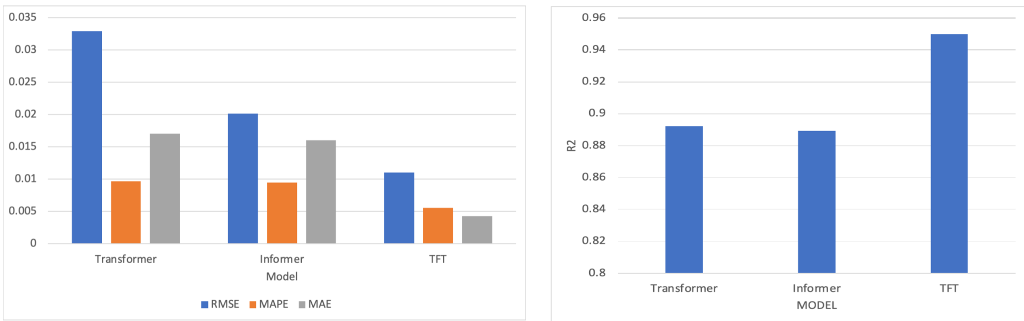


Figure 8. The visualization result of the three models' performance.

These results imply that the TFT performs best in handling the currency exchange rate prediction, possibly because it was designed to capture complex patterns in time series. The Informer and Transformer also perform well but cannot achieve outstanding results like TFT for this specific task. The differences may derive from the special treatment of the time dimension in its model architecture and its ability to capture and integrate various factors affecting the predictive variables.

Additionally, from the perspective of training time and model convergence speed, the Informer is able to reach stable and accurate predictions within a relatively few 60 epochs, which might make it more efficient than the traditional Transformer and the TFT. However, by considering the performance after model training, the TFT has demonstrated the highest R^2 value in currency exchange rate predictions. Although the TFT might require a more complex training process, its return on investment in model performance is optimal.

5. Conclusions

This paper aims to analyze and discuss the accuracy and performance of models through exchange rate predictions. This paper takes use of three models: Transformer and its advanced versions, Informer and TFT. We collected four exchange rate datasets, namely, NZD/USD, NZD/CNY, NZD/GBP, and NZD/AUD, and applied them to the three models for training and validation. Our experiments were conducted on the Google Colab platform, four evaluation criteria were utilized to analyze and compare the performance of the three models.

All three models achieved satisfactory prediction effects on the four datasets. However, comparisons indicated that the TFT model offered the best performance in exchange rate prediction, especially regarding accuracy and capturing trends in data changes. The Informer balanced efficiency and accuracy, demonstrating excellent predictive capabilities in fewer epochs. This is the reason why its sparse attention mechanism, which reduces computational complexity. Among the three models, the Transformer performed the least ideally, with relatively higher RMSE and MAE values and the lowest R^2 value.

The limitations of this paper mainly fall into three parts. Firstly, the variables selected for this project are limited, only including primary exchange rate data. However, exchange rate trends are influenced by other complex factors, such as national policies, inflation rates, and investor psychological expectations. Thus, the lack of comprehensive feature selection will inevitably lead to unavoidable errors in prediction. Based on this, it is possible to consider incorporating more factors that affect exchange rates in the data selection process. Secondly, due to limited time, each model's selection of parameters and functions was primarily based on relevant literature and materials, which may introduce subjectivity and randomness. Therefore, further research and experimentation are needed to select the optimal parameters. Thirdly, the experiments in this paper are all based on the Transformer model framework. It is vital to conduct experimental comparisons with other cutting-edge models to comprehensively analyze and determine the best model for predicting exchange rates.

Although this paper has made great progress in exchange rate prediction, numerous shortages and issues still require further investigation. Therefore, our future research work will be conducted in the following aspects. To enhance the accuracy of our models in predicting exchange rates, it is necessary to include more economic indicators and other relevant factors influencing exchange rates in the data collection process. Hence, further research work and experimental validation are required to optimize model parameters. In addition, we plan to expand the experimental data by using currencies from other representative countries as benchmarks for exchange rate prediction. We will also explore and compare more recent models to further enhance the effectiveness and accuracy of exchange rate forecasting, thereby providing valuable reference recommendations for the financial markets.

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