

Forecasting AUD/USD Forex Trends Using Advanced CNN-Based Hybrid Models

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ABSTRACT

Trading foreign currencies worth trillions of dollars takes place daily in the Forex market, characterised by highly volatile movements. One approach to mitigating risk in Forex trading decisions is through forecasting techniques. In this research study, we investigate the effectiveness of advanced deep learning models, including convolutional neural networks (CNN), long short-term memory (LSTM), bidirectional long short-term memory (BiLSTM), transformer and their hybrid combinations for forecasting exchange rates.

KEYWORDS

Forex, LSTM, BiLSTM, CNN, transformer, deep learning

INTRODUCTION

In this study, advanced deep learning models CNN-LSTM, CNN-BiLSTM and CNN-transformer (Dave et al., 2025) were used to forecast the price of the AUD/USD currency pair and evaluate the results of such predictions for identifying correction points in the Forex market, which can serve as optimal entry points to maximise profitability. The models were trained and evaluated using major historical data from Yahoo Finance (Olorunnimbe & Viktor, 2022) (from 2006 to 2025). The study aims to improve forecasting accuracy and inform financial decision-making by leveraging data-driven AI techniques.

BACKGROUND

Forecasting foreign exchange rates, which are highly volatile, is a challenge for both academic researchers and financial practitioners. Traditional statistical approaches and neural network models often fall short in capturing the abstract temporal dependencies and noise present in currency price movements. Therefore there has been a shift towards more sophisticated deep learning models capable of modelling dependencies and high-level features from time-series data.

In recent works in this topic, Olorunnimbe & Viktor (2022) reviewed deep learning applications in stock markets with a focus on studies that include back testing for real-world relevance. Ayitey et al. (2022) used a two-layer stacked-long short-term memory (TLS-LSTM) neural network and the Hurst exponent to improve the accuracy for the pair of currencies AUD/USD. Pahlevi et al. (2023) used LSTM and GRU models to forecast Forex trends. Saadati and Manthouri's (2024) proposed method combined LSTM, CNN and an attention mechanism to predict Forex price movement. Bilokon and Qiu (2023) compared transformer and LSTM to see whether transformer could beat LSTM in financial time-series prediction. Shi et al. (2021) proposed a hybrid stock-price prediction model combining autoregressive integrated moving average (ARIMA), attention-based CNN-LSTM and XGBoost to capture nonlinear patterns and improve forecasting accuracy. Qi et al. (2021) enhanced Forex trend prediction using event-driven features and deep learning, achieving high accuracy on EUR/GBP data. Ranaldoa and de Magistris (2022) showed that hybrid models combining CNN with LSTM or GRU outperform standalone models in Forex rate-prediction across multiple timeframes.

METHODOLOGY

The methodology consisted of four main stages:

1. **Data collection and preprocessing:** Historical Forex data was collected from Yahoo Finance (Ayitey et al., 2022) at a daily interval with different sequence lengths (7, 14, 30 and 60 days). We used the features Open, High, Low and Close (OHLC). Entries with missing values were removed, the data was sorted by date, and then preprocessed using StandardScaler to normalise the values.
2. **Model design and implementation:** Three model types were considered:
 - a. **CNN-LSTM:** Uses CNN as a feature extractor before LSTM extracts temporal features for time-series forecasting.
 - b. **CNN-BiLSTM:** Combines CNN's local feature extraction with BiLSTM's bidirectional learning.
 - c. **CNN-transformer:** Uses CNN as a feature extractor and transformer for temporal feature extraction for time-series forecasting.
3. **Training:** Each model was trained independently on the same datasets.
4. **Evaluation:** To evaluate the performance of the forecasting models, various statistical measures, including mean square error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE) and the coefficient of determination (R^2), were used to provide a comprehensive and accurate assessment of the models' predictive quality (Ayitey et al., 2022) (Figure 1).

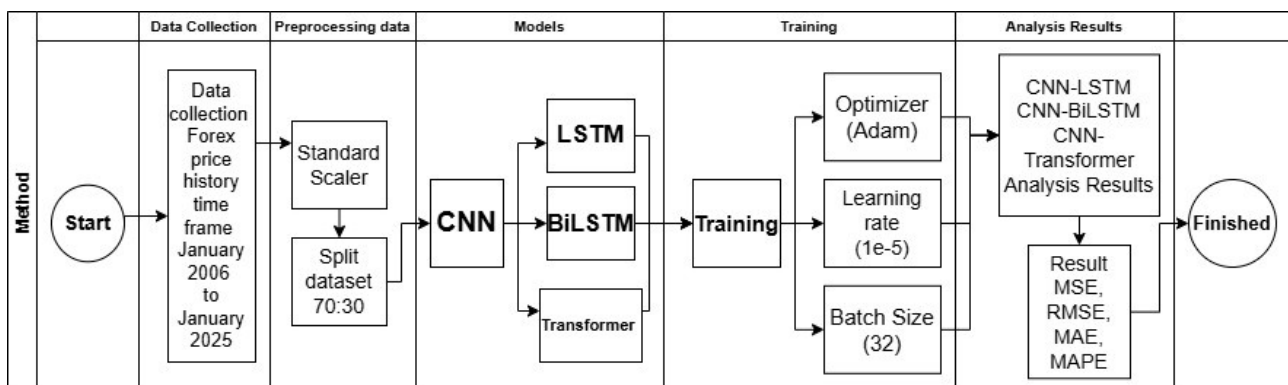


Figure 1. Process of the prediction system.

RESULTS AND DISCUSSION

In this research, we can examine the effectiveness of deep learning models for forecasting exchange rates and comparisons across different hybrid models. Among all, the CNN-LSTM model achieved the highest accuracy, with lower error rates and better generalisation. The superior performance of CNN-LSTM may be attributed to its ability to capture both local spatial patterns and long-term temporal dependencies. The relatively weaker performance of the CNN-transformer model may be due to the need for a larger training dataset. Additionally, the choice of sequence length had a notable impact on model performance. For instance, CNN-LSTM performed best at a sequence length of 60 days, which means that as the sequence length increases models need to be more complex. One limitation of this study is the focus on only one currency pair. The AUD/USD currency pair is among the most liquid in the Forex market, with a relatively low price impact of trading volume. On average, over 25 billion USD is required to move its exchange rate by one standard deviation, reflecting its market depth and efficiency (Ranaldoa & de Magistris, 2022). Therefore, its use in empirical analysis is well justified from

a liquidity perspective. Future research should extend the analysis to more diverse pairs and explore integration with additional macroeconomic and sentiment-based indicators. Ultimately, our results could help traders make better choices when trading in the Forex market.

Evaluation metrics, including MSE, MAE, RMSE, MAPE and R²-squares, were used to quantify performance. The CNN-BiLSTM model, while effective, was outperformed by the CNN-LSTM model in all scenarios. Detailed results are provided in Table 1.

We showed the comparisons of the MSE of three different deep learning models, CNN-BiLSTM, CNN-LSTM and CNN-transformer, across various input window sizes (7, 14, 30 and 60 days) (Figure 2). As shown in Figure 2, CNN-LSTM consistently shows the lowest MSE across all window sizes, especially at 60 days (0.007); CNN-BiLSTM has higher MSE at 14 days (0.16), but improves significantly at 60 days (0.1061); CNN-transformer performs moderately at shorter windows but shows higher MSE at 30 days (0.132). These results suggest that CNN-LSTM offers superior prediction accuracy in this setting, particularly for longer time windows.

Table 1. Results for AUD/USD.

Models	Length	MSE	RMSE	MAE	MAPE	R ² -square
CNN-BiLSTM	7	0.0298	0.171	0.139	7.226%	0.677
CNN-LSTM		0.015	0.125	0.094	4.966%	0.829
CNN-Transformer		0.064	0.253	0.194	9.980%	0.304
CNN-BiLSTM	14	0.160	0.125	0.092	4.80%	0.825
CNN-LSTM		0.037	0.192	0.150	7.751%	0.596
CNN-Transformer		0.063	0.251	0.196	10.03%	0.310
CNN-BiLSTM	30	0.0155	0.124	0.095	4.980%	0.830
CNN-LSTM		0.041	0.203	0.170	8.94%	0.542
CNN-Transformer		0.132	0.363	0.320	17.23%	-0.446
CNN-BiLSTM	60	0.1061	0.325	0.289	15.43%	-0.177
CNN-LSTM		0.007	0.083	0.070	4.163%	0.919
CNN-Transformer		0.050	0.224	0.166	8.433%	0.438

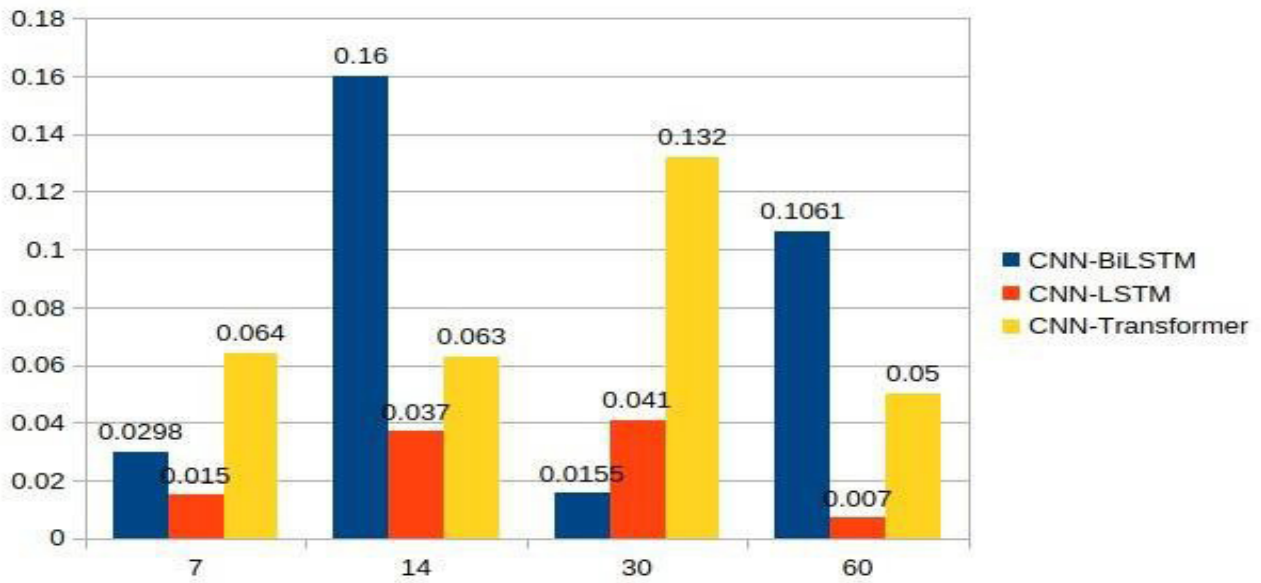


Figure 2. Comparison of MSE values for different models over various input window sizes.

CONCLUSION

In this work, we used daily interval time-series data to assess how well the models predicted Forex. Based on the evaluation metrics across different sequence lengths, the CNN-LSTM model consistently outperformed the other hybrid models for the AUD/USD currency pair. It achieved the lowest average RMSE (0.151), MAE (0.121) and MAPE (6.95%). For example, at the sequence length of 60 days, CNN-LSTM achieved an RMSE of 0.083, which is 74.46% lower than CNN-BiLSTM (0.325) and 62.95% lower than CNN-transformer (0.224). Similarly, its R^2 score of 0.919 was the highest among all models, indicating a strong fit. The MAPE value for some of the models is high, because the MAPE is highly sensitive to small actual values; therefore, if the actual difference between two currencies, or the actual target value the model is trying to predict, is a very small number, then even a minor prediction error in absolute terms can represent a huge percentage error.

Overall, CNN-LSTM demonstrated superior generalisation and prediction accuracy, especially for longer historical input sequences, making it the most effective hybrid model in our experiments for forecasting AUD/USD trends. The CNN-transformer model did not achieve good results in higher sequence lengths compared to the two other models. We suspect this is because the model needs to be more complex, and it also had negative R^2 values observed in some models, particularly for the 30-day and 60-day sequences, indicating poor model generalisation, and performance worse than a naive predictor that simply forecasts the mean exchange rate for all future values. This highlights the limitations of certain architectures at specific sequence lengths and underscores the importance of selecting appropriate model complexity and input size.

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