An Investigation on Forecasting of Indian Rupee Performance Against Global Currencies Using Hybrid Deep Learning Models

*Neeraj Sharma[1], Vaibhav Jain[2]

[1] Department of AIML, Gokaraju Rangaraju Institute of Engineering and Technology, Hyderabad, India
neeraj1749@grietcollege.com

[2] Department of Computer Science and Engineering, Institute of Engineering and Technology, DAVV, Indore, India
vjain@ietdavv.edu.in

Abstract. Hybrid models have gained popularity due to their capacity to identify intricate patterns in time-series data using deep learning architectures. Accurate exchange rate forecasting is essential for risk management and economic decision-making in the extremely unpredictable Forex market. to predict how the Indian Rupee will fluctuate in value with relation to the US dollar, the British pound, and the euro. This study assesses the performance of three hybrid deep learning models: Convolutional Recurrent Neural Network (CRNN), Convolutional Neural Network with Long Short-Term Memory (CNN + LSTM), and Autoencoder with LSTM. Our findings show that the CNN + LSTM model consistently performs better than the other models, producing predictions that are more reliable and accurate. The Autoencoder + LSTM model performs poorly, despite CRNN's respectable performance, suggesting that more tuning is required. This study emphasizes how hybrid models may improve Forex forecasts and how important it is to choose the right hybrid models for particular financial jobs. These projections give investors, financial managers, and legislators critical information for organizing, hedging, and reducing currency risk in international activities.

Keywords: Deep learning, Neural network, Convolutional neural network, Time series analysis, Exchange rate prediction, LSTM, CNN, FOREX Forecasting, Currency Risk Management, Strategic Financial Planning, Managerial Decision Support

1. Introduction –

To predict currency exchange rates, a variety of techniques have been developed, ranging from sophisticated artificial intelligence-based procedures to traditional statistical methods. Machine learning, deep learning, and hybrid deep learning models have garnered a lot of attention lately. International commerce, investment, and economic stability all depend on the FOREX market, the biggest and most liquid financial market in the world. For all parties involved, from investors to politicians, accurate exchange rate forecasting is essential because it guides choices about risk management, arbitrage, and hedging.

To find patterns and connections between currency movements, ML algorithms like ARIMA, SVM, decision trees, and random forests examine historical data. They are good at capturing both linear and nonlinear relationships.

Because deep learning models, namely RNNs and LSTM networks, can read sequential data, they have shown impressive efficacy in FOREX predictions. These models can improve forecast accuracy by finding long-term correlations and underlying trends in time series data. Hybrid models have become effective time-series forecasting tools because they integrate the best features of many deep learning architectures. These models are especially well-suited for intricate financial datasets.

In order to predict the exchange rates of INR-USD, INR-GBP, and INR-EUR over a five-year period, we investigate the effectiveness of three hybrid models: CNN, CNN + LSTM, and Autoencoder + LSTM. Our objective is to determine the best model for Forex forecasting and offer insights into its real-world applications by evaluating their performance using important error metrics such as R-squared error, RMSE and MAE.

2. Related Work –

Since currency rate prediction is so important, a variety of linear and non-linear models have been developed to outperform the random walk model. With the emergence of Artificial Neural Networks (ANNs), researchers and investors see potential in their ability to tackle the complexities of the foreign exchange market. R. Meese et al.

© The Author(s) 2025
R. Nagariya et al. (eds.), *Proceedings of the International Conference on Sustainable Business Practices and Innovative Models (ICSBPIM-2025)*, Advances in Economics, Business and Management Research 349,
https://doi.org/10.2991/978-94-6463-872-1_4

[1] have noted that when the prediction horizon is within a range of months, econometric models are ineffective in forecasting exchange rates.

For forecasting of time-series data, ANNs are preferred due to their self-adaptive, data-driven nature with minimal restrictive assumptions, making them valuable in financial forecasting, where data is abundant but its generation process remains unclear [2]. Additionally, ANNs function as universal approximators [3], and despite some conflicting results, they have shown effectiveness in predicting exchange rates. Since long time, the ARIMA model has been a standard for time series forecasting and is used as a guide for more recent methods [4].
It does, however, assume linear and stationary time series data because it is a univariate model.

C. Zhang et al. have examined recent developments in deep learning for FOREX forecasting from 2020 to 2022 [9].
A. Biswas et al. [8] examined the effect of macroeconomic factors like Gross Domestic Product, trade balances, and government revenue on exchange rates, whereas L. Ni et al. [6] suggested a hybrid (CRNN) model for time series forecasting. Y. Fang et al. [7] investigated how geographical dependencies in time series data differ between samples and suggested fine-grained modeling with spatial correlations. Using GA-NN as a hybrid ML technique for FOREX prediction and ASTAR for statistical modeling, S.W. Sidehabi et al. [10] integrated statistical and ML methodologies.

Certain research on predicting the value of the Indian Rupee in relation to certain major world currencies was discovered. After researching the current theoretical model, Gona et al. [11] developed a model that included variables such as inflation for the Indian Rupee relative to the US dollar. By integrating ANN models with genetic algorithms and predicted INR-USD exchange rates, Sarangi et al. [12] highlighted the applicability of hybrid models. By integrating CNN and RNN models, Sharma et al. [13] used the hybrid model CRNN to anticipate the Indian Rupee's exchange rates against the three main world currencies, the USD, EUR, and GBP. [14] Bijin et al. suggested a multiple regression analysis-based model that uses import and crude oil prices as independent factors and rupee values as the dependent variable to predict future values of the Indian Rupee.
After reviewing the existing work, we identified a research opportunity in analyzing the patterns of major foreign currencies concerning the Indian Rupee (INR) and examining the impact of hybrid models on FOREX market predictions.

3. Objective –

The purpose of this study is to use hybrid models to forecast how the Indian Rupee (INR) will perform in relation to the dollar, euro, and pound. In particular, it contrasts CNN + LSTM, Autoencoder + LSTM, and C-RNN's forecasting skills for FOREX prediction.

4. Methodology –

- The methodology used can be broadly categorized into four steps:
- Data Collection: Download historical exchange rate data (INR/EUR).
- Data Preprocessing: Normalize the data and create sequences.
- Forecasting: Train models using CRNN, CNN + LSTM, and Autoencoder + LSTM.
- Evaluation: To assess the model's performance, use the RMSE, MAE, and R2 measures.

4.1 Data Collection:

The three currency pairs—INR-USD, INR-GBP, and INR-EUR—have their historical exchange rate data downloaded from Yahoo Finance in this stage.

4.2 Data Preprocessing:

In this stage, the data is cleaned and formatted appropriately for machine learning models in order to get it ready for training. Additionally, data pre-processing consists of the following three sub-steps:

- **Normalizing** The 'Close' prices are scaled between 0 and 1 using the normalizing technique MinMaxScaler. This guarantees that the model can learn efficiently and steers clear of problems arising from significant magnitude variations in data.

- **Sequence Creation** Applying a sliding window technique to create time-based sequences of historical data. For instance, forecasting the exchange rate for the following day using data from the preceding 30 days.

- **Train-Test Split** Separate the data into sets for testing and training. Usually, 20% of the data is used for testing, while 80% is used for training. In order to maintain the temporal connections, make sure that the data is divided chronologically (no shuffling).

4.3 Forecasting (Using the Three Approaches):

Approach 1: CRNN (Convolutional Recurrent Neural Network):

Model Structure Conv1D and LSTM layers are combined in this method. Long-term temporal relationships are captured by the LSTM layer, while local patterns are extracted from the time series data by the Conv1D layer.

Training The model is trained on the prepared sequences using the Adam optimizer and the MSE loss function.

Approach 2: CNN + LSTM:

Model Structure A Conv1D layer is followed by a MaxPooling1D layer for feature extraction. The output is passed to an LSTM layer to capture the sequential patterns of the data.

Training Similar to the CRNN model, this approach uses the Adam optimizer and MSE loss function for training the model.

Approach 3: Autoencoder + LSTM:

Model Structure In order to extract features from the data, the autoencoder must first be trained. The data is compressed by the autoencoder's encoder and reconstructed by the decoder. After that, an LSTM layer receives the encoder's characteristics in order to forecast time series.

Training The autoencoder is trained first, followed by training the LSTM model using the features extracted by the encoder.

4.4 Evaluation:

In this stage, we make predictions on the test set using the trained models. Model performance was evaluated using three common forecasting metrics: R-squared (R^2), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). These metrics enabled a comparative performance assessment to identify the most suitable architecture for accurate currency rate forecasting.

4.5 Implementation –

To conduct the exchange rate forecasting, we utilized three hybrid deep learning frameworks: CRNN, CNN + LSTM, and Autoencoder + LSTM. The historical data for INR/USD, INR/EUR, and INR/GBP exchange rates, spanning from December 16, 2019 to December 15, 2024, was obtained from Yahoo Finance. The datasets, comprising daily closing values, were initially scaled using the Min-Max normalization technique and then organized into time-series input sequences suitable for model training.
Each model architecture was trained independently on the prepared datasets:

- **CRNN** combines convolutional layers to capture local patterns and LSTM layers to identify long-range temporal relationships.
- **CNN + LSTM** applies convolutional operations to extract spatial features before passing them through LSTM layers that model sequential dependencies.
- **Autoencoder + LSTM** first compresses and reconstructs the input data using an autoencoder, then uses the encoder's output as input to the LSTM for sequence prediction.

4.6 Results –

Model evaluation was performed using three widely accepted error measures: RMSE, MAE, and R^2, across all three currency pairs (INR/USD, INR/GBP, INR/EUR). Tables 1 and 2 present the performance summaries of the hybrid models.

Table 1. Performances of Hybrid Models on INR/GBP and USD

	INR/GBP Performance			INR/USD Performance		
Model	RMSE	MAE	R^2	RMSE	MAE	R^2
CNN + LSTM	5.54e-05	4.20e-05	0.9055	2.10e-05	1.50e-05	0.9089
Autoencoder + LSTM	2.54e-04	2.20e-04	-0.9791	7.22e-05	5.79e-05	-0.0727
CRNN	1.20e-04	8.30e-05	0.5828	5.41e-05	4.67e-05	0.3985

Table 2. INR/EUR Performance

Model	RMSE	MAE	R^2
CNN + LSTM	7.77e-05	6.08e-05	0.7730
Autoencoder + LSTM	2.16e-04	1.77e-04	-0.7553
CRNN	8.60e-05	6.67e-05	0.7217

INR/USD & INR/GBP Results For the INR/USD currency pair, the CNN + LSTM model delivered the most accurate predictions, recording the lowest RMSE (2.10e-05), lowest MAE (1.50e-05), and highest R^2 (0.91), indicating a strong model fit. The CRNN achieved moderate accuracy (RMSE: 5.41e-05; MAE: 4.67e-05; R^2: 0.40), while the Autoencoder + LSTM performed least effectively (RMSE: 7.22e-05; MAE: 5.79e-05; R^2: -0.07).

Similarly, for the INR/GBP dataset, CNN + LSTM continued to outperform the other models (RMSE: 5.54e-05; MAE: 4.20e-05; R^2: 0.91). The CRNN yielded moderate results (RMSE: 1.20e-04; MAE: 8.30e-05; R^2: 0.58), while the Autoencoder + LSTM model struggled significantly (RMSE: 2.54e-04; MAE: 2.20e-04; R^2: -0.98).

INR/EUR Results When applied to INR/EUR predictions, CNN + LSTM maintained superior performance, achieving an RMSE of 7.77e-05, an MAE of 6.08e-05, and an R^2 of 0.77. The CRNN again showed moderate predictive strength (RMSE: 8.60e-05; MAE: 6.67e-05; R^2: 0.72), while Autoencoder + LSTM produced the weakest results (RMSE: 2.16e-04; MAE: 1.77e-04; R^2: -0.76).

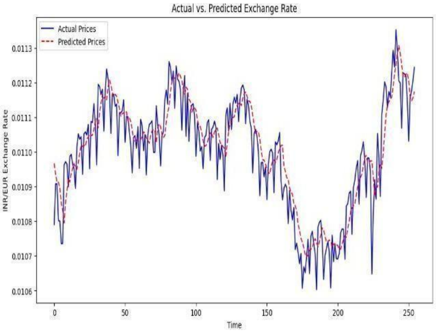

Fig1. INR/EUR CNN + LSTM Actual vs. Predicted

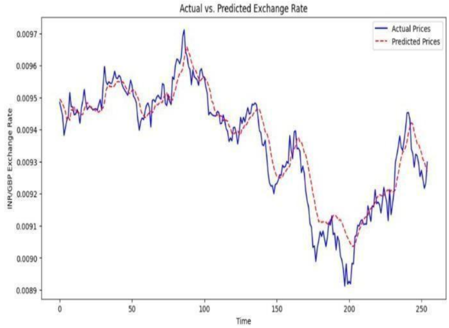

Fig2. INR/GBP CNN + LSTM Actual vs. Predicted

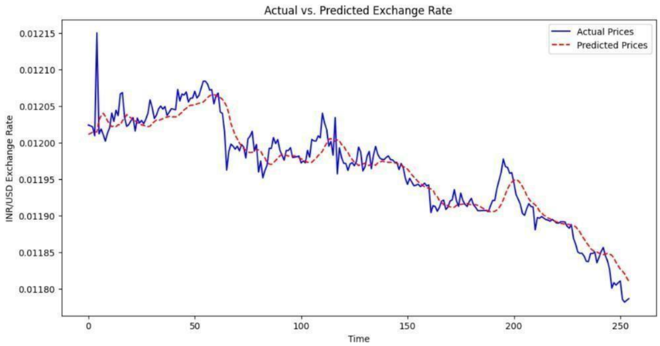

Fig. 3 INR/USD CNN + LSTM Actual vs. Predicted

Figures 1–3 present actual versus predicted values for the three currency pairs, with CNN + LSTM applied. While the INR/EUR and INR/GBP predictions aligned closely with actual trends, the INR/USD forecast revealed minor deviations.

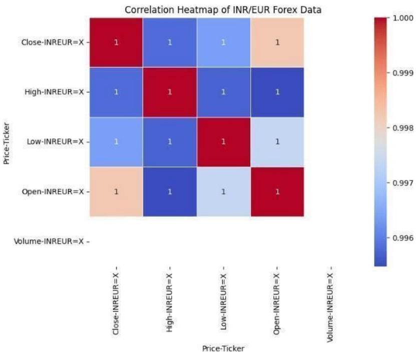

Fig 4. Correlation Heatmap of INR/EUR Forex Data

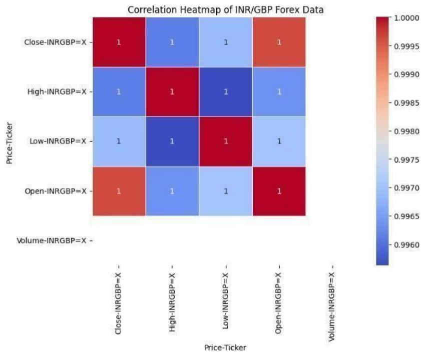

Fig 5. Correlation Heatmap of INR/GBP Forex Data

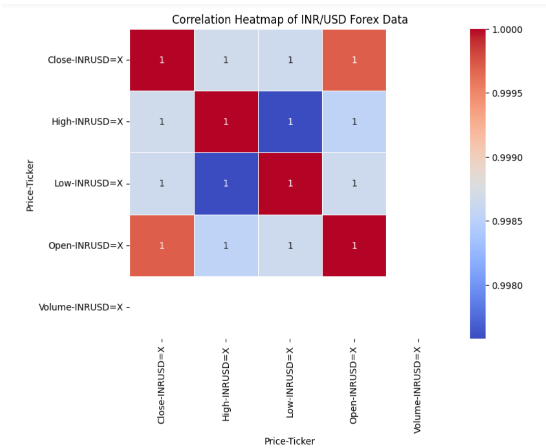

Fig. 6 INR/USD CNN + LSTM Heatmap

As can be seen in Fig. 4, the heatmap displays extremely significant correlations (around 1.000) between the INR/EUR open, high, low, and close values. Compared to the others, the cheap price has a somewhat less correlation (~0.996-0.997), but it is still quite significant. The poorest correlation (~0.996) between volume and price-related metrics suggests that changes in volume may not always translate into price adjustments. The close, high, low, and open prices all exhibit almost perfect connection (~1.000), as seen in Fig. 5. Compared to the Open and Close, the Low price has a somewhat weaker correlation (~0.996-0.997). The correlation pattern between the INR and USD is somewhat similar to that of the preceding two currency pairs, as seen in Fig. 6. A large correlation (~1.000) still exists between the Close, High, Low, and Open prices. all three heatmaps display a similar correlation pattern. When it comes to price-related metrics, INR/USD has a somewhat greater connection than INR/EUR and INR/GBP.

5. Conclusion –

This study evaluated the predictive capabilities of three hybrid deep learning models—CNN + LSTM, CRNN, and Autoencoder + LSTM—across INR/USD, INR/GBP, and INR/EUR FOREX datasets. The findings consistently highlight CNN + LSTM as the most effective model, achieving the lowest RMSE and MAE values alongside the highest R^2 scores across all currency pairs. These results reaffirm its reliability in capturing complex Forex patterns and forecasting exchange rate movements.

The CRNN model demonstrated moderate predictive accuracy, with performance varying across datasets. While it performed better than Autoencoder + LSTM, it consistently lagged behind CNN + LSTM in terms of accuracy and explanatory power.

The Autoencoder + LSTM model exhibited the weakest predictive performance, with higher RMSE and MAE values and negative R^2 scores, indicating poor forecasting capability. This suggests that the autoencoder component struggled to extract meaningful time-series features, making it unsuitable for Forex prediction in its current form.

Overall, the study underscores the effectiveness of CNN + LSTM in financial market predictions, while CRNN serves as a viable but less accurate alternative. The Autoencoder + LSTM model's limitations highlight the need for further refinement in time-series feature extraction techniques for Forex forecasting applications.

These findings are not only technically significant but also crucial for financial managers and business leaders aiming to incorporate data-driven strategies in global currency exposure management. The research contributes to managerial finance by enhancing risk anticipation and resource optimization.

References

1. R. Meese and K. Rogoff, "Empirical exchange rate models of the seventies: do they fit out of sample?" Journal of International Economics, vol. 14, pp. 3–24, 1983.
2. M. Qi and G.P. Zhang, "An investigation of model selection criteria for neural network time series forecasting," European Journal of Operational Research, vol. 132, pp. 666-680, 2001.
3. K. Horik, M. Stinchcombe, and H. White, "Multilayer feedforward networks are universal approximators," Neural Networks, vol. 2, no. 5, pp. 359–366, 1989.
4. H. Hwarng and T. Ang, "A Simple Neural Network for ARMA(p,q) Time Series," OMEGA : International Journal of Management Science, vol. 29, pp. 319–333, 2002.
5. C. U. Yıldıran and A. Fettahoğlu, "Forecasting USDTRY rate by ARIMA method," Cogent Economics & Finance, vol. 5, no. 1, p. 1335968, 2017.
6. L. Ni, Y. Li, X. Wang, J. Zhang, J. Yu, and C. Qi, "Forecasting of forex time series data based on deep learning," Procedia computer science, vol. 147, pp. 647–652, 2019.
7. Y. Fang, K. Ren, C. Shan, Y. Shen, Y. Li, W. Zhang, Y. Yu, and D. Li, "Learning decomposed spatial relations for multi variate time-series modeling," in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 37, no. 6, pp. 7530 7538, 2023.
8. A. Biswas, I. A. Uday, K. M. Rahat, M. S. Akter, and M. R. C. Mahdy, "Forecasting the United State Dollar (USD)/ Bangladeshi Taka (BDT) exchange rate with deep learning models: Inclusion of macroeconomic factors influencing the currency exchange rates," Plos one, vol. 18, no. 2, p. e0279602, 2023.
9. C. Zhang, N. N. A. Sjarif, and R. Ibrahim, "Deep learning models for price forecasting of financial time series: A review of recent advancements: 2020–2022," Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, p. e1519, 2023.

10. S. W. Sidehabi and S. Tandungan, "Statistical and machine learning approach in forex prediction based on empirical data," in 2016 International Conference on Computational Intelligence and Cybernetics, pp. 63-68, IEEE, 2016
11. Gona, B. R., & Sahoo, M. (2020). Exchange rate policy modeling and forecasting the exchange rate: Indian rupee vis-à-vis the US dollar. Journal of Public Affairs, 20(3), e2073.
12. Sarangi, P. K., Chawla, M., Ghosh, P., Singh, S., & Singh, P. K. (2022). FOREX trend analysis using machine learning techniques: INR vs USD currency exchange rate using ANN-GA hybrid approach. Materials Today: Proceedings, 49, 3170 3176.
13. Sharma, N., Dwivedi, G., & Dwivedi, A. (2024). Forecasting of Indian Currency Exchange Rates Time Series Data Based on Deep Learning. In Multifaceted approaches for Data Acquisition, Processing & Communication (pp. 202-207). CRC Press. -
14. Philip, B., Bajaj, K., & Pareek, W. (2023, January). Indian rupee: is it unpredictable? A regression model to predict the value of the Indian rupee. In International Conference on Economics, Business and Sustainability (pp. 127-143). Singapore: Springer Nature Singapor

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (http://creativecommons.org/licenses/by-nc/4.0/), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.