A Novel FIG-LSTM Ensemble Machine Learning Technique for Currency Exchange Rate Forecasting

Temitope Alade
School of Computing Sciences
University of East Anglia
Norwich, UK
T.Alade@uea.ac.uk

Ogonna Okafor
Dept. of Computer Science
Nottingham Trent University
Nottingham, UK
ogonna.okafor2022@my.ntu.ac.uk

***Abstract*—Accurately predicting currency exchange rate behaviour remains a major challenge for all stakeholders (e.g. traders, investment firms, banks, etc.) in the foreign exchange (forex) market. Developing machine learning models that offer more accurate and potentially more reliable predictions is identified as a critical objective for the forex market. To address this issue, this paper proposes an ensemble machine learning model that integrates fuzzy information granule (FIG) with long short-term memory (LSTM) in a gated recurrent unit (GRU) to achieve a better forex forecasting performance. The proposed model uses open, high, low, close (OHLC) data and relevant technical indicators such as moving average, bollinger bands, %b, bandwidth, moving average convergence divergence (MACD), relative strength index (RSI), and average true range (ATR) as inputs. The outputs of the combined FIG and LSTM models are passed into a trained GRU model to make the final forex prediction. To evaluate the predictive performance of the proposed model, experiments are conducted using one-day candles of three of the most traded currency pairs, EUR/USD, USD/GBP and USD/CAD from 01 August 2019 to 31 December 2023 data set. The proposed model shows better forecasting performance in terms of root mean squared error (RMSE), mean absolute percentage error (MAPE), mean absolute error (MAE), and coefficient of determination (R^2) values when compared with conventional LSTM, FIG and GRU prediction models. The proposed FIG-LSTM model also outperforms a state-of-the-art GRU-LSTM hybrid prediction model.**

***Index Terms*—Machine learning, exchange rate forecasting, fuzzy time series, long short-term memory, fuzzy information granule, gated recurrent unit**

I. Introduction

With hundreds of currency combinations to choose from, the influence of economic and geopolitical events, as well as traders' expectations on changing market conditions, the foreign exchange (forex) market is the largest and most volatile market in the world [1]. Accurately predicting currency exchange rate fluctuations is vital to all stakeholders (e.g. traders, investment firms, banks, etc.) to support investment decisions and policy making. A wide variety of exchange rate forecasting models have been proposed over the years using statistical methods such as the autoregressive integrated moving average (ARIMA) [2], structural models [3] and Bayesian theory based models [4]. A common problem with these approaches is the assumption that the time series being predicted is linear and stationary [5]. According to [6], the financial market is non-stationary and nonlinear. With increased availability of historical data, rise in computing power and advances in machine learning, the use of machine learning algorithms for forex market prediction has drawn considerable attention. Deep learning models such as long short-term memory (LSTM) and gated recurrent unit (GRU) have been explored in [7] and [8] respectively, and shown to produce better forex price prediction results than statistical models. Fuzzy logic techniques have been successfully used to perform price predictions in [9] and demonstrated comparable predictive accuracy to deep learning models and other machine learning algorithms. Machine learning techniques are able to model complex, nonlinear relationships in the data and can adjust to changing market conditions. More recently, hybrid forecasting approaches [10] which combine machine learning techniques with other approaches have shown to provide better forecasting performance than standalone techniques. Combining different prediction methods enables taking advantage of each component model strengths and potentially overcoming the limitations of individual models. This paper proposes a novel FIG-LSTM ensemble model that combines fuzzy information granulation (FIG) with LSTM in a GRU ensemble to enhance forex price forecasting. A combined FIG and LSTM model in a GRU ensemble overcomes the weakness in fuzzy rules based methods in handling multivariate features and can significantly improve forecasting performance. There are currently no studies on exchange rate forecasting that combines neural networks and fuzzy systems in an ensemble for more accurate predictions. The proposed model is applied to three of the most traded currency pairs, EUR/USD, USD/GBP, and USD/CAD, and its forecasting accuracy is evaluated using root mean squared error (RMSE), mean absolute percentage error (MAPE), mean absolute error (MAE), and coefficient of determination (R^2) values. To evaluate the performance of the proposed FIG-LSTM model, the conventional LSTM, FIG and GRU prediction models, as well as a state-of-the-art GRU-LSTM hybrid prediction model [18] are constructed and included in comparison experiments. Results show that the proposed architecture outperforms individual machine learning models and the GRU-LSTM hybrid architecture. The remainder of the paper is organized as follows. Machine learning algorithms for forex prediction are examined in section II, the proposed model and data collection methodology are shown in section III, experimental results and findings are discussed in section IV, and conclusions are drawn in section V.

II. Machine Learning Techniques for Forex Price Forecasting

The use of machine learning techniques for forex market prediction has drawn considerable attention in recent years. Machine learning methods encompass a broad range of algorithms that enable computers to learn patterns from data without explicit programming [11]. These techniques can be broadly categorized into supervised learning, unsupervised learning, reinforcement learning, hybrid approaches, and ensemble learning methods. Each category offers unique perspectives on the intricate task of predicting currency movements.

Popular supervised learning algorithms such as support vector machine (SVM), artificial neural networks (ANN) and recurrent neural networks (RNNs) have been successfully used in [12] to obtain good exchange rate forecasting thanks to their ability to generalize well and handle nonlinearity. Deep learning methods such as LSTM approaches have become increasingly popular. They leverage ANN with multiple layers (deep neural networks) [13]. In [14], the impact of news sentiment exchange rate was investigated by using a FinBERT-based model, a deep learning approach and demonstrated the model's superiority over alternative sentiment analysis approaches in predicting forex market movements.

In unsupervised learning, the machine learns patterns from a large amount of unlabeled data and predicts the potential distribution of the data. Unsupervised feature extraction using stacked autoencoders was successfully used for forex prediction in [15].

Reinforcement learning, a robust autonomous learning framework where the machine interacts directly with the environment has also been successfully applied in exchange rate forecasting. In [16], the deep Q-learning model was shown to significantly outperform the baseline buy and hold strategy in forecasting EUR/USD and USD/JPY price movements.

Hybrid methods are those that combine elements from different modeling approaches to leverage their respective strengths and forecasting capabilities [17]. Studies in [18] proposed the use of a hybrid GRU-LSTM models to improve the accuracy of forex projections. It was shown that the hybrid GRU-LSTM provides more accurate predictions of forex trends. An integrated model that combined wavelet denoising, ARNN, and ARIMA was proposed in [19]. Results obtained demonstrates superior performance in predicting USD/JPY five-minute data, showcasing the synergies achieved through hybridizing different techniques.

Ensemble learning methods, on the other hand, involve combining multiple models to improve overall performance using techniques such as bagging (Bootstrap Aggregating) and boosting (combining weak learners into a strong learner) [20]. Incorporating ensemble learning methods, studies in [21] presented an approach which combines EmcSVM and fuzzy NSGA-II for efficient trend classification. The ensemble learning method outperformed existing crisp trading systems, achieving high precision, recall rates, annual ROI, and a modest drawdown when tested on real data from the EUR/USD currency pair over six years (2014 to 2019).

Exchange rate forecasting with 100% accuracy may not be possible but their overall forecasting accuracy and performance can be improved. As such, this paper proposes an ensemble learning approach that combines fuzzy information granule (FIG) with long short-term memory (LSTM) in a gated recurrent unit (GRU) to achieve a better forex forecasting performance. Fuzzy logic is a mathematical framework that deals with uncertainty by allowing for degrees of truth [22]. Fuzzy-based methods use fuzzy sets and rules to handle imprecise or uncertain information [23]. A fuzzy-based method was investigated in [24] to predict trends through the application of Fuzzy rough sets. Their method produced high-quality forecasts for short horizons and small change thresholds across fifteen currency pairs, emphasizing the effectiveness of fuzzy-based models. It is worth noting that no previous study has explored neuro-fuzzy systems in ensembles, such as combining the FIG system and LSTM with a trained GRU model.

III. Methods and Data Set

A. Proposed FIG-LSTM Machine Learning Model

This paper develops an ensemble machine learning model that integrates fuzzy information granule (FIG) with long short-term memory (LSTM) in a gated recurrent unit (GRU) to achieve an improved forex forecasting accuracy. The workflow diagram of the proposed FIG-LSTM learning is shown in Fig. 1. The standard architecture of FIG, LSTM and GRU models is shown in Fig. 2.

- FIG FTS method involves breaking down the time series into successive pieces of simpler subseries represented by fuzzy sets [23]. It provides interpretability and comprehensibility in the analysis process. In this study, the granulation method and hyperparameter tuning conducted in [25] is adopted as it fulfills the need to leverage fuzzy logic and exploit the relationships between historical data points in the forex market.
- LSTM network is a variation of recurrent neural network (RNN) which adds long and short-term memory to the network. It was first introduced by Hochreiter and Schmidhuber [26] and it is the most commonly used model in recursive RNNs. An LSTM network architecture consists of interconnected memory cells. The cell state is a key element of the LSTM network. The memory cell consists of three gates namely, input, forget and output gate. The input gate decides whether to add new information to the cell state, the forget gate decides which information is to deduct from the cell state, and the output gate decides what new information is going to be stored in the cell state.
- GRU is a type of recurrent neural network (RNN) proposed by [27] to enable each recurrent unit to adaptively capture dependencies of different time scales. GRU incorporates two gating mechanisms, an update gate and reset gate to control the flow of information within the unit. The update gate enables the GRU model to capture how much of past information from the previous state is required for future timestep, while the reset gate

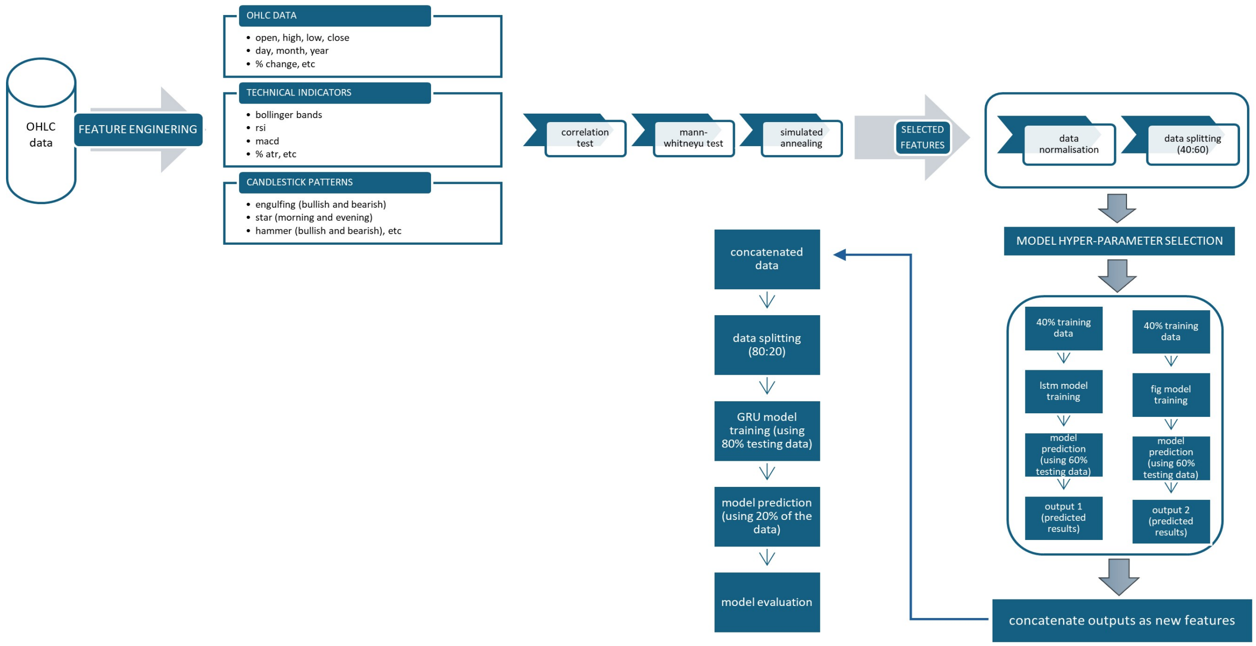

Fig. 1. Proposed FIG-LSTM workflow

helps to detect information that should be ignored, and information that should be considered in computing the next hidden state.

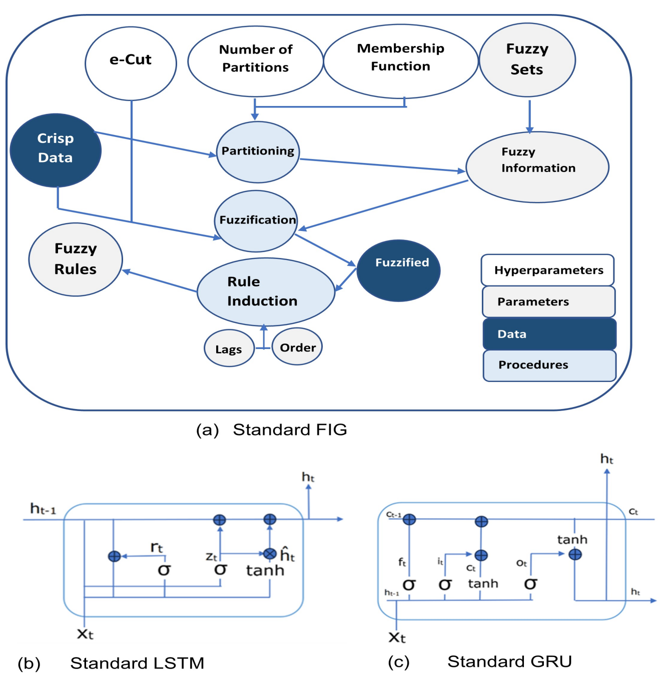

Fig. 2. Standard architecture of FIG, LSTM and GRU models

- The proposed FIG-LSTM model is implemented using LSTM and GRU models, each consisting of a single hidden layer with 256 neurons. The models also include two dense layers with 2048 neurons and 1 single neuron respectively. The FIG FTS model is designed with an order of 2 and employs K-Nearest Neighbours (KNN) with a value of 3. The LSTM and FIG-FTS models are trained using 1-day interval data and the outputs from these models are then concatenated and split into training and testing sets in an 80:20 ratio. The training data is fed as input to the GRU model, the test data is passed into the trained model to obtain the final forecast and the models performance is evaluated. The FIG-LSTM model combines the capabilities of fuzzy logic (FIG) and the temporal understanding of sequential data provided by LSTM. This fusion allows the model to capture both the inherent uncertainty in financial markets and the temporal dependencies in market movements. Simulated annealing is incorporated for feature selection and ensures that the model uses the most relevant features. This process enhances the model's ability to focus on critical market indicators, improving its overall predictive performance. The GRU model allows the model to learn the optimal weights during training instead of using fixed weights for combining FIG and LSTM predictions. This automatic weighting ensures that more accurate predictions contribute to the final ensemble output, improving the robustness and adaptability of the overall model.

Hyper-parameters must be determined before training the model. Hyper-parameters are fine-tuned to obtain optimal prediction models. The hyper-parameters considered for tuning include learning rate (0.001, 0.002, 0.003), number of units (32, 64, 128, 256, 512), dropout rate (0, 0.1, 0.2, 0.3, 0.4), and dense units (32, 64, 128, 256, 512, 1024, 2048). Hyper-parameter tuning for the LSTM model is determined using the KerasRegressor wrapper, along with the GridSearchCV algorithm in python. The GridSearchCV algorithm is also used to generate predictions with 2-fold cross-validation. The Adam optimiser [28] is used to find the optimal learning rate. The maximum number of epoch is set to 100, the batch size of 14 instances for each iteration is used. The same parameter settings are applied to the GRU model. All experiments were performed using Python programming language with libraries such as TensorFlow, Scikit-learn, NumPy, PyFTS and Pandas.

B. Data Set and Feature Engineering

The data set used consist of exchange rates of three of the most traded currency pairs, EUR/USD, USD/GBP and USD/CAD covering the period from 01 August 2019 to 31 December 2023. The data was retrieved from [29] and consist of one-day timeframe data where each data set contains a total of seven attributes namely, Date and Time, Open price, High price, Low price, Close price, Change in Pips, and Change in Percentage. The dataset was divided into two: 40% of the dataset was used for LSTM and FIG-FTS model training, and 60% was used for testing purposes. Test results were combined and further divided into two: 80% of it was used for GRU model training, and 20% for final testing.

To identify features and patterns from the data set for model training, feature engineering methods based on candlesticks pattern and technical indicators were applied. One-day candlestick patterns was used to predict market the price movement. Candlestick chart comprises two main parts [30]; the body, and the wicks (upper and lower) as shown in Fig. 3. The body represents the price range between the opening and the closing prices within a time interval, while the wicks represent the maximum and minimum price reached during the time interval. If the closing price is higher than the opening price, the body is colored white or green color in European and American forex markets, indicating a bullish trend. If the closing price is lower than opening price, the body is colored with red indicating a bearish trend. In this study, the open, close, high and low of each bar is transformed into stationary representations by capturing relative sizes of the candlestick bar parts, the body, the lower wick and the upper wick. Technical indicators are series of data points obtained by applying a formula to price time series data to generate additional data that helps to analyse market trends, volatility, momentum, and other aspects of price movements [31]. Seven relevant technical indicators namely:- moving average, bollinger bands, %b, bandwidth, moving average convergence divergence (MACD), relative strength index (RSI), and average true range (ATR) are implemented according to calculations in [31].

To prepare the data set for analysis, manually calculated features and technical indicators were added to the data set, and missing values added as a result of this were discarded to ensure the integrity and consistency of the data set. Three new columns, namely day, month, and year, were generated from the date column and one-hot encoded before being used by the the model. One-hot encoding converts categorical variables into binary columns so that they can be used as features in machine learning algorithms. The standard Min-Max normalization technique [32] was used to normalize the remaining numerical columns in the dataset to values between 0 and 1. This ensures that there are no zeros and negative values.

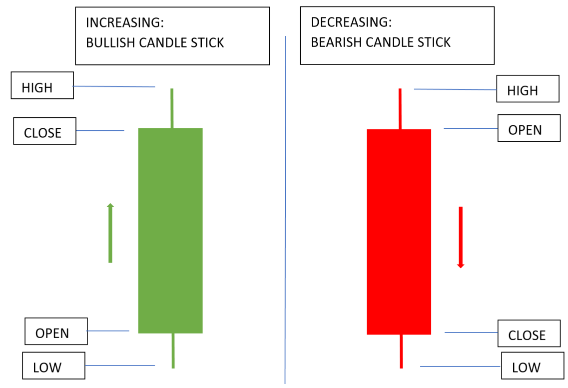

Fig. 3. Candlestik patterns

To select the most important features from the data set, a feature selection technique known as simulated annealing (SA) [33] is applied. SA is one of the most popular optimization approaches that generates options that evolve over time. It starts with an initial subset of features, which is iteratively modified by adding or removing features. SA uses evaluation metric such as mean squared error to measure each subset's performance, and accepts or rejects modifications based on a probability criterion.

C. Performance Evaluation Methods

The prediction accuracy of the proposed model is evaluated using RMSE, MAPE, MAE and R^2. These metrics are the most commonly used for regression analysis [10].
RMSE measures the average difference between the actual values and values predicted by the model. It estimates how well the model is able to predict the actual value and can be represented mathematically as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i-1}^{n}(y_i - \hat{y})^2} \tag{1}$$

MAPE measures the absolute percentage difference between the actual and predicted values, and is derived as follow:

$$MAPE = \frac{1}{n}\sum_{i-1}^{n}\left|\frac{y_i - \hat{y}}{y_i}\right| \times 100\% \tag{2}$$

MAE represents the arithmetic mean of absolute errors, it is obtained by averaging the difference between the actual and predicted values as follows:

$$MAE = \frac{1}{n}\sum_{i-1}^{n}|y_i - \hat{y}| \tag{3}$$

R^2 indicates how good the prediction model fits the dataset. R^2 values ranges between 0 and 1 and is derived as follows:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \overline{y})^2} \tag{4}$$

In (1) - (4), n is the number of data samples; $\hat{y}$ is the predicted value; and y is the actual value. The closer the values of RMSE, MAPE and MAE are to 0, the higher the accuracy performance of the prediction model. On the other hand, the closer the value of R^2 is to 1, the better the model is at predicting the actual value.

IV. Experimental Results

In this section, the forecasting performance of the three conventional models including LSTM, FIG, and GRU, and the GRU-LSTM hybrid prediction model proposed in [18] is compared with the proposed FIG-LSTM model to verify their accuracy. For convenience, LSTM, FIG, and GRU models will be referred to as the conventional models. Experiments are conducted using one-day candles of three of the most traded currency pairs, EUR/USD, USD/GBP, and USD/CAD from 01 August 2019 to 31 December 2023 data set. The FIG-LSTM ensemble model is trained along with the conventional models, and the GRU-LSTM hybrid using the same data set. Feature extraction is enhanced using simulated annealing, and hyperparameter tuning is conducted on the LSTM model, with the same configuration applied to the GRU model. The parameter settings are given in the Table 1.

TABLE I
Table of Parameters

Parameter	LSTM	GRU	FIG
Hidden Layer	1	1	-
Neurons	256	256	-
Dense Layers	2 (2048, 1)	2 (2048, 1)	-
Optimizer	Adam	Adam	-
Learning Rate	0.03	0.03	-
Activation	ReLU	ReLU	-
Dropout	0.1	0.1	-
Batch Size	14	14	-
Epochs	100	100	-
K Nearest Neighbours	-	-	3
Order	-	-	2
Number of Partitions	-	-	16
Alpha Cut	-	-	0.1
Membership Function	-	-	Gaussian

In Figures 4, 5 and 6, the y-axis represents the predicted normalized exchange rates, and the x-axis denotes the number of samples or time steps in days. The actual rate which represents the actual normalized exchange rates from the test data set is shown in black color, the FIG-LSTM model is marked in green color, the LSTM model is marked in red color, the GRU-LSTM model is marked in blue color, the FIG model is marked in gold color, and the GRU model is marked in purple color.

Fig. 4 presents a comparison of exchange rate predictions by the proposed FIG-LSTM model, the conventional models, and the GRU-LSTM hybrid model with the actual rate for the EUR/USD currency pair. It is observed that the FIG-LSTM model has learnt the exchange rate movements of the EUR/USD currency pair and its values closely aligns with the actual rate. The proposed FIG-LSTM model demonstrates superior accuracy and precision over the conventional models, and the GRU-LSTM hybrid model. The conventional models, and the GRU-LSTM hybrid model exhibit varying degrees of deviation from the actual rate.

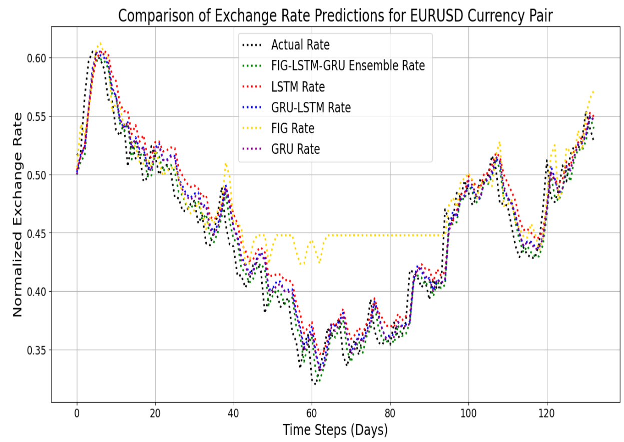

Fig. 4. Prediction performance for EUR/USD

Fig. 5 compares exchange rates predicted by the proposed FIG-LSTM model, the conventional models, and the GRU-LSTM hybrid model with the actual rate for the USD/GBP currency pair. It is clearly shown in Fig. 5 that the FIG-LSTM model achieves the best performance as it matches the actual rate values more closely. The conventional models, and the GRU-LSTM hybrid model exhibit more significant deviations from the actual rate. More specifically, the prediction values of proposed FIG-LSTM model aligns more closely to the actual rate than the GRU-LSTM hybrid model, demonstrating its superior forecasting accuracy.

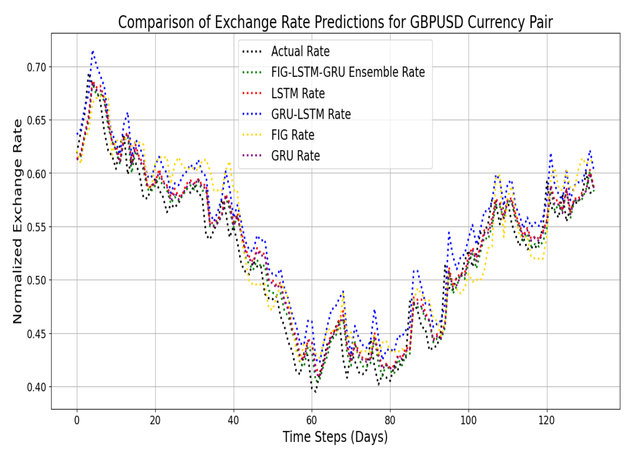

Fig. 5. Prediction performance for GBP/USD

Fig. 6 shows the comparison of exchange rates predicted by the proposed FIG-LSTM model, the conventional models, and the GRU-LSTM hybrid model against the actual rate for the USD/CAD currency pair. The FIG-LSTM model achieves the best results and shows a higher degree of agreement with the actual rate than the conventional models, and the GRU-LSTM hybrid model, demonstrating its superior performance.

To prove the effectiveness and forecasting accuracy of the proposed FIG-LSTM model, its performance is further

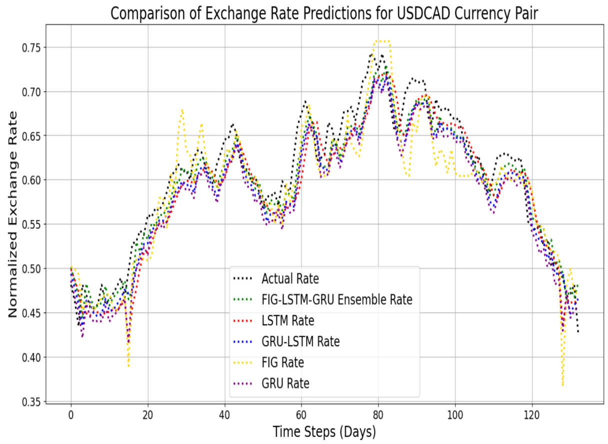

Fig. 6. Prediction performance for USD/CAD

evaluated and compared with the conventional models, and the GRU-LSTM hybrid model using RMSE, MAPE, MAE and R^2 values for EUR/USD, USD/GBP and USD/CAD currency pairs in Tables II, III and IV respectively. The best results are highlighted in bold.

Table II presents the accuracy performance of the conventional models, the GRU-LSTM hybrid model, and the proposed FIG-LSTM model for EUR/USD currency pair. The results obtained show that the proposed FIG-LSTM model outperforms the conventional models and the GRU-LSTM hybrid model. The proposed FIG-LSTM model is the most accurate approach as it achieves the lowest RMSE, MAPE and MAE values, and the highest R^2 value for the EUR/USD currency pair.

TABLE II
EUR/USD PERFORMANCE

MODELS	RMSE	MAPE	MAE	R^2
LSTM	0.02110	3.8784	0.01695	0.9064
FIG	0.04839	9.3615	0.03681	0.5078
GRU	0.01844	3.2284	0.01418	0.9285
GRU-LSTM Hybrid	0.01825	3.1312	0.01385	0.9299
FIG-LSTM (proposed)	**0.01786**	**3.0018**	**0.01334**	**0.9330**

Table III presents the accuracy performance of the conventional models, the GRU-LSTM hybrid model, and the proposed FIG-LSTM model for the USD/GBP currency pair. The results indicate that the FIG-LSTM model has an exceptionally higher forecasting ability than the conventional models and the GRU-LSTM hybrid model, achieving the lowest RMSE, MAPE and MAE values, and the highest R^2 value for the USD/GBP currency pair.

TABLE III
USD/GBP PERFORMANCE

MODELS	RMSE	MAPE	MAE	R^2
LSTM	0.01913	2.9996	0.015189	0.9324
FIG	0.02869	4.6696	0.024098	0.8480
GRU	0.01817	2.7890	0.014150	0.9391
GRU-LSTM Hybrid	0.02811	4.8642	0.024388	0.8540
FIG-LSTM (proposed)	**0.01703**	**2.5596**	**0.013108**	**0.9464**

Table IV presents the accuracy performance of the conventional models, the GRU-LSTM hybrid model, and the proposed FIG-LSTM model for the USD/CAD currency pair. Clearly, the best results are obtained by the FIG-LSTM model in terms of RMSE, MAPE, MAE and R^2 values for the USD/CAD currency pair. The FIG-LSTM model demonstrates a very good fits with the experimentally acquired data than the conventional models, and the GRU-LSTM hybrid model.

TABLE IV
USD/CAD PERFORMANCE

MODELS	RMSE	MAPE	MAE	R^2
LSTM	0.02934	3.9776	0.02381	0.8571
FIG	0.03533	4.4666	0.02697	0.794
GRU	0.03076	4.3506	0.02622	0.843
GRU-LSTM Hybrid	0.02534	3.473	0.02107	0.8935
FIG-LSTM (proposed)	**0.02154**	**2.8809**	**0.01731**	**0.9229**

V. CONCLUSION

In this paper, a novel ensemble machine learning model that combines FIG with LSTM in a GRU is developed to improve currency exchange rate forecasting accuracy. The proposed model consists of a trained FIG, and LSTM algorithms as base learners. The outputs of the FIG, and LSTM models are then passed into a trained GRU model to make the final prediction. The FIG-LSTM model was tested with real daily prices of three of the most traded currency pairs, EUR/USD, USD/GBP and USD/CAD currency pairs from 01 August 2019 to 31 December 2023. Results obtained shows that the proposed FIG-LSTM model outperforms well-known individual models including LSTM, FIG, GRU and the GRU-LSTM hybrid model across all performance evaluation metrics. The outstanding performance achieved by the FIG-LSTM model confirms that the training sample of the model effectively learns the exchange rate patterns through the predictor variables and is an effective and promising approach to forecast forex rates. This study contributes to efforts towards developing machine learning techniques for accurate and timely predictions to support decision-making in the forex market. The proposed method can be applied to more currency pairs, as well as stocks, bonds, and cryptocurrency as a future research direction.

REFERENCES

[1] Bank for International Settlements, ”Foreign Exchange Turnover in April 2019”, https://www.bis.org/statistics/rpfx19_fx.htm” [Accessed 31st December 2023].

[2] G. E. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, ”Time Series Analysis: Forecasting and Control,” Hoboken, NJ, USA: Wiley, 2015.

[3] K. Anton, ”A Structural Model of Exchange Rate Dynamics,” Review of Business and Economics Studies, vol.3, pp. 86-92 2014.

[4] J. P. Byrne, D. Korobilis, and P. J. Ribeiro, ”Exchange rate predictability in a changing world,” J. Int. Money Financ., vol. 62, pp. 1–24, Apr. 2016.

[5] L. Cao, F. Tay, ”Financial Forecasting Using Support Vector Machines,” Neural Comput. Appl., vol. 10, pp 184–192, 2001.

[6] R. Salles, K. Belloze, F. Porto, P. H. Gonzalez, and E. Ogasawara, “Nonstationary time series transformation methods: An experimental review.,”Knowl Based Syst., vol. 164, pp. 274-291, 2018.

[7] S. Ahmed, S.-U. Hassan, N. R. Aljohani, and R. Nawaz, “FLF-LSTM: A novel prediction system using Forex loss function,” Appl. Soft Comput., vol. 97, Dec. 2020, Art. no. 106780.

[8] K. Cho, B. V.Merriënboer, D. Bahdanau, and Y. Bengio, "On the properties of neural machine translation: Encoder-decoder approaches," in Proc. 8th Workshop Syntax, Semant. Struct. Statist. Transl., Doha, Qatar, pp. 103–111 Oct. 2014.

[9] S. Zeng, S.-M. Chen, and M. O. Teng, "Fuzzy forecasting based on linear combinations of independent variables, subtractive clustering algorithm and artificial bee colony algorithm," Inf. Sci., vol. 484, pp. 350-366, May 2019, doi: 10.1016/j.ins.2019.01.071.

[10] Z. Hajirahimi and M. Khashei, "Hybridization of hybrid structures for time series forecasting: A review," Artif. Intell. Rev., vol. 56, pp. 1201–1261, May 2022.

[11] D. Esposito and F. Esposito, "Introducing machine learning,". Microsoft Press, 2020.

[12] S. Galeshchuk, "Neural networks performance in exchange rate prediction," Neurocomputing, vol. 172, pp. 446-452, Jan. 2016.

[13] A.M. Ozbayoglu, M.U. Gudelek, and Sezer, O.B., "Deep learning for financial applications: A survey", Applied Soft Computing, vol. 93, p.106384, 2020.

[14] F. Xing, D.H. Hoang and D.V. Vo, "High-frequency news sentiment and its application to forex market prediction," In Proceedings of the 54th Hawaii International Conference on System Sciences (HICSS), Oct. 2020.

[15] D.K. Mohanty, Ajaya Kumar Parida, Shelly Suman Khuntia, "Financial market prediction under deep learning framework using auto encoder and kernel extreme learning machine," Applied Soft Computing, Vol. 99, 2021, 106898, ISSN 1568-4946, doi.org/10.1016/j.asoc.2020.106898.

[16] S. Sornmayura, "Robust forex trading with deep q network (dqn)", Assumpt. Bus. Adm. Coll. vol.39, pp 15–33, 2019.

[17] J. Pathak, A. Wikner, R. Fussell, S. Chandra, B.R. Hunt, M. Girvan, and E. Ott, "Hybrid forecasting of chaotic processes: Using machine learning in conjunction with a knowledge-based model," Chaos: An Interdisciplinary Journal of Nonlinear Science, 28(4), 2018.

[18] M.S. Islam and E. Hossain, "Foreign exchange currency rate prediction using a GRU-LSTM hybrid network," Soft Computing Letters, 3, p.100009, 2021.

[19] Z. Zeng and M. Khushi, "Wavelet Denoising and Attention-based RNN- ARIMA Model to Predict Forex Price," 2020 International Joint Conference on Neural Networks (IJCNN), Glasgow, UK, 2020, pp. 1-7, doi: 10.1109/IJCNN48605.2020.9206832.

[20] M.A. Ganaie, M. Hu, A.K. Malik, M. Tanveer, and P.N. Suganthan, "Ensemble deep learning: A review. Engineering Applications of Artificial Intelligence," vol.115, p.105151, 2022.

[21] A. Sadeghi, A. Daneshvar, and M.M. Zaj, "Combined ensemble multi-class SVM and fuzzy NSGA-II for trend forecasting and trading in Forex markets," Expert Systems with Applications, vol.185, p.115566, 2021.

[22] R. Bělohlávek, J.W. Dauben, and G.J. Klir, "Fuzzy logic and mathematics: a historical perspective," Oxford University Press, 2017

[23] J.E. Medina Reyes, S. Cruz Aké, and A.I. Cabrera Llanos, "New hybrid fuzzy time series model: Forecasting the foreign exchange market," Contaduría y administración, 66(3), 2021.

[24] J.C. Garza Sepulveda, F. Lopez-Irarragorri, and S.E. Schaeffer, "Forecasting Forex Trend Indicators with Fuzzy Rough Sets," Computational Economics, 62(1), pp.229-287, 2023.

[25] P.C. de Lima e Silva, C.A. Severiano Jr, M.A. Alves, M.W. Cohen and F.G. Guimareaes, "A New Granular Approach for Multivariate Forecasting," in V. Cota, D. Barone, D. Dias, L. Dameazio (eds) Computational Neuroscience. LAWCN 2019. Communications in Computer and Information Science, vol 1068. Springer, Cham.

[26] S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural Comput., vol. 9, no. 8, pp. 1735-1780, 1997.

[27] J. Chung, C. Gulcehre, K. Cho, Y. Bengio, "Empirical evaluation of gated recurrent neural networks on sequence modeling," arXiv: 1412.3555, 2014.

[28] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," 2014, arXiv:1412.6980. [Online]. Available: https://arxiv.org/abs/1412.6980.

[29] Myfxbook, "Forex Market Historical Data,", 2023 [Online] Available at: Forex Historical Data — Myfxbook [Accessed 31st December 2023].

[30] E. Ahmadi, M. Jasemi, L. Monplaisir, M. A. Nabavi, A. Mahmoodi, and P. A. Jam, "New efficient hybrid candlestick technical analysis model for stock market timing on the basis of the support vector machine and heuristic algorithms of imperialist competition and genetic," Expert Syst. Appl., vol. 94, pp. 21-31, Mar. 2018.

[31] M. Ozturk, I.H. Toroslu and G. Fidan, "Heuristic based trading system on Forex data using technical indicator rules," Applied Soft Computing, 43, pp.170-186, 2016.

[32] R. Salles, K. Belloze, F. Porto, P. H. Gonzalez, and E. Ogasawara, "Nonstationary time series transformation methods: An experimental review.," Knowl Based Syst., vol. 164, pp. 274-291, 2018.

[33] S. Kirkpatrick, C.D.J. Gelatt and M.P. Vecchi, "Optimization by Simulated Annealing," Science220:671–79, 1983.