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MULTI-SOURCE FINANCIAL DATA INTEGRATION VIA LSTM-GRU-ATTENTION MODELS FOR ROBUST FOREX PREDICTIONS

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Abstract

Previous studies have shown that utilizing data sources such as historical or technical data along with deep learning approaches can increase the accuracy of forex price prediction. However, relying on a single data source, such as historical data alone, limits predictive performance as it fails to capture the entire complexity of the market. This study aims to demonstrate that merging financial data from four different sources can significantly improve prediction accuracy. This study proposes a hybrid LSTM-GRU-Attention deep learning model, leveraging historical, fundamental, technical, and sentiment data, to predict the closing price of the GBP/USD currency pair, which is actively traded on a global scale. QuantManager, Forexfactory, and DailyFX data were collected over three timeframes: 30-minute, 1-hour, and 1-day, from January 1, 2013 to December 31, 2023, respectively. The model's performance was evaluated using MSE, RMSE, and MAE metrics. The proposed model with multi-source data demonstrated substantial error reductions compared to historical data only models from previous studies, achieving RMSE decreases from 17% to 89% and MAE reductions from 22% to 94% across 30-minute, 1-hour, and 1-day timeframes. The integrated multi-source data model outperformed models that integrated only historical data, across all timeframes, highlighting the benefits of improved forex prediction accuracy.

Keywords: Price prediction, Financial data integration, Deep learning in the forex market, Fundamental, Sentiment

1. INTRODUCTION

The forex market, known for its high volatility and sensitivity to political, economic, and sentiment-driven factors, provides an ideal testing ground for complex prediction models.

While many studies have focused primarily on historical time series data, recent research shows that including other data types, such as fundamental, technical, or sentiment data, improves prediction performance. Yıldırım et al. (2021) found that integrating historical data with fundamental and technical data boosts forecast accuracy. However, combining multiple data types presents challenges, such as inconsistencies, difficulties capturing complex interrelationships, and potential context loss. For instance, fundamental data has significant impacts only during release times, limiting continuous price tracking in models that rely solely on this type of data (Pornwattanavichai et al., 2022). Models centered on technical indicators often miss market dynamics best captured by fundamental and sentiment data (Cheng et al.,

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2022; Lu et al., 2020; Rodríguez et al., 2001). Similarly, while sentiment data offers valuable market insights, used alone it may miss other critical factors, reducing predictive precision (Atha & Bolla, 2022).

Given these challenges, the primary goal of this research is to determine prediction efficacy of the GBP/USD closing price when integrating historical, fundamental, technical, and sentiment data.

Recent advances in deep learning have outpaced traditional methods in forecasting forex prices. Prominent models such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) have shown enhanced performance, with hybrid models achieving even greater predictive precision (Ahmed et al., 2020; Mabrouk et al., 2022; Panda et al., 2022; Zeng & Khushi, 2020). However, conventional models such as CNN and LSTM have limitations. CNNs, while effective at feature extraction, struggle with changing data distributions, making them less suited for dynamic market environments (Hosseini et al., 2017). LSTMs address long-term dependencies but process sequences in one direction only, limiting context integration in volatile markets (Choe et al., 2021; Siami-Namini et al., 2019). Although the GRU model adequately handles sequential data, it suffers with long-term dependencies due to its simpler structure, which has limited memory control in comparison to LSTM models (Chung et al., 2014).

To address these limitations, this study introduces a hybrid LSTM-GRU-Attention model. This model combines LSTM memory and GRU efficiency. The attention mechanism enables the prioritization of critical input segments, boosting accuracy amid significant market volatility (Vaswani et al., 2017).

Considering that forex prediction accuracy varies across timeframes due to volatility, this study examines the proposed model consistency across 30-minute, 1-hour, and 1-day timeframes. By analyzing a comprehensive dataset with historical, fundamental, technical, and sentiment data, this study aims to identify the timeframe offering optimal forecasting accuracy.

The performance of the proposed model will be benchmarked against RNN, CNN, LSTM, and GRU models. Performance will be evaluated using Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) providing a comparative measure of the model's predictive power across various temporal scales.

The key contributions of this study are as follows:

1. This study presents a novel approach for predicting forex closing price accurately by combining fundamental, technical, and sentiment data with historical time series data. This thorough data integration addresses the constraints of utilizing single or dual-source models, resulting in a more accurate portrayal of market trends and increased prediction dependability.
2. The suggested LSTM-GRU-Attention model surpasses baseline models (CNN, RNN, LSTM, and GRU) in the 30-minute, 1-hour, and 1-day timeframes. The suggested hybrid model, using multi-source financial data, is shown to increase forex prediction accuracy by successfully capturing market dynamics across timescales and providing a versatile model for various trading techniques.
3. This study bridges theory with practical financial modeling.
4. The model has broad applicability beyond finance, including sectors such as marketing, healthcare, and supply chain management, where sentiment and sequential analysis are important.

In this study, "historical-only data" refers to independent historical data, whereas "multi-source data" includes a combination of historical, fundamental, technical, and sentiment data. "Proposed model" refers to the LSTM-GRU-Attention model.

2. LITERATURE REVIEW

2.1 The Role of Multi-Source Financial Data in Forex Price Prediction

Predicting forex market prices is critical, influenced by historical, fundamental macroeconomic, technical, and sentiment factors. Historical data plays a crucial role, capturing past price trends and market behavior, which forms the basis for future forecasting. Nuraeni et al. (2020) demonstrated the efficacy of Neural Networks optimized with Particle Swarm Optimization (PSO) in accurately predicting forex rates, highlighting the value of historical data with advanced modeling.

Macroeconomic indicators such as interest rates, GDP, inflation, and employment are commonly used to predict currency movements (Faust et al., 2003; Stavrakeva & Tang, 2020). However, these characteristics are not updated regularly, making real-time prediction difficult (Kaltwasser, 2010; Nassirtoussi et al., 2015).

Technical analysis, which examines past market data, aids in forecasting future price trends. Park and Irwin (2007) and Taylor and Allen (1992) confirmed its profitability in forex markets, though it falls short in capturing all market dynamics. Bettman et al. (2009) and Boobalan (2014) found combining technical with fundamental analysis yields greater accuracy of predictions.

Sentiment analysis has become popular, leveraging social media and news data to gauge market attitudes. Komariah et al. (2016) demonstrated the significant predictive power of sentiment data. Li and Ming (2023) and Yasir et al. (2019) found that combining sentiment with historical data enhanced exchange rate prediction accuracy.

2.2 Advancements in Deep Learning for Forex Price Prediction

Recent developments in deep learning algorithms have greatly improved currency price predictions in the forex market. RNNs are very useful for time series forecasting problems, such as foreign exchange rate prediction, as they model sequential data.

Dautel et al. (2020) demonstrated RNNs' ability to grasp temporal relationships between financial events, resulting in higher predictive accuracy than traditional models. In related research, Tsai et al. (2018) used CNNs to discover trading patterns using visual representations of price trends. Their findings demonstrated that CNNs can collect fine-grained data and accurately estimate future currency movements.

Fischer and Krauss (2018) used LSTMs to forecast the S&P 500, proving that they outperform conventional models such as Random Forest and Logistic Regression with noisy time series data.

Recent work on hybrid models has shown promising results. Islam and Hossain (2021) proposed a GRU-LSTM-based model to predict exchange rates, testing it across multiple currencies, including GBP/USD. Their study found that the model outperformed traditional RNN and LSTM models, especially for short-term currency movements.

Faru et al. (2023) applied transfer learning to a hybrid RNN-LSTM model, enhancing performance for GBP/USD predictions and reducing RMSE due to the hybrid structure. Sako et al. (2022) examined RNN, LSTM, and GRU models, finding GRU superior for identifying trends in exchange rates, especially in volatile markets.

Furthermore, Lien Minh et al. (2018) developed a GRU model that integrated Stock2Vec with sentiment analysis, yielding higher accuracy than standalone LSTM and GRU models. Panda et al. (2022) proposed a CNN-Random Forest (CNN-RF) model that combined price history and sentiment scores, outperforming AutoRegressive Integrated Moving Average (ARIMA), Multilayer Perceptron (MLP), Linear Regression (LR) in MAE, and RMSE metrics.

Collectively, these studies underscore the efficacy of hybrid models in forex prediction, integrating historical, fundamental, technical, and sentiment data, for enhanced accuracy.

3. METHODOLOGY

3.1 Data Collection

GBP/USD is used as a sample currency pair in this study to measure forecast accuracy for closing prices 30 minutes, 1 hour, and 1 day in advance. QuantManager software was used to collect historical GBP/USD time series data at 30-minute, 1-hour, and 1-day intervals from January 1, 2013 to December 31, 2023. ForexFactory.com provided fundamental reports on Gross Domestic Product (GDP), Consumer Price Index (CPI), interest rates, and employment statistics from January 1, 2013 to December 31, 2023. These reports influence currency swings and the economy (Salisu & Olaniran, 2022; Sánchez & Liborio, 2012). DailyFX provided daily news headlines for USD and GBP from January 1, 2013 to December 31, 2023. Table 1 shows the data collection information.

Table 1 Data Collected for Forex Prediction Analysis

Data source	Data type	Number of rows
QuantManager	Historical (30 - minutes GBP/USD)	137092
QuantManager	Historical (1- hour GBP/USD)	68549
QuantManager	Historical (1- day GBP/USD)	3438
ForexFactory.com	Fundamental (Macroeconomic data from UK, USA)	1335
DailyFx.com	Sentiment (News headlines)	54551

3.2 Data Preprocessing on Fundamental Data

The first step was to convert the feature dimensions from rows to columns. Missing values were addressed with Python's "fillna" function, which sets NaN values to 0. The dataset was then standardized using min-max normalization, as shown in Table 2.

Table 2 Sample Fundamental Dataset After Data Preprocessing

Date	Interest Rate Decision (GBP)	GDP (GBP)	Retail Sales (USD)	Unemployment Rate (USD)
2013.03.07	0.0050	0.0014	0.0077	0.0773
2013.03.08	0.0000	0.0019	0.0093	0.0770
2013.03.13	0.0000	0.0023	0.0110	0.0769
2013.03.14	0.0000	0.0027	0.0091	0.0767
2013.03.15	0.0000	0.0031	0.0073	0.0766
2013.03.21	0.0000	0.0036	0.0054	0.0764

3.3 Generating Technical Analysis Data from Daily Historical GBP/USD Price Data

The second step was to generate technical analysis data from the 30-minute, 1-hour, and 1-day GBP/USD historical pricing data using Bollinger bands, Average True Range (ATR), Stochastic oscillator, Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD) methods. Table 3 shows a sample technical dataset with features from a 1-day timeframe of GBP/USD.

Table 3 Sample Technical Dataset Generated from a 1-Day Timeframe of GBP/USD

Date	ATR	LB	MB	UB	SMA5
2012.01.02	0.74252	0.27200	0.74237	0.74258	0.74282
2012.01.03	0.74190	0.29241	0.74253	0.74246	0.74240
2012.01.04	0.76673	0.28366	0.74244	0.74280	0.74321
2012.01.05	0.76411	0.30177	0.74150	0.74239	0.74340
2012.01.06	0.73962	0.30997	0.74107	0.74228	0.74363
2012.01.07	0.73226	0.28004	0.73950	0.74178	0.74434

3.4 Data Preprocessing on Sentiment Data

The third step involved cleaning the economic news headlines with regular expressions. Irrelevant articles unrelated to the US and UK were filtered, converted to lowercase, and stripped of duplicates, punctuation, contractions, and numbers. Sentiment analysis followed using the NLTK-VADER Lexicon, assigning compound scores from -1 to 1.

$$Compound\ score = \sum_{i=1}^{N} (S_i / \sqrt{S_i^2 + \alpha}) \qquad (1)$$

To accomplish this, the Python libraries NLTK and vaderSentiment were imported, as well as stopwords and the SentimentIntensityAnalyzer. Table 4 displays the dataset for sentiment scores. The average sentiment scores were produced for each date.

Table 4 Sample Sentiment Score Dataset

Date	Raw news title	News title	Sentiment score
2012.04.05	GBPUSD Moves to Support Prior to News	gbpusd moves to support prior to news	0.4019
2012.04.25	GBPUSD Reaches Range Resistance	gbpusd reaches range resistance	0.0516
2015.01.06	GBP/USD Technical Analysis: Eyeing Support Below 1.52	gbpusd technical analysis eyeing support below	0.4019
2015.01.08	GBP/USD Trades at Long Term Support Line	gbpusd trades at long term support line	0.8658
2015.01.08	GBP/USD Technical Analysis: Passing on Short Trade for Now	gbpusd technical analysis passing on short trade for now	-0.7906

2015.01.09	GBP/USD Vulnerable to Slowing U.K. Inflation - BoE Testimony in Focus	gbpusd vulnerable to slowing uk inflation boe testimony in focus	-0.2263

3.5 Combining Historical Data with Fundamental, Technical, and Sentiment Data

The fundamental, technical, and sentiment data were combined with GBP/USD historical time series data into three merged datasets based on 30-minute, 1-hour, and 1-day timeframes. Table 5 shows a sample merged multi-source dataset from a 1-day timeframe of GBP/USD.

Table 5 Sample Merged Multi-Source Dataset from a 1-Day Timeframe of GBP/USD

Date	Time	Close	ATR	Retail Sales (MoM) (USD)	Un-employment Rate (USD)	Sentiment score
2022.08.25	00:00	1.18222	0.01045	0.00086	0.03643	-0.42150
2022.09.08	00:00	1.15198	0.01056	0.00214	0.03671	0.65970
2022.09.15	00:00	1.14513	0.01132	0.00300	0.03614	-0.11315
2022.09.22	00:00	1.12621	0.01129	0.00250	0.03586	-0.25530
2022.09.29	00:00	1.11707	0.01996	0.00200	0.03557	-0.29970
2022.10.06	00:00	1.11605	0.02065	0.00150	0.03529	0.06743

3.6 Experimental Setup

The proposed model was compared to the baseline deep learning methods, CNN, RNN, LSTM, and GRU, to demonstrate the effectiveness of incorporating historical, fundamental, technical, and sentiment data. Experiments used three merged multi-source datasets of 30-minute, 1-hour, and 1-day timeframes. Assessment criteria for the models entailed MSE, RMSE, and MAE.

3.7 Theoretical Framework of the Proposed LSTM-GRU-Attention Model

The theoretical framework integrates historical, fundamental, technical, and sentiment data to improve GBP/USD price prediction accuracy of closing prices for 30-minute, 1-hour, and 1-day timeframes. As shown in the proposed sentiment-based LSTM-GRU-Attention model diagram in Figure 1, the data collection began with obtaining 10 years of GBP/USD price data in 30-minute, 1-hour, and 1-day timeframes, fundamental macroeconomic indicators, and daily economics news. During the data preprocessing phase, technical analysis algorithms generated technical data from historical price data, fundamental data underwent normalization, and daily economics news was cleaned and classified using the VADER model, which assigns sentiment scores.

After preprocessing, these four datasets, historical, fundamental, technical, and sentiment, were merged into a unified input for the proposed LSTM-GRU-Attention model. Figure 2 shows the proposed model architecture, including an input layer, an LSTM-GRU layer, an attention layer, and a fully connected layer.

Figure 1 LSTM-GRU-Attention Model Diagram

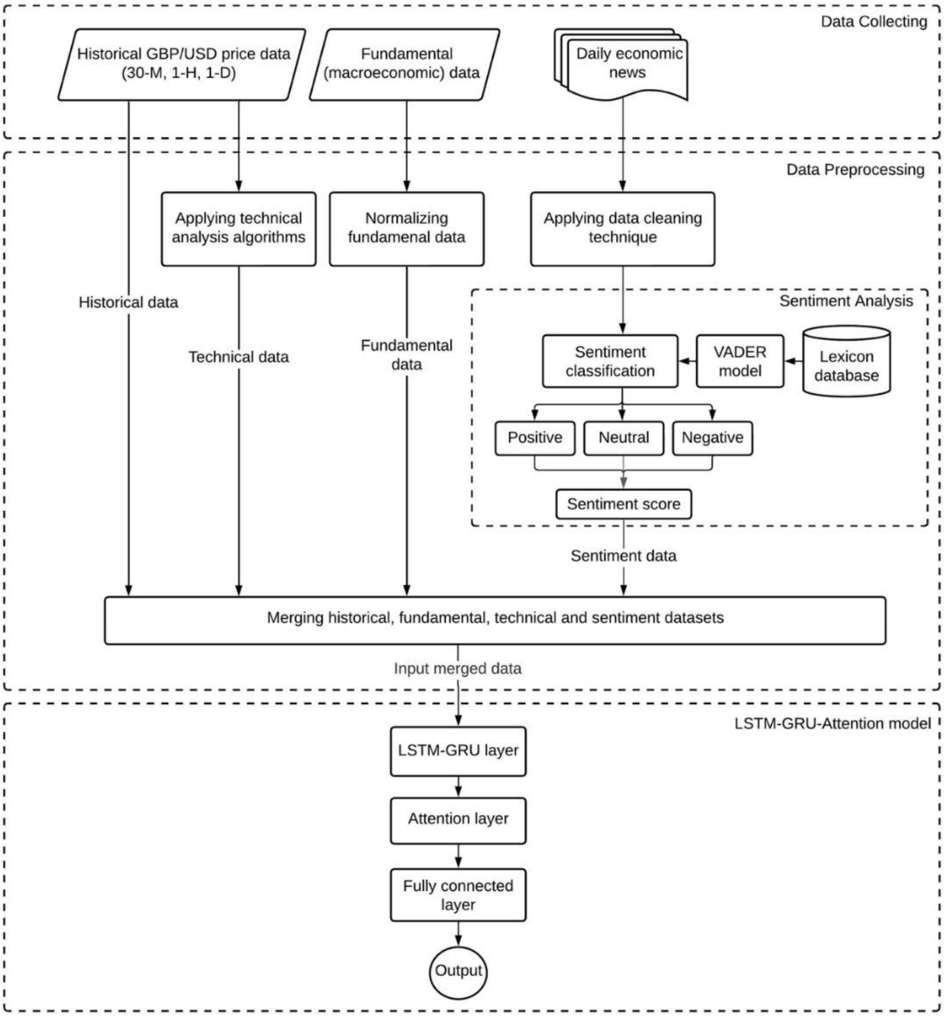
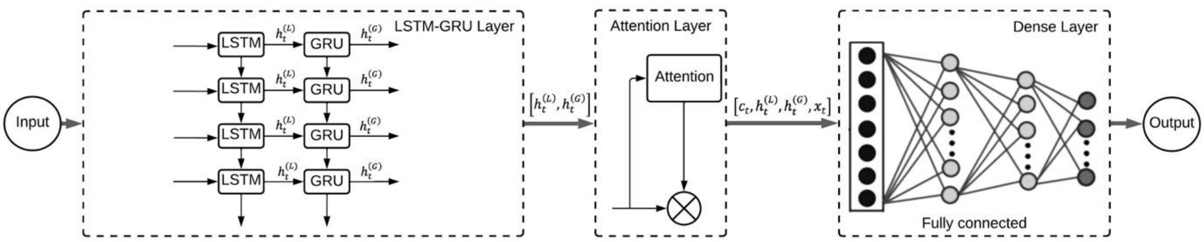


Figure 2 The Proposed Model Architecture Diagram



3.8 Mathematical Equations of the Proposed Model

The proposed model architecture begins with an LSTM layer that controls data flow through the forget, input, and output gates and cell state. It utilizes activation functions sigmoid and tanh to control the flow of information via its gates. The forget gate identifies data from the preceding cell state that should be eliminated, as shown in Equation (2).

$$f_t = \sigma\left(W_f * \left[h^{L}_{(t-1)}, x_t\right] + b_f\right) \quad (2)$$

As shown in Equation (3), the input gate decides which new information should be updated in the cell state.

$$i_t = \sigma\left(W_i * \left[h^L_{(t-1)}, x_t\right] + b_i\right) \quad (3)$$

Equation (4) shows that a candidate cell state is generated to store potential updates. The updated cell state combines the retained information from the forget gate with the new updates from the input gate, as shown in Equation (5).

$$\tilde{C}_t = \tanh\left(W_c * \left[h^L_{(t-1)}, x_t\right] + b_c\right) \quad (4)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (5)$$

Equation (6) illustrates that the output gate determines which portion of the cell state to output.

$$o_t = \sigma\left(W_o * \left[h^L_{(t-1)}, x_t\right] + b_o\right) \quad (6)$$

The final state of the LSTM layer is the updated hidden state, calculated by combining the cell state and output gate through an activation function, as shown in Equation (7).

$$h^L_t = o_t * \tanh(C_t) \quad (7)$$

The subsequent layer is the GRU layer, which takes the hidden states produced by the LSTM layer as the input. These hidden states enable the reset and update gates of the GRU to maximize temporal patterns and improve sequential learning. In this layer, the reset gate controls the quantity of prior information to be discarded, as shown in Equation (8).

$$r^G_t = \sigma\left(W^G_r * \left[h^L_t, h^G_{(t-1)}, x_t\right] + b^G_r\right) \quad (8)$$

Equation (9) shows that the update gate balances the contribution of the previous hidden state and the new candidate state to the current hidden state.

$$z^G_t = \sigma\left(W^G_z * \left[h^L_t, h^G_{(t-1)}, x_t\right] + b^G_z\right) \quad (9)$$

The candidate hidden state is computed using the weighted combination of the reset gate and input, as shown in Equation (10).

$$\tilde{h}^G_t = \tanh\left(W^G_h * \left[r^G_t * h^G_{(t-1)}, x_t\right] + b^G_h\right) \quad (10)$$

The updated hidden state is subsequently computed by integrating between the prior hidden state and the candidate hidden state, as shown in Equation (11).

$$h^G_t = \left(1 - z^G_t\right) * h^G_{(t-1)} + z^G_t * \tilde{h}^G_t) \quad (11)$$

The third layer is the attention layer, allowing the model to focus on the important features of the input sequence, consequently enhancing prediction accuracy by better utilizing key information. In this layer, attention scores are calculated by assigning weights to the hidden states coming from the LSTM and GRU layers, as illustrated in Equation (12).

$$e_t = \sigma\left(U_a * \left[h_t^L, h_t^G\right] + b_a\right) \tag{12}$$

These scores are then normalized into probabilities using the Softmax function, as shown in Equation (13).

$$\alpha_t = \text{softmax}(e_t) \tag{13}$$

These scores aggregate hidden states into context vectors c_t, refining predictions, as shown in Equation (14).

$$c_t = \sum(\alpha_t * [h_t^L, h_t^G]) \tag{14}$$

Finally, the fully connected layer combines the context vector and hidden states to predict outputs, as shown in Equation (15).

$$y_t = W_y * \left[c_t, h_t^L, h_t^G, x_t\right] + b_y \tag{15}$$

3.9 Hardware Resources and Dataset Preparation

The experimental setup utilized a Google Colab Pro subscription with 51 GB RAM, 166.77 GB HDD, and 8 NVIDIA V100 GPUs, running Linux SMP (Kernel Version: 6.1.58+). Each experiment used 80% of the data for training and 20% for testing against CNN, RNN, LSTM, and GRU models. The proposed model included an LSTM layer with 128 hidden units and a tanh activation, followed by a GRU layer with the same configuration. An attention layer with a sigmoid activation and a single dense layer for regression completed the structure.

3.10 Algorithm of the Proposed Model

```
Input:
   X_train, y_train, neurons, output_dim, optimizer, loss_fn, metrics_list
Output:
   Trained neural network model
Begin:
   1.  Initialize LSTM_ATTGRU_model as Sequential.
   2.  Add LSTM Layer: LSTM(neurons, input_shape=(sequence_length, input_dim),
activation="tanh", return_sequences=True)
   3.  Add GRU Layer: GRU(neurons, activation="tanh", return_sequences=True)
   4.  Add Attention Layer: SeqSelfAttention(activation="sigmoid")
   5.  Add Flatten Layer.
   6.  Add Dense Output Layer: Dense(output_dim, activation="linear")
   7.  Compile Model: LSTM_ATTGRU_model.compile(optimizer=optimizer,
loss=loss_fn, metrics=metrics_list)
   8.  Train Model: LSTM_ATTGRU_model.fit(X_train, y_train, epochs=50,
batch_size=32)
   9.  Evaluate Model: LSTM_ATTGRU_model.evaluate(X_train, y_train)
End.
```

4. RESULTS AND DISCUSSION

The proposed model was applied to predict the closing price of the GBP/USD currency pair 30 minutes, 1 hour, and one day ahead of the actual time. Predictions were compared with the CNN, RNN, LSTM, and GRU baseline models, as well as other deep learning models proposed by Islam and Hossain (2021), Sako et al. (2022), and Faru et al. (2023). The models' performances were measured using standard regression metrics, including MSE, RMSE, and MAE. In predictive modeling, low MSE, RMSE, and MAE values indicate a low error rate and, hence, better prediction.

The results were separated into two categories: the first evaluated the model with historical-only data; the subsequent one evaluated the model with multi-source data. Tables 6, 7, and 8 illustrate the results of MSE, RMSE, and MAE measures over 30-minute, 1-hour, and 1-day timeframes.

Table 6 MSE, RMSE, and MAE Results of Historical-Only vs. Multi-Source Data in a 30-Minute Timeframe of GBP/USD

	historical-only data			**multi-source data**		
Model	**MSE**	**RMSE**	**MAE**	**MSE**	**RMSE**	**MAE**
Proposed	**0.0000040**	**0.0019130**	**0.0013650**	**0.0000019**	**0.0013675**	**0.0008592**
CNN	0.0000132	0.0036291	0.0032197	0.0000107	0.0032684	0.0015177
RNN	0.0000164	0.0040489	0.0030254	0.0000025	0.0037872	0.0024324
LSTM	0.0000070	0.0026506	0.0018329	0.0000050	0.0022420	0.0014338
GRU	0.0000066	0.0025762	0.0018985	0.0000024	0.0015465	0.0010978

Table 7 MSE, RMSE, and MAE Results of Historical vs. Multi-Source Data in a 1-Hour Timeframe of GBP/USD

	historical-only data			**multi-source data**		
Model	**MSE**	**RMSE**	**MAE**	**MSE**	**RMSE**	**MAE**
Proposed	**0.0000207**	**0.0045480**	**0.0036167**	**0.0000031**	**0.0017659**	**0.0011512**
CNN	0.0000530	0.0065557	0.0061430	0.0000131	0.0036244	0.0020258
RNN	0.0000426	0.0065304	0.0058001	0.0000095	0.0030797	0.0023319
LSTM	0.0000469	0.0068465	0.0065874	0.0000066	0.0025660	0.0017342
GRU	0.0000509	0.0071320	0.0068356	0.0000059	0.0024216	0.0017273

Table 8 MSE, RMSE, and MAE Results of Historical vs. Multi-Source Data in a 1-Day Timeframe of GBP/USD

	historical-only data			**Multi-source data**		
Model	**MSE**	**RMSE**	**MAE**	**MSE**	**RMSE**	**MAE**
Proposed	**0.0000680**	**0.0082330**	**0.0060260**	**0.0000630**	**0.0079410**	**0.0056400**
CNN	0.0002850	0.0168680	0.0150050	0.0000790	0.0089030	0.0065100

RNN	0.0001670	0.0129260	0.0088360	0.0000730	0.0085380	0.0064410
LSTM	0.0001160	0.0107580	0.0074100	0.0000710	0.0084330	0.0062040
GRU	0.0001420	0.0119210	0.0087230	0.0000770	0.0088030	0.0059360

Across all timeframes, the models using multi-source data consistently demonstrated reduced error rates regarding MSE, RMSE, and MAE, compared to models using historical-only data. The metric results from comparing historical-only and multi-source data integration models within a 30-minute timeframe are used below to demonstrate the benefits of multi-source data integration.

According to the metric results shown in Table 6, the proposed model with multi-source data achieved an MSE of 0.0000019, RMSE of 0.0013675, and MAE of 0.0008592, outperforming the proposed model integrated with only historical data, which recorded an MSE of 0.0000040, RMSE of 0.0019130, and MAE of 0.0013650. Other models also showed significant improvements; GRU with multi-source data reached an MSE of 0.0000024, RMSE of 0.0015465, and MAE of 0.0010978, while CNN and RNN models experienced significant decreases in error measures. This highlights the value of multi-source data integration across models. A similar trend was observed in the 1-hour and 1-day timeframes; models with multi-source data performed better than the non-integrated model, as shown by the results given in Tables 7 and 8. Figures 3, 4, and 5 show bar charts for the RMSE and MAE evaluation metrics of all models in 30-minute, 1-hour, and 1-day timeframes, comparing historical-only versus multi-source data.

Figure 3 Evaluation Metrics for RMSE and MAE for the 30-minute Timeframe

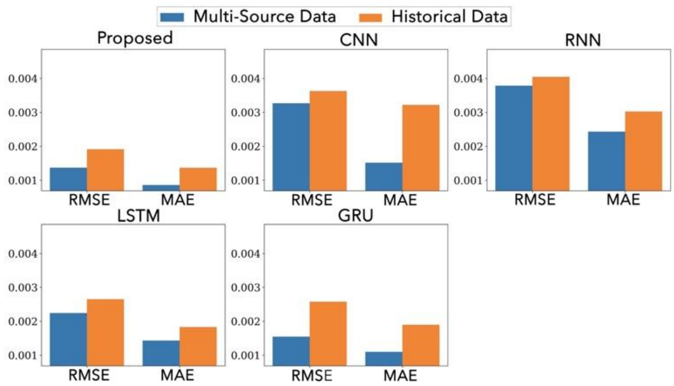


Figure 4 Evaluation Metrics for RMSE and MAE for the 1-hour Timeframe

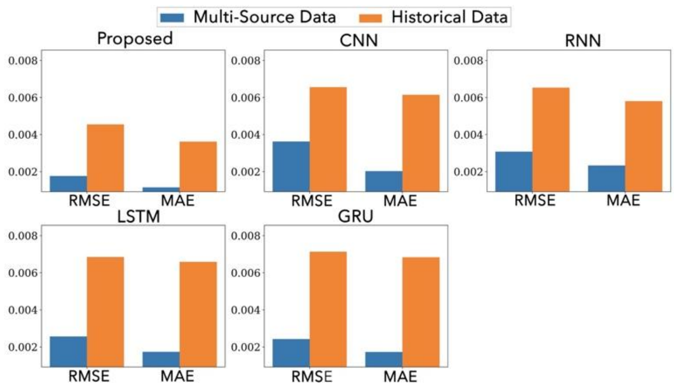
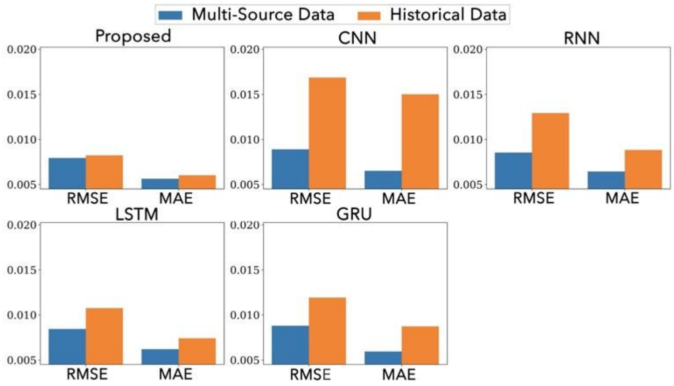


Figure 5 Evaluation Metrics for RMSE and MAE for the 1-day Timeframe



Based on these results, the proposed model is shown to consistently outperform baseline models such as CNN, RNN, LSTM, and GRU across all timeframes, with or without data integration. This outperformance can be attributed to the advanced architecture of the proposed model, which effectively combines LSTM and GRU components to handle sequential data and long-term dependencies. Simultaneously, the attention mechanism focuses on the most relevant data points, enabling the model to dynamically adapt its focus to short-term swings, which is crucial for capturing sudden price movements in the forex market.

The proposed model demonstrates superior performance, especially in short-term prediction, based on the analysis of MSE, MAE, and RMSE metrics across the 30-minute, 1-hour, and 1-day timeframes. The 30-minute timeframe records the lowest MSE (0.0000019), MAE (0.0008592), and RMSE (0.0013675), indicating its suitability for high-frequency forecasting with greater accuracy. These figures highlight the differences in prediction patterns across models and timeframes, while the recognized trend emphasizes the importance of multi-source data in the model in increasing prediction accuracy.

Figures 6, 7, and 8 show model performance across the 30-minute, 1-hour, and 1-day intervals for closing price predictions, utilizing test datasets of historical-only and multi-source data against actual data using baselines and the proposed model. The suggested model effectively captures long-term patterns within a 1-day timescale, exhibiting minimal variation and underscoring its stability. In the 1-hour timeframe, it adeptly handles mid-interval changes, surpassing baseline models. The model demonstrates exceptional adaptability with the 30-minute interval characterized by peak volatility, markedly decreasing error rates. The outcomes underscore the resilience of the suggested methodology, augmented by the incorporation of multi-source data for accurate forecasting.

Figure 6 30-minutes: Closing Price Predictions – Historical-Only vs. Multi-Source Data

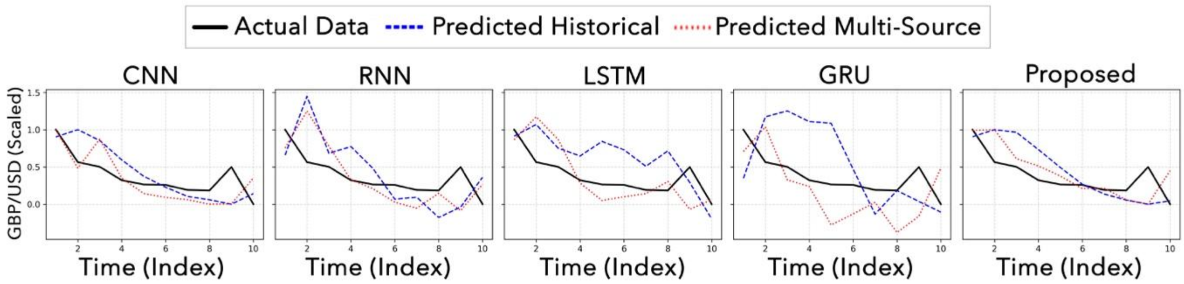


Figure 7 1-hour: Closing Price Predictions – Historical-Only vs. Multi-Source Data

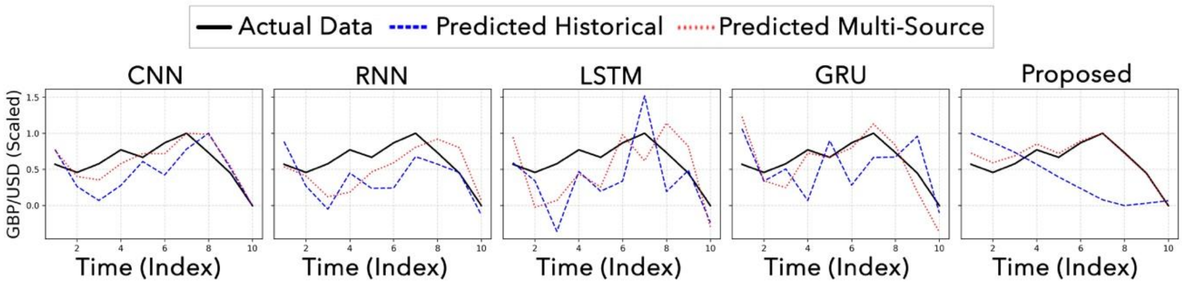
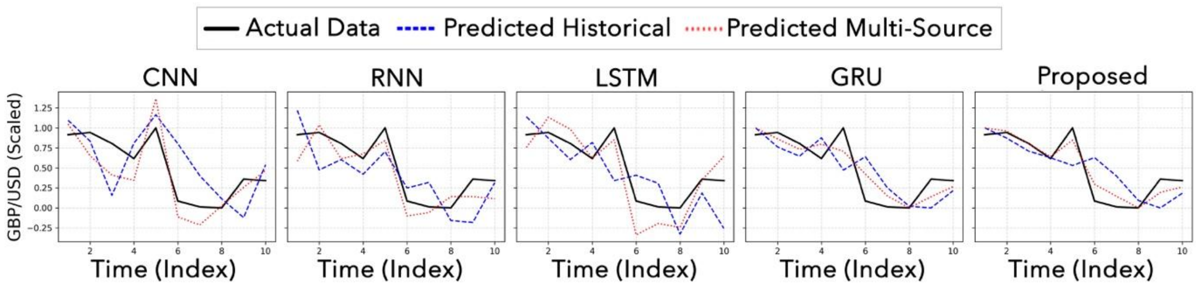
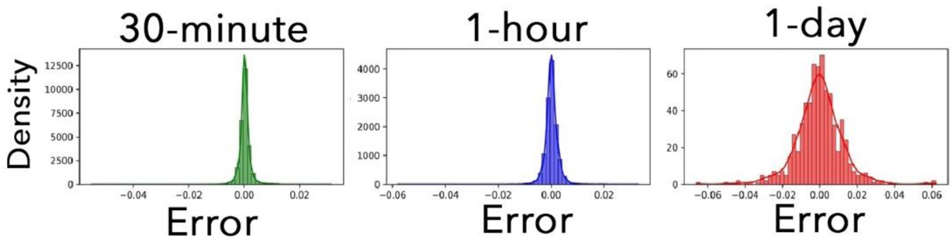


Figure 8 1-day: Closing Price Predictions – Historical-Only vs. Multi-Source Data



The residual analysis further supports this finding, as tighter residual distributions in the 30-minute timeframe highlight reduced error dispersion and enhanced predictive consistency. In comparison, the 1-hour and 1-day timeframes show slightly higher error rates but maintain consistent improvements over traditional historical-only models, as shown in Figure 9. Integrating multi-source data contributes to capturing complex market dynamics, thereby ensuring more reliable and precise forex predictions across varying timeframes.

Figure 9 Residual Error Distribution of Proposed Model Across 30-minute, 1-hour, And 1-day Timeframes

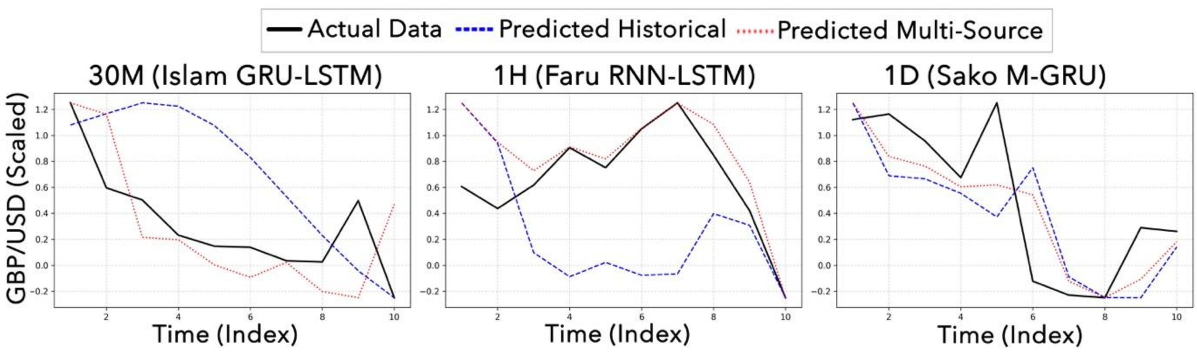


Recent studies show that incorporating multiple data sources in forex prediction models significantly improves accuracy. Semiromi et al. (2020) conducted an advanced analysis combining news sentiment with historical currency data for GBP/USD predictions. They gathered news stories and applied sentiment analysis using custom financial dictionaries. This combined strategy effectively captured market responses following news releases, achieving prediction accuracies exceeding 60% and underscoring the potential of multi-source data integration for enhanced forecasting. Similarly, Xu et al. (2023) presented a GRU-based model integrating GBP/USD historical data with the Chicago Board Options Exchange Volatility Index (CBOEVIX). This integration significantly reduced prediction errors, with MSE dropping from 0.00031 (without VIX data) to 0.00012 and RMSE decreasing from 0.01765 (without VIX data) to 0.01082, representing a 61% MSE reduction and a 38.7% RMSE decrease. Nassirtoussi et al. (2015) and Rostamian and O'Hara (2022b) also agreed that integrating multiple data sources enhances forex prediction accuracy compared to using historical data alone. This approach captures complex market relationships and dynamics, producing more precise forecasts.

Confirming the superior predictive accuracy of multi-source models in line with these studies, the proposed model, which incorporates historical, technical, fundamental, and sentiment data, displays comparable advancements. This validation highlights the importance of multi-source data integration in reducing MSE, RMSE, and MAE. Evaluating the model's performance across 30-minute, 1-hour, and 1-day timeframes as shown in Table 6-8 and Figure 3-5, which reveal that incorporating diverse data sources leads to significant error reductions compared to using historical data alone.

For further validation of the proposed study, comparisons were made with Islam & Hossain (2021), Sako et al. (2022), and Faru et al. (2023), who utilized GRU-LSTM, MGRU (Multivariate-GRU), and RNN-LSTM hybrid models for forex prediction of GBP/USD closing price. While these studies focused on historical data, the proposed study introduces multi-source data integration with an LSTM-GRU-Attention hybrid model. Fair evaluations were ensured by testing each model on historical and multi-source datasets within their original timeframes: 30-minute (Islam & Hossain, 2021), 1-hour (Faru et al., 2023), and 1-day (Sako et al., 2022). Closing price comparison between test datasets of historical and multi-source data for these models are shown in Figure 10. This figure reveals that multi-source data significantly enhances prediction accuracy compared to historical data alone. Within 1-day, 1-hour, and 30-minute time frames, predictions used by the multi-source data consistently align more closely with actual values, even in comparative studies. This demonstrates that integrating historical, fundamental, technical, and sentiment data provides greater robustness, effectively capturing fluctuations and reducing deviations in dynamic forex markets. This trend underscores the transformative impact of multi-source data for precise, adaptive, and high-frequency prediction scenarios.

Figure 10 Closing Price Predictions Comparison Between Historical and Multi-Source Data Across 30-minute, 1-hour, and 1-day Time Frames in Different Studies



Performance metrics of MSE, RMSE, and MAE also provided rigorous and balanced assessments, shown in Tables 9, 10, and 11.

Table 9 MSE, RMSE, and MAE Results Comparison with Proposed Model and GRU-LSTM model (Islam & Hossain, 2021) in the 30-minute Time Frame

	historical-only data			multi-source data		
Model	**MSE**	**RMSE**	**MAE**	**MSE**	**RMSE**	**MAE**
Proposed	**0.0000040**	**0.0019130**	**0.0013650**	**0.0000019**	**0.0013675**	**0.0008592**
Islam & Hossain (2021)	0.0002988	0.0172872	0.0156881	0.0000033	0.0018183	0.0011011

Table 10 MSE, RMSE, and MAE Results Comparison with Proposed Model and RNN-LSTM Model (Faru et al., 2023) in 1-hour Time Frame

	historical-only data			multi-source data		
Model	**MSE**	**RMSE**	**MAE**	**MSE**	**RMSE**	**MAE**
Proposed	**0.0000207**	**0.0045480**	**0.0036167**	**0.0000031**	**0.0017659**	**0.0011512**
Faru et al. (2023)	0.0000692	0.0083213	0.0060224	0.0000494	0.0070319	0.0049305

Table 11 MSE, RMSE, and MAE Results Comparison with Proposed Model and MGRU Model (Sako et al., 2022) in 1-day Time Frame

	historical-only data			multi-source data		
Model	**MSE**	**RMSE**	**MAE**	**MSE**	**RMSE**	**MAE**
Proposed	**0.0000680**	**0.0082330**	**0.0060260**	**0.0000630**	**0.0079410**	**0.0056400**
Sako et al. (2022)	0.0001496	0.0122293	0.0099219	0.0000927	0.0096260	0.0073100

The comparative analysis reveals intriguing patterns in model performance across different timeframes. For the 30-minute timeframe, while the proposed LSTM-GRU-Attention hybrid model and the GRU-LSTM hybrid model (Islam & Hossain, 2021) benefitted from multi-source data integration, the proposed model achieved notably lower error rates. With multi-source data, the proposed model recorded an MSE of 0.0000019, RMSE of 0.0013675, and MAE of 0.0008592, outperforming the GRU-LSTM model's MSE of 0.0000033, RMSE of 0.0018183, and MAE of 0.0011011. In the 1-hour timeframe, the RNN-LSTM hybrid model (Faru et al., 2023) saw substantial error reductions with multi-source data. However, the proposed model still demonstrated superior accuracy, achieving an MSE of 0.0000031, RMSE of 0.0017659, and MAE of 0.0011512 compared to the RNN-LSTM's MSE of 0.0000494, RMSE of 0.0070319, and MAE of 0.0049305. Similarly, for the 1-day timeframe, although the MGRU model (Sako et al., 2022) performed well with multi-source data, its MSE of 0.0000927, RMSE of 0.0096260, and MAE of 0.0073100 remained higher than the proposed model's values of 0.0000630, 0.0079410, and 0.0056400 respectively, when leveraging multi-source data.

Interestingly, the reduction in error rates (MSE, RMSE, and MAE) for the proposed model becomes more pronounced in shorter timeframes, such as 30 minutes, compared to longer timeframes, such as 1 day. While multi-source data enhances the prediction accuracy of all models, the proposed model adapts incredibly well to capturing short-term fluctuations, as seen in the 30-minute timeframe, without compromising long-term trends evident in the 1-day timeframe.

The evaluation results show that the proposed LSTM-GRU-Attention hybrid model consistently surpassed baseline models in terms of MSE, RMSE, and MAE across all timeframes, affirming its resilience and flexibility in predicting the closing price of the GBP/USD currency pair. The comparison graphs of RMSE and MAE for the proposed model and other models across different time frames are shown in Figures 11, 12, and 13.

Figure 11 Evaluation Metrics for RMSE and MAE Between the Proposed Model and Islam and Hossain (2021) Model Over A 30-minute Time Frame

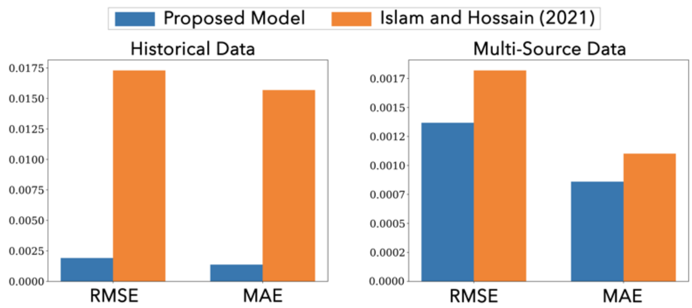


Figure 12 Evaluation Metrics for RMSE and MAE Between the Proposed Model and Faru et al. (2023) Model Over A 1-hour Time Frame

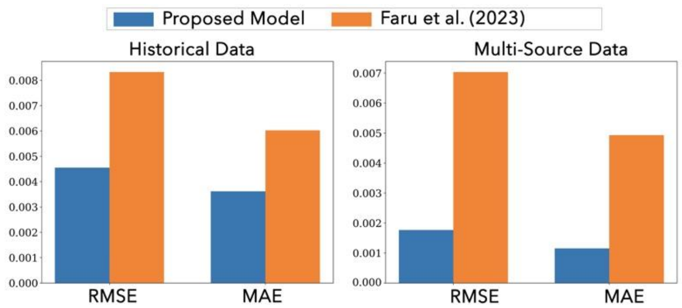
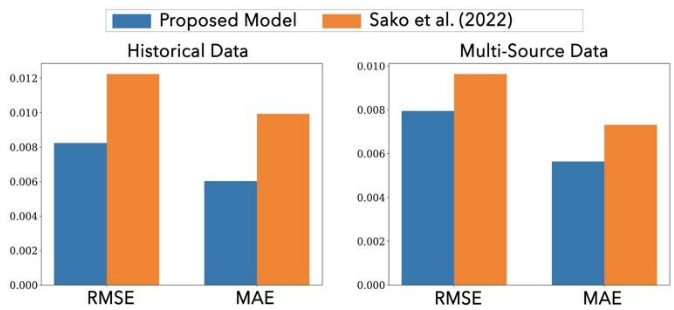


Figure 13 Evaluation Metrics for RMSE and MAE Between the Proposed Model and Sako et al. (2022) Model Over A 1-day Time Frame



The percentage error reduction rates were calculated by comparing RMSE and MAE values between the proposed and compared models. The formula used for this calculation is as shown in Equation (16).

$$\text{Error reduction } \% = \left(\frac{\text{Other model Error} - \text{Proposed model Error}}{\text{Other model Error}}\right) * 100 \qquad (16)$$

For each timeframe, 30-minute, 1-hour, and 1-day, the historical-only and multi-source datasets were utilized to evaluate the proposed model's performance compared to models from other studies. The proposed LSTM-GRU-Attention hybrid model showed significant error reduction compared to the GRU-LSTM model by Islam and Hossain (2021), the RNN-LSTM model by Faru et al. (2023), and the MGRU model by Sako et al. (2022), demonstrating superior performance across diverse timeframes through the utilization of multi-source data integration and a resilient architecture.

For the 30-minute timeframe, the proposed model achieves RMSE and MAE reductions of 24.78% and 21.96%, respectively, compared to Islam and Hossain (2021), highlighting its adaptability in capturing short-term fluctuations. In the 1-hour timeframe, the RMSE of the proposed model is reduced by 74.89% and the MAE by 76.65% compared to Faru et al. (2023), showcasing its exceptional capability to predict medium-term trends with high accuracy. For the 1-day timeframe, the proposed model still excels, reducing RMSE by 17.47% and MAE by 22.83% compared to Sako et al. (2022), reflecting its resilience in addressing long-term patterns, as shown in Tables 12 and 13.

For example, in the 1-hour timeframe, the RMSE for Faru et al. (2023) is 0.0070319, while the proposed model has an RMSE of 0.0017659. The RMSE reduction is:

$$\left(\frac{0.0070319 - 0.0017659}{0.0070319}\right) * 100 = 74.89\% \qquad (17)$$

By integrating historical, fundamental, technical, and sentiment data, the proposed model adapts effectively to different timeframes, outperforming all compared studies.

Table 12 Percentage Error Reduction Based on Historical Dataset

Timeframe	RMSE reduction (%)	MAE reduction (%)	Comparison study
30-Minute	88.93	91.30	Islam & Hossain (2021)
1-Hour	45.37	39.92	Faru et al. (2023)
1-Day	32.67	39.29	Sako et al. (2022)

Table 13 Percentage Error Reduction Based on Multi-Source Dataset

Timeframe	RMSE reduction (%)	MAE reduction (%)	Comparison study
30-Minute	24.78	21.96	Islam & Hossain (2021)
1-Hour	74.89	76.65	Faru et al. (2023)
1-Day	17.47	22.83	Sako et al. (2022)

Based on the discussion of results comparing single-source models with the proposed multi-source data model, it can be confirmed that integrating historical, fundamental, technical, and sentiment data significantly enhances predictive performance. The proposed model consistently outperformed other studies using historical-only data regarding MSE, RMSE, and MAE, demonstrating lower error metricies and improved precision. Multi-source data integration captures diverse market factors, providing a comprehensive view that reduces prediction errors and enhances model reliability and accuracy in forex price forecasting.

5. CONCLUSION AND RECOMMENDATIONS

This article explored the effectiveness of the proposed approach to addressing the complicated linkages of the forex market by combining multiple data sources, resulting in better forecast performance. These extensive comprehensions are also useful for increasing awareness of existing markets among a target audience and helping the audience to feel more empowered regarding those markets. This study also demonstrates the capacity of the model to detect non-linear features and interdependencies in financial time series data.

Nevertheless, there are a few limitations that should be considered. First, model performance depends on the quality and availability of the data used for training, validation, and forecasting, as the merged dataset of historical, fundamental, technical, and sentiment data can be incomplete or noisy based on the sources and preprocessing steps used. Second, the suggested model is complex and challenging to comprehend, particularly given the combination of LSTM, GRU, and attention mechanisms. Finally, issues with computational complexity, such as data processing power and hyperparameter tuning, are a problem in terms of both cost and speed, especially for real-time applications. It is therefore important to propose strategies for data quality enhancement, model interpretability, and resource utilization to improve use of the model in decision-making within financial markets.

Future research could extend the proposed model to forecast the Thai Baht (THB) against other currencies, such as THB/USD, and assess its applicability to other financial time-series domains, including stock market prices in Thailand. Such extensions would further demonstrate the adaptability and strength of the suggested hybrid model.

In addition, it is essential to enhance the interpretability of the hybrid model as the LSTM, GRU, and attention mechanisms, are not easily comprehensible to stakeholders regarding the model decision-making process. Methods which are easy to explain are more understandable and accessible. It is, therefore, possible to increase the efficiency of sentiment analysis using other Natural Language Processing (NLP) tools, such as Bidirectional Encoder Representations from Transformers (BERT) based models or transformer architectures. Additionally, extending the feature space by including social media mood and geopolitical events may lead to more realistic and accurate financial forecasts.

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