Predicting Financial Markets with Deep Learning Methods: Analyzing AAPL Stock, BTC-USD and EUR/USD Exchange Rates

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Abstract: A combination of advanced recurrent and convolutional networks is proposed in this study for financial asset price estimation. The performance of Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) and the hybrid CNN-LSTM is evaluated, as the latter has not been thoroughly studied despite being able to find both spatial and temporal patterns [6]. This research covers three kinds of financial assets—Apple stocks (AAPL), Bitcoin cryptocurrency (BTC-USD) and the Euro to U.S. Dollar exchange rate (EUR/USD), in contrast to many that only analyze stocks [2,6,11,13,14], cryptocurrencies [16,19] or, very rarely, exchange rates. Such an approach allows us to apply predictive models to different markets. I gathered financial history from Yahoo Finance and then included four major technical indicators: SMA, EMA, RSI and MACD, while other studies might just use the raw data itself or a smaller number of indicators [15,17]. Standardized data was divided into sequences for a prediction period of 60 days. Assessing the model involved means of MAE and R^2, giving a more balanced result than obtained by using just RMSE or MAPE [13–15]. Choosing these methods allows for a broader and reusable approach for financial time series forecasting, as compared to previous studies limited in architecture or evaluation [2,14,15].

Keywords: Deep Learning; Financial Market Prediction; LSTM; GRU; CNN-LSTM.

1.Introduction

Regular price predictions in financial markets exist as a complicated scientific pur-suit because financial time series data shows significant volatility and non-linearity [6]. Autoregressive Integrated Moving Average (ARIMA) serves as one of the most common forecasting techniques used for financial market prediction [1,6]. Simple linear models that currently exist cannot sufficiently represent organizational financial data patterns since their scope in different markets and assets is restricted [6,9]. Financial predictions benefit from deep learning models which learn complex time-series patterns because these systems can analyze dependencies within sequential data patterns [14,17].

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The Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) variants of recurrent neural networks (RNNs) along with deep learning have proven very effective at forecasting financial time series data according to [5,17]. These models have demonstrated excellent capability in tracking extensive sequential relationships which results in their effective use for stock market and cryptocurrency prediction tasks [11,13]. The combination of Convolutional Neural Networks (CNN) and LSTM networks through hybrid models called CNN-LSTM has demonstrated excellent outcomes for increasing financial price prediction accuracy [5,19].

This research investigates the application and comparison between LSTM and GRU and CNN-LSTM models which analyze financial market price prediction while simultaneously examining stock (Apple Inc. - AAPL) and cryptocurrency (Bitcoin - BTC-USD) and foreign exchange (EUR/USD). The collected financial data from Yahoo Finance received additional enhancement through widely applied market analysis indicators that included Simple Moving Average (SMA) and Exponential Moving Average (EMA) alongside Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD) [16,18]. The models received preprocessing followed by normalization and sequential data transformation before they engaged in predicting 60-day asset price predictions.

The evaluation of model performance included the use of Mean Absolute Error (MAE) and Coefficient of Determination (R^2) as identified in [4,15]. The metrics serve as quantitative indicators to evaluate both the prediction accuracy and operational efficiency when dealing with financial time series information. The scientific literature shows that deep learning models provide superior results than conventional machine learning approaches when used for financial forecasting in markets with volatility and high data frequencies [2,10].

This research uses comparative assessments between LSTM GRU and CNN-LSTM models to establish what constitutes the most efficient deep learning technique for financial asset price prediction. The research provides beneficial knowledge which enables investors together with traders together with financial analysts to make better decisions through AI-driven models during markets that change frequently.

2. Literature Review

The stock market analysis depends fundamentally on fundamental analysis along with technical analysis as its traditional evaluation methods. Fundamental analysis provides financial performance assessments through financial statement analysis and company valuation assessment based on public availability of business information. Fundamental analysis enables investors to find appropriate stock prices by analyzing financial and industrial market data which allows them to locate both underpriced and expensive stocks. Technical analysis works through price chart and volume data evaluation to help create future market expectation. The Moving Average Convergence Divergence (MACD) and moving averages function as technical indicators for generating buy and sell signals. The techniques struggle to establish clear connections among the complex stock price determining elements although they demonstrate limited effectiveness. The advantages of machine learning models especially neural networks become apparent to solve this problem.

Financial time series benefit from Long Short-Term Memory (LSTM) models which excel at recognizing complex relationships along with detecting nonlinear patterns in such data sets. Stock market forecasting literature demonstrates that Pang X et al. [11] used LSTM models to address traditional learning models' flaws in their study. Long-term temporal dependencies are managed effectively by these models because financial time series require this functionality. Chong, Han, & Park (2017) established deep learning methods achieve superior results than linear models for stock prediction but encounter difficulty during evaluation periods (ref-Marketanalysis).

Research conducted by Hiransha, Gopalakrishnan, Menon, & Soman (2018) has validated that CNNs outperform all other neural networks for stock price prediction tasks under diverse circumstances. The networks demonstrate superior pattern detection capabilities in stock prices which proves them better than established models including ARIMA in particular circumstances. The advancements address classical methods' limitations specifically because they understand market movement complexities better [11].

Nelson, Pereira & de Oliveira (2017) performed an evaluation of LSTM models that analyzed stock price rise or decline predictions reaching above 55% precision. The prediction achievement of neural networks for modeling market trends has been demonstrated despite an average success rate at moderate levels [10].

Sentiment analysis when implemented inside machine learning models demonstrates remarkable potential for successful integration. The implementation of neural networks has been effective for investor sentiment analysis of both social media content and financial news data. Network predictions have become more precise since they now integrate investor emotional data which controls stock market price movements. The research presented by Yu (2014) backs his discovery that deep neural networks (NN) produce better stock trading forecasts for Amazon data than traditional approaches [11].

Deep learning finance research expands constantly and the applications explained above lead the current wave of financial innovation. The models experience stability issues when market volatility increases such as the situation during the COVID-19 pandemic period. The combination of investor sentiment data and economic indicators with deep learning models shows promise for both enhanced prediction accuracy and improved investment decision support to managers of capital assets.

LSTMs and CNNs have proved effective in stock price prediction yet they face persistent barriers which affect their functioning during times of elevated market volatility.The present models demonstrate effective results but scientists and researchers need to develop them further to achieve complete potential which will help expand financial applications The emerging research field of deep learning methods together with new assessment methodologies for sentiment analysis shows promising progress in this area of study [10].

3. Methodology

3.1. Data

The study obtained its financial data from Yahoo Finance between January 1st 2015 to September 1st 2024. The data contains three asset classes with their information collected daily: Apple Inc. stocks (AAPL) and Bitcoin cryptocurrency (BTC-USD) along with the EUR/USD Forex exchange rates. We obtained the closing values and trading volumes of each asset because these two metrics play essential roles in trend evaluation. Our attempt to enhance dataset quality and prediction precision included incorporation of multiple technical indicators that include Simple Moving Average (SMA), Exponential Moving Average (EMA), Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD). These technical indicators enable traders to see market direction trends together with market volatility and reversal point potential. Min-Max scaling normalization occurred on the data to promote better model convergence rates. The dataset structured with 60-day sequences enabled models to use historical information for forecasting future price values.

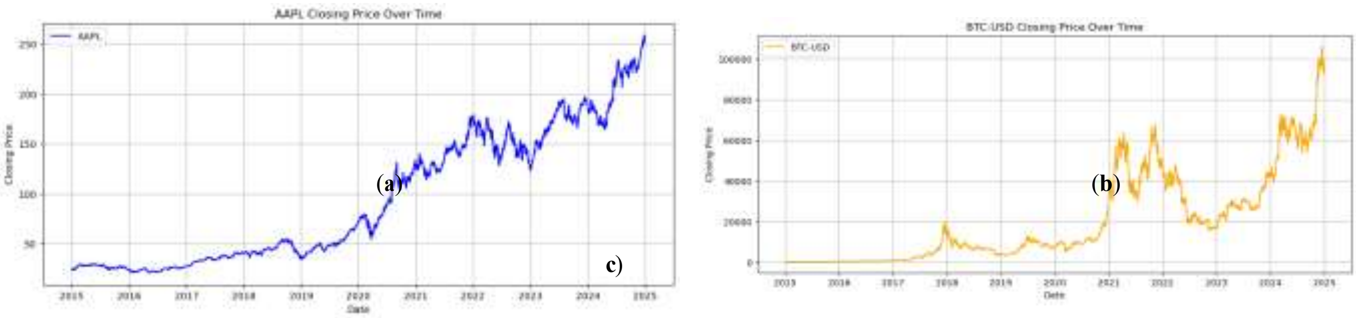


Figure 1. Historical data of AAPL, BTCUSD and EURUSD (1.1.2015-31.12.2020).

3.2. Research Methods

The development of deep learning financial market price predictions depends on data preparation and model selection as well as evaluation methods. Three artificial neural network architectures were used in this study which included Long Short-Term Memory (LSTM) together with Gated Recurrent Unit (GRU) and Convolutional Neural Network–LSTM (CNN-LSTM). The researchers used Keras together with TensorFlow libraries in Python for model design and training while NumPy, Pandas, Matplotlib, and Scikit-learn processed and visualized the data.

The research worked with daily closing price data and trading volumes from three different investment categories comprising Apple Inc. (AAPL) stock prices as well as Bitcoin (BTC-USD) crypto values together with EUR/USD foreign exchange pair prices. Four widely implemented technical indicators—Simple Moving Average (SMA), Exponential Moving Average (EMA), Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD)—were added to the dataset for improving model precision. The selected technical indicators give data analysts useful information about market price movements together with momentum signals and signals for potential turning points.

- **Relative Strength Index (RSI):** The Relative Strength Index functions as an oscillating indicator to measure price movement intensity for spotting points of market oversold or overbought conditions. The average success and failure values during a 14-day measurement period produce a value range that oscillates between 0 to 100. A traditional rule states that when RSI crosses above 70 the asset tends to become overbought, potentially leading to price downside corrections, and a reading beneath 30 shows asset oversold conditions that could trigger price increases [3]. Adjustments in these RSI levels must be considered according to the unique asset characteristics and market circumstances. The RSI successfully detects market turning points through its capability to identify price movements that extend beyond their recent trading range at excessive speeds. RSI analysis becomes more accurate when measuring it against price movement because a bearish signal occurs when price extends its peak while the RSI maintains or drops below its previous maximum, sending a warning about rising market dislocations [12]. A bullish divergence takes place when price sets a new bottom while RSI registers at a level higher than its earlier low, indicating upcoming upward price trends.

$$\mathrm{RSI} = 100 - \frac{100}{1+RS} \tag{1}$$

Where the term **RS (Relative Strength)** is the ratio between the average gains and the average losses over a reference period *N* (typically $N = 14$):

$$RS = \frac{\text{Average gains over N periods}}{\text{Average losses over N periods}} \tag{2}$$

- **Moving Average Convergence Divergence (MACD)**

The Moving Average Convergence Divergence functions as a trend-following indicator that reveals the price relationship between two security moving averages [7]. The value of MACD is obtained through a mathematical operation that subtracts the 26-period EMA from the 12-period EMA. The MACD line connects with a signal line that usually exhibits a 9-period exponential moving average calculation from the MACD line data. MACD signal formation from crossings between the MACD line and the signal line serves as a trading indicator where bullish events occur when the MACD crosses above the signal and bearish occasions manifest when the MACD crosses below the signal. The MACD histogram displays the difference between the MACD line versus the signal line, thus showing a graphical interpretation of the indicator's movement. The analysis becomes valuable whenever there is a MACD–price action mismatch, which indicates impending reversals.

$$\mathbf{MACD(t) = EMA_{12}(t) - EMA_{26}(t)} \qquad (3)$$

$$\mathbf{Signal(t) = EMA_{9}(MACD(t))} \qquad (4)$$

Where:
– $\mathbf{EMA_{12}(t)}$ is the 12-period exponential moving average,
– $\mathbf{EMA_{26}(t)}$ is the 26-period exponential moving average,
– **Signal(t)** is the 9-period EMA of the MACD line.

• Simple Moving Average (SMA)

A Simple Moving Average determines asset price averages through summation of closing prices in defined periods divided by the measurement length. SMA uses identical weightage for every data point during calculations, which makes it a recognized and popular indicator to smooth prices and detect trends [8]. Potential support and resistance levels get detected through the use of the SMA.

$$SMA_N(t) = \frac{1}{N}\sum_{i=0}^{N-1} P(t-i)$$

– $\mathbf{SMA_n(t)}$ is the simple moving average over N periods.
– **P(t − i)** is the price at time $t - i$, for the last N periods.
– The sum is calculated over the last N values.

• Exponential Moving Average (EMA)

The Exponential Moving Average operates as a moving average which gives priority to current price data, thereby providing a more responsive trend indicator compared to the Simple Moving Average.

The EMA provides better responsiveness than the SMA. The EMA computing process combines recent price movements using a specific weight calculation.

$$\mathbf{EMA_n(t) = \alpha \cdot P(t) + (1 - \alpha) \cdot EMA_n(t - 1)} \qquad (6)$$

– $\mathbf{EMA_n(t)}$ is the exponential moving average over N periods.
– $\mathbf{P(t)}$ is the price at time t.
– $\mathbf{EMA_n(t - 1)}$ is the previous EMA value.
– The smoothing factor is given by: $\boldsymbol{\alpha} = \mathbf{2 / (N + 1)}$.

During training, the model received datasets whose features underwent MinMaxScaler processing to achieve scale values between 0 and 1 because this allowed neural networks to learn more effectively. The evaluation of model performance required real market values, so predictions were transformed from their scaled format back to their original values.

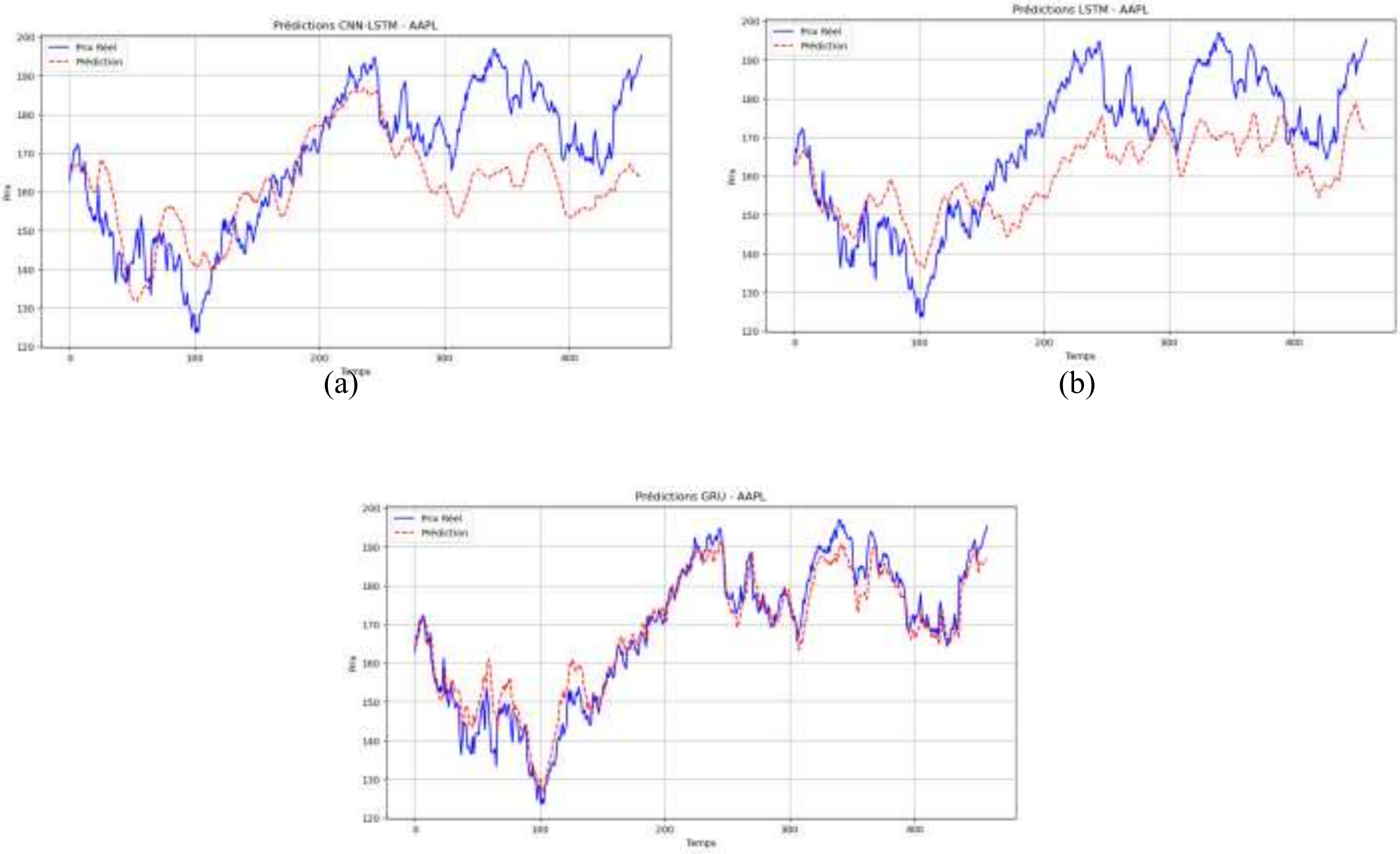
The available information was separated evenly between training and testing components, with training receiving 80% of the data and testing receiving the remaining 20%. A fifty-day historical market dataset served as input to forecast the coming sixty-day market price outcomes.

The building of models took place through Keras's Sequential API. The long-term dependencies within financial time series were successfully processed by LSTM and GRU networks through their repeated recurrent layer structure. Local patterns in the data were extracted through convolutional layers that the CNN-LSTM model applied before LSTM layers processed the sequence relationships. Training sessions reached 100 epochs along with 32 items per batch and utilized the Adam optimizer to perform efficient weight updates.

The evaluation utilized the transformed price values for actual measurements, while MAE and R^2 scores measured the model performance.

4. Results

4.1. AAPL Stock price prediction with LSTM, GRU and CNN-LSTM



(a) (b)

(c)

Figure 2. Comparison of actual and predicted AAPL stock prices using LSTM, GRU and CNN-LSTM.

Table 1. Performance Summary Table for APPL.

Model	MAE	R²
LSTM	21.322865	-0.667647
GRU	14.765218	0.126337
CNN-LSTM	25.111654	-1.108788

The research on Apple Inc. (AAPL) stock data reveals essential insights into the performance of different neural network architectures for stock price prediction. Both Mean Absolute Error

(MAE) and R^2 values are used to evaluate the forecast accuracy of stock prices and the prediction fit relative to actual data.

With an MAE value of 21.32, the LSTM model produces predictions that deviate, on average, by 21.32 units from the actual stock prices. The model shows limitations in predicting stock closing prices, as a more accurate prediction requires smaller MAE values. Furthermore, the model is less effective than basic mean-based predictions, as indicated by its negative R^2 value of -0.67. A negative R^2 demonstrates poor model performance, signaling that the model failed to capture data variance patterns, which leads to inaccurate market predictions. These results suggest that the LSTM architecture may require adjusted settings, enhanced features, or more precise training to accurately predict AAPL stock prices.

The GRU model surpasses LSTM performance, achieving an MAE of 14.77 due to more accurate predictions. However, the predictions still exhibit a considerable error, indicating they are not fully precise. The model shows a weak positive correlation in its predictions, reflected by an R^2 value of 0.13. While GRU outperforms LSTM, it does not capture a substantial portion of the stock price variance. The positive R^2 score suggests a slight advantage over LSTM in learning patterns, but its limited performance indicates it cannot deliver consistently reliable predictions. Further improvements could be achieved by testing additional hyperparameters and applying advanced data preprocessing techniques.

The hybrid CNN-LSTM model, on the other hand, achieves the highest MAE of 25.11, despite being designed to extract local patterns through convolutional layers before passing sequences to the LSTM layers. The model's predictions deviate significantly from actual values, exceeding the errors of both LSTM and GRU models. Its R^2 value of -1.11 is lower than both the baseline mean model and the other models, demonstrating weak performance in modeling price patterns. Although CNN layers can extract patterns in time series data, their contribution was insufficient for this particular prediction task. The convolutional component may have failed to enhance the model's ability to capture temporal dependencies in stock prices, resulting in unsatisfactory performance. The complexity of CNN-LSTM architectures appears inappropriate for this problem, as simpler models like LSTM or GRU could potentially yield better results.

The predictive performance of LSTM, GRU, and CNN-LSTM models suffered from several limitations when forecasting AAPL closing prices:

- **LSTM and CNN-LSTM** models performed poorly, with negative R^2 values indicating failure to accurately capture market dynamics. The addition of CNN layers in CNN-LSTM did not lead to substantial improvements, showing that these layers did not enhance prediction accuracy in this context.
- **GRU** achieved the best results among the tested models, with a lower MAE than LSTM and CNN-LSTM, though its forecast accuracy remained insufficient for reliable predictions. GRU managed long-term dependencies better than LSTM, leading to superior performance, but overall results were still inadequate for dependable stock price forecasting.
- **Overall predictive accuracy** was weak across all models. High MAE values and low R^2 scores highlight their insufficient performance. Stock price forecasting for AAPL proves to be extremely challenging for deep learning models, as accurate predictions require more extensive data and improved modeling techniques.

4.2. BTC price prediction with LSTM, GRU and CNN-LSTM

(a) **(b)**

(c)

Figure 3. Comparison of actual and predicted BTC prices using LSTM, GRU and CNN-LSTM

Table 2. Performance Summary Table for BTC.

Model	MAE	R^2
LSTM	8074.831279	0.606356
GRU	10250.092527	0.406289
CNN-LSTM	9875.668741	0.453544

By running the models on Bitcoin (BTC) data, researchers gained essential insights into how LSTM, GRU, and CNN-LSTM networks perform in forecasting cryptocurrency price shifts. The study uses Mean Absolute Error (MAE) and R^2 to evaluate model performance in terms of prediction accuracy and goodness of fit.

Predictions generated by the LSTM model achieved a Mean Absolute Error of 8,074.83. This indicates that, on average, the model's predicted Bitcoin prices deviate by $8,074.83 from the actual prices. Given Bitcoin's high volatility, this level of error is considered acceptable. The LSTM model shows a positive correlation of 0.61 between predicted values and actual data points. Its ability to detect recurring patterns in Bitcoin price movements allows the model to make reasonably accurate predictions. Performance could be further improved through additional parameter optimization, longer training cycles, and inclusion of more dataset variables.

The GRU model, in contrast, exhibits inferior performance to LSTM, producing an MAE of 10,250.09. This higher average error indicates that GRU predictions deviate more from actual Bitcoin prices than LSTM predictions.

So it shows weaknesses regarding its ability to grasp complex time-dependent Bitcoin price patterns. The 0.41 R^2 value reveals the GRU model has less successful prediction performance compared to LSTM regarding actual price levels. The GRU model showcases limited ability to predict new data because its R^2 value remains lower than LSTM and the other models. The predictive ability of the GRU model exists but it fails to demonstrate better results than LSTM structures without further improvements.

The CNN-LSTM algorithm performs similarly to the GRU model with an MAE of 9875.67 but demonstrates a slight improvement over the latter model. Test results indicate that the CNN-LSTM model fails to outperform basic LSTM and GRU models in Bitcoin price prediction even though it requires a more complex structure. The R^2 score of 0.45 reflects that predictions made by the model show a moderate relationship to actual values yet remain below the threshold for powerful predictions. The performance of the CNN-LSTM model indicates that although convolutional layers can extract local patterns in the data, their application might not lead to optimal Bitcoin price prediction.

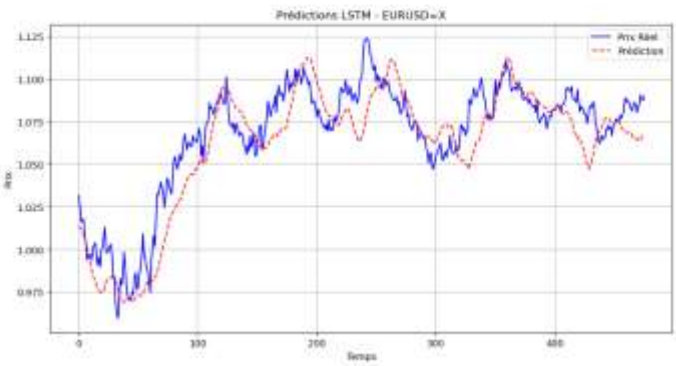
Results from the Bitcoin data analysis using the LSTM, GRU, and CNN-LSTM models reveal important aspects about forecasting in volatile cryptocurrency markets. Here are the key takeaways:

- The LSTM model achieved the highest performance scores through its 8074.83 MAE and 0.61 R^2 score. The predictive model produced error at a high level but it achieved better pattern detection outcomes when compared to GRU and CNN-LSTM models. The R^2 value indicates that Long Short-Term Memory (LSTM) establishes itself as the optimal network choice to detect lengthy relationships inside the price time series.
- The GRU model proved less effective than LSTM because it showed an unsatisfactory performance, including an MAE of 10250.09 and an R^2 of 0.41. Despite showing some ability to record price movement trends, the model performed worse because its higher MAE score and lower R^2 value demonstrate its limitation in correctly forecasting Bitcoin prices, especially because of its restricted ability to process long-term dependencies in the data.

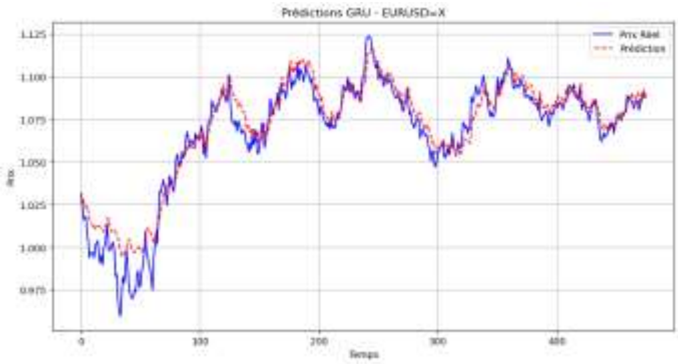
- The CNN-LSTM model delivered performance comparable to the GRU model, with an MAE of 9875.67 and an R^2 value of 0.45. The usage of convolutional layers shows constraints when predicting cryptocurrency prices in this particular outcome. In this context, the CNN layers failed to bring improved value because the model performed comparably to or worse than basic LSTM models.

All models demonstrated predictive patterns, yet their performance remained subpar primarily because Bitcoin price moves naturally show high volatility and complexity. Advanced deep learning methods face substantial difficulty while trying to analyze the non-linear cryptocurrency market dynamics because prediction errors remain high and R^2 values fall between low and moderate ranges. The successful improvement of cryptocurrency prediction models demands supplementary features that include sentiment analysis together with macroeconomic data or alternative machine learning methods.

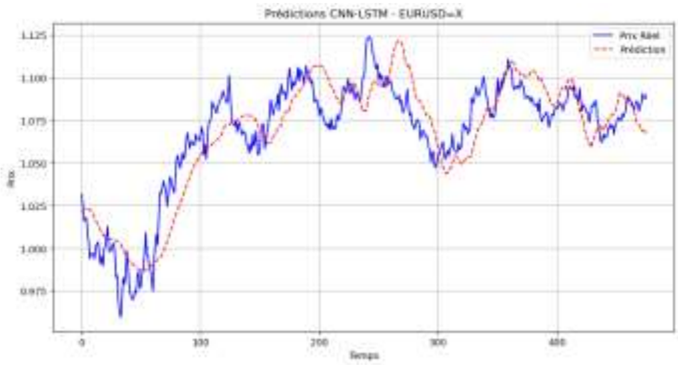
4.3. EURUSD price prediction with LSTM, GRU and CNN-LSTM



(a)



(b)



(c)

Figure 4. Comparison of actual and predicted EURUSD prices using LSTM, GRU and CNN-LSTM.

Table 3. Performance Summary Table for EURUSD.

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Model	MAE	R^2
LSTM	0.037482	-3.566379
GRU	0.038011	-3.798972
CNN-LSTM	0.041392	-3.199258

The evaluation process of EUR/USD exchange rate data reveals how LSTM, GRU, and CNN-LSTM architectural frameworks perform when predicting changes in currency market value. Mean Absolute Error (MAE) along with R^2 are used to assess model results according to standard regression metrics. The MAE presents average prediction errors to analysts, while R^2 shows model prediction accuracy.

The LSTM model produces predictions with an average difference of 0.0375 from the actual EUR/USD exchange rates, reflected in its MAE of 0.037482. These prediction error levels are considered low based on this data. However, a very low R^2 value of -3.57 raises serious concern. An R^2 value below zero indicates that the model produces results significantly worse than basic mean predictions. The LSTM model encounters difficulty in understanding the natural fluctuations of the EUR/USD exchange rate, as indicated by its poor R^2 value, even though the MAE remains reasonable. The exchange rate volatility appears challenging for the model due to complex non-linear market dynamics.

The MAE value produced by the GRU model measures 0.038011, similar to the score achieved by the LSTM model. The average prediction error of GRU becomes equivalent to LSTM's average prediction error rate when evaluating both models. The R^2 value of -3.80 demonstrates worse performance than the mean baseline model by the GRU model. The negative R^2 indicates a clear failure of the GRU model in learning the critical relationship between past data and the EUR/USD exchange rate. The identical MAE scores between LSTM and GRU models highlight the insufficient ability of GRU to detect key patterns in currency market dynamics, resulting in its below-average R^2 score.

The CNN-LSTM model, with convolutional and LSTM layers, achieved a 0.041392 error rate. Comparatively, the CNN-LSTM model reflects the greatest error level, making it the least precise solution for predicting the EUR/USD exchange rate. Similar to the other models, the CNN-LSTM presents a negative R^2 score of -3.20, demonstrating that it produces worse predictions than a baseline model predicting data mean values. No improvement emerges in pattern extraction from the currency market despite the use of convolutional layers in the CNN-LSTM structure. The model's performance does not increase notably when convolutional layers are incorporated for this EUR/USD prediction task.

Calculations of EUR/USD data using the three models (LSTM, GRU, and CNN-LSTM) produced crucial insights about the challenges of currency exchange rate prediction. The main outcomes show the following informations:

- Both MAE measurement and predictive accuracy results of the LSTM model demonstrated strong performance compared to other proposed models, with an MAE of 0.037482. However, the model performs worse than a basic mean prediction due to its negative R^2 value of -3.57. The LSTM model proved incapable of discovering significant patterns in the data because EUR/USD price movements contained complex factors that the learning algorithm failed to address properly.

- The GRU model matched the LSTM performance regarding MAE values (0.038011), but resulted in an inferior R^2 score of -3.80. The higher prediction error coupled with the lower R^2 confirmed that GRU failed to exceed LSTM in prediction success and in modeling the data relationships. GRU performs poorly in forecasting EUR/USD exchange rates, indicating its unsuitability for this task.
- Although the CNN-LSTM model used an advanced hybrid structure, it produced the highest MAE of 0.041392 and a negative R^2 of -3.20. The convolutional layers failed to provide additional benefit for exchange rate prediction accuracy. The dual convolutional and LSTM layers could not detect time-dependent relationships effectively, leading to inferior performance compared to single LSTM or GRU models in terms of accuracy and goodness-of-fit metrics.

All three regression models performed poorly, as indicated by their negative R^2 values, which show that they failed to explain the patterns in EUR/USD exchange rate data. Forecasting currency exchange rates is a challenging problem that likely requires advanced techniques or additional features, such as economic indicators and sentiment analysis, combined with alternative artificial intelligence approaches.

The small MAE values nevertheless reflect appreciable errors when forecasting the EUR/USD exchange rate. These results illustrate the difficulty of accurately predicting exchange rates in foreign markets, given their high complexity and marked volatility. Future research should explore new strategies and parameters to optimize and enhance model performance effectively.

The EUR/USD dataset displayed insufficient performance from the LSTM, GRU, and CNN-LSTM models because all models reported negative R^2 scores. Although the LSTM model achieved better performance than GRU and CNN-LSTM models for MAE calculation, it showed limited success in capturing exchange rate dynamics.

5. Conclusions

The different nature of financial assets, along with their volatility levels, influences how effective deep learning models are in generating predictions on AAPL stock, Bitcoin, and the EUR/USD exchange rate. The unique behavioral patterns of these models during market predictions support the hypothesis that no single architecture can dominate across all market types.

The results from the GRU model delivered superior performance on AAPL stock prediction, yielding the smallest MAE and a positive R^2 value, demonstrating its capability to handle the gradual nature of equity market trends. The data showed that LSTM and CNN-LSTM experienced reduced performance because these models appeared to overfit the data and detect short-term noise patterns.

The BTC market volatility required LSTM to deliver superior performance, achieving the lowest MAE and highest R^2 statistics. LSTM demonstrates exceptional capability in handling long-term dependencies, analyzing irregular patterns within highly volatile time series. The volatile nature of cryptocurrency prices may require deeper time-dependent memory functions, which explains the reduced performance of GRU and CNN-LSTM models in this context.

For EUR/USD, all implemented models exhibited persistently poor performance, as indicated by negative R^2 scores and comparable MAE values. The deep learning models failed to adequately capture currency market behavior because external macroeconomic factors were absent from the available features.

Model selection practices should always consider the unique characteristics of the evaluated asset. Stock market data required GRU, while the volatile nature of Bitcoin favored LSTM as the preferred model. Predictive power for forecasting the EUR/USD pair proved inconsistent across all models because price-based features alone were insufficient. Adaptability and the inclusion of relevant features remain essential for obtaining optimal predictive outcomes in financial time series forecasting.

Abbreviations

The following abbreviations are used in this manuscript:

- **LSTM** – Long Short-Term Memory
- **GRU** – Gated Recurrent Unit
- **CNN** – Convolutional Neural Network
- **SMA** – Simple Moving Average
- **EMA** – Exponential Moving Average
- **RSI** – Relative Strength Index
- **MACD** – Moving Average Convergence Divergence
- **MSE** – Mean Squared Error
- **MAE** – Mean Absolute Error
- **R^2** – Coefficient of Determination
- **ARIMA** – Autoregressive Integrated Moving Average
- **RNN** – Recurrent Neural Networks
- **BTC** – Bitcoin
- **NN** – Neural Networks

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