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FORECASTING CURRENCY RATES USING MACHINE LEARNING MODELS

Accurate forecasting of foreign exchange (FOREX) currency rates is crucial for various financial activities. However, both the time interval and the chosen model can have a significant impact on forecasting accuracy. Therefore, investigating the effect these elements have on the prediction accuracy of multivariate time series data representing Open, High, Low, and Close (OHLC) prices in FOREX markets, requires further research.

The aim of paper is to evaluate and compare the performance of different quantitative forecasting models (VAR, LSTM, GRU, Random Forest) in predicting Foreign Exchange (FOREX) currency rates across various timeframes (daily (D), 4-hourly (H4), hourly (H1), 15-minute (M15)).

The performance of VAR, LSTM, GRU, and Random Forest – was evaluated on four FOREX datasets. These datasets included data from different Timeframes including D, H4, H1, M15. Each model was trained on historical data, and then their prediction accuracy was assessed on unseen test data. Accuracy was measured using MAE and MSE.

The influence of timeframe and machine learning methods on forecasting exchange rates EUR/USD is studied. Effectiveness of various forecasting models was analyzed.

Random Forest model outperformed other models on every Dataset (Timeframe) with astounding result of MAE = 0.00004 and MSE = 0.000000007 on M15 Dataset. Future research will focus on: developing a forecasting method based on fuzzy logic; constructing a model capable of online learning with real-time data; and creating a decision support system for algorithmic trading.

Keywords: LSTM, GRU, Random Forest, forecasting, multivariate timeseries, FOREX.

ABBREVIATIONS

FOREX — Foreign Exchange;
GRU — Gated Recurrent Unit;
LSTM — Long short-term memory;
MAE — mean absolute error;
MSE — mean squared error;
OHLC — Open, High, Low, Close;
VAR — Vector Autoregression.

NOMENCLATURE

$f_i(x)$ is a base model, typically a decision tree;
$g(x)$ is a final prediction;
k is a number of endogenous variables;

m is a input features observed at time t;
t is a time period, numbered $t = 1, \ldots, T$;
x is a original value;
$\{x_1, x_2, \ldots, x_T\}$ is a time series;
X is a 2-dimensional tensor (or matrix);
x' is a normalized value;
$x_{\max}$ is a maximum value of the original data;
$x_{\min}$ is a minimum value of the original data;
y is the target variable;
y_t is a vector of length k representing the variables at time;
$\hat{y}_{t+k}$ is a predicted value of the target variable at time $t + k$.

1. Introduction. The Foreign Exchange Market (Forex) is the world's largest financial market, enabling the trading of currencies and other assets, such as metals. Its high liquidity makes it an essential platform for international trade and investment [1].

To make informed trading decisions in the Forex market, investors and traders rely on various analysis methods. Fundamental analysis focuses on identifying a currency's "fair value" by considering economic data and financial indicators. Technical analysis, on the other hand, utilizes price charts and technical indicators to identify historical price patterns and potential future movements. The core principle of technical analysis is that all relevant market information is already reflected in the price itself.

While fundamental and technical analysis are widely used for market decisions, quantitative analysis offers a distinct approach. Quantitative analysis views market prices as time series data and employs sophisticated mathematical models and statistical techniques to forecast future price movements. This data-driven approach complements traditional analysis methods by providing a more objective and systematic way to identify trading opportunities.

Within quantitative analysis, there exists a vast array of models, encompassing statistical methods, machine learning and deep learning models. Each type of model offers unique advantages and addresses specific challenges in market prediction.

However, the effectiveness of these quantitative models varies greatly. This paper will delve into the efficiency of different model types, including statistical methods, machine learning algorithms, and deep learning architectures, to identify the most promising approaches for market prediction

So the object of study is foreign currency rates (FOREX) on the markets, represented by OHLC data and the subject of study is the efficiency of different machine learning models in forecasting exchange rates at different time intervals.

A significant amount of research has explored quantitative forecasting in financial markets. However, these studies often focus on predicting a single variable, typically the closing price, using univariate time series analysis. This approach overlooks the rich information available within market data. Our work takes a more comprehensive approach by investigating the forecasting of multivariate time series using OHLC data (Open, High, Low, Close). This allows us to capture the full range of price movements within a specific timeframe. Additionally, we explore the impact of timeframe on efficiency. By analyzing the effectiveness of these models across different time horizons (e.g., daily, hourly), we aim to provide a more nuanced understanding of their predictive capabilities.

The purpose of this work is to compare the efficiency of various forecasting models employed in quantitative analysis when applied to different timeframes.

To achieve the purpose of the work, the following problems shall be solved:

– to analyze existing forecasting models;
– to create and prepare data sets;
– to implement and train forcasting models for each data set;
– to make a comparative analysis of the obtained results.

2. Problem Statement. Given a time series, where each is a vector of input features observed at time, the task is to develop a predictive model that utilizes historical data represented as a 2-dimensional tensor of shape to forecast a target variable at a future time point. The goal is to accurately predict the future target value using the model.

Given a time series for predicting a future target variables, the challenge lies in identifying the most efficient forecasting model across various timeframes. To achieve this, we will employ different models on multivariate time series data with varying time horizons. The MAE and MSE will be calculated for each model's predictions to assess their accuracy and identify the most efficient model for specific time intervals based on their lowest values.

3. Review of the literature. Financial market forecasting is a notoriously intricate task. Despite the valuable insights gleaned from popular methods like technical and fundamental analysis [1], accurately predicting future price movements requires navigating a complex interplay of economic data, market sentiment, and other factors. This highlights the need for a more systematic and objective approach to identify efficient forecasting models. Quantitative analysis emerges as a complementary approach, leveraging mathematical models and statistical techniques to dissect market data and objectively predict future price movements [2].

While Vector Autoregression (VAR) models, a popular statistical approach to forecasting, have been explored in previous research [3, 4], their ability to capture all the dependencies within financial data remains a challenge.

This necessitates exploring more intricate models. Machine learning algorithms, with their ability to learn from vast datasets and identify hidden patterns, offer a compelling alternative. Using the machine learning models described in [5], we aim to develop a more comprehensive understanding of market dynamics and identify the most efficient forecasting approach across different timeframes. In particular, these are models of Long Short-Term Memory (LSTM) networks [6], Gated Recurrent Units (GRUs) [6] and Random Forests [7].

In [8] statistical model was compared with LSTM. Paper [9] compared LSTM with Random Forest.

Our study will compare classic statistical model VAR with LSTM, GRU and Random Forest. Moreover, we will determine the impact of timeframe on efficiency.

4. Matherials and Methods. VAR model. A VAR model [4] describes the evolution of a set of k variables, called endogenous variables, over time. Each period of time is numbered, $t = 1, \ldots, T$. The variables are collected in a vector, y_t, which is of length k. Equivalently, this vector might be described as a $(k \times 1)$-matrix. The vector is modelled as a linear function of its own lagged values. The inclusion of lagged values allows the model to capture the dynamic interdependencies between the variables.

LSTM model. Long Short-Term Memory (LSTM) networks [6] are a special type of neural network that can learn from long sequences of data, unlike regular RNNs which struggle with remembering distant information.

LSTMs have an internal memory that helps them remember important information from past data points. This allows them to understand how events further back in time can influence future events, something regular RNNs struggle with.

LSTM has forget gates, input gates, and output gates. These gates control how information flows within the LSTM's memory. They can decide what information to keep, what to forget, and how to combine it with new data to make better predictions.

GRU model [6]. Gated Recurrent Units (GRUs) are another type of neural network similar to LSTMs, but with a slightly simpler approach. They also aim to learn from long sequences of data and address the vanishing gradient problem.

Like LSTMs, GRUs have internal mechanisms (gates) that control how information flows within their memory. These gates, named update, reset, and candidate, decide what information to keep from the past, what to forget, and what new information to integrate.

The key difference is that GRUs use a single set of gates instead of the separate forget, input, and output gates in LSTMs. This makes them slightly more efficient computationally.

In simpler terms, both LSTMs and GRUs are like neural networks with good memories for past data. GRUs achieve this with a slightly more streamlined approach compared to LSTMs.

Random Forest.

Random Forest [7] is a powerful machine learning technique for predictive analytics. It falls under the category of ensemble learning, where the final prediction is derived by combining the outputs of multiple, simpler models. Formally, these models can be expressed as:

$$g(x) = f_0(x) + f_1(x) + \ldots + f_i(x).$$

This approach of combining multiple models to improve predictive performance is known as model ensembling. In Random Forests, each base decision tree is built independently using a random subset of the data (bootstrapping). This helps to reduce variance and improve the overall robustness of the final model.

Normalization is used to bring data to a common scale. In this study, the min-max technique was employed:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}. \quad (1)$$

Accuracy indices.

To assess how well the models learned, we used a measure called Mean Squared Error (MSE) [10] as the loss function during training. This helps us identify if the model is becoming too focused on training data and might not perform well on unseen data (overfitting).

In addition to MSE, we also evaluated the model's performance on unseen data using Mean Absolute Error (MAE) [11, 12]. MAE is a robust measure of prediction accuracy that calculates the average absolute difference between the predicted values and the actual values. Unlike MSE, which squares the errors and thus penalizes larger errors more heavily, MAE provides a straightforward interpretation of the average error magnitude.

5. Experiments. *1. Datasets.*

We applied the four machine learning techniques to the EUR/USD data sets from the finance.yahoo.com Website to perform Time Series Forecasting (TSF) for OHLC predictions.

Four data sets collected from different Timeframes are used. Each of them includes data for two year time period November 18, 2021 to November 17, 2023 and has 9 columns. First and second columns labeled as Date and Time were combined into single feature called "Date Time". The following four columns labeled as Open, High, Low, Close were used as input features. And they were used as target variables as well. The column names and explanations are presented in table 1.

Table 1.

Column names and explanations

Name	Explanation	Comment
Date	Date of Bar	Merged into
Time	Time of Bar	single feature
Open	Opening price	
High	Highest price of bar	Input features
Low	Lowest price of bar	& Targets
Close	Closing Price	
Volume	Volume of Bar	
Tick Volume	Volume of Tick	Ignored
Spread	Difference between	

Information about the generated datasets:

1. data set M15 has 50 001 rows, data was collected every 15 minutes;
2. data set H1 has 12 503 rows, data was collected hourly;
3. data set H4 has 3 128 rows, data was collected every 4 hours;
4. data set 1D has 522 rows, data was collected daily.

Data were normalized values to a range of [0, 1] using the Min-Max normalization technique as shown in (1).

The data were divided into training set (first 70% rows) and test set (last 30% rows).

2. Scheme of experiment.

VAR model was implemented as stated in [4]. And applied to all datasets.

A Random Forest model was constructed utilizing the scikit-learn library [14]. This model was then applied to all datasets for analysis.

The LSTM and GRU models were implemented as follows. Firstly, the data underwent a pre-processing step involving min-max scaling (1) to normalize the feature values. Subsequently, the data was segmented into batches, each with a size equivalent to the look-up window employed for the forecasting models. This window represents the amount of historical data fed into the model. We chose window sizes that corresponded to one week of data for each dataset: 480 for 15-minute intervals, 120 for hourly intervals, 30 for 4-hour intervals and 5 for daily intervals.

The construction of our models was accomplished utilizing the TensorFlow [13] library.

To investigate the impact of model complexity on performance, we constructed Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models with varying numbers of hidden layers. A 1-layer model served as the baseline, representing the simplest configuration. Additionally, a 4-layer model was implemented, where the number of hidden layers matched the combined quantity of features and target variables. Finally, a more complex model with 10 hidden layers was constructed. The selection of 10 layers was based on empirical observations, as models with a greater number of layers exhibited signs of overfitting.

The optimal number of neurons within the hidden layers and the learning rate hyperparameters were determined through hyperparameter tuning using KerasTuner [15].

To prevent overfitting and underfitting, the optimal number of training epochs was determined by employing the EarlyStopping callback from TensorFlow. This callback automatically halts training when the validation performance ceases to improve for a predefined number of epochs, effectively identifying the optimal stopping point.

The visualization of the model outputs and actual values was achieved using the Mplfinance library [16].

6. Results. Table 2 presents the results obtained for the datasets, following the methodology outlined in Section 4.

Table 2.

Mean Absolute Error (MAE) and Mean Squared Error (MSE) Values by Dataset and Forecasting Method

		M15		H1	
		MAE	MSE	MAE	MSE
VAR		0.0123	0.000233	0.01239	0.0002364
LSTM	1 Layer	0.000276	0.000000154	0.000462	0.000000562
	4 Layers	0.000283	0.000000169	0.000487	0.00000056
	10 Layers	0.000296	0.000000177	0.000370	0.000000606
GRU	1 Layer	0.000235	0.000000132	0.000486	0.000000526
	4 Layers	0.000257	0.000000145	0.000627	0.000000764
	10 Layers	0.000323	0.000000189	0.000616	0.000000712
Random Forest		0.000043	0.000000007	0.000112	0.000000036
		H4		D	
		MAE	MSE	MAE	MSE
VAR		0.0124	0.00023	0.0124389	0.000235
LSTM	1 Layer	0.00098	0.000002	0.00395	0.000025
	4 Layers	0.000984	0.000002	0.00333	0.00002
	10 Layers	0.00108	0.000002	0.00996	0.000185
GRU	1 Layer	0.00110	0.000002	0.00300	0.000015
	4 Layers	0.001055	0.000002	0.00241	0.0000118
	10 Layers	0.001197	0.000002	0.0026	0.000012
Random Forest		0.000286	0.00000018	0.00095	0.0000016

The colored cells in Table 2 highlight the Mean Absolute Error (MAE) values corresponding to the forecasting method that achieved the best performance on each dataset.

The analysis of the results reveals that the classic statistical method of Vector

Autoregression (VAR) consistently yielded the highest MAE values, indicating its underperformance compared to other models. Conversely, the Random Forest model emerged as a standout performer, exhibiting exceptionally low MAE values across various datasets. This suggests its potential as a robust forecasting tool in this context.

In Figures 1–4 compared top results of each method.

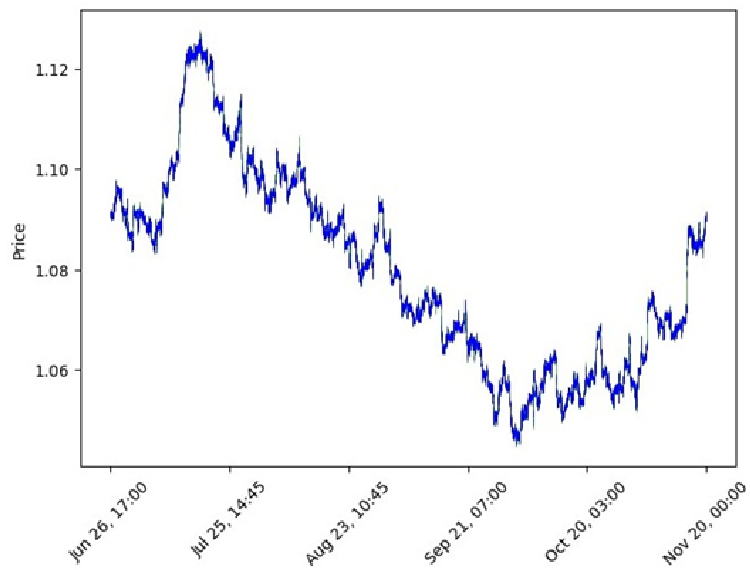

Figure 1. Actual values (green) compared with values predicted by LSTM model on M15 Dataset.

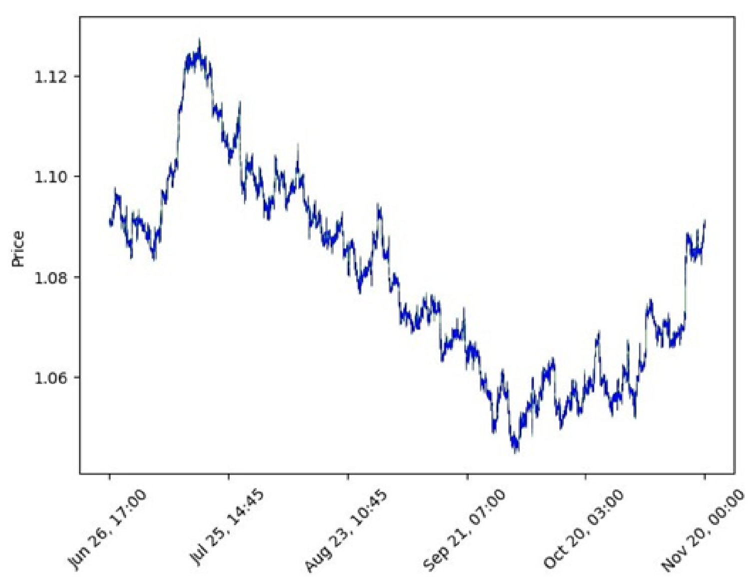

Figure 2. Actual values (green) compared with values predicted by GRU model on M15 Dataset.

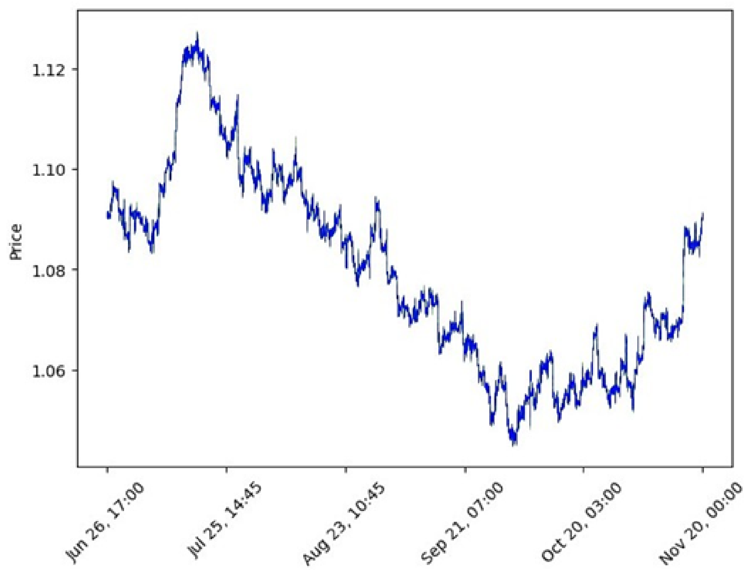

Figure 3. Actual values (green) compared with values predicted by Random Forest model on M15 Dataset.

7. Discussions. All models except VAR performed relatively well with peak performance of MAE ~ 0.0003 on the M15 dataset.

However, current research has determined that Random Forest is outperforming other models on the task of forecasting multivariate timeseries. The only disadvantage of Random Forest is its low forecasting capabilities based on real-time data (online forecasting).

8. Conclusions. The problem of comparing the efficiency of various forecasting models employed in quantitative analysis when applied to different timeframes is being solved.

The scientific novelty of the obtained results is as follows:

1. VAR, Random Forest, LSTM, GRU models were used for multidimensional forecasting of OHLC data on the exchange rate of the EUR/USD currency pair generated at different time intervals;
2. the hyperparameters of the models and the architecture of neural networks were adjusted in accordance with the tasks under consideration;
3. to identify the most effective forecasting models, a critical analysis of the results was carried out, taking into account the visualisation of the forecast and accuracy metrics;
4. according to the results of the study, the best forecasting model was Random Forest with MAE $= 0.4 \cdot 10^{-4}$, MSE $= 0.7 \cdot 10^{-8}$.

The practical significance of our findings lies in the development of software equipped with various forecasting models. Experiments have demonstrated the effectiveness of these models on specific timeframes. This software can empower CFD (Contract for Difference) traders with the ability to predict market movements based on data-driven insights. Furthermore, the models and the underlying methodology presented in this work can serve as valuable resources for other researchers seeking to advance the field of financial forecasting.

Future research is to develop a method for forecasting such time series based on fuzzy logic. This will allow the results to be used not only to predict future values, but also to convert the forecasts into actionable recommendations for CFD traders, such as ‘Buy’, ‘Sell’ or ‘Wait’. It is also planned to develop a decision support system for algorithmic trading that will provide traders with the ability to execute trades automatically based on forecasts and recommendations generated by forecasting models.

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Кондрук Н. Е., Гецко С. В. Прогнозування курсів валют засобами машинного навчання.

Точне прогнозування валютних курсів (FOREX) має вирішальне значення для різних видів фінансової діяльності. Однак, як часовий інтервал, так і обрана модель можуть мати значний вплив на якість прогнозів. Тому вивчення впливу цих елементів на точність прогнозування багатовимірних часових рядів даних, що представляють ціни відкриття, максимуму, мінімуму та закриття (OHLC) на ринках FOREX, потребує подальших досліджень.

Метою роботи є оцінка та порівняння ефективності різних кількісних моделей прогнозування (VAR, LSTM, GRU, Random Forest) у передбаченні валютних курсів на міжнародних валютних ринках (FOREX) за різними часовими інтервалами (денний (D), 4-годинний (H4), годинний (H1), 15-хвилинний (M15)).

Ефективність VAR, LSTM, GRU та Random Forest було оцінено на чотирьох наборах даних FOREX. Ці датасети включали дані з різних таймфреймів, включаючи D, H4, H1, M15. Кожна модель була навчена на історичних даних, а потім їх точність прогнозування була оцінена на невидимих тестових даних. Точність була виміряна за допомогою метрик MAE та MSE.

Досліджено вплив таймфрейму та методів машинного навчання на прогнозування валютних курсів ЄВРО/ДОЛАР США. Проаналізовано ефективність різних моделей прогнозування.

Модель Random Forest перевершила інші моделі на кожному наборі даних (таймфреймі) з вражаючим результатом MAE = 0.00004 та MSE = 0.000000007 на датасеті M15. Подальші дослідження будуть зосереджені на: розробці методу прогнозування на основі нечіткої логіки; побудові моделі, здатної до онлайн-навчання на даних в реальному часі; створенні системи підтримки прийняття рішень для алгоритмічної торгівлі.

Ключові слова: LSTM, GRU, Random Forest, прогнозування, багатовимірні часові ряди, FOREX.

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