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PREDICTIVE SYSTEM FOR THE BEHAVIOR OF THE FINANCIAL ASSET (EUR/USD) IN THE FOREX MARKET USING MACHINE LEARNING TOOLS: CASE: ECUADOR.

SISTEMA DE PREDICCIÓN DEL COMPORTAMIENTO DEL ACTIVO FINANCIERO (EUR/USD) EN EL MERCADO FOREX, UTILIZANDO HERRAMIENTAS DE APRENDIZAJE AUTOMÁTICO. CASO: ECUADOR

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ABSTRACT

The present research focuses on the development of a prediction system for the EUR/USD currency pair, recognized for its stability and attractive profitability in the global market, yet subject to episodes of volatility. The study seeks to mitigate the impact of traders' emotional management, known as "psychotrading," a variable that can compromise the effectiveness of technical strategies in the field of trading. With the purpose of reducing the influence of the human factor in decision-making, the methodology proposed by Tinoco-Figueroa S. (2024) was adopted, who applied algorithms such as Lorentz distance and approximate nearest neighbors in the analysis of the BTC/USD currency pair. This research incorporates the use of Recurrent Neural Networks, specifically the LSTM (Long Short-Term Memory) model, given its ability to model financial time series with high accuracy. The technical implementation was carried out in the Visual Studio Code – VSCODE development environment, using the Python programming language. Historical data were obtained from the MetaTrader5 platform, establishing a real-time connection to collect information from the last 60 days with 15-minute intervals. Initially, a diagnostic assessment was conducted, followed by the design of the strategy and evaluation of the system's performance through specific metrics. The results were compared with those obtained by Tinoco-Figueroa S. (2024), and improvement actions were proposed along with the presentation of the model's limitations.

Palabras clave:
inteligencia artificial, psicotrading, trader, redes neuronales recurrentes, python

RESUMEN

La presente investigación se centra en el desarrollo de un sistema de predicción para el par de divisas EUR/USD, reconocido por su estabilidad y atractiva rentabilidad en el mercado global, pero sujeto a episodios de volatilidad. El estudio busca mitigar el impacto de la gestión emocional del trader conocida como “psicotrading”, una variable que puede comprometer la efectividad de estrategias técnicas en el ámbito del trading. Con el propósito de reducir la influencia del factor humano en la toma de decisiones, se adopta la metodología propuesta por Tinoco-Figueroa S. (2024), quien aplicó algoritmos como la distancia de Lorentz y vecinos más cercanos aproximados en el análisis del par de divisas BTC/USD. En esta investigación se incluye el uso de Redes Neuronales Recurrentes, específicamente el modelo LSTM (Long Short-Term Memory), dada su capacidad para modelar series temporales financieras con alta precisión. La implementación técnica se realizó en el entorno de desarrollo Visual Studio Code – VSCODE, utilizando el lenguaje de programación Python. Los datos históricos fueron obtenidos desde la plataforma MetaTrader5, estableciendo una conexión en tiempo real para recopilar información de los últimos 60 días con intervalos de 15 minutos. En principio se realizó un diagnóstico inicial para posteriormente plantear la estrategia y evaluar el desempeño del sistema mediante métricas específicas, se comparó con los resultados obtenidos por Tinoco-Figueroa S. (2024), y se propusieron acciones de mejora junto con la exposición de las limitaciones del modelo.

Introduction

This study aims to predict the price of a financial instrument traded on the stock exchange. The EUR/USD currency pair was chosen because it is a popular financial asset that has historically demonstrated stability, yet also exhibits a certain degree of volatility. Furthermore, these currencies are used by countries with the world's largest and strongest economies, making it an attractive financial instrument. For the prediction, we will use the methodology proposed by Tinoco-Figueroa, S. (2024), employing two algorithms: 1. the "Lorentz Distance" and 2. "Approximate Nearest Neighbors," with the aim of contributing to this study by incorporating a third algorithm: 3. Recurrent Neural Networks (RNN).

It is well known that predicting the price of financial assets is a major challenge; the use of cutting-edge technologies has enabled investors to manage risk more effectively than traditional methods. However, the problem of predicting the price of a financial instrument is a multifaceted task that requires constant effort; Since ancient times, this issue has been a subject of debate, which is why methods have constantly been implemented to improve the predictive capabilities of the models or approaches used. The fact is that the problem of prediction stems not only from knowledge but also from learning to manage emotions—a concept known in the trading world as "psychotrading"; To paraphrase Naranjo K. and González G. (2022): "…deep-seated feelings… cannot be avoided, but they can be controlled, as they play a very important role if one wishes to trade in these financial markets…". With the advent of Artificial Intelligence (AI), it has become possible to automate the process and eliminate "psychotrading" from the forecasting equation; This has its advantages and disadvantages: systems do not feel; they act based on algorithms, which is an advantage if the trader does not know how to manage their emotions, but it is a disadvantage if the trader is capable of effectively grasping what the market is saying, thereby excluding or at least minimizing the emotional aspect of trading in financial markets; However, prediction systems today effectively capture what the market is actually signaling. It would seem that "psychotrading" can be avoided, since failing to exclude this variable from the equation involves various challenges that are often difficult to manage. The solution to this problem is to eliminate the psychological trading pressures that most traders face every day and provide a statistically robust and financially profitable system that achieves high success rates in its trades, with the aim of improving upon the proposal by Tinoco-Figueroa, S. (2024), with a success rate of 92.86% and a Sharpe ratio of 0.13 for the BCH/USD currency pair.

Valer, S. (2023) demonstrated through an empirical study that the use of recurrent neural networks in predicting the prices of financial instruments has yielded good results; therefore, recurrent neural networks—which essentially mimic the behavior of the human brain in decision-making—will be incorporated in an effort to improve the predictive capacity of the study conducted by Tinoco-Figueroa, S. (2024); that is, a prediction system based on three algorithms will be created and ultimately evaluated using performance metrics and compared with the aforementioned study to assess its effectiveness.

First, the initial context that gave rise to the research is presented, outlining the challenges faced by financial traders when executing their strategies in the markets. It is recognized that, regardless of the technical quality of a strategy, a lack of control over the emotional component (psychotrading) can lead to poor decisions and adverse outcomes.

Next, the data collection methodology is established, detailing the financial platform selected for obtaining information and justifying its selection based on the study's requirements. Similarly, the approach used for data cleaning is described, with the goal of constructing a structured dataset (dataframe) free of biases and variables that could introduce confusion into the analysis; it should be noted that a dataframe is a two-dimensional data structure, organized into rows and columns, similar to a spreadsheet or a database table.

The following is a preliminary assessment that characterizes the financial asset under study through the presentation of various charts that facilitate exploratory analysis. These include: charts showing the closing price for the last 60 days at 15-minute intervals, closing price distribution, box plots, and correlation analysis between variables in the dataframe. Next, the proposal derived from the analysis and the results obtained during the data collection process is presented, with the aim of capitalizing on the identified opportunity; the development of the EUR/USD price prediction system is described, addressing the technical aspects of the implemented code, such as the creation of the loop (a control structure that allows instructions to be repeated until a specific condition is met), as well as the elements contained within that loop: lists, technical indicators, conditions for opening and closing positions, signal generation, and the application of the three algorithms that constitute the methodological basis of the study.

Next, we systematically present the results obtained from the implementation of the EUR/USD currency pair price prediction system. A comprehensive evaluation is conducted of the selected performance metrics, such as the mean squared error (MSE), the coefficient of determination (R^2), and other relevant metrics that allow for an assessment of the accuracy and efficiency of the proposed model. This evaluation is supplemented by a direct comparison with the methodology developed by Tinoco Figueroa S. (2024), in order to identify similarities, differences, and possible improvements regarding the predictive approach. Next, the results obtained are analyzed in terms of their practical applicability in real-world trading scenarios, taking into account both the model's performance with historical data and its ability to adapt to changing market conditions. The strengths of the developed system, as well as its technical and operational limitations, are discussed.

Finally, a structured set of actions aimed at improving the overall performance of the proposed system is proposed. These actions include, first and foremost, the operational optimization of internal processes, with the goal of reducing redundancies, improving computational efficiency, and facilitating functional scalability. Second, it is recommended to move toward a systematic modularization of components, which would allow for greater flexibility in managing updates, unit tests, and context-specific adaptations; and it is suggested that geometric and causality metrics be incorporated as part of the model evaluation framework, in order to enrich the structural analysis of the data and strengthen the system's explanatory power when dealing with complex and nonlinear phenomena.

Although the studies, research, and legal updates conducted in the areas of taxation and finance have demonstrated progress, there are still opportunities for improvement in the field of stock market investment. The background of this research is outlined below:

Ecuadorian Regulatory Framework

The legal framework governing trading activities in Ecuador is defined by four regulations: 1) The Organic Monetary and Financial Code – Book II – Securities Market Law (2014) and its implementing regulations, 2) the Organic Law on Electronic Commerce, Digital Signatures, and Data Messages (2002), 3) The Tax Code (2005). Although these laws do not broadly regulate international trading activity, this activity appears to be regulated for financial assets listed on the Quito and Guayaquil stock exchanges; It is important to note that within Ecuador there are few local trading platforms that offer this service. By way of comparison, purchasing a financial asset on the New York or London stock exchanges is not the same as doing so on the Quito or Guayaquil exchanges, since there are not as many buyers and sellers on Ecuador's stock exchanges, making the local market less attractive for short-term trading activities; The opposite could be true for long-term investors, whose goal is to generate returns over longer periods. In 2022, the National Assembly of Ecuador passed 4) the Organic Law on the Development, Regulation, and Control of Financial Technology Services, also known as the Fintech Law. Articles 3 and 5 of the law establish its scope of application, which are:

"… i) Technological infrastructure for processing payment methods;
(ii) Financial technology services;
iii) Specialized electronic deposit and payment companies;
iv) Securities market technology services; and, (emphasis added)
v) Insurance technology services."

Article 8 of the Fintech Act establishes that the institutions responsible for monitoring compliance with the regulations are: 1) The Central Bank of Ecuador, 2) the Superintendency of Companies, Securities, and Insurance, and 3) the Superintendency of Banks or the Superintendency of Popular and Solidarity Economy, within the scope of their respective jurisdictions; however, Article 8.7 of the Organic Monetary and Financial Code establishes that oversight of these companies shall be the responsibility of the Superintendency of Companies, Securities, and Insurance.

In the regulatory analysis conducted by Ochoa Castillo, S. (2024), the author states that, although current regulations govern trading activity within the country, these regulations are local in scope; there are no tax laws or regulations governing the purchase and sale of financial assets on international platforms. Consequently, individuals who profit from trading do not pay taxes—they would be required to do so if they bought or sold financial assets on local platforms or through local brokers. In other words, trading is not prohibited, but there is no tax regulation governing it; however, while regulations do exist for platforms offering financial services within the local securities market, there are no taxes for traders who buy or sell through international brokers or platforms, aside from the foreign exchange exit tax (ISD), which does not constitute a direct tax on trading profits; regulating this activity will be a challenge for the Ecuadorian tax system.

Theoretical Framework

Linear Methods

Because they are easy to interpret, they have an advantage over other models, such as ARIMA or ARIMAX models. With the introduction of ARCH and GARCH models in the 1990s, greater emphasis was placed on data volatility; however, the estimated errors often exhibit excess kurtosis. (Frances and Ghijsels. 1999, cited by Garcia, M., et al. (2013.)

Nonlinear Methods

It is well known that the prices of financial assets fluctuate in a nonlinear manner, which some authors consider to be a more effective method for prediction; among these are artificial neural networks, which have the ability to capture the nonlinear relationships between input and output values. Zemke, 1999. (cited by Garcia, M., et al. (2013) argues that markets with fewer transactions are easier to predict. He uses machine learning techniques to predict the value of the WIG index through binary decisions. The four techniques he uses are: prediction with neural networks, Bayesian classifier, K-nearest neighbor, and K-nearest neighbor prediction scrutinized. In his study, he concluded that the K-nearest neighbor technique and neural networks, with 64% accuracy, yield better predictions because the stock market is dominated by nonlinear relationships in the data. See Lu, Chang, Chen, and Lee, 2009. (cited by García, M., et al. (2013) predicted the B-Share Index of the Shanghai Stock Exchange using the MARS (multivariate adaptive regression splines), BPN (backpropagation neural network), SVR (support vector regression), and MLR (multiple linear regression). The study concluded that the MARS model produced better predictions in terms of error and accuracy than the others, with an error rate of 1.5% and an accuracy of 82%. In another study by Gurasen, Kayakutlu, and Daim (2011). (cited by Garcia, M., et al. (2013) compares three models to assess their effectiveness: the multilayer perceptron (MLP), the Dynamic Artificial Neural Network (DNA2), and a hybrid model combining neural networks and GARCH. The models were evaluated using the mean squared error and the mean absolute deviation, and the study concluded that the classic MLP model yields the best results.

Hybrid Models

As their name suggests, these models combine different techniques—both linear and nonlinear. In a study conducted by Wang, Wang, and Zhang Guo, 2012. (cited by Garcia, M., et al. 2013) presents a hybrid model (PHM), which combines the ARIMA, exponential smoothing (ESM), and BPNN models to capture both linear and nonlinear relationships in a time series. Monthly data from China's SZII index and the Dow Jones Industrial Average Index (DJIAI-USA) were used. The results demonstrated that the PHM hybrid model delivers better performance in terms of error and accuracy than other models such as ARIMA, ESM, and BPNN, due to its robustness. Another study conducted by Dai, Wu, and Lu (2012) is noteworthy for the results it achieved in predicting the Nikkei 225 and Shanghai B-share indices, with accuracy rates exceeding 80%. They proposed a time-series forecasting model by combining nonlinear independent component analysis with neural networks. Their results were outstanding: not only did this approach improve upon the forecasting accuracy of the neural network approach, but it also outperformed the three comparison methods. Valer, S. (2023) conducted a study to predict the prices of four financial assets (Tesla, the S&P 500, Bitcoin, and oil), using three methodologies: 1. Linear Regression, 2. Support Vector Regression (SVR) and Neural Networks (LSTM and GRU): The results show that none of the models deliver outstanding performance in terms of R^2 when attempting to predict the entire time series in days, however, if the prediction period is halved, the trends become predictable, and it is even possible to obtain exact prices; of the three models, those based on neural networks provide the best predictions. Tinoco-Figueroa, S. (2024), in his study "Machine Learning in Financial Markets," presents a price prediction model based on the "Lorentz Distance" and the use of the "Approximate Nearest Neighbors" algorithm for trading activities, that is, short-term investments, applied to the BCH/USD currency pair; the results show a success rate of 92.86%.

Prediction Models Using Macroeconomic Variables

There are some studies that demonstrate the relationship between financial assets and macroeconomic variables, such as the inflation rate, the interest rate, the dollar exchange rate, and GDP, among others. Kwon and Shin (cited by García, M., et al. (2013), in their study based on a cointegration test and a Granger causality test, found that stock market indices are cointegrated with a set of macroeconomic variables—the production index, exchange rate, trade balance, and money supply—which have a direct long-run equilibrium relationship with each stock market index; Similarly, Caldas and Pires (cited by García, M., et al. (2013) used macroeconomic variables such as country risk and Brazil's main stock market index (Ibovespa), along with the econometric techniques of Ordinary

Least Squares (OLS) and the Generalized Method of Moments (GMM), to demonstrate that monetary policy, public debt management, credibility, and reputation affect country risk and the performance of the Brazilian stock market.

Selection of the Methodology to Be Used

Since an intervention project was selected, we will now explain the characteristics of the theoretical model used to develop the proposal. The following describes the characteristics of the method developed by Tinoco-Figueroa, S. (2024), which serves as the basis for developing the proposed project.

The method to be used is based on the methodology proposed by Tinoco-Figueroa, S. (2024), in which two algorithms were incorporated into the BCH/USD financial asset prediction model: the first is called the “Lorentz distance” and the second is called “Nearest Neighbor Approximation.” In data science, the Lorentz distance is used as a measure of similarity in multidimensional datasets, and the nearest neighbors algorithm identifies similar points in a multidimensional space and uses them to predict trends; this has been tested in their study and has yielded good results—a success rate of 92.86% and a Sharpe ratio of 0.13; the aim of this study is to incorporate Recurrent Neural Networks into this method to improve predictive capacity and expected returns relative to the risk assumed, since we know that, according to theory, the application of Recurrent Neural Networks has improved predictive ability in financial data, as shown in the studies by Zemke (1999), Dai, Wu, and Lu (2012), and Valer, S. (2023).

Method

Methodology for Data Collection and Processing

The methodology used for data collection and processing is based on the methodology used by Tinoco-Figueroa (2024); the difference lies in the tools used for data processing. Tinoco-Figueroa’s (2024) study was conducted in Google Colab, and data was obtained from Alpaca Markets; whereas in this study, the VSCODE tool was used with the Python 3.11.3(.venv) interpreter, and the data was obtained from the MetaTrader5 broker. The same environment and data provider were not used because Alpaca Markets does not quote the EUR/USD currency pair; it is a provider that offers only currency pairs involving cryptocurrencies. The data was then organized into a DataFrame with the following variables:

Open = opening price
High = highest price of the day
Low = lowest price of the day
Close = closing price
tick_volume = transaction volume

The data is collected in real time, covering a 60-day period with a 15-minute time interval. It is important to note that, in order to collect real-time data, it was necessary to work simultaneously with the MetaTrader 5 desktop application and VSCODE, thereby enabling the terminals to be linked for connection and data collection.

The key algorithm in this study is the Lorentzian distance. To this end, the `advanced_ta` library—a library for advanced technical analysis—was installed. Once the module was imported, the “LorentzianClassification” function was used to obtain the Lorentzian distance (space-time in relativity). Technical indicators were calculated and sorted in the data frame. These indicators are:

RSI = Measures the Strength of the Movement
WT = Momentum Indicator
CCI = Detects overbought/oversold conditions
ADX = Measures trend strength
SMA = Simple Moving Average

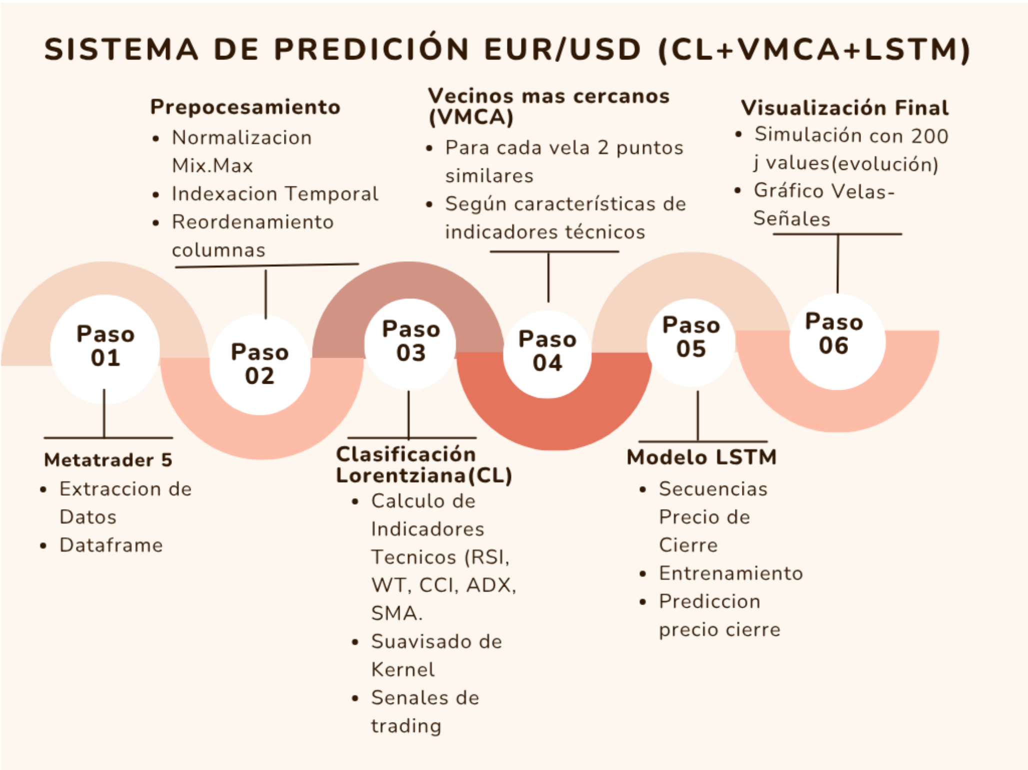
In addition, the neighborsCount function was used, with which the model searched for historical patterns similar to the current pattern over the last 4,130 candlesticks; in other words, this function enabled classification based on the closest approximate neighbors, detected recurring patterns in the market, generated trading signals based on historical behavior, and filtered out data noise.

Conceptual Diagram of the System

The diagram shown illustrates the modular architecture of the prediction system, ranging from the data acquisition phase to the modeling, inference, and performance evaluation processes. This schematic diagram provides a structured overview of the system's operational capabilities, highlighting the sequential integration of analytical, classificatory, and predictive components.

Figure 1

Conceptual Diagram of the System



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Step 1

He installed it in the VSCODE terminal and imported the following modules:

Matplotlib.dates: Handling Dates in Time Charts.

Mplfinance: A bookstore specializing in candlestick charts.

Chain: It allows you to efficiently concatenate multiple iterables.

Warnings: Controls or suppresses warnings during execution.

Datetime, timedelta, date: Manipulating dates and times, useful for time series.

MetaTrader 5: Official API for connecting to the MetaTrader 5 trading platform. It allows you to download market data, place orders, etc.

Pandas: Data manipulation in DataFrame-like structures.

Pandas_ta: A Pandas extension for applying technical indicators such as RSI, SMA, MACD, etc.

NumPy: Efficient numerical computation, especially with arrays.

Matplotlib.pyplot: Data visualization in graphs.

Pytz: Time zone management, useful for synchronizing market data.

Advanced_ta.LorentzianClassification: Implements a classifier based on Lorentz functions, which is useful for detecting patterns or anomalies in time series.

MinMaxScaler: Scale the data between 0 and 1, as required for neural networks.

Sequential, LSTM, Dense: Keras components for building neural networks, in this case an LSTM (Long Short-Term Memory) network, which is ideal for modeling time series such as financial prices.

Mean_squared_error, mean_absolute_error, r2_score: Metrics for evaluating model performance.

Math: Standard mathematical functions (logarithms, roots, etc.).

To connect to MetaTrader 5 from VS Code, I had to create a demo account in the application and keep it logged in so that VS Code could connect. This is because MetaTrader 5 does not manage credentials on its own and requires the MT5 terminal to be open and logged in with an active account.

Lists were created to store the results and include them in the DataFrame, with the goal of evaluating the simulations during the preliminary testing and verifying the results in the prediction. The lists are as follows:

total_trades_list = Total Number of Trades

winning_trades_list = Number of Winning Trades

lost_trades_list = Number of Losing Trades

win_rate_list = Percentage of (Number of Winning Trades / Number of Losing Trades)

pips_acum_list = Cumulative total of pips gained or lost per strategy

real_pips_acum_list = Similar to pips_acum_list but adjusted for actual costs

j_values = Parameter

sharpe_ratio_list = Measures risk-adjusted return

Data Download and Preparation: The data was downloaded from the MetaTrader 5 broker and prepared in a DataFrame.

Step 2

Based on the three established algorithms, a prediction system was created, which is explained as follows:

Min-Max Normalization: The data was normalized on a scale from 0 to 1; this prevents variables with large values from dominating the model.

Temporal Indexing: The data was organized chronologically by assigning timestamps.

Reordering columns: The columns are sorted in the following order: open, high, low, close, tick_volume.

Step 3

Looping over the values of j: The prediction system was implemented within the main loop, where the parameter "j" was varied in increments of 1 to simulate the effectiveness of the strategy.

Lorentzian Classification: A Lorentz distance-based classifier is applied, using technical indicators such as RSI, WT, CCI, ADX, and SMA as features. Additionally, filters for volatility, market regime, and kernel smoothing are configured. The goal is to detect entry signals (long or short positions).

Step 4

Nearest neighbors: In the Lorentzian classifier, the `neighbors=2` function was used. This parameter controls the smoothness and sensitivity of the model; the value 2 aims to strike a balance between accuracy and generalization by comparing each point with its two nearest neighbors in Lorentzian space.

Step 5

LSTM Normalization and Modeling: Closing prices are normalized to model the price's time series dynamics, and sequences are created to train the LSTM neural network, which will predict the next closing price; the more simulations the model has, the better trained it will be.

Trade Construction: A DataFrame is created to record each detected signal

Signal Evaluation: Each signal is compared to determine whether it was a winner or a loser

Cumulative Pips Calculations: The pips earned on each trade of the same type are added together, which allows you to assess the cumulative profitability.

Model training: Internal parameters are adjusted so that the model's predictions come as close as possible to the actual values; this is the neural network's learning process.

Step 6

Final display: Once the model has been simulated using 200 values of j (parameter), the prediction system is evaluated from both a statistical and financial perspective to assess its robustness and profitability.

The following are the indicators that will be used to evaluate the model:

- Mean Square Error (MSE): A value close to 0 is expected, as this will indicate that the model's predictions are very close to the actual values.
- Root Mean Square Error (RMSE): A value close to 0 is expected, as this will indicate that the model is predicting accurately
- Mean Absolute Error (MAE): A value close to 0 is expected; this will confirm the idea that the model predicts values that are at least very close to the actual values.
- Coefficient of Determination (R^2): A value close to 1 is expected, as this will indicate that the model accurately captures the market structure—that is, the algorithms are accurately understanding the dynamics of the financial asset.

- Success Rate: A success rate of more than 85% is expected; this means that out of every 10 operations performed, 8.5 are successful. Although the success rate in the study by Tinoco-Figueroa S. (2024) was 92.86%, a rate higher than 85% is very acceptable; however, we will strive to improve upon the rate reported in that study.
- Sharpe Ratio: A rate higher than 0.5% is expected; this would indicate an acceptable return relative to the risk taken. The Sharpe ratio in the study by Tinoco-Figueroa S. (2024) was 0.13%; although this is considered an acceptable rate given the number of pips accumulated, efforts will be made to improve it.
- Accumulated Pips: We expect positive pips, as this will indicate that the strategy is profitable.
- Actual Accumulated Pips: Unlike cumulative pips, the actual costs of each trade are taken into account, and positive pips are expected.

Results

Results of the Information Survey

With a time frame of up to 60 days, 4,223 candlesticks are generated (Table 1 shows the first 5 candlesticks), each of which has 8 columns. The "time" variable is in UNIX timestamp format and is derived from the most current data available at the time the code is executed.

Table 1

15-minute data frame for 60 days

(4223, 8)

No Vela	time	open	high	low	close	tick_volume	spread	real_volume
0	1754956800	116,068	116,123	116,067	116,114	20	51	0
1	1754957700	116,114	116,118	116,100	116,114	90	45	0
2	1754958600	116,114	116,130	116,105	116,127	249	30	0
3	1754959500	116,127	116,149	116,109	116,140	179	29	0
4	1754960400	116,139	116,182	116,122	116,141	553	8	0

As shown in Table 1, for candle No. "0," the "tick volume" variable is equal to 20, which indicates "low activity"—that is, few buyers and sellers—with a high spread of No. "51," suggesting that there was low liquidity during that candle. It is important to note that the spread is the difference between the bid price and the ask price; we observe that "real_volume" is 0, which means that the MetaTrader 5 broker does not have information for this variable.

Figure 2

EUR/USD Closing Price (15-minute interval) over 60 days

Figure 2 shows the movement of the closing price of the EUR-USD asset, which has a low of 1.15463 and a high of 1.18948, respectively—a difference of 348.5 pips (percentage point or minimum unit of price change)—over a 60-day period. Depending on the lot size, this could represent a significant gain or loss.

Whereas the EUR-USD currency pair normally remains stable, it has nevertheless exhibited volatility in the market, demonstrating its sensitivity to economic or political events.

Next, Figure 3 shows the type of distribution followed by the EUR-USD currency pair; it is a normal distribution, which means it is bell-shaped or approximately symmetrical; It suggests that although the most common peak price has been around 1.17000 over the past 60 days, the range of the histogram (from 1.15463 to 1.18948) shows significant variations, which supports the idea of a market with moderate-to-high volatility; however, its symmetry demonstrates that prices were relatively balanced, meaning there was no extreme bias in the exchange rate.

Figure 3

Distribution of Closing Prices

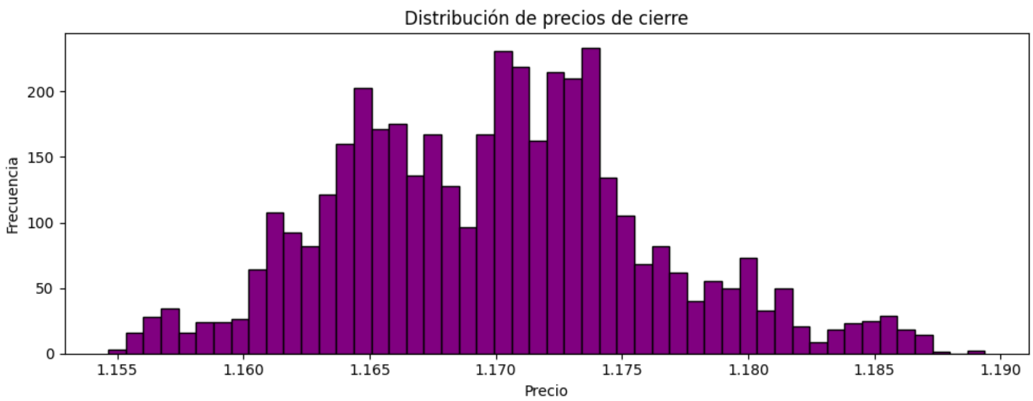
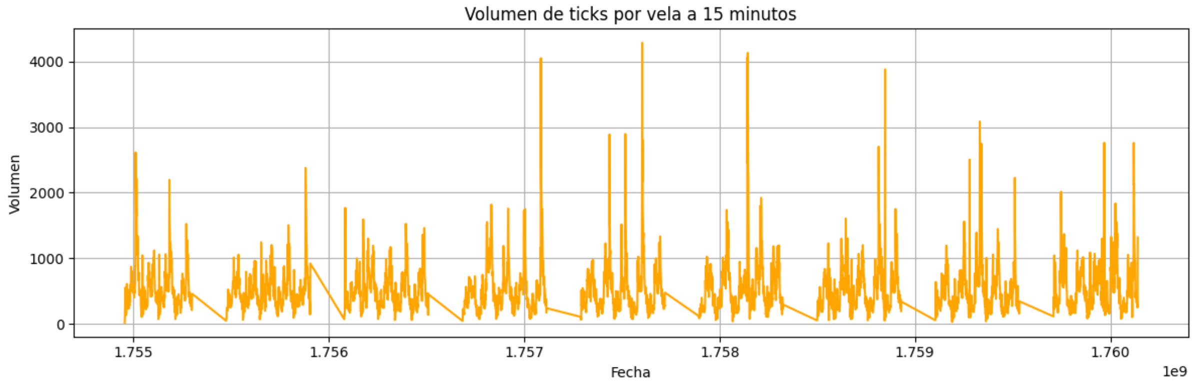


Figure 4 shows the level of activity for each candlestick. It is evident that there are times when activity exceeds 4,000 ticks—that is, there have been more than 4,000 buy and sell transactions during that candlestick—which indicates high investor participation. Conversely, there are times when low participation is evident, which may indicate price consolidation or low investor interest.

Figure 4

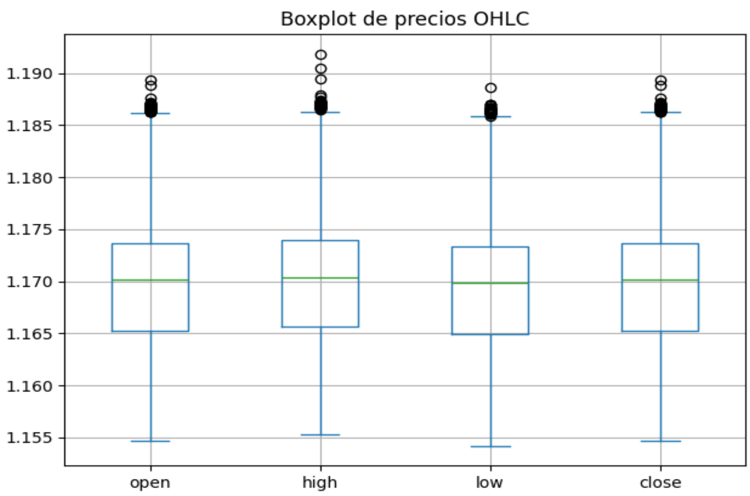
Tick volume per 15-minute candle



Now, Figure 5 shows a "box plot" with the variables from the DataFrame (except for tick_volume, due to the scale of the data) to visualize the statistical distribution of the data. The green line shows the median, the box shows where 50% of the data is concentrated, and the whiskers (the blue line) show the range of the data, and the black dots represent outliers.

Figure 5

OHLC Price Box Plot

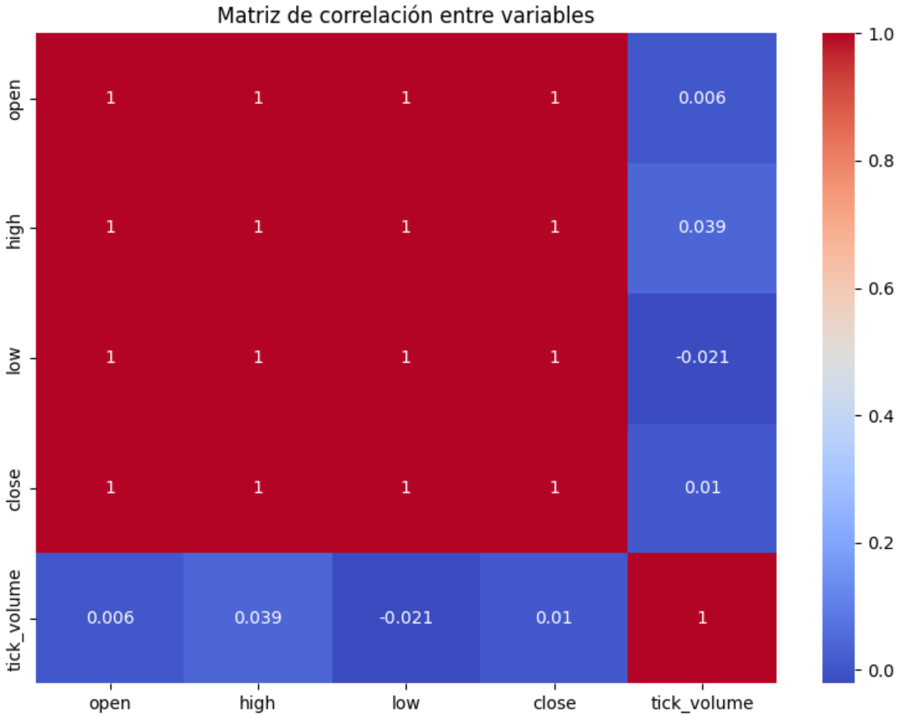


The data shows low dispersion, as the median and the box are aligned across all variables, suggesting symmetry and the absence of significant noise—that is, consistent and stable data behavior. However, there are outliers, indicating the presence of extreme movements in certain candlesticks, which points to high volatility or sudden breaks.

Figure 6 shows the correlation between the variables in the DataFrame; the variables "open," "high," "low," and "close" are perfectly correlated with one another. In contrast, "tick_volume" shows very low correlations with the other variables, indicating that there may be high activity without significant price movements.

Figure 6

Correlation Matrix Between Values



The following is a summary table outlining the key findings of the analysis:

Table 2
Summary of Key Findings by Figure

Chart	Variable	Key Findings
EUR/USD Closing Price (15 min, 60 days)	Closing price	Minimum value (1.15463) – maximum value (1.18948), a difference of 348.5 pips over 60 days (opportunity)
Closing Price Histogram	Closing price	Market with moderate-to-high volatility, relatively balanced prices
Tick Volume per Candlestick (15 min)	Transaction Volume	Periods of high trading volume (4,000 ticks per candle) and periods of low trading volume, which may indicate price consolidation or low investor interest (quote: 1.17000).
OHLC Price Box Plot	Opening Price, Highest Price of the Day, Lowest Price of the Day, Closing Price	Low data dispersion, symmetry, and the absence of significant noise; however, there are outliers, indicating the presence of extreme movements in certain candlesticks (opportunity)
Correlation matrix between variables	Opening Price, Highest Price of the Day, Lowest Price of the Day, Closing Price, Trading Volume	The variables "open," "high," "low," and "close" are perfectly correlated with one another; in contrast, "tick_volume" shows very low correlations—the number of transactions in a single candlestick does not explain price movement.

Conclusions

In accordance with the stated objectives, the project has been successful in terms of statistical robustness; however, it has shown shortcomings in terms of profitability metrics; due to the nature of the financial asset used in the model, which, according to the initial assessment, exhibited stability and volatility only at certain times. Therefore, while the system demonstrated strength in its statistical predictive capacity, it was unable to capture sudden market movements to generate acceptable returns relative to the risk assumed. Following the methodology of Tinoco Figueroa S. (2024), historical data from the last 60 days were collected at 15-minute intervals, resulting in 4,223 candlesticks or data points; this information enabled the analysis and training of the proposed model; 200 simulations were performed in the VSCODE system, with the results presented below:

Statistical Performance Metrics

Mean Square Error: The result obtained from the 200 simulations was very low or close to zero—0.0000—which shows that the predicted values are quite close to the actual values; in other words, this indicates excellent predictive capability.

Square root of the mean square error: Like the previous indicator, this one yields very low values, ranging from 0.00067 to 0.00096 across the 200 simulations, which corroborates the earlier statement: the system performs well in statistical terms.

Mean Absolute Error: This metric, which indicates how much the model is off on average, yielded values very close to zero; in the 200 simulations, they ranged from 0.00047 to 0.00060, which means the model has very good predictive power.

Coefficient of Determination R^2: In all 200 simulations, the model yielded values greater than 0.98%, which means that it explains 98% of the variance—in other words, it has an excellent fit.

Success Rate: With 254 open trades, there were 226 winning trades and only 28 losing trades—that is, a success rate of 88.98% in the best simulation; however, it should be noted that in the worst-case simulation, the success rate did not fall below 87%, which demonstrates that the success rate is very high and indicates that the predictions are strongly correlated with the actual values. Although the rate is lower than the 92.86% reported by Tinoco Figueroa S. (2024), it is important to note that in the 200 simulations, the success rate remained consistent and stable, dropping by only one percentage point. This contrasts with the aforementioned study, in which one simulation showed a success rate of 84.62%—a decrease of more than 8 percentage points.

Profitability Performance Metrics

Accumulated Pips: The maximum value of the accumulated pips occurs at j = 2, with just 0.001695 pips, indicating a marginal return. This result suggests that, although the model may be correctly predicting market direction, the magnitude of the movements it capitalizes on is insufficient to generate significant operating profits.

Actual Accumulated Pips: The actual cumulative pips have a negative value of –2.54, which shows that the strategy fails to cover operating costs or offset the risk taken on. This result underscores the need to review entry and exit filters, the risk-reward ratio, and the trading management structure.

Sharpe Ratio: The maximum Sharpe ratio achieved is 0.05 in the interaction j=2, a value well below the minimum acceptable threshold (usually ≥ 1.0). This indicates that the strategy is not efficiently generating risk-adjusted returns, and that the model, while accurate in its predictions, does not translate that accuracy into net returns.

Figure 7

Trading Strategy Results (Tinoco-Figueroa) + LSTM for Different Values of j

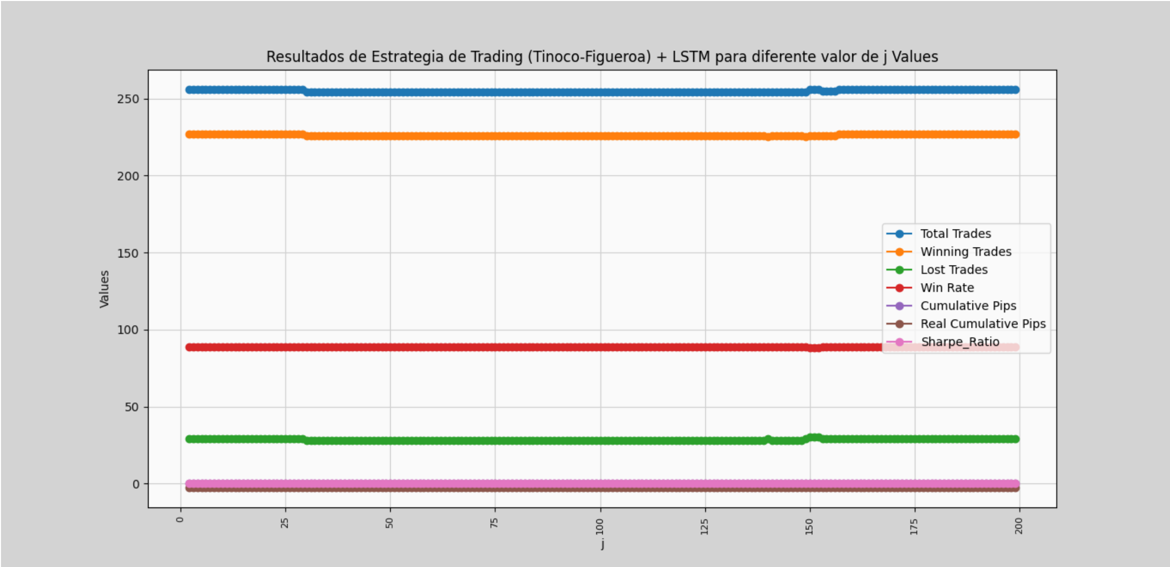


Figure 7 shows that, across the 200 simulations performed, each value of the parameter j generates more than 250 operations. A consistent trend can be observed: the number of winning trades exceeds 220, while the number of losing trades remains below 30. This translates to a success rate of over 87%, which demonstrates the model's high statistical predictive power. However, an analysis of profitability metrics such as the Sharpe Ratio and Real Accumulated Pips confirms that, despite its directional accuracy, the strategy fails to translate that advantage into net profits. This suggests that the system, while effective in terms of prediction, is not operationally cost-effective, possibly due to factors such as risk management, transaction costs, or the exit strategy for trades.

Figure 8

Candlestick Chart for the EUR/USD Financial Asset for the period from August 17 to October 15, 2025

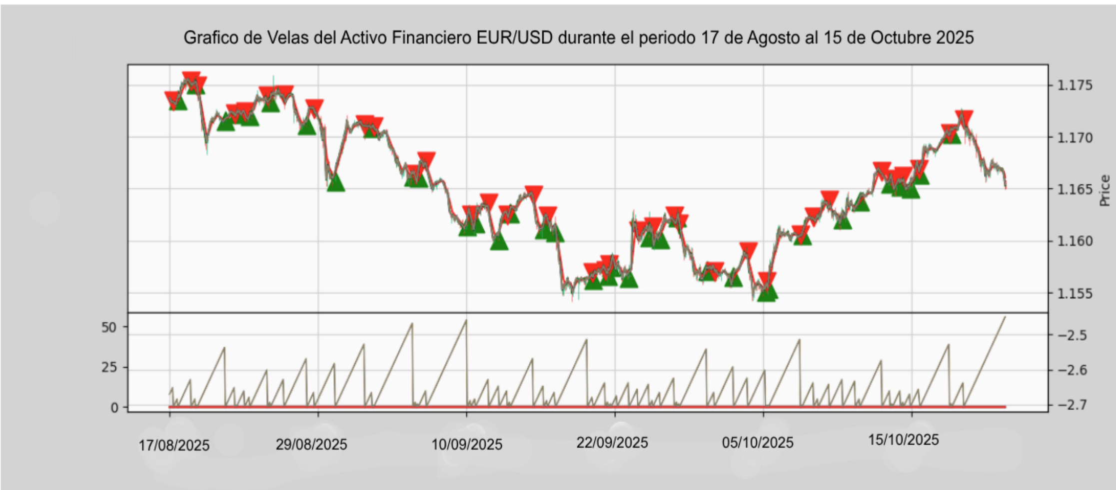


Figure 8 shows a candlestick chart with 60 days of data at 15-minute intervals. Based on the proposed strategy, it indicates the following: the red triangle indicates a downtrend—that is, the price closed lower amid the struggle between buyers and sellers (sell signal); Similarly, the green triangle indicates an uptrend, as the price closed higher (a buy signal).

Discussion

The methodology proposed by Tinoco-Figueroa S. (2024) analyzed a highly volatile financial asset (BTC/USD); it appears that this approach better captures market changes, unlike a more stable asset such as the one analyzed in this study (EUR/USD), which, although the system performed well in terms of predictive ability, it did not capture relevant information such as when to enter or exit a position. It would therefore be interesting to test the proposed system with a highly volatile financial asset.

In accordance with the objectives established in this study, the proposed model has demonstrated satisfactory statistical performance, as evidenced by fit and accuracy metrics that validate its predictive capability in quantitative terms. However, when evaluating its practical applicability in real-world investment scenarios, it was observed that this performance did not translate into sustained, growing returns over time.

This discrepancy suggests that, while the model is technically robust from a statistical perspective, it still has limitations in its ability to generate tangible economic benefits, which highlights the need for future improvements aimed at optimizing its financial effectiveness

Therefore, the results obtained in this study demonstrate that the proposed model has high predictive power, although its operational profitability is limited. This paradox presents concrete opportunities for future development, both in the technical and academic spheres. The following are the recommended lines of action:

Proposals

Operational Optimization and Modularization

The proposal is to include, in the design of a modular validation system, dynamic operational filters that can be adjusted by time slot, transaction volume, and volatility. This architecture would make it possible to adapt the signals generated by the model to actual market conditions, thereby reducing exposure to scenarios of low liquidity or high uncertainty. In addition, it is recommended to encapsulate the simulation logic in reusable functions that facilitate test automation and the export of key metrics.

Integration of Geometric Metrics and Causality

Finally, given the interest in geometric models such as the Lorentz Distance Classification and Approximate Nearest Neighbors, we propose incorporating curvature and temporal distortion metrics to assess the stability of signals based on the asset's historical performance. This integration would make it possible to construct a framework of operational causality, in which entry and exit decisions are based not only on statistical patterns but also on the market's geometric structures.

Limitations

Although the objectives set were achieved, the following are the limitations encountered during the course of the project:

Following the methodology of Tinoco Figueroa S., the analysis was conducted over a 60-day time horizon with a 15-minute time interval; however, 4,223 candlesticks were obtained, which may not be representative.
Although volatility filters were established, it appears that the methodology proposed by Tinoco-Figueroa S. (2024) better captures this characteristic for a highly volatile asset, but not for a more stable asset; therefore, it would be important to establish a modular validation module that allows for the activation and deactivation of operational filters based on the trading session, volume, or volatility.

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