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Applying Machine Learning methodologies to enhance trading decisions in cryptocurrency assets

Aplicación de metodologías de Machine Learning para mejorar las decisiones de compraventa de activos basados en criptomonedas

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KEYWORDS:

Cryptocurrency trading, digital assets, sentiment analysis, recurrent neural networks, price prediction, technical indicators, backtesting

ABSTRACT

Cryptocurrency trading involves the buying and selling of digital assets, such as Bitcoin (BTC) and Ethereum, with the aim of obtaining financial gains through specialized platforms known as exchanges. The relevance of this practice lies in its ability to capitalize on the notable market volatility, allowing for significant returns. This study focuses on the application of machine learning algorithms for strategic decision-making in the cryptocurrency realm, with a particular emphasis on sentiment analysis derived from Reddit.com posts to evaluate market perception. The inherent volatility of the cryptocurrency market, along with psychological influences and information asymmetries, underscores the importance of sentiment analysis for predicting price movements and optimizing trading strategies. This analysis classifies sentiment into positive, negative, or neutral categories, thereby guiding trading decisions. Additionally, a recurrent neural network is employed to predict BTC prices using historical data, complementing the sentiment analysis. The evaluation of technical indicators allows for identifying the optimal time to operate in the market, and backtesting reveals notable returns, especially in BTC with 49.88%, Ethereum (38.74%), Binance Coin (32.89%), Cardano (29.74%), and Solana (27.64%). The study demonstrates that machine learning models offer accurate predictions and reduce biases compared to traditional trading platforms. Nonetheless, the need for continuous adaptation and diversification is highlighted due to market volatility and regulatory uncertainties. Future research is suggested to focus on testing strategies across various cryptocurrencies and consulting with financial experts to mitigate risks and enhance investment outcomes.

PALABRAS CLAVE:

Trading de criptomonedas, activos digitales, análisis de sentimientos, redes neuronales recurrentes, predicción de precios, backtesting

RESUMEN

El trading de criptomonedas implica la compra y venta de activos digitales, como Bitcoin (BTC) y Ethereum, con el fin de obtener beneficios financieros a través de plataformas especializadas conocidas como exchanges. La relevancia de esta práctica reside en su capacidad para capitalizar la notable volatilidad del mercado, permitiendo la obtención de rendimientos significativos. Este estudio se centra en la aplicación de algoritmos de aprendizaje automático para la toma de decisiones estratégicas en el ámbito de las criptomonedas, con un enfoque particular en el análisis de sentimientos extraídos de publicaciones en Reddit.com para evaluar la percepción del mercado. La inherente volatilidad del mercado de criptomonedas, junto con influencias psicológicas y asimetrías de información, subraya la importancia del análisis de sentimientos para prever movimientos de precios y optimizar estrategias de trading. Este análisis clasifica el sentimiento en categorías positivas, negativas o neutras, orientando así las decisiones de trading. Además, se emplea una red neuronal recurrente para predecir los precios de BTC utilizando datos históricos, complementando el análisis de sentimientos. La evaluación de

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indicadores técnicos permite identificar el momento óptimo para operar en el mercado, y el backtesting revela rendimientos notables, especialmente en BTC con 49.88%, Ethereum (38.74%), Binance Coin (32.89%), Cardano (29.74%) y Solana (27.64%). El estudio demuestra que los modelos de aprendizaje automático ofrecen predicciones precisas y reducen los sesgos en comparación con las plataformas de trading tradicionales. No obstante, se destaca la necesidad de adaptación y diversificación continua debido a la volatilidad del mercado y a las incertidumbres regulatorias. Se sugiere que futuras investigaciones se enfoquen en probar estrategias

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1. INTRODUCTION

EIn the controversial world of the financial market, the convergence of blockchain and artificial intelligence (AI) marks the beginning of a radical transformation that redefines the rules of the game through a robust financial ecosystem where each transaction is safeguarded by unbreakable security. At the same time, it adapts in real-time to anticipate and mitigate risks, elevating the management and supervision of transactions to an unprecedented level of sophistication. It is crucial to highlight that, in recent decades, the market has undergone a series of technological transformations that have reconfigured its operational dynamics. From the digitalization of transactions to the incorporation of advanced algorithms, each of these stages has laid the groundwork for the emerging synergy between blockchain and AI.

Blockchain technology has revolutionized the traditional financial model by eliminating the need for centralized intermediaries to conduct transactions [1]. Conventional financial methods, which rely on multiple intermediaries, often face issues such as transaction delays, increased costs, and greater exposure to fraud. In contrast, the decentralized and cryptographic structure of this technology provides a secure, transparent, and immutable record of each transaction within a digital ledger [2]. This approach enhances operational efficiency and reduces costs, offering a more effective and economic alternative for managing financial transactions.

In turn, AI has experienced notable advancements in reshaping the financial landscape. The prowess of AI algorithms to process and analyze colossal volumes of data in real time provides financial institutions with invaluable information [3]. AI applications in the sector extend across a broad range of functions, from risk management and fraud detection to enhancing customer service and developing sophisticated investment strategies [4]. A cardinal element of AI, machine learning (ML), plays a crucial role in market trend prediction, portfolio refinement, and identifying potential risks. This predictive capability empowers financial entities to make informed decisions and fosters unparalleled agility in international financial systems.

In this regard, the integration of blockchain and AI technologies creates a synergistic effect that amplifies the inherent virtues of each of these innovations [5]. The decentralized ledger provided by blockchain ensures robust security and integrity of financial data, while the advanced analytical capabilities of AI offer deeper insights and sharp predictive ability. This technological combination enhances the accuracy of information, boosting unparalleled analytical capacity and thereby consolidating a financial infrastructure of superior reliability.

An exemplary case of this formidable alliance of innovations derived from Industry

4.0 is the optimization of "Know Your Customer" (KYC) processes, essential for client identification and verification, as well as for preventing money laundering and other illicit activities. In this context, ML algorithms provide real-time analysis of customer data, while blockchain technology ensures the protection and immutability of KYC records. This synergy accelerates the onboarding of new clients and mitigates the risk of identity theft and fraud [5].

Meanwhile, as traditional banking models, grounded in manual processes and outdated systems, struggle to keep pace with rapid advancements in financial technologies [6], the integration of blockchain and AI emerges as a vital driver for modernizing financial practices. Decentralized finance (DeFi) platforms, powered by these advanced technologies, are experiencing significant growth. Utilizing smart contracts and AI algorithms, these platforms offer decentralized financial services such as lending, financing, and trading, which eliminate intermediaries and democratize access to banking services.

In recent years, several research studies have focused on applying artificial intelligence in cryptocurrency trading. For example, Koehler et al. used AI-enhanced bitcoin trading algorithms to improve investment strategies in the highly dynamic cryptocurrency market [7]. Similarly, Amirzadeh et al. developed a survey of AI-based price prediction models in cryptocurrencies, comparing different machine learning algorithms and evaluating their effectiveness in predicting price movements [8]. Additionally, Tungdajahirun et al. provided a comprehensive overview of AI applications in cryptocurrency trading, discussing various AI techniques, including machine learning and deep learning, and their potential advantages in this field [9]. However, these studies primarily examine the theoretical benefits and limitations of AI in cryptocurrency trading, highlighting the potential advantages without performing experimental applications.

Other studies have explored the use of machine learning and deep learning techniques, analyzing their performance, accuracy, and efficiency but without applying these techniques directly to the cryptocurrency market [10] [11]. Finally, Feizian and Amiri combined machine learning and sentiment analysis to predict cryptocurrency prices [12]. This is the closest work to what is presented here, as it explores the impact of investor sentiment on price movements and evaluates the performance of a hybrid model, yet it stops at price prediction without applying these results in a real market context.

This article aims to implement an efficient technological methodology designed to optimize cryptocurrency trading activities using AI algorithms.

2. BLOCKCHAIN AND CRYPTOCURRENCIES

Blockchain technology, or distributed ledger technology, is defined as a sophisticated system designed to ensure transparent, immutable, and highly secure documentation of transactions. According to [13], this technology is distinguished by its decentralized structure, operating over a peer-to-peer (P2P) network without fixed clients and servers; in this setup, nodes simultaneously assume the roles of both clients and servers with each other. Such a network model not only facilitates an equitable distribution of control and management of the ledger, in contrast to traditional centralized systems where a single entity holds absolute control over the database, but also reduces the risk associated with a single point of failure and significantly enhances resistance against attempts at manipulation and breaches [14].

Moreover, blockchain technology is distinguished by its exemplary immutability: once a transaction is recorded and validated by the network, it becomes unalterable and irreversible. This is due to the implementation of advanced cryptography and chained data structures, where each block includes a cryptographic hash of the previous block, thus ensuring the integrity and uninterrupted continuity of the recorded information [15].

Additionally, blockchain offers an outstanding level of transparency. Although transactions can maintain anonymity, their records remain public and accessible to all network participants. This feature allows for direct auditing and verification of information without the need for intermediaries, thereby increasing trust in the system [16].

Finally, security represents another fundamental characteristic of blockchain, employing advanced cryptographic mechanisms to safeguard both transactions and stored data. The requirement to achieve consensus among participating nodes before incorporating a new transaction into the ledger enhances this security, providing robust protection against attempts at fraud [17].

This technology, with its ability to provide an immutable and secure record, has transcended its initial use in cryptocurrencies like Bitcoin and Ethereum, finding notable applications in various areas. For example, in supply chain management, it facilitates detailed tracking and rigorous traceability of products; in the healthcare sector, it enhances interoperability and security of medical data; electronic voting benefits from its transparency and auditability; while financial records gain precision and protection against fraud. This vast potential has sparked considerable interest in academic research and practical adoption across multiple industries [18].

Regarding cryptocurrencies, they emerge as an innovative investment option, distinguished by their underlying blockchain technology. From this perspective, the European Central Bank (ECB) defines them as a digital representation of value that is not issued by any central authority, credit institution, or recognized electronic money issuer, and that, under certain circumstances, can be used as an alternative means of payment to conventional money [19]. In turn, [20] describes them as a payment system over the Internet based on a P2P architecture, which incorporates a security element based on cryptography and where the value is transmitted electronically between parties.

The most prominent features of these digital assets include their virtual nature, independence and transparency, as well as their holistic approach combined with simplified accessibility. Similarly, the associated anonymity component, notable operational efficiency, and ongoing technological advancements further solidify their preeminent role in the contemporary financial landscape.

3. METHODOLOGY

The methodology outlined in this study was based on a rigorously structured sequence of strategic steps. All these procedures are summarized in a workflow showing in Figure 1.

3.1. Sentiment Analysis focused on cryptocurrencies

Sentiment analysis is a technique used to understand the emotional tone of text or speech, and has become increasingly relevant in the volatile world of cryptocurrencies. By analyzing the opinions and emotions expressed in news articles, social media posts, and online forums, sentiment analysis can provide valuable insights into market trends, investor sentiment, and potential price movements.

One of the primary applications of

sentiment analysis in cryptocurrencies is to gauge investor sentiment. By tracking the emotional tone of discussions on social media platforms like Twitter and Reddit, analysts can identify emerging trends, anticipate market reactions, and potentially predict price movements. For example, a surge in positive sentiment surrounding a particular cryptocurrency might indicate growing investor confidence and potentially drive up its price.

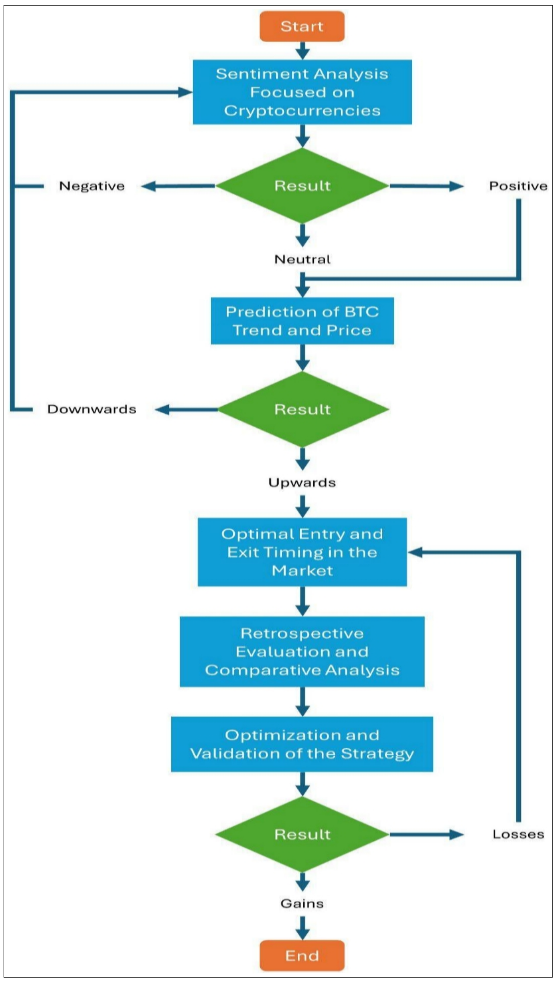

Figure 1. Proposed workflow for optimizing a trading strategy.
Note: *The figure presented is an original creation by the authors.*

In addition to tracking investor sentiment, sentiment analysis can also be used to identify and assess the impact of news events on cryptocurrency markets. By analyzing the sentiment expressed in news articles related to regulatory changes, technological advancements, or market-moving events, analysts can gauge how these events are likely to influence investor behavior and market prices.

The need to conduct sentiment analysis of cryptocurrencies is well-justified by several reasons of considerable relevance and importance. First, the inherent volatility of the cryptocurrency market and financial assets is noteworthy. The prices of these assets often experience significant fluctuations over relatively short periods, a phenomenon driven by a complex interplay of factors such as supply and demand, news and economic events, as well as investor speculation.

Furthermore, it is essential to consider the determining influence of psychology on buying and selling decisions. These decisions are not based solely on fundamental analysis but are deeply shaped by individual emotions and expectations. Psychological phenomena such as fear, greed, and euphoria have the potential to create speculative bubbles and abrupt crashes, thus distorting market behavior.

So, as a first step, a thorough survey was conducted on the popularity of cryptocurrencies in trading forums. The sentiment analysis applied in this work was performed using advanced Natural Language Processing (NLP) techniques such as VADER sentiment analysis tools [21], and native tools from Python's NLTK (Natural Language Toolkit) library, as code excerpt shown in Figure 2.

The sentiment analysis primarily focused on Bitcoin (BTC), given that this cryptocurrency has the largest market capitalization (see Table 1). This focus was justified by the fact that any fluctuation in the price of BTC tends to significantly impact on the global cryptocurrency market.

```python
# Sentiment Analysis
import nltk
from nltk.sentiment.vader
import SentimentIntensityAnalyzer
from nltk.tokenize
import word_tokenize  RegexpTokenizer # Tokenize Words
from nltk.corpus import stopwords

#NLTK´s databases
nltk.download('vader_lexicon') # get lexicons data
nltk.download('punkt') # for tokenizer
nltk.download('stopwords')
...
#Count on each label
news.label.value_counts
Neutral     217
Positive    118
Negative     65
```

Figure 2 . Sentiment analysis Python's code excerpt.

Table 1. Top Assets by Market Capitalizations

Ranking Position	Asset	Capitalization	Price
1	Gold	$ 14.045 T	$ 2.092
2	Microsoft	$ 3.087 T	$ 415.50
3	Apple	$ 2.774 T	$ 179.66
4	Nvidia	$ 2.056 T	$ 822.79
5	Saudi Aramco	$ 2.042 T	$ 8.40
6	Amazon	$ 1.851 T	$ 178.22
7	Alphabet (Google)	$ 1.710 T	$ 138.08
8	Silver	$ 1.310 T	$ 23.28
9	Meta Plataforms (Facebook)	$ 1.280 T	$ 502.30
10	Bitcoin	$ 1.253 T	$ 63,791
11	Berkshire Hathaway	$ 881.51 B	$ 407.11
12	Eli Lilly	$ 743.14 B	$ 782.12

Note: *The information is expressed in US dollars (USD). "B" refers to Billion dollars, which translates to "mil millones de dólares" in Spanish. Taken from [2].*

The study was based on sentiment analysis of the last five hundred user posts in interval dates from 12/01/2024 to 29/02/2024 on the digital platform "Reddit.com." This platform, which recorded 7.57 billion visits in the last month according to data from [22], is distinguished by its decentralized nature as a social news aggregator, content classifier, and social network. Its structure prevents information manipulation and facilitates the acquisition of more accurate data on the perception, both positive and negative, of cryptocurrencies in society. Reddit.com is a space that promotes the free expression of opinions, resulting in a clearer identification of various perspectives on cryptocurrencies. The results of the previously described sentiment analysis led to three possible scenarios: positive, negative, or neutral.

A positive result reflected favorable news for the market, praise-filled comments, and expectations of an appreciation in price. Consequently, it was inferred that the value of Bitcoin (BTC) and cryptocurrencies in general would experience an upward trend in the short term following the sentiment analysis. The algorithm designed for this purpose examined the last thousand comments (number adjustable according to the time period considered in the study) posted on Reddit about BTC. In contrast, a negative scenario was established when the analysis revealed unfavorable comments, pessimistic or alarmist news, which generated expectations of a decrease in price.Thus, in the event of a positive result, one might consider executing bullish trading operations or proceeding with the sale of BTC or other accumulated cryptocurrencies, with the aim of maximizing the selling price. Conversely, if the result is negative, bearish operations could be explored. However, the authors of this paper advise against such a strategy, given that the price of BTC has historically shown a general upward trend. Alternatively, one might choose to refrain from trading and hold onto the cryptocurrencies in anticipation of a potential price appreciation. In the case of a neutral result, one could opt to maintain the current position (hold). This would imply keeping the trading position open, with the strategy of waiting for the price to experience a significant movement, either upward or downward, before making a more informed and precise decision.

3.2 Prediction of BTC Trend and Price

To strengthen the initial decision in the trading strategy under development, it was proposed to forecast price of Bitcoin (BTC) using neural networks. Figure 3 shows Python's code to carry out this task. The model used is an artificial neural network (ANN) based on a Long Short-Term Memory (LSTM) architecture; a type of recurrent neural network (RNN) specialized in analyzing sequential data. In this model, the input data is structured in three dimensions, with each sequence represented by the shape (backcandles, 8). Here, backcandles denote the number of past periods used for prediction, establishing a time window, while 8 represents the number of features per period. The model's architecture includes an LSTM layer with 150 units, which is particularly beneficial for capturing long-term dependencies and processing temporal relationships. This layer is crucial for learning patterns in the sequential BTC price data that are significant for making accurate future predictions. Following the LSTM layer, the model includes a dense layer with a single neuron to produce a one-dimensional output, as the task is to predict a single value —BTC price. The final layer applies a linear activation function, suitable for regression tasks, as it allows continuous output that reflects the nature of the target variable, "BTC prices".Also, model uses the Adam optimizer, which is a robust choice for parameter-rich problems due to its adaptability to gradient variations. The mean squared error (MSE) is selected as the loss function, aimed at minimizing the discrepancy between predicted and actual prices, a standard approach for regression objectives. During training, the model uses a batch size of 15, 30 epochs, balancing the training speed and the model's learning capacity. Additionally, a validation split of 10% is applied, allowing the model to evaluate its performance on unseen data and providing a measure to control overfitting.

This LSTM-based model is designed to capture temporal patterns in historical BTC prices and produce predictions based on trends learned over time. The layers are specifically configured to retain long-term memory, while the linear output layer ensures an output compatible with regression requirements. This setup aims to produce precise predictions, aligning with the ANN's architecture and objective.

Although the general prediction of BTC or cryptocurrency prices may indicate an upward or downward trend, it is crucial to precisely determine the optimal timing for market operations. Whether throughout the day, week, or month, depending on the time frame selected for the tool. This challenge was addressed through the application of technical indicators, which provide strategic guidance to optimize trading opportunities.

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import yfinance as yf
import pandas_ta as ta
data = yf.download(tickers = 'BTC-USD',
       start='2014-09-23', end = '2024-03-01')
#Data normalization
from sklearn.preprocessing import MinMaxScaler
sc = MinMaxScaler(feature_range=(0,1))
data_set_scaled = sc.fit_transform(data_set)
#LSTM initialization
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers import Dropout
from keras.layers import Dense
from keras.layers import TimeDistributed
import tensorflow as tf
import keras
from keras import optimizers
from keras.callbacks import History
from keras.models import Model
from keras.layers import Dense, Dropout, LSTM, Input,
Activation, concatenate
import numpy as np
np.random.seed(10)
lstm_input = Input(shape=(backcandles, 8),
name='lstm_input')
inputs = LSTM(150, name='first_layer')(lstm_input)
inputs = Dense(1, name='dense_layer')(inputs)
output = Activation('linear', name='output')(inputs)
model = Model(inputs=lstm_input, outputs=output)
adam = optimizers.Adam()
model.compile(optimizer=adam, loss='mse')
model.fit(x=X_train, y=y_train, batch_size=15,
epochs=30, shuffle=True, validation_split = 0.1)
```

Figure 3. ANN-LSTM Python's code used to forecast price of Bitcoin (BTC).

3.3 Optimal entry and exit timing in the market

Technical indicators are fundamental tools in financial market analysis, used for evaluating and forecasting price trends based on historical data. These indicators are calculated from past prices, trading volumes, and other relevant variables, and are graphically represented to facilitate their interpretation and analysis. Their primary objective is to identify patterns of behavior that may recur in the future, providing investors with a valuable tool for making informed decisions about the optimal timing for acquiring or liquidating assets.

There are various types of technical indicators, each with a specific methodology and approach, designed to provide detailed insights into the behavior of the financial market. Among the most notable are:

1) *Trend indicators*, such as moving averages (both simple and exponential) and the Average Directional Index (ADX), are essential tools for identifying the overall market direction. Moving averages smooth out daily price fluctuations, making it easier to detect the prevailing trend. The Exponential Moving Average (EMA) gives more weight to recent prices, making it more responsive to recent changes compared to the Simple Moving Average (SMA). This sensitivity is especially useful for quickly identifying trend reversals. The ADX, on the other hand, assesses the strength of a trend without differentiating between uptrends and downtrends, focusing solely on trend intensity [23].
2) *Momentum indicators*, such as the Relative Strength Index (RSI) and the Stochastic Oscillator, measure the speed of price movement, helping identify potential reversal points. The RSI compares recent gains and losses to indicate whether an asset is overbought or oversold, while the Stochastic Oscillator gauges the closing price relative to the high-low price range over a set period [23].
3) *Volume indicators*, On-Balance Volume (OBV) and the Money Flow Index (MFI) use trading volume to confirm trend strength. OBV adds volume on up days and subtracts it on down days, helping identify price movements driven by volume. The MFI combines volume with price, functioning as a volume-weighted version of the RSI to assess capital inflows and outflows in the market [23].
4) *Volatility indicators*, like Bollinger Bands and the Average True Range (ATR), measure the extent of price fluctuations. Bollinger Bands consist of a moving average surrounded by bands based on standard deviation, helping to identify periods of high and low volatility. ATR provides the average price movement range over a specified period, useful for evaluating volatility and anticipating potential sharp changes in the market [Murphy, 1999].

Technical analysis, based on the use of technical indicators, is founded on the idea that history tends to repeat itself and that prices follow identifiable and exploitable trends. Therefore, these indicators have become a crucial part of investment and trading strategies, enabling analysts and traders to anticipate market movements and manage the risks associated with their financial decisions more precisely. Figure 4 shows Python's code used to compare the different technical indicators.

```python
from xgboost import XGBClassifier  #Gradient-boosted decision tree
from sklearn.metrics import accuracy_score, log_loss

attributes = ['RSI', 'CCI', 'AO', 'MOM', 'MACD_12_26_9', 'MACDh_12_26_9', 'MACDs_12_26_9', 'ATR', 'BOP', 'RVI', 'DMP_16', 'DMN_16', 'STOCHk_14_3_3', 'STOCHd_14_3_3', 'STOCHRSIk_16_14_3_3', 'STOCHRSId_16_14_3_3', 'WPR','EMAF', 'EMAM', 'EMAS']

X = df[attributes]
y = df['Target']

train_pct_index = int(0.7 * len(X)) #Data for training
X_train, X_test = X[:train_pct_index], X[train_pct_index:]
y_train, y_test = y[:train_pct_index], y[train_pct_index:]

model = XGBClassifier() #Model to be used
model.fit(X_train, y_train)
pred_train = model.predict(X_train)
pred_test = model.predict(X_test)

acc_train = accuracy_score(y_train, pred_train)
acc_test = accuracy_score(y_test, pred_test)
```

Figure 4. Python's to carry out comparison between indicators.

3.4 Retrospective evaluation and comparative analysis

The vast array of technical indicators available for cryptocurrency trading required meticulous analysis to determine their effectiveness. At this stage, a program was developed to identify the most relevant indicators for predicting the price of BTC, using machine learning algorithms. As a result of this process, the most significant technical indicators for predicting the price of BTC were obtained. The most effective indicators were used to develop a strategy aimed at evaluating the most opportune moment to enter or operate in the cryptocurrency market (see Figure 5).

```
from sklearn.metrics import confusion_matrix #Summa-
rizes the model
from sklearn.metrics import classification_report #De-
tailed report
matrix_train = confusion_matrix(y_train, pred_train)
matrix_test = confusion_matrix(y_test, pred_test)

print(matrix_train)
print(matrix_test)

report_train = classification_report(y_train,
pred_train)
report_test = classification_report(y_test, pred_test)
print(model.get_booster().feature_names)
['RSI', 'CCI', 'AO', 'MOM', 'MACD_12_26_9',
'MACDh_12_26_9', 'MACDs_12_26_9', 'ATR', 'BOP', 'RVI',
'DMP_16', 'DMN_16', 'STOCHk_14_3_3', 'STOCHd_14_3_3',
'STOCHRSIk_16_14_3_3', 'STOCHRSId_16_14_3_3', 'WPR',
'EMAF', 'EMAM', 'EMAS']
```

Figure 5. Python's code to get the most significant technical indicators.

Once the trading or investment strategy was established, it was implemented through a software program. This program conducted a thorough backtesting, that is, a simulation of the strategy's performance using historical market data. Backtesting provides the ability to assess the potential profitability of a strategy by calculating essential metrics such as annual return rate, Sharpe ratio, and maximum drawdown, among others. Additionally, it facilitates testing with a variety of parameters and variables, allowing for the optimization of the strategy and enhancement of its performance. This process also aids in identifying the risks associated with the strategy, such as loss frequency and volatility. Ultimately, it gives the trader greater confidence in the robustness and viability of the strategy before its implementation in the real market.

Additionally, the strategy's behavior was analyzed with various parameters, and it was subsequently optimized to achieve the highest possible performance. The objective of this optimized strategy is to implement it across the 40 cryptocurrencies with the highest market capitalization, so that its performance can be examined for each one and, subsequently, identify which offers the greatest potential for profitability. Based on the results derived from backtesting and comparative analysis between cryptocurrencies, informed decisions are made regarding the optimal way to apply the strategy. These decisions encompass options such as trading or cryptocurrency mining, tailored to the specific strategy adopted and the prevailing market conditions. Nevertheless, it is crucial to keep in mind that past performance does not guarantee future results, as the market is inherently dynamic, and conditions can undergo significant changes. Additionally, historical data may contain errors or be incomplete, which could negatively affect backtesting results. Furthermore, a strategy that is excessively optimized for a specific period may not retain its effectiveness in the future.

3.5 Optimization and validation of the strategy

To consolidate the trading strategy, a meticulous process of optimization and results analysis was undertaken. This process involved careful calibration of parameters with the aim of maximizing the strategy's performance. The tools used to achieve this goal can be found in *Backtesting.py* github, this repository contains a Python framework for assessing the viability of trading strategies on historical data. Additionally, a thorough comparative analysis was conducted to evaluate the strategy's results across different time periods to assess its robustness and consistency under varying conditions. Figures 6 and 7 show a short Python's code and a heatmap to reach this goal.

Although the purpose of the article has been adequately fulfilled, it is essential to consider the additional steps necessary for the thorough validation and testing of the designed strategy. It is anticipated that the strategy will be implemented on a prestigious trading platform, such as BingX.com, in order to assess its performance in a real market environment.

Subsequently, a test will be conducted using capital from potential investors, with the aim of verifying the strategy's effectiveness under actual operating conditions and ensuring its robustness and reliability in practice.

```
from backtesting import Backtest, Strategy #tool for
backtesting
from backtesting.lib import crossover,plot_heatmaps
import pandas_ta as ta
import talib
from ipynb.fs.full.watchlist import Watchlist #pip in-
stall ipynb defs (class or function); full (all)
#Example of strategies used, ask for the full code.
class A(Strategy):
class SimpleBuy(Strategy):
class RSIcross(Strategy):
stats,heat = bt.optimize(emaF=range(5,15,1)
,emaS=range(45,65,1), maximize='Return [%]',
return_heatmap=True)
plot_heatmaps(heat)
```

Figure 6. Python's code example to optimize and validate the strategy.

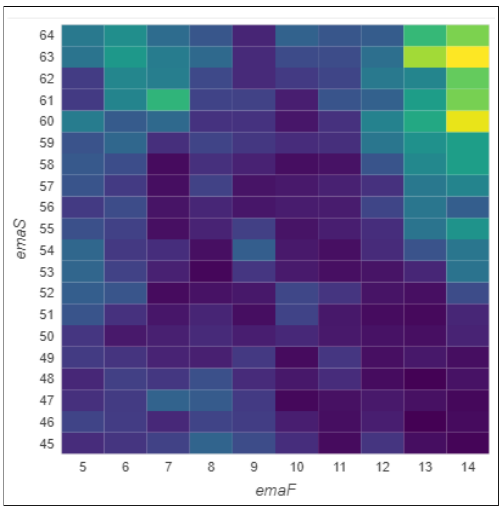

Figure 7. Heatmap.
Note. *An example of Heatmaps used to determine the best strategy for trading. The figure presented is an original creation by the authors.*

Lastly, but by no means less significant, it is envisioned that the developed algorithms will play a pivotal role in the decision-making process. These algorithms are designed to optimally manage digital assets, thus facilitating precise evaluation of the feasibility of selling, holding, or acquiring cryptocurrencies at specific times. Their implementation will enable efficient and strategic management of the assets, offering decisive guidance in optimizing cryptocurrency investments.

4. RESULTS

As evidenced by Figure 8, sentiment analysis revealed that most of news articles were classified as neutral. Consequently, building on the discussion presented in the preceding section, subsequent algorithms were employed to predict market trends. The expectation was to achieve favorable returns, thereby endorsing the implementation of a strategic approach conducive to the proposed technical-economic plan within the studied time frame.

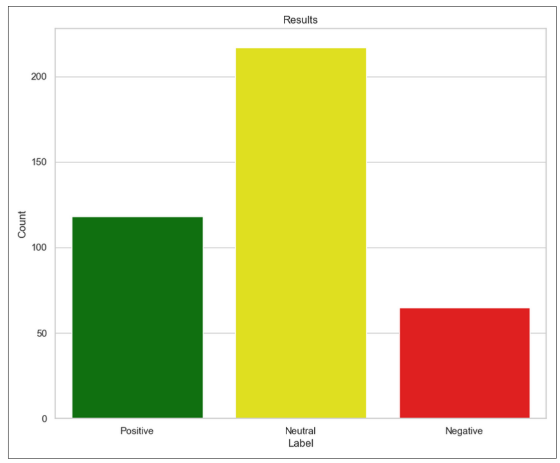

Figure 8. Sentiment Analysis Results.
Note. *The sentiment analysis conducted on Reddit offers valuable insights into public opinion regarding a range of topics. The application of Natural Language Processing (NLP) techniques significantly enhances the automation of this process, thereby yielding more precise and reliable results. The figure presented is an original creation by the authors.*

At this stage, a word cloud was also generated (see Figures 9 and 10), which serves as an ideal complement to sentiment analysis. This graphical representation facilitates the visualization of the most prominent terms used in the posts, providing a deeper and more nuanced understanding of the analyzed content.

Thereafter, the task of forecasting the price of BTC was undertaken. Initially, daily BTC price data was downloaded from YahooFinance.com, covering the period from 2014 to 2024, with prior assurance of the quality and reliability of the information. The data were subjected to a rigorous process of processing and normalization, during which outliers or inconsistent values were removed. Following this, the recurrent neural network was trained by dividing the dataset into 80% for training and 20% for testing.

Figure 9. Terms associated with positive sentiment.
Note. *The figure presented is an original creation by the authors.*

Figure 10. Terms associated with negative sentiment.
Note. *The figure presented is an original creation by the authors.*

Finally, the accuracy of the model was subjected to a comprehensive evaluation using the test dataset and various metrics, such as Mean Absolute Error (MAE) and Mean Squared Error (MSE). After validating the predictive model, it was implemented to project the future price of BTC. It should be noted that, since predictions are based on probabilities, their accuracy cannot be guaranteed in its entirety.

The results obtained demonstrate that the proposed algorithm provides a suitable approximation of BTC prices for both intraday values and future predictions. It is worth noting that the algorithm's accuracy is comparable to that of professional trading platforms such as TradingView.com. However, it is important to emphasize that these platforms rely on speculative models that can be influenced by subjective factors, such as the mood of analysts, whereas the proposed algorithm is not subject to such biases, representing a significant advantage. Conversely, it is essential to recognize that price predictions should be confined to short time periods, which for this work, specifically in the context of BTC, are considered short periods of 5 days to one week, as forecasts may otherwise become unreliable due to volatility or potential price manipulation in cryptocurrencies. Figure 11 shows BTC price prediction with the proposed algorithm.

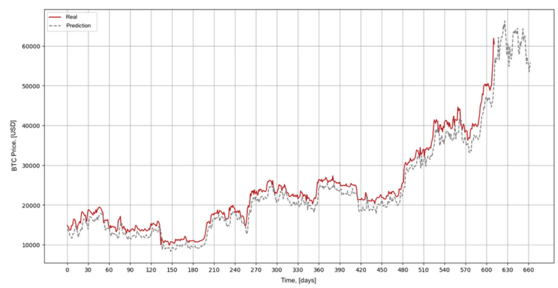

Figure 11. BTC price forecasting using RNN.
Note. *The graph starts on June 25th, 2022. The projection of BTC prices constitutes a task of high complexity and challenge. BTC prices exhibit high volatility, being susceptible to a wide range of factors such as asset adoption, applicable regulations, relevant news, and geopolitical events. This multifaceted dynamic demands a sophisticated approach to accurately capture market fluctuations. The figure presented is an original creation by the authors.*

Following this, the task of identifying and selecting the top fifteen technical indicators was conducted, based on the references consulted from Stockcharts.com and Investopedia.com. This process ensured the inclusion of a comprehensive range of indicators, encompassing categories such as trend, momentum, volume, and volatility. Thereafter, the values of these indicators were computed using the historical BTC price data as the basis. This selection was made using the gradient-boosted decision tree algorithm XGBoost (see Figure 12).

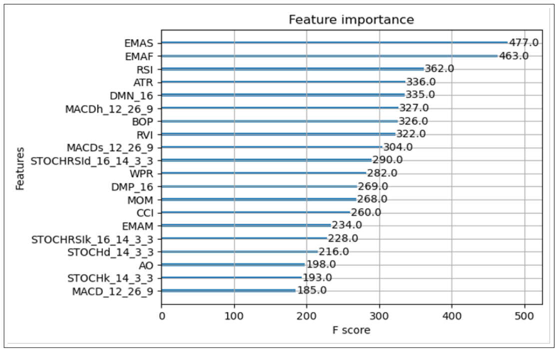

Figure 12. Most relevant technical indicators in BTC price prediction.
Note. *The selection of indicators proves valuable for identifying those of greatest relevance in predicting BTC price. However, although this process provides significant guidance, it does not guarantee absolute success. The figure presented is an original creation by the authors.*

In alignment with the above, the three technical indicators that demonstrated a predominant influence on the determination of BTC price were the EMAS with a period of 55, the EMAF with a period of 10, and the RSI with a period of 16.

Consequently, based on the selected technical indicators, a meticulous backtesting analysis was made to evaluate the potential profitability of the trading strategy before its implementation in a real market environment. Initially, a strategy was designed using the EMAS with a period of 55 and the EMAF with a period of 10, with the results detailed in Table 2.

Table 2. Comparative analysis of financial performance among trading strategies.

Strategy	Profits Rate (%)
EMAS:55	8 881
EMAF: 10 RSI: 16	8 786
EMAS:55 EMAF: 10 RSI: 16	204

Trading strategy was optimized to identify the optimal periods for the EMA that would maximize the profit percentage. It was determined that strategies employing an EMAF with a period of fourteen units and an EMAS with a period of sixty-three units yielded a significantly higher return compared to other period combinations, achieving approximately 49.881%. Ultimately, the evaluation of the strategy revealed that, among the 40 cryptocurrencies with the highest market capitalization, during the period from September 23, 2014, to March 1, 2024, the digital currencies with the highest return were Bitcoin, Ethereum, Binance Coin, Cardano, and Solana, as illustrated in Table 3. This assessment was conducted considering return, risk, and the Sharpe Ratio.

Table 3. Financial performance evaluation of various strategies.

Cryptocurrency	Return Rate (%)	Investment Risk	Sharpe Ratio
Bitcoin (BTC)	49.881	0.25	2
Ethereum (ETH)	38.742	0.3	1.8
Binance Coin (BNB)	32.891	0.28	1.7
Cardano (ADA)	29.74	0.27	1.6
Solana (SOL)	27.639	0.26	1.5
Polkadot (DOT)	25.588	0.25	1.4
Dogecoin (DOGE)	23.537	0.24	1.3
Shiba Inu (SHIB)	21.486	0.23	1.2
Avalanche (AVAX)	19.435	0.22	1.1
Terra (LUNA)	17.384	0.21	1

Note: *Cryptocurrencies with the highest return may change over time.*

5. CONCLUSIONS AND RECOMMENDATIONS

In this work it was shown that cryptocurrency trading using optimized strategies such as those based on EMAS and EMAF has the potential to generate highly attractive returns on investment, for example, 49.8% for BTC. The implementation of artificial intelligence algorithms provides the ability to capitalize on the intrinsic volatility of the cryptocurrency market, thus enabling more informed and precise investment decisions. It is a fact that part of this volatility is influenced by global sentiment, cryptocurrency adoption, and transaction security. However, it is imperative to emphasize that the performance of any strategy can fluctuate significantly. Therefore, it is not possible to guarantee the success of the strategies proposed in this study across all timeframes or periods.

While AI can be a valuable tool in crypto trading, it's essential to understand the inherent risks associated with relying solely on AI-driven strategies. One of the primary risks is the potential for AI to misinterpret or misinterpret data. AI algorithms are trained on historical data, and if that data is biased or incomplete, the AI may make inaccurate predictions. For instance, an AI model trained on data from a bull market (characterized by a sustained period of rising price) may struggle to adapt to a bear market (characterized by a prolonged period of declining prices), leading to significant losses.

Also, the Cryptocurrency market is regulated differently in different countries and jurisdictions. Without defined cryptocurrency trading algorithm regulations, investor protection, market integrity, and systemic risk are in danger. Regions must create guidelines for algorithmic trading transparency, fairness, and accountability.

It is strongly recommended to conduct rigorous testing with a variety of cryptocurrencies and different time intervals to determine the optimal configuration of the investment strategy over time. Additionally, it is imperative to stay informed and up to date regarding cryptocurrency regulations in Mexico, as this area remains a gray zone within the country's financial regulatory framework. Furthermore, it is prudent to consult with a financial advisor with extensive experience in the field of cryptocurrencies. Also, diversification of the investment portfolio should be considered a primary strategy to mitigate risk and reduce exposure to market volatility.

In conclusion, while AI can be a valuable tool in crypto trading, it's essential to approach it with caution and a clear understanding of the risks involved. By carefully considering the limitations of AI and combining it with human judgment, traders can mitigate the risks and potentially achieve better outcomes.

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