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Original Article

Cardano Cryptocurrency Price from Twitter. A Prediction Algorithm from Machine Learning

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Abstract - *Cryptocurrencies are a growing market that has attracted the attention of many investors in recent years. While cryptocurrencies offer a secure and decentralized form of payment, this market is highly volatile. Factors influencing price changes include the balance of supply and demand, its utility, trading indicators, and market confidence. The present research aims to predict the price of the Cardano cryptocurrency by using machine learning techniques, specifically SVM, LSTM and BiLSTM models. In addition to accounting for financial indices, Twitter activity was used as a data source to measure market sentiment. The study analyzes various predictive horizons, including time ranges of 1 day, seven days, 14 days, 21 days and 30 days. The results obtained were validated with different performance indicators, and it was determined that the model predicts Cardano prices one month ahead with a MAPE of less than 22%, providing valuable information for investors interested in the volatile Cardano cryptocurrency market.*

Keywords - *Cardano, Cryptocurrencies, Machine Learning, Neural Network, Twitter.*

1. Introduction

Cryptocurrencies are presented as the new economic and technological trend that will revolutionize the financial markets. With a market that reached more than three billion dollars, cryptocurrencies are considered by many investors as the haven asset against the economic crises of 2020 and 2021. Still, recent events such as the collapse of the Terra (Luna) cryptocurrency in May 2022, losing 99.99% of its value, show that this market is not risk-free and even tends to be more volatile than traditional markets [8].

The cryptocurrency market, just like the stock and currency market, is governed by supply and demand; however, it presents substantial differences in terms of the way transactions are conducted, price fluctuations and market regulations. The intrinsic value of cryptocurrencies lies in the blockchain technology that allows the transaction, creation and verification of digital assets in a decentralized and anonymous way.

Blockchain is defined as a system of interlinked nodes in a peer-to-peer network that allows transactions to be validated by each component [6]. Blockchain technology renders obsolete the government's role as currency producer and intermediary of transactions, which increases the cryptocurrency market's volatility due to the lack of institutional regulation [15]. However, decentralising digital currency with Blockchain technology makes cryptocurrencies a more reliable transaction method [1]. The first cryptocurrency, Bitcoin, is the most famous and valued crypto asset. Even so, Bitcoin is not the only token on the market, as there are more than 10 thousand cryptocurrencies with unique features and functionalities, the most known being Ethereum, Cardano, Solana and Polkadot, which have a Blockchain that allows the creation of more functional applications than Bitcoin. Among the cryptocurrencies above, Cardano is the one on which this paper focuses.

Cardano is a cryptocurrency whose blockchain is based on the proof-of-stake and Ouroboros mechanism to carry out its operations. Cardano, whose digital token is ADA, has operational mechanisms that will only be included in the update of the second most important cryptocurrency in the market: Ethereum.

For this reason, this new asset has attracted the attention of investors, engineers and programmers. It has also interested individuals outside the field, large corporations, politicians and the media. The latter group has been very active on social networks, using their influence and large audience to open debates on new trends and speculations about cryptocurrency prices. Among the different social networks, Twitter is the one that especially presents attractive data for investors because it is a network that reflects market expectations expressed in the sentiments and fears of the publications [28].

Likewise, this network is a real-time sample of collective reactions with a contagion effect and can anticipate market trends [9]. An example of Twitter's impact on the price of cryptocurrencies could be observed with the Dogecoin cryptoasset. After Elon Musk tweeted, mentioning only the name of the cryptocurrency, the cost of Dogecoin increased by 50% [12]. Cases like this generated researchers' interest in testing the correlation between Twitter interactions and the cryptocurrency market.

In light of these considerations, this research endeavours to fill a notable gap in the existing literature by employing a machine learning approach to predict the price movements of the Cardano cryptocurrency based on Twitter activity. This study seeks to contribute valuable insights into the intersection of social media dynamics and cryptocurrency markets, shedding light on the predictive potential of machine learning models in this evolving landscape.

2. Background

2.1. Data Extraction and Sentiment Analysis

In one study, the financial variables analyzed were the observed day's opening, closing, lowest, highest, and trading volumes. At the same time, the data collected from Twitter went through a study using the TextBlob Sentiment package to identify the tweet polarity and reflect the market analysis [1].

On the other hand, tweets from another research were collected with a supervised NLP model and went through a preprocessing stage using the Natural Language Toolkit package [26]. While the two models mentioned above work within a single language, other works conduct the market sentiment study in English and Japanese [30, 20].

Unlike the other research, some works perform a market sentiment study with the Term Frequency-Inverse Document Frequency (TF-IDF) method without any package or library. This gives us more data to train the model and be more accurate with text mining on Twitter [30]. Another method used for sentiment analysis is lexicon-based, which uses keywords from extracted dictionaries to classify tweets as positive and negative [27]. This same model is replicated in another paper demonstrating how social networks affect the price of public financial assets [7].

Another paper performs an additional analysis by working market sentiment with two types of variables: continuous and binary [21]. Additionally, the paper uses different machine learning models to predict stock prices using Twitter as a database for sentiment analysis.

2.2. Machine Learning Models

Data analysis through machine learning models is the part in which we found the most differences between the articles. One article presents a study based on deep learning models such as the Gated Recurrent Unit (GRU) and Long-Short Term Memory (LSTM), from which it was determined that the GRU model has the best prediction capacity [1].

In contrast to these results, we find authors who support the previous conclusion and discard the LSTM model since they obtained a percentage error of 34.92% [26]. Similarly, another study using a bidirectional LSTM model obtained worse results than Artificial Intelligence models such as logistic regression [30].

Still, several authors support the use of LSTM networks. Some researchers propose that a bidirectional LSTM model tends to be the best-performing model for predicting the price of Bitcoin and that it will become better as the data increases [18]. The use of LSTM networks for predicting the price of a cryptocurrency is supported by a study in which they demonstrate the LSTM model's effectiveness in predictive analysis of a time period of up to 50 days in a row for the price of Bitcoin [17].

Among the research using the LSTM model, we also find research that manages to predict the price of Bitcoin with 89.13% certainty [14]. In machine learning that does not use neural networks, we detected the use of Support Vector Machine (SVM) models [27].

In this study, they validate the use of this model for Bitcoin cryptocurrency price prediction with a certainty of up to 94.89%. In another study of used machine learning models other than traditional ones, which are Support Vector Machine (SVM), Clustering and Ordinary Least Squares Regression (OLSR) [20].

Among these models, the one with the best accuracy was the SVM. In addition, this work employed an Application Programming Interface (API) that extracted real-time data to make predictions and validate the model. In addition to the Support Vector Machine, the research of [13] tests the Elastic Net model for making predictions in cases of depression via Twitter. Error analysis shows that this model has an R2 equal to 0.025 and an r equal to 0.16. Outside machine learning models, we find more basic Artificial Intelligence models [24]. Their study posits a quartile regression to determine the correlation and predictability of stock prices based on Twitter activity in South Africa.

In addition, we detect models such as vector autoregressive, with which they concluded that Twitter sentiment analysis can advance predictions about a stock's price variation [9]. On the other hand, some authors propose a forecast based on a time series autoregressive model [15]. Finally, some articles used tools like IBM Watson to perform predictive analysis of selected cryptocurrencies [25].

3. Methodology

The research was experimental since it sought to process the polarity of tweets and indicators of buying and selling shares as independent variables to predict a dependent variable, the Cardano cryptocurrency. Considering that the work's purpose is to evaluate the relationship between variables and even predict their behaviour, it can be stated that it exposes a correlational scope.

On the other hand, the research has a mixed data processing approach as it systematically integrates quantitative (price and indicators) and qualitative (tweets) data. Machine Learning (ML) was used in the research process to create the prediction algorithm. Some of the techniques used were Natural Language Processing (NLP) for sentiment analysis and Pearson correlation analysis to evaluate the relationship of the variables.

On the other hand, the Python library import tool was used to extract the information that feeds the model from the Twitter and Yahoo Finance platforms. From Twitter, the publications between January 2021 and April 2023 were extracted, and from Yahoo Finance, the Cardano prices for this same time period were imported. The sample obtained consists of 742,757 tweets in the 26 months selected. The methodological process followed was structured in five consecutive stages. Table 1 and Figure 1 present below the process description by stages and diagram, respectively.

Table 1. Process description

Step	Partial Objective	Platform	Tool
Twitter data extraction	Obtain the sample of the dependent and independent variables.	Google Colab	snscrape library for Twitter
Sentiment analysis	Assign each tweet a score according to polarity (-1 to 1) and subjectivity (0 to 1).	Google Colab	NLP libraries: Textblob sentiment
Yahoo finance data extraction	Collect information on trading volume opening and closing price per day.	Yahoo Finance	Bookstore and finance
Trading indicators analysis	Identify buy and sell signals with the momentum trading strategy algorithm.	Google Colab	Pandas libraries
Correlation analysis	Confirm the correlation between variables	Google Colab	Seaborn library and use of heat maps
Machine learning models execution	Run Cardano price prediction algorithms	Google Colab	Tensorflow and Keras libraries
Error analysis	Identify the most accurate prediction model with the lowest Mean Absolute Percentage Error (MAPE)	Google Colab	Tensorflow library

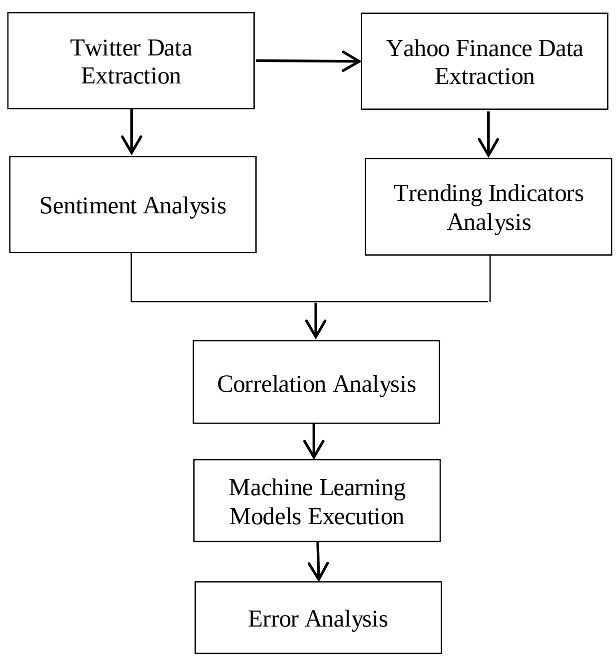

Fig. 1 Process diagram

3.1. Twitter Data Extraction

The Twitter data was extracted using the Python snscrape library. This library gathers information from social networks such as Facebook, Instagram, Reddit and Twitter to identify components such as posts, hashtags, profiles and likes.

In the present research, snscrape was included to extract tweets published between January 2021 and April 2023 with mentions or hashtags of the word Cardano or the acronym of the ADA cryptocurrency. For each of these publications, a timestamp, the author, the tweet's content, the number of retweets and the number of likes are detailed.

3.2. Sentiment Analysis

After obtaining the tweets, the TextBlob library was used to perform sentiment analysis of the text of the posts. TextBlob is an API for Natural Language Processing (NLP) tasks and can process more than 20 languages. The software combines several libraries and functions, such as Google translator and Natural Language Toolkit (NLTK), to determine the opinion or emotions implicit in a text.

TextBlob's sentiment function allows it to process tweets and evaluate the polarity of the text from -1 to 1 according to its negative (-1) or positive (1) connotation. Additionally, the library scores the subjectivity of the tweet from 0 to 1, according to its objectivity or subjectivity, respectively. The results of both variables must be separated and converted to float format so that they can serve as input in Machine Learning models.

After quantifying the polarity of the tweets, we sought to measure the reach of each post. As more people get to read the post, the more likely it is to have an impact on potential investors. However, the number of likes was considered a better indicator than the number of views because the interaction with the tweet shows a more significant impression on the user. Under this assumption, the polarity of the tweets was multiplied by the number of likes to obtain a polarity variable according to the reach of each publication.

Subsequently, we must modify the date format to obtain a daily polarity value comparable to the data extracted from the closing price of cryptocurrencies. For this purpose, the sentiment rating of the tweets was summed without considering the hours, minutes and seconds in the timestamp. In this way, the obtained Twitter sentiment analysis will allow us to assess the daily market expectations and how these may influence Cardano's price in the following days.

3.3. Yahoo Finance Data Extraction

On the other hand, Cardano's price information was obtained from Yahoo Finance. The sample used to train the algorithm is the historical data from January 2021 to April 2023. For each day within this period, the variables of the opening and closing price; the maximum and minimum price of the day and the volume of transactions were collected.

Cardano's closing price is the variable we seek to predict in the present research. For this reason, we need to include a column with the future price of the cryptocurrency assigned to each evaluated day to train the Machine Learning model. It was decided to make predictions for one day, one week, two weeks, three weeks and one month (30 days).

3.4. Trading Indicators Analysis

The trading indicator used was the momentum trading strategy algorithm. This algorithm uses past price trends to identify and capitalize on future asset trends. If a positive price trend is revealed, a price growth signal is created (+1); in the opposite case, a price decrease signal is created (-1).

The parameters used are the Fast-Moving Average (FMA) and the Slow-Moving Average (SMA). The FMA is used to identify short-term trends (9 days), while the SMA identifies long-term trends (21 days). The smaller the difference in days between the moving averages, the more risk the model is exposed to.

The buy and sell signals are created when there is a change in trend, which implies that the value of one of the moving averages exceeds the other. The buy signal is created when the FMA exceeds the SMA, and the signal is represented by the positive two values, resulting from the difference of the signal value at instant t with the instant t-1. In contrast, the sell signal is created when the SMA exceeds the FMA, represented by the two negative values.

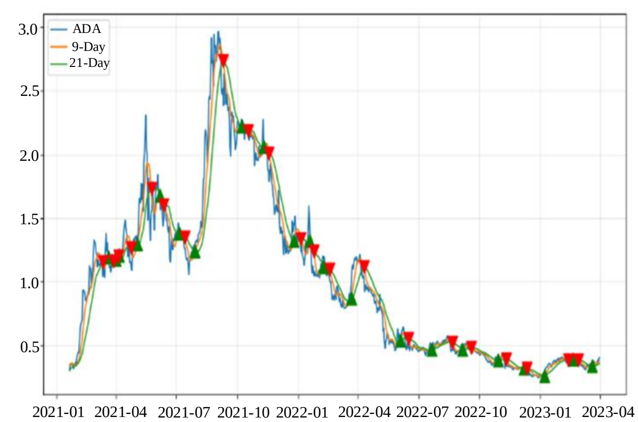

Fig. 2 Cardano buy and sell signals with momentum trading strategy

3.5. Correlation Analysis

For each day of the sample, the values of the polarity of tweets are aligned with the closing price of the Cardano cryptocurrency. Correlation analysis allows for determining a relationship between 2 continuous variables. Pearson's correlation coefficient, which demonstrates a linear association between the elements, will be used for the research. If the correlation result is closer to 1, it shows a high direct correlation, while values close to -1 indicate a high indirect correlation. On the other hand, if the result is close to 0, it indicates no correlation between the variables. The following equation represents the model:

$$r = \frac{n*\sum Xi*Yi - \sum Xi*Yi}{\sqrt{[n*\sum Xi^2 - (\sum Xi)^2]*[n*\sum Yi^2 - (\sum Yi)^2]}} \quad [11]$$

The equation presents the values of Xi as each characteristic's observations, while Yi is the observations of the dependent variable. The value of n represents the number of records [18]. To visualize the results of the correlations (r) graphically, a heat map was used through the Pyplot module extracted from the Python Matplotlib library.

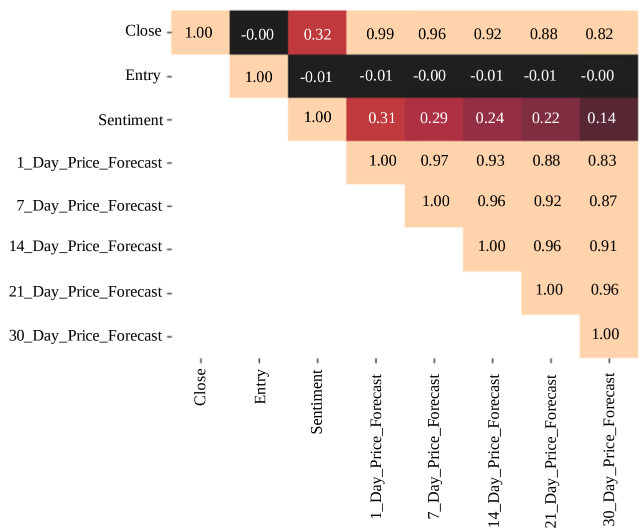

Fig. 3 Correlation heat map

It was observed on the heat map that as we increase the prediction horizon, the correlation between the closing price and market sentiment decreases.

3.6. Multicollinearity and Backwards Elimination Analysis

Multicollinearity refers to a situation in which the independent variables are highly related. This causes the coefficients or weights assigned to the correlated variables to be unstable and unreliable, producing difficulties in the model to interpret the importance of each variable in the target variable. The backwards elimination technique is used to counteract the effect of multicollinearity and improve the model's performance.

This is an attribute selection technique that, through a decision tree model, calculates the statistical significance of the inputs at a 5% significance level, eliminating the least significant variable (the one with the highest p-value) until the model is left with only statistically significant variables.

3.7. Machine Learning Models Execution

3.7.1. Long-Short Term Memory (LSTM)

Having finished processing the data and establishing the correlations, we proceeded to run the Deep Learning model to predict the closing price of Cardano. This model is a variation of the recurrent neural networks called Long-Short Term Memory (LSTM), which differs from the rest by having a memory cell that can hold information for indefinite periods of time, having control over the information that enters, that which is stored and that which is forgotten to the previous state Et-1 to produce a new state Et. This architecture avoids neural networks' back propagation problems, reducing computation time and memory usage [1].

The decision of what information is retained from the previous state Et-1 in the analyzed cell state Et is made through a sigmoid function (a) that yields results within in an interval of 0 and 1, where the closer the value is to one implies a higher importance to retain the information.

Once this step was completed, a sigmoid function and a hyperbolic tangent (b) were used to decide which information from the analyzed state enters the memory cell. Finally, another sigmoid function and hyperbolic tangent (Ct) were applied to determine the output values of the memory cell. This process was repeated for each value presented in the time series.

$$(a) f_t = sigmoidal(W_f[a_{t-1}, x_1] + b_f)$$
$$(b)\ C_t = \tanh(W_c * [x_t, h_t - 1] + b_c) \quad [10]$$

It should be noted that the model was trained with the cross-validation method, using part of our data for training and the rest for validation. Several percentage distributions of the data for training and validation of the model were performed to avoid underfitting and overfitting, reducing the model error.

Finally, the R2 measure was used to measure the model fit. The values obtained range from 0 to 1, where 0 means that the model does not explain any variability in the data, and 1 means that the model does explain the variability in the data.

$$R^2 = \frac{\sum_{i=1}^{N}(A_i - A)^2 (P_i - P)^2}{\sum_{i=1}^{N}(A_i - A)^2 * \sum_{i=1}^{N}(P_i - P)^2} \quad [5]$$

The Cross validation method and the training using R2 allowed a more accurate prediction model and decreased errors between the real and predicted values. The hyperparameters were adjusted based on the error metrics obtained with different variations of the values of the number of layers, number of neurons and activation methods until the best distribution was found.

Table 2. LSTM hyperparameter setting

Parameters		Value
Batch Size		220
Epochs		150
Input Layer	Type	LSTM
	# Neurons	10
	Activation	ReLU
Intermediate Layer 1	Type	Dense
	# Neurons	5
	Activation	ReLU
Intermediate Layer 2	Type	LSTM
	# Neurons	64
	Activation	ReLU
Intermediate Layer 3	Type	Dense
	# Neurons	5
	Activation	ReLU
Intermediate Layer 4	Type	Dense
	# Neurons	10
	Activation	ReLU
Output Layer	Type	Dense
	# Neurons	1
	activation	No Activation

3.7.2. Bidirectional Long-Short-Term Memory (BiLSTM)

The BiLSTM (Bidirectional Long Short-Term Memory) neural network is a variant of Recurrent Neural Networks (RNN) used to model data sequences, such as time series. While a traditional LSTM network processes the line in one direction, from left to right or right to left, a BiLSTM processes the sequence simultaneously, capturing past and future information.

The structure of a BiLSTM consists of two LSTM layers, one that processes the sequence in direct order and one that processes the line in reverse order. Each LSTM layer has a memory cell that can retain information over time. The information in the memory cell is updated through a series of gating-based operations.

In the case of an LSTM network, a sigmoid gate is used to decide what information is retained from the previous state and what information is forgotten. In addition, a sigmoid function and a hyperbolic tangent are used to determine what information enters the memory cell and what data leaves the memory cell.

In a BiLSTM, these operations are applied in both direct-order sequence processing and reverse-order processing. This allows the network to capture both past and future dependencies of each point in the sequence, which can be beneficial for time series prediction.

Table 3. BiLSTM hyperparameter setting

Parameters		Value
Batch Size		220
Epochs		150
Input Layer	Type	BiLSTM
	# Neurons	128
	Activation	ReLU
Intermediate Layer 1	Type	BiLSTM
	# Neurons	64
	Activation	ReLU
Intermediate Layer 2	Type	Dense
	# Neurons	5
	Activation	ReLU
Intermediate Layer 3	Type	BiLSTM
	# Neurons	32
	Activation	ReLU
Intermediate Layer 4	Type	BiLSTM
	# Neurons	16
	Activation	ReLU
Intermediate Layer 5	Type	Dense
	# Neurons	5
	Activation	ReLU
Intermediate Layer 6	Type	Dense
	# Neurons	10
	Activation	ReLU
Output Layer	Type	Dense
	# Neurons	1
	Activation	No Activation

3.7.3. Support Vector Machines (SVM)

It was also decided to run a second supervised learning algorithm: Support Vector Machines (SVM). SVMs are mainly applied for binary classification and regression but can also be used for variable selection, outlier identification and clustering. The model seeks to find the optimal hyperplane that maximizes the perpendicular distance between the hyperplane and the nearest point of each class in the dataset. In other words, SVMs seek to achieve better generalization on unseen data.

In the case of the present research, the data are not linearly separable, so the kernel trick is employed to bring the data to a higher dimension where they can be separated. Specifically, we use the Gaussian kernel (RBF), which is governed by the following equation:

$$G(x_j, x_k) = \exp\left(-\left\|x_j, x_k\right\|^2\right) \quad [16]$$

Thus, the SVM regression function integrated in Python with the Gaussian kernel and the R2 fit measure were used to train the model and then validated with cross-validation.

Table 4. SVM parameters adjustment

Parameters	Value
Kernel	rbf
C	1.00E+03
Gamma	Auto

3.8. Error Analysis

Finally, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Mean Squared Error (MSE) error measures were used to evaluate model performance [3]. First, MSE is the commonly used error measure in regression models. The calculation divides the mean squared errors between the actual values and the values resulting from the prediction under the following mathematical formula:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(A_i - P_1)^2 \quad [5]$$

The RMSE is the standard deviation of the prediction errors or residual values, which show the distance of the actual data from the forecast, which is calculated with the following equation:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(A_i - P_1)^2} \quad [5]$$

On the other hand, the MAE is another error measure that calculates the mean of the absolute difference between the actual and predicted values.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|A_i - P_i| \quad [5]$$

Finally, the MAPE is similar to the MAE, with the difference being that it shows the overall absolute error of the projection compared to the actual data in percentage value.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|A_i - P_i|}{A_i} * 100 \quad [5]$$

The four previously mentioned error measures were analyzed to measure the effectiveness of Machine Learning (ML) models: LSTM and SVM.

3.8.1. Analysis of Variance (ANOVA)

One-factor analysis of variance is a statistical technique used to compare the means of 2 or more groups [19]. It is used to determine whether one group differs significantly from the other. One-factor ANOVA is used to evaluate the influence of a single factor on the results.

The ANOVA result can be interpreted as the p-value associated with the independent variable. If the p-value is less than the confidence level, it can be concluded that at least one of the groups differs significantly from the others. If the p-value is more significant than the significance level, it cannot be concluded that there is a substantial difference between the groups. The null hypothesis that ANOVA wants to test is:

$$H_0: u_1 = u_2 = u_k$$
$$H_a: at\ least\ one\ average\ is\ different \quad [22]$$

The ANOVA formula was applied to evaluate the difference in prediction results between the BiLSTM, LSTM and SVM models.

4. Results

The models aim to predict Cardano's closing price within different time periods: one day, one week, two weeks, three weeks and one month. For this reason, a table summarizing the error values for each of these prediction ranges for the two ML models was developed.

With these results of the error analysis, we can determine that the most accurate model for Cardano's closing price prediction is BiLSTM with an error 1.6% lower than LSTM and 3.7% lower than SVR in the 1-day prediction and 1.5% and 8.2% respectively lower for 30 days.

Also, it can be observed that as the prediction period increases, so does the percentage error. This is a market characteristic, as cryptocurrencies are volatile assets with transactions 24 hours a day, so having an accurate prediction within a month is almost impossible. The ANOVA formula was then applied to identify whether there is a difference between using LSTM, BiLSTM or SVM as a prediction model.

Table 5. Average error analysis for BiLSTM, LSTM and SVM models

1 Day Prediction							
Models	**MAPE**	**MAE**	**MSE**	**RMSE**	**R2 (Train)**	**R2 (Test)**	**CV**
SVR	0.106	0.087	0.020	0.141	0.987	0.952	0.965
LSTM	0.085	0.067	0.009	0.092	0.983	0.979	0.543
Bi LSTM	0.069	0.058	0.007	0.081	0.987	0.983	0.543
7 Day prediction							
Models	**MAPE**	**MAE**	**MSE**	**RMSE**	**R2 (Train)**	**R2 (Test)**	**CV**
SVR	0.168	0.154	0.079	0.276	0.943	0.812	0.767
LSTM	0.130	0.120	0.032	0.179	0.929	0.924	0.767
Bi LSTM	0.120	0.114	0.030	0.171	0.934	0.930	0.767
14 Day Prediction							
Models	**MAPE**	**MAE**	**MSE**	**RMSE**	**R2 (Train)**	**R2 (Test)**	**CV**
SVR	0.215	0.206	0.158	0.385	0.876	0.629	0.583
LSTM	0.198	0.180	0.067	0.258	0.855	0.839	0.583
Bi LSTM	0.187	0.171	0.064	0.251	0.864	0.847	0.583
21 Day Prediction							
Models	**MAPE**	**MAE**	**MSE**	**RMSE**	**R2 (Train)**	**R2 (Test)**	**CV**
SVR	0.247	0.230	0.181	0.420	0.809	0.565	0.515
LSTM	0.251	0.206	0.094	0.305	0.777	0.776	0.515
Bi LSTM	0.233	0.206	0.095	0.307	0.784	0.772	0.515
30 Day Prediction							
Models	**MAPE**	**MAE**	**MSE**	**RMSE**	**R2 (Train)**	**R2 (Test)**	**CV**
SVR	0.299	0.304	0.480	0.660	0.743	-0.129	0.239
LSTM	0.232	0.236	0.125	0.349	0.710	0.707	0.239
Bi LSTM	0.217	0.217	0.076	0.277	0.721	0.802	0.239

In the context of one-day-ahead predictions, a notable enhancement in predictive accuracy was observed through the Mean Absolute Percentage Error (MAPE) criterion when contrasting unidirectional standard algorithms, exemplified by Support Vector Machine (SVM), with unidirectional neural networks such as the Long Short-Term Memory (LSTM) model. Specifically, the MAPE exhibited a 19.8% reduction.

Furthermore, in the comparison of SVR with a bidirectional neural network, namely the Bidirectional LSTM (Bi-LSTM), a substantial decrease in MAPE by 34.9% was noted. Intriguingly, the MAPE demonstrated an 18.8% decrease when contrasting the two neural networks, favouring the utilization of a bidirectional model over a unidirectional model. Upon subjecting the MAPE values derived from each timestamp and model to a t-test, the statistical analysis revealed a significant variance in prediction errors between the models.

This statistical evidence underscores the superior predictive capacity of the Bi-LSTM model across all timestamps. In the results of the ANOVA statistical model, we can compare the difference in accuracy between the prediction with SVM, LSTM and BiLSTM.

It is observed that the null hypothesis is accepted in the prediction at two and three weeks, i.e., in these cases, there is no significant difference between the results of the models. However, we can state that the Bi-LSTM model performs better at the one-day, one-week and one-month forecast horizons.

Table 6. Error analysis with ANOVA

	df	sum_sq	mean_sq	F	PR(>F)	Result
1 Day prediction						
	df	**sum_sq**	**mean_sq**	**F**	**PR(>F)**	**Result**
C(Model)	2	0.005599	0.0028	5.478538	0.010068	H_0 is ruled out
Residue	27	0.013797	0.000511			
7 Day prediction						
	df	**sum_sq**	**mean_sq**	**F**	**PR(>F)**	**Result**
C(Model)	2	0.011723	0.005861	6.290988	0.005717	H_0 is ruled out
Residue	27	0.025156	0.000932			
14 Day Prediction						
	df	**sum_sq**	**mean_sq**	**F**	**PR(>F)**	**Result**
C(Model)	1	0.00001	0.00001	0.00817	0.918972	H_0 is accepted
Residue	18	0.02135	0.001186			
21 Day Prediction						
	df	**sum_sq**	**mean_sq**	**F**	**PR(>F)**	**Result**
C(Model)	2	0.002097	0.001049	0.598124	0.556965	H_0 is accepted
Residue	27	0.047332	0.001753			
30 Day Prediction						
	df	**sum_sq**	**mean_sq**	**F**	**PR(>F)**	**Result**
C(Model)	2	0.016914	0.008457	3.762618	0.036188	H_0 is ruled out
Residue	27	0.060685	0.002248			

5. Discussion

Based on the results in Table 7, our model outperforms other models in its ability to predict cryptocurrency prices. The other research results were not obtained based on Cardano but on other cryptocurrencies, such as Bitcoin or Dogecoin, which could have been exposed to other variables. Hence, the comparison is not entirely accurate.

A synthesis graph is shown to better visualise the difference with the results reviewed in the literature review.

Table 7. Comparison of errors of various prediction intervals to a time interval

Model	MAPE	RMSE	MAE
LSMT	0.085	0.092	0.067
SVR	0.106	0.141	0.087
BiLSTM	0.069	0.081	0.058
LMH-BiLSTM [18]	0.023		
LSTM [1]	0.027		
GRU [1]	0.091		
LSTM [2]	0.073		
LR [4]	0.077		
ARIMA [29]	0.082		
LSTM [23]	0.038		
LSTM [26]	34.92		

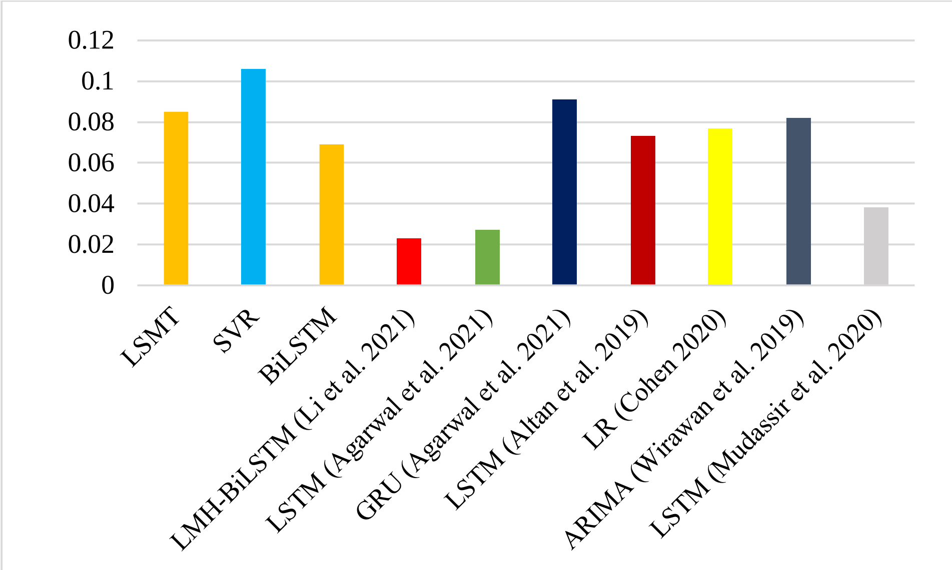

Fig. 4 Porcentual error comparison graphic

From the above figure, we can observe that our BiLSTM model outperforms 5 of the referenced models in prediction performance while the remaining models significantly outperform it.

This observation underscores the superiority of a sophisticated model endowed with the capability to discern temporal relationships among variables, showcasing its capacity to outperform models lacking this aptitude. The efficacy of the Bi-LSTM model is attributed to its distinctive capability to capture dependencies in both forward and backward directions. This unique feature equips the model with a heightened capacity to comprehend intricate temporal relationships, encompassing the data's extended dependencies and non-linear variations.

Moreover, employing market sentiment as a variable on a volatile asset could exert a more pronounced impact on its price than a less volatile asset, where rational investors and companies own a significant portion and are less susceptible to social media influence.

Another reason for the outperformance of the Bi-LSTM model proposed in this paper is a sequential structure with a seven-layer depth. The advantages of employing a more profound architecture are pronounced in sequential modelling compared to simpler models.

One notable benefit lies in the hierarchical representation of features, wherein each layer captures patterns at varying levels of abstraction. This hierarchical learning enables the model to automatically extract complex features in a structured manner, facilitating the abstraction of both low-level and high-level representations within the dataset.

Moreover, the expressive capacity of the model is enhanced with increased layer depth, empowering it to discern intricate and non-linear relationships, thereby potentially improving overall performance.

However, adopting a sequential model with heightened depth introduces challenges that demand careful consideration. Notably, the risk of overfitting becomes more prominent, particularly when the dataset is limited. Regularization techniques, dropout layers, or batch normalization can be strategically applied to address this concern.

Furthermore, the computational complexity associated with training and inference in deeper models necessitates substantial computational resources. Despite these challenges, the advantages of hierarchical representation and enhanced expressive capacity underscore the potential of sequential models in capturing intricate patterns within sequential data, as shown in Figure 4.

In the study [1], they used an LSTM network and a GRU network, which they considered as additional independent input variables such as the volume of transactions in the day, the opening price, the closing price, the highest price, and the lowest price. It is worth noting that this prediction was made on the Dogecoin cryptocurrency, obtaining a 2.7% error in the LSTM network and a 9.1% error in the GRU network.

When comparing Gated Recurrent Unit (GRU) and Bidirectional Long Short-Term Memory (Bi-LSTM) models, the complexity of capturing long-term dependencies stands out as a crucial factor. GRUs may encounter difficulties preserving information over extended periods due to their design, which combines forget and input gates into a single update gate. This limitation can impact their ability to capture intricate dependencies in sequential data. While GRUs have fewer parameters, contributing to computational efficiency and reduced overfitting risk, this simplicity may hinder their expressiveness in scenarios requiring a more complex model. Additionally, the simplified gate structure of GRUs may compromise their ability to learn intricate patterns, particularly when long-term dependencies are vital.

Also, LSTMs process sequences unidirectionally, considering information solely from past time steps. This unidirectional flow may constrain their ability to fully leverage future context, especially in tasks where bidirectional dependencies play a crucial role. In contrast, Bi-LSTMs, capturing information in both forward and backward directions, provide a more comprehensive context for sequence modelling. LSTMs may struggle to capture complex patterns requiring an understanding of both past and future context simultaneously, making B-iLSTMs more adept in scenarios where bidirectional dependencies are essential, as can be shown when comparing the presented model with the LSTM model from the study [26].

On the other hand, the research [18] uses a Variational Mode Decomposition (VMD) - hybrid bidirectional LSTM network. In addition, they took as input variables the transaction volume of the day, the transaction tax, the number of Bitcoins mined in the day, the gold price in dollars, and the Google trends of Bitcoin. Analyzing these factors, the research obtained a percentage error of 2.3%.

The paper [23] also implements an LSTM network for Bitcoin without considering market sentiment analysis. Instead, the authors analyze Bitcoin blockchain factors such as Hash ratio, mining difficulty, mining profit, and the number of Bitcoins sent from one holder to another. With these factors within the neural network, the authors obtain a percentage error of 3.8%. These models open the possibility of implementing other input variables referring to the Cardano blockchain or other indicators of the cryptocurrency market and other markets in our models to make the network more complex and obtain new correlations. This way, we can observe the variables' impact and predict the market's behaviour as best as possible.

6. Conclusions

The present research fulfilled the main objective of predicting the price of the Cardano cryptocurrency from Twitter activity with a Machine Learning model. The obtained error rates show that even the price of Cardano can be predicted within 30 days with 80% accuracy. The results confirm the direct correlation between tweet polarity and cryptocurrency price and denote the influence of market sentiment on the stock market. Additionally, the ANOVA statistical formula results show that the SVM, LSTM and BiLSTM models have the same accuracy when making 1-day, 1-week or 1-month predictions. Still, for 2-week or 3-week predictions, the latter model is more accurate.

Also, a relevant finding of the present research is that Machine Learning models fed only the financial indicators; moving average buy and sell signal; and have a higher percentage error than those that consider the polarity of tweets. The results confirm our hypothesis that market sentiment should be a factor to be considered by investors to obtain better profitability in the volatile cryptocurrency market.

On the other hand, the research has limitations that could be explored in the future. To begin with, the scope of the study only seeks to predict the prices of one cryptocurrency - Cardano. Multiple cryptocurrencies such as Bitcoin, Ethereum, and Dodgecoin, which even have a higher sensitivity to opinions posted on social networks, could be evaluated.

Likewise, the models' parameters could be adjusted, and even other ML models, such as Random Forest and Decision Tree, could be tested to reduce error rates. Finally, it should be noted that cryptocurrencies are gaining more relevance in today's world, so it is important to understand the factors that affect their price and learn how to predict them.

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