

# Using Transformers and Deep Learning with Stance Detection to Forecast Cryptocurrency Price Movement

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**Abstract**—The volatility of cryptocurrencies and exclusivity of crypto communities has made cryptocurrency investment inaccessible for common people. With Machine Learning, harnessing social media trends that affect price in a random field like cryptocurrency will provide everybody the ability to earn money. Although existing research utilizes sentiment analysis to label posts based solely on English, this project will use NLP to perform stance detection with respect to a certain entity to make predictions. The second part of this project will apply this stance detection to real-world prices, using an RNN to turn stance data into price data. The stance detection model, RoBERTa, reached an accuracy of 80%. An independent price prediction model using an RNN achieved a mean absolute error of \$1144, a relatively minimal error considering that the price of crypto reaches \$60000. This endeavor proves the difficulty in proving cryptocurrency prices, but the model's steady improvement indicates that future work on social media trends may be promising after all.

**Index Terms**—Cryptocurrency, Sentiment Analysis, Stance Detection, Neural Networks, Natural Language Processing

## I. INTRODUCTION

With the rise of social media, statements by highly influential individuals and concerted efforts by online groups have affected the cryptocurrency market in unprecedented ways. Elon Musk's Twitter posts regarding Dogecoin, a relatively small cryptocurrency at the time, increased the coin's value by 50% [1], while other celebrities including Floyd Mayweather and Kim Kardashian have been accused of pump-and-dump schemes after supporting currencies that lost 97 percent of their value after initial hype [2]. By researching and developing a machine learning model to perform stance detection towards cryptocurrency on social media platforms such as Twitter, the model will be able to account for this volatility and predict movement to a high degree of accuracy. Through this model, traders and investment bankers could account for this

volatility and potentially increase their profits when trading cryptocurrency.

One branch of machine learning, sentiment analysis, has been increasingly used by market professionals and researchers to predict the price of cryptocurrencies. While the use of sentiment analysis to reflect the general sentiment of social media towards certain currencies has been more effective than former methods, sentiment analysis alone cannot adequately determine the stance of social media statements [3]–[6]. Rather than an overall attitude towards a social media post, stance detection simply finds whether the statement supports a price increase or decrease with respect to a target entity [7].

Finally, this paper aims to use cryptocurrencies, rather than traditional stock assets, to determine social media's influence on performance. While stocks have also been found to be related to social media [8], cryptocurrencies like Bitcoin and Ethereum can be significantly moved by social media and are 15 times more volatile than traditional stocks due to lower market caps and decentralization [9], making them much more accessible to determine trends from minimal social media activity. Unlike stock markets, cryptocurrencies are decentralized which makes them less susceptible to fluctuations due to a governing body.

Previous work has been done regarding general stock prediction and specifically with cryptocurrency. [10] used a Hidden Markov Model (instead of RNN's and Stance Detection) and found that Twitter data was skewed, instead opting for a dataset generated by another social media platform, Reddit. To clarify, a Hidden Markov Model uses observations along with predetermined probabilities of certain events happening in order to generate an overall probability of an event. [11] used Convolutional Neural Networks, Long Short Term Processing (LSTM), and Bidirectional LSTMs through VADER (a tool made for sentiment analysis on social media). It also

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chronologically lagged the data with a 1-day, 3-day, and 7-day lag, and found that the BiLSTM with a 1-day lag was the most effective. BiLSTMs use both forward (social media) and backward (cryptocurrency prices) processes to increase the information available to the system and eventually extract the mediating information (correlation). [12] used various supervised machine learning algorithms such as Linear Regression and Recurrent Neural Networks with Long Short Term Memory cells to predict the price of Bitcoin with a high degree of accuracy.

The approach used in the following paper will aim to increase accuracy using stance detection rather than sentiment analysis and fine-tune a recurrent neural network to a greater degree of accuracy using ensembling.

The remainder of this paper is structured as follows: Section II discusses the pertinent literature for this discussion, Section III discusses the methods of data retrieval in detail, Section IV discusses both the details of the models along with an explanation of their application on the dataset, Section V discuss the results, and Section VI ends with a brief conclusion.

## II. LITERATURE REVIEW

### A. History of Cryptocurrency and Traditional Price Prediction

The formation of Bitcoin in 2008 [13] precipitated a meteoric rise in cryptocurrencies and blockchain technologies. As the nature of cryptocurrencies has changed from proof-of-work to proof-of-stake [14], or focused on climate sustainability, they have had a larger social impact. Even today, price prediction on crypto is based on many basic concepts, including fundamental analysis [15], where investors take into account all traits of the currency and past performance. However, analysts have started using computers to assist in their efforts to make profits.

### B. General Machine Learning Approaches

A multitude of papers have used other forms of machine learning methods (linear regression, decision trees, multi-layer perceptions, and SDAEs) [16]–[19] in order to determine cryptocurrency prices. [20] used both news headlines and cryptocurrency-related tweets as data, and used a different, but also a highly effective method of data labeling. This paper used logistic regression mainly, rather than neural networks. [21] used ARIMA models (combination of linear regression models) to determine the price of cryptocurrencies based solely on Elon Musk’s tweets. However, after extensive testing, RNN-based (recurrent neural network) approaches have appeared to be the most effective, likely because this method is the best at factoring in data over time through the time-series method approach [22].

### C. Reviewing Vanilla RNNs and Other Variants

RNNs have been popular with researchers in the past few years due to their aforementioned ability to fit well to time-series data, since they use past data to make future trend predictions. However, researchers have started innovating on simple RNNs, beginning with the LSTM, or Long Short Term

Memory model. This model is more effective than RNNs in most, if not all cases regarding cryptocurrency [23]–[26]. Finally, on top of LSTMs, some researchers have used GRUs (Gated Recurrent Units), another form of RNN to predict cryptocurrency prices, to earn even greater accuracy [28], [29]. However, while GRUs have been effective, they have some limitations, including an inability to predict prices during periods of volatility, and a reduction in the parameters given to the model. Thus, LSTMs are more optimal for this application. Fig.1 shows the layers within repeating modules of each of the three neural networks [27].

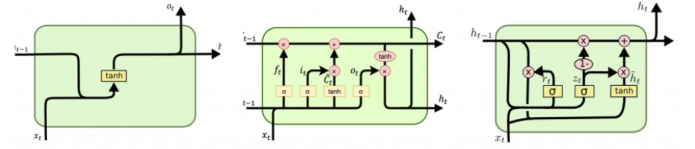


Fig. 1. A vanilla RNN, LSTM, and GRU

### D. Use of Transformers and BERTs

Finally, researchers in the field of Natural Language Processing look to transformers to perform sentiment analysis on pertinent data. A wide variety of transformers, including FinBERT and Seq2Seq have been used for financial sentiment predictions with a high level of accuracy [30]–[32]. [33] combines the transformers with a Convolutional Neural Network, and [34] takes a similar approach to this paper by combining the sentiment analysis of a transformer with the predictive power of an RNN.

## III. METHODOLOGY

### A. Data Retrieval

1) *Bitcoin Tweets*: Tweets about Bitcoin were derived from the Twitter API. To provide a clean data set for the transformer models, researchers hand-labeled 2,500 tweets as either -1 for a negative stance towards Bitcoin, 0 for a neutral stance, and 1 for a positive stance. Each label was then confirmed for accuracy. This data was then converted to a .csv file in order to be parsed, before finally being split up into a train and test set using sklearn’s metrics library. This data had many features, including date, username, followers, hashtags, time, and the text of the tweet; however, these were to be excluded from training due to their lack of relevance to stance.

2) *Yahoo Finance Data*: Using the yfinance python library, historical price data was collected on the cryptocurrency Bitcoin from January 1st, 2018 to January 1st, 2022 to use as a train set, and from January 2nd, 2022 to July 26th, 2022 to use as a validation set. The five features that yfinance provides users are: Open, Low, High, Close, and Adj Close. The data point that was chosen for this project was the close price because it most accurately represented daily market activity.

## B. Transformers

Transformers, simply put, are used to process language using different types of neural network layers. When a tokenized input is given, the transformer first positionally encodes words, by giving them vectors based on their position in the sentence. A multi-head attention layer then creates an attention vector, which finds how relevant a given word is to other words in the sentence. A feed-forward neural network turns these vectors into values to be used by the decoder. The decoder begins by using this output to create decoder attention vectors, after which both the encoder and decoder attention vectors are used to produce a final result. Finally, a linear and softmax layer fit the data and turned it into a probability function.

1) *FinBERT*: Initially, the approach toward finding an effective sentiment analysis tool revolved around finding pre-trained models, one of which was FinBERT. Created in 2019, FinBERT was trained using a large corpus of financial text. Using Huggingface's library of transformers along with the pipeline function, this model was paired with a Finbert Tokenizer to make the data readable to the natural language processor. The model was first tested on the first 1000 values, before being filtered and being retested to evaluate its performance on solely positive and negative values. For clarification, the values inputted into the model were taken from the text of the Twitter data, rather than adding other values like hashtags, dates, or usernames. This made the model much more accurate.

Using FinBERT, the results generated from FinBERT on the train data were then compared with the hand-labeled sentiment that had been completed prior to this test.

2) *RoBERTa*: This research requires stance detection which is essentially one's sentiment towards a particular stock. To maximize the accuracy in identifying one's stance through a Twitter post a widely used model called RoBERTa was used. RoBERTa stands for Robustly Optimized BERT Pre-training approach and is one of the best models used for sentiment analysis. RoBERTa improved upon BERT (Bidirectional Encoder Representations from Transformers) by changing its architecture and training methods to attain better results. A test set was created to use on the model by collecting around 2500 verified tweets regarding Bitcoin. Then, each tweet was manually identified as having a negative, neutral, and positive stance towards Bitcoin, labeled -1, 0, and 1, respectively. Similar to other models, it was found that RoBERTa works poorly when having to identify a neutral stance. Therefore, to improve the results all neutral data was dropped. When RoBERTa was first tested on the test set, the model achieved an accuracy of .5 or 50% which meant that fine-tuning was required. To train and finetune the model, all negative stances were converted to 0 and all positive stances to 1. The data was split into 70% train data and 30% test data to retrain the model once again.

## C. Ensembled Logistic Regression

1) *Refining the Data*: This was an essential prerequisite to ensure that the model predicted the sentiment accurately.

Firstly, the handmade tokenizer converted the tweets to lowercase and removed any special characters in the tweets that may have had the potential to skew the results in the wrong direction. This was done by declaring a list and filtering each tweet using 'if not char.isalnum()'. Next, it replaced said special characters with empty spaces as they were neutral. After that, the tweets were further refined by removing all English stop words from an imported library.

2) *Generating the Model*: In this specific model, a matrix table is created, where each row represents a sentence and each word has a separate column for itself that represents its frequency. All tweets are now available in a tokenized form. Various algorithms like logistic regression, decision tree, and random forest were trained on this dataset.

## D. Recurrent Neural Network (RNN)

Unlike stocks, cryptocurrency prices are backed by little fundamental analysis; they have no underlying assets or revenue streams to back them, so price largely depends on market interest. As a result, technical analysis performed on cryptocurrencies will not need to account for hidden influences that stocks face. To supplement the stance detection approaches outlined above, an alternative methodology was used to analyze financial time series data independent of overall population sentiment. Recurrent neural networks (RNN), a derivative of feed-forward neural networks, are a suitable tool used for time series graph forecasting given their effectiveness in processing sequences of inputs.

After collecting the yfinance data, the data was then scaled in order to increase the accuracy of the model. Dropping all other features besides Close, the data was then normalized using the Min-Max scaler from the "sklearn" library. This scaled values on the following metric:

$$X_{scaled} = X_{std} \cdot (\max - \min) + \min \quad (1)$$

The LSTM (Long Short Term Memory) layer, used in RNNs, took an input of a 3D array with dimensions: the number of samples, timestep, and features. For the training data, the samples were the normalized close price of the current day, the timestep was a nested array of X previous days' close prices (experimented with this value before settling on 15 previous days as the timestep), and the sole feature was the close price, the shape of which was reflected by the LSTM model. The layered architecture that was created included an initial LSTM layer of 50 nodes that took the training array as input, a second LSTM layer of 50 nodes, a Dense layer of 25 nodes, and a final Dense layer that would output a normalized price. the model used the Adam optimizer, and calculated loss using Mean Absolute Error, which punished outliers more than other metrics.

The size of the training set, close prices over a 4 year time period, was important as more historical data gave the model more trends to analyze. The timestep used in the data was large enough such that it wouldn't overfit to the trends of a short period of time and short enough such that it wouldn't underfit.

TABLE I  
FINBERT CONFUSION MATRIX

Positive	Neutral	Negative
21	107	5
4	342	19
15	419	68

TABLE II  
FINBERT CONFUSION MATRIX AFTER CLEANUP

Positive	Neutral	Negative
5	212	15
0	0	0
35	656	77

The timestep settled on 15 previous days, as the model fit most accurately here.

#### IV. RESULTS

##### A. FinBERT

Without any tuning and testing the first 1000 values, FinBERT came back with a confusion matrix that was sub-optimal (see Table I).

Overall, this initial run had an accuracy of 43.1%. However, while 93.6% of the neutral values were identified correctly, these true positives only accounted for 39.4% of the values outputted as neutral. Overall, this model was skewed towards the middle and tended to mark the vast majority of positive and negative values as neutral. Since both the positive and negative columns had middling results, the model was retested but with the neutral values removed. This test only confirmed the suspicions brought up in the last test. Interestingly, while the precision of the negative values was high (83.7%), this was only a result of the low recall (10.0%). The overall accuracy suffered due to the data cleanup.

Since both the positive and negative columns had middling results, the model was retested but with the neutral values removed (see Table II).

This test only confirmed the suspicions brought up in the last test. Interestingly, while the precision of the negative values was high (83.7%), this was only a result of the low recall (10.0%). The overall accuracy suffered due to the data cleanup.

Upon further inspection, the main reason for this disparity between FinBERT’s effectiveness with usual stock market tweets and the dataset used in this paper is the subject matter of this dataset. Cryptocurrency has unique terminology that makes it hard for a regular stock market connoisseur to follow. Thus, a model based on a traditional stock corpus would not pick up crypto slang at all. This problem called for the making of a model from scratch, which was achieved using the RNN later on.

TABLE III  
LOGISTIC REGRESSION CONFUSION MATRIX

Positive	Neutral
52	201
66	853

##### B. Logistic Regression

Initially, the model predicted values at an accuracy of approximately 78% (see Table III). But this was an artificially inflated value as the model had a 95% accuracy in predicting positive values but only 25% for negative ones. This was due to a class imbalance that allowed the model to predict too many positive values in comparison to negative.

##### C. RoBERTa

Before training the model, it achieved an accuracy of 50% meaning that the model was highly inaccurate and unreliable in predicting stance detection. Furthermore, it became clear that the base model needed training and fine-tuning. The tweets were manipulated by dropping irrelevant words and characters to improve accuracy. Furthermore, hyper-parameter tuning was done by changing the training arguments to find the best accuracy. Finally, RoBERTa could predict a tweet’s stance towards Bitcoin with an accuracy of 80%.

	precision	recall	f1-score	support
0	0.85	0.76	0.80	470
1	0.75	0.84	0.79	388
accuracy			0.80	858
macro avg	0.80	0.80	0.80	858
weighted avg	0.80	0.80	0.80	858

Fig. 2. Classification Report of RoBERTa

##### D. RNN

The RNN model trained over 100 epochs and used a batch size of 64 to regulate the amount of data into the LSTM layer at a time. An early stoppage function was used to prevent the model from overfitting, tracking the mean absolute error and stopping the model training if it noticed a downtrend; the patience was set at 20.

This model used yfinance Bitcoin close prices over the time period January 2, 2022 to July 26, 2022 as a validation set. This data was formatted into a three-dimensional array similar to the training dataset with the timestep corresponding to the previous 5 days close price. The validation array yielded dimensions of 191 samples by 5 days timestep by 1 close Price feature. The model predicted close prices over the dates January 16, 2022 to July 26, 2022 with a mean absolute error of \$1144.85. The graph below shows the model’s price prediction, with the y-axis corresponding to Bitcoin price, and the x-axis corresponding to 191 days from January 16, 2022

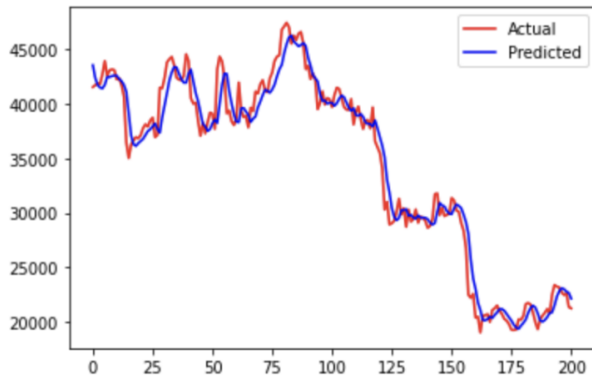


Fig. 3. Graph of RNN Results plotting Bitcoin price (USD) vs Time (days after 1/2/2022)

to July 26, 2022. The blue line corresponds to the prices of the next day that the model predicted, and the red line shows what the actual prices were on each given day.

## V. CONCLUSION

As cryptocurrencies boom in their value and popularity, the common modern investor is left with little tools to determine whether or not their money is well spent. For those with little to no experience or resources, cryptocurrency remains an intimidating and inaccessible field for many. However, as social media becomes increasingly central in the world of crypto, many analysts have been attempting to connect this social media presence to concrete price changes in cryptocurrency. This paper considers Twitter data pulled from the Twitter API over a few months, consisting of tweets regarding cryptocurrency. In order to create and train a functional price-predicting model through an RNN, data from the yfinance library regarding Bitcoin prices was used to tune the recurrent neural network.

The goals heading into the project were to create an accurate stance detection model, which was accomplished through the creation of an 80% accurate RoBERTa model. In addition, the method using Logistic Regression, although somewhat flawed, still achieved 78% accuracy. The second goal was to create an accurate price-prediction model. This goal was not achieved to the highest standard, as the model (Recurrent Neural Network) had a mean absolute error of \$1144 over a 5-day span, a statistic that would be detrimental to investors in the real world. Possible sources of error include an error in the human-labeled stance that eventually threw off the RoBERTa model. In terms of the RNN, a lack of widespread or in-depth data may have contributed to its relative failure. In addition, many confounding factors including acquisitions, celebrity sentiment, and the general volatility of cryptocurrency would have thrown off the RNN numerous times.

In the future, more work should revolve around increasing the accuracy of the models through increased training data and hyperparameter tuning. Some tools that could be used for

optimization include GridSearchCV and Bayesian optimization. Another plausible method includes training a multitude of models and performing ensembling. In addition, another future project would be the creation of a connected stance detection and price prediction model, which was difficult during the creation of this paper due to a lack of access to a wide range of data. Finally, various variables could be changed in order to see the effect of other extenuating factors on the performance or general results of the model. This includes using different social media sites like Reddit or Facebook. Other variables include the types of models used. As indicated previously, models like GRUs (Gated Recurrent Units) are similar to the LSTM model used in this paper and have been found to be more accurate. These numerous changes could revolutionize the results of this paper, and more importantly, progress in the cryptocurrency space. A lack of understanding has plagued cryptocurrency and investment in crypto assets for far too long. A deeper understanding of the relationship between simple, parsable data like social media would allow investors across the world to tap into this vast and growing market.

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