# ON TECHNICAL TRADING AND SOCIAL MEDIA INDICATORS IN CRYPTOCURRENCY PRICE CLASSIFICATION THROUGH DEEP LEARNING

#### A PREPRINT

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February 18, 2021

## **ABSTRACT**

Predicting prices of cryptocurrencies is a notoriously hard task due to the presence of high volatility and new mechanisms characterising the crypto markets. In this work we focus on the two major cryptocurrencies for market capitalization at the time of the study, Ethereum and Bitcoin, for the period 2017-2020. We present a comprehensive analysis of the predictability of price movements comparing four different deep learning algorithms (*Multi Layers Perceptron (MLP)*, *Convolutional Neural Network (CNN)*, *Long Short Term Memory (LSTM)* neural network and Attention Long Short Term Memory (ALSTM)) and using three classes of features. In particular, we consider a combination of technical (e.g. open and close prices), trading (e.g. moving averages) and social (e.g. users' sentiment) indicators used as input to our classification algorithm. We compare a restricted model composed of technical indicators only, and an unrestricted model including technical, trading and social media indicators. The results show that the unrestricted model outperforms the restricted one, i.e. including trading and social media indicators, along with the classic technical variables, leads to a significant improvement in the prediction accuracy consistently across all algorithms.

Keywords: Cryptocurrency, Deep Learning, Social Media Indicators, Trading Indicators, Artificial Neural Networks

# 1 Introduction

During the last decade, the global markets have witnessed the rise and exponential growth of cryptocurrencies traded and exchanged with a daily market capitalization of hundreds of billions of USD Dollars globally (reaching  $\approx 1$  trillion as of January 2021).

Recent surveys<sup>1</sup> report a spike in demand and interest for the new crypto assets from institutional investors, attracted by the novel features and the potential rise in value in the current financial turmoil, despite the risk associated with price volatility and market manipulation.

Boom and bust cycles often induced by network effects and wider market's adoption, make prices hard to predict with high accuracy. There is a large body of literature concerning this issue and proposing a number of quantitative approaches for cryptocurrency prices prediction [13, 15–18]. The rapid fluctuations in volatility, autocorrelations and multi-scaling effects in cryptocurrencies have also been extensively studied [22], also with respect to their effect on Initial Coin Offering (ICO) [10, 11].

<sup>&</sup>lt;sup>1</sup>See Fidelity Report.

An important consideration that has gradually emerged from the literature is the relevance of the "social aspect" of crypto trading. The code underlying blockchain platforms is developed in an open-source fashion on Github, recent additions to the crypto ecosystem are discussed on Reddit or on specialised channels in Telegram, and Twitter offers a platform where often heated debates on the latest developments take place. More precisely, it has been shown that sentiment index can be used to predict bubbles in prices [5] and that the sentiment extracted from topic discussions on Reddit correlates with prices [28].

Open-source development also plays an important role in shaping the success and value of cryptocurrencies [21,25,27]. In particular, a previous work by Bartolucci et al. [2] – which this work is an extension of – showed the existence of a Granger causality between the sentiment and emotions time series extracted from developers' comments on Github and returns of cryptocurrencies. For the two major cryptocurrencies – Bitcoin and Ethereum – it has been also shown how including the developers' emotions time series in prediction algorithms could substantially improve the accuracy.

In this paper, we further extend previous investigations on price predictability using a deep learning approach and focusing on the two major cryptocurrencies by market capitalization, Bitcoin and Ethereum.

We predict price movements by mapping the punctual price forecasting into a classification problem: our target is a binary variable with two unique classes, upward and downward movements, which indicate prices rising or falling. In the following we will compare the performances and outcome of four deep learning algorithms: the Multi-Layer Perceptron (MLP), the Multivariate Attention Long Short Term Memory Fully Convolutional Network (MALSTM-FCN), the Convolutional Neural Network (CNN) and the Long Short Term Memory neural network (LSTM).

We will use as input the following classes of (financial and social) indicators: (i) technical indicators, such as open and close price or volume traded, (ii) trading indicators, such as the momentum and moving averages calculated on the price, (iii) social media indicators, i.e. sentiment and emotions extracted from Github and Reddit comments.

For each deep learning algorithm we consider a *restricted* and *unrestricted* data model at a hourly and daily frequency. The *restricted model* consists of data concerning technical variables for Bitcoin and Ethereum. In the *unrestricted model* we include, instead, the technical variables, trading and social media indicators from Github and Reddit.

Consistently across all four deep learning algorithms, we are able to show that that the unrestricted model outperforms the restricted model. At hourly data frequency, the inclusion of trading and social media indicators alongside the classic technical indicators improves the accuracy on Bitcoin and Ethereum price prediction, increasing from a range of 51-55% for the restricted model to 67-84% for the unrestricted one. For the daily frequency resolution, in the case of Ethereum the most accurate classification is achieved using the restricted model. For Bitcoin, instead, the highest performance is achieved for the unrestricted model including only social media indicators.

In the following sections we will discuss in details the algorithms implemented and the Bootstrap validation technique used to estimate the performance of the models.

The paper is organised as follows. In Section 2 we describe in detail the data and indicators used. In Section 3, we discuss the methodology of the experiments conducted. In Section 4 we present the results and their implications and in Section 5 we discuss the limitations of this study. Finally, in Section 6 we summarise our findings and outline future directions.

## 2 Dataset: Technical and Social Media Indicators

This section discusses the dataset and the three categories of indicators used for the experiments.

## 2.1 Technical Indicators

We conducted our analysis on Bitcoin and Ethereum price time series with an hourly and daily frequency resolution. We considered all the available technical variables, extracted from the  $Crypto\ Data\ Download\$ web services<sup>2</sup>, in particular the data from Bitfinex.com exchange<sup>3</sup> service. We considered the last 4-year period, spanning from 2017/01/01 to 2021/01/01, for a total of 35638 hourly observations.

In our analysis, we separate the technical indicators into two main categories: pure technical and trading indicators. Technical indicators refer to "direct" market data such as opening and closing prices. Trading indicators refer to derived indicators such as the moving averages.

The technical indicators are listed below.

<sup>&</sup>lt;sup>2</sup>https://www.cryptodatadownload.com/data/bitfinex/

<sup>&</sup>lt;sup>3</sup>https://www.bitfinex.com/

- Close: the last price at which the cryptocurrency traded during the trading period.
- Open: the price at which the cryptocurrency first trades upon the opening of a trading period.
- Low: the lowest price at which the cryptocurrency trades over the course of a trading period.
- High: the highest price at which the cryptocurrency traded during the course of the trading period.
- Volume: the number of cryptocurrency trades completed.

Tables 1 and 2 show the summary statistics for the technical indicators. In Figures 1 and 2 we also show the plot of the historical time series for the technical indicators.

	High	Open	Low	Volume	Close
mean	7972.769	7928.018	7879.276	176.319	7928.894
std	5519.337	5471.592	5416.295	306.62	5472.983
min	769.1	760.38	752	0	760.38
25%	4161.6875	4137.995	4113.822	30.592	4138.475
50%	7459.995	7428.09	7390.47	80.699	7428.41
<b>75%</b>	9790.952	9751.84	9701.427	199.322	9752.37
max	41999.99	41526.95	41000.24	8526.751	41526.95

Table 1: Summary statistics for the time series of Bitcoin's technical indicators.

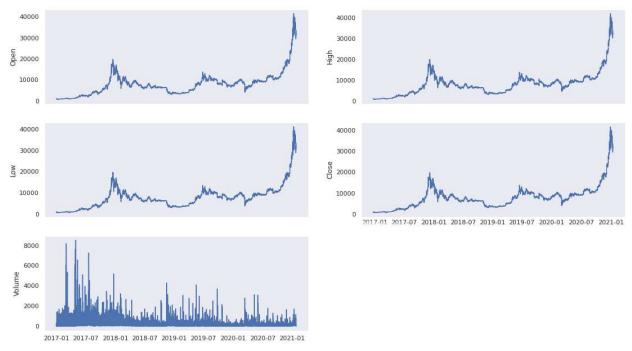


Figure 1: Plot of the time series of Bitcoin's technical indicators.

From the knowledge of these technical indicators it is possible to calculate the trading indicators. More precisely, we used the *StockStats* Python library to generate them.

We used 36 different trading indicators as shown in Table 4. The lag values represent how previous values  $(t-1,\ldots,t-n)$  are used as input. The *window size* indicates the number of previous values used to evaluate the indicator at time t, e.g. to calculate  $ADXR_t$  at time t we use  $ADX_{t-1},\ldots,ADXR_{t-10}$ , ten previous values.

We provide here the definition of the five main trading indicators.

• Simple Moving Average (SMA): calculated as the arithmetic average of the cryptocurrency closing price over some period (known as *timeperiod*).

	High	Open	Low	Volume	Close
mean	313.202	310.856	308.253	1658.835	310.896
std	248.731	246.069	242.971	6903.628	246.135
min	8.17	8.15	8.15	0	8.15
25%	161.182	160.202	159.06	192.327	160.21
50%	232.79	231.34	229.765	569.79	231.365
<b>75%</b>	390.0575	388.0075	385.73	1632.640	388.025
max	1440.54	1430.94	1411	903102.685	1431.4

Table 2: Summary statistics for the time series of Ethereum's technical indicators.

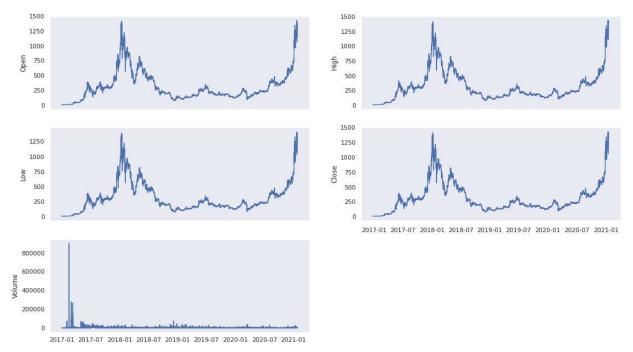


Figure 2: Plot of the time series of Ethereum's technical indicators.

- Weighted Moving Average (WMA): it is a moving average calculation that assigns higher weights to the most recent price data.
- Relative Strength Index (RSI): it is a momentum indicator that measures the magnitude of recent price changes. It is normally used to evaluate whether stocks or other assets are being overbought or oversold.
- Price Rate Of Change (ROC): it measures the percentage change in price between the current price and the price a certain number of periods ago.
- Momentum: it is the rate of acceleration of a security's price, i.e. the speed at which the price is changing. This measure is particularly useful to identify trends.
- On Balance Volume (OBV): it is a technical momentum indicator based on the traded volume of an asset to
  predict changes in stock price.

Tables 3 and 5 show the statistics of the trading indicators for the considered period of analysis. In Figures 3 and 4 we can see the same trading indicators in a historical time series plot. Technical and Trading indicators are used in the next sections to create a model for the prices classification.

#### 2.2 Social Media Indicators

This section describes how the time series of social media indicators are constructed from Ethereum and Bitcoin developers comments on Github and users' comments on Reddit respectively. In particular, for Reddit we considered the four sub-Reddit channels listed in Table 6. The time period considered ranges from January 2017 to January 2021.

	SMA	WMA	RSI	ROCP	MOM	OBV
mean	7924.974	7926.275	51.797	0.0013	8.685	126972.751
std	5465.393	5467.642	14.484	0.027	298.311	33544.231
min	767.801	766.912	2.426	-0.321	-5260.55	18811.069954
25%	4135.225	4134.525	42.374	-0.0083	-53.64	110336.0947
50%	7427.187	7427.521	51.877	0.001	4.97	126464.383
<b>75%</b>	9753.094	9751.604	61.151	0.011	70.732	147814.358
max	40996.6	41106.93	98.641	0.314	4069.26	213166.214

Table 3: Summary statistics for the time series of Bitcoin's trading indicators.

Trading Indicator	Lag	Window size
SMA: Simple Moving Average	-	10
WMA: Weighted Moving Average	-	10
RSI: Relative Strength Index	-	10
ROC: Price Rate Of Change	-	10
Mo: Momentum:	-	10
OBV: On Balance Volume	1	-
permutation (zero based)	1	-
log return	1	-
max in range	1	-
min in range	1	-
middle = (close + high + low) / 3	1	-
compare: le, ge, lt, gt, eq, ne	1	-
count: both backward(c) and forward(fc)	1	-
SMA: simple moving average	-	10
EMA: exponential moving average	-	10
MSTD: moving standard deviation	-	10
MVAR: moving variance	-	10
RSV: raw stochastic value	-	10
RSI: relative strength index	-	10
KDJ: Stochastic oscillator	-	10
Bolling: including upper band and lower band.	1	-
MACD: moving average convergence divergence	-	5
CR: price momentum index	1	-
WR: Williams Overbought/Oversold index	1	-
CCI: Commodity Channel Index	1	-
TR: true range	1	-
ATR: average true range	1	-
line cross check, cross up or cross down.	1	-
DMA: Different of Moving Average (10, 50)	1	-
DMI: Directional Moving Index, including	1	-
DI: Positive Directional Indicator	1	-
ADX: Average Directional Movement Index	-	5
ADXR: Smoothed Moving Average of ADX	-	10
TRIX: Triple Exponential Moving Average	-	10
TEMA: Another Triple Exponential Moving Average	-	10
VR: Volatility Volume Ratio	1	=

Table 4: Trading indicators with associated lags and window size. Lags represent how previous values at  $(t-1,\ldots,t-n)$  are used as input. Window size represents the number of previous values used to compute the indicator at time t, e.g. to calculate  $ADXR_t$  at time t we use  $ADX_{t-1},\ldots,ADXR_{t-10}$ .

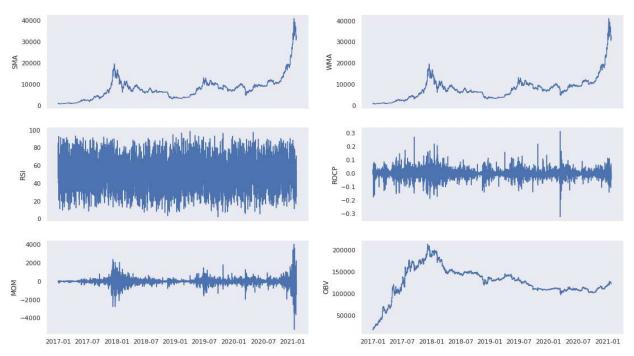


Figure 3: Plot of the time series of Bitcoin trading indicators.

	SMA	WMA	RSI	ROCP	MOM	OBV
mean	310.723	310.78	51.18	0.002	0.378	6.776e+05
std	245.768	245.87	14.246	0.035	16.607	5.739e+05
min	8.147	8.163	3.797	-0.317	-239.48	-4.993e+04
25%	160.202	160.252	42.063	-0.012	-2.8	9.864e + 04
50%	230.916	230.962	51.038	0.000934	0.09	5.185e+05
<b>75%</b>	388.081	388.125	60.338	0.016	3.67	1.246e+06
max	1404.89	1411.776	95.799	0.333	262.36	1.667e+06

Table 5: Summary statistics for the time series of Ethereum's trading indicators.

Cryptocurrency	Technical Discussions	Trading Discussions
	r/Bitcoin r/Ethereum	r/BitcoinMarkets r/EthTrader

Table 6: List of sub-Reddit channels considered in the analysis.

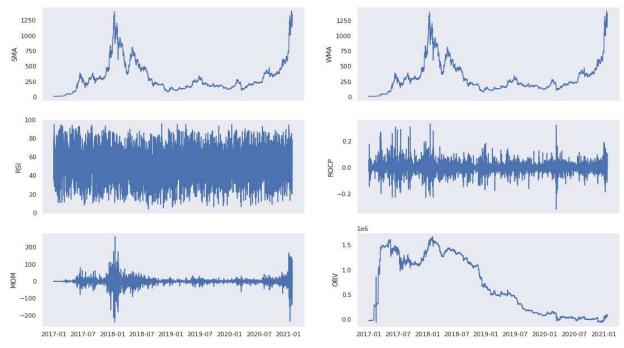


Figure 4: Plot of the time Series of Ethereum trading indicators.

Examples of a developer's comment extracted from Github for Ethereum and user's comment extracted from Reddit r/Ethereum can be seen in Tables 7, 8. Quantitative measures of sentiment and emotions associated with the comments, as reported in this example, are computed using state-of-the-art textual analysis tools (further detailed below). These social media indicators computed for each comment are emotions as love (L), joy (J), anger (A), sadness (S), VAD (valence (Val), dominance (Dom), arousal (Ar)) and sentiment (Sent).

Comment	L	J	A	S	Val	Dom	Ar	Sent
Perhaps there's simply nothing new to translate? The reason I updated Transifex in the first place was to be sure the strings with subtle English changes (that don't change the meaning) didn't reset the translation - so those were imported from the old translations. Though I seem to recall at least one truly new string - Transaction or such.	0	0	0	1	1.93	1.88	1.26	0

Table 7: Example of a Github comment and corresponding emotions (love (L), joy (J), anger (A), sadness (S)), VAD (valence (Val), dominance (Dom), arousal (Ar)), politeness and sentiment (Pol and Sent respectively).

## 2.3 Social Media Indicators Evaluation Through Deep Learning

We extracted the social media indicators using deep, pre-trained, neural networks called Bidirectional Encoder Representations from Transformers (BERT) [8]. BERT and other Transformer encoder architectures have been successful in performing various tasks in natural language processing (NLP) and represent the evolution of Recurrent Neural Network (RNN) typically used in NLP. They compute vector-space representations of natural language that are suitable for use in deep learning models. The BERT family of models uses the Transformer encoder architecture to process each token of input text in the full context of all tokens before and after, hence the name: Bidirectional Encoder Representations from Transformers. BERT models are usually pre-trained on a large corpus of text, then fine-tuned for

Comment	L	J	A	S	Val	Dom	Ar	Sent
All the tosspots focusing on Vitaliks wealth completely miss the point. If the crypto you are supporting has a purpose it will garner interest in the real world therefore the capital will flow to it. All is measured on the merit and proper fundamentals and not twitterbot pump and dumps	0	0	0	0	2.13	1.98	2.26	-1

Table 8: Example of Reddit comment and correspondent emotions (love (L), joy (J), anger (A), sadness (S)), VAD (valence (Val), dominance (Dom), arousal (Ar)), politeness and sentiment (Pol and Sent respectively).

specific tasks. These models provide dense vector representations for natural language by using a deep, pre-trained neural network with the Transformer architecture represented in Figure 5.

Transformers are based on the Attention Mechanism where RNN units would encode the input up until timestamp t into one hidden vector  $h_t$ . The latter would then be passed to the next timestamp (or to the decoder in the case of a sequence-to-sequence model). By using the attention mechanism, one no longer tries to encode the full source sentence into a fixed-length vector. Instead, one allows the decoder to attend to different parts of the source sentence at each step of the output generation. Importantly, we let the model learn what to attend to based on the input sentence and what it has produced so far.

The Transformer architecture allows for the creation of NLP models trained on very large datasets as we have done in this work. It is feasible to train such models on large datasets thanks to pre-trained language models, which can be fine-tuned on the particular dataset without the effort of re-training the whole network.

The weights learnt by the extensively pre-trained models can be later reused for specific tasks by simply tailoring the weights to the specific dataset. This would allow us to exploit what the pre-trained language model has learnt with a finer weight tuning by capturing the lower-level intricacies of the specific dataset.

We used Tensorflow and Keras Python libraries with the Transformer package to leverage the power of these pre-trained neural networks. In particular, we used the *BERT-base-case* pre-trained model. Figure 6 shows the architectural design used to train the three NN classifiers used to extract the social media indicators. This figure shows the three gold datasets used to train our final models, namely Github, Stack Overflow and Reddit.

In particular, we used a sentiment-labelled dataset consisting of 4423 posts mined from Stackoverflow user's comments to train the sentiment model for Github: comments on both platforms are written using the technical jargon language of software developers and engineers. We also used an emotion-labelled dataset of 4200 sentences from Github [23]. Finally, we used a sentiment-labelled dataset containing more than 33K labelled Reddit users's comments<sup>4</sup>.

Tables 9, 10 and 11 show the performance of sentiment and emotion classification on the two different dataset: Github and Reddit.

	precision	recall	f1-score
negative	0.92	0.89	0.90
neutral	0.97	0.98	0.98
positive	0.95	0.95	0.95
accuracy			0.95
macro avg	0.95	0.94	0.94
weighted avg	0.95	0.95	0.95

Table 9: Sentiment Classifier Evaluation For Reddit.

<sup>&</sup>lt;sup>4</sup>https://www.kaggle.com/cosmos98/twitter-and-reddit-sentimental-analysis-dataset

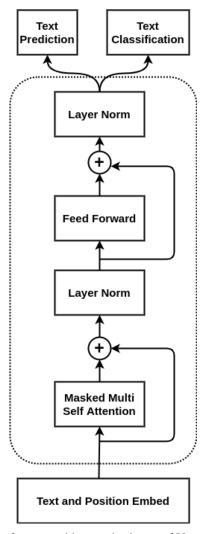


Figure 5: Transformer architectural scheme of Vaswani et al. [29].

	precision	recall	f1-score
negative	0.98	0.85	0.91
neutral	0.84	0.94	0.89
positive	0.96	0.97	0.96
accuracy			0.92
macro avg	0.93	0.92	0.92
weighted avg	0.93	0.92	0.92

Table 10: Sentiment Classifier Evaluation For Github.

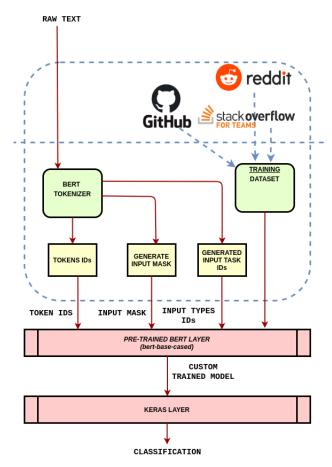


Figure 6: Scheme of the general bidirectional encoder representation from Transformer.

	precision	recall	f1-score
anger	0.83	0.77	0.80
sadness	0.89	0.89	0.89
joy	0.86	1.00	0.92
love	1.00	1.00	1.00
accuracy			0.89
macro avg	0.89	0.91	0.90
weighted avg	0.89	0.89	0.89

Table 11: Emotion Classifier Evaluation For Github.

### 2.3.1 Social Media Indicators on Github

Both the Bitcoin and Ethereum projects are open-source, hence the code and all the interactions among contributors are publicly available on GitHub [26]. Active contributors are continuously opening, commenting, and closing the so-called "issues". An issue is an element of the development process, which carries information about discovered bugs, suggestions on new functionalities to be implemented in the code, new features, or new functionalities being developed. It constitutes an elegant and efficient way of tracking all the development process phases, even in complicated and large-scale projects with a large number of remote developers involved. An issue can be "commented", meaning that developers can start sub-discussions around it. They usually add comments to a given issue to highlight the actions being undertaken or provide suggestions on the possible resolution. Each comment posted on GitHub is timestamped; therefore it is possible to obtain the exact time and date and generate a time series for each affect metric considered in this study.

For emotion detection we use the BERT classifier explained in 2.3 trained with the public Github's emotion dataset developed by Ortu et al. [24] and extended by Murgia et al. [23]. This dataset is particularly suited for our analysis as the algorithm for emotion detection has been trained on developers' comments extracted from the Jira Issue Tracking System<sup>5</sup> of the Apache Software Foundation, hence within the Software Engineering domain and context of Github and Reddit (considering the selected subreddits). The classifier can detect love, anger, joy and sadness with an  $F_1$  score<sup>6</sup> close to 0.89 for all of them.

Valence, Arousal and Dominance (VAD) represent conceptualised affective dimensions that respectively describe the interest, alertness and control a subject feels in response to a particular stimulus. In the context of software development, VAD measures may indicate the involvement of a developer in a project as well as their confidence and responsiveness in completing tasks. Warriner et al.'s [30] has created a reference lexicon containing 14,000 English words with VAD scores for Valence, Arousal, and Dominance, that can be used to train the classifier, similarly to the approach by Mantyla et al. [20]. In [20] they extracted the valence-arousal-dominance (VAD) metrics from 700,000 Jira issue reports containing over 2,000,000 comments and showed that issue reports of different type (e.g., feature request vs bug) had a fair variation of valence. In contrast, an increase in issue priority typically increased arousal.

Finally, sentiment is measured using the BERT classifier explained in 2.3 trained with the public dataset used in similar studies [3,4]. The algorithm extracts the sentiment polarity expressed in short texts in three levels: positive (1), neutral (0) and negative (-1) sentiment.

Our analysis focuses on three main classes of affect metrics: emotions (love, joy, anger, sadness), VAD (valence, arousal, dominance) and Sentiment. As we specify in Section 2.3, we use a tailor-made tool to extract it from the text of the comments for each affect metric class.

Once numerical values of the affect metrics are computed for all comments (as shown in the example in Tables 7 and 8), we consider the comments timestamps (i.e. dates when the comments was posted) to build the corresponding social media time series. The affect time series are constructed aggregating sentiment and emotions of multiple comments on each hour and day depending on the time resolution considered (hourly and daily).

For a given social media indicator, e.g. *anger*, and for a specific time resolution, we construct the time series by averaging the values of the affect metric over all comments posted on the same day.

In Table 12 and 13 we report in more details the summary statistics of the social indicators' time series for both cryptocurrencies respectively. We also report in Figure 7 and 8 the time series for all social media indicators for Bitcoin and Ethereum, respectively

## 2.3.2 Measuring Affects Metrics on Reddit

The social media platform *Reddit* is an American social news aggregation, web content rating, and discussion website that reaches about 8 billion page views per month. It is a top-rated social network in English-speaking countries, especially Canada and the United States. Almost all the messages present are written in English, while the minority, are in Spanish, Italian, French and German.

Reddit is built over multiple subreddits, where each subreddit is dedicated to discussing a particular subject. Therefore, there are specific subreddits related to major cryptocurrency projects. For each cryptocurrency in this work, two subreddits are analysed, one technical and one trading related. In Tab. 6 the considered subreddits. are shown. For each subreddit, we fetched all comments from January 2017 to January 2021.

<sup>&</sup>lt;sup>5</sup>ITS are software platform used by open source communities and private software companies to manage the development process.

<sup>&</sup>lt;sup>6</sup>The  $F_1$  score tests the accuracy of a classifier. It is calculated as the harmonic mean of precision and recall.

	sentiment	arousal	valence	dominance	joy	love	sadness	anger
mean	0.141	2.273	3.321	3.365	0.0729	0.056	0.227	0.109
std	0.774429	2.953897	4.324653	4.376877	0.293435	0.248373	0.566562	0.393479
min	-11	0	0	0	0	0	0	0
25%	0	0	0	0	0	0	0	0
50%	0	1.27	1.85	1.87	0	0	0	0
<b>75%</b>	0	3.29	4.8	4.87	0	0	0	0
max	15	38.88	60.78	62.28	6	4	11	17

Table 12: Summary statistics of Github affect metrics for Bitcoin.

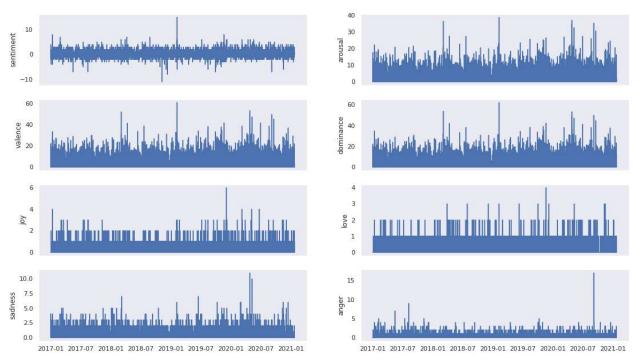


Figure 7: Social Media Indicators time series extracted from Github Bitcoin developers comments.

	sentiment	arousal	valence	dominance	joy	love	sadness	anger
mean	0.0842	0.7934	1.1405	1.147	0.0182	0.0761	0.0961	0.0356
std	0.6754	1.7082	2.4653	2.477	0.1407	0.5284	0.3570	0.2052
min	-4	0	0	0	0	0	0	0
25%	0	0	0	0	0	0	0	0
50%	0	0	0	0	0	0	0	0
<b>75%</b>	0	1.08	1.54	1.62	0	0	0	0
max	31	35.19	52.5	54.35	3	31	6	4

Table 13: Summary Statistics of Github Social Media Indicators for Ethereum.

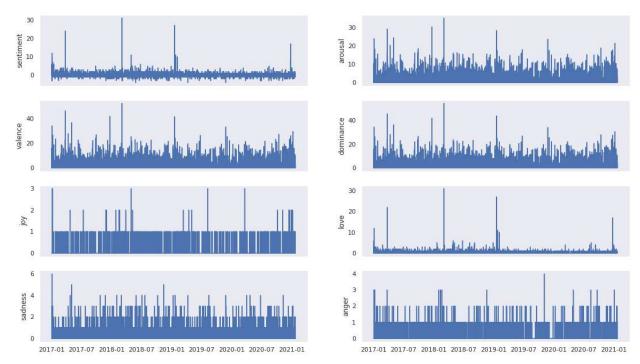


Figure 8: Social Media Indicators time series extracted for Github Ethereum developers comments.

For emotion detection we use the BERT classifier explained in 2.3 trained with the public Github's emotion dataset developed by Ortu et al. [24] and extended by Murgia et al. [23]. This dataset is particularly suited for our analysis, as already explained in the previous section.

	sentiment	arousal	valence	dominance	joy	love	sadness	anger
mean	1.8582	8.6046	12.0466	11.7412	0.6492	0.2509	0.5579	2.2197
std	4.3498	17.3895	24.4038	23.7624	1.7040	0.8278	1.4223	4.7780
min	-9	0	0	0	0	0	0	0
25%	0	0	0	0	0	0	0	0
50%	0	1.09	1.54	1.51	0	0	0	0
<b>75%</b>	2	10.25	14.22	13.88	1	0	0	2
max	101	492.99	680.41	662.39	42	27	34	133

Table 14: Summary Statistics of Reddit Social Media Indicators for subreddit r/Bitcoin.

	sentiment	arousal	valence	dominance	joy	love	sadness	anger
mean	0.0842	0.7934	1.1405	1.147	0.0182	0.0761	0.0961	0.0356
std	0.6754	1.7082	2.4653	2.477	0.1407	0.5284	0.3570	0.2052
min	-4	0	0	0	0	0	0	0
25%	0	0	0	0	0	0	0	0
50%	0	0	0	0	0	0	0	0
<b>75%</b>	0	1.08	1.54	1.62	0	0	0	0
max	31	35.19	52.5	54.35	3	31	6	4

Table 15: Summary Statistics of Reddit Social Media Indicators for subreddit r/Ethereum.

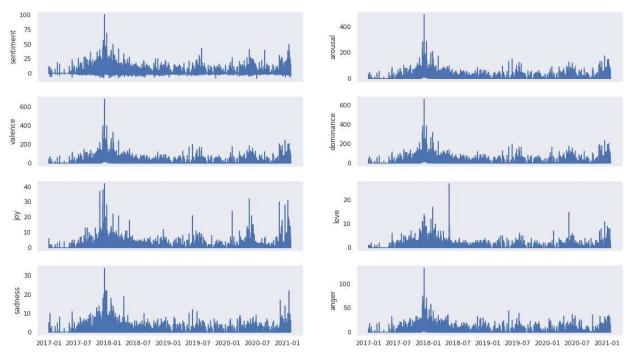


Figure 9: Social Media Indicators time series extracted for Reddit for subreddit r/Bitcoin.

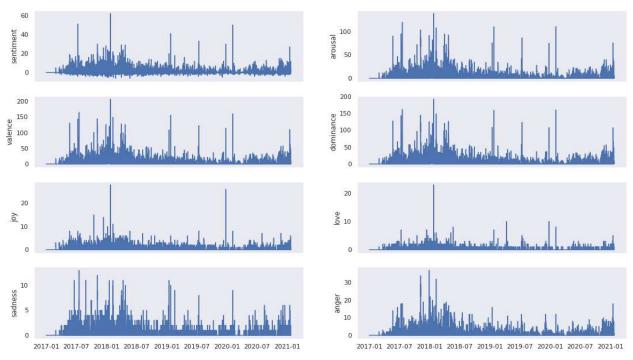


Figure 10: Social Media Indicators time series extracted for Reddit for subreddit r/Ethereum.

	sentiment	arousal	valence	dominance	joy	love	sadness	anger
mean	0.9264	4.0327	5.6617	5.5688	0.2419	0.1059	0.3383	1.0095
std	2.7650	10.7106	14.9023	14.6243	0.8616	0.4553	1.0275	2.8993
min	-9	0	0	0	0	0	0	0
25%	0	0	0	0	0	0	0	0
50%	0	0	0	0	0	0	0	0
<b>75%</b>	0	2.32	3.2925	3.26	0	0	0	0
max	52	245.32	332.84	329.4	34	15	22	88

Table 16: Summary Statistics of Reddit Social Media Indicators for subreddit r/Bitcoinmakets.

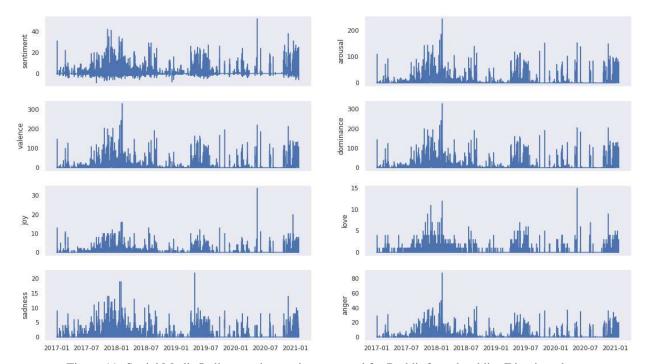


Figure 11: Social Media Indicators time series extracted for Reddit for subreddit r/Bitcoinmakets.

	sentiment	arousal	valence	dominance	joy	love	sadness	anger
mean	0.8150	2.8479	4.0716	4.0046	0.2123	0.0855	0.2072	0.5983
std	2.1528	6.1395	8.7652	8.6220	0.6807	0.3959	0.6641	1.577632
min	-6	0	0	0	0	0	0	0
25%	0	0	0	0	0	0	0	0
50%	0	0	0	0	0	0	0	0
<b>75%</b>	1	3.25	4.65	4.6	0	0	0	1
max	62	138.39	207.38	191.95	28	23	13	37

Table 17: Summary Statistics of Reddit Social Media Indicators for subreddit r/Ethtraders.

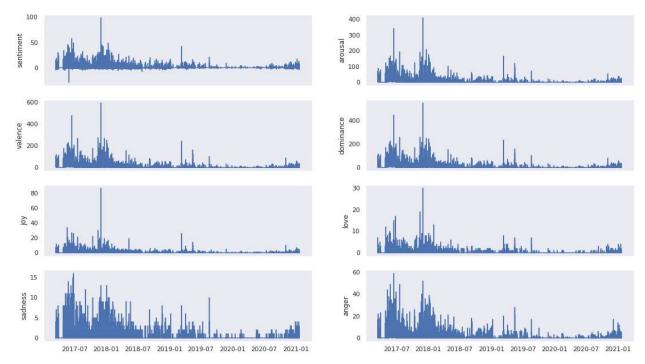


Figure 12: Social Media Indicators time series extracted for Reddit for subreddit r/Ethtraders.

The classifier can detect love, anger, joy and sadness with an  $F_1$  score<sup>7</sup> close to 0.89 for all of them. For VAD metrics we used the same approach in 2.3.1 while for sentiment we used previous approach with BERT deep learning algorithm trained with a public golden dataset for Reddit comments available in the biggest and well known web platform for sharing datasets Kaggle.com<sup>8</sup>.

Tables 14 and 16 and Figures 9 and 11 show statistics and time series for the two Bitcoin's subreddits while Tables 17 and 15 and Figures 10 and 12 show statistics and time series for the two Ethereum's subreddits.

## 2.4 Price Movement Classification

The target variable is a binary variable with two unique classes listed below.

- **Upward movements**: This class, labeled with *up* and encoded with 1, represents the condition of increasing prices.
- **Downward movements**: This class, labeled *down* and encoded with 0, represents the condition of falling prices.

Figure 13 shows the class distribution and the dataset for hourly and daily frequency, highlighting that we are dealing with fairly balanced classification problems in the case of hourly frequency and slightly unbalanced in the daily frequency case.

Table 18 shows the details about the instances of classes down and up, with 48,5% and 51.5% respectively for Bitcoin and 49,8% and 50,2% for Ethereum with and hourly frequency. For daily frequency we have 44,8% and 55.2% for Bitcoin and 48,5% and 51,5% for Ethereum of down and up class instances. For Bitcoin daily frequency we have a slightly unbalanced distribution toward up classes, in this case we will consider fl-score along with accuracy to asses the model performance.

## 2.5 Time Series Processing

Since we are using a supervised learning problem, we prepare our data to have a vector of x inputs and an y output with temporal dependence. In this case, the input vector x is called *regressor*. The x inputs include the model's

<sup>&</sup>lt;sup>7</sup>The  $F_1$  score tests the accuracy of a classifier and it is calculated as the harmonic mean of precision and recall.

<sup>&</sup>lt;sup>8</sup>https://www.kaggle.com/cosmos98/twitter-and-reddit-sentimental-analysis-dataset

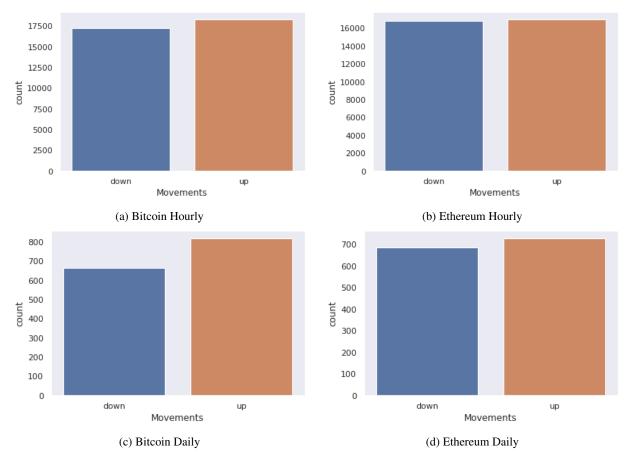


Figure 13: Hourly (13a,13b) and Daily (13c,13d) Price Movement Classes Distribution.

Frequency	Cryptocurrency	Class	Counts	Percentage
	Bitcoin	up	17246	48,5%
Hourly	Dittoili	down	18271	51,5%
Hourry	Ethereum	up	16844	49,8%
	Linereum	down	16956	50,2%
	Bitcoin	up	665	44,8%
Daily	Dittoili	down	817	55,8%
Daily	Ethereum	up	684	48,5%
	Einereum	down	727	51,5%

Table 18: Class instances counts and percentages for Bitcoin and Ethereum at an hourly or daily frequency.

predictors, i.e. one or several values from the past, the so-called lagged values. Inputs correspond to the values of the selected features discussed in the previous sections. The target variable y is a binary variable, which can be either 0 or 1. The 0 (down) instance represents downward price movements. A 0 instance at time t is obtained when the difference between the  $close\ price$  at time t and the  $open\ price$  at time t+1 is less than or equal to 0. The 1 (up) instance represents upward price movements, i.e. a rising price condition. A 1 instance is obtained when the difference between the  $close\ price$  at time t and the  $open\ price$  at next time step t+1 is greater than 0. We considered two time series models:

- *Restricted*: the input vector x consists of only technical indicators (open, close, high, low, volume).
- *Unrestricted*: the input vector x consists of technical, trading and social indicators.

For both the *restricted* and *unrestricted* model we used 1 lagged value for each indicator. The purpose of this distinction is to ascertain and quantify whether the addition of trading and social indicators to the *regressor* vector leads to an effective improvement in the Bitcoin and Ethereum price changes classification.

# 3 Methodology

This section describes the deep learning algorithms considered in our analysis, followed by a discussion on the fine tuning of the hyper-parameters.

### 3.1 Multilayer Perceptron

A multilayer perceptron (MLP) is a class of feed-forward artificial neural networks (ANNs), characterised by multiple layers of perceptrons and a typical activation function.

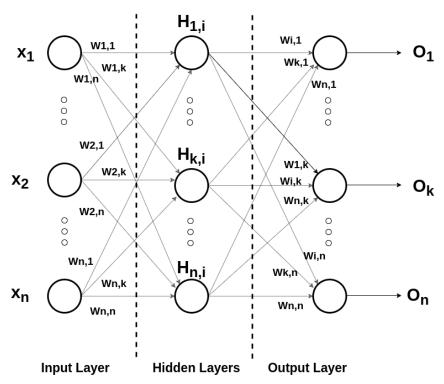


Figure 14: Scheme of the Multilayer Perceptron architecture.

The most common activation function are:

$$y(v_i) = \tanh(v_i) \text{ and } y(v_i) = (1 + e^{-v_i})^{-1},$$
 (1)

where  $v_i$  is the weighted vector of inputs.

When composed of a single hidden layer as in Figure 14, MLPs are called "vanilla" neural networks (in jargon and for practical use). In general, MLPs refer to neural network architectures with two or more hidden layers.

A MLP comprises three main node categories: input layer nodes, hidden layer nodes and output layer nodes. All nodes of the neural network are perceptrons that use a nonlinear activation function, except for the input nodes. MLP differs from a linear perceptron because of its multiple layers and nonlinear activation functions.

In general, MLP Neural networks are resilient to noise and can also support learning and inference when values are missing. Neural networks do not make strong assumptions about the mapping function and readily learn both linear and nonlinear relationships. An arbitrary number of input features can be specified, providing direct support for multidimensional forecasting. An arbitrary number of output values can be specified, providing direct support for multi-step and even multivariate forecasting. For these reasons, MLP neural networks may be particularly useful for time series forecasting.

In recent developments of deep learning techniques, the rectifier linear unit (ReLU), a piecewise linear function, is frequently used to overcome numerical problems associated with sigmoid functions. Examples of ReLU are the hyperbolic tangent varing between -1 and 1, or the logistic function between 0 and 1. The output of the i-th node (neuron) here is  $y_i$ , and the weighted sum of the input connections is  $v_i$ .

By including the rectifier and softmax functions, alternative activation functions have been developed. Radial basis functions include more advanced activation functions (used in radial basis networks, another class of supervised neural network models).

Since MLPs are fully connected architectures, each node in one layer connects with a specific weight  $w_{i,j}$  to every node in the following layer. The neural network is trained using a supervised method called back-propagation and an optimiser method (the Stochastic Gradient Descent is the first and widely used method). After data is processed, learning occurs in the perceptron by adjusting the connection weights, depending on the amount of error in the output relative to the expected result. Back-propagation in the perceptron is a generalisation of the least mean squares (LMS) algorithm.

When the  $n_{th}$  training sample is presented to the input layer, the amount of error in the output node j is  $e_j(n) = d_j(n) - y_j(n)$ , where d is the predicted value and y is the actual value that the perceptron should generate. The back-propagation method then adjusts the node weights to minimise the entire output error provided by Eq. (2):

$$\epsilon(n) = \frac{1}{2} \sum_{j} e_j^2(n) . \tag{2}$$

The adjustment of each node's weight is further computed using the gradient descent in Eq. (3), where  $y_i$  is the output of the previous neuron and  $\eta$  is the learning rate:

$$\Delta w_{j,i}(n) = -\eta \frac{\partial \epsilon(n)}{\partial v_j(n)} y_i(n) . \tag{3}$$

The parameter  $\eta$  is commonly set as a trade-off between the weights' convergence to a response and the oscillations around the response.

The induced local field  $v_i$  varies and one can compute its derivative:

$$-\frac{\partial \epsilon(n)}{\partial v_j(n)} = e_j(n)\phi'(v_j(n)) -\frac{\partial \epsilon(n)}{\partial v_j(n)} = \phi'(v_j(n))\sum_k -\frac{\partial \epsilon(n)}{\partial v_k(n)}w_{k,j}(n) ,$$
(4)

where  $\phi'$  is the derivative of the activation function described above, which itself does not vary. The analysis is more difficult when modifying the weights of a hidden node, but it can be shown that the relevant quantity is the one showed in Eq. (4). This algorithm represents a back-propagation of the activation function as Eq. (4) depends on the adjustment of the weights of the  $k_{th}$  layer, which represent the output layer and this adjustment in turn changes depending on the derivative of the activation functions of the hidden layer weights.

### 3.2 Long Short Term Memory

Long Short-Term Memory networks are a specialised version of Recurrent Neural Network (RNN) able to capture long-term dependencies in a sequence of data. RNNs are a type of artificial neural networks with a particular topology specialised in the identification of patterns in different types of data sequences: natural language, DNA sequences, handwriting, word sequences, or numerical time series data streams from sensors and financial markets [12] for example. Classical recurrent neural networks have a significant disadvantage related to their inability to address long

sequences and capture long-term dependencies. RNNs could instead be used only for short sequences with short-term memory dependencies. LSTM were introduced to address the long-term memory problem and are derived directly from RNN to capture long-term dependencies. An LSTM neural network is organised in units called cells, performing transformations of the input sequence transformation by applying a series operations. An internal state variable is retained by an LSTM cell when forwarded from one cell to the next and is updated by the so-called Operation Gates (forget gate, input gate, output gate) as shown in Figure 16. All three gates have different and independent weights and biases, so the network can learn how much of the previous output and current input to maintain and how much of the internal state to pass to the output. Such gates control how much of the internal state is transmitted to the output and operate similarly to other gates. An LSTM cell unit consists of:

- 1. A cell state: this state brings information along the entire sequence and represents the memory of the network.
- 2. A *forget gate*: it filters the relevant information to be kept from previous time steps.
- 3. An *input gate*: it decides what information is relevant to be added add from the current time step.
- 4. An *output gate*: it controls the amount of output at the current time step.

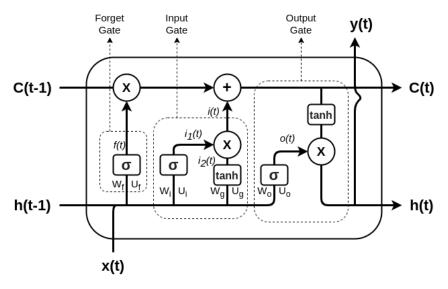


Figure 15: LSTM Cell Gate.

The first step is the forget gate. This gate takes as input past or lagged values and decides how much of the past information should be forgotten and how much should be saved. The input from the previous hidden state and the current input are transferred through the sigmoid function to the output gate. An output is close to 0 when that piece of information can be forgotten, while it is close to 1 when that piece of information is to be saved, as follows:

$$f(t) = \sigma(x(t) * U_f + h(t+1) * W_f)$$
 (5)

The matrices  $W_f$  and  $U_f$  contain, respectively, the weights of the input and recurrent connections. The subscript f can be either indicate the forget gate.  $x_t$  represents the input vector to the LSTM and  $h_{t+1}$  the hidden state vector or output vector of the LSTM unit.

The second gate is the input gate. At this stage the cell state is updated. The previous hidden state and the current input are initially presented as inputs to a sigmoid activation function (the closer the value is to 1, the more relevant the input is). To boost the network-tuning, it also passes the hidden state and current input to the  $\tanh$  function to compress values between -1 and 1. Then the output of the  $\tanh$  and of the sigmoid are multiplied element by element (in the formula below the symbol \* indicates the multiplication element by element of two matrices). The sigmoid output, in Equation 6 determines the information that is important to keep from the  $\tanh$  output:

$$i_1(t) = \sigma(x(t) * U_i + h(t+1) * W_i) , i_2(t) = \tanh(x(t) * U_g + h(t+1) * W_g) , i(t) = i_1(t) * i_2(t) .$$
 (6)

The cell state can be determined after the input gate activation. Next, the cell state of the previous time step is multiplied element-by-element by the forget gate output. This leads to dismissing values when multiplied by values close to 0 in the cell state. The input gate output is added element-wise to the cell state. The new cell state in Equation 7 is the output:

$$C(t) = \sigma(f(t) * C(t-1) + i_t). \tag{7}$$

The final gate is the output gate, which specifies the next hidden state's value, which includes a certain amount of previous input information. Here the current input and the previous hidden state are summed up and forwarded to the sigmoid function. The new cell state is then transferred to the tanh function. At the end, the tanh output with the sigmoid output is multiplied to determine which information the hidden state can carry. The output is a hidden new state. The new cell state and the new hidden state are then shifted to the next stage by Equations 8:

$$o(t) = \sigma(x(t) * U_o + h(t-1) * W_o),$$
  

$$h(t) = \tanh(C_t) * o(t).$$
(8)

To conduct this analysis, we used the Keras framework [7] for deep learning. Our model consists of one stacked LSTM layer and a densely connected output layer with one neuron.

#### 3.3 Attention Mechanism Neural Network

The Attention Function is one of the key aspects of Deep Learning algorithms, an extension of the Encoder-Decoder Paradigm, developed to improve the output on long input sequences. Figure 16 shows the key idea behind the AMNN, which is to allow the decoder, during decoding, to access encoder information selectively. This is achieved by creating a new context vector for each decoder step, computing it according to the previous hidden state as well as all encoder's hidden states, assigning them trainable weights. In this way, the Attention Technique gives the input series a different priority and pays more attention to the most important inputs.

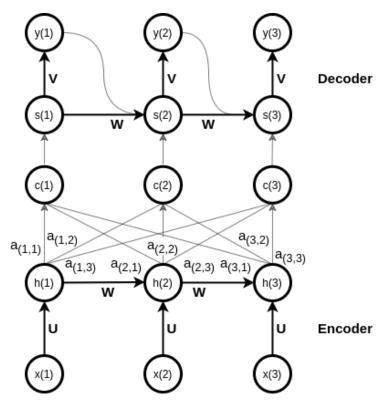


Figure 16: Attention Mechanism Neural Network.

The encoder operation is very similar to the Encoder-Decoder hybrid operation itself. The representation of each input sequence is determined at each time step, as a function of the previous time step's hidden state and the current input.

The final hidden state includes all encoded information from the previous hidden representations and the previous inputs.

The key distinction between the Attention mechanism and the Encoder-Decoder model is that with each decoder step t, a new background vector c(t) is computed. We proceed as follows to measure the context vector c(t) for time step t. First of all, the so-called alignment scores e(j,t) are calculated with the weighted sum in Eq. (9) for each combination of the time step j of the encoder and time step t of the decoder:

$$e(i,t) = V_a * \tanh(U_a * s(t-1) + W_a * h(i)).$$
(9)

 $W_a$ ,  $U_a$  and  $V_a$  are learning weights in this formula, which are referred to as *attention weights*. The  $W_a$  weights are linked to the encoder's hidden states, the  $U_a$  weights are linked to the decoder's hidden states, and the  $V_a$  weights determine the function that computes the alignment score. The scores e(j,t) are normalized at each time step t using the softmax function over the time stages of the encoder j, obtaining the attention weights  $\alpha(j,t)$  as follows:

$$\alpha(j,t) = \frac{\exp(e(j,t))}{\sum_{j=1}^{M} \exp(e(j,t))}.$$
(10)

The *importance* of the input at time j is represented by the attention weight  $\alpha(j,t)$  for decoding the output of time t. The context vector c(t) is estimated according to the attention weights as the weighted sum of all hidden values of the encoder as follows:

$$c(j,t) = \sum_{j=1}^{M} \alpha(j,t)h(j).$$

$$(11)$$

According to this method, the so-called attention function is triggered by the contextual data vector, weighting more the most important inputs.

The contextual vector c(t) is now forwarded to the decoder to calculate the probability distribution for the next possible output. This decoding operation refers to all the time steps present in the input. The current hidden state s(t) is then calculated according to the recurring unit function, taking as input the contextual vector c(t), the hidden state s(t-1) and the output  $\hat{y}(t-1)$  according to the equation:

$$s(j,t) = f(s(t-1), \hat{y}(t-1), c(t)). \tag{12}$$

Using this function, the model can identify the relationship between the different parts of the input sequence and the corresponding parts of the output sequence. The softmax function is used to calculate the output of the decoder in the weighted hidden state at each time t:

$$\hat{y}(t) = softmax(V_s(t)). \tag{13}$$

Concerning the LSTM, the Attention mechanism provides better results with long input sequences, due to the attention weights.

In this study, we specifically use a Multivariate Attention LSTM with Fully Convolutional Network (MALSTM-FCN) proposed by Fazle et al. [14, 15]. Figure 17 shows the architecture for the MALSTM-FCN including the number of neurons per layer. The input sequence goes in parallel to a fully convolutional layers and Attention LSTM layers, and is concatenated and passed to the output layer via a softmax activation function for binary classification. The fully convolutional block contains three temporal convolutional blocks of 128, 256 and 256 neurons respectively, used as feature extractors. Each convolutional layer is succeeded by batch normalisation, before the concatenation. The dimension shuffle transposes the temporal dimension of the input data, so that the LSTM is given the global temporal information of each variable at once. As a result, the dimension shuffle operation reduces the computation time of training and inference without losing accuracy for time series classification problems [15].

#### 3.4 Convolutional Neural Network

A Convolutional Neural Network (*CNN*) is a specific class of neural networks most commonly used for deep learning applications concerning image processing, image classification, natural language processing and financial time series analysis [6].

The most critical part of the CNN architecture is the *convolutional* layer. This layer performs a mathematical operation called *convolution*. In this context, a convolution is a linear operation that involves a multiplication between a matrix

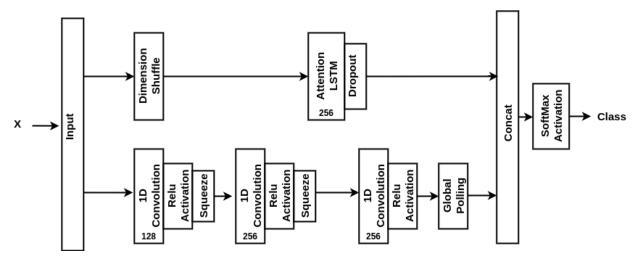


Figure 17: Attention LSTM cells to construct the MALSTM-FCN architecture [15].

of input data and a two-dimensional array of weights, known as a filter. These networks use convolution operation in at least one of their layers.

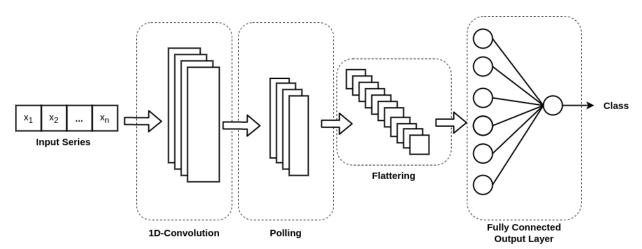


Figure 18: Convolutional Neural Network for time series forecasting.

Convolutional neural networks share a similar architecture with traditional neural networks, including an input and an output layer and multiple hidden layers. The main feature of a CNN is that its hidden layers typically consist of convolutional layers that perform the operations described above. Figure 18 depicts the general architecture of CNNs for time series analysis. We use a one-dimensional convolutional layer instead of the usual two-dimensional convolutional layer typical in image processing tasks. This first layer is then normalised with a *polling layer* and later *flattened* so that the output layer can process the whole time series at each step t. In this case, many one-dimensional convolution layers can be combined in a deep learning network.

For the CNN implementation, we used the Keras framework [7] for deep learning. Our model consists of two or more stacked 1-dimensional CNN layers, one densely connected layer with N neurons for polling, one densely connected layer with N neurons for flattering, and finally the densely connected output layer with one neuron.

#### 3.5 Hyper-parameters tuning

The *hyper-parameters tuning* is a method for the optimisation of the hyper-parameters of a given algorithm. It is used to identify the best configuration of the hyper-parameters that would allow the algorithm to achieve the best performance, evaluated with respect to a specific prediction error. For each algorithm, the hyper-parameters to be optimised are selected, and for each hyper-parameter an appropriate searching interval is defined, including all values

to be tested. The algorithm is then fitted on a specific portion of the dataset with the first chosen hyper-parameter configuration. The fitted model is tested on a portion of data that has not been previously used during the training phase. This testing procedure returns a specific value for the chosen prediction error.

Algorithm	Parameter	Searching Interval				
MLP	epochs hidden layers batch size optimizer activation neurons	100, 250, 500, 1000 1, 2, 3, 4, 5 32, 64, 128, 256, 512 adam, Nadam, Adamax, RMSprop, SGD relu, tanh, softmax 16, 32, 64, 128, 256				
LSTM	epochs hidden layers batch size optimizer activation neurons	100, 250, 500, 1000 1, 2, 3, 4, 5 32, 64, 128, 256, 512 adam, Nadam, Adamax, RMSprop, SGD relu, tanh 16, 32, 64, 128, 256				
MALSTM-FCN	epochs hidden layers batch size optimizer activation neurons	100, 250, 500, 1000 - 32, 64, 128, 256, 512 adam, Nadam, Adamax, RMSprop, SGD -				
CNN	epochs hidden layers batch size optimizer activation neurons	100, 250, 500, 1000 1, 2, 3, 4, 5 32, 64, 128, 256, 512 adam, Nadam, Adamax, RMSprop, SGD relu, tanh, softmax 16, 32, 64, 128, 256				

Table 19: hHyper-parameter searching intervals for different neural network architectures.

The optimisation procedure via the Grid Search procedure [19] ends when all possible combinations of hyper-parameter values have been tested. The hyper-parameter configuration yielding the best performance in terms of the selected prediction error is therefore chosen as the optimised configuration. Table 19 show the hyper-parameters' searching intervals for each implemented algorithm. Since MALSTM-FCN is a deep neural network-specific architecture, the number of layers, neurons per layer and activation function of each layer are already pre-specified (as explained in Section 3.3).

To ensure the robustness of the hyper-parameter optimisation procedure, we use a model validation technique to assess how the performance achieved by a given model will generalise to an independent dataset. This validation technique involves the partition of a data sample into a training set, used to fit the model, and a validation set used to validate the fitted model and a test set to assess the final optimised generalisation power of the model. In our analysis, we implemented the *Boostrap Method* [9] with 37.8% of *out-of-bag samples* and 10000 iterations to validate the final hyper-parameters.

## 4 Empirical Evidence

In this section, we report and discuss the main results of the analysis. In particular, we discuss the outcome for both the restricted and unrestricted models. These results are evaluated in terms of the standard classification error metrics: accuracy, fl\_score, precision and recall.

# 4.1 Hyper-Parameters For The Restricted Model

We briefly discuss here the fine-tuning of the hyper-parameters of the four deep learning algorithm mentioned in Section 3.5 considering the hourly frequency resolution. Table 20 shows the best results obtained for the different

neural networks models, using the *Grid Search* technique in terms of the classification error metrics. The best identified parameters with the related results obtained for the *MALSTM-FNC* and *MLP* models are reported in table 20.

Algorithm	Parameter	Values	Accuracy $(\mu \pm \sigma)$	<b>Prediction</b> $(\mu \pm \sigma)$	Recall $(\mu \pm \sigma)$	<b>f1-score</b> $(\mu \pm \sigma)$
MLP	epochs hidden layers batch size optimizer activation neurons	250 2 256, Nadam relu 128	$0.537 \pm 0.029$	$0.472 \pm 0.143$	$0.511 \pm 0.025$	$0.495 \pm 0.027$
LSTM	epochs hidden layers batch size optimizer activation neurons	250 2 256, Adamx tanh 256	$0.535 \pm 0.034$	$0.456 \pm 0.200$	$0.485 \pm 0.082$	$0.503 \pm 0.285$
MALSTM-FCN	epochs hidden layers batch size optimizer activation neurons	250 - 256, Adamx -	$0.542 \pm 0.034$	$0.456 \pm 0.200$	$0.485 \pm 0.082$	$0.503 \pm 0.201$
CNN	epochs hidden layers batch size optimizer activation neurons	250 2 128, Nadam tanh 128	$0.435 \pm 0.024$	$0.486 \pm 0.210$	$0.485 \pm 0.082$	$0.453 \pm 0.265$

Table 20: Restricted model - Neural networks optimal parameters.

The neural network that achieved the best accuracy is MALSTM-FNC, with an average accuracy of 53.7% and a standard deviation of 2.9%. Among the implemented machine learning models, the one that achieved the best f1-score is again MALSTM-FNC, with an average accuracy of 54% and a standard deviation of 2.01% (the LSTM obtained the same f1-score but we observe a higher variance).

# 4.2 Hyper-Parameters For The Unrestricted Model

Table 21 shows the best results obtained for the Neural Networks models, via the *Grid Search* technique with respect to the classification error metrics. The best identified parameters with the related results obtained for the *CNN* and *LSTM* models are reported in table 21.

The results obtained for the unrestricted model highlight that the addition of trading and social media indicators to the model leads to an effective improvement in average accuracy, namely the prediction error. This result is consistent for all implemented algorithms, and this allows us to exclude that this result is a statistical fluctuation or that it may be an artefact of the particular classification algorithm implemented. The best result obtained with the unrestricted model is achieved using the CNN model, with a mean accuracy of 87% and a standard deviation of 2.7%.

#### 4.3 Results and Discussions

Table 22 shows the results obtained using the four deep learning algorithms for the **hourly** frequency price movements classification task. This table presents the results for the restricted (upper part) and unrestricted (lower part) model. Firstly, it can be noted that for all four deep learning algorithms, the performance of the unrestricted model outperforms the restricted model in terms of accuracy, precision, recall and F1 score. The accuracy ranges from 51% of for the restricted MLP to 84% for CNNs and LSTMs.

The fact that the result is consistent across all four classifiers, further confirm that is not due to statistical fluctuations, but rather to the higher predictive of the unrestricted model. For Bitcoin, the highest performances are obtained using the CNN architecture and for Ethereum by the LSTM.

Algorithm	Parameter	Values	Accuracy $(\mu \pm \sigma)$	<b>Prediction</b> $(\mu \pm \sigma)$	Recall $(\mu \pm \sigma)$	<b>f1-score</b> $(\mu \pm \sigma)$
MLP	epochs hidden layers batch size optimizer activation neurons	500 3 256 Nadam relu 128	$0.81 \pm 0.025$	$0.984 \pm 0.180$	$0.541 \pm 0.060$	$0.698 \pm 0.908$
LSTM	epochs hidden layers batch size optimizer activation neurons	1000 3 256 Adamx tanh 256	$0.86 \pm 0.027$	$0.918 \pm 0.033$	$0.873 \pm 0.228$	$0.895 \pm 0.175$
MALSTM-FCN	epochs hidden layers batch size optimizer activation neurons	500 - 256 Adamx -	$0.73 \pm 0.027$	$0.75 \pm 0.241$	$0.611 \pm 0.175$	$0.673 \pm 0.060$
CNN	epochs hidden layers batch size optimizer activation neurons	1000 2 256 Nadam relu 256	$0.87 \pm 0.027$	$0.782 \pm 0.175$	$0.913 \pm 0.060$	$0.842 \pm 0.228$

Table 21: Unrestricted model - Neural networks optimal parameters.

We have also further explored the classification via the unrestricted model at hourly frequency considering two sub-models: a sub-model including technical and social indicators and the other with all the indicators (social, technical and trading). In this way, it is possible to disentangle impact of social and trading indicators on the models' performance. We used a statistical t test on the distributions of accuracy, prediction, recall and F1-score for the two unrestricted sub-modules finding that adding social indicators does not add a significant improvement to the unrestricted model. For this reason, in Table 22 we omitted the unrestricted model including social and technical indicators only.

Table 23 shows the results obtained by the four deep learning algorithms for **daily** frequency price movements classification. This table presents results for both the restricted (upper part) and unrestricted (lower part) model. The unrestricted model is further divided in *technical-social* and *techical-social-trading* sub-models to better highlight the contribution of social and trading indicators to the model separately.

The MALSTM-CNF achieves the best classification performance for Ethereum with 99% of accuracy using the restricted model composed of only technical indicators. For Bitcoin, the best results are achieved by MLP with F1-score of 55% and accuracy of 60% with the unrestricted model with **only social media indicators** and technical indicators (in this case, we consider F1-score and accuracy for Bitcoin because of the slightly unbalanced class distribution described in Section 2.4). For the daily frequency classification, we can see that in general technical indicators alone performs better in the classification of next day price movement. The more indicators we add to the model, the more the performance decrease. Another general result is that the accuracy, precision, recall and F1-score for daily classification of Ethereum price movements are far better than those for Bitcoin. Results for daily classification are in line with other studies [1] for the hourly and daily classification with a significant improvement when considering the hourly unrestricted model. The social media indicators turn out to be particularly relevant at the daily frequency for the Bitcoin case. This result is in agreement with the recent result on the impact social media sentiment on cryptocurrencies markets [2]: the effects of social media on markets show a long lag, which is not captured nor relevant at an hourly frequency.

# 5 Threats To Validity

In this section, we discuss potential limitations and threats to validity of our analysis. First, our analysis focuses on Ethereum and Bitcoin: this may constitute a threat to external validity as conducting the analysis for different cryptocurrencies may lead to different results.

Model	Algotithm	Cryptocurrency	Class	Accuracy	Precision	Recall	F1-score
			down		0.57	0.28	0.38
		bitcoin	up		0.54	0.80	0.64
	MID		average	0.55	0.56	0.55	0.51
	MLP		down		0.52	0.77	0.62
		ethereum	up		0.55	0.29	0.38
			average	0.53	0.54	0.53	0.50
			down		0.52	0.50	0.51
		bitcoin	up		0.55	0.57	0.56
	MALSTM-FNC		average	0.54	0.54	0.54	0.54
	WINDSTWI-FIVE		down		0.52	0.80	0.63
		ethereum	up		0.57	0.26	0.36
Restricted			average	0.53	0.54	0.53	0.50
Restricted			down		0.49	0.29	0.37
		bitcoin	up		0.53	0.73	0.61
	LSTM		average	0.52	0.51	0.52	0.49
	LOTIVI	_	down		0.51	0.70	0.59
		ethereum	up		0.51	0.31	0.39
			average	0.51	0.51	0.51	0.49
			down		0.52	0.65	0.57
		bitcoin	up		0.56	0.42	0.48
	CNN		average	0.53	0.54	0.53	0.53
		, a	down		0.50	0.75	0.60
		ethereum	up	0.50	0.56	0.31	0.40
			average	0.52	0.53	0.52	0.49
		bitcoin	down		0.87	0.57	0.69
	MLP		up		0.70	0.92	0.79
			average	0.75	0.78	0.75	0.74
		ethereum	down		0.80	0.79	0.80
			up	0.00	0.80	0.80	0.80
			average	0.80	0.80	0.80	0.80
		1.4	down		0.97	0.32	0.48
		bitcoin	up	0.67	0.61	0.99	0.75
	MALSTM-FNC		average	0.67	0.78 0.98	0.67	0.62 0.27
		ath awaren	down		0.98	0.15 1.00	0.27
		ethereum	up	0.58	0.34	0.58	0.70
Unrestricted			down	0.56	0.79	0.38	0.49
		bitcoin			0.79	0.90	0.84
		DICUII	up average	0.83	0.84	0.70	0.82
	LSTM		average down	0.03	0.79	0.83	0.83
		ethereum	up		0.79	0.76	0.83
		Cincicum	average	0.84	0.84	0.70	0.83
			down	0.04	0.82	0.87	0.84
		bitcoin	up		0.87	0.82	0.85
		DIVEOIII.	average	0.84	0.84	0.84	0.84
	CNN		down		0.72	0.97	0.83
		ethereum	up		0.95	0.61	0.74
			average	0.79	0.83	0.79	0.78
T-1-1-22. A	ov Precision Recall	E1 f Dt	_				

Table 22: Accuracy, Precision, Recall, F1 score for Restricted and Unrestricted models for each Deep Learning Algorithm With Hourly Frequency.

Model	Features	Algotithm	Cryptocurrency	Class	Accuracy	Precision	Recall	F1-score
Model	reatures	Aigonniii	Cryptocurrency	down	Accuracy	0.00	0.00	0.00
			bitcoin	up		0.59	0.00	0.00
		Man		average	0.58	0.36	0.58	0.44
		MLP		down		0.96	1.00	0.98
			ethereum	up		1.00	0.96	0.98
				average	0.98	0.98	0.98	0.98
			1.24 2	down		0.51	0.47	0.49
			bitcoin	up	0.54	0.56 <b>0.54</b>	0.59 <b>0.54</b>	0.58 <b>0.54</b>
		MALSTM-FNC		average down	0.54	1.00	0.99	0.99
			ethereum	uown		0.99	1.00	0.99
Restricted	41			average	0.99	0.99	0.99	0.99
Restricted	technical			down		0.00	0.00	0.00
			bitcoin	up		0.57	1.00	0.73
		LSTM		average	0.57	0.33	0.57	0.41
			-41	down		0.98	0.98	0.98
			ethereum	up average	0.99	0.99 <b>0.99</b>	0.99 <b>0.99</b>	0.99 <b>0.99</b>
				down	0.55	0.38	0.10	0.16
			bitcoin	up		0.60	0.89	0.72
		CNINI		average	0.58	0.51	0.58	0.50
		CNN		down		0.88	1.00	0.94
			ethereum	up		1.00	0.88	0.94
				average	0.94	0.94	0.94	0.94
<del></del>	<u> </u>			down		0.59	0.21	0.31
			bitcoin	up		0.61	0.90	0.72
		MLP		average	0.60	0.60	0.60	0.55
			_	down		0.79	0.95	0.87
			ethereum	up	0.07	0.95	0.79	0.87
				average	0.87	0.88	0.87	0.87 0.41
			bitcoin	down		0.41	0.41	0.41
			Dittoili	up average	0.46	0.31	0.31	0.31
		MALSTM-FNC		down	0.10	0.72	0.70	0.71
			ethereum	up		0.77	0.78	0.77
	technical +			average	0.75	0.75	0.75	0.75
	social		bitcoin ethereum	down		0.44	0.10	0.17
		LSTM		up	0.46	0.47	0.86	0.60
				average	0.46	<b>0.45</b> 0.88	<b>0.46</b> 0.83	<b>0.38</b> 0.85
				down		0.88	0.83	0.83
			cincicum	up average	0.87	0.87	0.91	0.87
				down	0.07	0.42	0.47	0.44
			bitcoin	up		0.56	0.52	0.54
		CNN		average	0.50	0.50	0.50	0.50
		CIVIT		down		0.77	0.83	0.80
			ethereum	up	0.01	0.85	0.79	0.82
Unrestricted				average	0.81	0.81	0.81	0.81
			bitcoin	down		0.59 0.47	0.20 0.84	0.30 0.60
			Sittoili	up average	0.49	0.47	0.64	0.60
		MLP		down	,	0.84	0.91	0.87
			ethereum	up		0.91	0.84	0.87
				average	0.87	0.88	0.87	0.87
				down		0.41	0.41	0.41
			bitcoin	up	0.54	0.62	0.62	0.62
		MALSTM-FNC		average	0.54	0.54	0.54	0.54
			othoroum	down		0.79 0.91	0.88 0.83	0.83 0.87
	technical +		ethereum	up average	0.85	0.91 <b>0.86</b>	0.83	0.87 <b>0.85</b>
	social +			down	0.00	0.44	0.31	0.36
	trading		bitcoin	up		0.43	0.58	0.49
		LSTM		average	0.44	0.44	0.44	0.43
		LSTNI		down		0.92	0.87	0.89
			ethereum	up		0.86	0.91	0.88
				average	0.89	0.89	0.89	0.89
			hitasin	down		0.52	0.55	0.54
			bitcoin	up average	0.57	0.62 <b>0.57</b>	0.59 <b>0.57</b>	0.60 <b>0.57</b>
		CNN	ethereum	down	0.57	0.57	0.85	0.89
				uowii		0.92	0.83	0.89
				average	0.89	0.90	0.89	0.89
Table 22. A a	<del>' ,</del>	sion Decell El e		Ü				

Table 23: Accuracy, Precision, Recall, F1 score for Restricted and Unrestricted models for each Deep Learning Algorithm For Daily Frequency.

Secondly, threats to internal validity concern confounding factors that can influence the obtained results. Based on the empirical evidence, we assume that technical, trading and social indicators are exhaustive in the case of our model. There may exists nonetheless other factors omitted from this study, which could influence the price movements.

Finally, threats to construct validity focus on how accurately the observations describe the phenomena of interest. The detection and classification of price movements are based on objective data that describe the whole phenomenon. In general, technical and trading indicators are based on objective data and are usually reliable. Social media indicators are based on empirical measures obtained via deep learning algorithms trained with publicly available datasets: these datasets may carry intrinsic bias, which are in turn translated into classification errors of emotion and sentiment.

#### 6 Conclusions

Several attempts have been made in the most recent literature to model and predict the erratic behaviour of prices or other market indicators of the major cryptocurrencies. Notwithstanding massive efforts devoted to this goal by many research groups, the analysis of cryptocurrency markets still remains one of the most debated and elusive tasks. Several aspects make grappling with this issue so complicated. For instance, due to its relatively young age, the cryptocurrency market is very dynamic and fast-paced. The emergence of new cryptocurrencies is a routine event, resulting in unexpected and frequent changes in the makeup of the market itself. Moreover, the high price volatility of cryptocurrencies and their 'virtual' nature are at the same time a blessing for investors and traders, and a curse for any serious theoretical and empirical modelling, with huge practical implications. The study of such a young market, whose price behaviour is still largely unexplored, has fundamental repercussions not only in the scientific arena but also for investors and main players and stakeholders in the crypto-market landscape.

In this paper, we aimed to assess whether the addition of social and trading indicators to the "classic" technical variables would lead to practical improvements in the classification of price changes of cryptocurrencies considering hourly and daily frequencies. This goal was achieved implementing and benchmarking a wide array of deep learning techniques, such as *Multi-Layer Perceptron* (MLP), *Multivariate Attention Long Short Term Memory Fully Convolutional Network* (MALSTM-FCN), *Convolutional Neural Network* (CNN) and *Long Short Term Memory* (LTMS) neural networks. We considered in our analysis the two main cryptocurrencies, Bitcoin and Ethereum, and we analysed two models: a restricted model, considering only technical indicators, and an unrestricted model that includes social and trading indicators.

In the restricted analysis, the model that achieved the best performance, in terms of accuracy, precision, recall, and f1-score, is MALSTM-FCN with an average f1-score of 54% for Bitcoin and the CNN for Ethereum with hourly frequency. For the unrestricted case the best result is achieved by the LSTM neural network for both Bitcoin and Ethereum with an average accuracy of 83% and 84% respectively. The most important finding for the hourly frequency classification for the unrestricted model is that the addition of trading and social indicators to the model leads to an effective improvement in the average accuracy, precision, recall, and f1-score. We have verified that this finding is not the result of a statistical fluctuation, since all the implemented models yielded the same achievements. For the same reason, we can exclude that the results depend on the particular implemented algorithm. Finally, for the daily classification, the best classification performance has been achieved by MALSTM-CNF for Ethereum with 99% of accuracy when using the restricted model including only technical indicators. For Bitcoin, the best results are achieved by MLP with f1-score of 55% and accuracy of 60% with the unrestricted model including social media indicators and technical indicators, in this case, we consider f1-score and accuracy for Bitcoin because of the slightly unbalanced class distribution described in Section 3.4. For the daily frequency classification, we can see that in general technical indicators alone perform better in the classification of next day price movements. The more indicators we add to the model, the more the performance decreases.

Another general result is that the accuracy, precision, recall, and f1-score for daily classification of Ethereum price movements are far better than those for Bitcoin. Our results show that with a specific design and fine-tuning of deep learning architecture, it is possible to achieve high performance in the classification of price changes of cryptocurrencies.

### References

- [1] Akyildirim, E., Goncu, A., Sensoy, A.: Prediction of cryptocurrency returns using machine learning. Annals of Operations Research pp. 1–34 (2020)
- [2] Bartolucci, S., Destefanis, G., Ortu, M., Uras, N., Marchesi, M., Tonelli, R.: The butterfly "affect": Impact of development practices on cryptocurrency prices. EPJ Data Science 9(1), 21 (2020)

- [3] Calefato, F., Lanubile, F., Maiorano, F., Novielli, N.: Sentiment polarity detection for software development. Empirical Software Engineering pp. 1–31 (2017)
- [4] Calefato, F., Lanubile, F., Maiorano, F., Novielli, N.: Sentiment polarity detection for software development. In: 2018 IEEE/ACM 40th International Conference on Software Engineering (ICSE). pp. 128–128. IEEE (2018)
- [5] Chen, C.Y.H., Hafner, C.M.: Sentiment-induced bubbles in the cryptocurrency market. Journal of Risk and Financial Management 12(2), 53 (2019)
- [6] Chen, J.F., Chen, W.L., Huang, C.P., Huang, S.H., Chen, A.P.: Financial time-series data analysis using deep convolutional neural networks. In: 2016 7th International conference on cloud computing and big data (CCBD). pp. 87–92. IEEE (2016)
- [7] Chollet, F., et al.: Keras: The python deep learning library. Astrophysics Source Code Library pp. ascl–1806 (2018)
- [8] Devlin, J., Chang, M.W., Lee, K., Toutanova, K.: Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805 (2018)
- [9] Efron, B., Tibshirani, R.: The bootstrap method for assessing statistical accuracy. Behaviormetrika **12**(17), 1–35 (1985)
- [10] Hartmann, F., Grottolo, G., Wang, X., Lunesu, M.I.: Alternative fundraising: success factors for blockchain-based vs. conventional crowdfunding. In: 2019 IEEE international workshop on blockchain oriented software engineering (IWBOSE). pp. 38–43. IEEE (2019)
- [11] Hartmann, F., Wang, X., Lunesu, M.I.: Evaluation of initial cryptoasset offerings: the state of the practice. In: 2018 International Workshop on Blockchain Oriented Software Engineering (IWBOSE). pp. 33–39. IEEE (2018)
- [12] Hochreiter, S., Schmidhuber, J.: Long short-term memory. Neural computation 9(8), 1735–1780 (1997)
- [13] Jing-Zhi H., William H., J.N.: Predicting bitcoin returns using high-dimensional technical indicators. The Journal of Finance and Data Science (2018). https://doi.org/https://doi.org/10.1016/j.jfds.2018.10.001, http://www.sciencedirect.com/science/article/pii/S2405918818300928
- [14] Karim, F., Majumdar, S., Darabi, H., Chen, S.: Lstm fully convolutional networks for time series classification. IEEE access 6, 1662–1669 (2017)
- [15] Karim, F., Majumdar, S., Darabi, H., Harford, S.: Multivariate lstm-fcns for time series classification. Neural Networks 116, 237–245 (2019)
- [16] Katsiampa, P.: Volatility estimation for bitcoin: A comparison of garch models. Economics Letters **158**, 3–6 (2017)
- [17] Lahmiri, S., B.S.: Cryptocurrency forecasting with deep learning chaotic neural networks. Chaos, Solitons and Fractals 118, 35 40 (2019)
- [18] Lahmiri, S., Bekiros, S., Salvi, A.: Long-range memory, distributional variation and randomness of bitcoin volatility. Chaos, Solitons & Fractals **107**, 43–48 (2018)
- [19] Lerman, P.: Fitting segmented regression models by grid search. Journal of the Royal Statistical Society: Series C (Applied Statistics) **29**(1), 77–84 (1980)
- [20] Mäntylä, M., Adams, B., Destefanis, G., Graziotin, D., Ortu, M.: Mining valence, arousal, and dominance: possibilities for detecting burnout and productivity? In: Proceedings of the 13th international conference on mining software repositories. pp. 247–258 (2016)
- [21] Marchesi, L., Marchesi, M., Destefanis, G., Barabino, G., Tigano, D.: Design patterns for gas optimization in ethereum. In: 2020 IEEE International Workshop on Blockchain Oriented Software Engineering (IWBOSE). pp. 9–15. IEEE (2020)
- [22] Matta, M., Lunesu, I., Marchesi, M.: Bitcoin spread prediction using social and web search media. In: UMAP workshops. pp. 1–10 (2015)
- [23] Murgia, A., Ortu, M., Tourani, P., Adams, B., Demeyer, S.: An exploratory qualitative and quantitative analysis of emotions in issue report comments of open source systems. Empirical Software Engineering 23(1), 521–564 (2018)
- [24] Murgia, A., Tourani, P., Adams, B., Ortu, M.: Do developers feel emotions? an exploratory analysis of emotions in software artifacts. In: Proceedings of the 11th Working Conference on Mining Software Repositories. pp. 262–271. ACM (2014)
- [25] Ortu, M.: Mining software repositories: measuring effectiveness and affectiveness in software systems. (2015)

- [26] Ortu, M., Hall, T., Marchesi, M., Tonelli, R., Bowes, D., Destefanis, G.: Mining communication patterns in software development: A github analysis. In: Proceedings of the 14th International Conference on Predictive Models and Data Analytics in Software Engineering. pp. 70–79. ACM (2018)
- [27] Ortu, M., Orrú, M., Destefanis, G.: On comparing software quality metrics of traditional vs blockchain-oriented software: An empirical study. In: 2019 IEEE International Workshop on Blockchain Oriented Software Engineering (IWBOSE). pp. 32–37. IEEE (2019)
- [28] Phillips, R.C., Gorse, D.: Mutual-excitation of cryptocurrency market returns and social media topics. In: Proceedings of the 4th International Conference on Frontiers of Educational Technologies. pp. 80–86. ACM (2018)
- [29] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, L., Polosukhin, I.: Attention is all you need. arXiv preprint arXiv:1706.03762 (2017)
- [30] Warriner, A.B., Kuperman, V., Brysbaert, M.: Norms of valence, arousal, and dominance for 13,915 english lemmas. Behavior Research Methods **45**(4), 1191–1207 (dec 2013). https://doi.org/10.3758/s13428-012-0314-x