Ethereum Cryptocurrency Entry Point and Trend Prediction using Bitcoin Correlation and Multiple Data Combination

Abdellah EL ZAAR[1], Nabil BENAYA[2], Hicham EL MOUBTAHIJ[3],
Toufik BAKIR[4], Amine MANSOURI[5], Abderrahim EL ALLATI[6]
Laboratory of R and D in Engineering Sciences, FST Al-Hoceima,
Abdelmalek Essaadi University, Tetouan, Morocco[1,2,6]
Higher School of Technology, University Ibn Zohr, Agadir, Morocco[3]
IMVIA Laboratory, University of Burgundy, Dijon, France[4,5]

***Abstract*—Deep learning methods have achieved significant success in various applications, including trend signal prediction in financial markets. However, most existing approaches only utilize price action data. In this paper, we propose a novel system that incorporates multiple data sources and market correlations to predict the trend signal of Ethereum cryptocurrency. We conduct experiments to investigate the relationship between price action, candlestick patterns, and Ethereum-Bitcoin correlation, aiming to achieve highly accurate trend signal predictions. We evaluate and compare two different training strategies for Convolutional Neural Networks (CNNs), one based on transfer learning and the other on training from scratch. Our proposed 1-Dimensional CNN (1DCNN) model can also identify inflection points in price trends during specific periods through the analysis of statistical indicators. We demonstrate that our model produces more reliable predictions when utilizing multiple data representations. Our experiments show that by combining different types of data, it is possible to accurately identify both inflection points and trend signals with an accuracy of 98%.**

***Keywords*—Deep learning; cryptocurrency; bitcoin trend prediction; price action; convolutional neural network; transfer learning**

I. Introduction

Trading refers to buying and selling operations carried out on the financial markets. These operations are executed by traders from the trading room of a financial organization or the stock market institution, or from the Internet in the case of independent traders. The operations in financial markets are made in a secure and controlled environment which brings together hundreds of thousands of market participants who wish to buy and sell shares. The buying and selling activities operate electronically on well known platforms for trading. These platforms contain all information and tools that the trader needs to analyse the different markets. Hence, a strong knowledge about the market psychology is essential to trade in the live market. In trading, market movement can be observed and analyzed through various types of trading charts. These charts often contain technical indicators that assist traders in accurately predicting market trends and trading signals. Examples of popular trading charts include bar charts, line charts, point and figure charts, market profile charts, and candlestick charts. In this article, we will specifically focus on candlestick charts, which are widely used in financial markets for their visual representation of price movements and patterns (see Fig. 1).

Fig. 1. Candlesticks chart : Ethereum vs US Dollar in daily time frame.

Candlestick charts offer unique visual indicators that differentiate them from other types of trading charts. The shapes and patterns of candlesticks on these charts can provide valuable insights into price action. Candlesticks come in various sizes, and understanding the psychology behind the different body sizes is crucial in trading. Each candlestick is formed using the open, high, low, and close prices of the chosen time frame, and analyzing these components can provide valuable information for traders (see Fig. 2). The graph chart contains several types of candles which are decisional and have a strong effect on market trend. The most powerful candlestick patterns are: bearish engulfing bar, bullish engulfing bar, Doji, morning star, evening star, Hammer, shooting star, Harami and the Tweezers tops and bottoms [1], [2], [3].

In this research paper, we have implemented a deep learning algorithm based on Convolutional Neural Networks (CNNs) to predict the trend of Ethereum cryptocurrency. The main objective of this work is to develop an intelligent trading system that can assist traders in automating their trades, predicting market trends, and mitigating high volatility. The proposed system is designed to identify high probability setups and maximize profits. To achieve accurate predictions, we have utilized different data representations. We have found that combining multiple data representations significantly improves the efficiency of the algorithms during the training process, enabling them to learn data dependencies with high accuracy.

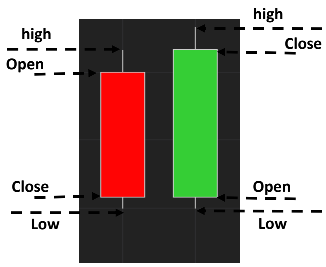


Fig. 2. Candlestick price levels.

In addition to incorporating candlestick pattern data and statistical indicators, we have also considered the Ethereum-Bitcoin correlation to precisely identify Ethereum price action.

When using such structured data, a Convolutional Neural Network (CNN) is superior for learning features dependencies in wide datasets. In addition to that, CNN can also provide satisfactory performance with 1-dimentional data [4], [5], [6], [7], [8]. When working with time series data, Long Short-Term Memory (LSTM) algorithm can also learn easily temporal patterns and dependencies using memory cells and gates [9], [10], [11], [12], [13]. To find the most effective architecture, two different 1-Dimensional Convolutional Neural Network training strategies are evaluated and tested : training from scratch strategy and transfer learning strategy.

The current state-of-the-art research in the field of financial time series forecasting using deep learning has primarily overlooked the relationship between predicted market movements and the optimal trading entry point [14], [15], [16]. Financial time series data often contain significant noise, posing challenges for accurate analysis and predictions. Notably, Ethereum cryptocurrency exhibits a price action pattern that closely resembles Bitcoin. However, Ethereum demonstrates comparatively less noise in its price action chart. The presence of fake breakouts and high volatility are considered major hurdles in employing deep learning for financial time series prediction. To address the issue of noise in financial time series data, particularly in the case of cryptocurrency markets like Ethereum, we employed 1D Convolutional Neural Networks (1DCNN) using various strategies. Utilizing 1D Convolutional Neural Networks (1DCNN) is a robust approach for analyzing financial time series data. These networks have demonstrated significant potential in capturing meaningful patterns and dependencies in sequential data. When applied to financial time series, 1DCNNs can effectively learn and extract relevant features such as price fluctuations, trends, and patterns from the input data. The inherent capability of 1DCNNs to capture both local and global dependencies makes them highly suitable for modeling complex relationships in financial time series. By leveraging their multi-layered architecture and convolutional operations, 1DCNNs can uncover valuable insights, enhance prediction accuracy, and assist in decision-making processes related to trading and investment strategies. In order to ensure precise trading entry points, we meticulously collected the data and performed comprehensive feature engineering. We trained and tested three learning strategies based on 1DCNN to compare their performance and determine the most effective strategy. 1DCNN have proven to be highly proficient in identifying short trends and establishing optimal trading entry points. Leveraging their specialized architecture and convolutional operations, 1DCNNs excel at capturing local dependencies and extracting relevant features from sequential financial data. By analyzing price fluctuations and other pertinent information, 1DCNNs can effectively detect and interpret short-term trends, providing valuable insights to traders. These networks possess the capability to uncover subtle patterns that might elude human analysts, leading to enhanced prediction accuracy and informed decision-making for trading strategies. With their robust ability to learn complex relationships within financial time series data, 1DCNNs have emerged as a powerful tool in the field of financial analysis, contributing significantly to successful trading strategies. To the best of our knowledge, this is the first work that uses market correlation combined with price action and moving average data to predict the Ethereum trend signal. Market correlation helps to understand the behaviour of price action and avoid volatility. In our case study, we based on Ethereum and Bitcoin correlation (Fig. 3). Theses two markets have strong relationship and have almost same price action.

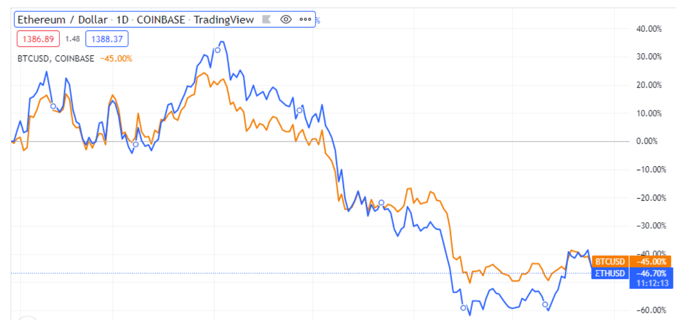


Fig. 3. ETH-BTC correlation.

It can be seen from Fig. 3 that Ethereum and Bitcoin have the same price movement, the thing that facilitates Ethereum trend prediction. This price correlation data combined with the other data representation that we used, can ameliorate the accuracy of our model. A detailed study is presented in Section IV. The rest of the paper is organised as follows: In Section II, we give a brief overview of some significant and recent contributions to market trend prediction using deep learning approaches and Section III describes the proposed approach.

II. RELATED WORK

The majority of works done in the field of market trend prediction using deep learning refer to the data issued from technical analysis of the market. This data is used to train machine learning models. Technical analysis aims to study market behaviour throughout price action data, statistical indicators and news. In the chart of the market, candlestick patterns Fig. 2 are considered as an important visual indicator that can help to analyse the price movement. These patterns are also used to predict the trend of the market. For example, in [17], J.Hao Chen and Y.Cheng Tsai proposed a two-step approach based on a GAF-CNN algorithm to recognize candlestick patterns automatically. They were able to identify eight types of candlestick patterns with 90.7%. In [18], the authors introduced a deep learning-based approach to forecast trend signals and determine trading entry points. Their method combines LSTM, 1DCNN, and the XGBoost algorithm. The experimental results demonstrate that their approach achieves a high level of accuracy in both predicting market movements and identifying optimal trading entry points. PL Seabe et al. [19], proposed three types of Recurrent Neural Networks (RNNs): Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bi-Directional LSTM (Bi-LSTM) for predicting exchange rates of three prominent cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), and Litecoin (LTC), based on their market capitalization. The proposed methodology demonstrates high performance, with Bi-LSTM exhibiting the most accurate predictions compared to GRU and LSTM. The Mean Absolute Percentage Error (MAPE) values for BTC, LTC, and ETH are reported as 0.036, 0.041, and 0.124, respectively, indicating the superior predictive capabilities of Bi-LSTM in this context. RMI.Kusuma et al. [20] used the Convolutional Neural Network to perform candlestick analysis, there method provides a satisfactory result with a recognition score of 92%. A. Andriyanto, A. Wibowo and NZ.Abidin [21] presented a CNN approach to identify the strength of a trend pattern in the movement of the stock market, the proposed approach produces an accuracy of 99% with a remarkable noise during the training process, this problem generally is behind the noisy dataset and a non suitable CNN strategy during the training process. In [22], JH.Chen et al. provide an approach based on the local search adversarial attacks algorithm to predict the patterns of candlesticks. The applied strategy gives good results with an attack ratio of 64.36%. J.Chen et al. [23] propose modeling strategies based on machine learning (ML) techniques. They introduce a vector autoregression (VAR)-based rolling prediction model for forecasting stock prices and a Gaussian feed-forward neural networks (GFNN)-based graphical signal identification method to recognize different types of stock price signals. The experimental results demonstrate improved performance; however, the method encounters challenges when dealing with high volatility signals. These difficulties can significantly impact trading strategies and long-term cumulative profits. In case of Bitcoin trend prediction, S.cavalli and M.Amoretti [24], proposed a methodology for building useful datasets that take into account social media data, the full blockchain transaction history, and a number of financial indicators. The data was trained and tested using CNN model with an accuracy of 74.2%. M Poongodi et al. [25] combined the Latent Dirichlet Allocation (LDA) and Neural Network to predict the Bitcoin trend using data issued from social media and forums. S Alonso-Monsalve et al. [26], implemented and compared various Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) architectures for predicting the trend of several cryptocurrencies, including Bitcoin, Dash, Ether, Litecoin, Monero, and Ripple. The proposed approaches demonstrated promising results, particularly for Bitcoin, Ether, and Litecoin cryptocurrencies. In [27], M Poongodi et al. implemented two machine learning techniques to Predict the price of Ethereum blockchain cryptocurrency in an industrial finance system. When using their proposed model, the SVM method has a higher accuracy (96.06%) than the LR method (85.46%). This can be explained by the SVM ability to classify 1-Dimentional data. T. Shintate and L. Pichl [28] provided a trend prediction classification framework named the random sampling method (RSM) for cryptocurrency time series that are non-stationary. Their proposed approach shows strong results and outperformed those based on LSTM.

III. Proposed Approach

The proposed approach for Ethereum entry point and signal prediction is illustrated in Fig. 4. The historical data of Ethereum and Bitocoin is extracted from the Exchange broker via the trading platform using python packages. The dataset is then used to train the Convolutional Neural Network (CNN) using two different strategies: 1-dimensional transfer learning and training from scratch strategy. The first block of the system extracts the Bitcoin OHLC dataset and the trend signal, then, it is combined with the price action of Ethereum and the data issued from the moving averages to predict the Ethereum trend. In the following we describe every Block in detail.

A. Dataset and Processing

The Bitcoin and Etherium cryptocurrencies historical data is extracted from the Exchange via the Broker. The data is characterized by the Open, High, Low and Close of prices during a time interval. OHLC data is used to analyse the price movement and calculate the statistical indicators. The collected dataset contains the OHLC prices of 4 (four) hour timeframe during one year from 11/2021 to 11/2022 as indicated in the Fig. 5. Two important Moving averages are used to determine the entry point and the signal trend: Simple Moving Average (SMA) and Hull Moving Average (HMA).

The Table I shows the used dataset to train our proposed approach. The dataset contains OHLC prices and the calculated Moving averages in addition to the bitcoin trend (1 for uptrend and 0 for downtrend):

B. Ethereum and Bitcoin Correlation

As illustrated in Fig. 3, it can be seen that Bitcoin (BTC) and Ethereum (ETH) have almost the same price action. According to the correlation analysis, Bitcoin (BTC) and Ethereum (ETH) have a strong positive relationship from the period of 2019 to 2022 . Notably, data from Coin Metrics (Fig. 6) highlighted that ETH-BTC correlation coefficient was nearing all-time high values, sitting at 0.90. For that reason we used BTC price action data to predict the movement and the signal trend of Ethereum cryptocurrency. The diversity and the quality of the data is very important to determine with high accuracy the trend signal of cryptocurrency markets. Therefore, we combined the price action data and the statistical indicators with the data provided by Bitcoin (BTC) price action to spot with high accuracy the trading entry point and price movement.

C. Ethereum and Moving Averages

Concerning the statistical indicators, we choose to work with both SMA (Simple Moving Average) and HMA (hull moving average). SMA indicator calculates the average of recent prices by the number of periods within this range of prices. SMA can be described by the following formula:

$$SMA = \frac{\sum_1^n P_n}{N} \tag{1}$$

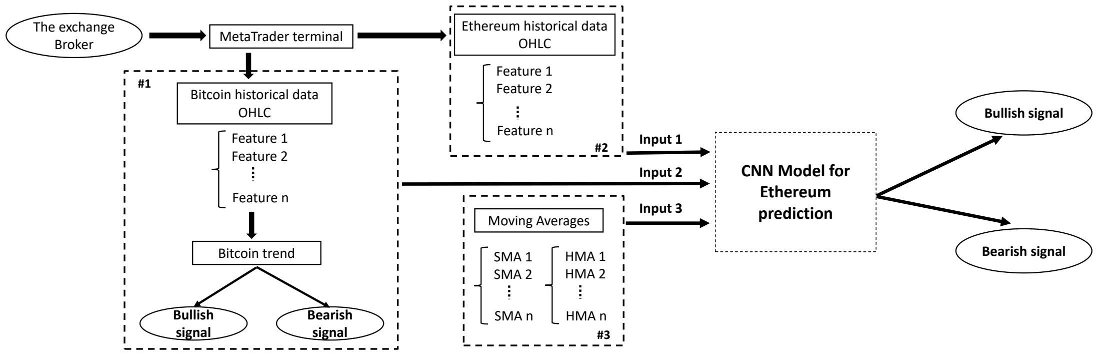


Fig. 4. System overview.

TABLE I. OHLC Dataset Combined with HMA, SMA Indicators and Bitcoin Trend Signal

	open	high	low	close	close_HMA_361	Close_SMA_19	BTC trend	Ethereum Trend
378	1733.25	1813.23	1729.69	1807.71	1705.174187	1805.202105	1	01
379	1807.71	1818.01	1763.28	1790.32	1705.906096	1808.170526	1	01
380	1790.32	1840.95	1782.22	1837.21	1706.676816	1813.645263	1	01
381	1839.34	1841.54	1790.68	1806.32	1707.426536	1814.555263	1	01
382	1806.32	1822.66	1792.01	1807.52	1708.156744	1812.817895	1	01
...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...
1359	3158.43	3167.58	3062.28	3102.27	3445.458519	3242.601579	0	00
1360	3102.27	3130.62	3052.56	3099.67	3448.097849	3230.160526	0	00
1361	3100.33	3149.47	3075.14	3112.04	3450.442989	3218.079474	0	00
3825	1307.58	1323.95	1307.09	1318.33	1233.700725	1295.621053	1	01
3826	1318.36	1336.41	1317.89	1328.69	1234.024134	1295.136842	1	01

(a) BTC close prices.

(b) ETH close prices.

Fig. 5. Bitcoin and Etherium close prices from 11/2021 to 11/2022.

P_n represents the closing price at specific period n, and N is the number of total periods. In this work we chose period (19) which reacts perfectly with the price.

HMA indicator can be calculated using two WMAs (Weighted Moving Average): one with the specified number of periods and one with half the specified number of periods.

$$WMA_1 = WMA(n/2) \tag{2}$$

$$WMA_2 = WMA(n) \tag{3}$$

Then, we calculate the non-smoothed Hull Moving Average:

$$HMA_{nonsth} = (2 \times WMA_1) - WMA_2 \tag{4}$$

The final smooth HMA is calculated with periods of non-smoothed HMA with the following formula:

$$HMA_{sth} = WMA(\sqrt{n}) \tag{5}$$

n represents periods of non smoothed HMA

In addition to their capacity to show the price movement, moving averages are also used to spot trend reversals and the inflection point of the market. It can be seen from the Fig. 7 that SMA(19) is more responsive to the price action and turns quickly than the HMA(361).

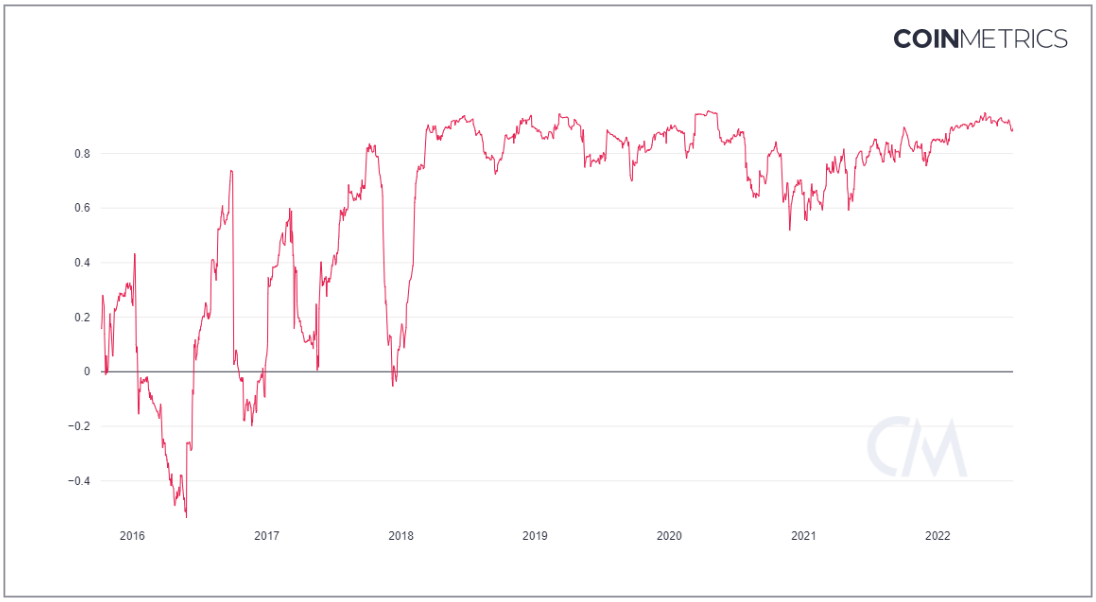


Fig. 6. Ehterium and Bitcoin (ETH-BTC) correlation chart based on coin metrics from 2016 to 2022.

The computation for the technical indicators relies on a number of *n* periods, that was set to 19 candlestick bars (4 hours time frame) for the Simple Moving Average (SMA) indicator, and 361 candlestick bars for Hull Moving Average (HMA) indicator. This parameter was defined at the start and it is optimized. The cross between the two moving averages using the optimised periods provide an excellent trading entry point. In addition to that it provides the start of the price movement.

Fig. 7. Hull moving average(HMA) period 19 and simple moving average(SMA) period 361 crossover.

A crossover occurs when two different moving average lines cross over one another. As indicated in Fig. 7 above, the red entry point marks the beginning of the signal trend and we have a bearish crossover. This takes place when a fast moving average (SMA 19) crosses down through a slow moving average (HMA 361). This implies that the trend is falling or becoming bearish.

At the green entry point, the trend changes again and this produces a bullish crossover. The fast moving average (SMA 19) is the first to react. It crosses up through the slow line (HMA 361). After the crossing, the two lines then follow the same path as the trend continues upwards.

D. CNN Architectures

To determine the entry point and the trend of the Etherium crypto-currency we implemented the Convolutional Neural Network. CNN algorithm is used to train our collected 1-Dimentional Data. Convolution and pooling layers are configured to learn 1D features using two different strategies: CNN learned from scratch and 1D transfer learning (see Fig. 8).

The two strategies are built using the convolutional neural network architecture indicated in Fig. 9. The output dimensions after every layer is presented in the Table II.

TABLE II. Model Summary

Model: Model

Layer (type)	Output Shape	Param #
conv1d_1 (Conv1D)	(None, 7, 64)	192
conv1d_2 (Conv1D)	(None, 6, 64)	8256
max_pooling1d_1 (MaxPooling1D)	(None, 3, 64)	0
conv1d_3 (Conv1D)	(None, 2, 128)	16512
conv1d_4 (Conv1D)	(None, 2, 128)	16512
max_pooling1d_2 (MaxPooling1D)	(None, 2, 128)	0
flatten_1 (Flatten)	(None, 256))	0
dense_1 (Dense)	(None, 256)	65792
dropout_1 (Dropout)	(None, 256)	0
dense (Dense)	(None, 2)	514

Total params: 107,778
Trainable params: 107,778
Non-trainable params: 0

The Table I indicates the data fed to convolutional neural network. The data contains seven (7) features: The Open, High, Low and Close (OHLC) features of Etherium (ETH), the moving averages (SMA 19) and (HMA 361) of Etherium (ETH) and Bitcoin (BTC) Trend. For the training from scratch strategy, the data is fed from the input to the output of the model, the output. In other side, the proposed 1-Dimentional transfer learning strategy consists on transferring the knowledge from a pretrained model using different dataset to a tar-

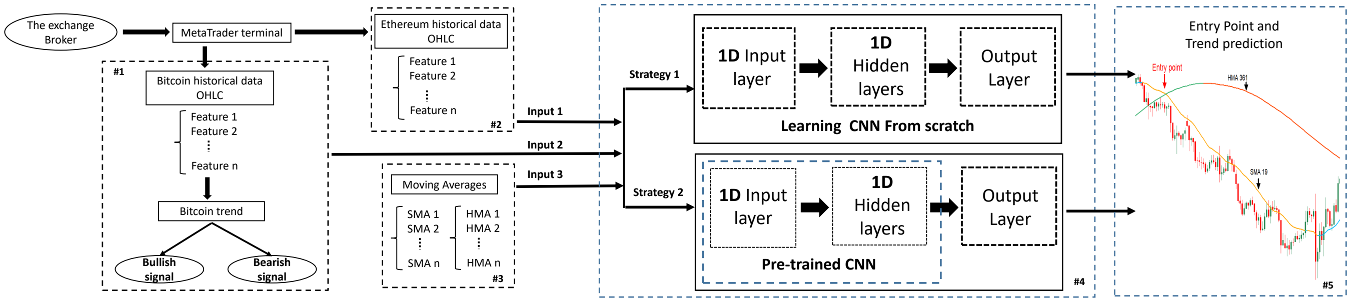


Fig. 8. CNN strategies.

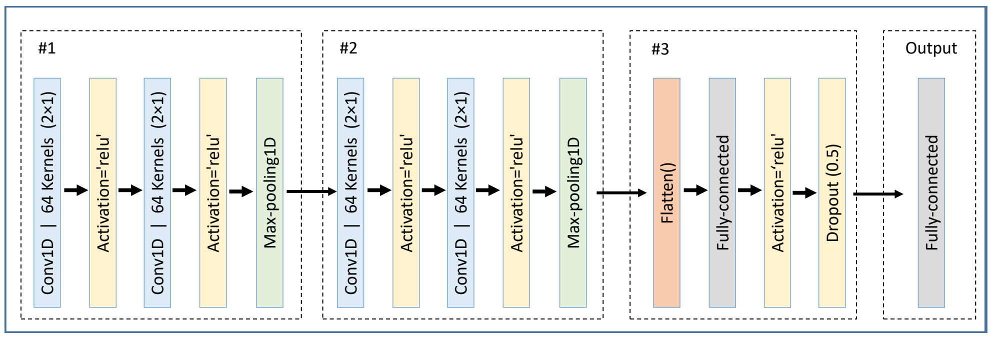


Fig. 9. CNN model architecture.

geted model (see Fig. 8). The pretrained model is trained using BTC OHLC dataset and used to perform the transfer learning strategy. The implementation of pre-trained models offers several benefits in analyzing the Etherium cryptocurrency market. These models facilitate the extraction of pertinent features and the recognition of common patterns and interdependencies, thereby enhancing the accuracy of forecasts and enabling better decision-making. The potential implications of employing one-dimensional transfer learning in finance are promising, as they have the potential to yield excellent results.

IV. Experiments and Results

A. Experiments and Parameterization

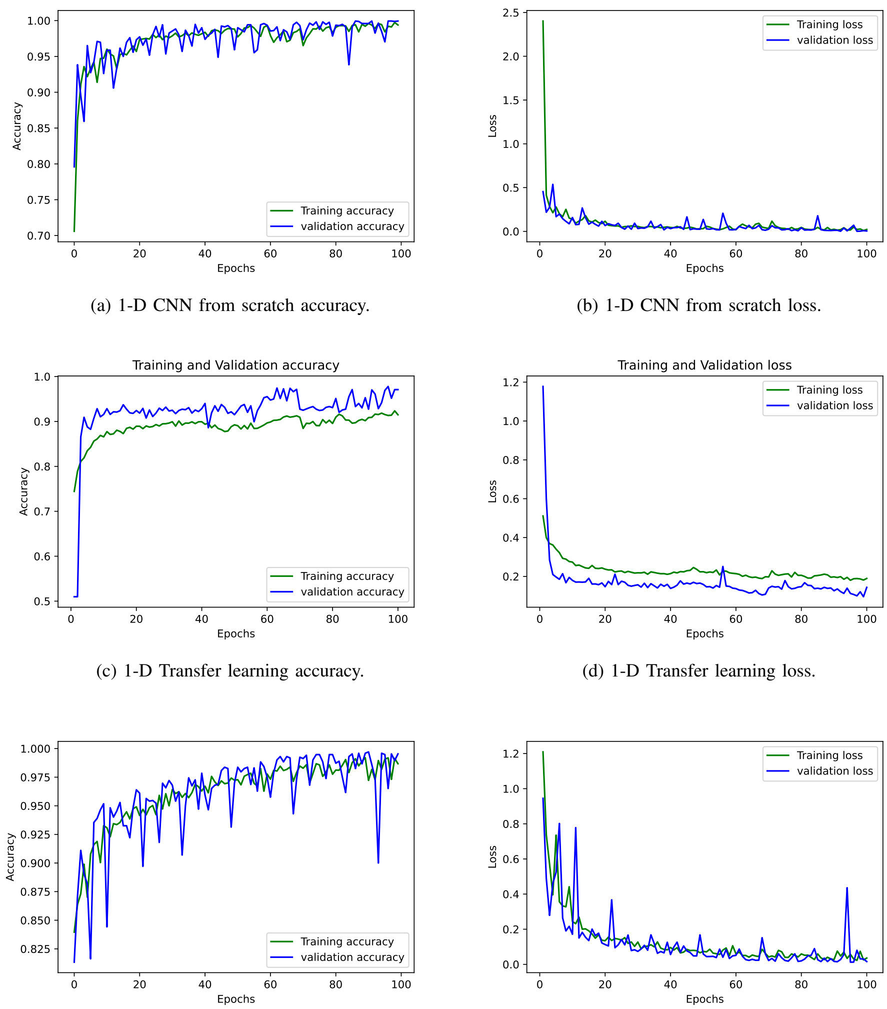
In this section we present the model behaviour and results using the approaches identified in Section III. The two approaches are evaluated in term of Training accuracy, training loss, testing accuracy and testing loss. The experiments were conducted using a system running on a six (06) core processor equipped with 56Go of RAM. The algorithms were implemented using the Python language and processed a multivariate dataset with 10747 samples. The experimental procedure starts with preparing the dataset. After the step of data collection and organisation mentioned in Section III-A, the data were saved in the CSV format for preprocessing convenience. As illustrated in Fig. 7, the entry point occurs when the two moving averages crossover is happening. Therefore, the trader can choose to buy if it is a bullish crossover or sell if it is a bearish crossover. In our case the entry point and also the trend signal are predicted by the proposed algorithms using the collected dataset attributes and parameters (Section III). The training accuracy according to the learning rate, the number of fully connected layers and Epochs of both learning strategies is indicated in Tables III, IV, VI, VII, V and VIII.

TABLE III. Accuracy of Convolutional Neural Network Trained from Sratch on Training Data

Model: 1D CNN				
FC layers	Learning rate	Epochs		
		100	150	200
1	0.1	0.5020	0.5031	0.5046
	0.01	0.5172	0.5215	0.5211
	0.001	**0.9984**	**0.9998**	**1.000**
	0.0001	0.9891	0.9943	0.9959
2	0.1	0.5212	0.5215	0.5180
	0.01	0.5277	0.5278	0.5125
	0.001	**0.9934**	**0.9979**	**0.9998**
	0.0001	0.9884	0.9876	1.0000
3	0.1	0.5023	0.5040	0.5048
	0.01	0.5171	0.5215	0.5217
	0.001	0.9751	0.9980	0.9999
	0.0001	**0.9952**	**1.000**	**1.0000**

B. Results and Discussion

In the study, the multi-layer perceptron was used as baseline. The sensitivity of the multi-layer perceptron was studied using different learning rates and a variety of the number of the fully connected layers (see Tables V and VIII). The accuracy metrics are calculated to compare the effectiveness of the proposed approaches using Training and validation data sets. In general both 1DCNN trained from scratch and 1D transfer learning using CNN provides high accuracy during the training and validation. When analysing the 1DCNN training from scratch accuracy (see Tables III VI), it can be seen that the learning strategy provides high accuracy only for Learning rate (LR) is superior or equal to



(a) 1-D CNN from scratch accuracy.

(b) 1-D CNN from scratch loss.

(c) 1-D Transfer learning accuracy.

(d) 1-D Transfer learning loss.

(e) Neural network accuracy.

(f) Neural network loss.

Fig. 10. Proposed approaches behaviour during the training and validation steps.

TABLE IV. Accuracy of Convolutional Neural Network using 1-D Transfer Learning Strategy on Training Data

Model: 1D CNN				
FC layers	Learning rate	Epochs		
		100	150	200
1	0.1	0.4974	0.5047	0.5145
	0.01	0.8037	0.8362	0.8586
	0.001	**0.9074**	**0.9337**	**0.9405**
	0.0001	0.8822	0.9180	0.9391
2	0.1	0.5009	0.5131	0.5079
	0.01	0.8192	0.8589	0.8845
	0.001	**0.9072**	**0.9130**	**0.9394**
	0.0001	0.8815	0.9203	0.9318
3	0.1	0.5125	0.5093	0.5102
	0.01	0.7475	0.7487	0.7484
	0.001	**0.9245**	**0.9142**	**0.9104**
	0.0001	0.8768	0.9220	0.9271

TABLE V. Accuracy of Neural Network on Training Data

Model: NN				
FC layers	Learning rate	Epochs		
		100	150	200
1	0.1	0.5119	0.5055	0.5137
	0.01	0.5215	0.5215	0.5215
	0.001	**0.9754**	**0.9860**	**0.9875**
	0.0001	0.8026	0.8786	0.9063
2	0.1	0.5064	0.5169	0.5073
	0.01	0.5215	0.5215	0.5215
	0.001	**0.9948**	**0.9997**	**1.0000**
	0.0001	0.9729	0.9767	0.9721
3	0.1	0.5111	0.5084	0.5093
	0.01	0.5195	0.5215	0.5215
	0.001	**0.9789**	**0.9846**	**0.9968**
	0.0001	0.9500	0.9660	0.9805

0.001 for both Training and validation data and regardless of the number of the Fully connected layers. In case of 1D transfer learning strategy, it can be seen from Tables IV and VII that the model shows high accuracy for learning rate equal or superior to 0.01. Deep neural networks are very sensitive to the learning rate value. A large value of LR may result an unstable training process as is the case when using both strategies with a LR=0.1, whereas a value

TABLE VI. ACCURACY OF CONVOLUTIONAL NEURAL NETWORK TRAINED FROM SCRATCH ON VALIDATION DATA

Model: 1D CNN				
FC layers	Learning rate	Epochs		
		100	150	200
1	0.1	0.5099	0.5099	0.5099
	0.01	0.5099	0.5099	0.5099
	0.001	**1.0000**	**1.0000**	**1.000**
	0.0001	0.9971	0.9988	0.9994
2	0.1	0.5099	0.5099	0.5099
	0.01	0.5099	0.5099	0.5000
	0.001	**1.000**	**1.000**	**1.000**
	0.0001	0.9983	0.9936	1.0000
3	0.1	0.5099	0.4901	0.5099
	0.01	0.5099	0.5099	0.5099
	0.001	0.9762	0.9843	1.0000
	0.0001	**0.9988**	**1.0000**	**1.0000**

TABLE VII. ACCURACY OF CONVOLUTIONAL NEURAL NETWORK USING 1-D TRANSFER LEARNING STRATEGY ON VALIDATION DATA

Model: 1D CNN				
FC layers	Learning rate	Epochs		
		100	150	200
1	0.1	0.5099	0.5099	0.5099
	0.01	0.8558	0.8698	0.9198
	0.001	0.9215	0.9733	0.9843
	0.0001	**0.9657**	**0.9866**	**0.9953**
2	0.1	0.5099	0.5099	0.5099
	0.01	0.8552	0.8599	0.8622
	0.001	0.9320	0.9797	0.9785
	0.0001	**0.9651**	**0.9913**	**0.9907**
3	0.1	0.5099	0.5099	0.5099
	0.01	0.9209	0.9820	0.8762
	0.001	0.9651	0.9750	0.9895
	0.0001	**0.9692**	**0.9878**	**0.9913**

too small may cause a long training process but effective. Learning rate refers to the step size that the weights are updated during training. It is a configurable hyper-parameter often in the range between 0.01 and 1.0. When analysing the model behaviour during the training process, it can be seen from Fig. 10 that the multilayer perceptron is unstable compared with the 1DCNN using learning from scratch and transfer learning strategies. This can be explained by the ability of CNN to learn perfectly data dependencies using the convolution and pooling functions. It can be analyzed also that the accuracy of 1DCNN attained 98.6% without overfitting and perturbations during the training process. The 1DCNN trained from scratch exhibits superior performance compared to the transfer learning strategy and the Multilayer Perceptron. Although the transfer learning strategy and the Multilayer Perceptron achieve high accuracy, the training process lacks stability. This observation can be attributed to the remarkable ability of the 1DCNN trained from scratch to accurately capture dependencies, particularly when analyzing Etherium close price data. To evaluate and test our model architectures, we used a test data which was not used for training and validation. Fig. 11a, 11b and 11c show the confusion matrices of the proposed approaches. The x-axis is the prediction and the y-axis is the true label. We observe that the three methods work perfectly on test data

It can be seen from the Tables IX, X, XI and XII that all the used methods perform perfectly with the unseen test data.

TABLE VIII. ACCURACY OF NEURAL NETWORK ON VALIDATION DATA

Model: NN				
FC layers	Learning rate	Epochs		
		100	150	200
1	0.1	0.5099	0.5099	0.5099
	0.01	0.5099	0.5099	0.5099
	0.001	**0.9872**	**0.9988**	**0.9983**
	0.0001	0.8238	0.8715	0.8953
2	0.1	0.5099	0.5099	0.5099
	0.01	0.5099	0.5099	0.5099
	0.001	**0.9988**	**0.9994**	**1.0000**
	0.0001	0.9500	0.9448	0.9483
3	0.1	0.5099	0.5099	0.5099
	0.01	0.5099	0.5099	0.5099
	0.001	**0.9913**	**0.9930**	**0.9953**
	0.0001	0.9715	0.9866	0.9901

TABLE IX. CLASSIFICATION REPORT USING CNN FROM SCRATCH

Class	Precision	Recall	F-score	Support
0	1.00	1.00	1.00	1003
1	1.00	1.00	1.00	1146
micro avg	1.00	1.00	1.00	2149
macro avg	1.00	1.00	1.00	2149
avg	1.00	1.00	1.00	2149

TABLE X. CLASSIFICATION REPORT CNN USING TRANSFER LEARNING STRATEGY

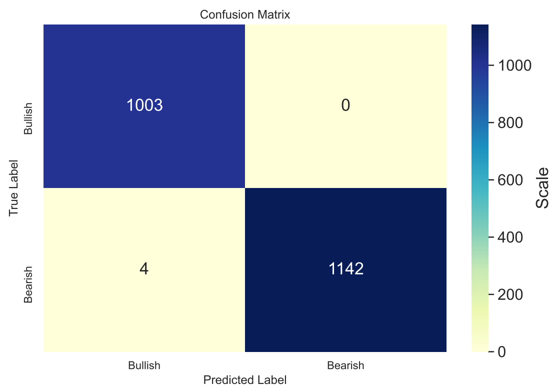
Class	Precision	Recall	F-score	Support
0	0.98	0.98	0.98	1003
1	0.98	0.98	0.98	1146
micro avg	0.98	0.98	0.98	2149
macro avg	0.98	0.98	0.98	2149
avg	0.98	0.98	0.98	2149

TABLE XI. CLASSIFICATION REPORT MLP

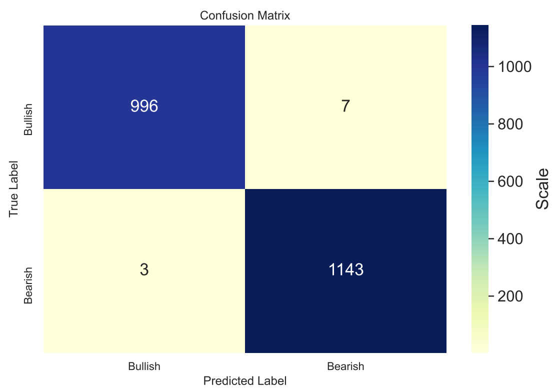
Class	Precision	Recall	F-score	Support
0	1.00	0.99	1.00	1003
1	0.99	1.00	1.00	1146
micro avg	1.00	1.00	1.00	2149
macro avg	1.00	1.00	1.00	2149
avg	1.00	1.00	1.00	2149

TABLE XII. PROPOSED MODEL STRATEGIES EVALUATION ON ACCURACY, PRECISION, RECALL AND F1 SCORE. WE USED A TEST DATA WHICH IS NOT USED IN TRAINING AND VALIDATION PROCESSES

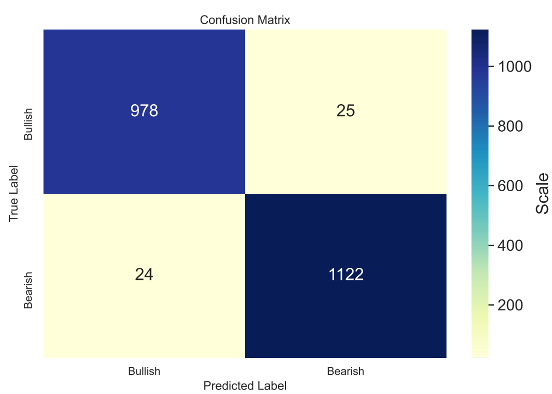
	Accuracy	Precision	Recall	F1 Score
Multi-layer perceptron	0.995	0.996	0.993	0.994
1D CNN trained fron scratch	**0.998**	**0.996**	**1.000**	**0.997**
1D CNN and transfer learning	0.977	0.976	0.975	0.975



(a) 1-D CNN from scratch confusion matrix.



(b) Multilayer perceptron confusion matrix.



(c) 1-D Transfer learning confusion matrix.

Fig. 11. Confusion matrices.

Note that the 1 dimensional Convolutional Neural Network trained from scratch obtained the highest accuracy, recall, precision and F1 score. This can be explained by the ability of the CNN to learn perfectly dependencies on providing historical data.

C. Profitability

In this section we will provide profit results based on our 1-DCNN learned from scratch entry point and trend prediction. As mentioned in Section III, our model predicts the entry point based on Simple Moving Average (SMA), Hull Moving Average (HMA) crossover and Bitcoin-Etherieum correlation. The proposed approach can predict with high accuracy the entry point and avoids the fake breakout.

Fig. 12. Profits based on 1D CNN from scratch entry point prediction.

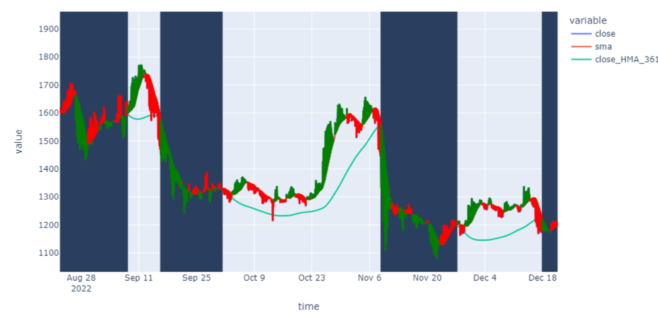


Fig. 13. Predicted positions using 1D CNN from scratch close.

Fig. 14. Profits based on MLP entry point prediction.

It can be seen from the Fig. 12 That the proposed method based on 1D CNN trained from scratch can reach a profit of 7K dollars in 6 months (from the period of 6 June 2022 to 21 December 2022). Based on predicted entry points (see Fig. 13) which is 14% of The initial Balance (50K Dollars). For the multilayer perceptron (see Fig. 14), the profit is 4.9K dollars with 9.8% of the initial balance based on predicted positions (see Fig. 15). In other side, the predictions based on transfer learning strategy (see Fig. 16) give 7% of the initial balance with a profit of

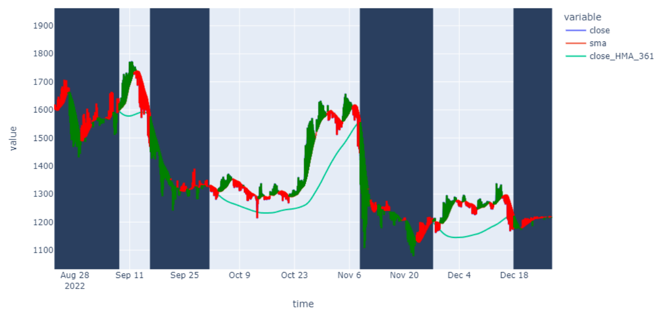


Fig. 15. Predicted positions using MLP close.

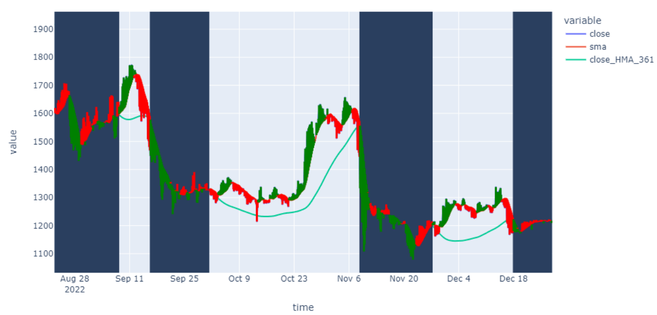


Fig. 16. Predicted positions using transfer learning close.

Fig. 17. Profits based on 1D CNN tranfer learning entry point prediction.

TABLE XIII. PROFITABILITY BASED ON ENTRY POINTS PREDICTED BY THE PROPOSED APPROACHES FOR AN ACCOUNT OF 50K DOLLARS

Proposed approach	Profits (USD)	Ppurcentage (%)
1D CNN transfer learning	3500	7%
Multilayer Perceptron	4900	9.8%
1D CNN trained fron scratch	**7000**	**14%**

3.5K Dollars (see Fig. 17). The Table XIII summarizes the profitability percentage using each of the proposed algorithms.

V. CONCLUSION

Market movement and entry point prediction using Deep learning algorithms can help traders to automate their trades and make more profits. The most important thing in trading is controlling the emotions. Indeed, fear, doubt and impulsiveness are the most common causes of capital loss. However, the solution is to employ Deep learning algorithms and a strong strategy. In our case we combined the BTC-ETH correlation with two key moving averages periods HMA(361) and SMA(19). The proposed methods yielded highly accurate results. Therefore, the trained models can be deployed and implemented in real time. Compared with the transfer learning strategy, and the MLP algorithm, the training from scratch provides a higher accuracy (99.8%). The 1D transfer learning strategy can provide better results when working with very large datasets. The difference in accuracy between the transfer learning strategy and learning from scratch is about 2%. In term of profitability using unseen data, the entry points and positions predicted by the 1DCNN from scratch can reach a profit of 14% of the initial balance compared with 7% for the transfer learning strategy and 9.8% for the multilayer perceptron. As a perspective, the proposed approach can be developed to find the relationship between several cryptocurrencies to predict the most profitable position during specific time interval. Moreover, the proposed algorithms will help to avoid fake breakouts during trading and identify the real trends.

VI. DECLARATION OF COMPETING INTEREST

I declare that I have no Conflict of Interest.

REFERENCES

[1] A. Heinz, M. Jamaloodeen, A. Saxena, and L. Pollacia, "Bullish and bearish engulfing japanese candlestick patterns: A statistical analysis on the s&p 500 index," *The Quarterly Review of Economics and Finance*, vol. 79, pp. 221–244, 2021.

[2] R. Naranjo and M. Santos, "A fuzzy decision system for money investment in stock markets based on fuzzy candlesticks pattern recognition," *Expert Systems with Applications*, vol. 133, pp. 34–48, 2019.

[3] A. Noertjahyana, Z. A. Abas, and Z. I. M. Yusoh, "Combination of candlestick pattern and stochastic to detect trend reversal in forex market," in *2019 4th Technology Innovation Management and Engineering Science International Conference (TIMES-iCON)*. IEEE, 2019, pp. 1–4.

[4] S. Kiranyaz, O. Avci, O. Abdeljaber, T. Ince, M. Gabbouj, and D. J. Inman, "1d convolutional neural networks and applications: A survey," *Mechanical systems and signal processing*, vol. 151, p. 107398, 2021.

[5] W. Tang, G. Long, L. Liu, T. Zhou, M. Blumenstein, and J. Jiang, "Omni-scale cnns: a simple and effective kernel size configuration for time series classification," in *International Conference on Learning Representations*, 2021.

[6] R. Assaf and A. Schumann, "Explainable deep neural networks for multivariate time series predictions." in *IJCAI*, 2019, pp. 6488–6490.

[7] T. Q. Feng, M. Choy, and M. N. Laik, "Predicting book sales trend using deep learning framework," *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 2, pp. 28–39, 2020.

[8] H. Lamtougui, H. El Moubtahij, H. Fouadi, A. Yahyaouy, and K. Satori, "Offline arabic handwriting recognition using deep learning: Comparative study," in *2020 International conference on intelligent systems and computer vision (ISCV)*. IEEE, 2020, pp. 1–8.

[9] Y. Yu, X. Si, C. Hu, and J. Zhang, "A review of recurrent neural networks: Lstm cells and network architectures," *Neural computation*, vol. 31, no. 7, pp. 1235–1270, 2019.

[10] A. Sherstinsky, "Fundamentals of recurrent neural network (rnn) and long short-term memory (lstm) network," *Physica D: Nonlinear Phenomena*, vol. 404, p. 132306, 2020.

[11] G. Choudakkanavar and J. A. Mangai, "A hybrid 1d-cnn-bi-lstm based model with spatial dropout for multiple fault diagnosis of roller bearing," *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 8, 2022.

[12] K. Albeladi, B. Zafar, and A. Mueen, "Time series forecasting using lstm and arima," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 1, 2023.

[13] H. Fouadi, H. El Moubtahij, H. Lamtougui, K. SATORI, and A. Yahyaouy, "Applications of deep learning in arabic sentiment analysis: Research perspective," in *2020 1st International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET)*. IEEE, 2020, pp. 1–6.

[14] R. P. Masini, M. C. Medeiros, and E. F. Mendes, "Machine learning advances for time series forecasting," *Journal of economic surveys*, vol. 37, no. 1, pp. 76–111, 2023.

[15] L. M. Bennett and W. Hu, "Filtration enlargement-based time series forecast in view of insider trading," *Journal of Economic Surveys*, 2023.

[16] Z. Hajirahimi and M. Khashei, "Hybridization of hybrid structures for time series forecasting: A review," *Artificial Intelligence Review*, vol. 56, no. 2, pp. 1201–1261, 2023.

[17] J.-H. Chen and Y.-C. Tsai, "Encoding candlesticks as images for pattern classification using convolutional neural networks," *Financial Innovation*, vol. 6, pp. 1–19, 2020.

[18] A. EL ZAAR, N. BENAYA, T. BAKIR, A. MANSOURI, and A. EL ALLATI, "Prediction of us 30-years-treasury-bonds mouvement and trading entry point using robust 1dcnn-bilstm-xgboost algorithm," 2023.

[19] P. L. Seabe, C. R. B. Moutsinga, and E. Pindza, "Forecasting cryptocurrency prices using lstm, gru, and bi-directional lstm: A deep learning approach," *Fractal and Fractional*, vol. 7, no. 2, p. 203, 2023.

[20] R. M. I. Kusuma, T.-T. Ho, W.-C. Kao, Y.-Y. Ou, and K.-L. Hua, "Using deep learning neural networks and candlestick chart representation to predict stock market," *arXiv preprint arXiv:1903.12258*, 2019.

[21] A. Andriyanto, A. Wibowo, and N. Z. Abidin, "Sectoral stock prediction using convolutional neural networks with candlestick patterns as input images," *International Journal*, vol. 8, no. 6, 2020.

[22] J.-H. Chen, S. Y.-C. Chen, Y.-C. Tsai, and C.-S. Shur, "Explainable deep convolutional candlestick learner," *arXiv preprint arXiv:2001.02767*, 2020.

[23] J. Chen, Y. Wen, Y. Nanehkaran, M. Suzauddola, W. Chen, and D. Zhang, "Machine learning techniques for stock price prediction and graphic signal recognition," *Engineering Applications of Artificial Intelligence*, vol. 121, p. 106038, 2023.

[24] S. Cavalli and M. Amoretti, "Cnn-based multivariate data analysis for bitcoin trend prediction," *Applied Soft Computing*, vol. 101, p. 107065, 2021.

[25] M. Poongodi, T. N. Nguyen, M. Hamdi, and K. Cengiz, "Global cryptocurrency trend prediction using social media," *Information Processing & Management*, vol. 58, no. 6, p. 102708, 2021.

[26] S. Alonso-Monsalve, A. L. Suárez-Cetrulo, A. Cervantes, and D. Quintana, "Convolution on neural networks for high-frequency trend prediction of cryptocurrency exchange rates using technical indicators," *Expert Systems with Applications*, vol. 149, p. 113250, 2020.

[27] M. Poongodi, A. Sharma, V. Vijayakumar, V. Bhardwaj, A. P. Sharma, R. Iqbal, and R. Kumar, "Prediction of the price of ethereum blockchain cryptocurrency in an industrial finance system," *Computers & Electrical Engineering*, vol. 81, p. 106527, 2020.

[28] T. Shintate and L. Pichl, "Trend prediction classification for high frequency bitcoin time series with deep learning," *Journal of Risk and Financial Management*, vol. 12, no. 1, p. 17, 2019.