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Deep-learning-assisted business intelligence model for cryptocurrency forecasting using social media sentiment

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Abstract

Purpose – Business Intelligence has gained a significant attraction in the recent past and facilitates managers for efficient business decision-making. Over the years, the attraction toward the cryptocurrency (CC) market has increased. Since the CC market is highly volatile, it is extremely sensitive to shocks and web data related to large events happening around the globe.

Design/methodology/approach – This research study provides a business intelligence model to predict five top-performing CCs. In this study, deep learning, linear regression and support vector regression (SVR) are used to predict CC prices. The sentiment of some mega-events is also used to enhance the performance of these models.

Findings – The results show that models of business intelligence such as deep learning and SVR provide better results. Moreover, the results show that the incorporation of social media sentiment data significantly improves the performance of the proposed models. The overall accuracy of the model improves approximately twofold when multiple event sentiments were incorporated.

Originality/value – The use of social media sentiment of global and local events for different countries along with deep learning for CC forecasting.

Keywords Business intelligence, Deep learning, Cryptocurrency forecasting, Social media sentiment

Paper type Research paper

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Introduction

In the modern global economy, digital currencies have shown a significant upbringing trend. In the last decade, virtual currencies such as cryptocurrencies (CCs) have become popular and common in worldwide financial transactions. Therefore, media and researchers have felt much attraction toward CC in recent times (Peng *et al.*, 2018). The reason behind this attraction is the innovative characteristics of CCs, their increasing acceptance and simplicity (Urquhart, 2017). In recent years, Bitcoin has become famous as the most dominant CC in the market (Katsiampa, 2017). The market capitalization of CC represents US$44bn, out of which 42% is captured by Bitcoin. Besides, CC is an attractive mode of payment because it is simpler as compared to the traditional mode of payments (Cocco *et al.*, 2017). In February 2015, around 100,000 companies accepted the presence of dominant CC like Bitcoin (Cuthbertson, 2015; Chokun, 2016).

The greatest challenge for market participants of CC is volatility, especially in Bitcoin. It is meaningful to idealize the approach that is useful to define the price movements of CC (McIntyre and Harjes, 2016). The volatility of CC (Bitcoin) is a motivation for market participants and the public to find a solution to their risk (Ciaian *et al.*, 2016). Investors earn high returns when they consider the accurate prediction of price movements (Huang *et al.*, 2005). In recent times, the number of studies regarding time series prediction of CC has increased. Some of these studies explore the important factors and attributes correlated with the variation of Bitcoin price (Andrews, 1993; Kristoufek 2013, 2015; Greaves and Au, 2015). Researchers suggest that the exchange rate behavior of Bitcoin is predictable (Kim *et al.*, 2016). Public opinions on social media platforms are important factors that influence the trading behavior of CC market participants (Garcia and Schweitzer, 2015). Moreover, in CC prediction, online platforms are very common where communities make their opinion about market events (Linton *et al.*, 2017). Several researches have targeted the relationship between CC and twitter to predict the prices (Garcia *et al.*, 2014; Garcia and Schweitzer, 2015). The CC market is highly volatile, therefore investment decisions get influenced by the sentiment triggered by the mega-events of different natures. Also, the social media sentiment of multiple events of dynamic nature remains underexplored in literature.

Therefore, this research study considers the five top-performing CCs and uses the support vector regression (SVR) and deep learning (DL) model of forecasting in the presence of investor sentiment. For this purpose, we collect the daily data of Bitcoin, Litecoin, Dash, Monero and Stellar CC over the period from April 2013 to November 2019. We consider the twitter data set of five mega-events for calculation of sentiment. The results of DL assisted the business intelligence model to improve when relevant input parameters increase. For this reason, we incorporate the event sentiment as an input of the DL model, and our results show that the accuracy has improved by twofold approximately. Finally, we compare our findings of DL and SVR with the linear regression, which is the most widely used technique of forecasting in econometrics.

This research study has several significant additions to the existing literature, which are discussed as follows.

(1) We use DL-assisted business intelligence models to predict cryptocurrencies, which provides more accurate results as compared to the existing econometric model of linear regression.

(2) We incorporate the twitter sentiment of multiple mega-events of dynamic nature happening across the globe as a factor to predict CC.

(3) We present a comparative analysis of forecasting based on machine learning models (SVR and DL) and linear regression.

This research study is organized as follows: the precise relevant literature is discussed in section 2, section 3 discusses data and methodology, results and discussion are presented in section 4, which is followed by the conclusion.

Literature review

The related work on CC prediction is divided into two main categories. In the first category, researchers have used econometric models to predict CC. Linear regression is a commonly used model in time series forecasting. On the other hand, there are several studies targeting CC prediction through machine learning algorithms. The detailed literature review is as follows.

Econometric model in cryptocurrency domain

In the literature, most of the studies related to CC are explanatory. One side of the literature focuses on the studies that use econometric-based techniques such as quantile regression, ordinary least square (OLS), vector autoregressive (VAR) and vector error correction (VEC). The main aim of these studies is to explore the significant factors to determine Bitcoin's price and returns. Some of the studies focus on the price formation of Bitcoin CC. Using the Granger causality test, a similar study presents the evidence that the Bitcoin prices Granger-cause the exchange-traded ratio in the short run. Furthermore, macroeconomic factors such as the US dollar index and consumer price index are also significant drivers of Bitcoin price movements (Zhu *et al.*, 2017). Apart from macroeconomic factors, market-specific fundamentals such as trading volume also affect Bitcoin prices. It is important to capture the nonlinearity and tail behavior while investigating the casual relationship among trading volume and Bitcoin prices. Daily data from December 2011 to April 2016 was used to predict Bitcoin returns. The results of the causality-in-quantile test show that volume can predict Bitcoin returns (Balcilar *et al.*, 2017). Some of the previous studies consider the past conditional volatility to predict the present volatility of Bitcoin. They follow GARCH (generalized autoregressive conditional heteroskedasticity)-based models to predict the daily volatility of Bitcoin prices, for example (Katsiampa, 2017). In time series forecasting, the problem of the nonlinear trends and structural changes is very common. For this reason, machine learning and neural network models are used to address these issues.

Machine learning

The other side of existing knowledge focuses on CC prediction using models of machine learning and artificial intelligence. There exists a handful of studies in the literature that predict the Bitcoin market. Binomial regressions, random forest algorithms and SVR are used to predict the sign of Bitcoin price changes. In a similar context, it is suggested to strategize the trading based on Bayesian regression models because it yields better returns when real data is used for testing (Shah and Zhang, 2014). The accuracy is approximately 55% for the up and down price movement of Bitcoin using optimization techniques of machine learning (Greaves and Au, 2015). A similar study uses Bayesian neural networks (BNN) and compared the results with SVR and linear model. This research parameterized the BNN to predict log prices and log volatility of three CC (Bitcoin, Ethereum and Dash) and three traditional currencies, that is, Euro, British Pound and Japanese Yen (Jang and Lee, 2018). Furthermore, GARCH and SVR have been combined in research, and results yield the evidence that *RMSE* and *MAE* of low-frequency data are much higher than the high-frequency data (Peng *et al.*, 2018). Similarly the prices of three CC namely Bitcoin, Ethereum and Ripple were predicted using the data collected from the coin desk. In this study, all the attributes were used as the inputs of the recurrent neural network (RNN) and long short-term memory network (LSTM) models. The results provide evidence that LSTM is a more accurate model (Christie and Huang, 1995a, b, McNally, 2016).

Several systems have been proposed regarding the trading strategies of CC. These systems are based on neural networks (NN) (Nakano *et al.*, 2018; Atsalakis *et al.*, 2019). Besides, generalized regression neural network (GRNN) has been used to predict Dash, Ripple and Bitcoin. This study also provides the evidence that *RMSE* of LSTMs based on daily data is 50% more accurate than GRNN (Lahmiri and Bekiros, 2019). A similar study used the LSTM to predict the daily price movements of different cryptocurrencies and found it more accurate as compared to gradient boosting model (Kwon *et al.*, 2019).

In the CC market, decision-making is also sensitive toward the information spread through word of mouth. The reason is that market participants show irrational behavior when they encounter the same information (Heimer, 2016). Sentiments based on online communities and platforms are crucial in the case of CC (Georgoula *et al.*, 2015; Polasik *et al.*, 2015). A study regarding Bitcoin price prediction incorporates the social signals related to information search and volume of word of mouth as an input. In this study, the twitter data set regarding Bitcoin for three years was used (Garcia and Schweitzer, 2015). Similarly, market sentiments act as driving factors for determining the Bitcoin exchange rate (Makrichoriti and Moratis, 2016). Therefore, in this research, we used the social media sentiment of some mega-events to predict the top five CCs. We use machine learning algorithms, SVR and DL by incorporating the twitter sentiment of mega-events as an input.

Data and methodology

The proposed methodology consists of three steps. In the first step, we collect the required data set of the top five CCs. In the second step, we perform a sentiment analysis of mega-events based on 9m tweets. In the last step, we predict the top five CCs. The data set includes open, close, high, low, volume and market capitalization of each currency. We use three different approaches to predict five top-performing CCs. Firstly, we use linear regression, SVR and DL model without incorporating social media sentiment. In the second step, we incorporate social media sentiment of multiple events of dynamic nature and predict five selected CC. A flow chart of the proposed methodology is presented in Figure 1.

It is easy to deduce that not all the CCs have the same starting dates because the CC market is relatively new. Table 1 shows a detailed data description of the top five CCs.

Sentiment analysis for twitter events

We start our sentiment analysis by applying Alex Davies word list (Christie and Huang, 1995a, b). We used this approach to check whether the simple approach is enough to compare the market movement. We classified the word list of 5,000 words into three categories, that is, positive, negative and neutral. In this process, a word list is prepared by tokenizing the tweets. The parsing algorithm is used for whitespace, punctuation, emotions and URL removal. An accurate and efficient dictionary is used to classify tweets into the positive, negative and neutral category. Furthermore, we used a separate list of 4,000 words to improve the training. Since this word list considers multiword expression and relationship of each word, it provides better results. Daily tweets are represented as percentages of positive, negative and neutral categories. Later on, positive and negative tweets are used to calculate the net expression of the daily sentiment.

We applied sentiment analysis using the twitter data set for the variety of mega-events that happened across the globe (Zubiaga, 2018). Table 2 shows the detail of the multiple

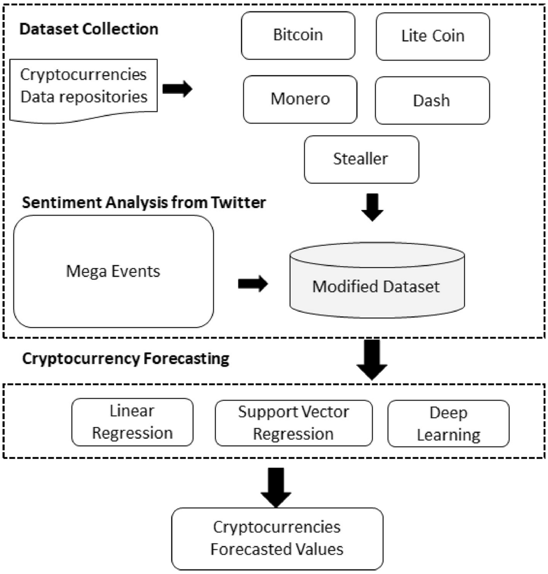

Figure 1. Methodology for cryptocurrency prediction

Table 1. Data description

Cryptocurrency		Range of data Starting date	Ending date	No of observations
1	Bitcoin	28-Apr-13	2-Apr-19	2,166
2	Litecoin	28-Apr-13	2-Apr-19	2,166
3	Dash	14-Feb-14	2-Apr-19	1874
4	Monero	21-May-14	2-Apr-19	1777
5	Stellar	5-Aug-14	2-Apr-19	1702

Table 2. Details of events and respective tweets

Events	Tweets	Events	Tweets
Gaza Attack 2014	2,886,322	Refugee Welcome 2015	1,743,153
Brexit 2016	1,826,290	Lahore Blast 2016	1,149,253
Hong Kong Protest (2014)	1,188,372		

events of dynamic nature along with the number of tweets in response to those events. Later on, we predict the selected top five CCs by using linear regression, SVR and DL models.

Forecasting models

SVR

By using the theory of statistical learning algorithms, SVM is proposed to control the structural risks proposed (Christie and Huang, 1995a, b, Sousa *et al.*, 2014). Later on, researchers augmented the original version of SVM, which is commonly used in modern researches to forecast time series data. (Sousa *et al.*, 2014).

Let's assume the following time series data.

$$D = (X_i, y_i)s, \quad 1 \le i \le N \tag{1}$$

In Eq. (1) X_i shows the given input with N elements at the time i and y_i represents the relevant output.

Following is the regression form of the assumed data set.

$$f(X_i) = W^T \varphi(X_i) + b \tag{2}$$

In equation (2), W and b represent weight and bias. X is an input vector, which is mapped by ϕ*(X)* into a higher-dimensional space. To find out the values of W and b, the following optimization problem is solved in equations (3) and (4).

$$Min 1/2 \ \|W\|2 + C\sum i = 1N(\varepsilon i + \varepsilon \cdot i \cdot *) \tag{3}$$

Subject to:

$$\begin{aligned} & yi - WT(\phi(x)) - b \le \xi + \varepsilon i \\ & WT(\phi(x)) + b - yi \le \xi + \varepsilon \cdot I \cdot * \\ & \varepsilon i, \varepsilon \cdot i \cdot * \ge 0 \end{aligned} \tag{4}$$

Here C shows the trade-off parameter between generalizability and simplicity, whereas the slack variables used for the cost of errors are represented by ξi and $\xi * i$. To use the linear regression model, the kernel trick is used to transform the data to higher dimensions. The regression is obtained using equation (5).

$$yi = f(X_i) = N\sum i = 1((\alpha i - \alpha i^*) \ K(X_i, X_j)) + b \tag{5}$$

Here Lagrange multipliers are represented by αi and $\alpha * I$, and equation (6) represents Gaussian radial function.

$$K(X_i, X_j) = \exp(-\|X_i - X_j\|2/(2\sigma \cdot 2)) \tag{6}$$

Linear regression

Time series data is predicted using linear models because of its simplicity in nature. In our data analysis, we use multiple exogenous and single endogenous variables. In linear regression model, we assume y as an endogenous variable having a linear relationship with the k exogenous variables $X_1, X_2, X_3, ..X_k$.

$$y = X_1\beta_1 + X_1\beta_1 + ...X_k\beta_k + \varepsilon \tag{7}$$

Also, $\beta_1, \beta_2, \beta_3 ... \beta_k$ are the given parameters. The $X_1, X_2, ... X_k$ are the coefficients and ε is the difference between actual and observed values.

β_j is the jth slope coefficient of explanatory variable X_j. It is defined as the expected change in dependent variable y due to a unit change in jth independent variable X_j. Assuming $E(\varepsilon) = 0$,

$$\beta_j = \partial E(y)/\partial X_j \tag{8}$$

Deep learning

The aim of using a DL approach is to obtain more robust results. The DL model is based on hidden layers where input is converted to feature space. Later on, the nonlinear function is applied, which continues until the process reaches the output layer. So NN is the process of information flow through hidden layers to get the output. In this study, we use a DL approach that is composed of a large number of neurons and hidden layers. Also, these layers are interlinked and perform in parallel. In regression models, this DL approach is commonly used. In the training process if the frequency of the data is increased, then it improves the performance of the model. The DL architecture consists of input layer, convolutional layers, pooling layers, rectified linear unit layers and fully connected layers. We used CNN and all the parameters are used with their default values (Nazir *et al.*, 2019). The details of the architecture are explained here:

Input layer. This is where the data set is provided as an input, and our data set consists of open, close, high, low, volume, market capitalization. Furthermore, we have also used the sentiment as a feature, so it is also used as an input.

Convolutional layers. These layers are the main core layers where extreme computations are performed. The layers perform all the convolutions and forward the response to the next layers for further processing. These layers have kernels known as filters that are spread over data to produce a 1D activation map.

Pooling layers. These layers are used between the convolutional layers to reduce the computational complexities. These layers are independent of the output depth, which is used as input for these layers. In this study, the pooling layer is used with size 2.

Fully connected layers. The high-level reasoning is done in fully connected layers after various convolutional and pooling layers. The neurons present in these layers are connected to the previous layers. This work has five convolutional layers with the same kernel size with the exception to the first layer, which has 96 kernels of size 1. The normalized output of the convolutional layer was received from the pooling layer and passed as an input to the next layer. The kernel sizes for the third and fourth layers are 384 while 256 kernels are used for the fifth layer. Similarly, the normalized and reduced output from the second layer is forwarded to the next layers. The 70–30 ratio is used for training and testing where 70% of data is used for training and 30% for testing.

Evaluation metrics

In time series, different evaluation metrics are used for prediction. These metrics are measured by taking the difference between actual and predicted values. (Economou *et al.*, 2011; Balcilar *et al.*, 2017). *RMSE* and *MAE* are commonly used as evaluation metrics in time series forecasting models. These are discussed as follows.

Root mean squared error – *RMSE.* To calculate *RMSE*, we use the following formula. It represents the average magnitude of the estimated error of forecasted values.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(\text{forecast}(t) - \text{actual}(t))^2}{n}} \tag{9}$$

Mean absolute error – *MAE.* This evaluation parameter is most widely used in time series forecasting. It is mean of the difference between actual and predicted values. In this case, we only consider the sign of the forecasted values. It can be calculated as:

$$MAE = \frac{\sum_{t=1}^{n}|\text{forecast}(t) - \text{actual}(t)|}{n} \tag{10}$$

Here, the difference between actual and forecasted values is taken and n is the total number of values.

Experimentation and results

This section presents the process of experimentation and the main results in detail.

Descriptive statistics

The descriptive statistics of five top-performing CCs are shown in Table 3.

The probability of the Jarque–Bera test is significant, which is the evidence that our data set of all the top five CCs follows no normal distribution. Due to a lack of availability of data, we could only find a limited data set. Since Bitcoin is the leading CC in the market, it has the highest mean, median and standard deviation. Furthermore, several observations are 2,166 in the case of Bitcoin. All the results are presented in Table 3.

Unit root

In time series data, the problem of stationarity is very common, and it needs to be addressed to get reliable results of the regression. When the mean and variance of a series are time-dependent, that is, mean and variance change overtime, then the data set is said to be nonstationary. In time series, the data set has to be stationary for reliable testing. This problem is called the unit root problem, and the augmented Dickey–Fuller test (ADF) is commonly used in the literature to check out the existence of the unit root problem. ADF tests the null hypothesis of unit root against the alternative no unit root. Linear regression provides reliable results if data has no unit root problem, which means that data series is stationary and H_1 is accepted.

In Table 4 we present the results of ADF test, which is applied to the top five CCs. The null hypothesis cannot be accepted when the ADF test statistic is greater than the critical value. Our results show that all the CCs are nonstationary at level except Dash. However, they become stationary when we take the first difference in the unit root equation. ADF test statistic using first difference in the unit root equation provides the calculated value, which is

Table 3.
Summary of the data

Currency	Mean	Median	Std. Dev	Jarque–Bera	Prob	Obs
Bitcoin	2373.443	623.060	3357.245	2807.666***	0.000	2166
Litecoin	31.685	4.6050	52.767	8780.965***	0.000	2166
Dash	120.888	9.910	215.799	9151.233***	0.000	1874
Monero	53.729	7.890	86.833	2797.080***	0.000	1777
Stellar	2.2656	1.820	1.589	78.972***	0.000	548

Note(s): *** represents the significance at 1%

Table 4.
Stationarity test

Currency	ADF test stat Level	First difference	Critical value (5%)
Bitcoin	−2.009	−8.595***	−2.862
Litecoin	−2.670	−8.275***	−2.862
Dash	−3.131**		−2.862
Monero	−2.286	−13.501***	−2.862
Stellar	−2.487	−12.368	−2.862

Note(s): **, *** represents the significance at 5% and 1%

greater than the critical value of −2.862 at 5%. Therefore, CCs of Bitcoin, Litecoin, Monero and Stellar are stationary at first difference.

Without sentiment

In this section, we present the prediction results of the top five CCs. We used different regression models namely LR, SVR and DL. The algorithms are trained using a 70–30 ratio; 70% data for training and 30% for testing. These three models were used with their default settings in our first experiment. For this purpose, daily data of all the five CCs was used. We predicted "close" value of CC by using open, low, high, trade volume and market capitalization as input parameters. Table 5 shows the results of both the evaluation parameters, that is, *RMSE* and *MAE*. The results provide the evidence that DL and SVR are more accurate than LR in case of all five CCs except Bitcoin and Litecoin where only SVR was more accurate than linear regression. As a whole SVR provides more accurate results considering all the five CCs. In this context, it is argued that SVR and DL-assisted business intelligence models yield more accurate results as compared to the state-of-the-art econometric model of forecasting.

Figure 2 shows the sketch of 700 predicted and actual values of Bitcoin and Litecoin CCs using the models of DL, SVR and LR. The results show that forecasted values for DL and SVR are better.

Figure 3 presents the sketch of 600 predicted and actual values of Monero, Dash and Stellar CCs using LR, SVR and DL models. It is clear that the difference between predicted and actual values is minimum in case of DL model.

With sentiment

In this section, we present the results of the second experiment that was conducted by considering the sentiment of twitter data set of mega-events. We predict the top five CCs using the multiple event sentiments data as an additional input. Table 6 shows the results of LR, SVR and DL models by incorporating the event sentiment of Gaza Attack (2014), Refugees Welcome 2015, Hong Kong protest 2014 and Brexit 2016 for Bitcoin CC. The results show that linear regression provides the least predictive power as compared to SVR and DL for Bitcoin, which is the top-performing CC. It is evident from the results that linear regression performs poorly as compared to SVR. The results document the evidence that in the presence of multiple event sentiments, the performance of DL has significantly improved except for the event sentiment of Refugee Welcome (2015). This indicates that the sentiment of Refugees Welcome (2015) is the least significant input as compared to other events. To maintain simplicity, the forecasted values are not plotted against the actual values.

Table 7 shows the results of LR, SVR and DL models by incorporating the event sentiment of Gaza (2014), Brexit 2016, Refugees Welcome 2015, Lahore Blast 2016 and Hong Kong protest 2014 for Litecoin CC. *MAE* and *RMSE* show that SVR and DL models provide more accurate results as compared to LR when event sentiment was taken as an input parameter. The results document the evidence that in the presence of multiple event sentiments, the performance of DL has significantly improved.

Table 8 shows the results of LR, SVR and DL models by incorporating the event sentiment of Gaza Attack (2014), Brexit 2016, Refugees Welcome 2015 and Hong Kong protest 2014 for Monero CC. The results of LR and DL improved when event sentiment of Gaza (2014) and Hong Kong protest 2014 was incorporated. Furthermore, DL and SVR provide more accurate results as compared to LR when event sentiment was taken as an input parameter.

Table 5.
Results of top five CCs without sentiment

W/O sentiment	Mean absolute error (MAE) Linear regression	Support vector regression	Deep learning	Root mean squared error (RMSE) LR	SVR	DP
Bitcoin	984.977 ± 943.664	27.451 ± 31.610	68.056 ± 48.188	1364.068 ± 0.000	41.865 ± 0.000	83.389 ± 0.000
Dash	8.256 ± 11.308	2.600 ± 3.548	3.634 ± 4.275	14.001 ± 0.000	4.399 ± 0.000	5.611 ± 0.000
Litecoin	1.282 ± 2.233	0.731 ± 1.280	1.994 ± 1.960	2.575 ± 0.000	1.475 ± 0.000	2.796 ± 0.000
Monero	2.359 ± 4.361	1.150 ± 1.683	1.553 ± 1.553	4.958 ± 0.000	2.038 ± 0.000	2.196 ± 0.000
Stellar	0.004 ± 0.008	0.002 ± 0.003	0.002 ± 0.003	0.010 ± 0.000	0.003 ± 0.000	0.003 ± 0.000

Table 9 shows the results of the LR, SVR and DL models by incorporating the event sentiment of Brexit (2016), Refugees Welcome 2015, Gaza Attack 2014 and Hong Kong protest 2014 for Dash CC. It is evident that the results improve after incorporating sentiment. The results also document the evidence that in the presence of multiple event sentiments, the performance of the DL model is better than SVR and LR.

In Table 10 we present the results of LR, SVR and DL models by incorporating the event sentiment of Brexit (2016), Refugees Welcome 2015, Gaza 2014 and Hong Kong protest 2014 for Dash CC.

The results suggest that event sentiment improves the performance of the classifiers during prediction. The results also document the evidence that in the presence of multiple event sentiments, the model of DL provides better results in comparison with SVR and LR.

Conclusion

In this study, a business-intelligence-based DL technique is proposed to predict the five top-performing CCs. We used daily data of CCs from April 2013 to April 2019. This study considers open, high, low, trading volume, market capitalization and multiple event sentiments as features to train the system. We used the twitter sentiments of the events, namely Brexit 2016, Lahore Blast 2014, Refugee Welcome 2015, Hong Kong protest 2014 and Gaza attack 2014. The five mega twitter events are used to calculate the sentiment consisting of around 9m tweets. We processed the textual data of almost 9m tweets in response to these five mega-events to calculate the event sentiment. Our results suggest that a business-intelligence-based DL and SVR model provides more accurate results as compared to the commonly used linear regression model. The sentiment of the mega-events also improved the performance of the algorithms. As a whole, the results of the DL model improved approximately twofold when event sentiments were incorporated in the model as an input. This study extends the literature on CC forecasting by using sentimental analysis in DL-assisted business intelligence models. In this context, the CC market turns out to be more sensitive toward public opinion on social media. Therefore, CC market regulators should consider this volatile behavior to avoid market crashes. Keeping this in view, individual investors should carefully construct their investment portfolios in the CC market and avoid irrational public herds on social media.

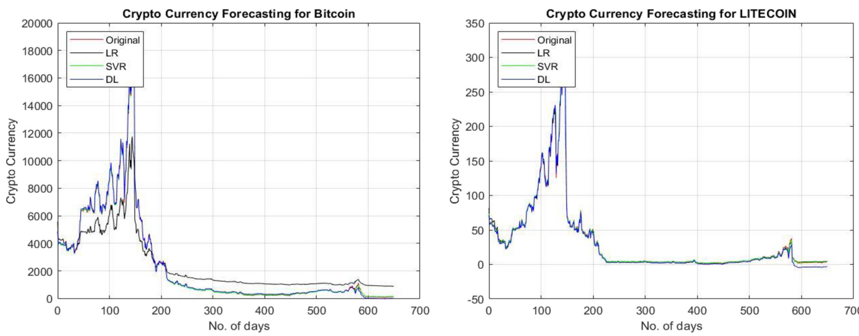

Figure 2. Graphs show random 700 forecasted values for original, linear regression, SVM and DL for Bitcoin and Litecoin CCs

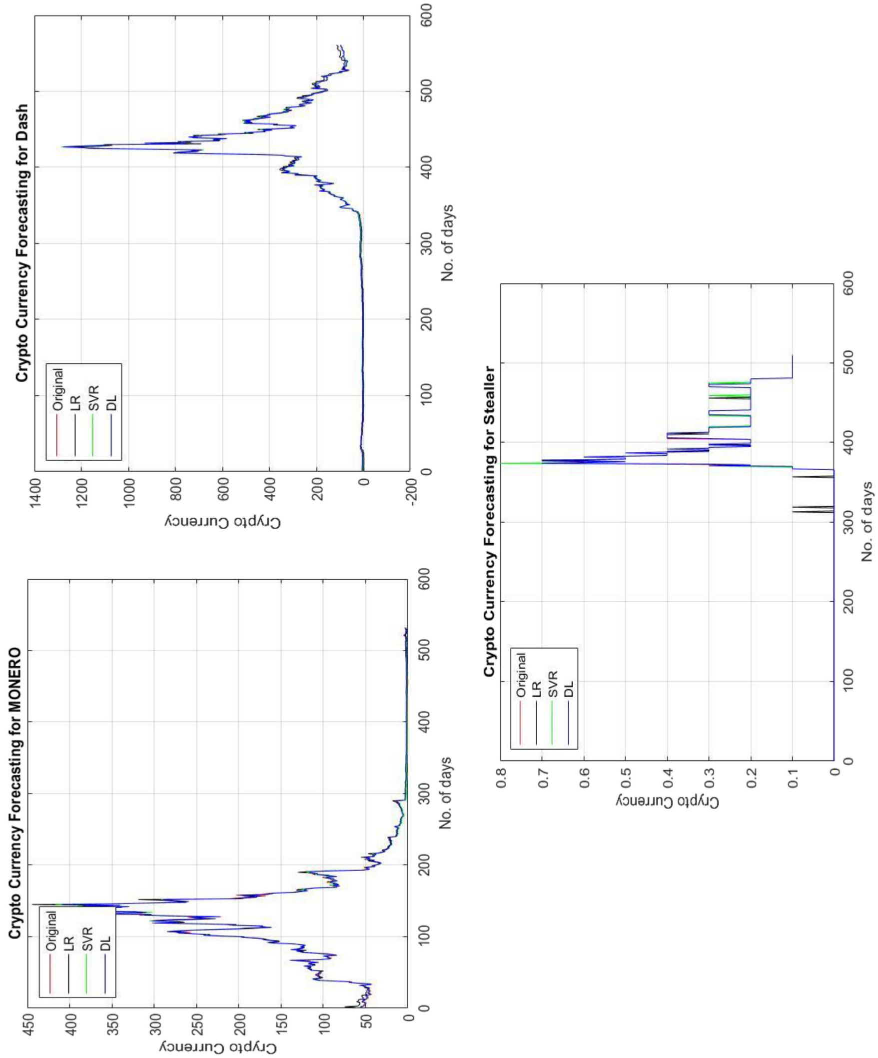

Figure 3.
Graphs show random 600 forecasted values for original, linear regression, SVM and DL for Monero, Dash and Stellar CCs

Table 6. Results of Bitcoin with multiple event sentiments

Bitcoin sentiment	Mean absolute error (MAE)			Root mean squared error (RMSE)		
	Linear regression	Support vector regression	Deep learning	LR	SVR	DL
Gaza	1125.129 ± 811.337	28.488 ± 33.321	45.124 ± 36.397	1387.149 ± 0.000	43.839 ± 0.000	57.973 ± 0.000
Refugee	1306.349 ± 967.806	34.620 ± 33.627	78.996 ± 46.169	1625.791 ± 0.000	48.263 ± 0.000	91.499 ± 0.000
Hong Kong	1208.420 ± 965.820	27.466 ± 31.972	41.267 ± 54.917	1546.961 ± 0.000	42.150 ± 0.000	68.694 ± 0.000
Brexit	1399.367 ± 987.678	31.311 ± 29.388	50.187 ± 47.368	1712.815 ± 0.000	42.943 ± 0.000	69.011 ± 0.000

Table 7.
Results of Litecoin with multiple event sentiments

Lite coin sentiment	Mean absolute error (MAE) Linear regression	Support vector regression	Deep learning	Root mean squared error (RMSE) LR	SVR	DL
Gaza	1.051 ± 1.819	0.658 ± 1.134	1.090 ± 1.301	2.101 ± 0.000	1.311 ± 0.000	1.698 ± 0.000
Refugee	1.664 ± 2.545	0.914 ± 1.157	1.158 ± 1.052	3.041 ± 0.000	1.475 ± 0.000	1.565 ± 0.000
Hong Kong	1.270 ± 2.461	0.668 ± 1.018	0.712 ± 1.074	2.769 ± 0.000	1.217 ± 0.000	1.289 ± 0.000
Brexit	1.850 ± 3.404	0.826 ± 0.959	1.943 ± 1.458	3.874 ± 0.000	1.266 ± 0.000	2.429 ± 0.000
Lahore	1.756 ± 2.375	0.827 ± 1.009	2.045 ± 1.100	2.954 ± 0.000	1.305 ± 0.000	2.322 ± 0.000

Table 8.
Results of Monero with multiple event sentiments

Monero sentiment	Mean absolute error (MAE) Linear regression	Support vector regression	Deep learning	Root mean squared error (RMSE) LR	SVR	DL
Gaza	2.342 ± 4.145	1.205 ± 1.685	1.238 ± 1.600	4.761 ± 0.000	2.071 ± 0.000	2.023 ± 0.000
Refugee	3.019 ± 5.085	1.415 ± 1.607	2.207 ± 1.544	5.913 ± 0.000	2.142 ± 0.000	2.693 ± 0.000
Hong Kong	2.247 ± 3.529	1.153 ± 1.469	1.372 ± 1.284	4.184 ± 0.000	1.868 ± 0.000	1.879 ± 0.000
Brexit	3.607 ± 5.678	1.334 ± 1.657	2.029 ± 2.349	6.727 ± 0.000	2.127 ± 0.000	3.104 ± 0.000

Table 9.
Results of dash with multiple event sentiments

Dash sentiment	Mean absolute error (MAE) Linear regression	Support vector regression	Deep learning	Root mean squared error (RMSE) LR	SVR	DL
Refugee	0.187 ± 0.175	0.065 ± 0.092	0.021 ± 0.027	0.256	0.113	0.034
Brexit	0.125 ± 0.217	0.099 ± 0.242	0.033 ± 0.038	0.250	0.261	0.050
Hong Kong	0.219 ± 0.397	0.038 ± 0.040	0.036 ± 0.029	0.453	0.055	0.046
Gaza	0.336 ± 0.415	0.072 ± 0.083	0.064 ± 0.060	0.534	0.110	0.088

Table 10.
Results of stellar with multiple event sentiment

Stellar sentiment	Mean absolute error (MAE) Linear regression	Support vector regression	Deep learning	Root mean squared error (RMSE) LR	SVR	DL
Refugee	0.000 ± 0.000	0.000 ± 0.000	0.000 ± 0.000	0.000 ± 0.000	0.000 ± 0.000	0.000 ± 0.000
Brexit	0.000 ± 0.000	0.000 ± 0.000	0.000 ± 0.000	0.000 ± 0.000	0.000 ± 0.000	0.000 ± 0.000
Hong Kong	0.000 ± 0.000	0.000 ± 0.000	0.000 ± 0.000	0.000 ± 0.000	0.000 ± 0.000	0.000 ± 0.000

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