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Manipulator Detection in Cryptocurrency Markets Based on Forecasting Anomalies

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ABSTRACT Today, there are constant changes in terms of securities in stock markets. In these stock market investments, investors use fundamental analysis tools and indicators very widely. In this way, it is possible to have some knowledge of the situations experienced in the markets and to make a profit. In this study, manipulations on Bitcoin are discussed. Popular machine and statistical forecasting methods have been used to detect these manipulations and the road maps to be followed in order to be detected in the most successful way have been shared. Social media sentiments, which were thought to have an effect on manipulations during the studies, were also evaluated with the most advanced text analysis methods and evaluated together with these price changes. The allegations that the prediction methods carried out before the crisis were more successful were investigated. The Covid-19 pandemic was evaluated as a period of global crisis and the studies that might be relevant were examined. It would not be wrong to say that the actors that make big gains in the stock markets are the ones that determine the direction of the stock market. The manipulation periods of the market actors to be successful in the virtual money markets have been tried to be verified by various estimation methods. These estimations can achieve up to F_1 score of 93% success according to our experimental result. Besides, it is stated that accounts with the highest volume of transactions in the periods, when anomalies were detected, were labeled as potential manipulators.

INDEX TERMS Anomaly detection, cryptocurrency markets, manipulator detection, machine learning, deep learning, time series analysis, sentiment analysis, Covid-19 pandemic.

I. INTRODUCTION

Manipulations play the most important role in the upward and downward trend of prices. If the stock market trend is up over a prolonged period of time then it is called a bull market. On the other hand, it is called a bear market when the stock market trend goes down. Investors who make instant oversold that cause it to go down are called ''bear'', while investors who realize the upward price increases by making instant overbought are called ''bull'' [1]. In fact, 'bear' and 'bull' investors are the same investors and are called whales in the market because they hold large amounts of cash and virtual currency.

Accounts hosting virtual currencies that are not a central authority do not necessarily belong to a real person or institution. Therefore, it becomes almost impossible to detect manipulator persons or institutions. At this point, blockchain transfer transactions are seen as the only reference source for how much input and output from which accounts. In terms of protecting investors, many applications that detect whales can be found through search engines. However, their reliability or basis cannot be verified and shared by any trusted authority.

In the study carried out, Bitcoin has been the reason of choice for the review, both because it is the first virtual currency and because it has the largest monetary volume in the virtual money market. The main motivation that drives us to do this study is that there is no general definition of manipulation. Therefore, by trying to detect all types of manipulation with machine learning and other methods used in the field of artificial intelligence, it is to reveal how effective the manipulators behind all these events can be in the

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detection phase. Machine learning, especially deep learning, has been used in multiple fields and industries [2]–[4].

Additionally, we achieved some experiments about manipulations happened in economically crisis periods which might be the reason of price changes on stock markets.

The experiments carried out are not only based on the analysis of daily, monthly, weekly or annual price data with artificial intelligence methods, but also consider the effect of sentiment analysis on social media on manipulations. Before this study, the Iterative Semi-Supervised Feature Selection (ISSFS) method [5], which we developed in order to analyze the text data more successfully, was also applied, and some solution suggestions were shared to further improve the sentiment analysis results of the method.

This study carefully examines the literature that investigates the detection of manipulations in crypto exchanges. First, it considers the ISSFS method bug that may lead to low performance problems on sentiment analysis experimental phases by working on big datasets. Successful forecasting methods in pricing and advanced sentiment analysis methods are examined, then adapted for the realistic scenario. At the last stage, manipulation points are determined with successful forecasting methods, followed by determining potential manipulation periods with the help of anomaly detection.

We prefer to use an anomaly detection to solve this problem because no publicly shared official data about real manipulator accounts. That's why we shared our results as potential manipulator accounts in the results section.

Shortly, main contribution points can be described in the following points:

- To identify potential manipulators in cryptocurrency markets more accurate and fastest as possible.
- Social media emotions impacts were investigated for manipulation periods.
- This is the first study that inspects manipulators by considering price anomalies in cryptocurrency sector.
- This is the first study that shared feasible business solution model to detect potential stock market manipulators on finance sector.
- It consists of performance improvements and optimization studies about ISSFS method.
- Elements that might affect the performance of successful forecasting methods used at the stock markets have been investigated in detail.

Overall, the rest of the article is organized as follows. Section 2 presents the corresponding literature. The methodology and experimental studies are discussed in Sections 3 and 4, respectively. The final section involves the result, discussion and conclusion. All studies in the article has been illustrated briefly on Figure 1. As you seen in the Figure 1, beginning from up to down, it is shown all experimental studies respectively.

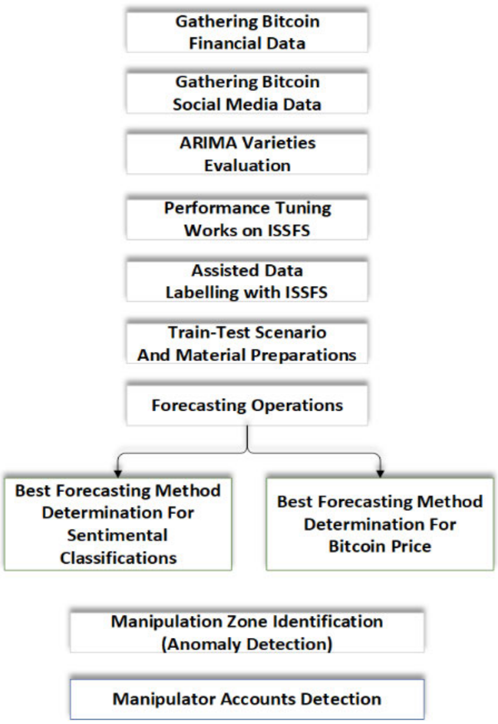

FIGURE 1. Experimental outline of studies.

II. RELATED WORKS

When the studies in the literature are examined, Aggarwal *et al.* [6] argue that the manipulations are beneficial in the growth of potentially deteriorating markets, given information about stock manipulations. They state that the biggest tool used by manipulators for manipulation is to provide liquidity.

Keidar et. al. [7] draw attention to the stock market abuse in blockchain exchanges and emphasize that a regulation for high volume and variable pricing is required for all global markets.

Babayan [8] draws attention to the 85% price drop in Bitcoin in 2018. The driving factor behind these drastic price changes is the low total monetary volume in crypto money markets. Until the first period of 2020, the total volume of virtual currencies is about 0.1% of the volume of global exchanges. Global market volumes shared by Desjardins [9] are shown in Table 1.

For this reason, it is possible for large investors to create big waves in relatively shallow virtual currency exchanges with less money. Thanks to these waves, they can easily affect prices in the direction they want. Looking at this situation by small investors, they identify overbought and oversold areas using technical analysis tools such as Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), Trend lines. Thus, they gain from the price fluctuations.

The critical point here is that the movement that will cause the trend line to break up or down is carried out by

TABLE 1. Global market volumes [9].

Category	Value ($ Billions, USD)	Source
Silver	$44	World Silver Survey 2019
Cryptocurrencies	$244	CoinMarketCap
Global Military Spending	$1,782	World Bank
U.S. Federal Deficit (FY 2020)	$3,800	U.S. CBO (Projected, as of April 2020)
Coins & Bank Notes	$6,662	BIS
Fed's Balance Sheet	$7,037	U.S. Federal Reserve
The World's Billionaires	$8,000	Forbes
Gold	$10,891	World Gold Council (2020)
The Fortune 500	$22,600	Fortune 500 (2019 list)
Stock Markets	$89,475	WFE (April 2020)
Narrow Money Supply	$35,183	CIA Factbook
Broad Money Supply	$95,698	CIA Factbook
Global Debt	$252,600	IIF Debt Monitor
Global Real Estate	$280,600	Savills Global Research (2018 est.)
Global Wealth	$360,603	Credit Suisse
Derivatives (Market Value)	$11,600	BIS (Dec 2019)
Derivatives (Notional Value)	$558,500	BIS (Dec 2019)
Derivatives (Notional Value - High end)	$1,000,000	Various sources (Unofficial)

large investors. For this reason, they force small investors to make reverse movements on the trend lines and make losses by blasting their stop-loss points. Such movements can be described as a kind of manipulation. The reason we use only one type of expression is precisely because there is no single definition in the monetary literature that describes manipulation in all its aspects. Gerace *et al.* [10] stated this in their first experimental study on Hong Kong stock exchanges.

Golmohammadi et. al. share some results about stock market manipulation forecast results by using supervised machine learning algorithms. Naïve Bayesian algorithm perform the best results with 53% of F_1 score [11] in 2014. In 2017, they propose a formal method [12] to improve performance using Contextual Anomaly Detection (CAD) to detect manipulation of oil and fuel stocks in the S&P 500. In their experiments, they apply feature selection techniques as well as machine learning. The method aims to improve the CAD algorithm by capturing the expected behavior of the exchange through the sentiment analysis of tweets about stocks. Based on the results, they share that the methods they suggest, eliminate 28% false positives.

Sridhar *et al.* [13] tries to detect stock market manipulations by using Ensemble Neural Networks in their study. They state that the use of Ensemble Neural Network will give the highest success for the methods realized in the Indian stock markets by comparing it with other methods.

Chen et. al. [14] seek to investigate the existence of manipulation models for investors and regulators. As a way of proving this, they reveal the necessity of auditing the trading networks of exchanges. They try to detect the price fluctuations that are related to each other using the Singular Value Decomposition (SVD). They share that there are many manipulation methods applies in the markets. Also, they imply that the supervision of crypto money markets should be strengthened.

Chen *et al.* [15] propose a bootstrap algorithm to detect users using "Pump & Dump" method is one of the manipulation methods. In this way, they examine user groups exhibiting abnormal trading behavior. Thus, they share that they are trying to provide useful information for investors and policy makers in the crypto money market.

La Morgia et. al. [16] have observed how fraud is committed. Then, they are drawing attention to the low liquidity in the crypto money markets. By sharing how they detected this fraud in real time during the "Pump & Dump" periods, they tried to prevent investors from harming them. As a result, they declare that it was possible to detect 'Pump & Dump' movements from the very beginning.

TABLE 2. Success rates comparison of Covid-19 periods (updated) [19].

Mid Stage of Covid-19 Period Results (Crisis)								Early Stage of Covid-19 Period Results (Pre-crisis)						
Method	Trend	F_1 Score (%)	Precision (%)	Recall (%)	Cum. F_1 Score (%)	MCC (0-1)	Accuracy (%)	Method	F_1 Score (%)	Precision (%)	Recall (%)	Cum. F_1 Score (%)	MCC (0-1)	Accuracy (%)
LSTM (5,20,64)	Inc	73	63	86	70	0.434	70	**LSTM (10,75,256)**	75	67	86	73	0.491	73
	Dec	67	82	56					71	83	62			
ARIMA (2,1,1)	Inc	35	100	21	55	0.356	63	**ARIMA (2,1,4)**	92	100	86	93	0,873	93
	Dec	74	59	100					94	89	100			
SARIMAX (11,0,9)	Inc	60	64	56	60	0.205	60	**SARIMAX (6,1,2)**	71	67	75	66,5	0.33	67
	Dec	60	56	64					62	67	57			
SVM Linear SVC	Inc	78	100	64	82	0.7	83	**SVM Linear SVC**	83	100	71	86	0.756	87
	Dec	86	76	100					89	80	100			
SVM Sigmoid SVC	Inc	75	90	64	79	0.614	80	**SVM Sigmoid SVC**	83	100	71	86	0.756	87
	Dec	83	75	94					89	80	100			
SVM Poly-SVC	Inc	78	100	64	82	0.7	83	**SVM Poly-SVC**	83	100	71	86	0.756	87
	Dec	86	76	100					89	80	100			
SVM NuSVR	Inc	78	64	100	73	0.56	73	**SVM NuSVR**	67	62	71	67	0.34	67
	Dec	67	100	50					67	71	62			
SVM Epsilon SVR	Inc	78	100	64	82	0.7	83	**SVM Epsilon SVR**	82	70	100	80	0.66	80
	Dec	86	76	100					77	100	62			

Adeyeye *et al.* [17] analyze the global financial crisis and stock market price behavior in Nigeria between 2004-2014. Volumetric changes at different times are examined for predictability. As a result, they report that Generalized Autoregressive Conditional Heteroskedasticity (GARCH) methods of prices in the stock market are quite successful in pre-crisis periods. Unlike the great success in the pre-crisis period results, they share that performance is lower in the post-crisis period.

In a study conducted by Zhang *et al.* [18] in 2020, stocks in the S&P 1200 Global ranking in the American stock market are examined using the "Minimum Spanning Tree" method. Then, they claim that Covid-19 does not have any negative effects on the stock market until the time of the study.

In another study we participated with Kaya U. [19], price estimation methods before and after Covid-19 are compared. Prices are estimated for the periods when Covid-19 restrictions began to be discussed. Experimental results were great success for the most methods. In the study, all forecasting methods are calculated for the dates between March 15, 2020 and June 28, 2020. Then, the performance results between the methods are shared. Based on these experimental results, Auto Regressive Integrated Moving Average (ARIMA) [20], which is a time series estimation method, is observed to be the most successful.

III. METHODOLOGY

We have experienced in a previous study [19] that price prediction methods achieve high performance for Bitcoin prices.

These results are gathered from vector data that consists of weekly opening prices, closing prices, lowest prices and highest prices of Bitcoin. According to these vector data, results are forecasted as being an ascension or descension for each consecutive week. Also, we considered to evaluate Seasonal Auto Regressive Integrated Moving Average with Exogenous Factors (SARIMAX) [20], which is another variant of ARIMA because of being the top performer on the previous study [19]. All combined results are illustrated on Table 2.

Afterwards, it was observed as a result of some experiments, this great performance is not provided under all circumstances.

At this stage, we examined the studies that could explain the reason for this issue. The result that high performance can be observed in experiments conducted in pre-crisis periods [17] has drawn our attention. It has been believed that the reason for this is that big investors have reduced their manipulative actions in order to see the risks before the crisis. Essentially this assumption allows us to understand how much the success of price estimation methods can actually play in detecting manipulation. Then, we created a business

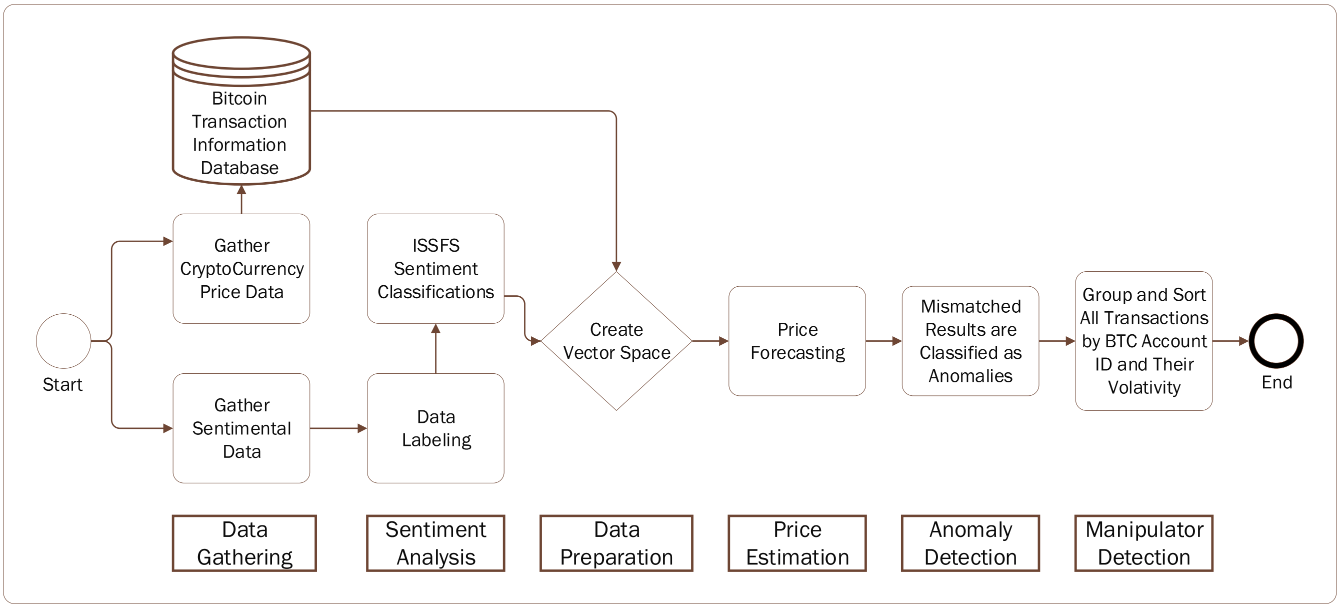

FIGURE 2. **Business model of manipulator detection.**

model to prove our assumption. The flows of the experiments performed in the proposed business model illustrated in Figure 2. It is, in essence, aimed to detect manipulators through these processes, involving data collection, price estimation and anomaly detection in general terms.

Dunning et. al [21] proved that an anomaly detection method suits better to search unknown characteristics patterns. These results encourage us to employ anomaly detection approach to estimate manipulation due to its unknown characteristics.

According to the proposed model, illustrated in Figure 2, price estimation methods have been re-executed for the periods considered to be manipulation. At this point, it is anticipated that the performance rates as a manipulation indicator will decrease at a considerable rate. Thus, trend changes in weeks or months that cause deviation in the system can be evaluated as anomalies. Also, the highest performance score and method of the system will be researched for each point. The success rates of subsequent studies will also be assumed as the performance scores of the methods obtained in the light of these studies. These studies have been concentrated in two different directions to inspect manipulation behavior with using sentiment analysis or not. Because our first intention is to analyze whether the sentiment analysis really causes the change in prices or not. Then, the methods that give the best performance were used to detect the manipulations. Afterwards, dates will be determined on the resource specified as the manipulation point and the performance rates will be calculated weekly and monthly. The weeks and months of failure of the system will be labeled as an anomaly zone, as significant reductions in overall performance are expected. Later, the 500 accounts with the highest volume of transactions between these dates will be determined by searching the database of Bitcoin transactions. This, in essence, allows us to determine manipulator accounts.

IV. EXPERIMENTAL STUDIES

In this study, due to the characteristics of the problem, we conducted a progressive experimental process. At this point, different data were used for different experiments performed at each stage. At the end of each stage, the achievements of the experiments were compared with each other, and the next stage was passed to be used in the following experiment, focusing on the purpose and high performance of the experiment.

A. PERFORMANCE METRICS

This section describes the performance metrics used to measure performance. F_1 score is the most common performance calculation technique used by the scientific world as benchmarking.

Sensitivity value and nominal value must be calculated in order to calculate this score. When calculating these values, it is expressed as the number of correctly classified positive samples (TP), the number of correctly classified negative samples (TN), the number of incorrectly classified positive samples (FP), and the number of incorrectly classified negative samples (FN).

After these numbers are calculated, precision and recall values are calculated.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

Precision value is calculated as shown in (1).

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

Recall is calculated as shown in (2). After these two values are calculated, F_1 measurement can be calculated as shown in Equation 3.

$$F_1 = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{3}$$

The accuracy value shows how close the analysis made in the experiment is to the true value. It shows how similar the new result will be to the previous result if this experiment is repeated under the same conditions. The calculation method is shown in (4).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{4}$$

Matthews Correlation Coefficient (MCC) is also used for performance calculation. It is especially used to measure the quality of binary classifications in statistical calculations. The calculation method is shown in (5).

$$MCC = \frac{TP*TN - FP*FN}{\sqrt{(TP+TN)*(TP+FN)*(TN+FP)*(TN+FN)}} \tag{5}$$

B. PERFORMANCE EVALUATION OF ARIMA VARIETIES

In the study conducted Fu *et al.* [22] utilize Gated Recurrent Unit (GRU) Neural Network methods to detects traffic density, and proves that ARIMA method generates more successful results than the Long Short-Term Memory (LSTM) method [23]. This motivated us to employ SARIMAX method, adapted by ARIMA, for experimental evaluations. The results are presented in Table 2. The data for these experiments are obtained from authors' previous study, can be seen in [19]. In addition, sentiment analysis on Twitter was included and the effects of their exclusion, concerning results, were also planned to be incorporated with the experiments. In the experiments, opening, closing, highest and lowest price data in USD dollars for Bitcoin were employed for each weekly and monthly price estimations.

In Table 2, the parameters used for ARIMA and another version of SARIMAX are defined at (p, d, q) form. AR (p) notation indicates the autoregressive model. The I (d) notation specifies the degree of difference in observations. The MA (q) notation refers to the moving average model. The parameters used for LSTM are 'Batch Size', 'Layer', 'Epoch' and 'Dropout' respectively.

C. EXPERIMENTAL DATA

The data used in the Bitcoin pricing phase of the experiments were taken from the ''Coinmarketcap'' [24] web page, which is widely used by most virtual currency followers. These received data comprises daily opening and closing prices and total volume amounts, considered as attributes (features). The data in sentiment analysis stages were taken from Twitter [25], a common platform where public thoughts can be expressed freely, through a web crawler software. Later, these data were recorded in the MSSQL SERVER 2017 database. The comments in the database cover the years between 2010 and 2019. Also, the number of comments, likes and retweets were gathered for each comment. The search sentences of the comments were selected as 'Bitcoin', 'Bitcoin Price', 'Bitcoin Forecast', 'BTC', 'BTC/USD', 'BTCUSD', which are the most used in searching for predictions and comments.

In order to determine the sentiment analysis methods used in this study, the methods that gave the best performance results were also examined in our previous study [19]. By considering this study, it is decided to employ the ISSFS method in sentiment analysis problem. The breakdown of past Bitcoin transactions used in the later stages of the study. Bitcoin data archive service that the 'Blockchair' [26] organization provides free access for academic use due to the large number of transfers and taking up too much storage space.

This data has approximately 350 GB of storage space which consists of all Bitcoin transaction information at last five years. They were all obtained through the API Key provided by the site administrators. In order to be processed later, a transfer tool was developed on a C #. NET and archived on MSSQL SERVER 2017 database. This data consists of Bitcoin account wallet information showing whether the sender or receiver, the amounts sent, both USD and Bitcoin units are included in detail.

Since there is no specific formula or equation for a clear definition or determination of manipulation, it was thought that estimation methods would be helpful in this regard.

The leading researches about price estimation were examined during this study. However, it should be noted that there is no data available that directly confirm the manipulation. Considering the possibility that this data cannot be found at all, it is thought that clustering algorithms come into play in this regard and try to reach a conclusion on the 'Bitcoin' transfer transactions in the account.

However, it was acknowledged that the answer of clustering studies about which category is really a manipulator cluster or not could not be considered healthy.

In addition, due to the excessive amount of Bitcoin transfer data, the continuous increase of the data to be processed and the increase in the need for processing has led to the need to create a general model here. At this point, a model was created in order to verify the road map of this study. In this way, it was thought that it would be more scientific and objective to use manipulation data to verify the results we obtained.

At this stage, we used a chart called 'Stages of Bubble' [27], published in 2020 and shown in Figure 3, which provides detailed information about Bitcoin manipulation and shows the steps of the manipulation by periods, to verify our results. This chart mentions the rapid price activity of Bitcoin as of 2017.

In this study, the areas from the ''First Sell Off'' stage of the graphic to the end of the ''Despair'' stage as the manipulation zone are defined. The date of June 12, 2017, which is the week corresponding to the starting point of the ''Bear Trap'' region, which is the first manipulation indicator, has been chosen as the starting point of the formation.

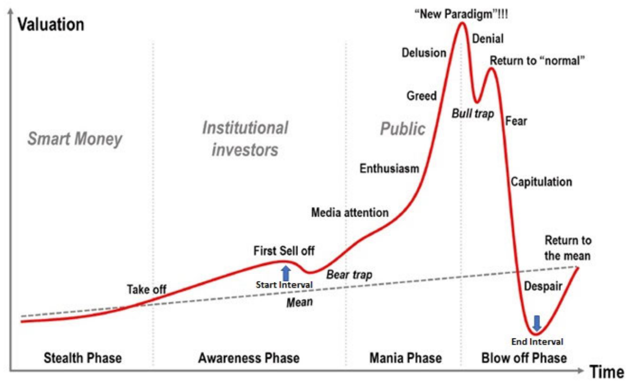

FIGURE 3. Stages of Bubble [20].

FIGURE 4. Adaptation of the stages of Bubble chart to the real scenario.

The expiry date was normally planned to be July 10, 2019, which is the end date of the 'Despair' phase. However, we had to limit it at this point due to lack of sentiment data. That is because we did not have the comment data after January 03, 2019. Hence this data is ignored. The whole formation, which is approximately 1.5 years in total, has been marked as a manipulation zone.

As another perspective, whales might be the reason of rapid increases and rapid sales. These whales accounts earn from small and medium-sized investors who are trying to make money based on technical analysis.

Their high liquidity advantage determines the course of the trend by exploding their stop-loss points with strong sells. Thus, they can buy Bitcoin at a low price until the next support point. These types of whales are described as bears.

On the other hand, whales can make large amounts of sudden purchases. They accelerate the formation of demand in the stock market by this way. These types of whales are described as bulls. Thus, it triggers the virtual currency price to make rapid increases or decreases in a short time and causes trend change. This cycle continues until the whales are able to make enough purchases, or till the whales take out the virtual coins.

It has been observed that the "Stages of Bubble" chart expresses the overbought and oversold areas very well in terms of our experimental study. For these reasons, the data in this graph were used at the stage of verifying success in the continuation of the study. In Figure 4, how this graphic looks in the real scenario is presented by specifying the manipulation start and end dates. The data used in these studies are identical in quality to the data used in our previous study [5] about sentiment analysis. In addition, 119,127 unclassified data to be used for the following periods were used in this study to improve the ISSFS method among these experiments.

These unclassified comment data were used in experiments performed for improvement studies. These are divided into stages, respectively. Fixed training and test sets were contained 5,675, 11,350, 22,700 and 55,400. Only first 5,675 data tagged by three different people. Sentiment categories determined by the majority of user tags.

Afterward, remaining unclassified data tagged by supervised classifiers. System train-test balance rate were always kept at 50% balance rate for each stage. Training and test clusters are therefore doubled at each stage. 55,400 training data were used only in the fifth stage studies and the remaining 29,677 pieces of data were used as the final unclassified data. The tests were carried out in this way due to a lack of data.

D. SENTIMENT ANALYSIS EXPERIMENTS

In this study, the most successful sentiment analysis methods for the defined problem are evaluated. The classification-built bases on the qualities of the data. This data analysis implemented together is seen as the most important factor that will increase the performance of the overall system. In this context, the first study is conducted to determine the method to be used in sentiment analysis. It is widely accepted that overtraining is one of the most common problem during the analysis of the text data. For this reason, we successfully applied the "Feature Selection" techniques that were proposed in authors' past studies [5], [19]. The feature selection approach adapted was the "Chi-Square" [28] method, which was successfully applied in sentiment analysis [29] The equation is given as below (6):

$$X_c^2 = \sum \frac{(O_i - E_i)^2}{E_i} \tag{6}$$

Results reveal that the ISSFS method increased the sentiment classification performance for all methods used in the experimental process with an average F_1 score difference of 10%. The main factor in the success of this method is the most determinant words in the categories are used to analyze the sentiments.

In addition, the system can learn incrementally due to gains obtained from each new data in a way that it is operational just like an intelligent system.

This proposed study is actually another step of authors' previous studies [5], [19]. The results and inferences encountered in the experiments share how to use ISSFS method in various ways.

Through implementation of Deep Neural Decision Forest (DNDF) [30] method, it is proved that DNDF presents similar results with the ISSFS method [5]. Hence, it was decided to

TABLE 3. Results obtained without feature selection application.

No Feature Selection Applied				
Category (Price)	SVM	CNN-5 Layer	DNDF	Random Forest
	F_1 Score			
Increase	0.60	0.54	0.53	0.63
Decrease	0.55	0.48	0.58	0.59
Neutral/ Unstable	0.29	0.32	0.30	0.34
Total Average	**0.55**	**0.49**	**0.47**	**0.58**

adapt the DNDF method for the experiments to compare the overall performance of the system. Table 3 presents the results of different classifiers without employing ISSFS method to select high quality features.

TABLE 4. Experiment results to determine optimal feature number for DNDF method.

#Exp.	#of Attribute	Epochs	Batch Size	#of Tree	Tree Depth	F_1 Score
1	375	1000	1000	5	10	**0.655**
2	375	1000	1000	10	80	0.633
3	500	1000	1000	5	10	0.611
4	500	1000	1000	10	80	0.577
5	750	1000	1000	5	10	0.6
6	750	1000	1000	10	80	0.567
7	1000	1000	1000	5	10	0.623
8	1000	1000	1000	10	80	0.611
9	4094	1000	1000	5	10	0.556
10	4094	1000	1000	10	80	0.504

Table 4, result table, illustrates the performance of DNDF method using ISSFS process. The optimum number of attributes from the dataset for the DNDF method was determined by considering the most effective words. These effective words generated by Random Forest method [31]. These generated words were also applied on the same dataset. Several parameters have been tested for the optimization process.

The test results of two different parameters providing the highest performance are illustrated in Table 4. The implementation was performed with a "NVidia RTX 2080Ti" model graphics card. The average execution time for the parameters is completed in 120 minutes. It should be noted that the other machine learning methods implemented in this study completed the given task less than 5 minutes.

However, it is observed that the performance the DNDF method have critically decreased after decreasing epoch and tree depth, which can be observed in Table 5.

TABLE 5. Experiment results for DNDF after feature selection method applied.

#Exp.	#of Attributes	Epochs	Batch Size	#of Trees	Tree Depth	F_1 Score
1	375	55	1000	5	10	0.59
2	500	55	1000	5	10	0.44
3	750	55	1000	5	10	0.44
4	1000	55	1000	5	10	0.41
5	4094	55	1000	5	10	0.35

These results are obtained under the same hardware settings within 15-20 minutes.

Based on the preliminary results, it is confirmed that the most suitable number of elements in the attribute set (features) for crypto exchanges is "375".

It should also be noted that this performance can be improved once the ISSFS method was applied just before the DNDF method implementation on the same dataset.

Table 6 presents a comparative analysis by considering researchers' previous study [5]. The values shown in Table 6 were illustrated for each category. Especially for each category new 1,000 unknown data were integrated into the system. Thus, it is aimed to analyze the performance of the system, which is updated with the ISSFS method in each level, with a fixed test set determined at the beginning.

On further studies, the remaining of unknown comments was added into the training set in order to evaluate ISSFS on a larger dataset. A dramatic decrease has been observed on the results of 1st configuration at stage 3, can be seen in Table 7. This motivates researchers to focus on the reason lies behind this dramatic decrease.

Consequently, we focused on the two potential defects of the ISSFS method. The first one was the disruption of the equilibrium in the training part, as each newly classified unknown interpretation was dominant for a category. The second one was the balance in selected features was ignored in every new model creation stage. Thus, the imbalance of the words that play a role in determining the categories enabled by some other categories well, while reducing the others. To observe balance condition, new experimental data sets and three different configurations were created respectively. The "Random Forest" algorithm has been applied as the appropriate classifier because it has achieved the highest success rates on sentiment analysis.

The main problem only depends on the overtraining of the system. Hence, the second and third configurations, are designed to overcome over training problem. Preliminary experiments prove that hold-out validation with 50% data for testing and 50% training for this case compensates the over training problem. In the third case, both the balance of comments in the training and test sets and the balance of the

TABLE 6. Experiment results obtained after feature selection application.

Semi-Supervised Feature Selection					
(Chi-Square-375 Features)					
F1-Score		SVM	Random Forest	CNN-5 Layer	DNDF
Supervised Feature Selection Method	Price Increase	0.69	0.68	0.54	0.53
	Price Decrease	0.6	0.64	0.48	0.58
	Unstable/ Neutral	0.43	0.44	0.32	0.30
	Total (Avg F_1)	**0.62**	**0.63**	**0.49**	**0.47**
ISSFS Stage 1	Price Increase	0.7	0.71	0.70	0.65
	Price Decrease	0.61	0.65	0.57	0.66
	Unstable/ Neutral	0.41	0.41	0.43	0.38
	Total (Avg F_1)	**0.63**	**0.65**	**0.61**	**0.56**
ISSFS Stage 2	Price Increase	0.72	0.75	0.71	0.62
	Price Decrease	0.64	0.67	0.62	0.70
	Unstable/ Neutral	0.42	0.43	0.40	0.40
	Total (Avg F_1)	**0.66**	**0.67**	**0.64**	**0.58**
ISSFS Stage 3	Price Increase	0.7	0.76	0.69	0.60
	Price Decrease	0.64	0.68	0.58	0.74
	Unstable/ Neutral	0.45	0.43	0.39	0.40
	Total (Avg F_1)	**0.64**	**0.69**	**0.62**	**0.58**
ISSFS Stage 3 + 5000 Unclassified Data	Price Increase	0.72	0.75	0.69	0.60
	Price Decrease	0.63	0.66	0.64	0.76
	Unstable/ Neutral	0.44	0.47	0.44	0.41
	Total (Avg F_1)	**0.65**	**0.68**	**0.64**	**0.59**

attributes used for training were provided. Consequently, in the system in which 375 determinative attributes are evaluated in total, equal numbers (125 attributes each) with the highest attribute score from each category are equally distributed to the set of training vectors.

The number of training data used in the experiments are given as: 5.675, 11.350, 22.700 and 55.400. In fact, since the number of training and test clusters is tried to be shared in a perfectly balanced way, these numbers are doubled after within each evaluation stage. Results are illustrated in Table 7.

It was clearly observed that the performance of the system increased and decreased unevenly with each newly added unknown data within the first configuration. In the second and third configurations, it is revealed that the results are improved to a certain level by comparison, after which the performance is not deteriorated as much as in the first configurations. At this point, it has been deduced that permutations in the second and third configurations must be tested so as to find the optimum performance.

TABLE 7. Assessment of ISSFS method's comprehensive studies.

1^{st} Configuration	Increase	Decrease	Neutral	Cum. F_1 Score
Stage 1	0.674	0.562	0.654	**0.633**
Stage 2	0.637	0.537	0.582	**0.590**
Stage 3	0.377	0.186	0.250	**0.282**
Stage 4	0.628	0.437	0.603	**0.561**
Stage 5	0.607	0.356	0.588	**0.523**
2^{nd} Configuration	**Increase**	**Decrease**	**Neutral**	**Cum. F_1 Score**
Stage 1	0.714	0.638	0.608	**0.661**
Stage 2	0.678	0.587	0.613	**0.631**
Stage 3	0.667	0.510	0.603	**0.600**
Stage 4	0.670	0.489	0.628	**0.602**
Stage 5	0.639	0.452	0.569	**0.561**
3^{th} Configuration	**Increase**	**Decrease**	**Neutral**	**Cum. F_1 Score**
Stage 1	0.621	0.603	0.667	**0.628**
Stage 2	0.654	0.637	0.623	**0.640**
Stage 3	0.655	0.646	0.588	**0.634**
Stage 4	0.659	0.642	0.563	**0.627**
Stage 5	0.601	0.621	0.484	**0.575**

In addition to these inferences, it is also observed that the complexity of the posts caused to decrease the performance of the levels. It has been considering that the system constantly educates itself. The reason for this was stated as "Neutral/ Unstable" of the short and long-term price prediction comments made in the same share. For these reasons, it has been anticipated that the method can be used more successfully in classifying categories that do not have dilemmas.

In the rest of the experiments, the most successful classification parameters generated in the third configuration. The third configuration is assumed to be in full balance by default, that has been used for estimation in the sentiment analysis parts.

E. IMPACT OF SOCIAL MEDIA SENTIMENTS ON MANIPULATION DETECTION

In the experiments at this stage, different parameters of these methods were tested both with and without the inclusion of sentiment analysis. To observe the effects of the speculation on social media, the results of sentiment analysis were generated using the ISSFS method and Support Vector Machine (SVM) classifier.

Although the course of the experiments continued through machine learning methods at this point, the same experiments were repeated and the results were shared in order to serve as

TABLE 8. Bitcoin trend observation results.

Methods		Weekly Parameters	Weekly Average MCC Score (0-1)	Weekly Average F1 Score (%)	Monthly Parameters	Monthly Average MCC Score (0-1)	Monthly Average F1 Score (%)
ARIMA	SA Included	(4,1,5)	0.0956	54,5	(1,1,5)	0.1791	58,5
	SA Not Included	(2,1,7)	0.15891	58	(5,1,5)	0.2567	62,5
SARIMAX	SA Included	(9,1,9)	0.1546	57,5	(8,0,6)	0.3144	64,5
	SA Not Included	(4,0,1)	0.2529	62,5	(5,0,5)	0.2516	55
SVM	SA Included	SVM Epsilon SVR	0.2917	64,5	SVM Linear SVC	0.2423	60
	SA Not Included	SVM Epsilon SVR	0.2695	63,5	SVM NuSVR	0.3186	60
LSTM	SA Included	(128, 4, 150, 0.1)	0.1093	54	(512, 15, 10, 0.1)	0.2423	60
	SA Not Included	(512, 2, 20, 0.1)	0.0825	54	(64, 5, 20, 0.1)	0.2423	60

an example for future studies, providing the most successful estimation results.

The data used in the experiments were created weekly and monthly periods separately. For each estimation method to use the test set for the date ranges shown on the "Stages of Bubble" graph (See Figure 3). In order to obtain a 1.5-year period, the price movement of the previous two years was also prepared to form the training set of the system. At the same time, the data to be used in all training and test clusters were added weekly and monthly bases, and the sentiment analysis classification results performed by ISSFS and SVM method as additional vectors namely, "Ascent", "Descent" and "Neutral".

The studies were implemented and experiments are conducted using Python and Anaconda, scikit-learn for SVM, Statsmodels for ARIMA and SARIMAX, Tensorflow and Keras for LSTM libraries. Based on the collected results shown in Table 8, the methods achieved high success in the periods of the financial crisis, analyzed in previous studies, failed as expected when reapplied over the date ranges considered as possible manipulation points. In the results obtained at this point, it has been determined that SARIMAX has not made a significant contribution to the manipulation detection of sentiment analysis since the beginning of the research.

V. RESULTS AND DISCUSSION

According to the latest performance results shown in Table 8 in the studies up to this stage, the machine learning method "SVM" and the time series forecasting method "SARIMAX" achieved most successful results in terms of estimating "Bitcoin Trend Detection problem for the crisis period.

However, we propose that the price estimation process must be completed before pre-crisis period so as to obtain the

FIGURE 5. Detected areas of anomalies by SVM classifier.

most efficient criteria. As a matter of fact, the performance of the SARIMAX method in the analyzes for the pre-crisis periods is very low compared to other methods.

Based on these results, it was observed that the results worsened with the inclusion of sentiments in the time series, but did not create a change for some methods or the results improved by 1% to 5%. Since the purpose of the experiments is to detect unusual trend movements in prices, it should be noted that the sentiment analysis results do not have great influence in determining abnormal trend movements.

It has also been found that the results obtained by various methods in the date intervals specified in the "Stages of Bubble" graph (See Figure 3) have deteriorated from a success rate of 93% to 54% for the first period after Covid-19. In addition to these results, the success rate of the methods deterioration does not relate in terms of comparing the pricing success of the methods.

According to these results, it has been proved that manipulations have made the performance results worsen for each case. Based on the results, the sentiment analysis data, which we saw to achieve the significant successful results on a weekly basis, were used to detect anomalies in the continuation of the study.

$$i_{1 \rightarrow Total\ Period\ Number}$$

$$\sigma_{BTC\_ADDRESS, F_{sum(BTC\_AMOUNT)}, F_{sum(BTC\_USD\_VOLUME)}, time > period(1)\_begin\_date\ and\ time < period(1)\_end\_date}(Transactions\_Table) \cup$$

$$\sigma_{BTC\_ADDRESS, F_{sum(BTC\_AMOUNT)}, F_{sum(BTC\_USD\_VOLUME)}, time > period(2)\_begin\_date\ and\ time < period(2)\_end\_date}(Transactions\_Table) \cup$$

$$\sigma_{BTC\_ADDRESS, F_{sum(BTC\_AMOUNT)}, F_{sum(BTC\_USD\_VOLUME)}, time > period(3)\_begin\_date\ and\ time < period(3)\_end\_date}(Transactions\_Table) \cup$$

$$\vdots$$

$$\sigma_{BTC\_ADDRESS, F_{sum(BTC\_AMOUNT)}, F_{sum(BTC\_USD\_VOLUME)}, time > period(i)\_begin\_date\ and\ time < period(i)\_end\_date}(Transactions\_Table)$$

FIGURE 6. **Database operations for manipulator detection.**

A. FINDING THE BEST METHOD FOR MANIPULATION DETECTION

Although it is declared that ARIMA is considered as the most successful approach in price estimations within the scope of the research according to early periods of covid-19, ARIMA was one of the worst methods for providing post covid-19 period results generated with LSTM. SARIMAX results were less successful for the both forecasting periods even they have common shares except for seasonal cycle parameters.

We can summarize that, there are many parameters has to be spent for processing times to find best parameters in both time series methods. These parameters must be chosen specifically for each different dataset. In this phase, we prefer to use SVM to detect manipulation periods because it is easy to get high performance default parameters on both periods.

Also, there is no need such detailed parameters for each condition. We did not take into the consideration the monthly results because of having low performance on test results and sudden price movement tendencies of cryptocurrencies.

Preliminary experiments reveal that SVM algorithm achieves the best results among other methods because of having more successful results for all tested periods. Our performance criteria depend on cumulative F_1 score of all tested periods. It has to exceeded 79.69% F_1 score for early Covid-19 period. On the other hand, the lowest success rate calculated as 58.56% F_1 score which has to be exceeded for post Covid-19 period by candidate forecasting methods. According to all results, SVM was the only candidate to provide all qualifications. Hence, studies continue in this direction.

B. MANIPULATOR DETERMINATION

As given in the results shared in Table 9, weeks that were wrongly estimated in the test set, decreasing the performance of the system, were labeled as "Anomaly" by SVM. Overall, possible manipulation regions obtained are illustrated in Figure 5 by enclosing a yellow rectangle on the graphic.

In fact, our manipulator detection algorithm depends on manipulation actions. There might be different approaches to solve this problem such as creation of a Deep Learning model for manipulator detection There are two challenging problems need to be resolved. First, there is no publicly shared Bitcoin manipulator data available or shared by any trusted authorities yet. And second, even if we assume that having this manipulator data, it would not be feasible to analyze all Bitcoin accounts (Approx. 460 million accounts until Dec. 2018) [32] with all their billions of transactions together which were mostly realized by trading bots. Even though, it is not certain that what kind of manipulation technics were applied because each manipulator has their own manipulation profile. Finally, we had assumed manipulator detection results would be worsen because of these existing inconsistencies.

That's why we focused on creating more sustainable, faster and much more applicable methodology to detect manipulators on Bitcoin cryptocurrency markets.

According to Aggarwal *et al.* [6] their biggest tool to use manipulation is providing high liquidity. Afterwards, the first 500 accounts with the highest volume in total in these 30 weeks were tagged and evaluated as a list from the database with special queries prepared.

By respecting the general ethical regulations, Bitcoin accounts detected in this research were not disclosed as a part of this study. Instead, the methods used to determine how these accounts can be determined are explained.

When the results were analyzed, it was observed that the 500 accounts with the highest number of transactions within the dates defined as manipulation were examined and the average Bitcoin cost was $4,721.388. It was determined that the lowest selling price was $1,934 in periods considered to be manipulation, and the highest selling price was $11,312.

The volume of the transactions performed in Bitcoin and dollar terms was determined as 19,978,954 Bitcoin and $81,018,924,212 for this 30-week period. This, in essence, reveals that how much more account holders gain from price differences in the environment they have created by manipulating.

These all database operations illustrated on Figure 6. In this figure, *i* defines weeks/months number used in the experimental test set. All of these results are added into same set. Then this set is grouped by Bitcoin addresses with calculating their total USD ($) transaction volume. Lastly, results are

TABLE 9. Detected anomaly periods by SVM epsilon SVR.

Start Date	End Date	Actual Result	Forecasted Result	Status
6/12/2017	6/18/2017	Descent	Ascent	Anomaly
6/19/2017	6/25/2017	Descent	Ascent	Anomaly
6/26/2017	7/2/2017	Ascent	Descent	Anomaly
7/3/2017	7/9/2017	Descent	Ascent	Anomaly
7/17/2017	7/23/2017	Ascent	Descent	Anomaly
7/31/2017	8/6/2017	Ascent	Descent	Anomaly
8/14/2017	8/20/2017	Descent	Ascent	Anomaly
8/21/2017	8/27/2017	Ascent	Descent	Anomaly
11/27/2017	12/3/2017	Ascent	Descent	Anomaly
1/15/2018	1/21/2018	Descent	Ascent	Anomaly
1/22/2018	1/28/2018	Ascent	Descent	Anomaly
1/29/2018	2/4/2018	Descent	Ascent	Anomaly
2/5/2018	2/11/2018	Ascent	Descent	Anomaly
2/12/2018	2/18/2018	Ascent	Descent	Anomaly
2/19/2018	2/25/2018	Descent	Ascent	Anomaly
2/26/2018	3/4/2018	Ascent	Descent	Anomaly
3/5/2018	3/11/2018	Descent	Ascent	Anomaly
3/26/2018	4/1/2018	Descent	Ascent	Anomaly
4/2/2018	4/8/2018	Descent	Ascent	Anomaly
4/30/2018	5/6/2018	Ascent	Descent	Anomaly
5/7/2018	5/13/2018	Descent	Ascent	Anomaly
7/2/2018	7/8/2018	Ascent	Descent	Anomaly
9/10/2018	9/16/2018	Ascent	Descent	Anomaly
9/24/2018	9/30/2018	Ascent	Descent	Anomaly
10/1/2018	10/7/2018	Ascent	Descent	Anomaly
10/22/2018	10/28/2018	Descent	Ascent	Anomaly
10/29/2018	11/4/2018	Ascent	Descent	Anomaly
11/5/2018	11/11/2018	Descent	Ascent	Anomaly
12/10/2018	12/16/2018	Ascent	Descent	Anomaly
12/31/2018	1/6/2019	Ascent	Descent	Anomaly

sorted by total transaction volume for detecting potential manipulator.

VI. CONCLUSION

This study addresses to apply machine learning and statistical forecasting methods to detect manipulations in Bitcoin market. Accordingly, the most commonly used price estimation methods, involving time series forecasting, machine and deep learning techniques were implemented to determine the weekly/monthly rising and falling trends of Bitcoin pricing.

The first priority was to make sure that price estimation methods could produce truly reliable results. To achieve this, we conducted our experiments by identifying a minimally manipulation-free zone.

Afterwards, the leading sentiment analysis techniques were used in order to understand the effect of social media posts on prices. During these studies, we also enhanced the ISSFS method, which was previously suggested by us for sentiment analysis. As a result of the improvements applied, it was observed that the regressions encountered while working on big data were eliminated. It was clearly observed that experiments regarding pre-crisis data and virtual money stock market trend prediction achievements were really remarkable.

According to the preliminary result, the comments made on the most popular social media platform we examined did have positive effects on the SVM and SARIMAX methods. LSTM had no positive or negative effects with sentiment results. Both weekly and monthly results of ARIMA did have negative effects while evaluating prices with sentiment results.

In addition to the given conclusion, manipulators played a major role in changing trends during all periods when anomalies were detected. These roles have been observed as raising, lowering and stagnating prices.

Finally, our studies reflect that the ISSFS method shows much more efficient manner on the sentiment classification when it was compared with deep learning alternatives which had similar perspective such as DNDF by the time efficiency and success rates. It has been also observed that they made huge profits thanks to these price manipulations. Besides, SVM achieves the best performance when used with sentiment analysis results and anomaly detection so as to identify manipulation zones and potential manipulators.

In total, around 200 experiments were carried out to realize this study. It is believed that this involves one of the most comprehensive research in terms of presenting scientific and realistic solutions about Manipulator detection in Bitcoin Market. This study has the potential to provide a roadmap for further studies.

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