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A local and global event sentiment based efficient stock exchange forecasting using deep learning

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ABSTRACT

Stock exchange forecasting is an important aspect of business investment plans. The customers prefer to invest in stocks rather than traditional investments due to high profitability. The high profit is often linked with high risk due to the nonlinear nature of data and complex economic rules. The stock markets are often volatile and change abruptly due to the economic conditions, political situation and major events for the country. Therefore, to investigate the effect of some major events more specifically global and local events for different top stock companies (country-wise) remains an open research area. In this study, we consider four countries- US, Hong Kong, Turkey, and Pakistan from developed, emerging and underdeveloped economies' list. We have explored the effect of different major events occurred during 2012–2016 on stock markets. We use the Twitter dataset to calculate the sentiment analysis for each of these events. The dataset consists of 11.42 million tweets that were used to determine the event sentiment. We have used linear regression, support vector regression and deep learning for stock exchange forecasting. The performance of the system is evaluated using the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The results show that performance improves by using the sentiment for these events.

1. Introduction

The stock exchange is an important index to provide a true picture of the economic condition of a country. It provides a solid ground to different investors to check the stability of a country and make investment plans. The stock exchange is a better platform to earn a profit as compared to bonds and banking traditional investments. The higher profit returns are often related to higher risk factors. This factor makes the stock investment a risky venture. These factors are often nonlinear and highly fluctuating. Therefore, the investors often purchase and sell the stocks in a short span. The investors often observe the patterns and make a decision based on those patterns. These patterns are used by different companies to help users make investment plans (Tabesh, Kelly, & Poulose, 2018). The patterns are usually affected by the sentiment of the community, the political and economic condition of the country. A well-known behavioral economics hypothesis is that market performance and public mood are correlated. This hypothesis argues that the investment is likely to increase if the people are in a good mood, happy and optimistic which ultimately leads to improving the performance of the stock market. The public mood quantification is an important task (Christie & Huang, 1995; Grover, Kar, & Ilavarasan, 2019; Zhang, Wang, & Zhu, 2019).

Stock exchange prediction is a process to cater to the risks factors involved in stock markets. The better the performance of the stock prediction algorithms, the less risk involved in the stock investment. There is a number of methods used for stock prediction categorized in two categories; statistical methods and computationally intelligent methods (Demirer & Kutan, 2006). The second category is based on artificial intelligence and can learn the nonlinear data patterns and provide better performance for the stock prediction. These methods

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include support vector machine, regression, and artificial neural network. Some researchers have also used deep learning-based algorithms for stock prediction. There are also some studies that include a Twitter sentiment to predict stock prices (Lakonishok, Shleifer, & Vishny, 1992). These methods enable the systems to predict stock prices more accurately. However, there is little work done in event-based stock exchange prediction. There is another shortcoming of the existing work is that researchers have yet not explored the effect of local and global events on different stock markets (Cakan & Balagyozyan, 2014; Choi, 2016; Christie & Huang, 1995; Hwang & Salmon, 2004).

In this work, we have done the stock exchange forecasting for US, Hong Kong, Turkey and Pakistan using linear regression, Support Vector Regression and deep learning. We have selected these countries from the list of developed, emerging and developing countries. We have taken four top stock companies for the US, Hong Kong, and Turkey while three companies for Pakistan. We explore the effect of some of the most famous events from 2012 to 2016. These events are categorized into local and global events for each country according to their impact. We investigate the effect of these events and analyze the impact for local and global events on these stock companies. We have collected the dataset for each stock company from 2000 to 2018 to investigate the performance of these events. The results show the improvement in the prediction results for different events according to their importance for the country. In general, the following are the main contributions of this research:

- We investigate the effect of different famous events on stock exchange prediction
- An event-based sentiment analysis method for stock forecasting is presented which employs the deep learning computational models
- Performance investigation is performed on linear regression, support vector regression and deep learning for stock forecasting

The remaining of the paper is organized as follows; Section 2 presents the related work in the field of stock prediction, Section 3 explains the proposed methodology and Section 4 presents the results followed by a conclusion.

2. Related work

The most emerging topic for research in real-life businesses and academics is stock market predictions. Researchers have tried to forecast the stock market for better business financial plans. These studies are based on the Efficient Market Hypothesis (EMH) and the random walk theory. (Fama, 1991; Fama, Fisher, Jensen, & Roll, 1969), used EMH by considering already available information that affects the current stock market. They predict the future price of a stock based on the current price using random walk pattern because the news is unpredictable in present and has the nature of instant happening. Therefore, (Walczak, 2001) argues that more than 50% accuracy is not possible in these scenarios. (Bollen, Mao, & Zeng, 2011; Qian & Rasheed, 2007; Qian & Rasheed, 2007; Vu, Chang, Ha, & Collier, 2012) proposed that stock market prices are predictable to some extent and it doesn't follow a random walk. (Schumaker & Chen, 2009b; Si et al., 2013; Tsibouris & Zeidenberg, 1995a, 1995b) showed that the 56% accuracy rate for directional stock prediction is considered as satisfying results.

Other than the EMH and random walk theories, for stock market prediction two different philosophies of trading is used: technical and fundamental analysis. The fundamental analysis is used for stock market prediction by studying macroeconomic factors, financial conditions, and operations of the company. Besides, the technical analysis used time series and historical prices. The movement of stock prices is in trends and historically tends to repeat itself. (Cervelló-Royo, Guijarro, & Michniuk, 2015; Patel, Shah, Thakkar, & Kotecha, 2015; Patel, Shah, Thakkar, & Kotecha, 2015; Ticknor, 2013; Zuo & Kita, 2012a, 2012b) analyzed only historical prices for stock prices prediction. (Zuo & Kita, 2012a, 2012b) followed Bayesian network to analyze data patterns, time series method such as Auto-Regressive model, Moving Average model (Patel et al., 2015a, 2015b) and Auto-Regressive Moving Average model (Zuo & Kita, 2012a).

Many researchers only focus on one stock to predict (Bollen et al., 2011; Qian & Rasheed, 2007; Si et al., 2013) and in a test set the number of instances (transaction dates) is usually low like 14 or 15 instances (Bollen et al., 2011; Vu et al., 2012). The result might not be sufficient due to the low instance test set.

2.1. Use of opinions from the text for stock market prediction

Social media especially twitter has gained a lot of attention as an information source and to develop public opinion (Wu & Shen, 2015). Some researchers (Liu & Zhang, 2012; Pang & Lee, 2008) showed that for the restaurant and product reviews sentiments analysis played a vital role. (Nassirtoussi, Aghabozorgi, Wah, & Ngo, 2014) applied sentiments analysis to improve stock prediction model by using information sources. The authors used main sources to combine information of textual context to financial models. Recently the information gathering source is social media (Aswani, Kar, Ilavarasan, & Dwivedi, 2018; Grover, Kar, Dwivedi, & Janssen, 2019; Singh et al., 2017), but in the past, the source was usually news forums(Wu & Shen, 2015; Schumaker & Chen, 2009a, 2009b). Then the sentiments were combined with the prediction model. A linear regression model used to integrate historical prices with textual content.

In previous studies, most of the work used the bag-of-words as a text representation to merge with the prediction model.(Schumaker & Chen, 2009b) analyzed it by using different textual representation like name entities, bag-of-words and noun phrases for financial news. Then information incorporated with linear regression to support vector machine regression as predictive models. They predict stock prices after 20 mints of news articles released by applying the models. The results show 0.04261 mean square error, 57.1% directional accuracy, and 2.06% return in a simulated trading engine.

(Antweiler & Frank, 2004) classified the messages in three classes from message boards by using naive Bayes: buy, hold and sell. The messages come under these three classes were aggregately measured as a bullishness and further analyzed three functions as an alternate to bullishness. Then it was incorporated into the regression model. Their model did not predict the stock returns significantly.

(Chiang, Li, & Tan, 2010) analyzed the relation between stock market indicators and collective indices like fear and hopes on a daily basis. Based on mood words they classify tweets as hope, fear and worry and so on. The authors proposed that the negative relation of emotional tweets were linked with Down Jones, NASDAQ and S&P 500, and positive relation to VIX. Even though, their model was not used to forecast stock prices.

(Bollen et al., 2011) used Google Profile and Opinion Finder of Mood State as a tracking tool for text content to examine Twitter on a daily basis in order to measure negative and positive moods. Then they classified mood in six dimensions such as happy, Vital, Alert, Kind, Calm and Sure and analyzed them. To predict DJIA values they used Self Organizing Fuzzy Neural Network model. The results show 86.7% accuracy and 1.79% Mean Absolute Percentage Error. Even though they used the test for a short period of time (December 1 to December 19, 2008). They report very high accuracy by using only 15 transaction dates in their test set.

(Xie, Passonneau, Wu, & Creamer, 2013) used the semantic frame to project new tree representation. They find that it works simpler by using stock prices graphically as compared to the bulk matter but containing a flaw of same category news whole day, proved to become a classify problem rather than stock graphics. (Rechenthin, Street, & Srinivasan, 2013) go through the Yahoo Finance Message Board and practiced using explicit and predicted sentiments along with the bag-of-words and meta-features to predict the stock movement. The keyword-

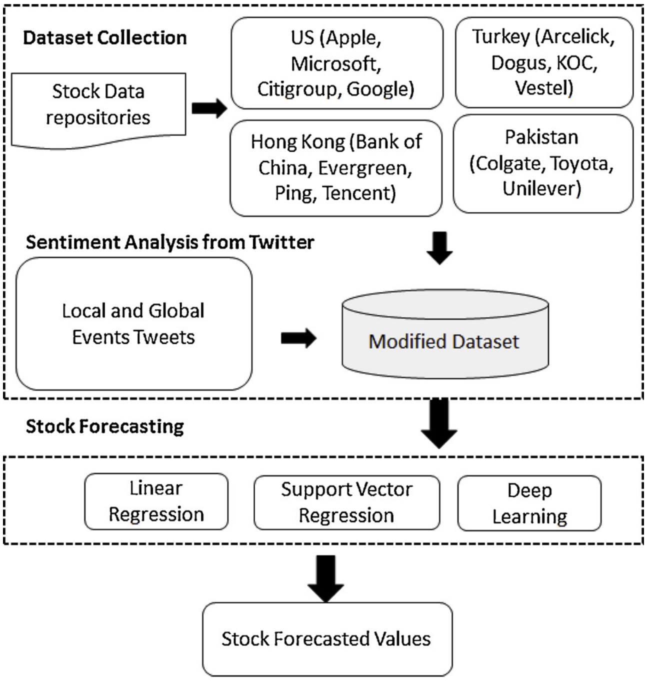

Fig. 1. Proposed Methodology for Stock Exchange Prediction.

based algorithm has been made to get to know all kinds of stock prediction (Vu et al., 2012) and was around 75% accurate according to 14 tested transactions in mid-weeks of September 2012. The limitation of existing work is that it is not based on events sentiment especially local and global events for specific countries for stock prediction.

3. Proposed methodology

The proposed system consists of three main modules; data acquisition, sentiment analysis of major global and local events for each country and stock exchange prediction. We have collected our stock exchange data for 15 companies from publicly available sources yahoo finance. Then we selected twitter dataset for different events for each country by checking its global and local importance for each respective country. Then we used three models; linear regression, support vector regression and deep learning to predict stock exchange The proposed methodology for this paper is presented in Fig. 1. First of all, the tweets are processed and we have calculated the sentiment of each event. This sentiment is combined with the stock exchange data which are used to train machine learning algorithms; linear regression, support vector regression, and deep learning. The algorithms used in this process are explained below:

3.1. Sentiment analysis of twitter feeds for the prediction of stock market movement

Sentiment analysis has played a vital part in finding our solution to use the outcomes of the module for learning our predictive model. We applied Alex Davies' word list (Christie & Huang, 1995) to start our sentiment analysis to see whether the simple approach is enough to compare the market movement. For this, we used the word list of almost five thousand words and classified them into positive, neutral and negative categories.

The process works this way, first, we tokenized the tweet into a word list. The whitespace and punctuation are being separated due to use of the parsing algorithm, and the URLS and emoticons are found in the tweet. We then used the negative, neutral and positive sentiments' more accurate and comprehensive dictionary. Precisely, we swapped that word list with our own generated word list by using SentiWordNet, which has more than 4000 thousand words. This word list helps to find better results due to considering the multi-word expression and relationship of each word. We had tried different ways to find the value of daily sentiments instead of averaging the probability of each tweet. We represent the percentage of positive, negative and neutral tweets per day. This way we neglected the neutral tweets and considered positive and negative percentages of the tweets. This gives a better and comprehensive description the of positive and negative sentiment of the day.

3.2. Forecasting models

3.2.1. Support vector regression

(Cortes & Vapnik, 1995) used the theory of statistical learning for machine learning algorithm and proposed SVM. The main reason behind this was to control the structural risks. Researcher modified the SVM version for regression. This SVM has been frequently used for fault prediction, time series prediction, and power load demand forecasting (Sousa, Jorge, & Neves, 2014).

Let's suppose if there is a time-series data which is given as follows:

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

Here in Eq. (1), X_i presents the input given at a time *i* with elements *N* and y_i is the output data. Then the regression can be represented as follows:

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

Here in Eq. (2), weight and bias are represented by W and b respectively. The input vector X can be mapped by φ(X) into a higher dimensional space. By solving the optimization problem using Eqs. (3) and (4) we can find the values of W and b.

$$\mathrm{Min}\ 1/2\ ||W||^2+ C \sum_{i=1}^{N} (\varepsilon_i+\varepsilon_i^*) \tag{3}$$

Subject to:

$$\begin{aligned} &y_i\text{-}W^T(\phi(x))\text{- } b\le\xi + \varepsilon i\\ &WT(\phi(x))+ b - yi \le \xi +\varepsilon_i^*\\ &\varepsilon_i,\varepsilon_i^{*3}0 \end{aligned} \tag{4}$$

The tradeoff between model simplicity and generalization ability can be represented by C. The slack variables ξi and ξ ∗ i that measure the error cost.

As the nonlinear data can be mapped from the original vector space to higher dimensional space using kernel mapping where linear regression model can be used. Therefore, the regression model for SVR can be obtained using Eq. (5):

$$y_i = f(X_i) =^N \sum_{i=1} ((\alpha_i\text{-}\alpha_i^*)K(X_i,X_j))+ b \tag{5}$$

Here the Lagrange variables multipliers are represented by αi and α ∗ i. Gaussian radial function (RBF) is the most widely used kernel with a width of σ as given in Eq. (6):

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

3.2.2. Linear regression

According to (Nunno, 2014) by the usage of different regression models like SVM, linear, and neutral network-based regression models stock market trends can be predicted.

Linear regression model amongst all given models has been used more because of its robust and simple nature. The methodology we used for our modeling is multiple independent and single dependent variables. The multiple linear regression model was used for such multiple variables (Klein & Datta, 2018). This is a generalized form of linear regression due to any reasons. It helps to deal with the dependence of more than one variables and resulted in different shapes rather than a single straight line.

Let y represents the dependent variable that is in a linear relationship with the k independent variables X_1, X_2, X_3. . . X_k through parameters β_1, β_2, β_3. . . β_k and is given as in equation (7),

$$y= X_l\beta_1+X_2\beta_2...X_k\beta_k+ \varepsilon \tag{7}$$

where the parameters β_1, β_2, β_3. . . β_k represents the regression coefficients with an association with X_1, X_2, X_3. . . X_k respectively and the random error which is the difference between observed and actual values are represented by ε.

The jth regression coefficient given as βj shows the anticipated change in y per unit change in jth independent variable Xj. Assuming E (ε) = 0 the βj can be calculated using Eq. (8),

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

3.2.3. Deep learning

By means of this network, our aim is to achieve similar if not better results than those achieved algorithms such as SVM. In neural network on each hidden layer, this network learns new feature space by first compute the linear transformation of the given inputs and then apply a nonlinear function which in turn will continue until we reach the output layer. Therefore we can define the neural network as information flow from inputs through hidden layers towards the output. We utilized the deep learning, which is usually defined as a network composed of large numbers of hidden layers and neurons which are interconnected, operate in parallel and learns from example. A common class of application for this deep learning model include regression problems where a mathematical model approximate set of data. The accuracy of such models is typically improved by utilizing additional data during the training process. We have used standard settings for deep learning based Convolutional Neural Network (CNN) (Nazir, Majeed, Ghazanfar, & Maqsood, 2019) for this purpose.

In this study, the input data for network generation were Open, High, Low, AdjClose, Volume, sentiment, and Close. The evaluation of the output obtained from the deep learning regression approach based on MAE and RMSE criteria. For this study, to predict 'Close' value for stock data our input parameters are Open, High, Low, AdjClose, Volume, and Sentiment. These parameters are already available in the datasets used for stock exchange prediction and sentiment is added from the event twitter data.

4. Experimentation and results

4.1. Dataset collection and twitter sentiment calculation

This study considers the top 4 performing companies of US, Hong Kong (Developed Markets), Turkey (Emerging Market) and Pakistan (Developing Market). Investor sentiments are calculated by using an intensive dataset of tweets regarding mega International events (Zubiaga, 2018). The following Table 1 presents the detailed description of these events, number of tweets and their nature. Daily stock

Table 2
Descriptive statistics for the Dataset of US.

	US			
	Apple	Citigroup	Google	Microsoft
Mean	0.000856	−0.000395	0.000845	0.000122
Median	0.000765	0.000000	0.000555	0.000000
Std. Dev.	0.026846	0.030963	0.018951	0.019267
Jarque-Bera	2838317.***	347267.0***	14524.65***	19012.41***
Observation	4737	4737	3574	4737

*** Significant at 1%.

Table 3
Descriptive statistics for the Dataset of Hong Kong.

	Hong Kong			
	Bank of China	EverGreen	Ping Insurance Co	Tencent Holding Ltd
Mean	0.005505	0.000131	0.000746	0.005505
Median	0.000000	0.000000	0.000000	0.000000
Std. Dev.	0.698779	0.020745	0.024829	0.698779
Jarque-Bera	22502383***	5440.047***	4837.821***	22502383***
Observation	3548	2958	3541	3548

*** Significant at 1%.

Table 4
Descriptive statistics for the Dataset of Turkey.

	Turkey			
	Arcelik	Dogus	Koc Holding	Vestel
Mean	0.000165	7.25E-05	−0.000385	4.42E-05
Median	0.000000	0.000000	0.000000	0.000000
Std. Dev.	0.027047	0.323655	0.044622	0.028994
Jarque-Bera	26646.75***	67833896***	7.63E + 08***	35462.96***
Observation	4784	4767	4768	4780

*** Significant at 1%.

Table 5
Descriptive statistics for the Dataset of Pakistan.

	Pakistan		
	Colgate	Toyota_Motors	Unilever
Mean	0.000122	0.000305	0.000243
Median	0.000000	0.000310	0.000671
Std. Dev.	0.013762	0.030941	0.014959
Jarque-Bera	63211.78***	38726.41***	9448.050***
Observation	4737	4737	4737

*** Significant at 1%.

Table 1
Dataset details along with local and global events for each company.

Markets	Local Events	Number of Tweets	Global Event	Number of Tweets	Companies
USA	Mexican Election 2012	191,788	Gaza under Attack 2014	2,886,322	Apple, Google, Citi Group, Microsoft
	US Election 2012	1,740,258	Brexit 2016	1,826,290	
			Refugee Welcome 2015	1,743,153	
Hong Kong	Hong Kong Protest (2014)	1,188,372	US Election 2012	1,740,258	Bank of China, Evergreen, Tencent Holding Ltd, Ping Insurance Group
Turkey	Cyprus Hijacked Plane	702,586	US Election 2012	1,740,258	Arcelik, Dogus, Koc Holding, Vestel
			Refugee Welcome 2015	1,743,153	
Pakistan	Lahore Blast 2016	1,149,253	US Election 2012	1,740,258	Colgate Company, Toyota Motors, Unilever

Table 6
ADF Unit Root Test.

		ADF Test Stat	Critical Value (5%)
US	Apple	−71.04***	−2.86
	Citigroup	−36.738***	−2.86
	Google	−59.15***	−2.86
	Microsoft	−72.075***	−2.86
Hong Kong	Bank of China	−50.86***	−2.86
	Ever Green	−39.25***	−2.86
	Ping Insurance Co.	−42.92***	−2.86
	Tencent Holiday Ux	−18.18***	−2.86
Turkey	Arcelik	−63.93***	−2.86
	Dogus	−24.28***	−2.86
	Koc	−68.007***	−2.86
	Vestel	−66.53***	−2.86
Pakistan	Colgate Co. Ltd.	−32.17***	−2.86
	Toyota Motors	−67.587***	−2.86
	Unilever	−72.72***	−2.86

*** Means significant at 1%. Results of Philip Perron also yield the same results and can be provided if required.

prices of selected companies are collected for the period of 18 years starting from Jan 2000 until Oct 2018. We selected some of the top companies from each country for stock prediction. We have also used a large dataset of tweets for different major events occur during 2012–2016. These events are categorized into local and global events for each country. The details of each country, corresponding stock markets and events are given in the following Table 1.

4.2. Evaluation metrics

There are different performance evaluation metrics used for stock prediction analysis. These metrics, as usually done in prediction, measures the difference between actual and predicted value (Balcilar, Demirer, & Ulussever, 2016; Chiang et al., 2010; Economou, Kostakis, & Philippas, 2011; Galariotis, Rong, & Spyrou, 2015). The metrics used to evaluate the performance of this system are RMSE and MAE. These metrics are evaluated here:

4.2.1. Root mean squared error – RMSE

This performance evaluation metric shows the average magnitude of estimation error in predicted values. It can be calculated using the following Eq. (9):

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

4.2.2. Mean absolute error – MAE

This error shows the average estimated error without considering the directions of the predicted values. Each of the calculated differences has equal weight and it can be calculated using Eq. (10)

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

In the equations above n represents the number of estimated values, $forecast(t)$ and $actual(t)$ represent the estimated value and the actual value w.r.t time t respectively.

4.3. Results and discussion

In this section, we present the results along with detailed discussion. The results of descriptive statistics are presented as follows in Tables 2–5. It is important the check the nature of data whether it is normal or not, Therefore Jarque-Bera test is used to investigate this issue. Moreover, the mean median and standard deviation show the variation in the data set.

The above Table 2 showed the values of the four companies like Apple, Citigroup, General Electronic, Google, and Microsoft. These US-based companies have the mean values of 0.000856, -0.000395, -0.000845, 0.000122 respectively. The median values of these companies are 0.000765, 0.000000, 0.000555, and 0.000000. The standard deviation of them is 0.026846, 0.030963, 0.018951 and 0.019267. Jarque- Bera values are 2838317., 347267.0, 14524.65, and 19012.41 and a total number of observations of them are 4737, 4737, 3574 and 4737 respectively. Jarque-Bera test provides significant evidence of non-normal distribution for all the variables.

The above Table 3 shows the companies of Hong Kong including Bank of China, EverGreen, Ping Insurance Co And Tencent Holding Ltd and their mean value, 0.005505, 0.000131, 0.000746, 0.005505, median values, 0.000000, Std. Dev. 0.6987789, 0.0207, 0.0248 and 0.698. Jarque- Bera 22502383, 5440.047, 4837.821, 22502383, and the total number of observations is 3548, 2958, 3541, and 3548, respectively. Jarque-Bera test provides significant evidence of non-normal distribution for all the variables.

The above Table 4 depicting the descriptive values of the Turkey-based companies, such as Arcelik, Dogus, Koc Holding and Vestel. And the values of these companies are following: the mean valves are 0.00016, 7.25E-05, -0.000385, and 4.42E-05, Median values are 0.000000 of all companies, Standard Deviations are 0.027047, 0.323655, 0.044622, and 0.028994, Jarque- Bera results are 26646.75, 67833896, 7.63E + 08 and 35462.96 respectively. Jarque-Bera test provides significant evidence of non-normal distribution for all the

Table 7
The results for all companies without any sentiment.

	Absolute Error (AE)			Root Mean Squared Error (RMSE)		
	Linear Regression	Support Vector Regression	Deep Learning	Linear Regression	Support Vector Regression	Deep Learning
Apple	5.073 +/- 0.196	0.337 +/- 0.028	0.383+/- 0.168	6.690 +/- 0.279	0.610 +/- 0.116	0.58 +/- 0.157
Google	2.549 +/- 0.111	0.372 +/- 0.053	1.340+/- 0.433	3.894 +/- 0.326	0.509 +/- 0.071	1.836+/- 0.436
Citigroup	2.821 +/- 0.172	2.051 +/- 0.160	2.4 +/- 0.86	5.044 +/- 0.357	3.842 +/- 0.484	3.877 +/- 0.69
Microsoft	1.247 +/- 0.047	0.237 +/- 0.020	0.284+/- 0.023	1.783 +/- 0.081	0.372 +/- 0.049	0.307+/- 0.033
Bank of china	0.025 +/- 0.002	0.024 +/- 0.003	0.029+/- 0.006	0.039 +/- 0.007	0.04 +/- 0.007	0.043+/- 0.010
Evergreen	0.373 +/- 0.014	0.099 +/- 0.009	0.087+/- 0.037	0.467 +/- 0.018	0.228 +/- 0.041	0.128 +/- 0.33
PING AN	1.290 +/- 0.045	0.302 +/- 0.018	0.3 +/- 0.050	1.626 +/- 0.072	0.538 +/- 0.085	0.530+/- 0.058
TENCENT	0.820 +/- 0.265	0.340 +/- 0.007	0.518+/- 0.133	1.4771 +/-0.522	0.428 +/- 0.011	0.688+/- 0.170
Arcelick	0.443 +/- 0.019	0.093 +/- 0.005	0.101+/- 0.009	0.640 +/- 0.033	0.145 +/- 0.008	0.142+/- 0.003
Dogus	0.063 +/- 0.004	0.056 +/- 0.005	0.073+/- 0.017	0.101 +/- 0.017	0.091 +/- 0.010	0.100 +/- 0.01
KOC	0.195 +/- 0.07	0.131 +/- 0.008	0.144+/- 0.014	0.257 +/- 0.012	0.186 +/- 0.016	0.195+/- 0.017
Vestel	0.036 +/- 0.002	0.001 +/- 0.00	0.017+/- 0.014	0.069 +/- 0.008	0.002 +/- 0.00	0.021+/- 0.015
Colgate	1.030 +/- 0.047	0.216 +/- 0.016	0.2 +/- 0.016	1.308 +/- 0.052	0.3 +/- 0.09	0.3+/- 0.09
Toyota	0.447 +/- 0.017	0.385 +/- 0.020	0.42 +/- 0.06	0.628 +/- 0.045	0.559 +/- 0.045	0.5 +/- 0.00
Unilever	0.117 +/- 0.004	0.111 +/- 0.004	0.1 +/- 0.01	0.164 +/- 0.008	0.16 +/- 0.011	0.19 +/- 0.03

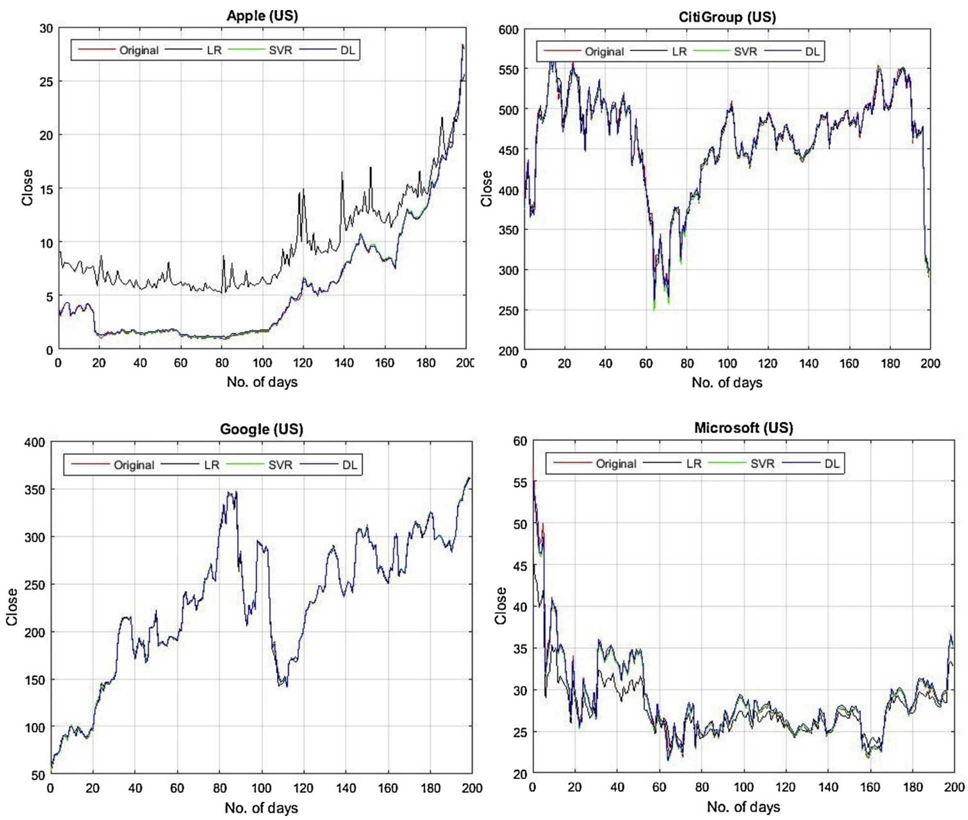

Fig. 2. The graphs show random 200 forecasted values for original, linear regression, support vector regression and deep learning for US-based companies.

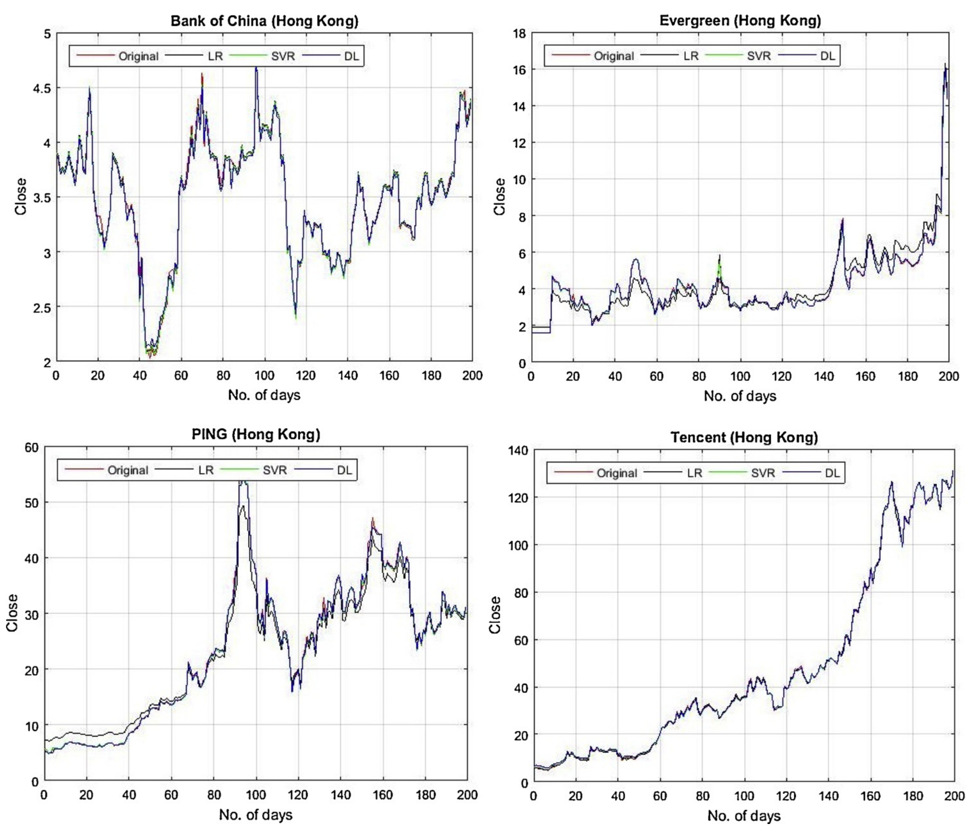

Fig. 3. The graphs show random 200 forecasted values for original, linear regression, support vector regression and deep learning for Hong Kong-based companies.

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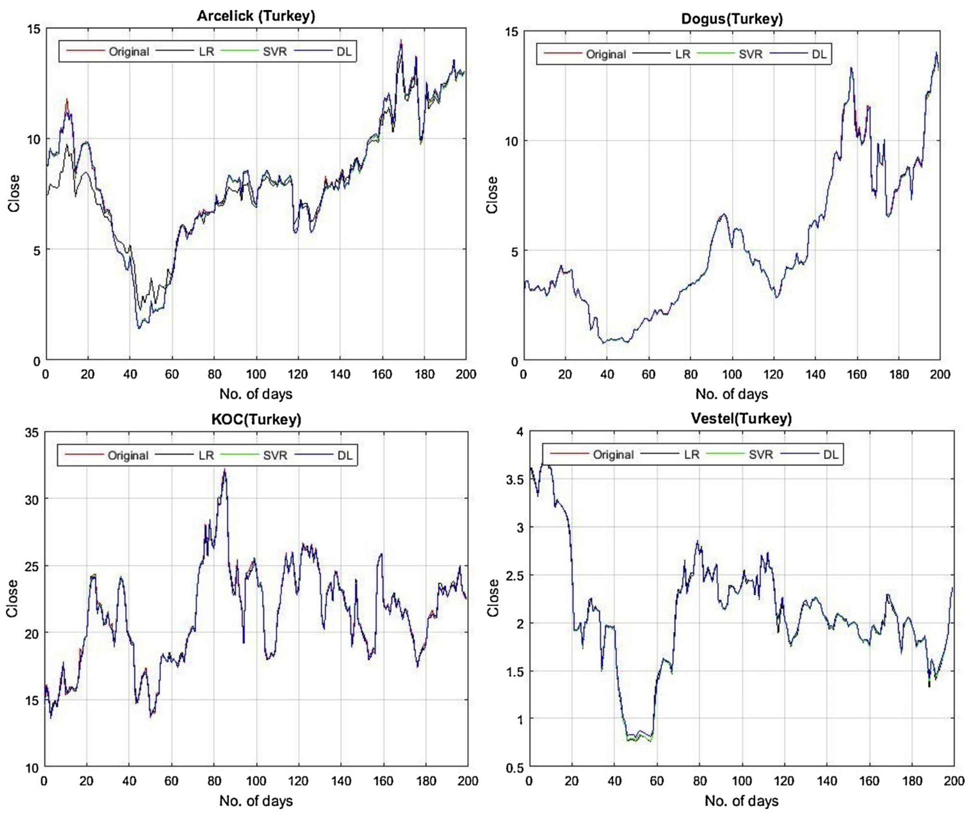

Fig. 4. The graphs show random 200 forecasted values for original, linear regression, support vector regression and deep learning for Turkey based companies.

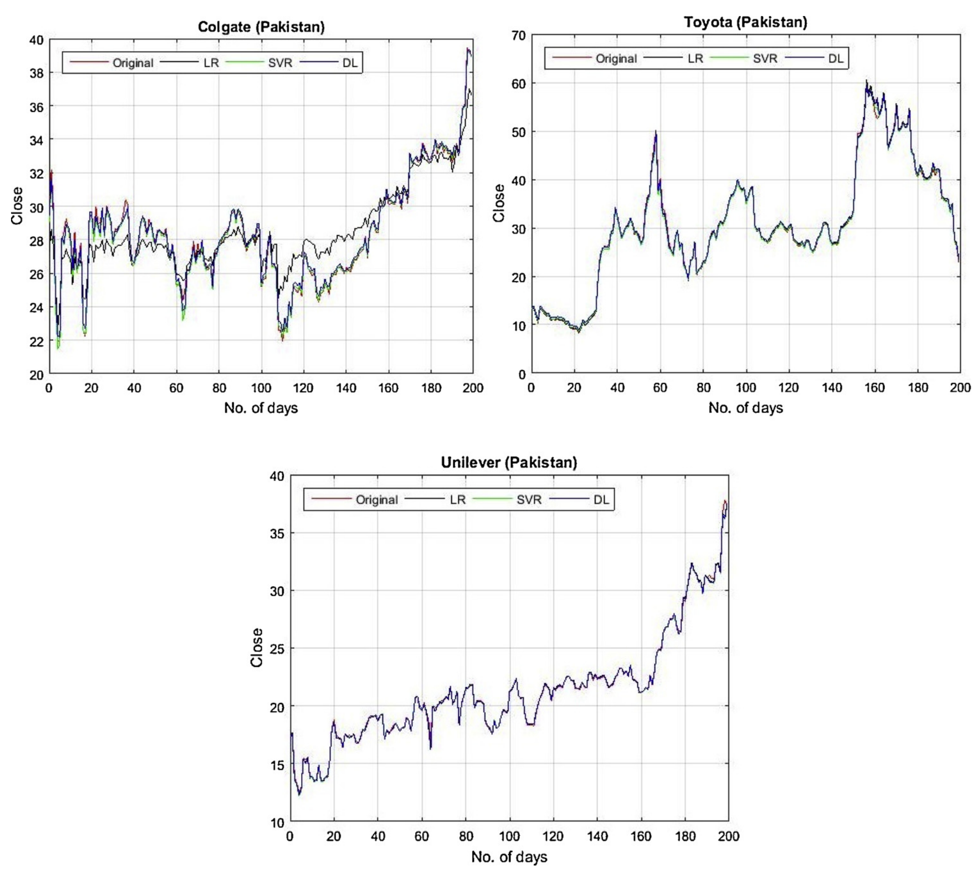

Fig. 5. The graphs show random 200 forecasted values for original, linear regression, support vector regression and deep learning for Pakistan based companies.

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Table 8
The results for all US companies using Mexican Election 2012 sentiment.

Mexican	Absolute Error (AE)			Root Mean Squared Error (RMSE)		
	Linear Regression	Support Vector Regression	Deep Learning	Linear Regression	Support Vector Regression	Deep Learning
Apple	0.154 +/- 0.017	0.019 +/- 0.004	0.115 +/- 0.093	0.284 +/- 0.087	0.033 +/- 0.012	0.608 +/- 1.402
CitiGroup	11.029 +/- 0.571	2.832 +/- 0.234	3.571 +/- 1.119	14.334 +/- 0.518	4.693 +/- 0.493	7.120 +/- 7.398
Google	1.668 +/- 0.090	0.114 +/- 0.021	0.344 +/- 0.090	2.328 +/- 0.204	0.143 +/- 0.022	0.564 +/- 0.367
Microsoft	0.329 +/- 0.019	0.213 +/- 0.015	0.262 +/- 0.049	0.462 +/- 0.028	0.334 +/- 0.028	0.361 +/- 0.076

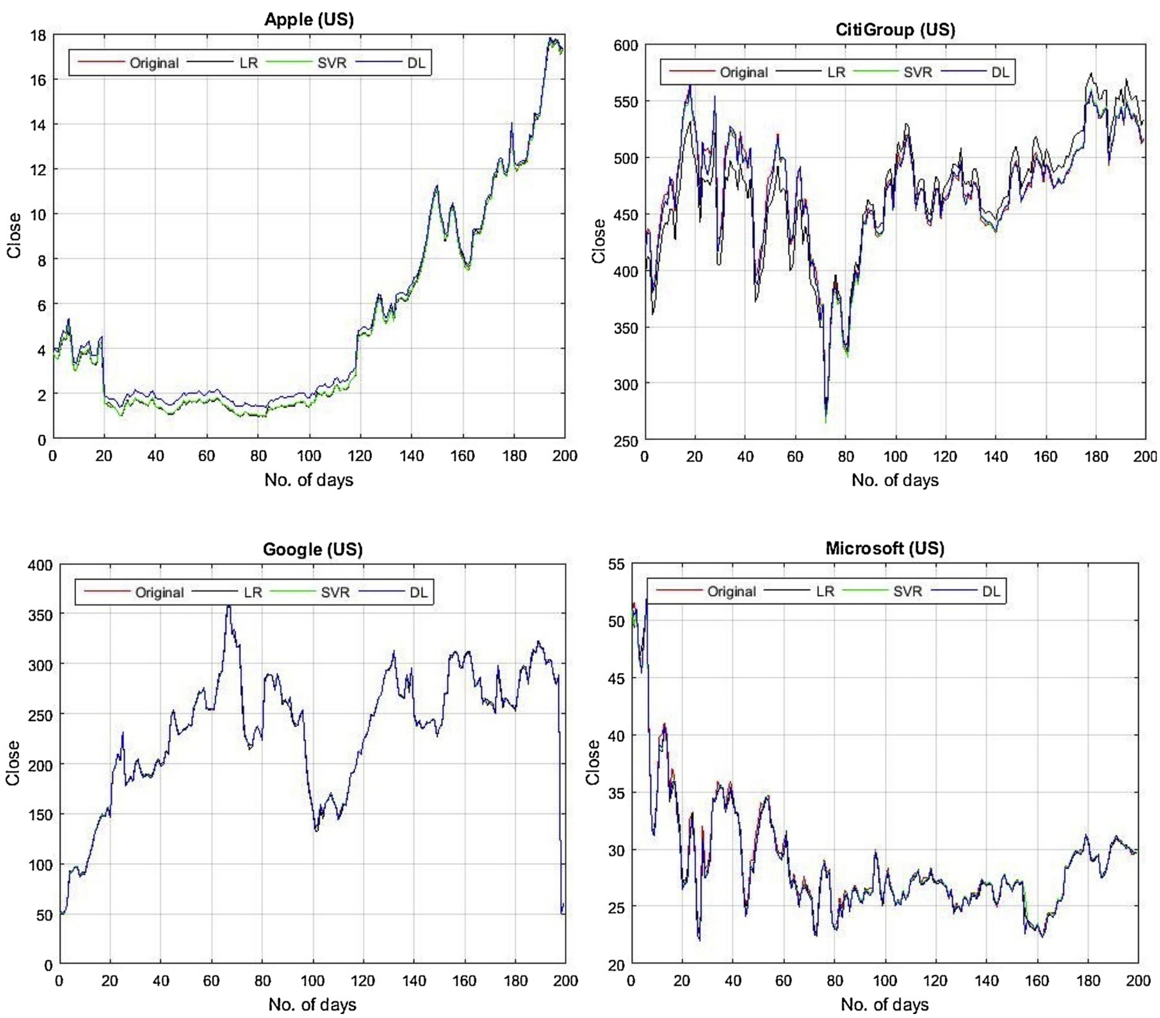

Fig. 6. The graphs show random 200 forecasted values of original, linear regression, support vector regression and deep learning for US-based companies against Mexican Election 2012.

Table 9
The results for all US companies using US election 2012 sentiment.

Us election	Absolute Error (AE)			Root Mean Squared Error (RMSE)		
	Linear Regression	Support Vector Regression	Deep Learning	Linear Regression	Support Vector Regression	Deep Learning
Apple	0.150 +/- 0.019	0.108 +/- 0.011	0.083 +/- 0.046	0.241 +/- 0.070	0.169 +/- 0.058	0.062 +/- 0.043
CitiGroup	10.737 +/- 0.194	2.772 +/- 0.143	2.111 +/- 0.708	12.147 +/- 0.301	2.644 +/- 0.381	2.537 +/- 0.689
Google	1.669 +/- 0.080	0.125 +/- 0.018	0.328 +/- 0.160	1.322 +/- 0.168	0.055 +/- 0.021	0.135 +/- 0.175
Microsoft	0.320 +/- 0.038	0.211 +/- 0.012	0.222 +/- 0.009	0.254 +/- 0.052	0.132 +/- 0.026	0.121 +/- 0.023

variables.

The above Table 5 is displaying the descriptive statistics of the different variables pertaining to data set of Pakistani companies used in our study.

4.3.1. Unit root test

In order to test the problem of a unit root, we use ADF unit root test. This test considers the null of unit root problem vs alternative of no unit root. Data has to be stationary in order to proceed with linear

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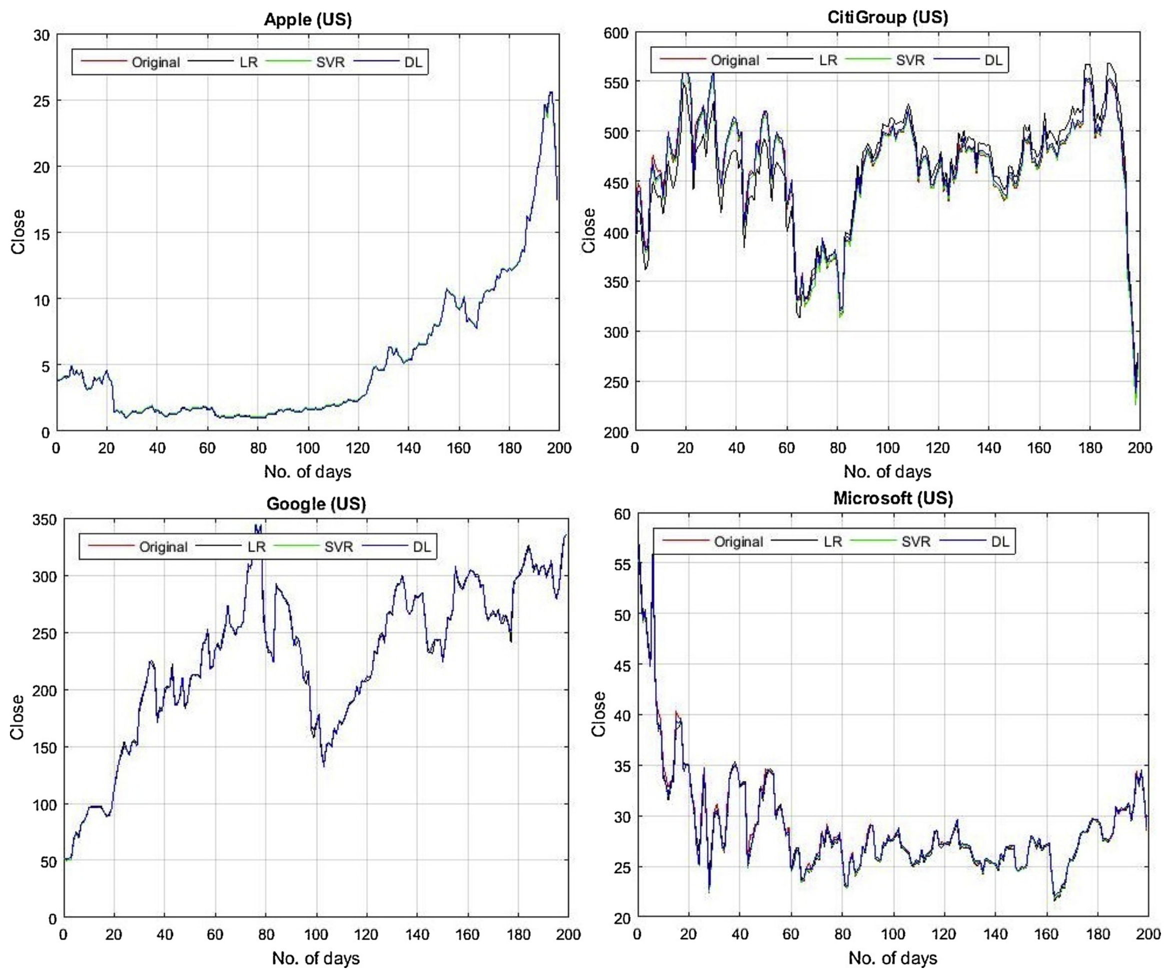

Fig. 7. The graphs show random 200 forecasted values of original, linear regression, support vector regression and deep learning for US-based companies against US Election 2012.

Table 10
The results for all US companies using Ghaza Under Attack 2014 sentiment.

Ghaza	Absolute Error (AE)			Root Mean Squared Error (RMSE)		
	Linear Regression	Support Vector Regression	Deep Learning	Linear Regression	Support Vector Regression	Deep Learning
Apple	2.571 +/- 0.201	0.186 +/- 0.023	0.241+/- .108	4.268 +/- 0.680	0.358 +/- 0.065	0.394+/0.130
CitiGroup	9.560 +/- 0.553	2.523 +/- 0.106	2.971+/- .007	13.313+/- 0.593	4.390 +/- 0.257	4.374+/- .777
Google	1.786 +/- 0.105	0.203 +/- 0.032	0.597+/-.263	2.483 +/- 0.225	0.261 +/- 0.040	0.832+/- 0.27
Microsoft	0.233 +/- 0.033	0.208 +/- 0.013	0.29+/- 0.115	0.336 +/- 0.048	0.328 +/- 0.024	0.38+/- 0.099

regression. If data set is not stationary it means that mean, median and variance are not time-dependent. On the other hand, if data is non-stationary then linear regression does not give reliable results. There is a number of tests which are used to investigate the problem of a unit root. Augmented Dicky fuller test is commonly used in the literature. We use the ADF unit root test to investigate the time dependence of mean, median, and variance.

Results of Unit root test for stationarity are reported in above Table 6. Since we could not reject the alternative of no unit root, therefore, all the stock returns series are stationary at level.[2]

4.3.2. Results using all data without event sentiment

In this section, we present the results for stock exchange prediction using different regression models includes linear regression, support vector regression and deep learning. To conduct the experiments, we have considered countries from the developed, emerging and under-developed list. The selected countries are the United States, Hong Kong, Turkey, and Pakistan. We have selected a total of 15 stock companies that are top listed in respective countries. The selected stocks for the US are Apple, Microsoft, Citigroup, and Google. The selected companies for Hong Kong are Bank of China, Evergreen, Ping AN and Tencent. The selected companies for Turkey are Arcelick, Dogus, KOC, and Vestel. The selected companies for Pakistan are Colgate, Toyota, and Unilever.

In our first experiment, we have used all three methods including linear regression, support vector regression and deep learning for all stock companies. All these methods are used with their default settings. These methods have been used on a large dataset of stock companies of almost 18 years or from the date of availability of the specific company. The detailed results in terms of RMSE and MAE are presented in Table 7.

[2] We applied DW-H test and serial correlation-LM test and found no evidence of autocorrelation in all the data sets. Results are available on request.

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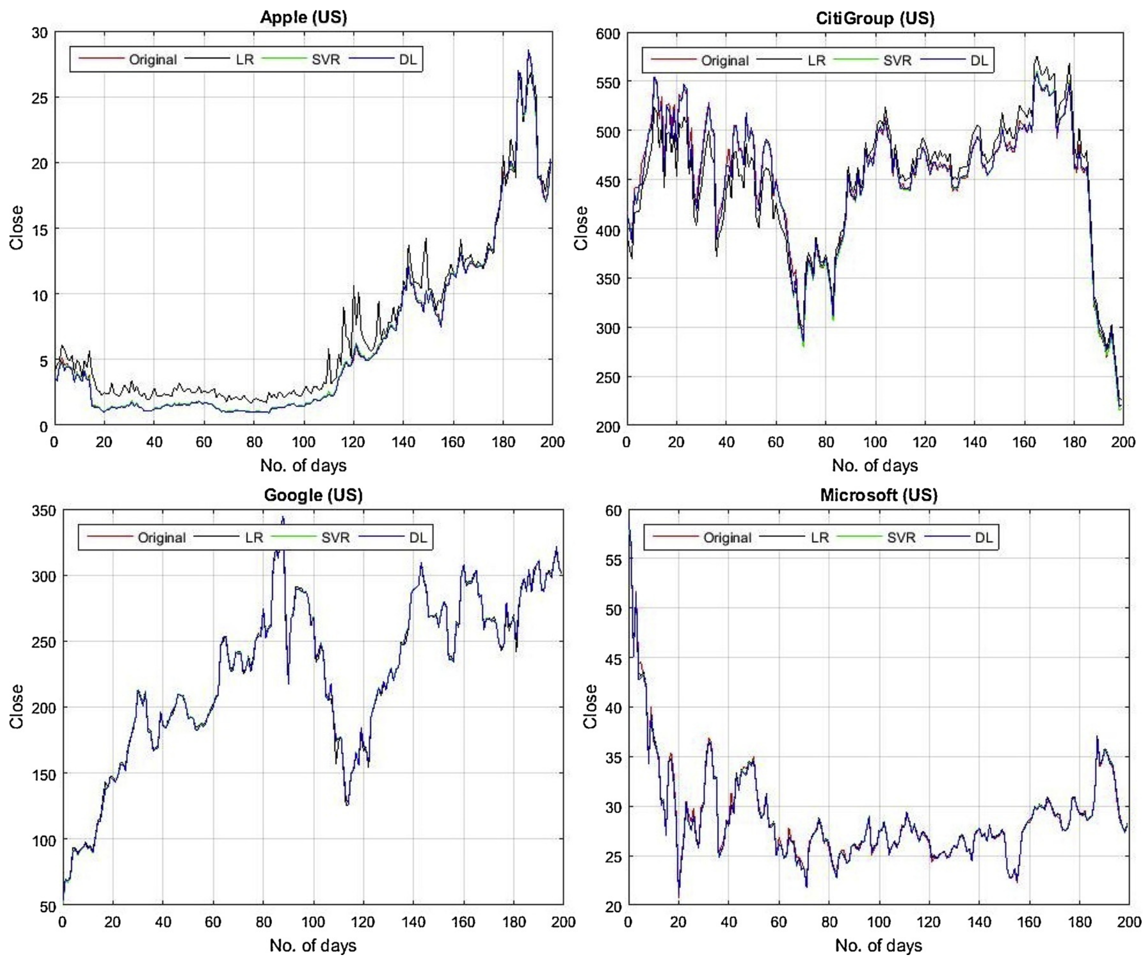

Fig. 8. The graphs show random 200 forecasted values of original, linear regression, support vector regression and deep learning for US-based companies against Ghaza Under Attack 2014.

Table 11
The results for all US companies using Brexit 2016 sentiment.

Brexit	Absolute Error (AE)			Root Mean Squared Error (RMSE)		
	Linear Regression	Support Vector Regression	Deep Learning	Linear Regression	Support Vector Regression	Deep Learning
Apple	4.634 +/- 0.188	0.245 +/- 0.019	0.30+/- 0.057	6.092 +/- 0.252	0.484 +/- 0.083	0.39+/- 0.064
CitiGroup	8.547 +/- 0.419	2.296 +/- 0.127	2.76+/- 0.862	12.555+/- 0.471	4.125 +/- 0.450	3.105+/- 0.78
Google	2.067 +/- 0.164	0.238 +/- 0.040	0.69+/- 0.303	2.953 +/- 0.332	0.306 +/- 0.051	0.649+/- 0.30
Microsoft	0.304 +/- 0.057	0.216 +/- 0.013	0.286+/- 0.07	0.432 +/- 0.084	0.332 +/- 0.035	0.275+/- 0.07

It is evident from the results that linear regression shows the worst results amongst the three methods used in this paper. The average RMSE for US companies are 4.35, 1.33 and 1.65 for linear regression and support vector regression and deep learning respectively. The average RMSE for Hong Kong companies are 0.90, 0.31 and 0.35 for linear regression and support vector regression and deep learning respectively. The average RMSE for Turkey companies are 0.27, 0.11 and 0.11 for linear regression and support vector regression and deep learning respectively. The average RMSE for Pakistan companies are 0.70, 0.34 and 0.33 for linear regression and support vector regression and deep learning respectively. The results in the form of graphs are presented in Fig. 2 for all four companies Apple, Citigroup. Google and Microsoft. The results are plotted only for 200 random predicted points for easy understandability.

The results for Hong Kong in graphical form is shown in Fig. 3 that shows the random 200 predicted points using all three methods along with the original values. The results show that linear regression gives the worst results amongst the three methods used in this paper. The remaining two results show good performance which is comparable and support vector regression gives the best results.

The results for Turkey in graphical form is shown in Fig. 4 that shows the random 200 predicted points using all three methods along with the original values. The results show that linear regression gives the worst results amongst the three methods used in this paper. The remaining two results show good performance and give the same results.

The results for Pakistani companies in graphical form is shown in Fig. 5 that shows the random 200 predicted points using all three methods along with the original values. The results show that linear regression also gives a very good performance but it is the worst amongst the three methods used in this paper. The remaining two results show good performance and almost gives the same results.

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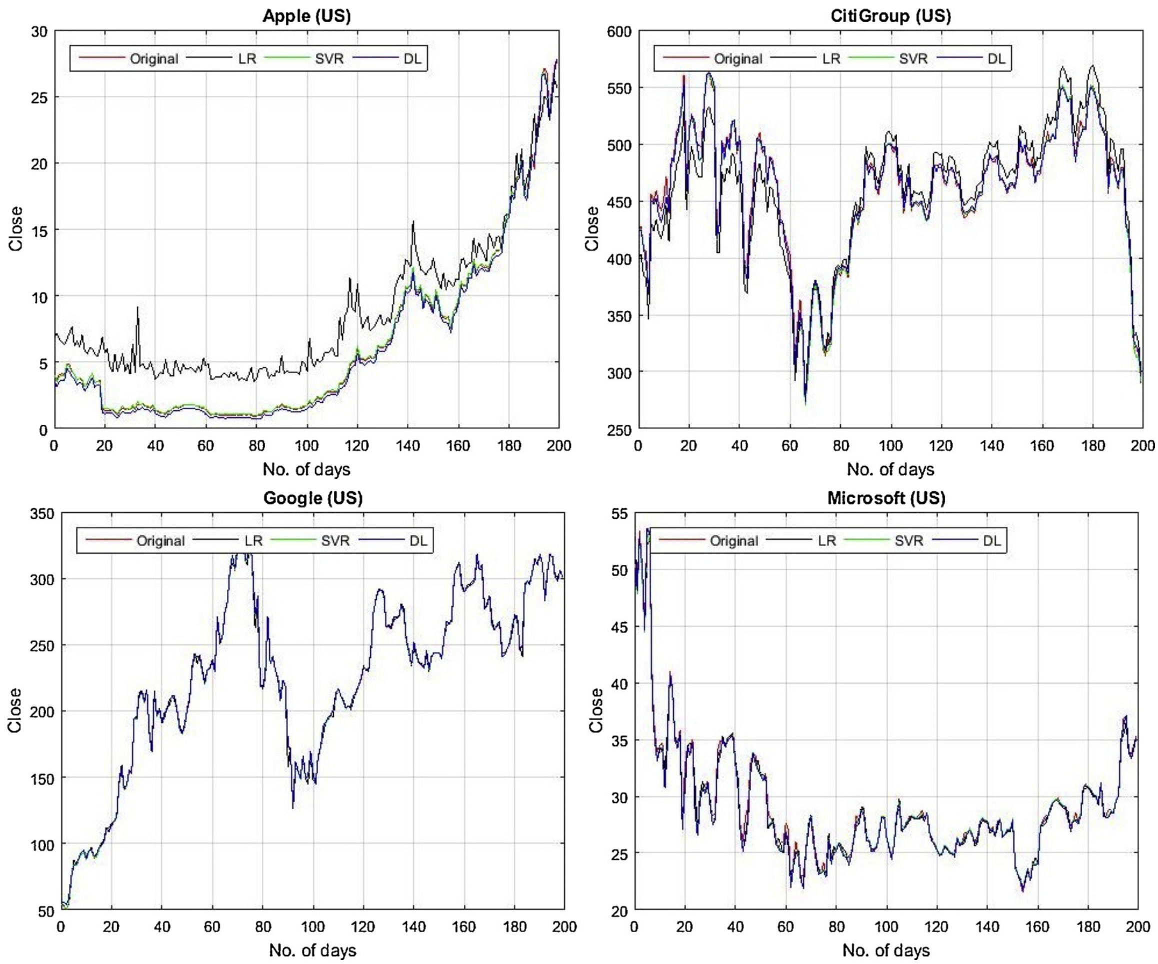

Fig. 9. The graphs show random 200 forecasted values of original, linear regression, support vector regression and deep learning for US-based companies against Brexit 2016.

Table 12
The results for all US companies using Refugee welcome 2015 sentiment.

Refugee	Absolute Error (AE)			Root Mean Squared Error (RMSE)		
	Linear Regression	Support Vector Regression	Deep Learning	Linear Regression	Support Vector Regression	Deep Learning
Apple	4.470 +/- 0.158	0.237 +/- 0.019	0.317+/- 0.17	5.959 +/- 0.196	0.470 +/- 0.079	0.502+/- 0.14
CitiGroup	8.768 +/- 0.366	2.342 +/- 0.109	2.857+/- 0.69	12.725+/- 0.434	4.188 +/- 0.280	4.385+/- 0.56
Google	1.955 +/- 0.074	0.271 +/- 0.029	0.706+/- 0.49	2.770 +/- 0.232	0.346 +/- 0.036	1.063+/- 0.44
Microsoft	0.298 +/- 0.051	0.213 +/- 0.013	0.249+/- 0.05	0.426 +/- 0.074	0.330 +/- 0.032	0.347+/- 0.06

4.3.3. *Results using event sentiment*

In our second experiment, we divided the events for each country into the local and global category. The said events' tweets are collected and sentiment analysis is conducted for each event. As the tweets for each event span more than one days, so the sentiment is calculated for each day separately. As the sentiment is usually classified as positive and negative, therefore, each day is classified as a positive sentiment day or a negative sentiment day. It is observed that positive sentiment is represented by +1 and negative sentiment is represented by -1. However, to show the sentiment of a day using +1 or -1 is not enough. Therefore, in this research, we have used a different parameter to calculate the overall sentiment of a single day. We have calculated the percentage positive tweets, percentage neutral and percentage negative tweets. Then we neglected the neutral tweets and subtracted the percentage of negative tweets from positive tweets. This gives an overall better index to show the sentiment of a day. This way we have calculated the percentage sentiment of each day of each event. This value is more informative as compared to a simple +1 or -1. Here we only consider the average results for each country to make comparison easy.

4.3.3.1. Results of US based companies. This section presents results for the US-based four companies using the sentiment analysis. The First event we considered is Mexican Election 2012. The average results have not improved as compared to earlier results calculated without considering this event. This shows there is not much effect of this event for US-based companies. The detailed results for each company are given in Table 8 and random 200 forecasted points are also shown for each company in Fig. 6.

The second event we considered for US companies is the US election 2012. The average results show a lot of improvement for all companies against all methods. These results show that a local event that occurs in the US has a very good impact on stock exchange prediction. The improvement in results is evident for all the companies which make prediction more accurate as shown in Table 9. The results in graphical form

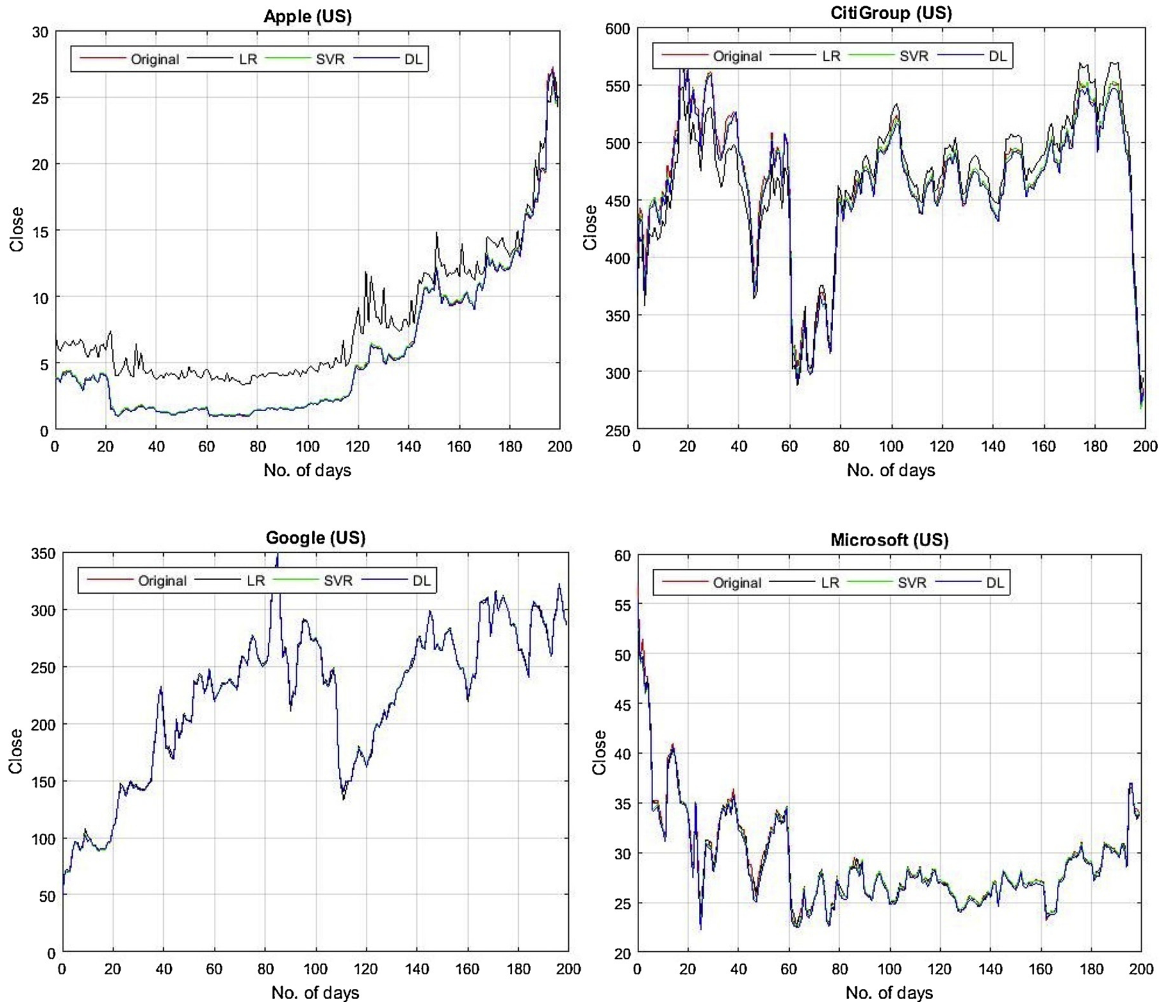

Fig. 10. The graphs show random 200 forecasted values of original, linear regression, support vector regression and deep learning for US-based companies against Refugee Welcome 2015.

Table 13
The results for all Hong Kong companies using Hong Kong Protest 2014 sentiment.

HongKong_protest	Absolute Error (AE)			Root Mean Squared Error (RMSE)		
	Linear Regression	Support Vector Regression	Deep Learning	Linear Regression	Support Vector Regression	Deep Learning
Bank of China	0.027 +/- 0.003	0.025 +/- 0.003	0.029+/-.005	0.042 +/- 0.008	0.043 +/- 0.009	0.043+/-.007
Evergreen	0.045 +/- 0.010	0.039 +/- 0.005	0.06+/-0.014	0.069 +/- 0.021	0.064 +/- 0.016	0.075+/-0.017
PING AN	–	0.336 +/- 0.085	0.34+/-0.085	–	0.572 +/- 0.346	0.57+/- 0.346
TENCENT	0.408 +/- 0.018	0.283 +/- 0.019	0.204+/- .03	0.480 +/- 0.020	0.409 +/- 0.123	0.281+/- .077

for all companies are also shown in Fig. 7.

The third event we considered is Ghaza Under Attack 2014. The average results have not improved as compared to earlier results calculated without considering this event. This shows there is not much effect of this event for US-based companies. The only improvement in results is for deep learning which is the only reduction of RMSE from 1.65 to 1.50 as shown in Table 10. The detailed results for each company are given in Table 10 and random 200 forecasted points are also shown for each company in Fig. 8.

The fourth event we considered is Brexit 2016. The average results have not improved for linear regression and support vector regression as compared to earlier results calculated without considering this event. However, there is an improvement of results for deep learning as shown in Table 11. This shows there is some effect of this event for US-based companies. The detailed results for each company are given in Table 11 and random 200 forecasted points are also shown for each company in Fig. 9.

The Fifth event we considered is Refugee welcome 2015. The average results have not improved as compared to earlier results calculated without considering this event. This shows there is not much effect of this event for US-based companies. The detailed results for each company are given in Table 12 and random 200 forecasted points are also shown for each company in Fig. 10.

4.3.3.2. Results of Hong Kong companies. This section presents results for the Hong Kong-based four companies using the sentiment analysis. The First event we considered is Hong Kong Protest 2014. The average results have improved as compared to earlier results calculated without considering this event. This shows there is a significant effect of this event for Hong Kong-based companies. The improved results achieved

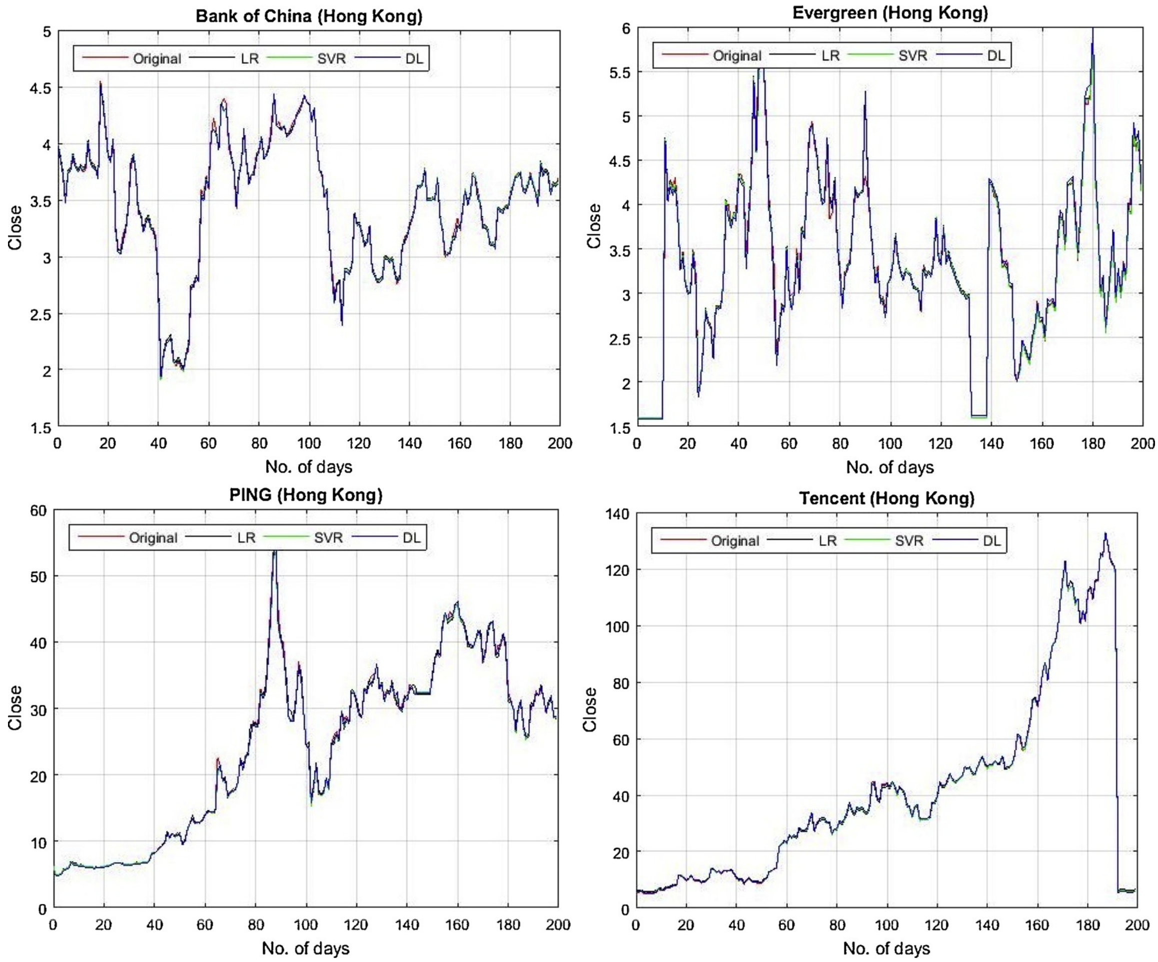

Fig. 11. The graphs show random 200 forecasted values of original, linear regression, support vector regression and deep learning for Hong Kong-based companies against Hong Kong Protest 2014.

Table 14
The results for all Hong Kong companies using US election 2012 sentiment.

US Election	Absolute Error (AE)			Root Mean Squared Error (RMSE)		
	Linear Regression	Support Vector Regression	Deep Learning	Linear Regression	Support Vector Regression	Deep Learning
Bank of China	0.047 +/- 0.004	0.028 +/- 0.004	0.033+/- .005	0.069 +/- 0.010	0.048 +/- 0.009	0.048+/- .009
Evergreen	0.079 +/- 0.010	0.042 +/- 0.003	0.052+/- .011	0.112 +/- 0.016	0.062 +/- 0.006	0.070+/- .009
PING AN	0.458 +/- 0.028	0.257 +/- 0.019	0.341+/-.146	0.638 +/- 0.041	0.432 +/- 0.044	0.452+/- .142
TENCENT	0.199 +/- 0.055	0.186 +/- 0.024	0.199+/- .055	0.262 +/- 0.070	0.298 +/- 0.155	0.262+/- .070

by the linear regression, support vector regression and deep learning are 0.20, 0.27 and 0.24 respectively. The detailed results for each company are given in Table 13 and random 200 forecasted points are also shown for each company in Fig. 11.

The second event we considered is the US election 2012. The average results have improved as compared to earlier results calculated without considering this event. This shows there is a significant effect of this event for Hong Kong-based companies. The improved results achieved by the linear regression, support vector regression and deep learning are 0.27, 0.21 and 0.21 respectively. This global event has more effect as compared to the previously discussed local event for Hong Kong. The detailed results for each company are given in Table 14 and random 200 forecasted points are also shown for each company in Fig. 12.

4.3.3.3. *Results of Turkish companies*. This section presents results for Turkey based on four companies using the sentiment analysis. The First event we considered is Hijack Plane Cyprus 2016. The average results have a minor improvement for support vector regression and deep learning as compared to earlier results calculated without considering this event. This shows there is a minor effect of this event for Turkey based companies. The detailed results for each company are given in Table 15 and random 200 forecasted points are also shown for each company in Fig. 13.

The second event we considered is Refugee welcome 2015. The average results have a minor improvement for support vector as compared to earlier results calculated without considering this event. This shows there is a minor effect of this event for Turkey based companies. The detailed results for each company are given in Table 16 and random 200 forecasted points are also shown for each company in Fig. 14.

The last event we considered is the US election 2012. The average results have improved as compared to earlier results calculated without considering this event. This shows there is a significant effect of this

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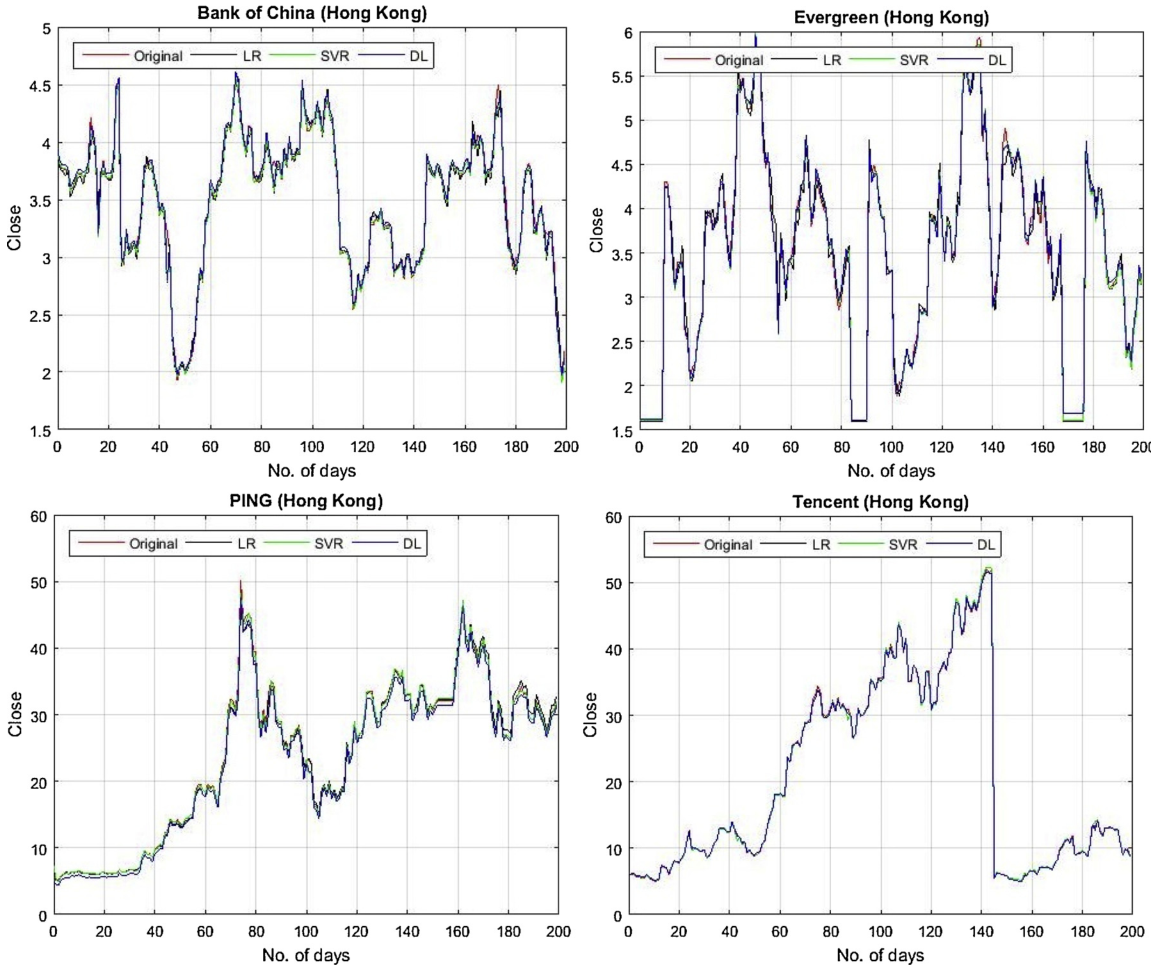

Fig. 12. The graphs show random 200 forecasted values of original, linear regression, support vector regression and deep learning for Hong Kong-based companies against US election 2012.

Table 15
The results for all Turkey companies using Hijack Plane Cyprus 2016 sentiment.

Cyprus	Absolute Error (AE)			Root Mean Squared Error (RMSE)		
	Linear Regression	Support Vector Regression	Deep Learning	Linear Regression	Support Vector Regression	Deep Learning
arcelick	0.434 +/- 0.027	0.068 +/- 0.006	0.081+/- .012	0.608 +/- 0.040	0.108 +/- 0.012	0.11+/- 0.011
dogus	0.465 +/- 0.023	0.053 +/- 0.004	0.065+/- .014	0.568 +/- 0.025	0.090 +/- 0.010	0.09+/- 0.013
Koc	0.441 +/- 0.038	0.139 +/- 0.013	0.155+/- .021	0.549 +/- 0.042	0.185 +/- 0.023	0.19+/- 0.028
vestel	0.023 +/- 0.002	0.001 +/- 0.000	0.007+/- .003	0.041 +/- 0.009	0.002 +/- 0.000	0.01+/- 0.003

event for Hong Kong-based companies. The improved results achieved by the linear regression, support vector regression and deep learning are 0.28, 0.07 and 0.08 respectively. This global event has more effect as compared to the previously discussed local event for Turkey. The detailed results for each company are given in Table 17 and random 200 forecasted points are also shown for each company in Fig. 15.

4.3.3.4. Results of Pakistani companies. This section presents results for Pakistan based on four companies using the sentiment analysis. The First event we considered is Lahore Blast 2016. The average results have a significant improvement for linear regression, support vector regression and deep learning as compared to earlier results calculated without considering this event. This shows there is a significant effect of this event for Pakistan based companies. The detailed results for each company are given in Table 18 and random 200 forecasted points are also shown for each company in Fig. 16.

The last event we considered is the US election 2012. The average results have improved as compared to earlier results calculated without considering this event. This shows there is a significant effect of this event for Pakistan based companies. This global event has more effect as compared to the previously discussed local event for Turkey. The detailed results for each company are given in Table 19 and random 200 forecasted points are also shown for each company in Fig. 17.

It is worth mentioning here that not all local and global events have a significant effect on stock markets. However, there are certain events that have a significant effect on stock markets. These events usually have a strong positive or negative sentiment for a country. It is also worth mentioning that the US election had a significant effect on all stock markets and companies.

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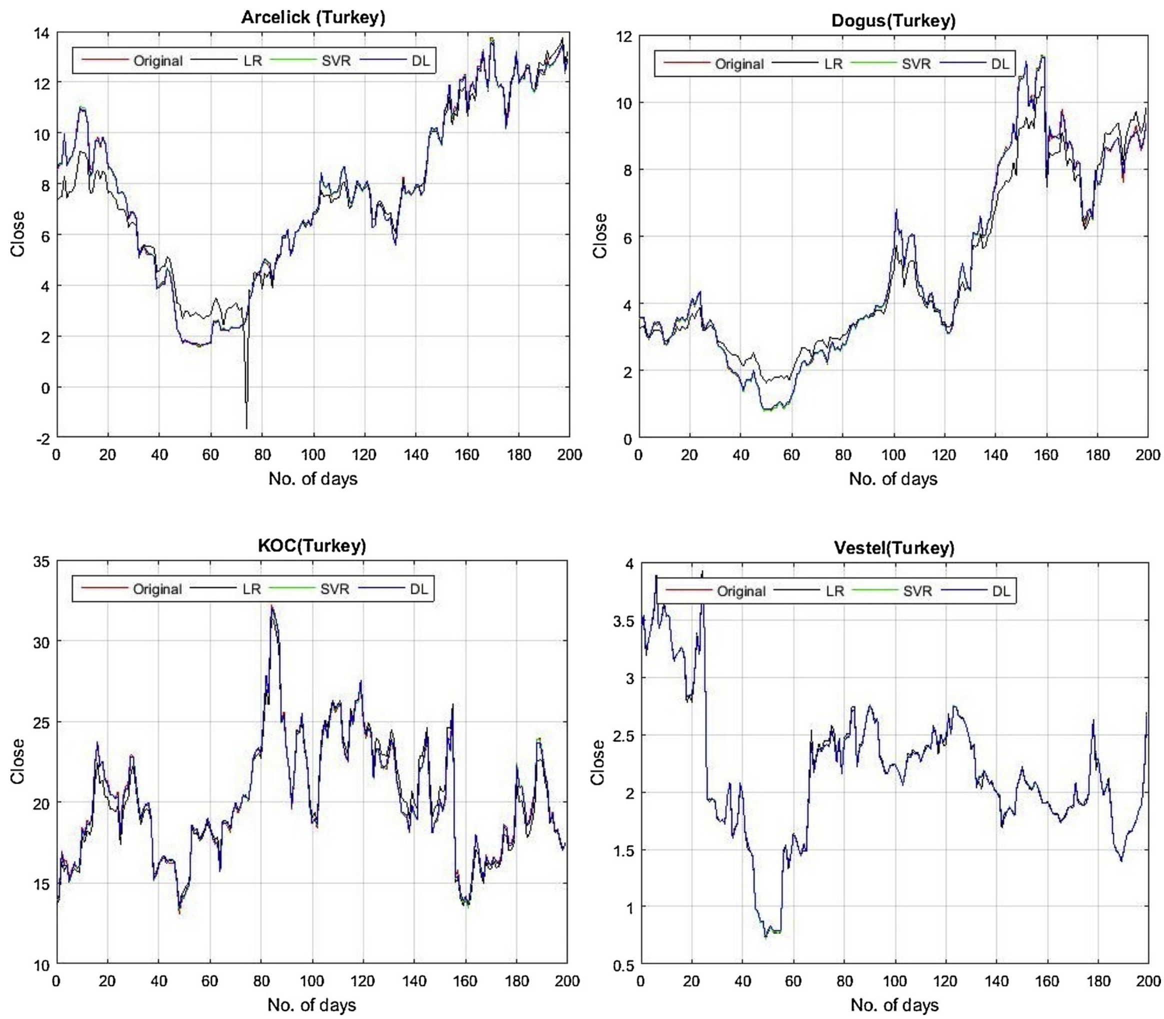


Fig. 13. The graphs show random 200 forecasted values of original, linear regression, support vector regression and deep learning for Turkey based companies against Hijack Plane Cyprus 2016.

Table 16
The results for all Turkey companies using Refugee welcome 2015 sentiment.

Refugee	Absolute Error (AE)			Root Mean Squared Error (RMSE)		
	Linear Regression	Support Vector Regression	Deep Learning	Linear Regression	Support Vector Regression	Deep Learning
arcelick	0.431 +/- 0.022	0.062 +/- 0.006	0.077+/- .019	0.607 +/- 0.034	0.098 +/- 0.012	0.107+/- .020
dogus	0.446 +/- 0.019	0.048 +/- 0.005	0.060+/0.014	0.547 +/- 0.022	0.084 +/- 0.009	0.089+/- .014
Koc	0.406 +/- 0.031	0.137 +/- 0.008	0.174+/- .035	0.500 +/- 0.037	0.183 +/- 0.016	0.213+/- .035
vestel	0.023 +/- 0.002	0.001 +/- 0.000	0.012+/- .007	0.040 +/- 0.008	0.002 +/- 0.000	0.016+/- .006

5. Discussion

5.1. Theoretical contribution

There has been a lot of research related to stock exchange prediction. The researchers have used both traditional and artificial intelligence-based advanced models for this purpose. In recent years, the focus has shifted towards artificial intelligence-based stock prediction models. These artificial intelligence-based models further use traditional machine learning techniques like linear regression and support vector regression. To find a more suitable prediction model for stock exchange prediction remains an important research avenue. The advancement in machine learning has seen a paradigm shift towards deep learning-based solutions. Deep learning-based models perform exceptionally well for classification and prediction purposes. In this work, we have used the deep learning model for stock exchange prediction and combined it with the country's events' sentiment.

The results presented above have established the predictability of stock returns by incorporating the sentiment of mega-events which act as a significant parameter while predicting the stock prices. Investor sentiment calculated on the basis of tweets in response to mega political events (local and global) increase the accuracy of stock prediction when different models are considered especially deep learning technique. Similar work is done by (Demirer & Kutan, 2006) in which they find weak correlation investor sentiment and change in stock prices when used with a linear model. However, their results yield strong evidence of significant relationship amongst mood of investor (sentiment) and changes in stock prices. They consider 60,000 tweets using 3 key hashtags during the period of 2016 UK local election. Future returns of small stocks, medium stocks, dividend-paying stocks, volatile stocks,

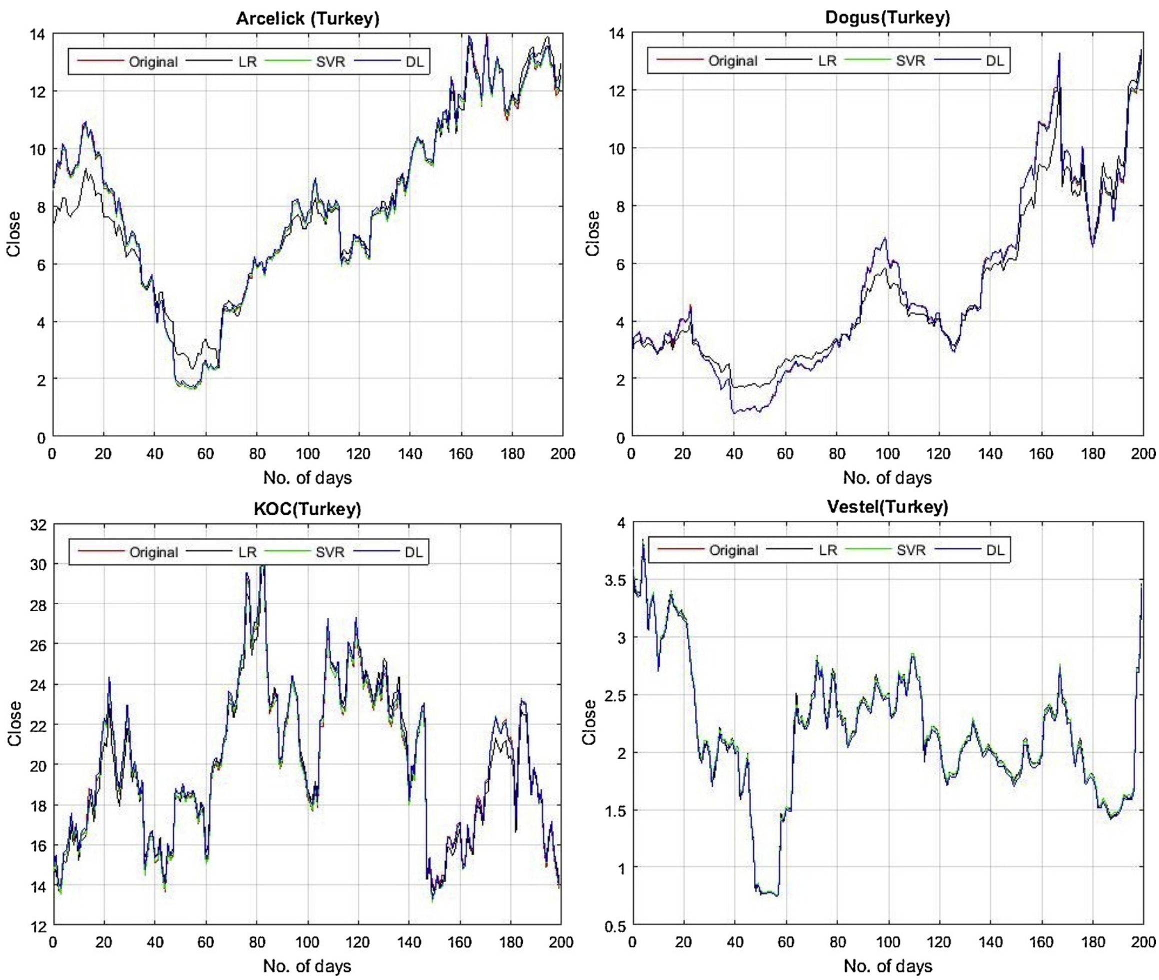


Fig. 14. The graphs show random 200 forecasted values of original, linear regression, support vector regression and deep learning for Turkey based companies against US election 2012.

Table 17
The results for all Turkey companies using US election 2012 sentiment.

Us election	Absolute Error (AE)			Root Mean Squared Error (RMSE)		
	Linear Regression	Support Vector Regression	Deep Learning	Linear Regression	Support Vector Regression	Deep Learning
arcelick	0.356 +/- 0.040	0.045 +/- 0.004	0.050+/-0.006	0.494 +/- 0.045	0.074 +/- 0.011	0.076+/- .013
dogus	0.172 +/- 0.010	0.022 +/- 0.002	0.029+/-0.009	0.211 +/- 0.010	0.035 +/- 0.005	0.040+/- .010
Koc	0.363 +/- 0.016	0.137 +/- 0.010	0.158+/- .030	0.393 +/- 0.015	0.179 +/- 0.013	0.201+/- .031
vestel	0.017 +/- 0.001	0.001 +/- 0.000	0.003	0.026 +/- 0.004	0.001 +/- 0.000	0.004+/- .001

non-profitable stocks, and non-dividend paying stocks are relatively low when investor sentiment is high and vice versa. Similarly, those stocks that are hard to value and arbitrage are more exposed to sentiments (Davies, 1987). Stock predictions based on social media tweets are also done by (Economou et al., 2011). They present evidence of significant relationship amongst social media sentiment and stock movements. In addition volume of tweets also has significant importance in stock predictions. In simple words the emotions expressed on twitter i.e hope, fear and worry give a complete “set of predictor” which in turn provides the least margin of error while the prediction of stock movements. (Chiang et al., 2010).

Investors form stochastic beliefs because of either over-optimism or pessimism (investor sentiment) that leads the asset prices to deviate from their intrinsic values. When investor sentiment wanes and economic fundamentals are revealed then mispricing of assets gets corrected (Christie & Huang, 1995; Bae, Karolyi, & Stulz, 2003; Karolyi & Stulz, 1996). As a result of pricing correction, investor sentiment and future stock return become negatively associated. Therefore investor sentiment gets significant predictive power to forecast stock returns movement. Since our results show that in the presence of investor sentiment based on mega-events around the globe have a significant role during stock return predictions, therefore, our results are in line with the above argument. Studies were done by (Christie & Huang, 1995) and (Davies, 1987) also endorses the significance of our results. The former argues that small stocks can be predicted on the basis of investor sentiments whereas the latter presents the evidence that the predictive pattern of investor mood depends on the characteristics of stocks such as firm size, volatility, and age.

In literature, most of the studies consider local political and economic events of short windows to calculate social media sentiment in order to predict stock returns. However, our research study contributes to the existing body of knowledge by considering both local and global

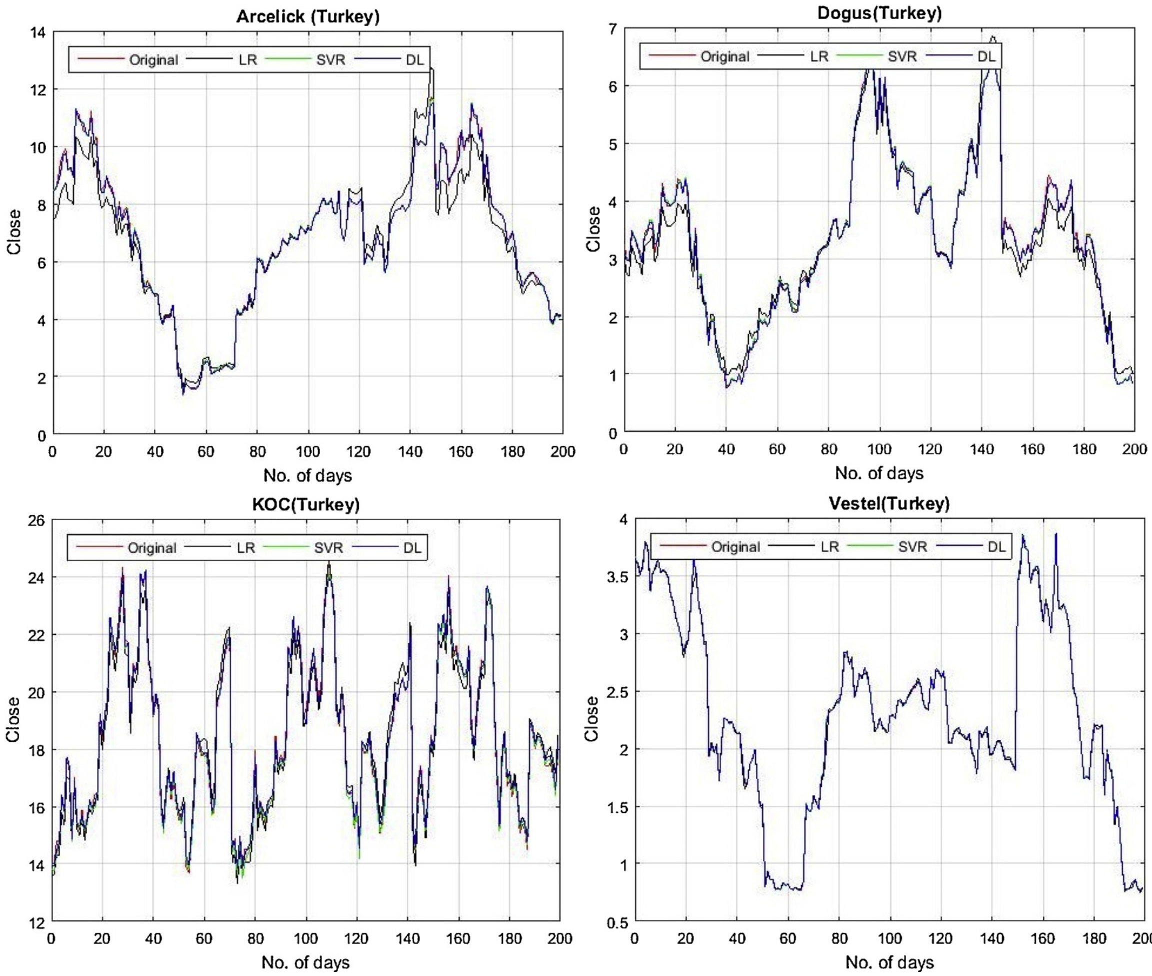


Fig. 15. The graphs show random 200 forecasted values of original, linear regression, support vector regression and deep learning for Turkey based companies against US election 2012.

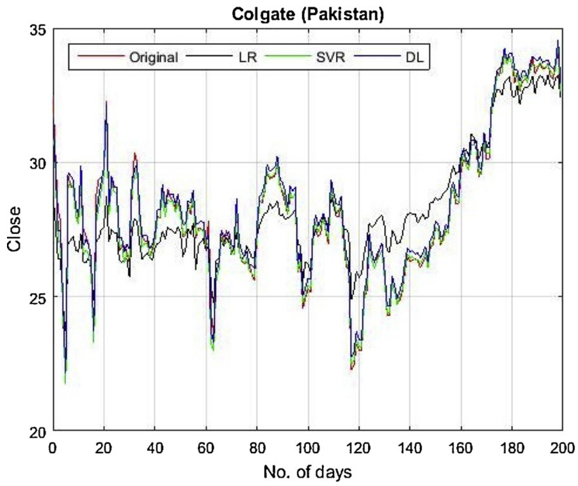
Table 18
The results for all Pakistan companies using Lahore Blast 2016 sentiment.

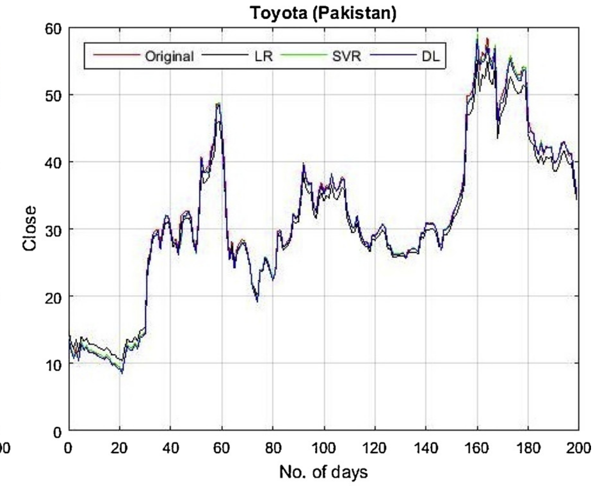
Lahore Blast	Absolute Error (AE)			Root Mean Squared Error (RMSE)		
	Linear Regression	Support Vector Regression	Deep Learning	Linear Regression	Support Vector Regression	Deep Learning
Colgate	0.905 +/- 0.025	0.210 +/- 0.020	0.268+/- .052	0.941 +/- 0.025	0.139 +/- 0.099	0.29+/- 0.695
Toyota	0.905 +/- 0.097	0.361 +/- 0.020	0.420+/- .092	0.860 +/- 0.089	0.325 +/- 0.040	0.345+/- .086
Unilever	0.918 +/- 0.032	0.108 +/- 0.007	0.136+/- .028	1.289 +/- 0.047	0.163 +/- 0.020	0.234+/- .165

mega-events to calculate sentiments and use it while the prediction of stock movement in three different groups of stock markets. Moreover, our research study considers an intensive data set of 11.42 million tweets which have rarely been used in the literature to calculate sentiments for stock prediction. Therefore our research study presents intensive insight information about the significance of social media sentiment and stock prediction.

5.2. Implications for practice

The relationship between public perception on social media about political events and stock market movement has been a point of discussion in recent researches (Nisar & Yeung, 2018). However, this research study considers an intensive data set and multiple mega-events to calculate investor mood(sentiment) on the basis of their social media response and check whether there is a link amongst sentiment and stock movement or not. The results provide strong evidence that the investor sentiment of social media that is calculated on the basis of global events like US elections 2012 has a significant role in stock predictions of developing (Pakistan), emerging (Hong Kong and Turkey) and developed (US) markets. Thus this study has a number of implications for both investors and policymakers. Since our research study provides strong evidence of predictive power of investor sentiment for stock prediction, therefore, the investors should keep this in mind and take care of this deep insight information while investing in the stocks which are more sensitive to local and global events. Investor sentiment may cause serious damage to their portfolio set if they follow a sentiment caused by a rumor, which in turn may become a reason of market inefficiency. If investors mimic each other because of such sentiments and trade in a similar direction, this will cause a serious anomaly in the market which may inject volatility in the market, therefore there must a system to educate investors to in order to avoid any consequence caused by any kind of sentiment. Thus, In our study we used sentiment of some mega-events that had occurred locally or globally for different





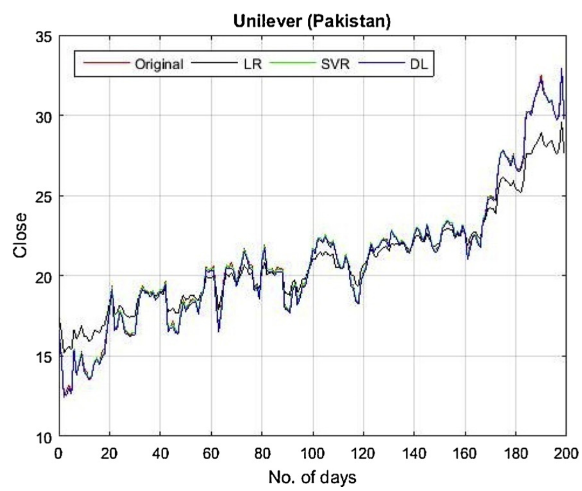


Fig. 16. The graphs show random 200 forecasted values of original, linear regression, support vector regression and deep learning for Pakistan based companies against Lahore Blast 2016.

Table 19
The results for all Pakistan companies using US election 2012 sentiment.

US Election	Absolute Error (AE)			Root Mean Squared Error (RMSE)		
	Linear Regression	Support Vector Regression	Deep Learning	Linear Regression	Support Vector Regression	Deep Learning
Colgate	0.989 +/- 0.019	0.195 +/- 0.012	0.221+/- .029	1.231 +/- 0.029	0.196 +/- 0.032	0.110+/- .041
Toyota	0.789 +/- 0.016	0.309 +/- 0.011	0.367+/- .084	0.727 +/- 0.021	0.246 +/- 0.024	0.478+/- .076
Unilever	0.878 +/- 0.043	0.104 +/- 0.010	0.117+/- .008	1.135 +/- 0.053	0.161 +/- 0.022	0.166+/- .016

set of countries (Developing, Emerging and Developed) and the findings suggest that sentiment of US election 2012 has a significant impact on stock prediction of all the stocks including top-performing stocks of Pakistan, Turkey, Hong Kong, and the US. (Grover, Kar, Dwivedi et al., 2019) argue that in the national calendar the elections are considered as the most critical events and they investigate the relationship amongst social media discussion and voting behavior of voters and found it significant. Therefore it is very important for individual investors to be very careful while making any opinion or sentiment about mega-events when it comes to financial decision making.

This study also provides a significant guideline for policymakers. They should keep in mind the sensitivity of stocks towards the social media response of mega-events. The results of the study imply that local or global events have a direct impact on the stock markets and this impact is often immediate. In addition, the post-event social media sentiment doubles the impact of the same mega event, therefore It is important to design strong policies to avoid market crashes. There is a need to impose circuit breakers and develop safety nets in order to prevent instability in the stock market that can be caused by any type of sentiment. In addition, there is a need to design policies to deal with rumors that are spread on social media regarding volatile macro-economic parameters. There is a need to have a system that guides individual investors to cope up any uncertain situation which may lead them to be trapped in noise trading. Since the findings of our research yield that top-performing stocks of Pakistan, Tukey, and Hong Kong are sensitive to social media sentiments in response to local and global event, therefore it is of core importance for the policymakers to keep track of the sensitivity of these stock markets associated with political events that occur especially around the globe.

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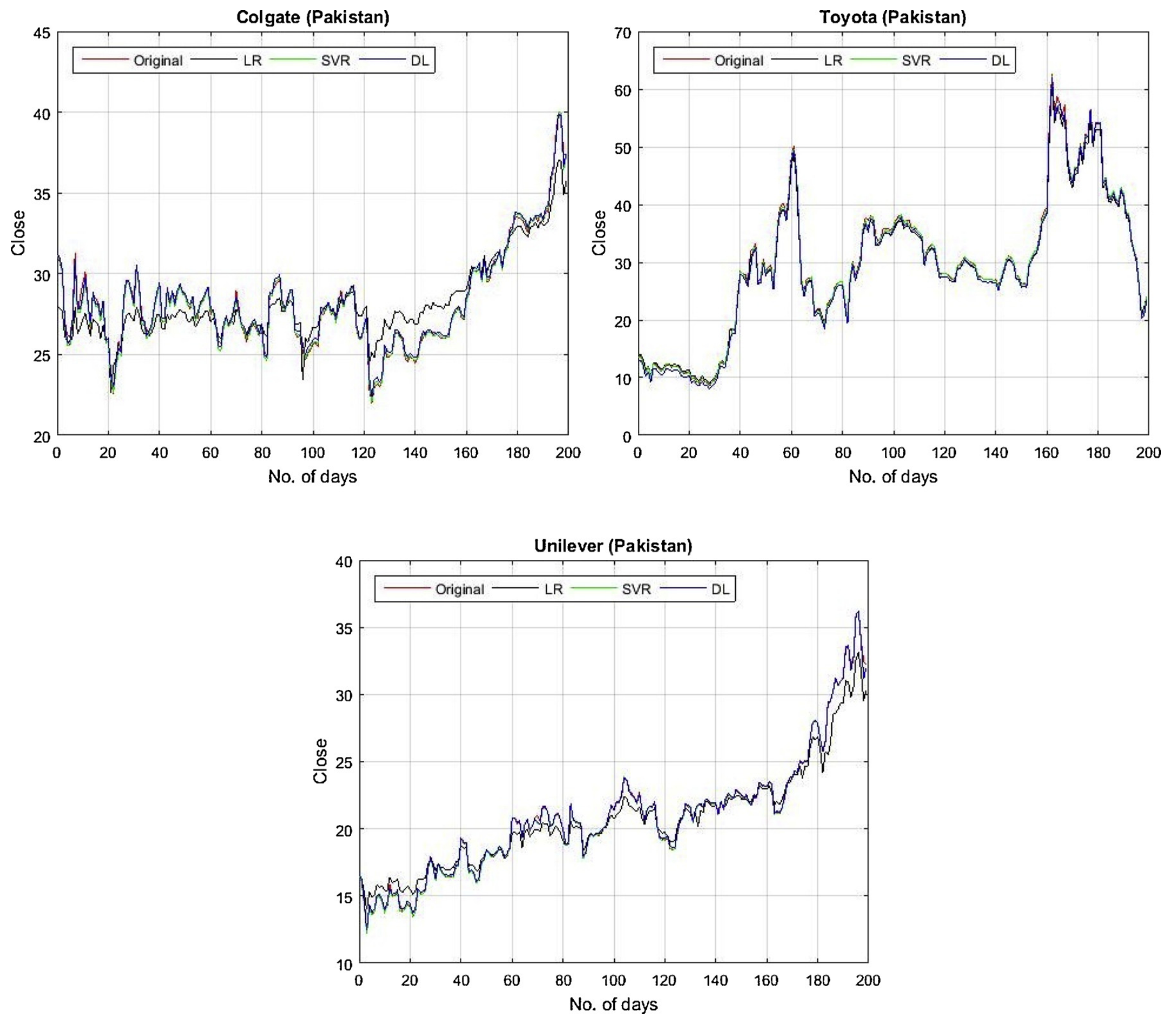

Fig. 17. The graphs show random 200 forecasted values of original, linear regression, support vector regression and deep learning for Pakistan based companies against US election 2012.

5.3. Limitation and future research direction

The study has used deep learning-based models along with event sentiment for stock exchange prediction. Though this study has used 11.42 million tweets to calculate the event sentiment the number of events considered is limited. This study used a total of 8 events for all countries. These events were categorized in local and global events and some events were the same for more than one country. These events were considered because of the availability of the datasets. There can be some other more events happened but the unavailability of the data is an issue to test their impact on the stock. There is a strong need to consider more events for each country to evaluate its effect. These events should also include major political and economic events.

The social media has seen enormous growth in recent years and researchers have utilized it for opinion mining in different domains. Twitter is the most widely used social media platform used for sentiment analysis. However, there are a large number of users on other social media platforms like Facebook. One of the future direction can be to use more than one social media platform to extract sentiment analysis for a particular event. In this way, the sentiment analysis of any event can be more authentic and strong. Another future direction can be to consider the events related to the political conditions of countries which are not politically stable. These events may have a huge impact on the stock exchange. The deep learning models are computationally expensive. These models need a huge amount of dataset to train. The performance of traditional machine learning models like linear regression and support vector regression improves to a certain level by increasing the dataset. After that, the performance remains the same even by adding mode dataset for training. While the performance of deep learning models keeps improving by adding mode data. The deep learning models use forward and backward propagation for weight learning which takes time to predict the final decision. In the future, an evolutionary approach can be used to learn weights. The evolutionary approaches can speed up the process to learn these weights which can ultimately reduce computational complexity.

Investor sentiment may also be used to check the presence of herding behavior in stock markets. Herding behavior is an anomaly which is defined as the irrational behavior of market participants to avoid their private information and mimic their peers. If herding behavior prevails in one stock market because of the social media sentiment then it may spill over to another market, thus this can be another research direction to investigate the presence of herding behavior in the stock market and its spillover across the borders in presence of social media sentiment regarding mega political and economic events.

6. Conclusion

Stock exchange prediction is an important aspect of the risk-free, efficient and reliable investment plan. Stock markets volatility not only depends upon the nonlinear nature of data and economic rules, but it also depends upon the community's sentiment and economic and political conditions of the country. Therefore, an efficient stock prediction algorithm should consider public sentiment, especially for mega political and geographic events. In this study, we have taken the Twitter data for eight mega-events from 2012 to 2016 and used for efficient stock forecasting using linear regression, support vector regression and deep learning. The results show that not all the major events have a serious impact on stock exchange prediction. However, more important local events can affect the performance of prediction algorithms. It has also been observed that some global events affect the stock markets of other countries. In this research, the US election was a major event that affects the stock markets of different countries. The performance for all three algorithms was evaluated on a dataset of a total of 11.42 million tweets. All algorithms show significant improvement for most of the events.

There are different future avenues available for this work. The news data is also playing an important part in stock exchange prediction. The stock markets are highly volatile and usually affected by the country's situation and news can be a good source to get this information. The news patterns can be predicted using machine learning techniques which then further can be used for stock market prediction. Another possible future direction can be a use of such large twitter dataset for the prediction foreign exchange rate and interest rate prediction. The foreign exchange rate and interest rate are highly volatile variables and can be affected by people's opinion.

The deep learning models are recently most widely used for stock exchange prediction. The deep learning models have a lot of layers involved in the structure. These models use back and forward propagation to match the output with the actual results. In case the output is not the same as the actual values the model again adjust the weights and produce the output. This process is time-consuming which makes deep learning model training slow. To handle this issue, evolutionary approaches can be used to find the most optimal weights which can make this process fast and efficient.

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