# Iranian stock market fluctuations: from social news to forecasting models

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***Abstract*—This research investigates the impact of news on stock price changes in the Tehran Stock Exchange. Due to the lack of Persian news analysis models for the capital market, news items are translated into English and analyzed using the FinBERT model. Market data is obtained from the Tehran Stock Exchange website and stored after price adjustment. Based on the deposit report, one stock is selected as a representative from each industry, and a separate model is trained for each stock. In the second phase, price changes are categorized into five groups and labeled. To improve accuracy, parameters such as changes in trading volume and the overall index are added to the model to achieve more accurate price change predictions. Finally, the challenges associated with using English models and the need to develop dedicated Persian models for capital market analysis are discussed.**

***Index Terms*—Sentiment analysis, news, stock price prediction, Tehran Stock Exchange, trading data, stock price change classification**

## I. Introduction

In the context of investments, the operative and correct evaluation of news and other information sources becomes vital for investors. Any news that spreads over social networks or through the media has the capacity to influence the cost of shares and the volatility of broad equity markets. These impacts always exert either direct or indirect influence on investors' behavior and asset price levels, thus tending to cause price movements mainly when news and other surprises spread out quickly.

This research aims to present an intelligent model that can predict potential future stock price changes by analyzing the sentiment of stock market-related news. To achieve this goal, stock-related news is collected from reliable sources and, after translation into English, analyzed for positive, negative, and neutral sentiment using the FinBERT model. These analyses are combined with daily financial information, including trading volume and frequency, to create a comprehensive dataset for training a machine learning model. A five-category classification of price changes—significant decrease, slight decrease, no change, slight increase, and significant increase—is then used to train a Random Forest model to predict the impact of new news on stock price changes.

This research not only deeply examines the impact of news on stock price changes but also takes a practical step towards improving investment analysis and enabling more intelligent investor decision-making. By providing an efficient tool, it allows for more accurate analysis and prediction of market fluctuations.

## II. Previous Works

Most investors' questions center around the influence of specific news events on the dynamics of financial assets, including stock markets. In this regard, a number of researches demonstrate that events and people's opinions are capable of influencing stock market movements and trends significantly. For example, Bollen et al. (2011) demonstrate that the sentiment in Twitter posts can predict changes in stock market behavior [1], and similar research is conducted by Mao et al. (2011), which compares news, Twitter, and search data for predicting market behavior [2]. Alanyali et al. (2013) show that there is a significant relationship between financial news and stock market movements. They use quantitative analyses and news data to examine how financial news influences market volatility [3]. Bordino et al. (2012) focus on predicting stock market volumes using web search queries and demonstrate that search data can be an effective tool for forecasting market behavior [4]. In other studies, Da et al. (2011) examine the role of public attention to news and media in stock market movements, concluding that attention to news and media can be a key factor in predicting market behavior [5]. Tetlock (2007) studies the role of media in shaping investor sentiment and its impact on stock markets [6]. Groß-Klußmann and Hautsch (2011) analyze financial market reactions to news using automated text analysis techniques, showing that news can have immediate and significant effects on stock prices in short time frames [7]. Additionally, Bordino et al. (2014) analyze user browsing behavior on Yahoo Finance and use it to predict stock trade volumes [8].

Current research attempts to integrate sentiment analysis, historical data of stock prices, and even commodity prices to improve the prediction of stock markets. Zaman et al. [9] develop a machine learning model that incorporates social media sentiment, financial news, and even oil prices as external factors along with historical data. Utilizing Gradient Boosting Classifier (GBM), their model achieves a remarkable prediction accuracy of 87.2% after combining oil sentiment and sentiment datasets. The study also reports oil social media sentiment effect on IBM stocks and how analysis of social media sentiment improves overall prediction accuracy [9].

Mehtab and Sen [10] apply deep learning, sentiment analysis, and machine learning to develop a novel hybrid approach for the prediction of stock price. They use data from 2015 – 2017 focusing on NIFTY 50 index of India. They utilize Twitter's sentimental data along with Long Short Term Memory (LSTM) models to analyze the sentiment in the market and compare it with the stock trends. Their results demonstrate high accuracy, and they further enhance their model using Self Organizing Fuzzy Neural Networks (SOFNN), which proves effective in predicting stock trends [10].

Both studies underscore the importance of integrating external data sources and advanced machine learning techniques for stock market prediction. While Zaman et al. emphasize the combination of sentiment analysis and oil prices, Mehtab and Sen leverage deep learning and social media data. The use of Gradient Boosting and LSTM algorithms in these studies illustrates their complementary approaches, each offering valuable insights into stock market prediction across different contexts.

In the field of news processing, particularly in Iranian financial markets, there is still a lack of specialized research. Studies focused on analyzing specific economic news for Iranian markets are significantly limited. Thus, this gap in existing research provides an opportunity for the development and expansion of studies in this area, particularly in analyzing economic news to predict trends in Iranian financial markets.

## III. Research Methodology

This research aims to examine the impact of news on stock price fluctuations in the Iranian stock market using a combined approach of sentiment analysis and technical analysis. The research method includes stages of data collection, preprocessing, modeling, and evaluation, which are detailed below:

### A. Data Collection

*1) News data collection :* To analyze the impact of news on the Iranian capital market, due to the lack of a suitable Persian model for analyzing Persian news, reputable Telegram news channels are utilized. These channels include 10 news sources with over 1.5 million users, such as the Last News channel, Fars News Agency, and others that cover credible news agencies from various fronts. The news includes the text of the report, the date and time of publication, and its source, which are extracted and stored in a database.

*2) Preprocessing of news data:*

- **Sentiment analysis**
  To analyze the impact of news on the market, the FinBERT model is used. This model assesses the effect of each piece of news on the global market with three probabilities (positive, negative, and neutral). Since this model is trained on English news, it is necessary to translate Persian news into English. This translation is done using machine translation tools; however, this approach is not ideal as the translation may reduce the model's accuracy and introduce errors.
- **Setting the news release schedule** News that is published after the market's closing hours is connected to the next trading day. Additionally, news released on holidays is allocated to the first trading day thereafter. The aim of this research is to examine the short-term impact of news on the market, which is typically related to the market's emotional reactions and is observed in the short period following the news release.

*3) Financial data collection:* For financial data, information related to the Iranian stock market is extracted from the TSETMC website. This data includes daily prices (opening, closing, highest, lowest, volume, etc.), capital increases, cash dividend distributions, and the overall market index for a 10-year period.

*4) Preprocessing of Financial Data :*

- **Adjustment of prices** Cash dividends and capital increases can cause a price jump because while the distribution of cash dividends reduces the share price, cash is credited to the shareholder's account. Similarly, in a capital increase, the share price decreases, but the number of shares held by the shareholder increases. However, since the price decrease does not necessarily equate to a loss, the share price is adjusted to account for the impact of capital increases and cash dividends, allowing for a more accurate analysis.
- **Calculation of daily changes** Daily and 3-day closing price changes and the total index, the number of transactions, and the volume of transactions of each share are calculated and stored.

### B. How to insert figures, charts, and tables

As we know, shares indirectly follow a large share; For example, in cryptocurrencies, Bitcoin is the leading cryptocurrency. In the Iranian stock market, there are many symbols of different industries. For this reason, the largest icon of each industry is chosen to represent the rest of the icons in that industry, and tests are run on them. After achieving the desired results for each stock with the data, a separate model is executed.

**The chosen symbol of any industry:**

1) **Chemical Products:** Pars (Pars Petrochemical)
2) **Basic Metals:** Steel (Foolad Mobarakeh Isfahan)
3) **Multi-Industry Companies:** Shasta (Social Security Investment)
4) **Metal Ore Extraction:** Kegel (Gol Gohar Mining and Industry)
5) **Petroleum Products, Coke, and Nuclear Fuels:** Shapna (Isfahan Oil Refining)
6) **Banks and Credit Institutions:** vebmelt (Bank Mellat)
7) **Investment Companies:** Vakhrazm (Kharazmi Investment)
8) **Automobile and Components Manufacturing:** khodro (Iran Khodro)

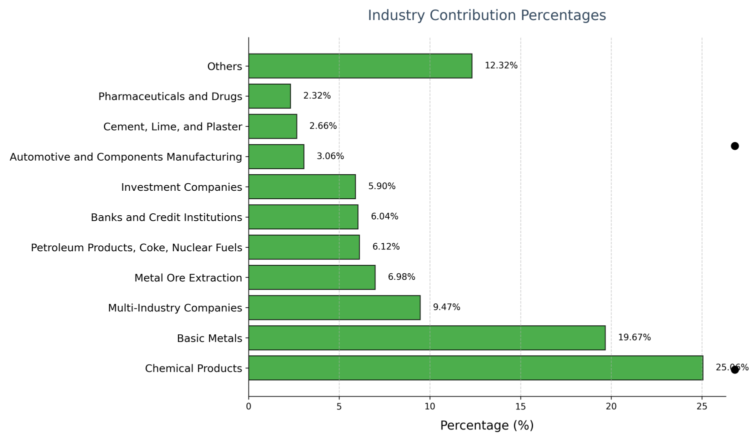


Fig. 1. Dispersion of stock market industries according to the report of Iran Stock Exchange Organization

9) **Insurance and Pension Funds:** Dana (Dana Insurance)
10) **Pharmaceuticals and Drugs:** daroo (Pharmaceutical Factories)
11) **Cement, Lime, and Plaster:** Sarum (Urmia Cement)

## IV. Modeling

For analysis and prediction, two main approaches are followed:

### *A. The first approach: evaluation with quantitative market data*

We implement this approach by using data from 10 popular Telegram news channels. All channels have over 1.5 million subscribers and are highly popular for providing reliable news. Since the channels publish different kinds of news, we also take into account the news service. We used the FinBERT model for classifying the news into positive, negative, or neutral categories. We use this classification and news source as the input to our models.

After trying out different methodologies, we realized that providing the model with the number of positive, negative, and neutral news for each channel on a daily basis improves our accuracy of predictions. Thus, we provide the model with the number of each type of news for each channel on a daily basis. We want to predict the percentage change in stock prices on the day. We use 20% of the daily news available to cross-validate the models and to calculate the average predicted price change.

The different models used are as follows:

- **Linear Regression**: Linear regression is a fundamental method for modeling the relationship between a dependent variable and one or more independent variables. It assumes that the relationship is linear and is widely used for its simplicity and interpretability [12]. However, it may fail to capture complex nonlinear patterns in the data.
- **Logistic Regression**: Logistic regression is a statistical model used for binary or multi-class classification. It models the probability of a binary outcome using a logistic function and is particularly useful when the dependent variable is categorical [12]. Despite its simplicity, it assumes a linear decision boundary, which may limit its performance on complex datasets.
- **Support Vector Machine (SVM)**: SVM is a powerful supervised learning algorithm used for both classification and regression tasks. It works by finding the hyperplane that maximizes the margin between classes, making it robust to overfitting, especially in high-dimensional spaces [13]. Kernel functions allow SVM to handle nonlinear relationships effectively.
- **K-Nearest Neighbors (KNN)**: KNN is a non-parametric method that classifies a data point based on the majority class among its k-nearest neighbors. It is simple and intuitive but can be computationally expensive for large datasets due to its need to compute distances between all pairs of points [14].
- **MLP (Neural Network)**: Multilayer perceptrons (MLPs) are a class of feedforward artificial neural networks that can model complex nonlinear relationships. They consist of multiple layers of neurons, each performing a weighted sum of inputs followed by a nonlinear activation function [15]. MLPs require careful tuning of hyperparameters and are computationally intensive.
- **Gradient Boosting**: Gradient boosting is an ensemble technique that builds models sequentially, with each new model correcting errors made by the previous ones. It is highly effective for both regression and classification tasks and is known for its high predictive accuracy [16]. XGBoost, a popular implementation of gradient boosting, is widely used in machine learning competitions.

The models are trained for each share separately. For example, for the steel part, the value of the loss function (MSE) is about 5, which is a relatively large error. However, an examination of the stock price prediction chart shows that the model correctly detects the ups and downs of the stock, even if the predicted numbers are not accurate. This ability to detect the direction of price movement can be very useful for traders. In the image below, the actual and predicted price trends for one month are displayed. As can be seen, the model has been able to identify the ups and downs of the share.

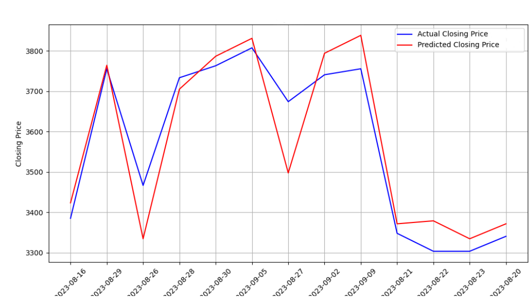


Fig. 2. Chart of original and predicted price over a period of time

### B. The second approach: evaluation with qualitative market data

For more accuracy, the price change percentage is calculated in three-day intervals and divided into five categories. Since in the Iranian market, the daily fluctuation range of each share is a maximum of 5% positive or negative, the maximum three-day change can be 15%. Data labeling is done as follows:

- Change more than (+5%): large increase
- Change between (+1%) and (+5%): small increase
- Change between (-1%) and (+1%): no change
- Change between (-1%) and (-5%): low decrease
- Change less than (-5%): large decrease

The following models are used to predict these categories:

- **Logistic Regression**: Logistic regression is well-suited for multi-class classification tasks, where the goal is to predict the probability of a sample belonging to a specific class [12].
- **Support Vector Machine (SVM)**: SVM is effective for classification tasks, especially when the data is not linearly separable. It uses kernel functions to map data into a higher-dimensional space where a linear separation is possible [13].
- **K-Nearest Neighbors (KNN)**: KNN is a simple and intuitive method for classification, relying on the principle that similar data points are likely to belong to the same class [14].
- **MLPClassifier**: MLPClassifier is a neural network-based model capable of learning complex patterns in the data, making it suitable for tasks where traditional methods may fail [15].
- **Gradient Boosting**: Gradient boosting is a powerful ensemble method that combines multiple weak models to improve classification accuracy, making it one of the most effective techniques for predictive modeling [16].

The results show that the accuracy is low in all models. This indicates that only using news is not enough, and other market parameters such as the volume of transactions, the number of transactions, and various indicators should also be considered. Therefore, the change in trading volume, the number of trades, and the change in the total market index on the previous day are added to the models.

### C. The best modeling mode

In the approach where market data, including the change in trading volume, the number of trading and the change in the total market index on the previous day, are added to the model, the results show that adding these variables to the model has a significant effect on improving the accuracy of forecasts. These results emphasize that these indicators can act as a complement to news information and the combined effects of news and market indicators provide a better understanding of market behavior. Figure 3 illustrates the flow chart of the steps of the methodology for the prediction of the stock market using financial parameters and social networks.

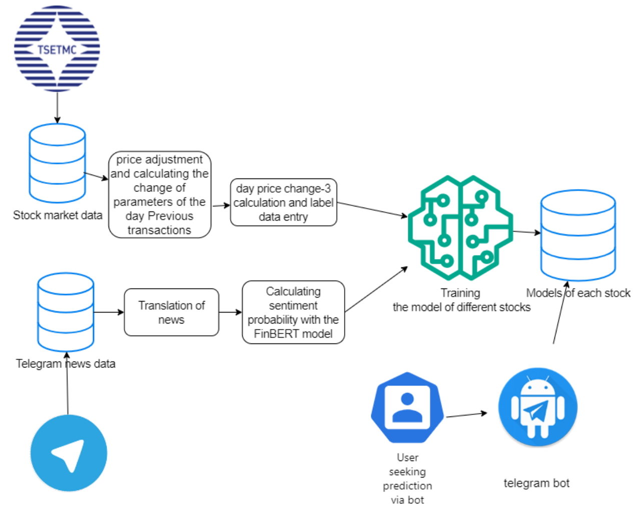


Fig. 3. Flow chart of the methodology steps for stock market prediction using financial parameters and social media

## V. Model Evaluation

### A. The First Approach: Evaluation with Historical Data

In this approach, the models are tested using historical data. To evaluate the performance, the data are divided into two sets of training (80%) and testing (20%). Criteria such as Mean Squared Error (MSE) are used for regression models and Accuracy for classification models. The results show that the accuracy of predicting exact amounts of price changes is low, but the general direction of changes (up or down) is correctly identified in most cases.

### B. The Second Approach: Evaluation in Three Different Modes

In this approach, the models are evaluated in three different modes and the results are reported as follows:

*1) The First Mode: Analysis with News:* In this case, only the news parameters (including the number of positive, negative, neutral news, and publishing channel) are used for modeling. The results are shown in the table below.

TABLE I
Results of the First Mode: Analysis with News

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| Logistic Regression | 38% | 15% | 38% | 21% |
| SVM | 38% | 21% | 38% | 21% |
| KNN | 31% | 27% | 31% | 28% |
| MLP Classifier | 37% | 26% | 37% | 27% |
| **Gradient Boosting** | **38%** | **29%** | **38%** | **24%** |

*2) The Second Mode: Analysis with Financial Parameters:* In this case, only the financial parameters, including the change in the total index, the change in the number of transactions, and the change in the volume of transactions from the previous day, are used for modeling. The results are reported in the table below.

TABLE II
RESULTS OF THE SECOND MODE: ANALYSIS WITH FINANCIAL PARAMETERS

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| Logistic Regression | 43% | 38% | 43% | 35% |
| SVM | 43% | 36% | 43% | 35% |
| KNN | 38% | 36% | 38% | 35% |
| **MLP Classifier** | **44%** | **37%** | **44%** | **38%** |
| Gradient Boosting | 41% | 35% | 41% | 37% |

*3) The Third Mode: Combined Analysis (News + Financial Parameters):* In this case, all parameters (news and financial parameters) are used in combination. The results are shown in the table below.

TABLE III
RESULTS OF THE THIRD MODE: COMBINED ANALYSIS (NEWS + FINANCIAL PARAMETERS)

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| Logistic Regression | 44% | 39% | 44% | 36% |
| SVM | 45% | 46% | 45% | 37% |
| KNN | 39% | 36% | 39% | 37% |
| MLP Classifier | 54% | 52% | 54% | 50% |
| **Gradient Boosting** | **62%** | **68%** | **62%** | **59%** |

## VI. COMPARISON WITH RELATED WORKS

Compared with similar studies, this research focuses on predicting stock market fluctuations in the Iranian capital market using news sentiment analysis and financial data. The paper by Zaman et al. [9] titled *"Stock Market Prediction Based on Machine Learning and Social Sentiment Analysis"* focuses on predicting stock market changes using historical data along with external factors such as social media sentiment, oil and gold trends, and financial news. The study achieves a high precision of 87. 2% in predicting international stock markets, utilizing machine learning models like *Gradient Boosting Classifier (GBM)* to incorporate sentiment analysis and commodity trends.

This study attempts to assess how news affects stock price fluctuations in the Tehran Stock Exchange. In this case, news articles collected from Telegram channels are analyzed sentiment-wise and are correlated with trading activity and movements of market indexes. This study shows that the accuracy of the prediction is improved greatly by incorporating parameters such as trading activity or the general market index. Following Zaman's study, *Gradient Boosting* proves to be the best model in the conducted experiments.

Although both studies utilize *Gradient Boosting* as the best model, the results differ due to the focus on distinct markets and data sources. Zaman et al. [9] obtain a higher precision (87. 2%) by integrating international data, social media sentiment, and commodity trends. However, the present study, focused on the Tehran Stock Exchange and based on news from Telegram and local financial data, achieves accuracy around 44%. This difference in outcomes is mainly due to the varied types of data used and the market contexts analyzed.

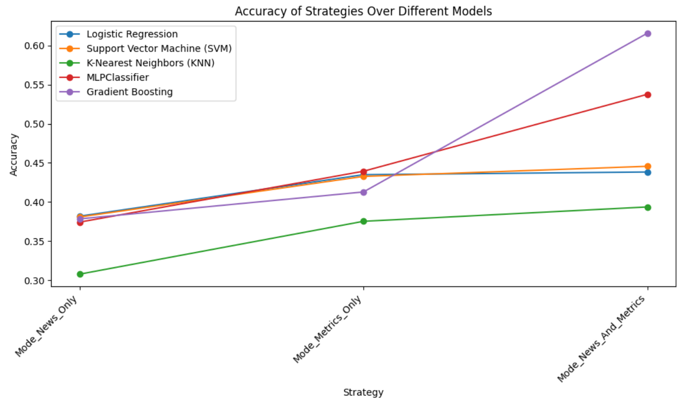


Fig. 4. Accuracy of Strategies Over Different Models

## VII. PRACTICAL USE OF MODELS BY TELEGRAM BOT

Telegram is used as an API for practical and immediate exploitation of the models. In this method, the desired news channels are introduced to the API so that the news is immediately stored in the database. Then, a Telegram bot is designed that allows users to check the impact of a news item on a share. For this, it is enough for the user to send the share name to the bot. Using the stored news and market data that it has access to, the robot checks whether the news in question may affect the share in the next three days or not. This feature allows investors to use models in a practical and effective way for their financial decisions. Of course, it should be mentioned that in the future it is possible to personalize the robot for each person so that he can see the impact of the news on his favorite stocks.


Fig. 5. Telegram bot answer example in Persian language

## VIII. Conclusion

In this research, an intelligent model was designed and implemented to predict stock price changes in the Tehran Stock Exchange through the analysis of news related to the capital market and financial data. One of the main innovations of this research was the use of combining news sentiment analysis from Telegram news sources with market financial data, which is an important step especially in the Iranian stock market where there are diverse information sources and few specialized analysis models.

The model used in this research, especially considering the challenges that arise in the analysis of Persian news, used the FinBERT tool for sentiment analysis. This model showed that despite problems such as translating news from Farsi to English, it is possible to achieve acceptable results that correctly predict the trend of price changes. This is especially useful for capital market analysts and investors as they can more accurately assess the impact of news on price movements.

In addition, by adding financial data such as changes in trading volume and total market indices, the model was able to provide more accurate forecasts, showing that financial information and news together can act as complementary components and significantly increase the accuracy of forecasts. This achievement is especially important in the field of analysis of Iran's financial markets, which still suffers from a lack of comprehensive analytical models.

Another highlight of this research was the design of the Telegram bot for practical exploitation of the models, which allows users to check the impact of news on stock prices in real time. This bot helps not only analysts but also investors to make better decisions based on available data.

Finally, considering the limitations in the translation of Persian news and the need for specific models of sentiment analysis in Persian, the development of local models for the analysis of Iranian capital market news can be the next important step in this field. This research not only helps to better analyze the behavior of the capital market, but by including different information and new tools, it is the foundation of future developments in this field.

## IX. Limitations and Future Work

Although this research achieved acceptable results, it also has limitations. Among other things, the news data is collected only from Telegram social networks and may not cover all news sources. Also, the FinBERT model is used to analyze the sentiments of news in English, and the translation of Farsi news may affect the final accuracy of the sentiment analysis. For future research, we can suggest the use of deep learning models such as LSTM or recurrent neural networks (RNN) for more advanced analysis and better prediction of market trends. Also, improving the data quality by adding news data from other diverse and reliable sources can help the accuracy of the model. Using native models of sentiment analysis in Persian language can be another suggestion to improve the results. In general, this research has taken an important step towards applying a combination of sentiment analysis and financial data in capital market forecasting and can be a valuable basis for the development of smart tools and more accurate financial decisions.

## Code Availability

The code related to this article is available on GitHub: Predicting-stock-price-changes-using-news.

## AI Usage Statement

The authors confirm that no artificial intelligence tools were used in the preparation of this article. The authors declare that they used artificial intelligence tools only to improve and edit the text of the article. The authors declare that they used artificial intelligence algorithms in data analysis, but the principal idea of the article, reasoning and conclusions, were not produced by artificial intelligence.

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