Examining the effectiveness of machine learning models in predicting the type of price hits with the price limit of Tehran Exchange Securities stocks with an emphasis on the model Histogram Gradient Boosting

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ABSTRACT

This study examines the prediction of the type of stock prices and the price limit using End-Of-Day information in the Tehran Stock Exchange market. By using the information of 65 stock during the period of February 2021 to February 2023 and by using machine learning models, the type of hits has been investigated in terms of prices. By using some evaluation criteria, the performance of each model has been investigated. When the price hits the limit during the day and does not continue until the end of the day, and the price of the last transaction of the stock is not equal to the price of the price limit, non continuous price limit and when the price of the last transaction is equal to the price of about, the transaction is continuous price limit it will happen. The best performance was related to the Histogram Gradient Boost-ing model in February 2023 with an accuracy rate of 90 Percent. As a result, according to the level of accuracy in predicting the type of hits, it is possible to use the results of this study in the type of stock buying and selling strategy and the possibility of forming buying and selling queues.

Keywords: price limit, machine learning models ,continuous price limit ,type of price hits

1. Introduction

The price limit of a stock is defined according to the closing price of the stock on the previous day The reason for the existence of this tool in financial markets, which is applied by market regulators, is to reduce extreme price movements in the market to prevent sudden volatility in the market. When the stock price reaches one of its upper or lower limits, all orders whose price exceeds the set price limit will be rejected. This will give investors who traded in spite of the market's excitement a chance to re-examine their analysis and in this way, overreaction in the market is reduced to a great extent (Adcock et al., 2023). One of the well-known events in financial markets is "Black Monday". After the extreme volatility and market crash of October 1987, studies were conducted that revealed that the rapid decline in stock prices may greatly increase the level of fear and excitement among investors and this will increase the uncertainty of investors, which will result in capital outflow and decrease in turnover in the financial markets. This has led market regulators to recommend some different tools such as trading stops and price limit for use in financial markets. price limit is currently being used in many financial markets of the world, especially emerging markets. US futures markets use price limit. Also, the price limit mechanism is used in the Chinese stock market as one of the largest financial markets in the world. In the South Korean market, the price limit has reached 30 percent in recent years. Price limit is used in a number of financial markets such as Japan, Thailand, Taiwan and Malaysia (H. Chen et al., 2023; Lien et al., 2019a; Nobanee et al., 2013; Seddighi & Yoon, 2018) . In Tehran Stock Exchange, the price limit has been used since 1999. Currently, a seven percent price limit is used in the main stock market. The price limit in Tehran Stock Exchange has undergone changes in recent years due to various conditions such as economic or political conditions. The table below shows the changes in the price limit.

Table 1: Changes in the Price limit of the Tehran Stock Exchange

Price limit	Time
Controlled by judgment	March 1999 - March 2001
The price limit is 1 to 5 percent, according to the P/E ratio	March 200 - May 2003
Negative 5 percent - Positive 5 percent	May 2003 - January 2006
Negative 2 percent - Positive 2 percent	January 2006 - April 2008
Negative 3 percent - Positive 3 percent	April 2008- October 2009
Negative 3.5 percent - Positive 3.5 percent	October 2009 - June 2010
Negative 4 percent - Positive 4 percent	June 2010 - May 2015
Negative 5 percent - Positive 5 percent	May 2015 - January 2021
Negative 3 percent - Positive 7 percent	January 2021 - April 2021
Negative 2 percent - Positive 7 percent	April 2021 - April 2021
Negative 5 percent - Positive 5 percent	April 2021 - March 2022
Negative 6 percent - Positive 6 percent	March 2022 - August 2022
Negative 7 percent - Positive 7 percent	August 2022 - Until now

Regarding the benefits of the price limit in the financial markets and the importance of this mechanism, extensive research has been done in the past years (Janardanan et al., 2019; Lu, 2016; Meng et al., 2014) . But the important issue is the difference of opinions and different results in the studies about the price limit. According to the results presented in the studies, there are positive and negative opinions regarding the use of the price limit. Proponents of using the price limit believe that, the price limit by creating a trading break, will reduce market excitement and create peace and the result will be the reduction of market volatility caused by the overreaction of investors. On the other hand, the opponents believe that this mechanism only postpones the volatility in the market and will also reduce the efficiency of the market. The reason for this is that if the prices reach the price limit and these limits reduce the market excitement, this is short term and this volatility will be transferred to the next days and will increase the market volatility. On the other hand, this mechanism causes when the prices are near the limits of the price limit, due to the magnet effect, it increases the speed of the stock price reaching the limits (X. Zhang et al., 2023) . In financial markets, some methods such as using market makers are used to control some effects of the price limit. Market makers, which can be investment funds, capital supply companies, or licensed individuals, control the adjustment and balancing of orders within the price range of the market's price limit. When prices are near the limits of the price limit, traders are more excited to enter the trade for fear of being stuck in heavy buy or sell queues. And this will cause the prices to quickly reach the limits of the price limit and a queue will be formed. By registering their orders in the market, market makers reduce queues for buying and selling and reduce illiquidity in the market. In many studies conducted in this field, only the advantages and disadvantages of the price limit have been examined. But this study will seek to predict the type of stock price encounters using the end of the stock day. By identifying the type of hits, in case of continuous price limit encounters, traders can predict the creation of heavy buying or selling queues and adjust their trading strategy accordingly. Also, in case of creating excitement in the market and overreaction of investors to some news, non continuous price limit encounters will be created, which after the passage of time, it is expected that the excitement in the market will subside and the stock price will approach the equilibrium price.

2 Literature Review

In this section, at first, the studies conducted in the field of price limit will be described, and then the used models will be discussed.

2.1 Theoretical Foundations

The reasons for modelling stock market fluctuations vary greatly. An increase in fluctuations may result in higher investment risks and maintenance costs, and, consequently, lower investment (Balounejad Nouri et al., 2024a). The price limit can behave differently for different volumes of transactions in financial markets. When a stock has a high trading volume in the market, the price limit can be somewhat effective and reduce volatility, but for low trading volume, it will have the opposite behaviour (Meng et al., 2014) . When the market price limit changes from the NPL[1] price range to the WPL[2] price range, The stock volatility will change and this volatility will be lower in NPL mode than in WPL mode (Farag, 2013) . Applying the price limit mechanism in financial markets when the price trend is downward can cause a sharp increase in market volatility, on the other hand, in calm market conditions, the price limit can reduce extreme volatility in the market (Tai-Leung et al., 2014) . The number of times the price hits the price limit will affect the stock's return and increasing the volatility limit will increase the volatility in the coming days (Farahbakhsh et al., 2024) .The behavior of the price limit of high-tech stocks will usually be larger price movements and respond positively and symmetrically to good and bad news, but this response is asymmetric for low-tech stocks (Ahmed & Alhadab, 2020) . The price limit makes the extreme price movements to some extent controlled and these extreme price changes are reduced to some extent (Belgiu & Drăgu, 2016a) . Stocks with freer float and institutional ownership will experience less volatility when the price limit increases (Yadudu, n.d.). One of the destructive effects of the price limit in the market is creating an underreaction in the market. In efficient markets, investors will react to new news. This reaction will lead to prices in the market immediately reaching their equilibrium level. But in emerging markets, new information will not reach all market investors at the same time and this causes investors to overreact to this news when new news is published or, on the contrary, to be unreactive to this news and this causes the market volatility to intensify (Balduzzi, 1995) . When traders do not have enough experience in the market, the price limit will obviously reduce the price level as well as mispricing, it will not improve the price limit to the news and will also increase the price movements (Bao et al., 2020) . Increased sentiment will increase volatility in the market (Balounejad Nouri et al., 2024b) .The effects of large and small companies on the market will not be the same in the upper and lower limits, small companies will experience more volatility in the lower range, in other words, small companies tend to bounce back after big price movements compared to big companies

[1] Narrow Price Limits
[2] Wider Price Limits

(Farag, 2015) . In the upward and downward movements of stocks, due to the overreaction of stocks due to the existence of price limit in the market, investors can get good returns (Joon Byun et al., 2012) . After stopping the trading and restarting the trading, the information will effectively affect the stock prices, but in the price limit, it may cause excessive reaction of investors (Y. H. Kim et al., 2008) . Creating a price limit can be very effective in curbing investor overreaction (Yang et al., 2018) . Big investors adopt strategies to raise the stock price and reach the limit of daily volatility and sell on the next day(T. Chen et al., 2017) . One of the adverse effects of the price limit is the delay in price discovery. The presence of price limit in the market will cause a delay in discovering the price (X. Zhang et al., 2016) . However, the price limit will cause a delay in discovering the stock price and interference in the market but in stocks that have high trading activity, these effects will decrease over time (Lu, 2016) . Price discovery and trade interference will depend on the size of the price limit (Yeh & Yang, 2010) . The magnet effect requires a hypothesis in the microstructure of the market, which includes a system of price attraction towards the limit of the price limit, the upper limit will be more inclined to show the magnetism effect (Yang et al., 2018) . When the price limit in the Chinese stock market changed by 10 Percent, the effect of this change on the market was investigated, this change caused an increase in informed transactions in the market, it also increased liquidity and market volatility (X. Zhang et al., 2023) . price limit will cause a magnet effect in the market (WONG et al., 2009) . By changing the price limit and increasing its limits, liquidity will improve and higher returns will be created (Wan & Zhang, n.d.) . Price limit will increase volatility and decrease liquidity, a stock that reaches its price limit will experience a decrease in liquidity (Danışoğlu & Güner, 2018) . After increasing the price limit, the number of traders' orders will increase significantly. In this case, investors' orders will increase, which can cause the market to become illiquid, also, the trading spread will increase and the depth of the market will decrease (Lien et al., 2019b) . The presence of price limit increases the liquidity of the market, when the supply and demand is unbalanced, the trading spread will increase and it will decrease the liquidity(Yeh & Yang, 2010) . Increasing the price limit will increase the trading spread and information asymmetry (C. F. Lin & Chiao, 2020) . Market efficiency will not only depend on the price limit and other factors can make the market unsettled, taking longer to reach equilibrium prices (Y. H. Kim et al., 2008) . In emerging markets where regulatory costs are high due to poor information disclosure and low efficiency, the price limit is effective according to the regulatory master's costs (Deb et al., 2010) . In markets where there is a possibility of price manipulation, there will be a higher probability of price limit (K. A. Kim & Park, 2010) . The value premium is significantly stronger in stocks that hit their limits less often (C. Lin et al., 2017) . The use of a type of dynamic price limit in the market is investigated (Deb et al., 2013) . The plan to connect Shanghai stocks to Hong Kong will improve price discovery conditions, but it will have a negative effect on investors (Tai Leung, 2019) .

2.2 Empirical Foundations

Different models can be used in predicting the impact of the price on the price limit, such as regression models or models based on machine learning. Machine learning is used to train machines to process data more efficiently and increase predictive accuracy (Mahesh, 2018) . One of the types of learning machines is called support vector machine, which has been widely used for analysis in recent years due to the simplicity and flexibility of this model and its high accuracy (Pisner & Schnyer, 2019) . Support vector machine is one of the most powerful algorithms in the field of classification and regression, this type of machine is used for classification (Cervantes et al., 2020) . A random forest is a set of several decision trees that will train the decision trees using a given set of data and specify the variables (Belgiu & Drăgu, 2016) . Random Forest was first introduced by Berryman in 2001. This model is used for classification and regression and are simple models that predict the outcome using binary methods [41] . Logistic regression is one of the machine learning models used for two-way discrete dependent variables [42] . Naive bayes is one of the most common classification algorithms in the field of machine learning. Naive bayes is a probabilistic algorithm based on bayes theory used for classification [43] . Decision tree is one of the popular machine learning algorithms used for classification and regression.

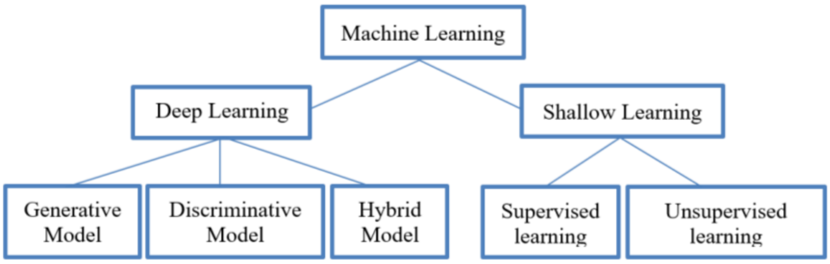

Fig. 1: Different approach of machine learning

3 Research Method

In this research, 62 stock from the main board of the Tehran Stock Exchange are used. The desired stocks have been selected from different industries of the stock market. The selected time period is from February 2021 to February 2023 and in this period of time, the price limit of Tehran Stock Exchange market was positive 5 percent and negative 5 percent During this period, prediction [44] . The Histogram-based Gradient Boosting model is one of the most efficient enhancement techniques and has a very favourable performance for predictions, these techniques with the sum of several weak techniques will increase the final accuracy [45] . Based on the studies, the machine learning approach can be shown as surface learning and deep learning as shown below [46] :

a total of 460 trading days have been completed, among these days, the days when each of the 62-stock hit their limits have been identified and selected. and the total number of collisions for all selected stocks is 2982 reported. In between, 1632 cases of non-continuous price limit hit, 1350 cases of continuous price limit hit have been reported. The information fields are shown in the table below:

Table 2: Time periods examined

period	Price limit	Time
Period1	Negative 5 percent - Positive 5 percent	April 2021 - March 2022
Period 2	Negative 6 percent - Positive 6 percent	March 2022 - August 2022
Period 3	Negative 7 percent - Positive 7 percent	August 2022 - Until now

3.1 Research Questions

In this research, we are faced with three questions, because we will look for the effect of the price limit on market transactions and also the degree of predictability of the type of hit with the price limit.

1) What effect does the price limit have on the Tehran Stock Exchange market?
2) Is it possible to predict the type of hit using end of day information?
3) Which period's forecasting performance was more favourable using information?

3.2 Hits are reported

In this research, according to the studies conducted, two types of hits have been reported [35] Noncontinuous price limit will occur when the stock price moves towards the range of volatility with the arrival of new information and hit with them but it will not remain in this range for a long time and return to its equilibrium price. The price of a stock may hit its price limit several times during the day and then return to the equilibrium price, which will be based on the first time the price hits the price limit. The continuous price limit state will occur when the arrival of new information causes the price to move towards its limits and cause the price to hit the limits and stay on one of the upper and lower limits, and the so-called price of the last transaction of the share is equal to the price of the upper or lower limits.

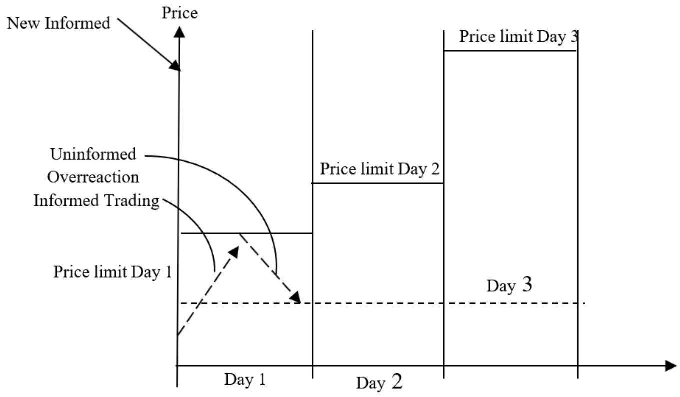

Fig. 2: Noncontinuous price limit hits

Fig. 2 when the news published in the market for the stock is such that if it has its full effect on the price, it will cause the price to hit the daily price limit, but this hit will not last until the end of that day and will return before the market closes on that day. In this case, before the price hits the limits, there are more informed transactions, but after the hit, the uninformed transactions will be more due to overreaction and the prices will return to their equilibrium limits. Fig. 3 when the published news cannot have its full impact on the price due to the existence of price limit, it causes the price to hit the price limit on that day. After that, the new information has its full effect on the price, the price reaches its equilibrium point, in this case, it is expected that there will be more informed trades before the hit, according to the studies, it is expected that informed trades are of medium volume trades in the market, the impact of this information is such that the clashes continue on the second day and finally on the third day, after the information has had its full effect, the prices reach their equilibrium limits [35] .

3.2 Data type

At first, all the hits for the desired stocks are collected in the time frame. After that, the type of hits will be determined and after that the desired variables have been calculated, and at the end, the final results of the investigated variables will be the input of the machine learning models, so that based on this information, the machine learning algorithms will perform their training and then they can predict the type of future encounters. The basis of dividing the information in this research into two categories of test and training data will be 80 percent and 20 percent.

3.3 Variables

In this research study conducted in 2013, the required variable has been introduced that will predict the performed behaviors and it can distinguish continuous price limit and non-continuous price limit hits. [35] . VMedium (small), the type of this variable is the type of transaction volume and this variable will be calculated from the difference in the ratio of transactions with medium size (small size) before the first hit with the daily price limit and after the first hit with the price limit. This variable will indicate informed and uninformed transactions before and after the hits price limit. According to the proposed hypotheses, medium volume trades indicate informed trades in the market, Therefore, this variable examines the change of informed and uninformed transactions before and after the hits price limit [17][47] . This ratio will be checked according to the following formula.

$$VMedium = \frac{(Medium\ volume\ after)}{(volume\ after)} - \frac{(Medium\ volume\ before)}{(volume\ before)} \quad (1)$$

(1)

$$Vsmall = \frac{(small\ volume\ after)}{(volume\ after)} - \frac{(small\ volume\ before)}{(volume\ before)} \quad (2)$$

Variable Hit-m (Hit-s), relative to the average (small) size that hits and shows the amplitude of the price limit during the day. This value is equal to the ratio of the average size (small) in one day to the total daily price limit that reaches its limits and is calculated through the following formula:

$$Hit - m = \frac{(Medium\ volume)}{(Total\ volume)} \quad (3)$$

$$Hit - s = \frac{(small\ volume)}{(Total\ volume)} \quad (4)$$

ΔOi, will show the changes in buying queues and selling queues during market trading. This variable calculates the imbalance ratio before hitting the daily price limit and after hitting it. The balance of orders will be calculated from the difference in the value of sellers and buyers at the beginning of transactions. A value greater than one indicates continued buying (selling) pressure around high (low) price limit. The negative value of this variable will indicate the return of buying or selling pressure in the market. The value between zero and one of this variable will indicate the continuation of buying or selling pressure with less pressure on that day. The value of this variable will be calculated according to the following formula:

$$\Delta Oi = \frac{value\ of\ buyer\ after}{value\ of\ buyer\ before} - \frac{value\ of\ seller\ after}{value\ of\ seller\ before} \quad (5)$$

There are other formulas used by some, which will be explained below, Market cap and size, which is equal to the logarithm of the market value of the desired stocks, which will be checked at the end of a trading day. Δ Oisign,

which is of zero and one type, and when the value of ΔOi is negative, it will take a value of 1, and otherwise it will take a value of zero. Non-of-Hits, The total number of transactions that hit their price limit in one day. Hit span, the duration in hours will be between the first transaction hitting the price limit and the first transaction after the last price limit. Trd, it is a measure of liquidity that will be obtained from the natural logarithm of Non-of-Hit. Hit-to-close, the time difference in hours is between the first hit of the range and the close of the market.

4 Search Results

In this research, the models were examined with evaluation indicators until the best performance in predicting the data related to the evaluation of the results was examined in the following:

Table 3: Results of machine learning models

Model	period	Precision	Recall	F1_Score	Accuracy Train	Accuracy Test
Logistic Regression	Period 1	0.75	0.78	0.74	0.79	0.75
	Period 2	0.79	0.79	0.79	0.78	0.80
	Period 3	0.59	0.56	0.57	0.59	0.58
Naive Bayes	Period 1	0.76	0.74	0.75	0.73	0.74
	Period 2	0.74	0.72	0.73	0.70	0.70
	Period 3	0.59	0.59	0.59	0.62	0.59
Decision Tree	Period 1	0.82	0.82	0.82	0.93	0.82
	Period 2	0.81	0.80	0.80	0.86	0.80
	Period 3	0.72	0.70	0.71	0.78	0.71

Model	period	Precision	Recall	F1_Score	Accuracy Train	Accuracy Test
Histogram Gradient Boosting	Period 1	0.88	0.89	0.88	1	0.90
	Period 2	0.86	0.85	0.85	1	0.86
	Period 3	0.73	0.73	0.73	1	0.73
Support Vector Machine	Period 1	0.79	0.79	0.79	0.89	0.80
	Period 2	0.87	0.88	0.87	0.87	0.86
	Period 3	0.70	0.70	0.70	0.73	0.70
Random Forest	Period 1	0.76	0.76	0.76	0.99	0.75
	Period 2	0.76	0.75	0.75	0.98	0.77
	Period 3	0.68	0.74	0.68	0.97	0.70

Model	period	Real	Noncontinuous price limit hit	Continuous price limit hit
Logistic Regression	Period 1	Noncontinuous price limit hit	23	9
		Continuous price limit hit	6	21
	Period 2	Noncontinuous price limit hit	28	9
		Continuous price limit hit	8	37
	Period 3	Noncontinuous price limit hit	72	137
		Continuous price limit hit	51	181
Naive Bayes	Period 1	Noncontinuous price limit hit	28	4
		Continuous price limit hit	11	16
	Period 2	Noncontinuous price limit hit	32	5
		Continuous price limit hit	19	26
	Period 3	Noncontinuous price limit hit	131	78
		Continuous price limit hit	106	126
Decision Tree	Period 1	Noncontinuous price limit hit	24	8
		Continuous price limit hit	3	24
	Period 2	Noncontinuous price limit hit	33	4
		Continuous price limit hit	13	32
	Period 3	Noncontinuous price limit hit	170	39
		Continuous price limit hit	93	139
Histogram Gradient Boosting	Period 1	Noncontinuous price limit hit	28	4
		Continuous price limit hit	3	24
	Period 2	Noncontinuous price limit hit	30	7
		Continuous price limit hit	5	40
	Period 3	Noncontinuous price limit hit	155	54
		Continuous price limit hit	67	165
Support Vector Machine	Period 1	Noncontinuous price limit hit	26	6
		Continuous price limit hit	6	21
	Period 2	Noncontinuous price limit hit	34	3
		Continuous price limit hit	8	37
	Period 3	Noncontinuous price limit hit	155	54
		Continuous price limit hit	80	52
Random Forest	Period 1	Noncontinuous price limit hit	22	10

		Continuous price limit hit	5	22
	Period 2	Noncontinuous price limit hit	25	12
		Continuous price limit hit	8	37
	Period 3	Noncontinuous price limit hit	135	74
		Continuous price limit hit	66	166

5 Conclusions

In this research, six methods of machine learning algorithm have been used and finally, based on the accuracy of each model, the best model will be selected. These models are based on the information extracted from the Tehran

Stock Exchange, for three time periods from February 2021 to February 2023, in which the price limit of two cases has changed, they have done their learning. In the first time period, the gradient amplification model histogram gradi gradient amplification model histogram gradient boosting with 90 percent accuracy, In the second period, the support vector machine model and histogram gradient boosting with 86 percent accuracy and in the third period, the histogram gradient boosting enhancement model has performed best compared to other machine learning models with an accuracy of 73 percent. Overall, it is clear from the obtained results that the best accuracy is related to the histogram gradient boosting. Also, the best prediction accuracy was related to the information of the first and second period, where the price limit was positive and negative 7 percent and positive and negative 6 percent, respectively. According to the accuracy of the forecasts obtained, investors in the market as well as portfolio companies can predict the behavior of the price of the range by analyzing the information available in the market, recognize the overreaction of the market and also avoid staying in the heavy queues of buying or selling in the market. In future projects, it is possible to use a variety of deep learning methods to increase the accuracy of learning models, also, in this research, a diverse portfolio of market stocks was selected, which can be selected index-making stocks or stocks with a similar correlation coefficient.

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