Artificial Intelligence in Technical Trading

(Determination of Resistance and Support Levels with weighted Technical Tools and ML)

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Abstract_ imagine a situation in which there is a logical fast senseless computer that can observe the whole history of a security and a half-logical, not enough fast in processing the huge amount of data, indecisive person who can decide just only based on a limited period of time and they would like both to take profit from trading of that security, which one can make more profit and loss less money on the trading?!!

When there are plenty of tools with different outputs and a long period of time as a history of the security, humankind cannot decide perfectly which output and how long of history to choose to optimize the one second decision of purchase or sale in an online trading platform.

The main idea of this paper is based on discovering a reliable method to determine the resistance and support levels of a security on a price chart with the help of nearly all the available tools in technical trading or price action methods, confidently. Moreover, I will give the idea of locating some particular technical tools, which are specific to a particular share, cryptocurrency, commodity or currency pairs in Forex that a trader can rely on them more than other tools and so make better decisions when observing the output of them in the PRZs.

All actions above are possible with the help of computers and computer programs, but when they all are done through the capabilities of AI, the result can be variously characteristic and more authentic.

To achieve the ultimate goal, I have used both supervised, unsupervised algorithms and the attributes of preprocessing such as feature selection and standardization.

I. INTRODUCTION

Technical analysis is the study of a market's price data, which is created by the emotions of traders. These mixed emotions, in the form of diagrams, fluctuate in some well-known patterns (i.e., Elliott waves patterns [1]) and some unknown ones. The aim of technical trading as a mixture of science and art is to benefit from *long* and *short* in the market. To many novices trading is as much harder as they believe but the biggest obstacle in trading is what is between their left and right ears. There are huge differences between the left-brain dominant person and the right-brain dominant one. The first person places more emphasis and confidence in *support* and *resistance levels* derived from mathematical formulas (pivot points [2], Fibonacci [3], technical indicators [4]). The second person puts more confidence in repetitive chart pattern techniques and the ensuing theories of measurement techniques and methodologies behind these formations (chart patterns [5], [6], [7], Japanese candlestick [8]). Despite these two significant differences between the way of human thinking, they both look for one common thing, that is making profit.

There are many approaches to earn profit in the stock market, but here we focus on the methods of technical trading which are the most used ones. The success in technical trading approach depends not just on determination of resistance and support levels, *Potential Reversal Zones*, but also on the correct choice of Indicators and Oscillators.

In this paper I aim to explain the idea of usage of methods from artificial intelligence in general and from machine learning (ML) in particular to discover the best prediction of PRZs beside other tools to improve our understanding of future *security* prices. The aimed perspective is provided from the following sequential procedures:

Fundamental Data: As we need six forms of provided data in each financial market to draw the supply and demand charts, there is no difference between the type of markets such as Stocks, Cryptocurrencies, Commodities and Forex as the proper data to feed into the program and predict the possible future prices. Each market provides not only time series (i.e., minutely, hourly, daily, monthly, yearly) but also *Open*, *Close*, *High*, *Low* prices and the *Volume* of traded securities in that specific time series. This section works with a locally stored financial data set in the form of a CSV file. Technically, such files are simply text files with a data row structure characterized by commas that separate single values.

Technical Trading Approach: To attain our essential means of technical trading approach, we need a mixture of indicators, oscillators and candlesticks (consult Appendix (C), (D)) which I produce with the help of fundamental data and some libraries and APIs in python.

Machine learning: Both the outputs from functions of technical trading approach and fundamental data make our training data to create the models. The employment of both supervised, unsupervised learning algorithms provided a strong possibility to reach our targets which are strong PRZs and weighted technical tools.

Meanwhile, during the process of Meta Feature Selection, we will encounter some important features that can best represent the behavior of securities in PRZs from the past to future. These features can be candlesticks, indicators or oscillators specific to that security that means traders can put more weight on them in trading.

initialize clusters as singletons: **for** $i \leftarrow 1$ **to** n **do** $C_i \leftarrow \{i\}$;
initialize set of clusters available for merging: $S \leftarrow \{1, \dots, n\}$;
repeat
    Pick 2 most similar clusters to merge: $(j, k) \leftarrow \arg min_{j,k \in S}\, d_{j,k}$;
    Create new cluster $C_l \leftarrow C_j \cup C_k$;
    Mark j and k as unavailable: $S \leftarrow S \setminus \{j, k\}$;
    if $C_l \neq \{1, \dots, n\}$ **then**
        Mark l as available, $S \leftarrow S \cup \{l\}$;
    foreach $i \in S$ **do**
        Update dissimilarity matrix $d(i, l)$;
until no more clusters are available for merging;

Algorithm 1(Agglomerative clustering pseudocode)

II. BACKGROUND

To obtain a better perspective of the consequences from this paper, readers are expected to be familiar with basic financial concepts such as technical trading strategies, means of technical trading and artificial intelligence methods of generating autonomous systems. Firstly, to furnish the fundamentals, I propose two important trading strategies:

Momentum trading: In momentum trading, the trader identifies a stock that is "breaking out" and jumps on to capture as much of the momentum on the way up or down as possible. They focus on stocks that are moving significantly in one direction on high volume. The typical time frame for momentum trading is several hours to several days, depending on how quickly the stock moves and when it changes direction.

Swing trading: Is the art of capturing the short-term trend. It is a style of trading that attempts to capture gains in a stock within one to seven days. Swing traders use technical analysis to look for stocks with short-term price momentum. These traders are not interested in the fundamentals or the intrinsic value of stocks, but rather in their price trends and patterns.

Consult Appendix(C), (D) for a complete detailed list of trading tools. Then I should outfit the readers with ML algorithms:

Discriminative and *Generative models*: In simple words, a discriminative model makes predictions on the unseen data based on conditional probability and can be used either for classification or regression problem statements. On the contrary, a generative model focuses on the distribution of a dataset to return a probability for a given example. When fitting a discriminative model, we usually maximize the conditional log likelihood

$$\sum_{i=1}^{N} \log p(x_i | x_i, \theta) \qquad (1)$$

, whereas when fitting a generative model, we usually maximize the joint log likelihood,

$$\sum_{i=1}^{N} \log p(y_i, x_i | \theta). \qquad (2)$$

Agglomerative clustering: As a generative model starts with N groups, each initially containing one object, and then at each step it merges the two most similar groups until there is a single group, containing all the data. Its pseudocode [9] is shown in Algorithm 1

Dendrogram [10]: The merging process can be represented by a binary tree, called a *dendrogram*, as shown in Figure 1. The initial groups (objects) are at the leaves (at the bottom of the figure), and every time two groups are merged, we join them in the tree. The height of the branches represents the dissimilarity between the groups that are being joined. The root of the tree (which is at the top) represents a group containing all the data. If we cut the tree at any given height, we induce a clustering of a given size.

Linkage: Ward's method [11] says that the distance between two clusters, A and B, is how much the sum of squares will increase when we merge them:

$$\begin{aligned}\Delta(A,B) &= \sum_{i \in A \cup B} || \vec{x}_i - \vec{m}_{A \cup B} ||^2 \\ &\quad - \sum_{i \in A} || \vec{x}_i - \vec{m}_A ||^2 \\ &\quad - \sum_{i \in B} || \vec{x}_i - \vec{m}_B ||^2 \\ &= \frac{n_A n_B}{n_A + n_B} || \vec{m}_A - \vec{m}_B ||^2 \end{aligned} \qquad (3)$$

Where $\vec{m}_j$ is the center of cluster j, and n_j is the number of points in it. Δ is called the merging cost of combining the clusters A and B. With hierarchical clustering, the sum of squares starts out at zero (because every point is in its own cluster) and then grows as we merge clusters. Ward's method keeps this growth as small as possible.

Wrapper methods: A subset of features is selected and a model is trained using them. Based on the inferences that we draw from the previous model; we decide to add or remove features from our subset. The problem is essentially reduced to a search problem. Some common examples of wrapper methods are **forward feature selection**, **backward feature elimination** and **recursive feature elimination**.

- ❖ **Forward Selection:** Forward selection is an iterative method in which we start with having no feature in the model. In each iteration, we keep adding the feature which best improves our model till an addition of a new variable does not improve the performance of the model.
- ❖ **Backward Elimination:** In backward elimination, we start with all the features and removes the least significant feature at each iteration which improves the performance of the model. We repeat this until no improvement is observed on removal of features.
- ❖ **Recursive Feature elimination:** It is a greedy optimization algorithm which aims to find the best performing feature subset. It repeatedly creates models and keeps aside the best or the worst performing feature at each iteration. It constructs the next model with the left features until all the features are exhausted. It then ranks the features based on the order of their elimination.

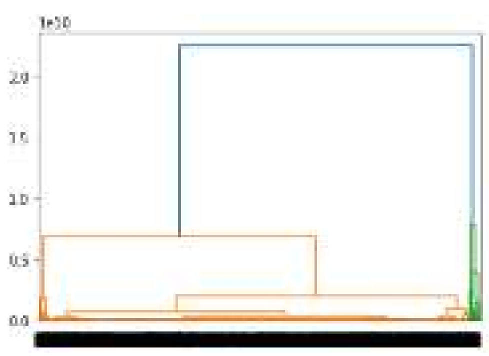

Figure 1(dendrogram of a ticker in Iranian Stock market)

III. GATHERING FUNDAMENTAL DATA

For the purpose of this paper, working just with datasets of OHLCV csv files, that can be obtained from many free sites is sufficient. A short list of them to download these files is collected for all the markets in the Appendix(B). Moreover, working with associated APIs is introduced as well.

To prepare the data to fit into the models, I have made two separate functions, in which indicators, oscillators and different types of candlesticks with the help of TALib library [11] and some self-made inner functions are calculated. These calculations are the main part of feature production.

IV. FEATURE PRODUCTION

The arduous part of data mining in supervised models are feature extraction and their initial labels from the raw data. Especially when the dataset is huge and it is impossible to label each row of the data manually. Therefore, it is meaningful to find an automatic way of labeling the data initially. To serve this purpose I have made a function, in which I use the *Zigzag* indicator to bring the initial labels for each row of data. In the Zigzag algorithm we look for the corresponding Min, Max in the particular period of time that is inserted by the user. We label the rows to 'minus one', *'one'* and *'zero'* for a dip, peak and *'not interested'* row, respectively.

The rest of indicators and oscillators such as RSI, MACD, Stochastic RSI and so on are used to provide the features of ML algorithms, while they can both supply the *convergence*, *divergence* of the prices and the confirmation of *overbought*, *oversell* in the diagram. A complete list of them with their definition that are used in the research is added in the Appendix (C). Since we are looking for a complete and sufficient set of features, I have added the candlesticks into the dataset to enrich the features but in meanwhile, as not all the features have values, we should drop the all-NULL rows to make an early preprocessing operation. As each pattern of candlesticks, especially momentum patterns in our research, has different strength and the mixture of them with indicators, oscillators and the resistance, support levels provide a powerful signal to open a trade or close the current one, I have provided all of them as a compact feature to fit them to our Meta Feature Selection phase. **Error! Reference source not found.** is the output of the functions, in which all the features with their related values for our experimental dataset is produced. It includes 4235 rows of days with 23 columns of OHLC prices of daily market and their volume of traded *shares* with corresponding specific extracted features. The Zigzag column represent the target labels. Moreover, the columns of produced features for each asset can be unlike in numbers and types.

	Open	Close	Low	High	Volume	Inside	3WhiteSoldiers	AdvancedBlock	BeltHold	DragonflyDoji	...	Harami	SpinningTop	Rsi	MACD	Zigzag
2001-03-25	2788.0	2800.0	2788.0	2802.0	110870	0	0	0	0	0	...	0	0	0.0	0	0
2001-03-26	2800.0	2788.0	2787.0	2810.0	98513	0	0	0	0	0	...	0	0	0.0	0	0
2001-03-27	2788.0	2795.0	2795.0	2800.0	158500	0	0	0	0	0	...	0	0	0.0	0	0
2001-03-28	2795.0	2846.0	2790.0	2846.0	80878	0	0	0	0	0	...	0	0	0.0	0	0
2001-03-31	2846.0	2838.0	2800.0	2848.0	177382	0	0	0	0	0	...	0	0	0.0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2021-07-14	2080.0	2056.0	2035.0	2125.0	421710088	0	0	0	0	0	...	0	0	0.0	0	0
2021-07-17	2080.0	2086.0	2051.0	2134.0	445324854	0	0	0	0	0	...	0	100	0.0	0	0
2021-07-18	2088.0	2041.0	2022.0	2067.0	542502856	0	0	0	-100	0	...	0	0	0.0	0	0
2021-07-31	2041.0	2024.0	1982.0	2088.0	449178311	0	0	0	0	0	...	0	-100	0.0	0	0
2021-08-01	2024.0	2013.0	1970.0	2088.0	470194978	0	0	0	0	0	...	0	-100	0.0	0	1

4235 rows × 23 columns

Figure 2(overview of a stock dataset with produced features and dropped features with all-Null rows in a daily period market from 2001 to 2021)

V. META FEATURE SELECTION

Since the scale of features are various according to our features production functions and initial fundamental data, a standardized process is needed before proceeding forward. The range of each feature based on studying asset could be integer or decimal numbers from the range of [-100, +100], [0, +100], [-1, +1] or a decimal number from zero to billions particularly in prices or traded volume. After standardized phase the data is ready to be fed into the feature selection phase. In this phase we are selecting some exhaustive features, which are all together a good criterion of trading decision to leverage the profit, particularly when we are analyzing the pricing charts non mechanized to decide whether to purchase or sell the security or even for the further processing in supervised learning, which is not our concern in determining the PRZs. When a trader is not sure about the direction of future movement of price in the market as it has hit the PRZ, whether to purchase or sell, the occurrence of each of the more weighted features, the selected features, can illuminate the more confident path to the future valuation of the security.

To be accurate in pinpointing the valuable features, wrapper method [12] has been used in view of the fact that it uses classifiers to obtain the best features related to those classifiers. But to acquire more accurate output I have used this method with a bunch of classifiers, which may produce dissimilar votes about each feature and then select the features that have the more positive votes, more than 90% positive vote, the majority vote. They can be our candidates in analyzing the price chart of the assessing asset, especially when deciding in the time of market is too tough because of huge amount of output data from different trading tools. I should aver from the fundamental data employing just the *CLOSE Price* and the *VOLUME* could be enough for some markets, which show very less fluctuation. Otherwise, employing of VOLUME and MEAN PRICE (4) or (5) could be useful.

$$Mean\ Price(OHLC) = \frac{Open+High+Low+Close}{4} \quad (4)$$

$$Mean\ Price(OHL) = \frac{Open+High+Low}{3} \quad (5)$$

In Figure 3 the whole steps of meta feature selection are shown. There are n numbers of classifiers to be used as estimators of wrapper method with differently *True, False* outputs for i to n produced features in phase one. The result is a dataset of $n \times n$, classifiers and features. A function of feature selector is run over the dataset to select the best features based on the determined threshold. The final result is a list of weighted features.

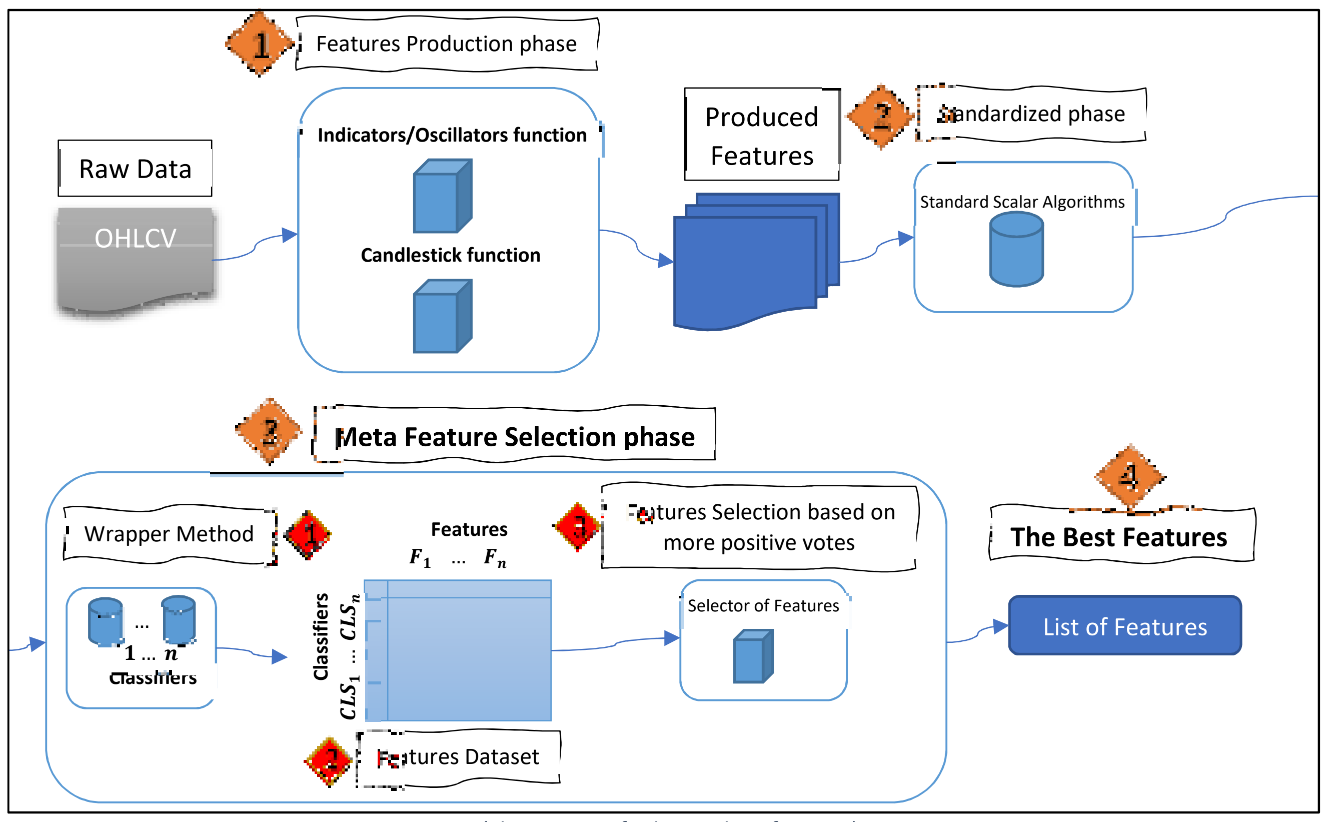

Figure 3(The process of selecting best features)

VI. Determination of Potential Reversal Zones

As detailed previously, initial labeling is the toughest part of supervised learning, though that could be a good idea to think about unsupervised algorithms. Since there are plethora of features in the dataset and clustering algorithms are sensitive to the outliers, we should use the list of selected features to eliminate the unimportant features from the dataset. The dataset to be fed into the dendrogram [10] chart is consisted of all rows and selected columns, features. The output of dendrogram is a visualization of probable clusters that could be selected for the unsupervised algorithms. As it is clear in Figure 1 vertical lines represent a cluster and any horizontal line that crosses them can give a number of junctions, which means the number of suitable clusters. In Figure 1 the satisfactory clusters could be 4, 5, 6 or 7 clusters [13]. As each PRZ has more touches, peak or dip in it, it becomes more powerful to obstacle the descending or ascending movement of prices. Therefore, it will be clear that we have various strong or weak PRZs in a price chart that could or could not reverse the trend. The aim of this part of paper is to locate some number of clusters, which determine the PRZs, the strength of the PRZs is derived from the numbers of reversal it has caused.

The plotting of *mean prices* on a OHLC chart with the use of interactive plotting tools [14] could provide a perfect perspective of PRZs with its peaks and dips. In Figure 4 after clustering of daily prices of an asset in a stock market, the best probable PRZs are plotted which are produced not just by observing the alone OHLC chart, rather by considering the whole history of that asset as well as the output of indicators and oscillators. The thickness of horizontal lines shows the more powerful PRZs, which in this case they are very close in the middle of figure.

As it is comprehensible, all the PRZs are related to the history of the security, but what if the trend smashes the PRZ and move forward regardless of downtrend or uptrend?!!
The relative PRZs could be guessed through the majestic discovery of Fibonacci, which exists anywhere in the nature and in addition in the nature each market. With the help of Fibonacci Extension or Retracement [3], the future unseen PRZs could be perceived.

Figure 4(determination of PRZs on a chart price)

VI. CONCLUSION

Many have argued that the financial markets are a random entity. According to the Random Walk Theory [15], price action is “serially independent.” This means that price history is not a reliable indicator of future price action. Although this theory does possess validity, since anything can happen in the financial markets, history has proven that within this randomness there is a degree of repetition. The exact detailed discovery of these repetitions with the assist of weighted technical tools and ML is the final objective of the paper.

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