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A Novel Outlier detection method for Time series data

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ABSTRACT

In this paper, we present a new definition for outlier: cluster-based outlier, which is meaningful and provides importance to the Time series data behavior. A measure for identifying the physical significance of an outlier is designed,which is called moment-based local outlier detection. In this work, a hybrid extreme range outlier detection approach in order to predict the each technical feature extreme values and outliers.

Keywords: Stock market technical data, outlier analysis, clustering approach , stock market.

I. INTRODUCTION

An outlier in a dataset is defined informally as an observation that is considerably different from the remainders as if it is generated by a different mechanism. Searching for outliers is an important area of research in the world of data mining with numerous applications, including credit card fraud detection, discovery of criminal activities in electronic commerce, weather prediction, marketing and customer segmentation.Technical analysis, which can be used for market timing decisions and price target forecasts, can be used to seek help. Technical analysis alerts investors to the imminent risk by suggesting the likely price and time levels as if the market could fall[5]. Passive investors can capitalize on such stock market falls by exiting their existing holdings in index funds at a higher price and buying them back later at a lower price or simply short selling index futures. With the help of various technical instruments, this can be done. An index is a compilation of the prices of a number of representative assets for the purpose of capturing the overall market behavior. Charles Dow, who developed the Dow Jones Industrial Average in 1896, conceived the idea of an index. All stock exchanges around the globe have built their own indices since then. Indices have numerous uses. Investors follow an index to understand the overall performance of the daily market, economists use it to study long-term relationships with other economic factors to analyze and predict business cycle and economic growth patterns, chartists plot and analyze an index's price and volume changes to predict future market direction. The Index also serves as a benchmark for evaluating the periodic performance of mutual funds[6]. Studies have found that the respective benchmark index is not beaten by mutual fund managers. Technical analysis metrics are simply a way to explain and measure the stock price trend. Filter benefits include quick computational times (usually much faster than wrapper selection methods) and simple scalability. Filter advantages include fast computational times (usually much faster than wrapper feature selection methods). For high-speed stock data, scalability is of particular importance where selection is required quickly and data dimensionality is high[7]. They further confirmed empirically that the sequential price jumps in equity prices were statistically and economically significant and were autocorrelated positively. Trading volume, however was found to be 60 percent higher and bid-ask spreads on pattern formation were lower. They examined the profitability of the candlestick pattern based trading strategy in U.S. markets. Following the completion of the pattern, the strategy involved buying a stock and holding it for ten trading days. The trading strategy suggested initiating trades on the day after completion of the pattern at the opening price. By holding the trading position for one to ten days, profitability was tested. A new trading position on the candlestick pattern formation was initiated and held for 10 days. The actual returns were compared using the bootstrap methodology to those obtained. Different trends have been implemented in different ways in different markets. So far, sufficient research on w.r.t candlestick patterns in Indian stock markets has not been undertaken to the best knowledge of the author. The Indian stock markets have become a hot destination for venture capital funds, mutual funds, hedge funds, PMS (portfolio management services), private equity funds, etc as a rapidly growing economy and an attractive destination for foreign portfolio investors coupled with mass domestic participation. In addition, increased financial awareness has motivated individuals to invest directly and embrace stock trading as a full-time profession. Thus in the Indian context, there is a need to test this oldest commercial technical school of thought. In addition, the study attempts to evaluate its profitability over various holding time periods using separate trading strategies. These are categorized broadly into patterns of reversal and continuation. A pattern of reversal means a change in the previous trend, and a pattern of continuation means that the previous trend will continue. So in order to use the candlestick for prediction, it is important to identify the trend. Such patterns require either a downtrend or an uptrend to be the present trend. Reversal patterns are classified as bullish and bearish reversal patterns, depending on the nature of the previous trend. The downtrend is paused by a bullish reversal pattern, which indicates that the stock price may not fall further and it begins to go either up or sideways. Hammer, inverted hammer, bullish engulfing, piercing pattern, morning star, bullish harami, three inside up three outside up, tweezer bottom, three white soldiers, etc, are some of the popular bullish reversal patterns. Likewise, a Bearish reversal pattern stops the upward trend, indicating that the stock price may not increase further and that it begins to go sideways or downwards. This study focuses exclusively on the patterns of reversal. Their profitability is evaluated by assuming that on the day following the pattern, a trading position is initiated at the opening price and held for one to ten days. In order to achieve better prediction efficiency, many researchers have applied artificial intelligence (AI) techniques to financial markets. ANN, GA, fuzzy logic, SVM and optimization models such as particle swarm optimization, ant colony optimization and teaching-based optimization are some of the popular techniques.

2. RELATED WORKS

Most of the outlier and clustering models are difficult to find the essential outlier detection measures due to the variance in ranges of each stock prices in the realtime market data[8]. Traditional outlier detecton models are used to find the outlier based on the static average range of all stocks and it is independent of each stock technical feature[9-11]. Also, most of the clustering models are difficult to group the trend based or extreme outlier based techical stock details on realtime data. [12] used adaptive fuzzy-GARC H and PSO to plan the model for stock index prediction. They selected an RBFNN model for data set training and predicted the SSE index.

3. PROPOSED MODEL

Filter based stock market outlier detection

In the section, a hybrid model is proposed to find the trend stocks on the realtime market data in a new filtered based clustering model on technical data. The continuous technical data types for trend prediction are evaluated for this model. A novel outlier based clustering model for real-time market data is developed and implemented by using the outlier and clustering measures. The flow chart of the proposed stock market trend prediction model is listed in figure 4. Initially, data from stock exchange sites such as tradingview or wallmine are taken from the real time market. The training data is used for stock-related technical factors like mark, price, ADX, ADR, RSI, MACD, news sentiment score, etc. Technical dat a preprocessing and clustering operations are performed on stock technical data.

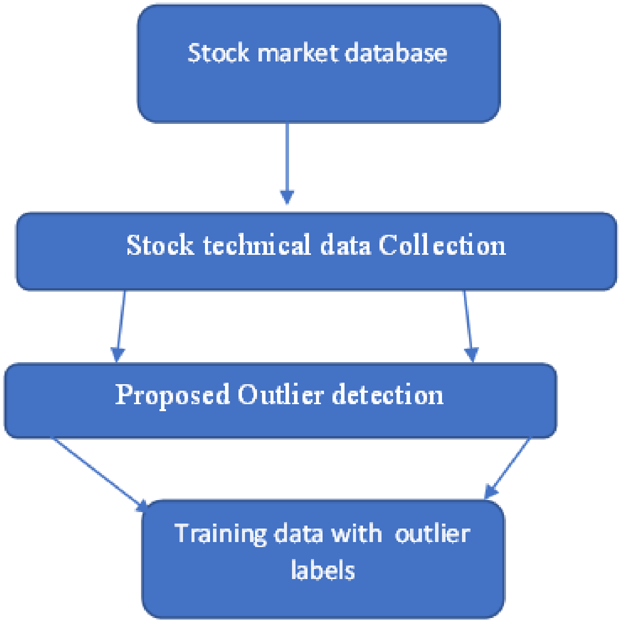

Figure 1: Proposed outlier detection framework

Algorithm 1: Proposed Timeseries outlier detection

Input: Training Data D, Features space A.
Output: Anomaly instances A, Non-anomaly instances N.

1. Read the training data D.
2. Compute the proposed gaussian probability measure to find the anomaly object in the given training data.
   A[]=SortedAttIndices();
   $\lambda1$=V(F(| A | /4));
   $\lambda2$=(V(F(| A | /2)+V(F(| A | /2+1)))/2;
   $\lambda3$=(V(F((| A | – | A | /4–1))) + V(F((| A | – | A | /4)))) /2;
   $\theta = \lambda3 - \lambda1$;
   UE[] = $\lambda3 + \eta.\log(\Gamma\theta)$
   LE[] = $\lambda1 - \eta.\log(\Gamma\theta)$

   $$\Gamma(v/2, x/2) = \int_{x}^{inf} r^{v-1}.e^{-r}\, dr$$

   UOutlier = $\lambda3 + \eta$.max((Γ($\lambda3$+ $\lambda1$,9)),log(($\Gamma\theta$))
   LOutlier = $\lambda1$ - η.max((Γ($\lambda3$-$\lambda1$,9)),log(($\Gamma\theta$))
   For i=1 to |A|
3. Do
4. If((V(F[i])<=UE[i]&&V(F[i]>UOutlier[i]|| (V(F[i])>=LE[i]&&V(F[i]<LOutlier[i])
5. Assign instance I as Anomaly .
6. D(|A|+1)=1;
7. Else
8. D(|A|+1)=0;
9. Done
10. Perform proposed Clustering model on the filtered dataset for trend prediction.

Table 1: Sample technical data collected from the tradingview website.

```
@relation data
@feature MFI numeric
@feature Volatility numeric
@feature STO numeric
@feature ATR numeric
@feature RSI numeric
@feature PPO numeric
@feature ADX numeric
@feature MACD numeric
@feature StochRSI numeric
@feature Price numeric
@feature 'Performance today' numeric
@feature Sentiment {Buy_Predict,Sell}
@data
FORTIS,69.39,1.76,57.21,2.46,58.8,0.23,35.8,0.96,33.33,139.5,-0.035832,Sell
LUMAXIND,42.85,2.81,39.01,49.8,47.86,-1.09,10.15,10.79,24.35,1752.55,-1.052953,Sell
BINDALAGRO,20.45,5.72,11.3,0.79,32.72,-3.23,20.93,-0.38,0,13.75,-0.36232,Sell
CENTEXT,25.61,4.63,25.24,0.25,23.57,-3.37,24.08,-0.18,0,5.5,1.85185,Buy
MARUTI,89.18,1.85,93.49,135.29,61.76,3.32,25.99,127.96,58.37,7048.9,-3.719995,Sell
```

Algorithm 1, describes the proposed extreme level outlier detection model in order to find the low level and high level extreme regions for the severity prediction. In this algorithm, to each attribute, outliers are detected using the extreme values computations given in step2. In the step2, extreme lower limit , extreme upper limit and outlier regions are defined using the input training data. Step 3-4 represents the conditios for the anomaly detection to filter the abnormal ranges. Step 6-8 represents the outlier labels to each feature as class label.

4. EXPERIMENTAL RESULTS

Experimental results are simulated with java and third party data in real time. In this model, different stocks data and it's technical data are taken into account for trend prediction. Also, by using various statistical features are used to find outliers. Statistical measures are evaluated using java libraries from third parties.

```
MAHSEAMLES,23.18,2.02,20.72,9.56,44.72,-0.5,10.99,-0.31,0,474.3,0.327866,Buy
GPPL,37.63,3.45,35.64,3.24,46.07,-0.19,22.14,1.31,0,93.45,-0.373141,Sell
JPINFRATEC,45.77,6.67,37.75,0.16,44.27,-14.14,26.49,-0.2,66.67,2.5,4.166663,Buy
FIEMIND,47.32,3.12,33.17,15.6,51.18,-0.17,14.13,3.58,0,496.55,-0.769386,Sell
LITL,0,0,0,0,19.67,0,61.58,0,0,0.3,0,Buy
AUTOLITIND,63.77,5.61,31.92,2.11,51.85,-0.94,50.21,0.43,34.11,37.15,-1.196801,Sell
TORNTPOWER,61.41,2.35,51.43,6.09,53.4,0.38,24.44,1.87,40.08,257.85,-0.559191,Sell
DCM,77.09,5.01,61.19,2.94,41.87,-2.46,17.31,-0.94,33.33,58.6,-0.170362,Sell
KEI,54.82,3.81,63.73,15.62,53.72,-0.3,27.43,7.41,66.67,413.6,0.890351,Buy
GREENPLY,69.2,3.36,79.08,5.61,62.85,5.22,41.84,6.05,0,166.9,-0.029951,Sell
HBLPOWER,43.77,4.37,43.87,1.1,46.7,-3.01,14.27,-0.21,33.36,24.85,-1.19284,Sell
COSMOFILMS,78.9,3.77,67.13,7.84,59.93,3.64,25.28,5.41,33.33,204.2,-1.85052,Sell
BIOCON,57.31,1.97,59.84,11.95,42.11,-0.12,12.62,-1.32,0.71,613.7,0.979023,Buy
INSECTICID,68.19,3.03,48.86,19.69,51.25,-0.45,10.07,3.19,62.35,638.6,-1.579718,Sell
PRIMESECU,39.34,3.81,25.44,1.57,54.51,-1,12.64,-0.2,66.67,40.15,1.517073,Buy
GARDENSILK,50.4,5.23,8.74,0.98,34.07,-2.99,18.98,-0.32,0,18.6,-0.799998,Sell
VLSFINANCE,70.84,4.41,45.03,2.61,52.56,0.13,24.06,0.93,66.67,60,1.35135,Buy
BALMLAWRIE,40.13,2.45,16.98,4.33,36.59,-1.84,15.77,-1.62,33.33,176.25,-0.39559,Sell
NOIDATOLL,33.34,7.17,19.76,0.38,41.03,-2.47,23.87,-0.15,51.01,5.35,0.943391,Buy
GODREJPROP,83.42,4.47,70.86,40.95,58.7,9.72,38.45,48.08,49.34,889.95,-1.51062,Sell
M&MFIN,38.64,2.66,45.97,11,47.12,-0.94,10.36,-0.22,24.54,413.2,0.1697,Buy
SKMEGGPROD,47.95,4,49.2,2.09,48.91,-2.93,12.55,-0.71,62.7,51.15,-2.198849,Sell
USHAMART,45.94,6.25,8.54,2.12,38.65,0.88,23.66,-0.02,21.68,33.3,-0.149923,Sell
WIPRO,77.76,2.75,84.19,7.94,61.97,3.43,14.62,4.88,46.28,291.1,0.988727,Buy
PATSPINLTD,56.97,7.8,29.31,0.78,41.14,-2.04,11.6,-0.2,0,9.6,-3.999996,Sell
IITL,47.05,6.2,60.31,4.96,59.96,5.02,19.45,2.59,42.12,80,-0.062465,Sell
BAJAJCORP,52.36,2.92,66.02,10.81,46.97,2.47,29.13,5.52,33.33,385.95,-0.168131,Sell
CUMMINSIND,41.41,3,62.13,21.61,44.31,-0.68,12.87,-0.55,10.72,741.6,2.828614,Buy
MOTHERSUMI,69.7,3.49,74.22,5.49,55.76,-1.66,16.36,0.15,88.06,150.1,-1.63827,Sell
GAIL,44.69,2.6,55.46,8.96,46.98,-1.28,16.1,0.69,4.46,339.45,-1.565896,Sell
COROMANDEL,31.16,3.41,21.42,15,38.8,-3.81,26.19,-8.17,60.99,426.15,-1.251302,Sell
ICIL,60.54,6.48,19.25,3.01,43.41,-4.95,20.54,0.05,0,44.15,-4.951559,Sell
PANACEABIO,80.32,5.46,71.29,11.03,57.49,1.08,38.89,4.55,40.64,193.8,-2.905813,Sell
PBAINFRA,0,1.5,18.53,0.06,19.02,-10.47,52.56,-0.31,66.67,4,0,Sell
NITESHEST,67.43,6.39,19.58,0.39,48.88,-1.27,26.98,0.02,0,5.95,-2.459018,Sell
,24.35,47.49,41,-0.74,19.11,3.12,33.33,1465.35,-0.778684,Sell
LGBBROSLTD,45.21,2.46,21.8,9.5,46,-1.43,10.3,-3.8,66.67,393.85,2.099807,Buy
WELCORP,65.55,4.21,51.13,5.66,52.57,6.15,32.28,4.65,33.33,132.7,-1.301599,Sell
VTL,71.85,2.52,82.78,28.36,61.7,1.29,23.01,20.08,15.03,1126.55,0.244705,Buy
FDC,87.87,3.52,32.28,5.76,41.66,-2.61,13.54,-1.46,29.52,162.35,-0.794371,Sell
GAL,66.27,9.32,26.93,0.41,35.01,-3.83,28.14,-0.22,0,4.65,5.681818,Buy
BALAJITELE,39.25,3.28,12.12,2.56,37.1,-2.28,8.36,-1.41,0,76.95,-1.535515,Sell
HDIL,68.08,3.96,34.81,0.97,38.65,1.16,25.59,0.23,0,23.5,-4.081633,Sell
BALRAMCHIN,60.31,3.87,72.73,5.55,59.75,2.16,27.32,3.45,68.57,141.15,-1.534714,Sell
FINPIPE,40.3,2.96,27.7,13.93,36.7,-3.52,26.24,-7.23,33.33,466.15,-0.829698,Sell
MANGCHEFER,77.6,4.03,70.07,1.68,54.55,4.58,35.64,1.29,66.67,41.25,-0.960388,Sell
AIAENG,77.94,2.62,61.22,47.25,56.94,0.33,24.79,17.71,57.95,1809.5,0.522195,Buy
SASKEN,89.38,3.17,75.79,22.58,75.21,0.93,27.79,12.37,100,705.9,-1.023554,Sell
CARBORUNIV,18.91,2.65,20.43,9.9,45.02,0.68,17.85,1.2,1.3,372.85,0.067096,Buy
OMAXE,40.87,1.22,48.47,2.56,51.56,0.93,33.1,0.84,66.67,210.35,-0.047513,Sell
SUNPHARMA,39.94,2.51,22.89,11.41,44.85,-0.58,16.16,1.51,54.13,468.55,3.091306,Buy
UNITY,45.58,12.73,31.96,0.07,34.5,-18.91,27.4,-0.09,66.67,0.55,0,Buy
SADBHAV,14.68,3.32,19.16,7.97,52.96,-0.55,27.07,5.21,0,229.65,-2.172527,Sell
JKPAPER,66.63,3.15,75.92,4.74,57.4,1.8,21.69,2.94,9.26,145.65,0.379041,Buy
PVR,59.98,2.52,79.88,42.67,59.29,1.86,24.58,33.02,42.75,1670.55,-1.387208,Sell
WILLAMAGOR,24.85,5.15,12.2,2.39,34.35,-2.91,16.06,-0.97,23.55,45.2,-2.691066,Sell
```

Table 1, describes the sample collected data from the tradingview website to perform the outlier detection and clustering approaches. These data contains various technical stock related features as the training data.

Table 2: Outlier results

Table 2, illustrates the outlier detection result of the proposed model on the technical data. Here, extreme upper , extreme lower, upper outlier and lower outlier results are evaluated using the proposed outlier detection model.

For every attribute is considered and threshold values are calculated then deviation is computed based on deviation we are calculated outliers in four different levels which is lower level , lower extreme level , upper level , upper extreme level outliers .

proposed extreme level outlier detection model in order to find the low level and high level extreme regions for the severity prediction.

In this approach , to each attribute, outliers are detected using the extreme values computations .

In the step2, extreme lower limit , extreme upper limit and outlier regions are defined using the input training data.

Step 3-4 represents the conditios for the anomaly detection to filter the abnormal ranges.

Step 6-8 represents the outlier labels to each feature as class label.

```
Upper extreme value 11241.273881562447
lower extreme value -10898.448881562448
Upper outlier  value 5785.336940781223
Lower outlier value -5442.5119407812235
Upper extreme value 272.8537942403589
lower extreme value -225.50379424035893
Upper outlier  value 151.99189712017946
Lower outlier value -104.64189712017946
Upper extreme value 168.74560894311682
lower extreme value -156.48060894311683
Upper outlier  value 90.17530447155842
Lower outlier value -77.91030447155842
Upper extreme value 18.894887375432134
lower extreme value -10.614887375432135
Upper outlier  value 12.137443687716068
Lower outlier value -3.8574436877160676
Upper extreme value 239.6657399061175
lower extreme value -144.5607399061175
Upper outlier  value 146.69286995305873
Lower outlier value -51.58786995305875
Upper extreme value 951.5500486779478
lower extreme value -862.8350486779477
Upper outlier  value 507.9700243389739
Lower outlier value -419.2550243389739
Upper extreme value 1277.1458120570019
lower extreme value -1209.045812057002
Upper outlier  value 668.4679060285009
Lower outlier value -600.367906028501
Upper extreme value 18.45119486492589
lower extreme value -16.18119486492589
Upper outlier  value 10.465597432462944
Lower outlier value -8.195597432462945
Upper extreme value 29.303642348196693
lower extreme value -30.058642348196692
Upper outlier  value 15.366821174098346
Lower outlier value -16.121821174098347
Upper extreme value 653.7514890118435
lower extreme value -544.9314890118436
Upper outlier  value 361.32074450592177
Lower outlier value -252.50074450592177
Upper extreme value 5.914121182512236
lower extreme value -6.610908182512237
Upper outlier  value 3.5015194273154293
Lower outlier value -4.19830642731543
SPYL,0.25,28.95,0.05,25,30.04,11.11,0,-0.02,-7.92,2.25,24.999998,Buy,no
SUJANAUNI,0.3,13.23,0.06,24,45.05,22.22,37.73,-0.01,-4.5,29.62,20.0000
04,Buy,no
LPDC,5.45,12.95,0.38,8.35,66.16,59.94,66.67,0.04,-0.25,86.76,19.78021,B
uy,no
VHL,2281,13.22,92.49,4.47,42.56,49.58,40.17,-7.07,-2.09,51.42,10.140029,
Buy,yes
JETAIRWAYS,169.75,20.07,21.94,14.18,19.9,32.48,0,-10.57,-1.42,23.42,9.
728509,Buy,yes
CUBEXTUB,14.85,7.17,1,7.33,44.63,32.35,33.33,-0.11,-0.42,29.02,8.79121
5,Buy,no
ZENITHBIR,0.65,28.65,0.07,11.67,50.69,70.37,71.77,-0.02,-2.54,77.06,8.3
33325,Buy,no
GAMMNINFRA,0.65,19.2,0.07,11.67,42.67,62.96,0,0,1.24,64.28,8.333325
,Buy,no
RELCAPITAL,143.95,15.66,12.51,9.41,21.87,10.62,0,-6.49,-3.44,28.99,8.2
3308,Buy,no
DEEPIND,151.45,34.96,6.22,4.43,55.2,37.66,43.91,2.55,-1.14,45.09,7.8703
73,Buy,no
KAUSHALYA,0.8,27.52,0.04,5.33,50.35,70.37,70.86,-0.03,-4.89,83.47,6.6
66668,Buy,no
GLOBALVECT,117.9,32.27,8.23,7.1,79.23,79.92,100,9.71,10.83,95.23,6.4
0794,Buy,no
SURANAT&P,4.3,9.49,0.2,4.82,45.4,53.48,48.49,-0.03,-0.08,64.09,6.1728
39,Buy,no
GKWLIMITED,784.4,20.72,33.96,4.59,29.71,24.86,53.32,-29.61,-5.5,41.76
,5.935581,Buy,no
PRECWIRE,209.35,9.65,7.28,3.68,44.27,30.51,65.19,-1.89,-1.25,50.58,5.89
2772,Buy,yes
WSI,0.9,87.07,0.07,8.24,14.92,4.69,66.67,-0.35,-29.12,0.28,5.882347,Buy,y
es
SUZLON,7.2,21.34,0.52,7.32,57.89,69.14,66.67,0.27,0.47,57.5,5.882347,B
uy,yes
GRUH,298.05,34,8.92,3.17,58.12,71.36,66.67,5.59,2.28,74.68,5.785266,Bu
y,yes
GAL,4.65,28.14,0.41,9.32,35.01,26.93,0,-0.22,-3.83,66.27,5.681818,Buy,ye
s
ROHITFERRO,0.95,48.69,0.04,4.44,29.99,32.22,33.33,-0.07,-9.69,39.47,5.
555557,Buy,yes
BSELINFRA,1.9,12.1,0.16,8.89,41.52,36.97,0,-0.02,-0.12,51.81,5.555557,B
uy,yes
RAMSARUP,0.95,45.35,0.04,4.44,91.92,100,100,0.15,47.06,100,5.555557,
Buy,yes
PSL,1.05,19.64,0.08,8,45.35,55.56,0,0,0.01,3.84,55.79,4.999995,Buy,yes
MANINDS,70,29.58,2.22,3.33,48.82,24.23,31.01,0.49,-0.39,68.21,4.86891
4,Buy,yes
SUPREMEINF,21.65,28.2,1.5,7.26,38.91,18.42,86.97,-1.04,-10.29,69.36,4.
842615,Buy,yes
JBFIND,21.7,23.47,1.95,8.72,45.61,60.27,11.03,1.2,7.89,78.47,4.830918,Bu
y,yes
NEXTMEDIA,19.65,57.49,0.91,4.67,34.34,28.63,86.2,-1.88,-16.68,21.29,4.
799998,Buy,yes
PRADIP,1.1,35.05,0.03,2.86,44.74,62.78,66.67,-0.05,-8.2,28.45,4.761912,B
uy,yes
MADHUCON,7.85,22.61,0.47,6.27,49.75,27.75,0,0.42,13.08,32.01,4.6666
66,Buy,yes
KKCL,1328.7,16.58,35.98,2.83,51.81,39.81,50.81,4.99,-0.69,24.93,4.62616
6,Buy,yes
JYOTISTRUC,3.45,74.9,0.09,2.73,96.7,100,100,0.44,26.32,100,4.545458,B
uy,yes
MAHABANK,16.2,31.78,0.56,3.61,69.74,77.44,59.05,0.53,4.2,76.51,4.516
134,Buy,yes
IL&FSENGG,9.4,21.58,0.54,6.35,38.77,40.07,28.65,-0.24,-2.33,50.42,4.44
4441,Buy,yes
EDL,7.1,17.69,0.45,6.62,36.47,39.13,6.01,-0.18,-3.86,26.03,4.41176,Buy,y
es
UNITECH,1.2,13.98,0.08,6.67,38.99,22.22,7.38,-0.05,-4.69,25.95,4.347833
,Buy,yes
LUPIN,867.6,59.08,23.87,2.87,65.27,92.84,54.22,15.24,3.8,95.55,4.322726,
Buy,yes
SUPREMEIND,1169.4,27.79,31.63,2.82,52.2,65.78,33.33,12.73,1.63,62.09,
4.317576,Buy,yes
SABTN,4.95,24.71,0.31,6.67,52.55,32.75,100,-0.02,-5.95,45.64,4.210522,B
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uy,yes
MOTILALOFS,731.7,33.88,24.37,3.47,63.18,89.04,39.94,28.05,5.18,92.38,4.178834,Buy,yes
JPINFRATEC,2.5,26.49,0.16,6.67,44.27,37.75,66.67,-0.2,-14.14,45.77,4.166663,Buy,yes
TPNL,8.68,17.77,0.51,6.12,58.92,68.96,48.41,0.23,1.99,53.16,4.076741,Buy,yes
CURATECH,1.3,20.57,0.03,2.5,47.14,12.04,78.06,-0.01,-2.82,94.47,3.999996,Buy,yes
LGBFORGE,4,54.65,0.11,2.86,73.59,83.9,33.33,0.28,11.19,94.57,3.896107,Buy,yes
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5.CONCLUSION

In this work, a new outlier detection based clustering approach is proposed to predict the individual stock trend. The bullish and bearish patterns are hard to forecast using trend indicators or realtime stock sentiment news for the most part of the current technical indicators. Experimental findings showed that the current model is computationally effective in terms of finding outliers. In the future work, this model is extended to the hybrid trend prediciton model for the stocks techncial features data.

REFERENCES

[1] O. Aladesanmi, F. Casalin, and H. Metcalf, "Stock market integration between the UK and the US: Evidence over eight decades," Global Finance Journal, vol. 41, pp. 32–43, Aug. 2019, doi: 10.1016/j.gfj.2018.11.005.

[2] J. Bley and M. Saad, "An analysis of technical trading rules: The case of MENA markets," Finance Research Letters, vol. 33, p. 101182, Mar. 2020, doi: 10.1016/j.frl.2019.04.038.

[3] A. C. Briza and P. C. Naval, "Stock trading system based on the multi-objective particle swarm optimization of technical indicators on end-of-day market data," Applied Soft Computing, vol. 11, no. 1, pp. 1191–1201, Jan. 2011, doi: 10.1016/j.asoc.2010.02.017.

[4] O. Bustos and A. Pomares-Quimbaya, "Stock market movement forecast: A Systematic review," Expert Systems with Applications, vol. 156, p. 113464, Oct. 2020, doi: 10.1016/j.eswa.2020.113464.

[5] Z. Dai, X. Dong, J. Kang, and L. Hong, "Forecasting stock market returns: New technical indicators and two-step economic constraint method," The North American Journal of Economics and Finance, vol. 53, p. 101216, Jul. 2020, doi: 10.1016/j.najef.2020.101216.

[6] S. R. Das, D. Mishra, and M. Rout, "Stock market prediction using Firefly algorithm with evolutionary framework optimized feature reduction for OSELM method," Expert Systems with Applications: X, vol. 4, p. 100016, Nov. 2019, doi: 10.1016/j.eswax.2019.100016.

[7] D. P. Gandhmal and K. Kumar, "Systematic analysis and review of stock market prediction techniques," Computer Science Review, vol. 34, p. 100190, Nov. 2019, doi: 10.1016/j.cosrev.2019.08.001.

[8] Y. Xu, B. Iglewicz, and I. Chervoneva, "Robust estimation of the parameters of g-and-h distributions, with applications to outlier detection," Computational Statistics & Data Analysis, vol. 75, pp. 66–80, Jul. 2014, doi: 10.1016/j.csda.2014.01.003.

[9] S. Aghabozorgi and Y. W. Teh, "Stock market co-movement assessment using a three-phase clustering method," Expert Systems with Applications, vol. 41, no. 4, Part 1, pp. 1301–1314, Mar. 2014, doi: 10.1016/j.eswa.2013.08.028.

[10] H. Esmalifalak, A. I. Ajirlou, S. P. Behrouz, and M. Esmalifalak, "(Dis)integration levels across global stock markets: A multidimensional scaling and cluster analysis," Expert Systems with Applications, vol. 42, no. 22, pp. 8393–8402, Dec. 2015, doi: 10.1016/j.eswa.2015.06.053.

[11] B. Lee, L. Rosenthal, C. Veld, and Y. Veld-Merkoulova, "Stock market expectations and risk aversion of individual investors," International Review of Financial Analysis, vol. 40, pp. 122–131, Jul. 2015, doi: 10.1016/j.irfa.2015.05.011.

[12] T. Ikeda, "Multifractal structures for the Russian stock market," Physica A: Statistical Mechanics and its Applications, vol. 492, pp. 2123–2128, Feb. 2018, doi: 10.1016/j.physa.2017.11.129.