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Candlestick Technical Analysis on Select Indian Stocks: Pattern detection and Efficiency Statistics

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Abstract: Financial markets generate vast data every trading day. There are markets for equity shares, commodities, fixed income securities and currencies etc. Further, we do have organised markets for financial dderivatives. The exponential growth of financial markets isthe order of the modern-day. Developments in information and communication technology (ICT) helped the growth of financial markets and its operations to greater heights. One of the financial market analysis is Candlestick Technical analysis also is known as Japanese candlestick charting. It is the oldest form of financial market analysis originated in japan. This study measured the occurrence and tested the efficiency of various bullish reversal candlestick patterns on 17 stocks of India's leading stock market benchmark index NIFTY 50 for the period of 16 years from 2000 to 2015.Data mining with backtesting methodology is used to find the top 10 candlestick patterns with respect to the frequency of occurrence during the study period. The efficiency profitability is analysed using Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method , a multi-criteria decision making (MCDM) method on the backtested results for the 5-day holding period.The results of the study show that hammer (HMR), long engulfing pattern (LEB) and Rising window (RSW) are the top three ranked candlestick patterns.

Keywords: Technical Analysis, Candlesticks, TOPSIS and Indian stocks.

I. INTRODUCTION

Data analysis in financial markets is the most critical part. Financial market data analysis is mainly of two types one is fundamental analysis, and the other is technical analysis. Technical analysis is also is known as chart based study of financial market asset price data.Security Price and volume data namely open, high,low,close and daily tradednumber of shares are plotted as in a chart form (fig.1) with which visual studies are possible [17, 1].

Fig.1. A Candlestick Chart

Market Participants, Professional Traders and practitioners use the data for forecastingthe future direction of the price and trading decisions [2]. The price data plotting is done as a single plot or image for a particular time frame minute,daily,weekly or monthly.Plotted data will look like a candle (fig.2)

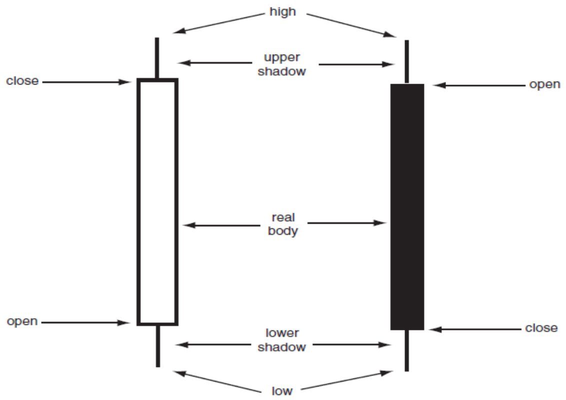

Fig.2. Bullish and Bearish Candlestick Depiction

The practice of using candlestick like plotting data was developed and adopted by Munehisa Homma (1724-1803) a Rice trader in Dojima Rice exchange, Japan.Munehisa Homma assumedthat price action reflectsthe sentiment of the market participants. The changing and trending way of prices resulted in different shaped candles. By observing and studying the shape of a single candle or a set of candlestick patterns,we can understand that after a patternoccurrence, there used to be a significant levelof price change.Therefore candlestick patterns are considered as a leading signal provider about and impending price action of security in the near term. Candlestick charting technique wasa widely used technique in South Asia till the late 1980s;Charles H Dow introduced charting in the west in the 1900s; afterwards, it slowly gained popularity and importance in the west.Candlestick technicals will have applications in various markets and different time frames. The effectiveness of technical analysis is one of the most argued topics in modern-day financial market analysis.There are arguments for and against technicalanalysis. Aconsiderable number of researchers have proven that technical analysis isdependable to some extent in reality.Studying and analysing past prices in addition to other data, one can make above-average returns. In a detailed study on 90 years of US-listed stocks data by using a mix of 26 different technical indicators [16], found that technical analysis isa dependable tool.Nowadays,the application of machine learning and computational intelligence techniques in analysing and predicting the stock market trend. Some of the models and systems are hidden Markov model, neural network, neuro-fuzzy system, genetic algorithm, mining association rules, support vector machine (SVM),

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principal component analysis (PCA) and rough set theory etc., [3]. Candlestick patterns are plenty in numbers and are described in natural language. It is challenging to adopt in computational methods [18].Though candlestick technical analysis is rejected by the weak form of efficiency, it is widely practised by market participants .The reversal patterns are formed to effective in Malaysian stock markets[6,19].Pattern recognition trading using KNN classifier revealed that candlestick technical patterns have considerable predictive power [20]. Genetic algorithmsbased fuzzy candlestick detection system proved superior returns [9]. One morestudy finds little use of both bullish and bearish candlestick reversal patterns since the mean returns of the most patterns are not statistically different from zero in the SET 500 market [13]. A recent study conveys that reversal candlesticks do not demonstrate the ability to predict the market trend and generated profitability is low on the stock market in Vietnam [21].

II. DATA AND METHODOLOGY

This study uses a data set of NIFTY50 index member stocks from Jan 2000 to Dec 2015.The stock price data used is of the type daily or end of the day (EOD). Every stock hasnearly 3980 daily data points.

A. Data Collection

The NIFTY50 is a leading benchmark index in India consist of 50 companies representing diversified industry sectors. Because of the long duration of 16 years of study, only 17 stocks (Table 1) continuously remained as a member of the benchmark index, only these stocks were considered as the sample for this study.

Table I List of sample stocks

Sl. No	Stock	Industry sector
1	ACC	Cement
2	AMBUJACEM	Cement
3	BHEL	Industrial manufacturing
4	CIPLA	Pharma
5	HDFC	Fin. services
6	HDFCBANK	Fin. Services
7	HEROMOTOCO	Automobiles
8	HINDALCO	Metals
9	HINDLEVER	FMCG
10	INFY	IT services
11	ITC	FMCG
12	M&M	Automobiles
13	RELIANCE	Energy
14	SBIN	Fin. services
15	TATAMOTORS	Automobiles
16	TATAPOWER	Power
17	TATASTEEL	Metals

The study considers daily historical data of seventeen sample stocks identified from the previous step. The daily data of the share consists of OPEN, HIGH, LOW, CLOSE and Volume data points for every share for the 16 years of period extracted from NSE India and CMIE Prowess database. The data adjusted for split and bonuses. Every stock has roughly 3983 data points for the sixteen years. The sample period underwent various economic events like the dotcom bubble, global financial crisis 2007-2009 periods. The sample period also has gone through country-specific and global geopolitical events.

B. Methodology

The collected EOD data 17 stocks are incorporated in the candlescanner software. Candlescanner is a technical analysis software package to identify,explore and analyse candlestick patterns in financial market data.It has the capability of measuring efficiency and based on which trading strategies can be designed for further refinement and usage.By using the software, the collected data are subjected for backtesting to identify occurrencesof 34 (Table 2) different bullish reversal and bullish continuation patterns for 5-day trading basis.The efficiency of the candlepatterns is studied within the five days of its occurrence. The occurred patterns are classified as given in Table 3.

Table II List of Bullish Reversal and Bullish continuation Patterns

Sl.No	Candlestick Pattern	Forecast
1	Abandoned Baby	Bullish Reversal
2	Belt Hold	Bullish Reversal
3	Doji Star	Bullish Reversal
4	Engulfing	Bullish Reversal
5	Hammer	Bullish Reversal
6	Harami Cross	Bullish Reversal
7	Harami	Bullish Reversal
8	Homing Pigeon	Bullish Reversal
9	Inverted Hammer	Bullish Reversal
10	Kicking Up	Bullish Reversal
11	Last Engulfing Bottom	Bullish Reversal
12	Matching Low	Bullish Reversal
13	Meeting Lines	Bullish Reversal
14	Morning Doji Star	Bullish Reversal
15	Morning Star	Bullish Reversal
16	Piercing	Bullish Reversal
17	Southern Doji	Bullish Reversal
18	Takuri Line	Bullish Reversal
19	Tasuki Line	Bullish Reversal
20	Three Inside Up	Bullish Reversal
21	Three Outside Up	Bullish Reversal
22	Three stars in south	Bullish Reversal
23	Three White Soldiers	Bullish Reversal
24	Tri star	Bullish Reversal
25	Turn Up	Bullish Reversal
26	Tweezer Bottom	Bullish Reversal
27	Unique three-river bottom	Bullish Reversal
28	Gapping Up Doji	Bullish continuation
29	Rising Window	Bullish continuation
30	Separating lines	Bullish continuation
31	Side-by-side white lines	Bullish continuation
32	Strong Line	Bullish continuation
33	Upside three Gap methods	Bullish continuation
34	Upside Tasuki Gap	Bullish continuation

Table III Candle efficiency classification

Signal Type	Returns
False	- Negative to 0 %
Low	0 to 2.0%
Medium	2 to 3.5 %
High	Above 3.5%

The top 10 most occurring candlepatterns and their efficiency data are given in table 4, and the detailed statistics are given in table 5.

Table IV Top 10 Candle Pattern Signal Efficiency in % (Full Sample Data)

Pattern name	Code	False	Low	Med.	High
Strong line	SLN	16.60	21.80	17.40	44.30
Harami	HMI	15.80	24.50	17.20	42.50
Long Engulfing Bottom	LEB	20.60	21.30	17.30	40.70
Raising Window	RSW	18.10	26.10	17.80	37.90
Turn Up	TUP	15.50	22.60	16.60	45.20
Engulfing	ENG	18.00	24.20	15.90	42.00
Three Inside Up	TNP	15.60	23.60	16.00	44.80
Tasuki Line	TSL	16.00	24.10	17.80	42.10
Homing Pigeon	HPN	17.10	23.60	17.90	41.50
Hammer	HMR	19.10	24.20	18.40	38.30

III. RETURNS AND ANALYSIS

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method, is one of the well-known multiple criteria decision making (MCDM) methods. The TOPSIS method introduces the shortest distance from the positive ideal solution (PIS) and the farthest distance from the negative ideal solution (NIS) to determine the best alternative.TOPSIS method has become a popular multiple criteria decision technique due to its theoretical rigorousness, a sound logic that represents the human rationale in the selection and the fact that it has been proved in as one of the most appropriate methods in solving traversal rank.

Table V Candle Pattern Occurrence statistics (Full sample Data)

S.no.	Pattern Name	Code	No. of occurrences	% of the total occurrence	Avg. freq. (days)
1	Strong Line	SLN	1568	18.39%	46
2	Harami	HMI	1035	12.14%	69
3	Last Engulfing Bottom	LEB	909	10.66%	79
4	Rising Window	RSW	729	8.55%	98
5	Turn Up	TUP	699	8.20%	103
6	Engulfing	ENG	674	7.90%	106
7	Three Inside Up	TNP	487	5.71%	147
8	Tasuki Line	TSL	394	4.62%	182
9	Homing Pigeon	HPN	369	4.33%	194
10	Hammer	HMR	277	3.25%	259

TOPSIS can be expressed in a series of steps as follows. The observation of the returns efficiency by different candlestick patterns is listed in table 6. The weights assigned for 'False' as 10 %, 'Low' as 10%, 'Med' as 20 % and 'High' as 60%. Based on the weights set, positive ideal solution and negative ideal solution have been concluded.

Table VICandlestick wise efficiency data

	FALSE	LOW	MED	HIGH
SLN	16.60	21.80	17.40	44.30
HMI	15.80	24.50	17.20	42.50
LEB	20.60	21.30	17.30	40.70
RSW	18.10	26.10	17.80	37.90
TUP	15.50	22.60	16.60	45.20
ENG	18.00	24.20	15.90	42.00
TNP	15.60	23.60	16.00	44.80
TSL	16.00	24.10	17.80	42.10
HPN	17.10	23.60	17.90	41.50
HMR	19.10	24.20	18.40	38.30
	Min	Max	Max	Max
Weights	**0.1**	**0.1**	**0.2**	**0.6**
PIS	15.5	26.10	18.4	45.20
NIS	20.6	21.30	15.9	37.90

The raw data is normalized to eliminate deviations with different measurement units and scales. The normalized decision matrix is calculated and depicted in table 7. Considering the respective weights of each criterion, the weighted normalized decision matrix can be computed by multiplying the importance weights of evaluation criteria.

Table VIINormalised Matrices

	FALSE	LOW	MED	HIGH
SLN	-0.14686	0.480574	0.224337	0.070504
HMI	-0.04005	0.178818	0.269204	0.211513
LEB	-0.68091	0.536455	0.246771	0.352521
RSW	-0.34713	0	0.134602	0.571868
TUP	0	0.391165	0.403807	0
ENG	-0.33378	0.212347	0.560843	0.250682
TNP	-0.01335	0.279404	0.538409	0.031335
TSL	-0.06676	0.223523	0.134602	0.242848
HPN	-0.21362	0.279404	0.112169	0.289851
HMR	-0.48064	0.212347	0	0.540533

Determining the PIS and NIS upon the normalised matrix is respectively shown in table 8 and table 9.

Table VIII Positive Ideal Solution

	FALSE	LOW	MED	HIGH
SLN	0.008011	-0.02012	-0.01795	0.282017
HMI	-0.00267	0.010059	-0.02692	0.197412
LEB	0.061415	-0.02571	-0.02243	0.112807
RSW	0.028037	0.02794	0	-0.0188
TUP	-0.00668	-0.01118	-0.05384	0.32432
ENG	0.026702	0.006706	-0.08525	0.17391
TNP	-0.00534	0	-0.08076	0.305518
TSL	0	0.005588	0	0.178611
HPN	0.014686	0	0.004487	0.150409
HMR	0.041389	0.006706	0.02692	0

Table IX Negative Ideal Solution

	FALSE	LOW	MED	HIGH
SLN	0.033378	0.026823	0.044867	-0.10341
HMI	0.044059	-0.00335	0.053841	-0.0188
LEB	-0.02003	0.032411	0.049354	0.065804
RSW	0.013351	-0.02123	0.02692	0.197412
TUP	0.048064	0.017882	0.080761	-0.14571
ENG	0.014686	0	0.112169	0.0047
TNP	0.046729	0.006706	0.107682	-0.12691
TSL	0.041389	0.001118	0.02692	0
HPN	0.026702	0.006706	0.022434	0.028202
HMR	0	0	0	0.178611

The distances (di+ and di-) of each alternative calculated. Relative closeness coefficient (Ci) is defined to determine the ranking order of all other options by calculating similarities to ideal solution and ranks obtained in table 10.

Table X Ranking Solution

di+	di-	ci	Rank	Pattern
0.283415879	0.316058	0.527225	**4**	SLN
0.199510597	0.178698	0.472486	**5**	HMI
0.132895589	0.151191	0.5322	**2**	LEB
0.043820582	0.049827	0.532067	**3**	RSW
0.329015953	0	0	**8**	TUP
0.195627391	0	0	**8**	ENG
0.31605764	0	0	**8**	TNP
0.178698173	0.049386	0.216525	**7**	TSL
0.151190964	0.04535	0.230739	**6**	HPN
0.049826593	0.178611	0.781881	**1**	HMR

IV. CONCLUSION

We discussed the use and effectiveness of candlestick technical analysis on 17 selected Indian NIFTY50 stocks. Technical analysis is a quantitative method in which analysis of price data takes place without any time series transformation of data. Based on TOPSIS model ranking patterns of 17 stocks during the study period hammer (HMR), long engulfing pattern (LEB) and Rising window (RSW) are the top three ranked candlestick patterns.There is scope for expanding this study with various other criteria for ranking. Trading return based performance and that too, with the stock specific method, will yield more robust results. Further, we conclude 20% of candlestick patterns are loss-making, 20 to 40% are low to average return earning patterns. 40 to 50% candlestick occurrences are high return yielding or highly efficient in nature. Candlestick technical analysis can be a useful trading tool provided proper stop-loss strategy is adopted to limit losses; thereby, efficiency could be considerably increased.

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