Precision Balancing: Machine Learning Models and Selective Strategies for Intraday Trading Success

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Abstract—This paper presents a two-step analysis to maximize gains through predictive methodologies for the stock prices of the top 10 contributors to the NIFTY 50 index. Initially, we conduct a comprehensive evaluation of six machine learning models—K-Nearest Neighbors (KNN), Random Forest Regressor (RF), Decision Tree (DT) Regressor, Support Vector Regression (SVR) without initialization, SVR (y=x) with initialization, and Linear Regression (LR)— within the context of intraday trading. LR and SVR (y=x) demonstrate superior performance compared to other models. Subsequently, we utilize findings from the LR model to formulate and assess five distinct intraday trading strategies (HIGH_SELL, LOW_BUY, ModHIGH, ModLOW, and HYBRID). Emphasis is placed on maintaining a delicate balance between capturing favorable trades and exercising selectivity. The HYBRID strategy proves effective, achieving a 140% gain over 30 trading days. ICICIBANK shows the maximum gain at 254.53%, LT follows this with a gain of 216.31%. The evaluation in the second step relies on a novel metric, $percentageGainMin$, which addresses the practical scenario of reusing capital for intraday trading. This research contributes insights for both researchers and practitioners, offering a comprehensive exploration of machine learning models and effective intraday trading strategies in the dynamic landscape of financial markets.

I. Introduction

Machine Learning (ML) and Artificial Intelligence (AI) have previously played a significant role in the field of stock prediction. Intraday trading, the practice of buying and selling financial instruments within a single trading day, is a common strategy on major Indian stock exchanges such as the Bombay Stock Exchange (BSE) [1] and the National Stock Exchange (NSE) [2]. A considerable body of literature exists on automating Intraday Trading through ML/AI methodologies [3], [4], [5], [6], [7]. The utilization of historical data and sentiment analysis applied to popular blogs is proposed for predicting next-day stock prices [3]. Research has also been conducted on using reinforcement learning specifically for Intraday Trading [5], [6], [7].

This paper outlines a two-step analysis aimed at optimizing gains through predictive methodologies for the stock prices of the top 10 contributors to the NIFTY 50 index. In the initial phase, we conduct a comprehensive assessment of six machine learning models—K-Nearest Neighbors (KNN), Random Forest Regressor (RF), Decision Tree (DT) Regressor, Support Vector Regression (SVR) without initialization, SVR (y=x) with initialization, and Linear Regression (LR)—specifically within the context of intraday trading. LR and SVR (y=x)

exhibit superior performance relative to other models. Building upon the LR model findings, we formulate and evaluate five distinct intraday trading strategies (HIGH_SELL, LOW_BUY, ModHIGH, ModLOW, and HYBRID). The emphasis is on maintaining a balanced approach between capturing favorable trades and exercising selectivity. The HYBRID strategy emerges as particularly effective, yielding a 140% gain over 30 trading days. ICICIBANK attains the highest gain at 254.53%, followed by LT with a gain of 216.31%. The evaluation in the second step relies on a novel metric, $percentageGainMin$, to account for reusing capital in intraday trading, providing a detailed perspective on consistent capital utilization in real-life scenarios.

We utilize 10 stocks for our analysis. The dataset for our analysis is sourced from the Yahoo Finance Website [8] and spans from October 01, 2007, to October 01, 2023, with a daily frequency. The data is structured in CSV format, comprising columns for DATE, OPEN, HIGH, LOW , and CLOSE prices. This comprehensive dataset allows us to delve into historical stock market trends and patterns. The selected stocks, including "RELIANCE," "TCS," "HDFCBANK," "ICICIBANK," "INFY," "BHARTIARTL," "HINDUNILVR," "ITC," "SBIN," and "LT," are chosen based on their significant contribution to the NIFTY 50 index as of January 2024 [9].

II. Performance Evaluation of ML Models

We present a comparative analysis of six distinct machine learning models. These models are trained using historical data, specifically the previous day's HIGH, LOW, CLOSE, and OPEN prices, and predictions are (made for next day's HIGH, LOW and CLOSE price) using the same set of features. The dataset was divided into two parts. The initial 80%, spanning from October 03, 2007 to July 29, 2020, was designated for training the models. Subsequently the remaining 20% of the data was used for testing purposes.

The models employed in this analysis include standard SVR, KNN, DT, RF, and LR models. The KNN model uses the values of its k-nearest neighbors, averaging them to predict outcomes. The DT model represents decisions through a tree structure that maps features to target values. RF operates by creating an array of decision trees during training, each based on diverse parameters. The final prediction is determined through the majority or average votes across all trees. SVR operates by identifying a function that approximates the mapping from input to output. We subsequently initialize SVR

Model	MAE	MSE	R2 Score
Linear Regression	0.0025	0.00000943	0.999993
Support Vector Machine	4.0403	18.1921	-12.4886
SVR (y=x)	0.0140	0.0002571	0.999809
K-Nearest Neighbors	1.6060	3.3527	-1.4859
Decision Tree	1.5462	3.1609	-1.3437
Random Forest	1.5591	3.2097	-1.3798

TABLE I: Evaluation Metrics for Predictions on $CLOSE$

Model	MAE	MSE	R2 Score
Linear Regression	0.0353	0.0017	0.9986
Support Vector Machine	3.8243	16.2537	-12.8931
SVR (y=x)	0.0267	0.0012	0.9990
K-Nearest Neighbors	1.3759	2.4529	-1.0967
Decision Tree	1.3518	2.3833	-1.0372
Random Forest	1.3461	2.3601	-1.0173

TABLE II: Evaluation Metrics for Predictions on $HIGH$

based on the proximity of prices, achieving gains with the $y = x$ initialization. The utilized parameters include $C = 1.0$, $kernel\_type = "linear"$, $\varepsilon = 0.1$). To manage computation time, the maximum iteration count is set to 500,000.

Considering the inherent closeness of the price data, LR model is further explored. LR, a fundamental regression model, captures the linear relationship between a dependent variable $output$ and num independent variables ($input_1, input_2, \ldots, input_{num}$). Here, β_0 is the intercept, $\beta_1, \beta_2, \ldots, \beta_{num}$ are regression coefficients and ϵ denotes the residual unexplained error. In our specific case, the LR Eq. takes the form of Eq. (1).

$$
\begin{aligned}
output =& \beta_0 + \beta_1 input_1 + \ldots + \beta_{num} input_{num} + \epsilon \\
=& \beta_0 + \beta_1 OPEN(prev) + \beta_2 HIGH(prev) \\
& + \beta_3 LOW(prev) + \beta_4 CLOSE(prev) + \epsilon
\end{aligned}
\tag{1}
$$

The model evaluation metrics include Mean Squared Error (MSE), which assesses the proximity of the regression line to a set of points, striving for minimal values to achieve precise predictions (Eq. 2). Mean Absolute Error (MAE) quantifies the absolute deviation between attributes, irrespective of their direction (Eq. 2). The R-squared (R2) Score indicates the ratio of explained variance to the total variance inherent in the data (Eq. 3). In the equations, i denotes the ith input sample, y_i represents the actual label value, $\hat{y}_i$ is the predicted output value, $\bar{y}$ denotes the mean of the observed true values, and n is the total number of samples. Favorable model performance is characterized by lower MSE and MAE, and higher R2 scores.

$$
\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2, \text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{2}
$$

Model	MAE	MSE	R2 Score
Linear Regression	0.0203	0.0007	0.9994
Support Vector Machine	3.8330	16.3864	-12.4636
SVR (y=x)	0.1394	0.0204	0.9832
K-Nearest Neighbors	1.4246	2.6359	-1.1658
Decision Tree	1.3696	2.4556	-1.0176
Random Forest	1.3891	2.5224	-1.0725

TABLE III: Evaluation Metrics for Predictions on LOW

$$
R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \tag{3}
$$

Values for all the stocks are normalised with respect to the maximum value of the parameter (HIGH, LOW or CLOSE) being predicted. These normalised values are averaged and showcased in Table I,II,III and Figure 1. Upon analysis using the tables and the figures, it is observed that for the prediction of CLOSE and LOW prices, LR outperforms all other models, achieving R2 scores of 0.999993007 and 0.9994, respectively. In contrast, Support Vector Machine, KNN, DT, and RF perform poorly with negative scores, while SVR with initialization provides strong competition to LR, attaining R2 scores of 0.999809368 and 0.9832. For the prediction of HIGH prices, SVR with initialization surpasses all other models with an R2 score of 0.9990. LR demonstrates competitive performance with an R2 score of 0.9986, while negative R2 scores persist for the remaining models.

LR and SVR (y=x) demonstrate superior performance compared to other models. In maintaining consistency, the subsequent study utilizes the results from LR. The study could have been conducted using the SVR (y=x) model as well. We have formulated five strategies utilizing the predicted results from the LR model, which will be detailed in Section IV. The General Structure and metrics are explicated in Section III to facilitate an understanding of the comparative effectiveness of each strategy. The findings of this study are presented in Section V, and finally, Section VI concludes the study.

### III. ALGORITHM OVERVIEW AND EVALUATION METRICS

Algorithm (1) showcases a general structure of all the algorithms. We iterate over 30 trading days and calculate $changeForThatDay$, $Sinvestment$, $mininv$ and numexec. The $changeForThatDay$ represents the gain or loss if a trade is executed on that particular day. $Sinvestment$ is the sum of investments on all days. $mininv$ denotes the minimum investment, considering the possibility of using the same amount or a portion for trades on other days. It is the maximum among all daily investment values. Subsequently, the $Schange$ is computed as the sum of $changeForThatDay$ values. The $positiveCount$ is incremented when a favorable trade occurs, defined as having a positive $changeForThatDay$ value. Finally, evaluation metrics $percentageGain$ and $percentageGainMin$ are determined by dividing $Schange$ by $Sinvestment$ and $mininv$ respectively, as illustrated in Equations (4) and (5). The three key evaluation metrics are:

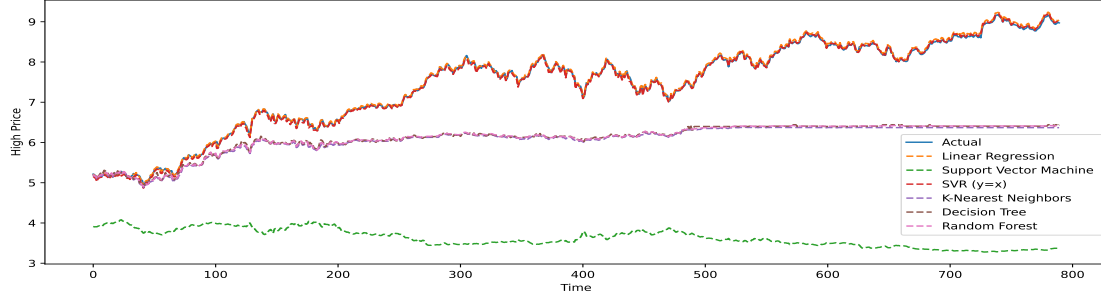- Percentage Gain ($percentageGain$):

$$
\text{percentageGain} = \frac{S_{\text{change}}}{S_{\text{investment}}} \tag{4}
$$

- Percentage Gain using $mininv$ ($percentageGainMin$):
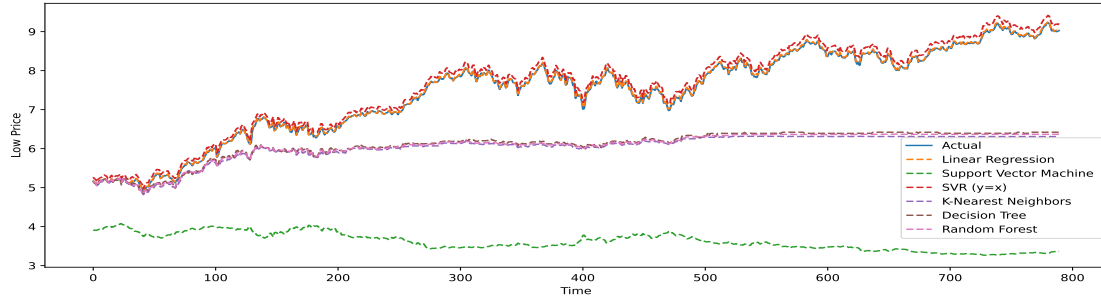
$$
\text{percentageGainMin} = \frac{S_{\text{change}}}{mininv} \tag{5}
$$
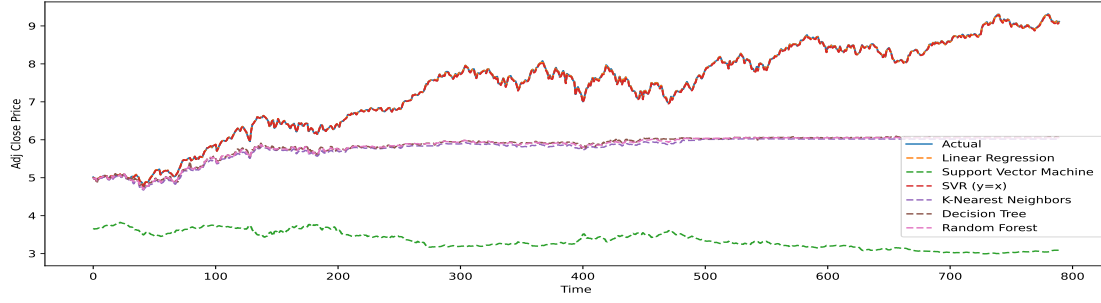
(a) Comparative Performance of Multiple ML Models in Predicting CLOSE Prices

(b) Comparative Performance of Multiple ML Models in Predicting HIGH Prices

(c) Comparative Performance of Multiple ML Models in Predicting LOW Prices

Fig. 1: Combined Figure for ML Model Comparison

Algorithm 1 General Structure

$Schange, Sinvestment$, numexec, positiveCount $\leftarrow 0$
for each day **do**
   // Calculate $changeForThatDay$, $Sinvestment$, $mininv$, numexec
   $Schange \leftarrow Schange + changeForThatDay$
   if $changeForThatDay > 0$ **then**
      positiveCount $\leftarrow$ positiveCount $+ 1$
   end if
end for
percentageGain $\leftarrow \frac{Schange}{Sinvestment}$
percentageGainMin $\leftarrow \frac{Schange}{mininv}$

- Number of Favourable Trades Executed ($positiveCount$):

$$\text{positiveCount} = \sum_i \begin{cases} 1, & \text{if } changeForThatDay_i > 0 \\ 0, & \text{otherwise} \end{cases}$$

(6)

IV. STRATEGIC ALGORITHMIC APPROACHES

Algorithms (2-6) constitute integral components of the overarching algorithm designed for the computation of variables such as $changeForThatDay$, $Sinvestment$, and $mininv$. These specific algorithms are intended to follow the general structure outlined in Algorithm (1), with the adaptations within the prescribed framework by Algorithms (2-6). For evaluation, intraday margin is considered to be 5%.

The algorithm (2) is designed to adopt a bearish approach (sell) in situations where the predicted high value is observed, i.e. it is lower than actual high value. Conversely, Algorithm (4) is formulated to adopt a bullish stance (buy) when the predicted low value is identified as higher than the actual low value.

We systematically assess one-sided trades, selectively executing only those trades that promise higher gains. This strat-

Algorithm 2 High Side Approach(HIGH_SELL)

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if predHIGH $<$ ActualHIGH **then**
    // Execute SHORT/SELL
    $changeForThatDay \leftarrow$ predHIGH $-$ ActualCLOSE
    $Sinvestment \leftarrow Sinvestment +$ predHIGH $\times$ margin
    numexec $\leftarrow$ numexec $+ 1$
    if predHIGH $\times$ margin $> mininv$ **then**
        $mininv \leftarrow$ predHIGH $\times$ margin
    end if
end if

Algorithm 3 Modified High Approach(MODH)

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if (predHIGH $-$ predCLOSE) $>$ (predCLOSE $-$ predLOW)
and predHIGH $<$ ActualHIGH **then**
    // Execute MODH LONG/BUY strategy
    $changeForThatDay \leftarrow$ predHIGH $-$ ActualCLOSE
    $Sinvestment \leftarrow Sinvestment +$ predHIGH $\times$ margin
    numexec $\leftarrow$ numexec $+ 1$
    if predHIGH $\times$ margin $> mininv$ **then**
        $mininv \leftarrow$ predHIGH $\times$ margin
    end if
end if

Algorithm 4 Low Side Approach(LOW_BUY)

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if predLOW $>$ ActualLOW **then**
    // Execute LONG/BUY
    $changeForThatDay \leftarrow$ ActualCLOSE $-$ predLOW
    $Sinvestment \leftarrow Sinvestment +$ predLOW $\times$ margin
    numexec $\leftarrow$ numexec $+ 1$
    if predLOW $\times$ margin $> mininv$ **then**
        $mininv \leftarrow$ predLOW $\times$ margin
    end if
end if

Algorithm 5 Modified Low Approach (MODL)

---

if (predHIGH $-$ predCLOSE) $<$ (predCLOSE $-$ predLOW)
and predHIGH $<$ ActualHIGH **then**
    // Execute MODL SHORT/SELL strategy
    $changeForThatDay \leftarrow$ ActualCLOSE $-$ predLOW
    $Sinvestment \leftarrow Sinvestment +$ predLOW $\times$ margin
    numexec $\leftarrow$ numexec $+ 1$
    if predLOW $\times$ margin $> mininv$ **then**
        $mininv \leftarrow$ predLOW $\times$ margin
    end if
end if

---

egy is outlined in Algorithm (3) and (5). The decision-making process involves evaluating whether the difference between the predicted CLOSE value and either the predicted HIGH or LOW values is greater. Trades are initiated only under the condition that these HIGH or LOW values materialize, i.e., when they are respectively lower than the actual high value or higher than the actual low value. Subsequently, we formulate the HYBRID (Algorithm (6)) algorithm, integrating both preceding algorithms. This involves a sequential assessment, first checking if the HIGH deviation is greater. If not, we then evaluate whether the LOW deviation is higher. No trade is executed if the HIGH deviation is superior but the HIGH value is not observed, or if the LOW deviation is superior and the LOW value is not observed.

V. RESULTS AND ANALYSIS

Tables IV present the outcomes with $pgain$, $pgainmin$, $Schange$, $mininv$, $Sinvestment$, numexec and $pCount$ values for 30 trading days for the chosen stocks. In the tables, $pgain$ and $pgainmin$ correspond to $percentageGain$ and $percentageGainMin$ respectively. Additionally, $pCount$ in the tables denotes $positiveCount$.

The HIGH_SELL and LOW_BUY strategies are logically sound but fall short in grasping the fundamental aspect of gain. Our observation suggests that they initiate trades at numerous points. We further assess the $positiveCount$ metric. In four instances (specifically, stocks TCS, HDFCBANK, INFY, LT), we identify cases where $positiveCount$ is lower than the number of trades executed. These instances pertain to the LOW strategy. Upon closer examination, it becomes evident that the gains at these points are either minimal or negative. The recognition of this fact emphasizes the importance of employing

a more selective approach in executing trades based on the predicted values.

The ModHIGH and ModLOW strategies exhibit a high degree of selectivity, executing only at specific, critical points. In three instances (TCS, HDFCBANK, INFY), the ModLOW strategy refrains from executing any trades. It is apparent that a certain level of flexibility is required, and a less stringent approach is advisable. Remarkably, the HYBRID strategy demonstrates comparable or superior performance, particularly when assessed in terms of $percentageGain$.

In our analysis, we recommend using $percentageGainMin$ as a more suitable measure for comparison compared to $percentageGain$. This metric provides a more detailed perspective by encapsulating the practicalities of trading with a consistent capital amount. This consideration holds particular relevance in the context of intraday trading, where real-life situations play a crucial role. When comparing performance through the metric of $percentageGainMin$, the HYBRID approach consistently outperforms other strategies in nearly all instances and matches the performance of the best strategy in other cases. It effectively identifies and capitalizes on favorable trades while concurrently demonstrating a noteworthy level of selectivity.

Upon averaging these percentages for $percentageGainMin$, the results are 118.83, 92.863, 111.47, 48.499, and 140.593 for HIGH_SELL, LOW_BUY, ModHIGH, ModLOW, and HYBRID approaches respectively. It is evident that the HYBRID approach exhibits a superior performance with a gain of 140%, outperforming the other approaches. ICICIBANK exhibits the highest gain at 254.53%, while LT follows with a gain of 216.31%. This can

TABLE IV: Performance Metrics for Selected Stocks Using Different Trading Strategies

RELIANCE	$pgain$	$pgainmin$	$Schange$	$mininv$	$Sinvestment$	numexec	$pCount$
HIGH_SELL	24.78	144.64	181.91	125.77	734.05	6	6
LOW_BUY	14.77	113.83	143.84	126.36	973.97	8	8
ModHIGH	25.71	125.46	157.79	125.77	613.73	5	5
ModLOW	18.60	55.14	66.99	121.50	360.06	3	3
HYBRID	23.08	178.72	224.78	125.77	973.79	8	8
TCS	$pgain$	$pgainmin$	$Schange$	$mininv$	$Sinvestment$	numexec	$pCount$
HIGH_SELL	35.76	139.17	250.29	179.85	699.84	4	4
LOW_BUY	0.37	5.44	9.77	179.64	2621.70	15	6
ModHIGH	35.76	139.17	250.29	179.85	699.84	4	4
ModLOW	0	0	0	0	0	0	0
HYBRID	35.76	139.17	250.29	179.85	699.84	4	4
HDFCBANK	$pgain$	$pgainmin$	$Schange$	$mininv$	$Sinvestment$	numexec	$pCount$
HIGH_SELL	32.95	127.61	105.56	82.72	320.33	4	4
LOW_BUY	4.65	106.27	88.32	83.10	1897.86	24	20
ModHIGH	32.95	127.61	105.56	82.72	320.33	4	4
ModLOW	0	0	0	0	0	0	0
HYBRID	32.95	127.61	105.56	82.72	320.33	4	4
ICICIBANK	$pgain$	$pgainmin$	$Schange$	$mininv$	$Sinvestment$	numexec	$pCount$
HIGH_SELL	26.43	105.01	51.21	48.76	193.78	4	4
LOW_BUY	14.31	194.68	96.25	49.44	672.76	14	14
ModHIGH	26.43	105.01	51.21	48.76	193.78	4	4
ModLOW	19.01	150.36	72.92	48.49	383.61	8	8
HYBRID	21.50	254.53	124.12	48.76	577.39	12	12
INFY	$pgain$	$pgainmin$	$Schange$	$mininv$	$Sinvestment$	numexec	$pCount$
HIGH_SELL	31.47	122.34	92.86	74.45	261.94	4	4
LOW_BUY	4.54	93.84	70.85	75.38	1897.50	24	16
ModHIGH	31.47	122.34	92.86	74.45	261.94	4	4
ModLOW	0	0	0	0	0	0	0
HYBRID	31.47	122.34	92.86	74.45	261.94	4	4
BHARTIARTL	$pgain$	$pgainmin$	$Schange$	$mininv$	$Sinvestment$	numexec	$pCount$
HIGH_SELL	27.33	76.35	27.68	39.60	597.12	6	6
LOW_BUY	18.88	84.53	30.60	41.45	977.50	8	8
ModHIGH	27.33	76.35	27.68	39.60	597.12	6	6
ModLOW	17.18	52.32	19.01	41.21	473.23	4	4
HYBRID	27.33	76.35	27.68	39.60	597.12	6	6
HINDUNILVR	$pgain$	$pgainmin$	$Schange$	$mininv$	$Sinvestment$	numexec	$pCount$
HIGH_SELL	26.78	108.09	68.33	40.41	496.94	4	4
LOW_BUY	13.50	67.54	42.50	41.74	947.03	12	12
ModHIGH	26.78	108.09	68.33	40.41	496.94	4	4
ModLOW	10.87	39.93	22.67	41.41	334.51	2	2
HYBRID	26.78	108.09	68.33	40.41	496.94	4	4
ITC	$pgain$	$pgainmin$	$Schange$	$mininv$	$Sinvestment$	numexec	$pCount$
HIGH_SELL	23.07	93.47	32.77	26.60	389.89	6	6
LOW_BUY	17.03	77.55	27.12	27.08	712.46	10	10
ModHIGH	23.07	93.47	32.77	26.60	389.89	6	6
ModLOW	12.70	48.14	17.41	26.91	278.47	4	4
HYBRID	23.07	93.47	32.77	26.60	389.89	6	6
SBIN	$pgain$	$pgainmin$	$Schange$	$mininv$	$Sinvestment$	numexec	$pCount$
HIGH_SELL	23.45	89.34	27.95	18.84	298.56	6	6
LOW_BUY	18.88	56.26	17.71	19.32	473.23	8	8
ModHIGH	23.45	89.34	27.95	18.84	298.56	6	6
ModLOW	16.08	42.60	14.68	19.10	216.78	4	4
HYBRID	23.45	89.34	27.95	18.84	298.56	6	6
LT	$pgain$	$pgainmin$	$Schange$	$mininv$	$Sinvestment$	numexec	$pCount$
HIGH_SELL	17.80	182.28	278.37	152.72	1563.99	11	11
LOW_BUY	12.45	128.69	193.19	150.12	1551.11	11	10
ModHIGH	27.61	127.86	195.26	152.72	707.32	5	5
ModLOW	25.05	96.50	135.09	139.98	539.33	4	4
HYBRID	26.50	216.31	330.34	152.72	1246.65	9	9

Algorithm 6 Hybrid Approach

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if (predHIGH − predCLOSE) > (predCLOSE − predLOW) and predHIGH < ActualHIGH **then**
    // Execute MODH LONG/BUY strategy
    $changeForThatDay \leftarrow$ predHIGH − ActualCLOSE
    $Sinvestment \leftarrow Sinvestment +$ predHIGH × margin
    numexec ← numexec + 1
    if predHIGH × margin > $mininv$ **then**
        $mininv \leftarrow$ predHIGH × margin
    end if
else if (predHIGH − predCLOSE) < (predCLOSE − predLOW) and predLOW > ActualLOW **then**
    // Execute MODL SHORT/SELL strategy
    $changeForThatDay \leftarrow$ ActualCLOSE − predLOW
    $Sinvestment \leftarrow Sinvestment +$ predLOW × margin
    numexec ← numexec + 1
    if predLOW × margin > $mininv$ **then**
        $mininv \leftarrow$ predLOW × margin
    end if
else
    // No Trade (no change)
    $changeForThatDay \leftarrow 0$
end if

---

be attributed to the effective combination of selectivity and capturing favorable trades inherent in the HYBRID approach.

VI. CONCLUSION

In summary, this study presents a comprehensive examination of machine learning models for intraday trading, resulting in the formulation and evaluation of distinctive trading strategies. The evaluation involves six prominent machine learning models (KNN, RF, DT, SVR without initialization, SVR (y=x), and LR), among which LR and SVR (y=x) emerge as superior performers, demonstrating their efficacy in predicting stock prices.

The introduction of the innovative metric, $percentageGainMin$, brings a practical dimension to the evaluation by addressing the real-life scenario of reusing capital in intraday trading. Subsequently, the study formulates and evaluates five distinct intraday trading strategies (HIGH_SELL, LOW_BUY, ModHIGH, ModLOW, and HYBRID). The HYBRID strategy stands out as the most effective, achieving an average gain of 140% across the selected 10 stocks over 30 trading days. ICICIBANK leads with the highest gain at 254.53%, followed by LT with a gain of 216.31%.

The individual evaluations of HIGH_SELL and LOW_BUY strategies reveal their logical soundness but expose shortcomings in capturing the fundamental aspect of gain. The ModHIGH and ModLOW strategies, characterized by a higher degree of selectivity, demonstrate improved performance, emphasizing the importance of a balanced approach. However, the HYBRID strategy, combining selectivity with the efficient capture of favorable trades, stands out as the most effective approach, surpassing other strategies in terms of $percentageGainMin$. This study's comprehensive analysis,

considering intraday margin, positive trade count, and practical trading scenarios, provides valuable insights for both researchers and practitioners in the field.

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