CHAPTER V

EXTREME LEARNING MACHINE ALGORITHM WITH DETERMINISTIC WEIGHT MODIFICATION FOR PREDICTING STOCK PRICE USING TECHNICAL INDICATORS

5.1 Introduction

Technical analysis of stocks or other financial instruments is done by utilizing a variety of mathematical indicators, chart patterns, and historical price and volume data. In technical analysis, future price movements are generally predicted using historical market data and trends, as opposed to fundamental research, which focuses on examining business financials, earnings, and macroeconomic factors.

The first phase used historical datasets for optimized ELM for stock prediction. Historical datasets include information from the past about trade volumes, stock prices, and other aspects of the market. You can utilize these datasets to find cycles, trends, and patterns that might reoccur in the future. An abundant source of knowledge, historical data makes it possible to spot trends, cycles, and patterns. This can be quite important for long-range forecasts. Massive datasets are ideal for modern machine-learning methods.

Models that forecast future price fluctuations based on historical data can be trained, and permit the use of statistical techniques and other quantitative analysis tools like time series analysis and moving averages. Nonetheless, the literature has discovered certain limitations. Because the market is dynamic, new and unforeseen aspects may not be taken into account when depending exclusively on historical data. Overfitting occurs when machine learning models that have been trained on previous data perform well on historical data but poorly on new data. Extensive and high-quality historical data are needed. Errors or inadequacies in the data might seriously affect forecasts. Technical analysts employ a variety of indicators to pinpoint trends, momentum, volatility, and overbought or oversold situations. These indicators are generated from price and volume data.

5.2 Technical Indicators

Technical indicators are mathematical computations that rely on data from past open interest, volume, and price movements. Moving averages, Bollinger bands, the RSI, and MACD are examples of common technical indicators. Large volumes of data are reduced by technical indicators into easily understood signals that help direct trading decisions. Timely entry and exit points are determined by identifying patterns like as trends, reversals, and continuations, which can be identified with the aid of indicators such as RSI and MACD. Since many technical indicators are updated instantly, traders can see changes in the market right away. Each of these indicators captures distinct facets of market activity, including momentum, trend strength, and reversal signs, and hence makes a distinctive contribution to stock market prediction. When combined, they can provide a more thorough market analysis and decrease false signals, increasing predicted accuracy. Further, the present research work considered ten different technical indicators, and details are discussed as follows.

a) Simple moving average (SMV)

In stock market research, the SMA is used to forecast trends and spot possible buy or sell signals. It is determined by taking the average of a predetermined number of previous closing prices over a given time frame. Select the time frame that you wish to use to compute the moving average. Depending on your trading technique and preferences, you can choose any period, however, common ones include 10 days,20 days, 50 days, and 200 days. The stock's closing prices for the chosen period are added together. The closing price total is divided by the number of sessions in the chosen time range. Reduces noise in turbulent markets by assisting in the smoothing of price movements to reveal trends over a given period. It is frequently employed in trend-following tactics.

$$MV = \frac{x_1+x_2+\cdots+x_n}{n} \tag{19}$$

b) 10-day moving average (MV)

A widely exploited technical indicator is the 10-day Moving Average (MA). It supports modifying transient variations in price data, yielding a more lucid depiction of the important design. Choose on a 10-day window to calculate the moving average. This suggests that you will be investigating the closing prices over the last ten trading days. Calculate the closing prices over the last 10 trading days. A short-term moving average helps spot short-term trends and reversals since it responds swiftly to recent price movements. The total closing price is separated by 10 which is well-defined as follows.

$$MV_{10} = \frac{x_1+x_2+\cdots+x_n}{n} \tag{20}$$

c) Momentum factors

Momentum factors are a useful tool for dealers and depositors to spot the trends and imaginable trading chances. Before making any trading conclusions it's critical to use momentum pointers in combination with other types of investigation and to take the greater market background into account. Determines the rate of price change, which aids in spotting trends that are accelerating or slowing down and may be signs to buy or sell.

$$M = C_t - C_{t-4} \tag{21}$$

d) Stochastic oscillator

A stochastic oscillator is one of the well-liked indicators for predicting changes in stock prices. It assesses a stock's closing price about its price series over a given time frame and it supports traders in defining if the market is oversold or overbought as well as probable trend reversals. Determines overbought and oversold circumstances, which can be used to forecast reversals, by comparing a stock's closing price to its range of prices over a certain period.

$$STCK = \frac{C_t - LL_{t-n}}{HH_{t-n} - LL_{t-n}} \times 100 \tag{22}$$

$$STCD = \frac{\sum_{i=0}^{n-1} K_{t-1\%}}{n} \tag{23}$$

e) RSI

The RSI was created by J. Welles Wilder Jr which is frequently used by traders and investors to spot possible trend reversals as well as overbought and oversold situations. Evaluate recent price movements' speed and amplitude to determine if they are overbought or oversold, which aids in predicting trend strength and reversals. It is used to gauge how quickly and how much a security's price is changing and is defined as follows,

$$\mathrm{RSI} = 100 - \frac{100}{1 + \left(\sum_{t=0}^{n-1} \mathrm{UP}_{t-1}/n\right) / \left(\sum_{t=0}^{n-1} \mathrm{DW}_{t=1}/n\right)} \tag{24}$$

f) Williams %R

It is an oscillator to regulate when a saving is overbought or oversold which is created by created by Larry Williams. It is comparable to the RSI but is mounted in reverse and has a distinct calculation method. Readings above -20 are looked upon as overbought whereas readings below -80 are looked upon as oversold. The Williams %R fluctuates between -100 and 0. Though more sensitive to recent price movements, this indicator is comparable to RSI and can be used to identify short-term reversals in overbought and oversold situations.

$$LW = \frac{H_n - C_t}{H_n - L_n} \times 100 \tag{25}$$

g) MACD

MACD aids traders in recognizing shifts in the velocity, strength, and direction of a stock's price movement over time. The longer-term EMA is subtracted from the shorter-term EMA to get the MACD. Determines the strength, direction, and possible reversals of a trend by examining the correlation between two moving averages, usually the 12-day and 26-day EMA.

$$= MACD(n)_{t-1} + \frac{2}{n+1}\ \ (Diff_t - MACD(n)_{t-1}) \tag{26}$$

h) CCI

CCI is a flexible momentum oscillator that pinpoints overbought and oversold circumstances as well as possible trend reversals in a range of financial markets. It developed (1970). The CCI calculates the link between the present price, moving average, and normal price range of strength over a given time frame. It helps identify early trend reversals and overbought and oversold situations by measuring the price's departure from its average.

$$CCI = \frac{M_t - SM_t}{0.015D_t} \times 100 \tag{27}$$

i) Price oscillator (PO)

PO is used in financial research to spot long-term patterns in asset prices which is computes the percentage difference between two moving averages of a security's price. PO plots fluctuations in the relationship between the short- and long-term moving averages to support in discovering possible buy and sell signals. It helps validate bullish or bearish market movements by using two moving averages to monitor price momentum and detect trends.

$$\mathrm{PO} = \frac{\mathrm{MA}_5 - \mathrm{MA}_{10}}{\mathrm{MA}_5} \tag{28}$$

C_t- Closing price. L_t- Lowest price. H_t- High price. LL_t- Lowest Low. HH_t-Highest high price. UP_t- Upward price and DW_t- Downward price.

5.3 Experimental Results and Analysis

Phase 2 of this research uses technical indicators as input to the optimized ELM with DWM which is termed DELM-T for predicting the stock market price. The DWM method is used to connect weights and bias of ELM for enhancing the performance. The present sub-section discusses the ability of the developed DELM-T method. Tables 12, 14, 16, 18, and 20 show the training performance of MSE, RMSE, MAE, MAPE, and R-Square values, respectively.

Tables 13, 15, 17, 19, and 21 show the testing performance of MSE, RMSE, MAE, MAPE, and R-Square values, respectively. Figures 15, 17, 19, 21, and 23, show the training performance of MSE, RMSE, MAE, MAPE, and R-Square values, respectively. Figures 16, 18, 20, 22, and 24, show the testing performance of MSE, RMSE, MAE, MAPE, and R-Square values, respectively.

In the training phase, the suggested technique obtained low MSE values when compared to other prediction algorithms. Such as 0.000628, 0.001024, 0.000792, 0.000596, 0.000552, and 0.000587 for S&P, Nifty 50, SBIN, ICICI, HDFC, and MSFT, respectively. The suggested technique obtained low RMSE values when compared to other prediction algorithms, such as 0.02505, 0.03253, 0.02814, 0.02441, 0.02349, and 0.02422 for S&P, Nifty 50, SBIN, ICICI, HDFC, and MSFT, respectively. The suggested technique obtained low MAE values when compared to other prediction algorithms, such as 0.0098, 0.0652, 0.0115, 0.0099, 0.0134, and 0.0099 for S&P, Nifty 50, SBIN, ICICI, HDFC, and MSFT, respectively.

The suggested technique obtained low MAPE values when compared to other prediction algorithms, such as 0.0016, 0.0064, 0.0029, 0.0006, 0.0045, and 0.0053for S&P, Nifty 50, SBIN, ICICI, HDFC, and MSFT, respectively. The suggested technique obtained high values when compared to other prediction algorithms, such as 0.9762, 0.9624, 0.9628, 0.9686, 0.9652, and 0.9541 for S&P, Nifty 50, SBIN, ICICI, HDFC, and MSFT, respectively.

Comparing the recommended method to other prediction algorithms during the testing phase, the MSE values were low: 0.000959, 0.000369, 0.000479, 0.000356, 0.000489, and 0.000467 for the S&P, Nifty 50, SBIN, ICICI, HDFC, and MSFT, respectively. In comparison to existing prediction algorithms, the recommended technique produced low RMSE values: 0.03096, 0.06074, 0.02188, 0.01886, 0.02211, and 0.06833 for the S&P, Nifty 50, SBIN, ICICI, HDFC, and MSFT, respectively. In comparison to previous prediction algorithms, the recommended technique produced low MAE values: 0.0098, 0.0652, 0.0115, 0.0099, 0.0134, and 0.0099 for the S&P, Nifty 50, SBIN, ICICI, HDFC, and MSFT, respectively.

In comparison to existing prediction algorithms, the recommended technique produced low MAPE values: 0.0063, 0.0049, 0.0024, 0.0025, 0.0026, and 0.0056 for the S&P, Nifty 50, SBIN, ICICI, HDFC, and MSFT, respectively. When compared to other prediction algorithms, the recommended method produced high R-Square values: 0.9539, 0.9662, 0.9954, 0.9622, 0.9866, and 0.9621 for the S&P, Nifty 50, SBIN, ICICI, HDFC, and MSFT, respectively.

Table 12 : Training performance comparisons for MSE

Methods	DELM-T	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S & P	0.000628	0.000738	0.000843	0.001291	0.00482	0.006293	0.009061
Nifty 50	0.001024	0.000129	0.001365	0.001517	0.001738	0.001995	0.002155
SBIN	0.000792	0.000875	0.000937	0.001045	0.001591	0.001836	0.002067
ICICI	0.000596	0.000758	0.000863	0.000983	0.001135	0.001455	0.001864
HDFC	0.000552	0.000691	0.000821	0.000973	0.001847	0.002851	0.003195
MSFT	0.000587	0.000653	0.000694	0.000792	0.000984	0.001587	0.001918

Table 13 : Testing Performance Comparisons for MSE

Methods	DELM-T	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S & P	0.000959	0.00105	0.00122	0.00294	0.00346	0.00598	0.00718
Nifty 50	0.000369	0.00582	0.00768	0.00892	0.01029	0.01529	0.01989
SBIN	0.000479	0.00068	0.000865	0.000942	0.001191	0.001395	0.001759
ICICI	0.000356	0.00048	0.000658	0.000893	0.001221	0.001426	0.001852
HDFC	0.000489	0.00059	0.000798	0.000931	0.001194	0.001352	0.001698
MSFT	0.000467	0.00061	0.00695	0.00749	0.00897	0.01099	0.0201

Table 14: Training performance comparisons for RMSE

Methods	DELM-T	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S & P	0.02505	0.02716	0.02903	0.03593	0.06942	0.07932	0.09518
Nifty 50	0.03253	0.01135	0.03694	0.03894	0.04168	0.04466	0.04642
SBIN	0.02814	0.02958	0.03061	0.03232	0.03988	0.04284	0.04546
ICICI	0.02441	0.02753	0.02937	0.03135	0.03368	0.03814	0.04317
HDFC	0.02349	0.02628	0.02865	0.03119	0.04297	0.05339	0.05652
MSFT	0.02422	0.02555	0.02634	0.02814	0.03136	0.03983	0.04379

Table 15 : Testing performance comparisons for RMSE

Methods	DELM-T	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S & P	0.03096	0.03240	0.03492	0.05422	0.05882	0.07733	0.08473
Nifty 50	0.06074	0.07628	0.08763	0.09444	0.10144	0.12365	0.14103
SBIN	0.02188	0.02607	0.02941	0.03069	0.03451	0.03735	0.04194
ICICI	0.01886	0.02190	0.02565	0.02988	0.03494	0.03776	0.04303
HDFC	0.02211	0.02429	0.02824	0.03051	0.03455	0.03677	0.04120
MSFT	0.06833	0.02469	0.08336	0.08654	0.09471	0.10483	0.14177

Table 16: Training performance comparisons for MAE

Methods	DELM-T	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S & P	0.0069	0.0079	0.0095	0.0106	0.0381	0.0451	0.0621
Nifty 50	0.007	0.0084	0.0092	0.0192	0.0281	0.041	0.0515
SBIN	0.0045	0.0051	0.0059	0.00631	0.0072	0.0095	0.0103
ICICI	0.0045	0.0058	0.0069	0.0081	0.0172	0.0377	0.0412
HDFC	0.0052	0.0063	0.0072	0.0079	0.0085	0.0093	0.01016
MSFT	0.0055	0.0067	0.0075	0.0084	0.0095	0.0101	0.0115

Table 17: Testing performance comparisons for MAE

Methods	DELM-T	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S & P	0.0098	0.0102	0.0106	0.0119	0.0125	0.0141	0.0152
Nifty 50	0.0652	0.0752	0.0886	0.0938	0.1022	0.1256	0.1495
SBIN	0.0115	0.0119	0.0124	0.0142	0.0172	0.0199	0.0208
ICICI	0.0099	0.0122	0.0153	0.0291	0.0315	0.0515	0.0821
HDFC	0.0134	0.0138	0.0145	0.0156	0.0176	0.0181	0.0201
MSFT	0.0099	0.0143	0.0127	0.0372	0.0511	0.0676	0.0859

Table 18: Training performance comparisons for MAPE

Methods	DELM-T	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S & P	0.0016	0.0024	0.0035	0.0059	0.0069	0.0088	0.0105
Nifty 50	0.0064	0.0079	0.0092	0.0102	0.0221	0.0281	0.0315
SBIN	0.0029	0.0046	0.0056	0.0064	0.0071	0.009	0.011
ICICI	0.0006	0.0008	0.0009	0.0018	0.0026	0.0039	0.0090
HDFC	0.0045	0.0057	0.0068	0.0072	0.0079	0.0094	0.0101
MSFT	0.0053	0.0059	0.0063	0.0071	0.0078	0.0099	0.0105

Table 19: Testing performance comparisons for MAPE

Methods	DELM-T	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S & P	0.0063	0.0068	0.0072	0.0080	0.0086	0.0098	0.0095
Nifty 50	0.0049	0.0053	0.0065	0.0078	0.0086	0.0094	0.0105
SBIN	0.0024	0.0031	0.0035	0.0051	0.0072	0.0099	0.0109
ICICI	0.0025	0.0037	0.0041	0.0067	0.0098	0.0139	0.0193
HDFC	0.0026	0.0039	0.0055	0.0069	0.0081	0.0095	0.0111
MSFT	0.0056	0.0061	0.0065	0.0076	0.0081	0.0095	0.0112

Table 20: Training performance comparisons for R-Square

Methods	DELM-T	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S & P	0.9762	0.9672	0.9467	0.9174	0.8999	0.8544	0.8197
Nifty 50	0.9624	0.9461	0.9165	0.8954	0.8542	0.8192	0.7615
SBIN	0.9628	0.9494	0.9154	0.8926	0.8762	0.8462	0.8164
ICICI	0.9686	0.9572	0.9286	0.9051	0.8725	0.8246	0.7916
HDFC	0.9652	0.9408	0.9358	0.9027	0.8726	0.8291	0.8165
MSFT	0.9541	0.9437	0.9248	0.9027	0.871	0.8389	0.8034

Table 21: Testing performance comparisons for R-Square

Methods	DELM-T	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S & P	0.9539	0.9437	0.9294	0.9027	0.8834	0.8564	0.8164
Nifty 50	0.9662	0.9601	0.9468	0.9121	0.8598	0.8262	0.8062
SBIN	0.9954	0.9785	0.9564	0.9256	0.8718	0.8302	0.7861
ICICI	0.9622	0.9495	0.9387	0.8836	0.8591	0.8261	0.7864
HDFC	0.9866	0.9782	0.9527	0.9293	0.8901	0.8519	0.7909
MSFT	0.9621	0.9467	0.9325	0.9027	0.8852	0.8561	0.8259

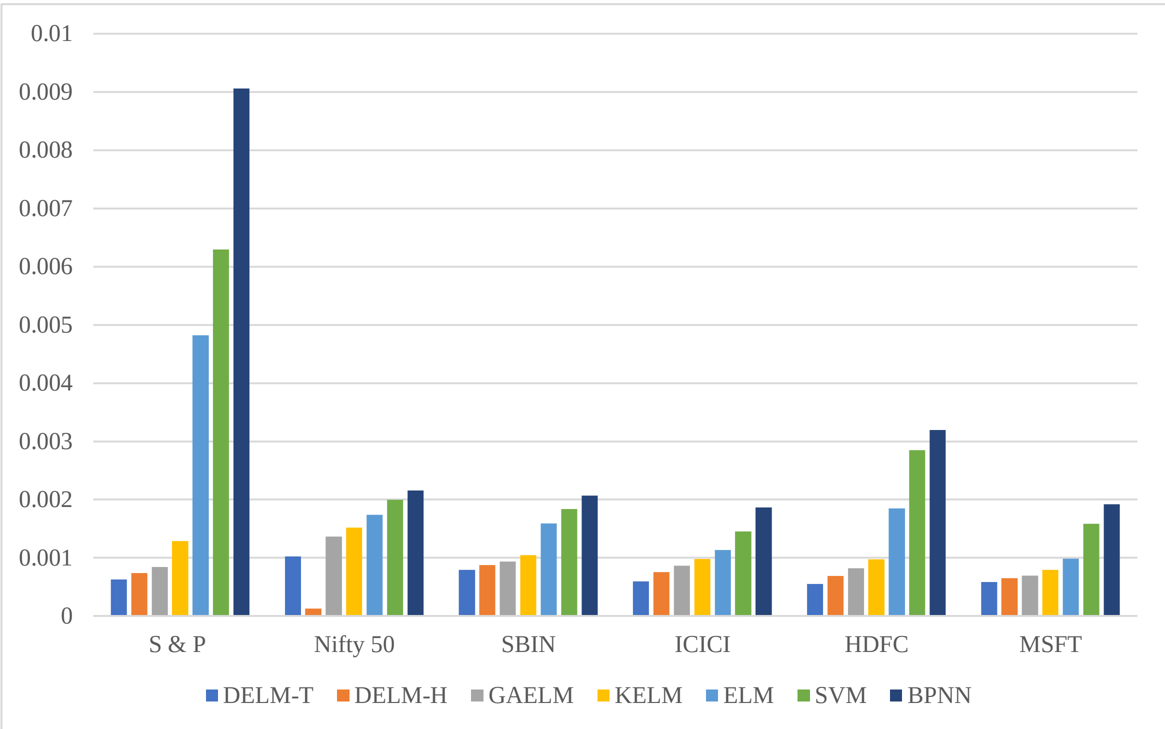

Figure 15: Training performance comparisons for MSE

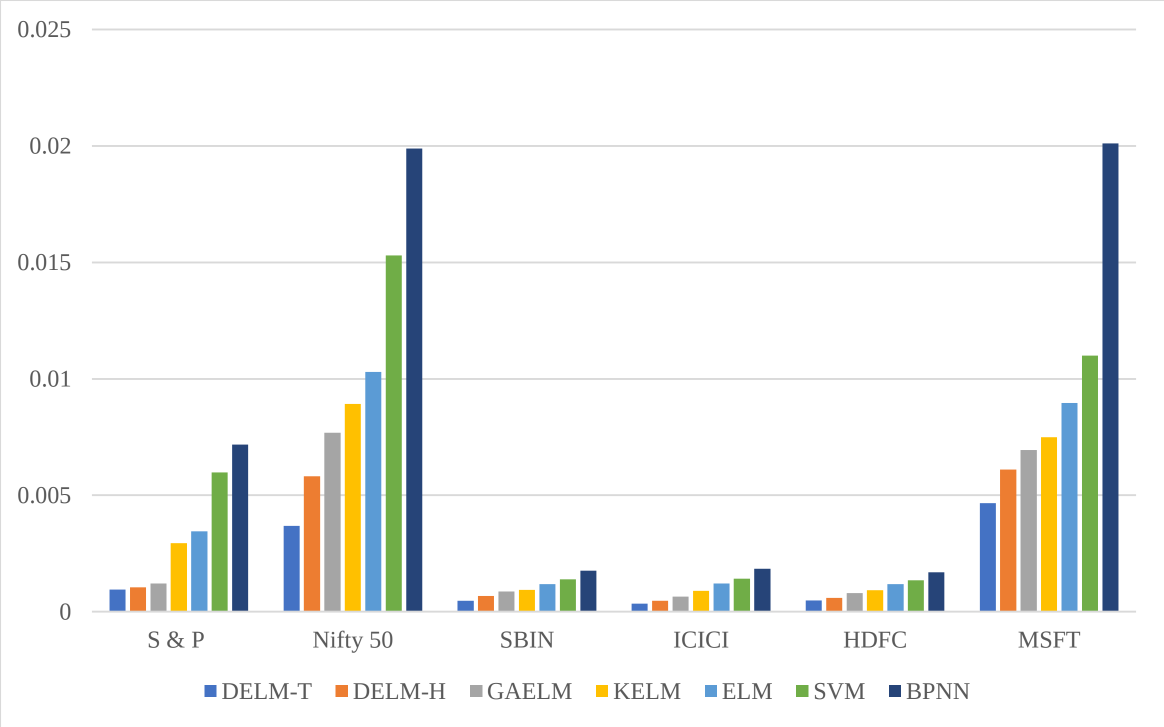

Figure 16: Testing performance comparisons for MSE

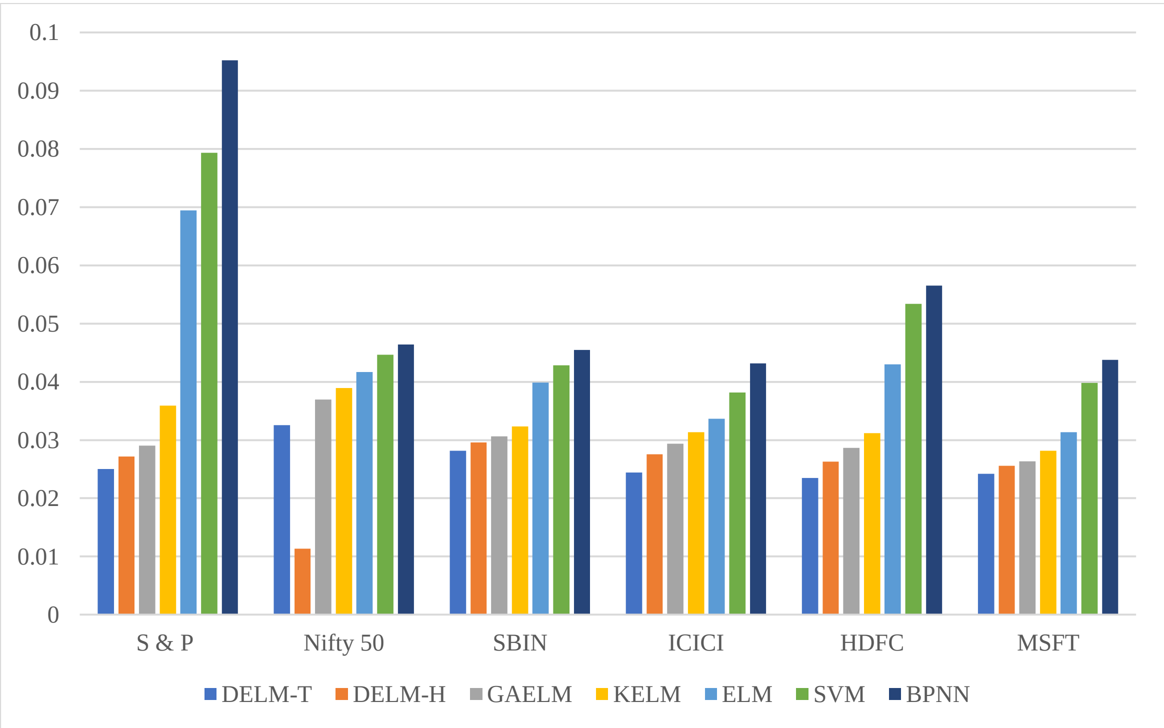

Figure 17: Training performance comparisons for RMSE

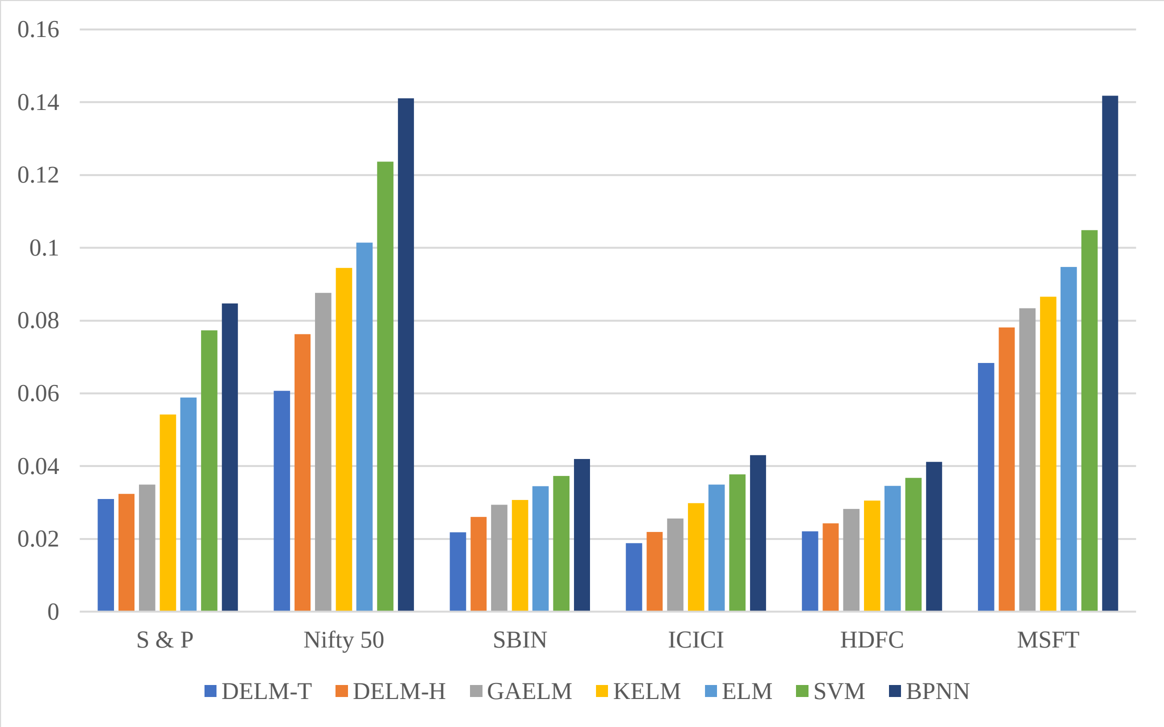

Figure 18 : Testing Performance Comparisons for RMSE

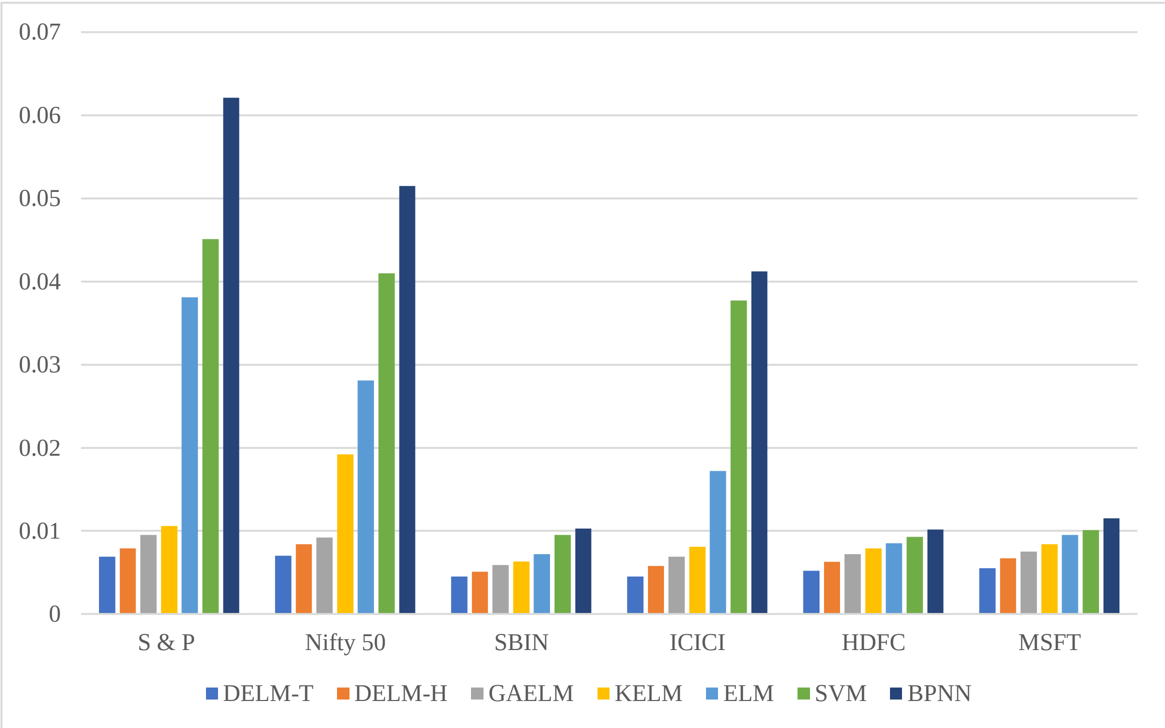

Figure 19 : Training performance comparisons for MAE

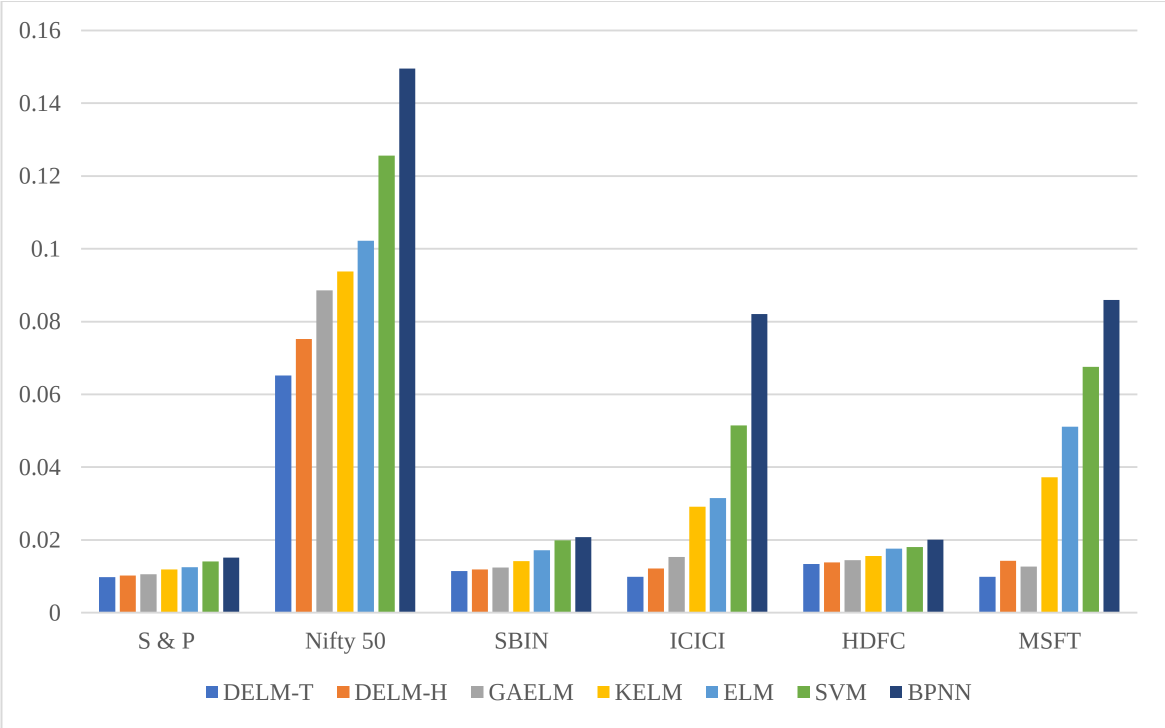

Figure 20: Testing performance comparisons for MAE

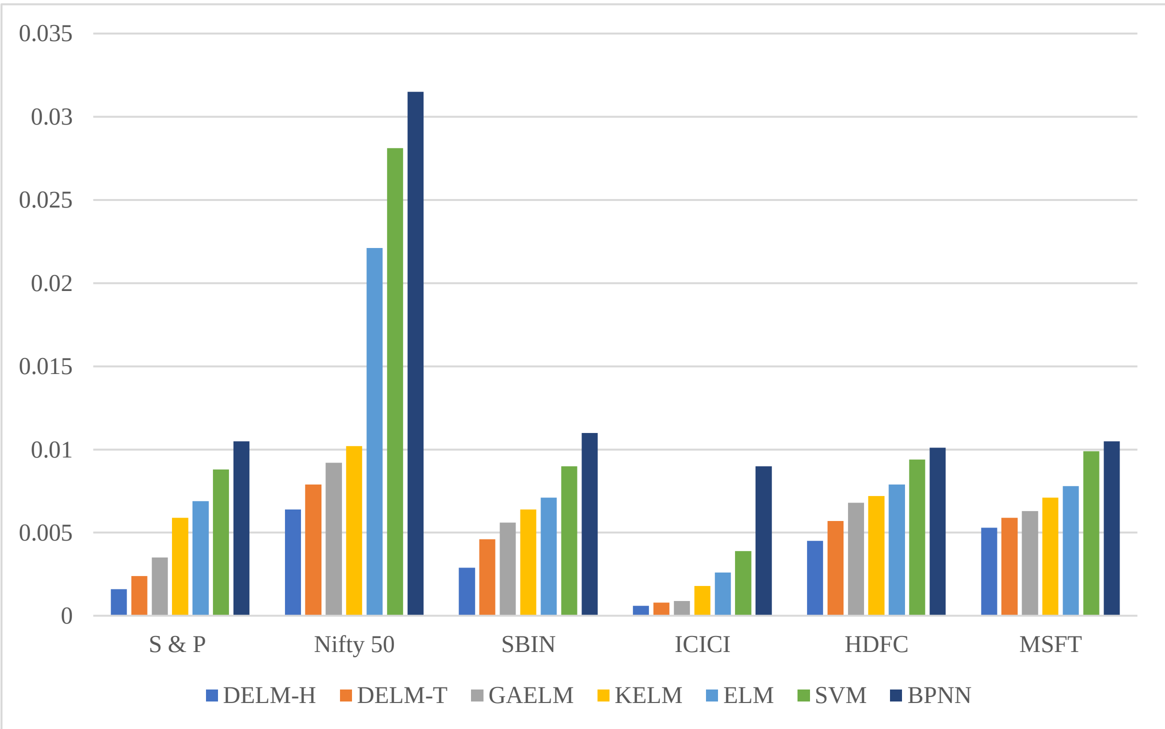

Figure 21: Training performance comparisons for MAPE

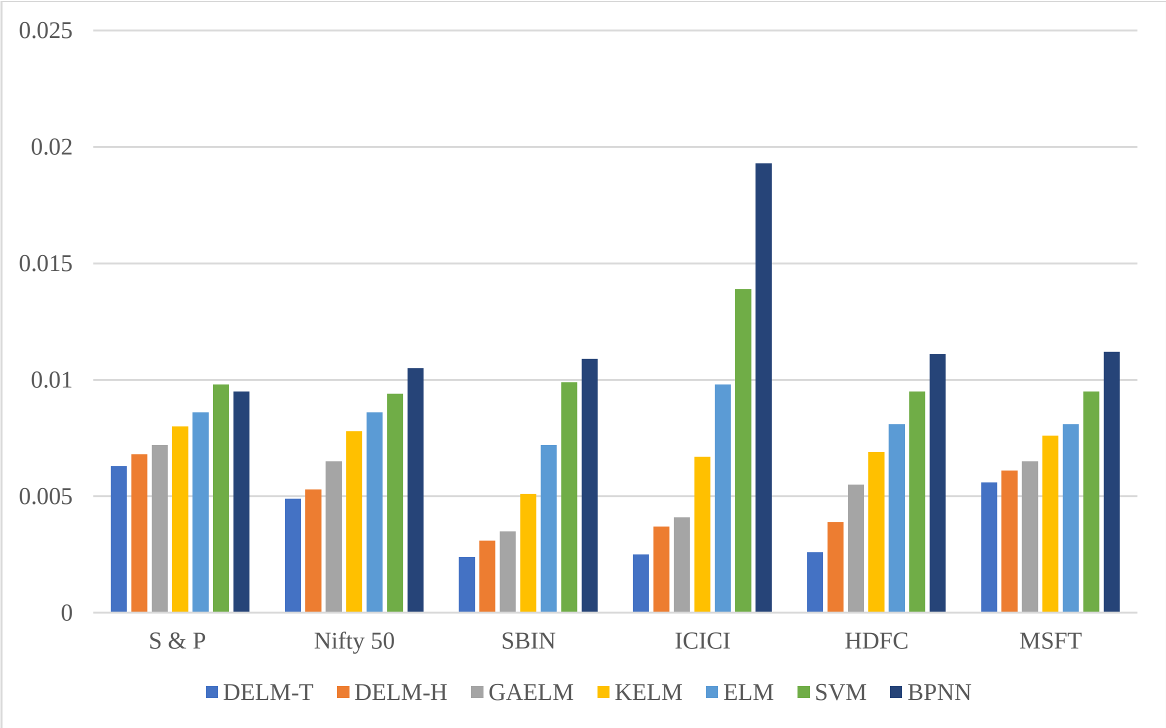

Figure 22 : Testing performance comparisons for MAPE

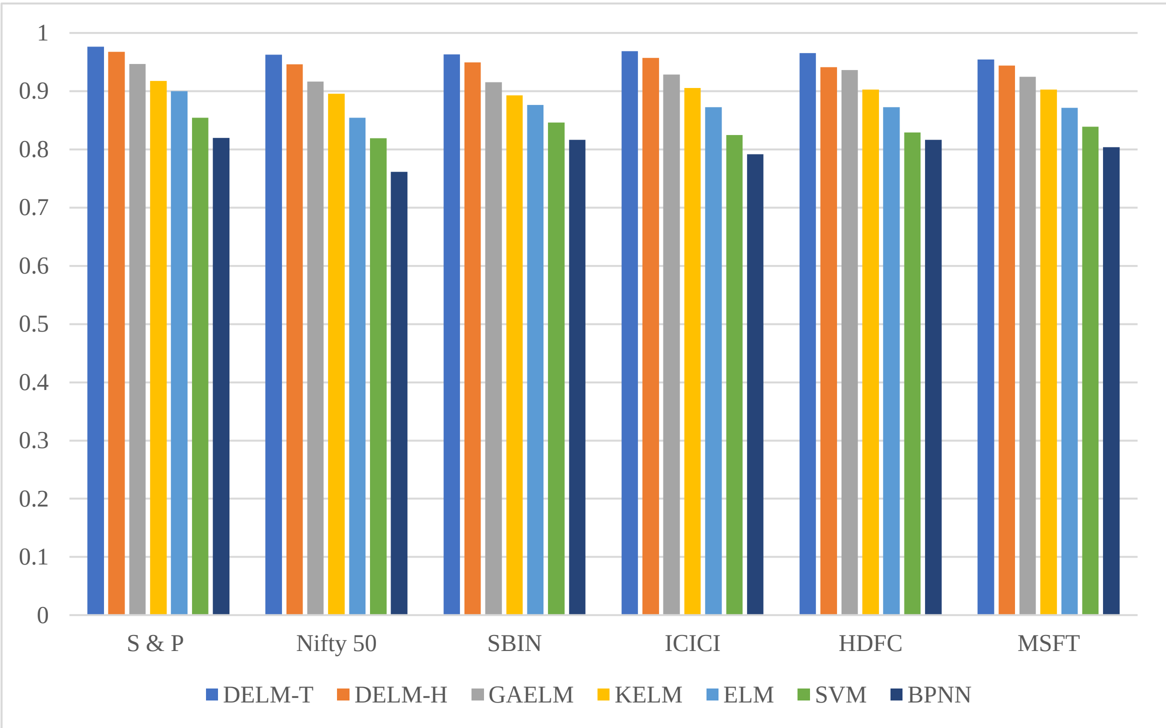

Figure 23: Training performance comparisons for R-Square

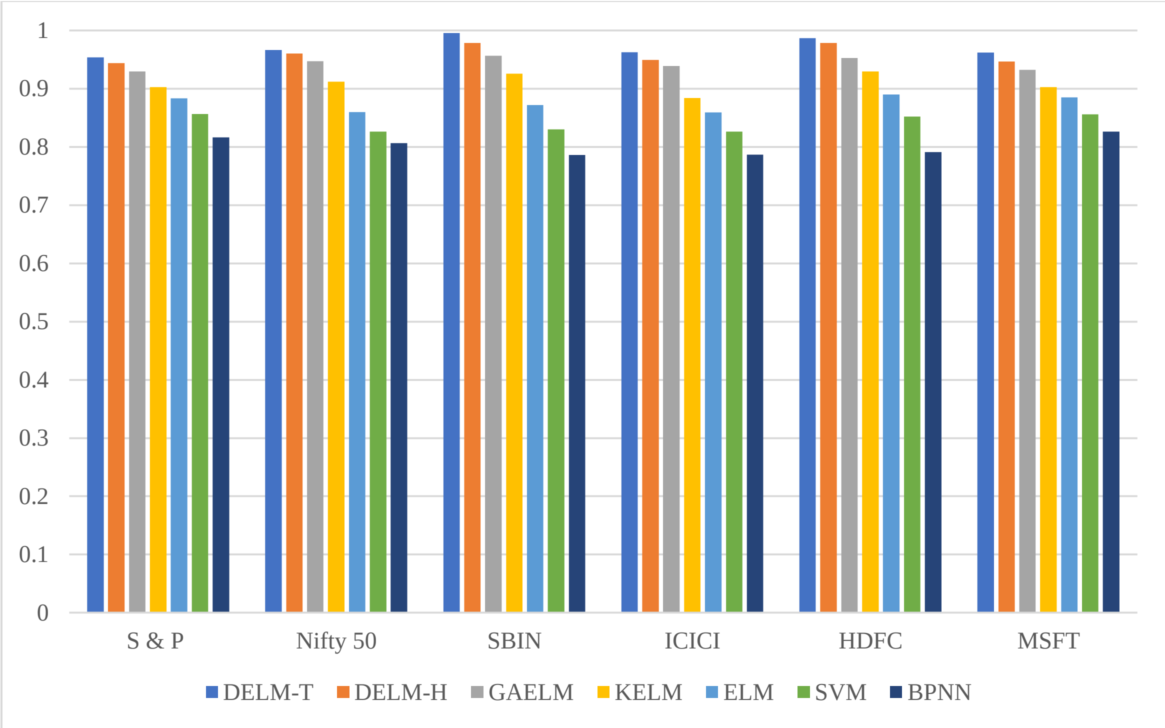

Figure 24: Testing performance comparisons for R-Square

5.4 Summary

As a result of this phase II of research work discusses the ability of the developed DELM-T method. In comparison to previous related prediction algorithms such as SVM, BPNN, and DELM-H the recommended optimized extreme learning machine algorithm with deterministic weight adjustment technique using technical indicators produced low MSE, RMSE, MAE, MAPE values and high R-Square values which is considerably efficient.