OWL REGRESSION BASED TECHNICAL INDICATOR AND INCREMENTAL DECISION DEEP CONVOLUTION FOR STOCK MARKET PREDICTION

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ABSTRACT
Stock market analysis is immensely paramount for investors in view of the fact that calculating the future course of action and grasping the fluctuating features of stock prices will reduce the risk of capital investment for profit. In Stock Market Prediction, the objective is to predict future financial stock value of a company. The current trend in stock market prediction is the utilization of Deep Learning (DL) algorithm that makes predictions on the basis of the values of current stock market indices by training on their previous values. By employing DL algorithms prediction of stock market can make prediction easier. In this work a nature inspire optimization and deep convolution learning method called, Owl Search Optimized Deming Regression and Incremental Decision Tree (OSODR-IDT) for stock market prediction is proposed. The OSODR-IDT based deep convolution learning method for stock market prediction is split into one input layer, two hidden layers and finally one output layer. The data collected from stock data collected from the internet, Stock Market Data - Nifty 100 Stocks (1 min) and 2 indices (Nifty 50 and Nifty Bank indices) is provided as input in the input layer. In the first hidden layer or the pooling layer minimizes the spatial dimensions of feature maps using Owl Search Optimized Deming Regression with the intent of obtaining optimal technical indicators to determine the best parameters (i.e. suitable day for buy and sell). With the optimal identification of technical indicators are transmitted to second hidden layer. In the second hidden layer an Incremental Decision Tree-based trading model is performed in the second hidden fully connected layer to generate the trading results. A comprehensive comparative results analysis stated the promising performance of the OSODR-IDT method for stock market prediction over the recent methods in terms of sensitivity, specificity, accuracy, training time, classification error and precision. Simulations performed to validate the proposed method in Python language were found to be improved in terms of precision by 11%..

1. Introduction

Stock market being a financial market lists out the shares of publicly listed corporations that are being sold and purchased. Stock market being an index of a country's economic health considers the performance of companies and comprehensive business environment. Also with the stock prices being decided by supply and demand, investing in stock market is yet found to be risky, however providing the probability for outstanding returns over the long term.

A multi-kernel method was introduced in [1] with news-based, technical and chip factor analysis to use market data provided by Taiwan Stock Exchange like institutional trading situations and stock price technical indicators. The main objective of designed method was to improve prediction accuracy of stock price dynamics. Here, the financial news was correlated with stock price dynamics and stock price technical indicators.

Moreover, the multi-kernel learning algorithm handled multifaceted data sources and assigned appropriate weights consistent with each data point therefore improving the overall prediction performance. Depending on frequency of word occurrences, a novel discriminant index was employed with the objective of extracting essential features with stock prices from financial news. By employing multi-kernel model increased the stock prediction accuracy. Though prediction accuracy was improved, computational complexity was not minimized by multi-kernel model.

An attention-based BiLSTM (AttBiLSTM) was introduced in [2] with trading strategy and verified TIs like stochastic oscillator, RSI, BIAS, and MACD. The two trading strategies were employed for DNN with TIs to verify their effectiveness. AttBiLSTM used concept of TIs with LSTM-attention time series model for stock price prediction. AttBiLSTM employed TIs with higher stock trend prediction accuracy. Though trend prediction accuracy was improved, the complexity level was not reduced by AttBiLSTM.

An active learning model called, Transformer Encoder Gated Recurrent Unit (TEGRU) architecture was introduced in [3] to construct classification model by considering time sequence data with sentiment indicators. Here, the TEGRU consisted of the transformer encoder to study the pattern time series data with multi-head attention and transmitted to GRU layer for stock price prediction. The accuracy mean absolute percentage error (AcMAPE) was used to reduce the misclassification of stock price trends. Though misclassification was minimized, the time complexity was not minimized by active learning model.

Chinese financial news was used to predict the stock price movement and to derive the trading strategy depending on news factors and technical indicators. The stock trend prediction (STP) approach was introduced in [4] to extract the keywords. A 2-word combination was used to generate meaningful keywords. Moreover, feature extraction and selection were used to attain the important attributes for building signal prediction model.

Technical indicators were used to confirm the trading signal for making trading signal more reliable. An enhanced approach termed genetic algorithm (GA)-based STP (GASTP) approach was employed to identify the hyperparameters automatically for constructing better prediction model. But, stock prediction accuracy was not improved by stock trend prediction approach.

Stock market accurate predictions are paramount for both stakeholders and investors to put together profitable investment plan of actions. The enhanced accuracy of a prediction method even with a modest edge can interpret into substantial monetary returns. Nevertheless, the stock markets' prediction is considered as a complicated research issue as far as complexity and volatility of the stocks' data. Over the past few years, the DL techniques have been successful in imparting boosted forecasts for sequential data.

A novel deep learning-based hybrid classification method integrating LSTM with temporal attention layer (TAL) was proposed in [5] with the intent of predicting stock market's direction accurately. Yet another method to improve accuracy of stock prediction employing LSTM and metaheuristic algorithms were presented in [6]. Also by employing this metaheuristic algorithms resulted in the minimization of error extensively.

Meanwhile, easy access for investment opportunities has made the stock market prediction complicated and volatile. A LSTM to predict the next-day closing price of the S&P 500 index was proposed in [7] with minimal error. Nevertheless, these methods were laborious in addressing non-stationary time series data.

A new prediction method employing DL combining conventional stock financial index variables and social media text features as inputs we employed in [8] to efficiently predict stock price.

Over the past few years, it has become progressively laborious and cumbersome to predict stock price due to the lack of future information concerning stock market that is highly volatile and very unpredictable. At the same time people ceaselessly search for more precise and effective mechanisms of stock trading specifically depending on personal judgement to make stocks price prediction accurately and precisely.

A method integrating multi-source data influencing stock prices and sentiment analysis, swarm intelligence algorithm via DL was proposed in [9]. By employing this integration mechanism resulted in the improvement of prediction effect with minimal error. However time series data were not focused. To concentrate on this issue, LSTM along with time series data was presented in [10]. By applying this technique resulted in the improvement in predicting prices accurately.

A review of data driven patterns employing DL techniques were investigated in [11]. A holistic review on hybrid deep learning methods for stock prediction was presented in [12]. A systematic survey on back testing concerning returns and volatility employing DL was investigated in [13]. A systematic review on forecasting stock market using DL and technical indicators was presented in [14].

The existing methods for stock market prediction though focused on classification accuracy aspects with minimal training time the error involved and the precision in classification was not concentrated. Therefore, there is requirement of designing efficient deep learning stock market trading method with precise results in addition to the minimization of error. To solve above said issue, this paper presents a nature inspired deep convolution learning method for stock market trading employing Owl Search Optimized Deming Regression and Incremental Decision Tree (OSODR-IDT) that that obtains computationally efficient results, finally corroborating the objective with maximum precision, recall, accuracy and minimum classification error.

1.1 Contributions of the work

The main contributions of this paper are as follows:

- We propose nature inspired deep convolution learning method for stock market trading employing Owl Search Optimized Deming Regression and Incremental Decision Tree (OSODR-IDT) for stock market prediction using Stock Market Data - Nifty 100 Stocks (1 min) data to facilitate precise trading results with minimal error in a swift manner.
- Our method can intuitively visualize the process of obtaining computationally-efficient fine-grained augmented image data using Owl Search Optimized Deming Regression-based optimal technical indicators identification via pooling layer that minimizes the classification error and therefore improves accuracy considerably.

- Our Owl Search Optimized Regression and Incremental Decision Deep Convolution for stock market prediction algorithm has strong robustness, with maximum sensitivity and specificity and can hence serve in stock market trading domains by facilitating wise decision regarding buy/sell of a stock.
- In order to evaluate the performance of our OSODR-IDT method in comparison to the conventional existing methods, we experiment on Stock Market Data - Nifty 100 Stocks. It shows that our method outperforms the existing methods in multiple performance metrics like, sensitivity, specificity, classification accuracy, training time, classification error and precision.

1.2 Organization of the work

This paper is organized as follows. In section 2, related works in the area of stock market prediction using deep learning are reviewed. In section 3, Owl Search Optimized Deming Regression and Incremental Decision Tree (OSODR-IDT) for stock market prediction and algorithm analysis are provided in detail. In section 4, experimental results for conducting the stock market prediction using OSODR-IDT method is provided. In section 5 using table and graphical representation by imparting detailed analysis with the proposed OSODR-IDT method and two other traditional methods stated in literature are discussed. Finally, concluding remarks is provided in section 6.

2. Related works

The Stock Market is one of the most received research topics over the past few years and predicting its nature is an epic necessity. However till now stock market prediction is quite demanding and it necessitates intensive study of pattern of data. Distinct statistical methods and Artificial Intelligence (AI) techniques are reduced to meet this demand and arrive at pertinent solution. A plethora of DL algorithms employing deep neural network (DNN) and convolution neural network was proposed in [15] with improved accuracy. A hybrid LSTM and DNN was presented in [16] to handle the issues of stock market prediction consisting of market volatility and complicated patterns with improved accuracy and less misclassification rate. An ensemble of extreme gradient boosting, adaptive boosting and gradient boosting was designed in [17] with minimal mean square error.

As a perceived complicated dynamic system, the stock market has many determining elements, to name a few being, high noise, long memory, non-stationary and non-linearity. It is laborious and cumbersome it straightforwardly via mathematical models. Hence, since log time, the stock market prediction has been a very demanding issue. To address on this factor, an encoder decoder method with attention mechanism was proposed in [18] with improved accuracy. Yet another deep reinforcement learning method was applied in [19] for automated stock market prediction. An ensemble of LSTM with DNN was presented in [20] integrating technical indicators to focus on the precision and recall aspects.

Forecasting time series data are pivotal decision support tools as far as real-world domains are concerned. Moreover, stock market is an exceptionally complicated domain, owing to its swiftly advancing temporal nature, in addition to the countless constituents having an influence on stock prices. A fusion deep learning method called, branch fine-tuned on financial news and a long short-term memory (LSTM) was proposed in [21] underscoring the positive influence of multimodal DL for accurate stock trend prediction. In [22] a stock market prediction (SMP) based on DL was presented to minimize error involved during classification. Despite improvement in precision with minimal error, however the scalability and memory aspects were not focused. To address on these two aspects, hybrid bi-directional LSTM was designed in [23] for real time prediction

Given the complicated nature of stock forecasting in addition to the intrinsic risks and variability, market trend analysis is required to take advantage of optimal investment opportunities for maximizing profit and timely disinvestment for loss reduction. In [24], a DL method with the intent of predict five different trends in stock market namely, rounded top, rounded bottom, upward, downward and double top was presented that in turn aided in both risk management and strategic planning. In [25] a fusion of mean variance and DL algorithms to impart precise generation of predicted return in terms of distinct financial contexts were proposed with minor predictive errors.

A comprehensive DL technique along with feature engineering were designed in [26] for stock market trend prediction. Yet another time series method employing LSTM and gated recurrent unit were proposed in [27] for accurate stock price forecasting. An augmented technique combining LSTM with Symbolic Genetic Programming (SGP) was presented in [28] with the intent of forecasting cross-sectional price returns in an accurate fashion. However consistence was not ensured. To focus on this consistency aspect, Federated Learning Enhanced Multi-Layer Perceptron (Fed-MLP) with LSTM was designed in [29]. By employing this technique resulted in the improvement of accuracy with minimal error.

A systematic and critical review of one hundred and twenty-two (122) pertinent research works was carried out in [30] that reported in academic journals over 11 years (2007–2018) in stock market prediction by employing machine learning. The techniques identified from the reports were grouped into technical, fundamental, and combined analyses. The grouping was carried out based on nature of dataset and number of data sources used, data timeframe and machine learning algorithms used. However, the error rate was not minimized by machine learning.

3. Methodology

In this section a method to deal with the optimization of technical indicators for stock market investment is presented. Price prediction is an issue involving great intricacy and typically some technical indicators are employed in predicting the stock markets trends. The foremost problems in the utilization of technical indicators lie in determining the parameters values.

We proposed the use of nature-inspired optimization model and deep learning to initially obtain the best parameter values (i.e., optimal technical indicators) towards stock market investment that will assist in the buying and selling of shares both precisely with minimal error. In this section a nature-inspired optimization AND deep convolution learning method called, Owl Search Optimized Deming Regression and Incremental Decision Tree (OSODR-IDT) for attaining high investments with stock data is proposed. The proposed method consists of four layers, namely one input layer, two hidden layers and one output layer for efficient stock market prediction. Figure 1 shows the structure of Owl Search Optimized Deming Regression and Incremental Decision Tree method.

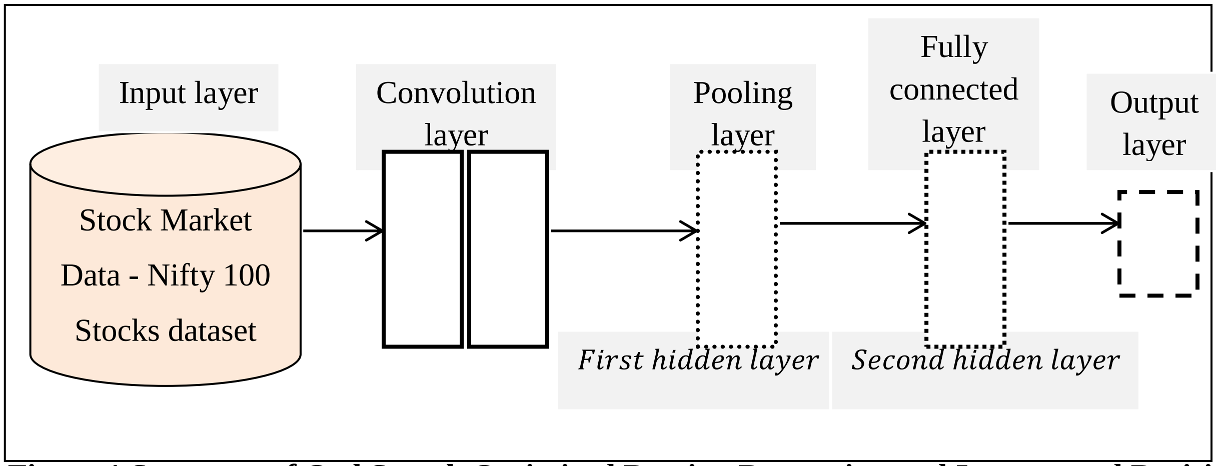


Figure 1 Structure of Owl Search Optimized Deming Regression and Incremental Decision Tree based stock market prediction

As shown in the above figure, the Owl Search Optimized Deming Regression and Incremental Decision Tree method is split into one input layer, two hidden layers and finally one output layer. In the input layer, the stock data are collected from Stock Market Data - Nifty 100 Stocks (1 min) and 2 indices (Nifty 50 and Nifty Bank indices) dataset and convolved to the first hidden layer. With the convolved data in the first hidden layer, optimal technical indicators are identified by applying Owl Search Optimized Deming Regression-based optimal technical indicators via pooling layer and sent to the second hidden layer. In the second hidden layer Incremental Decision Tree-based trading model is applied via fully connected layer. Finally the output results are sent to the output layer.

3.1 Input layer

Initially in the proposed method, number of stock data collected from the internet, Stock Market Data - Nifty 100 Stocks (1 min) and 2 indices (Nifty 50 and Nifty Bank indices) data obtained from https://www.kaggle.com/datasets/debashis74017/stock-market-data-nifty-50-stocks-1-min-data?resource=download is considered as input at input layer. Also, Nifty 100 stocks data along with two indices data with 55 technical indicators employed by Market experts are measured and made accessible for stock prediction. Moreover, the dataset contains historical daily prices for Nifty 100 stocks and indices currently trading on the Indian Stock Market.

Table 1 Dataset description

S. No	Feature name	Description	S. No	Feature name	Description
1	Date	Date of observation	31	CCI10	Commodity channel index - last 10 time frame data
2	Open	Open price of index - specific day	32	CCI15	Commodity channel index - last 15 time frame data
3	High	High price of index - specific day	33	Macd510	Moving Average Convergence/Divergence, fast period = 5 and slow period = 10
4	Low	Low price of index - specific day	34	Macd520	Moving Average Convergence/Divergence, fast period = 5 and slow period = 10
5	Close	Close price of index - specific day	35	Macd1020	Moving Average Convergence/Divergence, fast period = 10 and slow period = 20
6	Sma5	Simple moving average - 5 close price	36	Macd1520	Moving Average Convergence/Divergence, fast period = 15 and slow period = 20

7	Sma10	Simple moving average - 10 close price	37	Macd1226	Moving Average Convergence/Divergence, fast period = 12 and slow period = 26
8	Sma15	Simple moving average - 15 close price	38	Mom10	Momentum indicator of 10 close price
9	Sma20	Simple moving average for 20 close price	39	Mom15	Momentum indicator of 15 close price
10	Ema5	Exponential moving average for 5 close price	40	Mom20	Momentum indicator of 20 close price
11	Ema10	Exponential moving average for 10 close price	41	ROC5	Rate of change -: ((price/prevPrice)-1)*100 using 5 close price
12	Ema15	Exponential moving average for 15 close price	42	ROC10	Rate of change : ((price/prevPrice)-1)*100 using 10 close price
13	Ema20	Exponential moving average for 20 close price	43	ROC20	Rate of change : ((price/prevPrice)-1)*100 using 20 close price
14	Upperband	Upper band of Bollinger band	44	PPO	Percentage price oscillator
15	Middleband	Middle band of Bollinger band	45	RSI14	Relative Strength Index calculated - 14 close price
16	Lowerband	Lower band of Bollinger band	46	RSI8	Relative Strength Index calculated - 8 close price
17	HT_TRENDLINE	Hilbert Transform – Instantaneous Trendline	47	Slowk	Stochastic indicator k value
18	KAMA10	Kaufman Adaptive Moving Average - 10 close price	48	Slowd	Stochastic indicator d value
19	KAMA20	Kaufman Adaptive Moving Average - 20 close price	49	Fastk	Stochastic fast indicator k value
20	KAMA30	Kaufman Adaptive Moving Average of 30 price	50	Fastd	Stochastic fast indicator d value
21	SAR	Parabolic SAR	51	Fastksr	Stochastic Relative Strength Index k value
22	TRIMA5	Triangular moving average of 5 close price	52	Fastdsr	Stochastic Relative Strength Index d value
23	TRIMA10	Triangular moving average of 10 close price	53	ULTOSC	Ultimate oscillator
24	TRIMA20	Triangular moving average of 20 close price	54	WILLR	Williams' %R
25	ADX5	Average directional movement index - 5 close price	55	ATR	Average true range
26	ADX10	Average directional movement index - 10 close price	56	TRANGE	True range
27	ADX20	Average directional movement index - 20 close price	57	TYPPRICE	Typical price
28	APO	Absolute price oscillator	58	HT_DCPERIOD	Hilbert Transform - Dominant Cycle Period
29	CCI5	Commodity channel index - last 5 time frame data	59	BETA	Beta
30	Vol	Volume	60	MFI	Money Flow Index

The available data samples as provided in table 1 are of 1-minute intervals from Jan 2015 to Feb 2022. It includes 55 technical indicators along with OHLCV (Open, High, Low, Close, and Volume) data. The input layer transits the stock data (i.e. input vector) by performing convolution between features to the first hidden layer as given below.

$$IV = [St_1[F_1]\ St_1[F_2]\ \ldots\ St_1[F_n]\ St_2[F_1]\ St_2[F_2]\ \ldots\ St_2[F_n]\ \ldots\ \ldots\ \ldots\ \ldots\ St_k[F_1]\ St_k[F_2]\ \ldots\ St_k[F_n]\,] \quad (1)$$

From the above equation (1) the input vector 'IV' is formulated by taking into considerations 'k' stocks 'St_k' and 'n' features 'F_n' respectively. In this manner, the input vector or the features are extracted from raw input dataset by performing convolution between features.

3.2 Owl Search Optimized Deming Regression-based optimal technical indicators

In this section Owl Search Optimized Deming Regression-based optimal technical indicators identification is performed in the first hidden layer or the pooling layer. In the first hidden layer or the pooling layer, Owl Search Optimization (OSO) along with Deming Regressive Analysis model is applied for selecting optimal technical indicators by identifying the line of best fit for two-dimensional dataset [100 stocks (Nifty 100 stocks) and 2 indices (Nifty 50 and Nifty

Bank indices))] with minimal error and also reducing the input feature maps spatial dimensions to reduce the overall networks computation complexity.

Owl Search Optimization (OSO) employed in our work comprises of an initial population of owls (i.e. stocks along with features) in the search space, evaluating the fitness of owls (i.e., optimal technical indicators identification towards stock market investment wisely) and updating mechanism for new owls (i.e. updating stock market investment wisely). These three processes are performed via three-stage model as given below.

The first stage model towards optimal technical indicator identification is the initialization of population (i.e., initialization of stocks and features accordingly). The initial set of arbitrary solutions to an optimization problem denotes initial positions (i.e. stocks) of owls (i.e. features) in the forest. The population contains 'k' stocks (i.e., individuals) and each one is denoted by a '$d - dimensional\ vector$', as given below.

$$F_i = (F_{i1}, F_{i2}, \dots., F_{id}) \quad (2)$$

From the above representation (2), 'F_{ij}' denotes the '$j - th$' dimension of the '$i - th$' feature. With the intent of allocating initial features of each stock in the search space, the following formulate is being employed.

$$F_i = F_L + Rand(0,1) * (F_U - F_L) \quad (3)$$

From the above representation (3), 'F_L' and 'F_U', represents lower and upper bounds of '$i - th$' feature in '$j - th$' dimension respectively.

The second stage model towards optimal technical indicator identification is the owl's evaluation (i.e. feature evaluation) on a definite fitness function 'fit'. By taking into consideration the fitness, value relates to intensity information received through features oscillations, the best owl or the best features is assigned to the one that receives max intensity and at the same time the worst owl or the worst features that receives min intensity is discarded from further processing. Hence, to perform normalization the intensity information 'Int' of '$i - th$' feature is represented as given below.

$$Int(F_i) = \frac{fit(F_i) - F_{worst}}{F_{best} - F_{worst}} \quad (4)$$

$$F_{worst} = (\{fit(F_i): i = 1,2, \dots, n\}) \quad (5)$$

$$F_{best} = (\{fit(F_i): i = 1,2, \dots, n\}) \quad (6)$$

From the above equations (4), (5) and (6), the intensity information 'Int' of '$i - th$' feature is obtained based on the best 'F_{best}' and the worst 'F_{worst}' solutions in terms of the fitness value in the current population.

Finally, the third stage model towards optimal technical indicator identification is updating owls (i.e. features) location (i.e. positioning). Each feature updates its positioning toward the prey (i.e. optimal features or technical indicators). Here, the fittest owl (i.e. features) with the highest fitness value is the prey (i.e. optimal features or technical indicators). All the Owls (i.e. features) update their positioning by taking into consideration the historic price/volume toward the prey (i.e. optimal features or technical indicators) to forecast financial or stock market prediction. In our work, Deming Regression function is employed in finding the list of best fit for two dimensional dataset.

Let us assume that the available data '(F_i, St_i)' represent the available data of true values '(F_i', St_i')' that lie on regression line as given below.

$$F_i = F_i' + \varepsilon_i \tag{7}$$

$$St_i = St_i' + \eta_i \tag{8}$$

From the above equations (7) and (8) the errors 'ε_i' and 'η_i' are said to be independent to each other and ratio of variances is represented as given below.

$$\delta = \frac{\sigma_\varepsilon^2}{\sigma_\eta^2} \tag{9}$$

With the assumptions that '$\delta = 1$' for our optimal technical indicator process, then the line of best fit towards intensity change according to the ratio of variances is represented as given below.

$$IC_i \rightarrow F_i' = \beta_0 + \beta_1 St_i' \tag{10}$$

Based on the above intensity change 'IC_i', the features update their positioning by taking into consideration the historic price/volume and according to the change in intensity 'IC_i' optimal technical indicators are arrived at as given below.

$$TI = F_i^{t+1} = \{F_i^t + \beta * IC_i * (\alpha[High - Low] - F_i^t) Prob_{vm} \rightarrow UE\ F_i^t - \beta * IC_i * (\alpha[High - Low] - F_i^t) Prob_{vm} \rightarrow LE \tag{11}$$

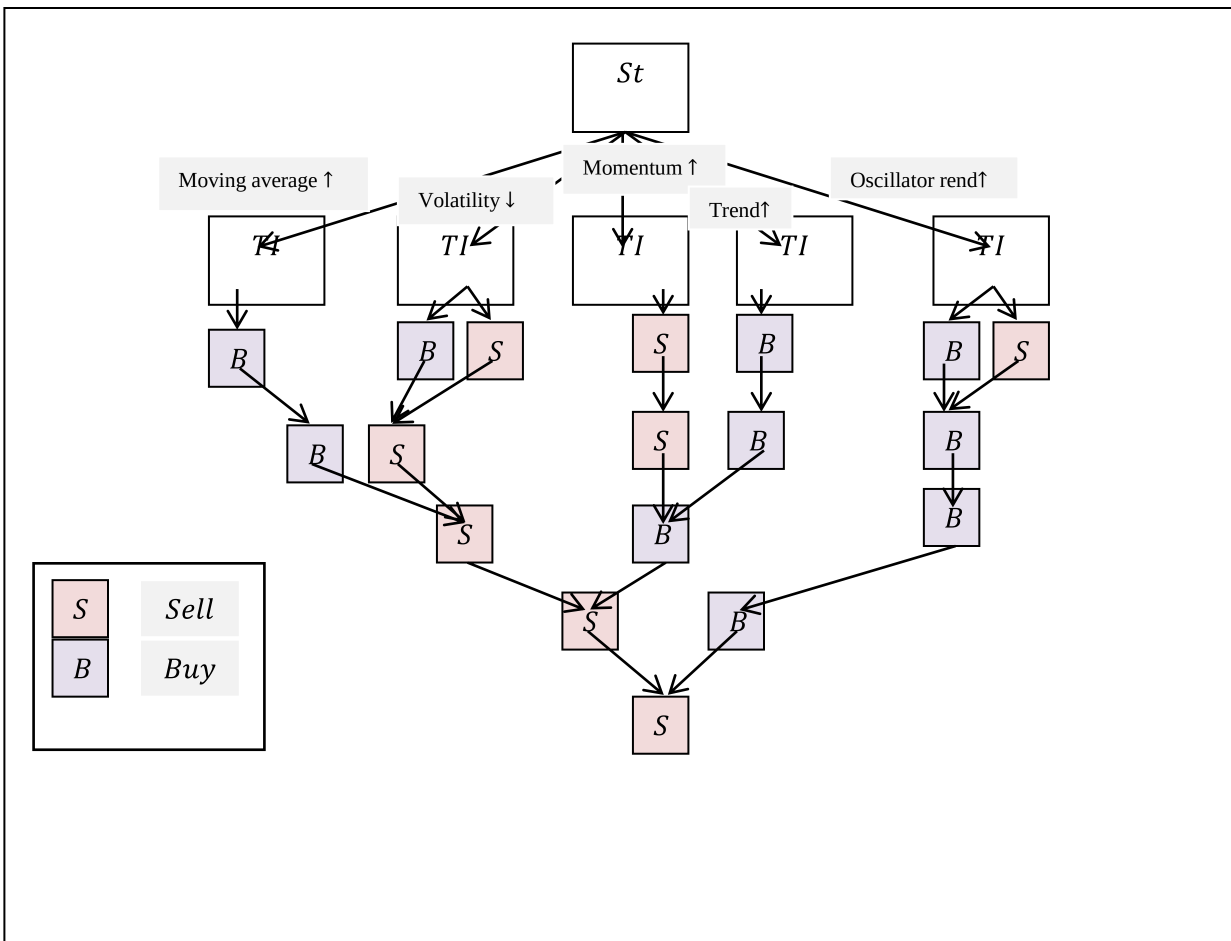
From the above equation (11) with the aid of the value of 'β' decreases from '$1.9\ to\ 0$', whereas the value of 'α' ranges between '[0,0.5]', the updated optimal technical indicators are identified according to the oscillators in price value creating high and low bands between two extreme values '$High, Low$ ' and accordingly when the probability of optimal technical indicator moving towards upper extreme '$Prob_{vm} \rightarrow UE$' or towards lower extreme '$Prob_{vm} \rightarrow LE$' respectively. Finally, the first hidden layer transmits the optimized technical indicators to second hidden layer.

Table 2 Optimal technical indicator identification

S. No	Technical indicators (i.e., features selected)	Features with corresponding technical and general indicators
1	Moving average indicator	SMA – 4 features
2	Volatility indicator	Bollinger band – 3 features
3	Momentum indicator	ULTOSC – 1 feature
		William % R – 1 feature
		MFI – 1 feature
4	Trend indicator	MACD – 5 features
		EMA – 4 features
		ADX – 3 features
		RSI – 2 features
5	Oscillator index	APO – 1 feature
		CCI5 – 1 feature
6	General indicators	Date of stock purchase – 1 feature
		High day high stock price at period 't' – 1 feature
		Low day low stock price at period 't' – 1 feature
		Open day open stock price at period 't' – 1 feature
		Close day close stock price at period 't' – 1 feature
7	Volume indicator	Vol – 1 feature

3.3 Incremental Decision Tree-based trading model

With the optimal technical indicators obtained, the second hidden layer employs Incremental Decision Tree to combine the indicators for creating the best trading strategy via fully connected layer. The strategies generated from proposed method yield the highest returns with an upward trend. The generated strategies suffer the lowest losses in a downward trend. The Incremental Decision Tree is introduced in the fully connected layer of deep convolution network for constructing a decision tree employing optimal technical indicators and stock market data towards creation of the best trading strategy (i.e. buy/sell/hold the stock). The proposed Incremental Decision Tree model starts with a root node initially being empty without descendants. Each incoming instance of the training set (i.e. stock market data along with optimal technical indicators) expands the decision tree or it traverses the tree until a leaf is reached, in which the object is stored as a class (i.e. buy/sell/hold the stock). Upon receiving each sample instance, the model measures dual statistical entities, i.e. entropy and information gain. Figure 2 shows the structure of the example Incremental Decision Tree-based trading model.



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trend and oscillator index along with the volume and general indicators), the decision regarding the buying 'B' or selling 'S' of stock market prediction is made. This decision is made by means of entropy and information gain in the fully connected second hidden layer of deep convolution

learning. The entropy for a collection of training instances (i.e. stock market data along 'St') 'St' is referred to as the measure of impurity of 'St' and is evaluated as given below.

$$Ent\ (St\ ) = \sum_{i=1}^{C} \quad - p_i\ log\ log\ 2\ p_i \tag{12}$$

From the above equation (12), 'p_i' refers to the proportion of samples belonging to a specific class and 'C' denotes the number of classes (i.e. buy/sell/hold the stock) in the training instance set. Next, the Information Gain (IG) for each attribute (i.e. optimal technical indicator) evaluates the anticipated minimization in entropy. In other words, the higher the IG more is the anticipated minimization in entropy. To be more specific, the IG evaluates how well a given attribute (i.e. optimal technical indicator) separates training samples (i.e. stock) according to their target classification (i.e. buy/sell/hold the stock). With these assumptions the Information Gain is measured as given below.

$$GAIN(St, TI) = Ent(St) - \sum_{v \in Values(TI)} \quad \frac{St_v}{St} Ent(St_v) \tag{13}$$

From the above equation (13) the Information Gain (IG) for each attribute (i.e. optimal technical indicator) '$Gain\ (St, TI)$' is evaluated based on the probable values for each attribute (i.e. optimal technical indicator) '$v \in Values(TI)$' with 'St_v' denoting the subset of 'St' for which attribute (i.e. optimal technical indicator) 'TI' has value 'v' respectively. With these evaluation results, finally, high investment returns are obtained in the output layer. The pseudo code representation of Owl Search Optimized Regression and Incremental Decision Deep Convolution for stock market prediction is provided below.

Input: Dataset 'DS', Stocks '$St = \{St_1, St_2, \dots, St_k\}$', Features '$F = \{F_1, F_2, \dots, F_n\}$'
Output: Error-minimized Optimal technical indicators identification
1: **Initialize** '$k = 50$' [stocks], '$n = 60$' [technical indicators], '$Rand = [0,1]$, '$\beta = decreases\ from\ 1.9\ to\ 0$', '$\alpha = [0,0.5]$' 2: **Begin** 3: **For** each Dataset 'DS' with Stocks 'St' and Features 'F' **//Input layer – convolutional layer** 4: Formulate input vector as given in (1) 5: Transit the stock data (i.e. input vector) to the first hidden layer **//Hidden layers** **//First hidden layer – pooling layer** **//Stage 1 – initial population** 6: Formulate initial population as given in (2) and (3) **//Stage 2 – owls (i.e. features) evaluation** 7: Evaluate all the features in the population or search space as given in (4), (5) and (6) **//Stage 3 –updating owls (i.e. features) location (i.e. positioning)** 8: Formulate available data of true values that lie on regression line as given in (7) and (8) in such a manner that '$\delta = 1$' 9: Formulate line of best fit towards intensity change as given in (10) 10: Transmit optimized technical indicators to second hidden layer as given in (11) **//Second hidden layer – incremental decision tree – fully connected layers** 11: **For** a collection of training instances (i.e. stock market data along 'St') 12: Measure entropy as given in (12)

13: Evaluate Information Gain as given in (13)
14: **If** '$\mu[Osc]$ $over + 100$'
15: **Then** stock can be purchased
16: **End if**
17: **If** '$\mu[Osc]$ $over - 100$'
18: **Then** stock can be sold
19: **End if**
20: **End for**
//Output layer
21: **Return** class results 'B' or 'S'
22: **End for**
23: **End for**
24: **End**

Algorithm 1 Owl Search Optimized Regression and Incremental Decision Deep Convolution for stock market prediction

As given in the above algorithm, with raw Stock Market Data - Nifty 100 Stocks (1 min) dataset including stocks of different companies features or technical indicators are subjected to nature inspired optimization and deep convolution learning methods for precise stock prediction with minimal error. With the raw data obtained as input in the input layer, initially convolution is applied to form the input data in the corresponding input vector representation. Second, in the first hidden layer the convolved input are pooled to obtain optimal technical indicators using Owl Search Optimized Deming Regression model. The optimal technical indicators using Owl Search Optimized Deming Regression model are moving average, volatility, momentum, trend, oscillator index along with volume and general indicators. Next in the second hidden layer the identified optimal technical indicators are passed to make precise stock prediction by employing Incremental Decision Tree-based trading model. Finally the stock prediction class of either buy or sell the stock is provided as output in the output layer.

4. Experimental setup

In this section, experimental evaluation of the proposed, nature inspire optimization and deep convolution learning method called, Owl Search Optimized Deming Regression and Incremental Decision Tree (OSODR-IDT) for stock market prediction and two existing methods multi-kernel [1] and attention-based BiLSTM (AttBiLSTM) [2] are implemented in Python high-level general-purpose programming language. The dataset used in this work is Stock Market Data - Nifty 100 Stocks (1 min) data acquired from https://www.kaggle.com/datasets/debashis74017/stock-market-data-nifty-50-stocks-1-min-data?resource=download. The entire experiment is conducted in an Intel Core i5- 6200U CPU @ 2.30GHz 4 cores with 4 Gigabytes of DDR4 RAM.

5. Performance evaluation

In this section the performance evaluation of six different metrics, sensitivity, specificity, accuracy, training time, classification error and precision is validated and analyzed. In stock market prediction, precision and recall are performance metrics that apply to sample data retrieved from a sample space. The mathematical formulates for sensitivity and specificity are given below.

$$Sen = \frac{TP}{TP+FN} \tag{14}$$

$$Spe = \frac{TN}{TN+FP} \tag{15}$$

From the above equation (14), the sensitivity rate 'Sen' is measured based on the true positive rate 'TP' (i.e., correctly predicted stock to buy as buy), and the false negative rate 'FN' (i.e., predicts the stock to sell as buy incorrectly). On the other hand, specificity rate 'Spe', from (15) is measured by taking into consideration the true negative rate 'TN' (i.e., correctly predicted stock to sell as sell), and the false positive rate 'FP' (i.e., predicts the stock to buy as sell) respectively. The classification accuracy or accuracy is measured as given below.

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \quad (16)$$

From the above equation (16), classification accuracy or accuracy 'Acc' is evaluated using the true positive rate (i.e., i.e., correctly predicted stock to buy as buy) 'TP', false positive rate (i.e., i.e., predicts the stock to buy as sell) 'FP' and the false negative rate (i.e., predicts the stock to sell as buy incorrectly) 'FN' and true negative rate (.e., correctly predicted stock to sell as sell) 'TN' respectively. Next one of the significant performance metrics playing a significant role in stock market prediction is the classification error. The classification error is mathematically represented as given below.

$$CE = \sum_{i=1}^{N} \frac{St_{WC}}{St_i} \quad (17)$$

From the above equation (17) the classification error 'CE' is measured by taking into considerations the stocks involved in simulation 'St_i' and the stock price wrongly classified 'St_{WC}'. Lower the classification error higher is the efficiency of the method and vice versa. Also a significant amount of time is said to be consumed during the training of stock market prediction and is referred to as the training time. The training time is mathematically stated as given below.

$$TT = \sum_{i=1}^{m} S_i * Time(Pred) \quad (18)$$

From the above equation (18) the training time 'TT' is measured using the stock samples 'S_i' and the actual time consumed in the overall prediction process '$Time(Pred)$'. It is measured in terms of seconds (sec). Finally the precision rate is evaluated as given below.

$$Pre = \frac{TP}{TP+FP} \quad (19)$$

From the above equation (19) precision 'Pre' is measured using the true positive 'TP' and false positive rate 'FP'.

6. Discussion

In this section to ensure fair comparison between the proposed method Owl Search Optimized Deming Regression and Incremental Decision Tree (OSODR-IDT) for stock market prediction and two existing methods multi-kernel [1] and attention-based BiLSTM (AttBiLSTM) [2], same samples from the Stock Market Data - Nifty 100 Stocks (1 min) dataset is employed. Comparisons are made accordingly by applying the same sample data only differing methods in use, i.e., OSODR, [1] and [2]. Table 3 and table 4 given below lists the tabulation results of sensitivity, specificity and accuracy by substituting the samples in equations (14), (15) and (16) for two different stocks, namely, ACC and ASIANPAINT.

Table 3 Comparative analysis of sensitivity, specificity and accuracy for ACC stock

Samples	Sensitivity			Specificity			Accuracy		
	OSODR-IDT	multi-kernel [1]	AttBiLSTM [2]	OSODR-IDT	multi-kernel [1]	AttBiLSTM [2]	OSODR-IDT	multi-kernel [1]	AttBiLSTM [2]
100000	0.99	0.98	0.98	0.46	0.36	0.33	0.94	0.92	0.91
200000	0.97	0.95	0.92	0.52	0.41	0.38	0.95	0.93	0.92
300000	0.94	0.92	0.9	0.58	0.45	0.42	0.93	0.89	0.85

400000	0.92	0.88	0.85	0.63	0.52	0.46	0.91	0.85	0.81
500000	0.95	0.9	0.87	0.6	0.57	0.49	0.94	0.87	0.84

Table 4 Comparative analysis of sensitivity, specificity and accuracy for ASIANPAINT stock

Samples	Sensitivity			Specificity			Accuracy		
	OSODR-IDT	multi-kernel [1]	AttBiLSTM [2]	OSODR-IDT	multi-kernel [1]	AttBiLSTM [2]	OSODR-IDT	multi-kernel [1]	AttBiLSTM [2]
100000	0.97	0.94	0.93	0.33	0.28	0.25	0.88	0.84	0.78
200000	0.92	0.9	0.86	0.4	0.33	0.3	0.9	0.85	0.8
300000	0.9	0.87	0.83	0.45	0.35	0.31	0.85	0.8	0.75
400000	0.88	0.84	0.8	0.4	0.38	0.33	0.89	0.82	0.77
500000	0.93	0.86	0.82	0.42	0.4	0.35	0.88	0.83	0.78

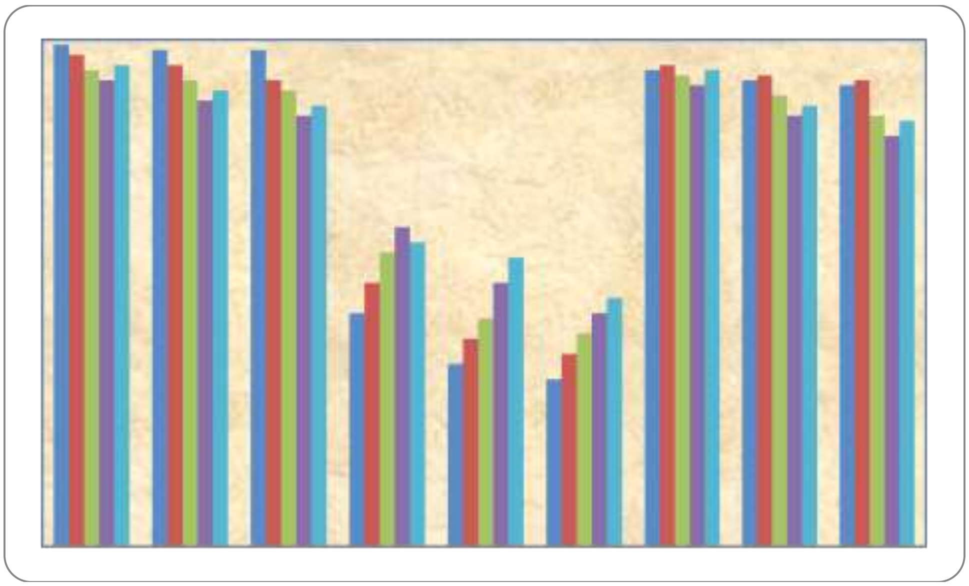

Figure 3 Sensitivity, specificity and accuracy versus samples for ACC stock

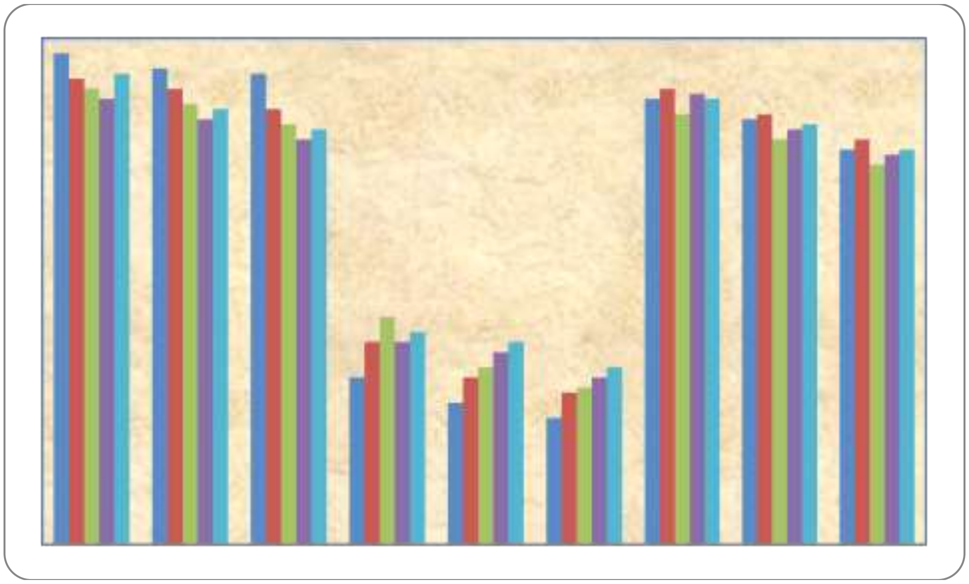

Figure 4 Sensitivity, specificity and accuracy versus samples for ASIANPAINT stock

Figure 3 and figure 4 given above shows the figurative representations of sensitivity, specificity and accuracy for two different stocks considered for simulation (ACC and ASIANPAINT). From both the above two graphical representations three inferences are made. First, the precision, recall and accuracy rate of ACC stock was found to be comparatively better than the precision, recall and accuracy rate of ASIANPAINT stock. Second, though a decreasing rate in terms of sensitivity, specificity and accuracy were found using all the three methods for both ACC stock and ASIANPAINT stock the performance metric analysis were found to be higher even for greater numbers of stocks. Third, the sensitivity, specificity and accuracy rate of both the stocks ACC and ASIANPAINT for the proposed OSODR-IDT method was found to be comparatively better than [1] and [2]. This is evidence from the results where the sensitivity, specificity and accuracy for the proposed OSODR-IDT method for an overall sample size of 100000 was found to be 0.99, 0.46and 0.94, whereas the sensitivity, specificity and accuracy of [1] was observed to be 0.98, 0.36, 0.92 and that of the [2] was found to be 0.98, 0.33 and 0.91 respectively. From this result it is evident that the sensitivity, specificity and accuracy of the proposed OSODR-IDT method were observed to be better than [1] and [2]. The reason behind these performance improvements was due to the application of Owl Search Optimization (OSO) along with Deming Regressive Analysis model for selecting optimal technical indicators. By selecting optimal technical indicators and applying it for stock market prediction resulted in the improvement of sensitivity, specificity and accuracy of the proposed OSODR-IDT method by 3%, 6% compared to [1] and [2] in case of sensitivity, 22%, 35% compared to [1] and [2] in case of specificity and finally, 5%, 8% compared to [1] and [2] in case of accuracy for ACC stock.

Table 5 given below lists the tabulation result of training time by substituting the samples in equation (18) for two different stocks, namely, ACC and ASIANPAINT.

Table 5 Comparative analysis of training time for ACC stock and ASIANPAINT stock

Samples	Training time (sec) –ACC stock			Training time (sec) – ASIANPAINT stock		
	OSODR-IDT	multi-kernel [1]	AttBiLSTM [2]	OSODR-IDT	multi-kernel [1]	AttBiLSTM [2]
100000	115	145	185	95	104	118
200000	125	160	200	115	130	155
300000	140	175	215	120	145	170
400000	125	155	185	135	155	195
500000	108	138	170	118	135	155

Figure 5 Training time versus samples for ACC and ASIANPAINT stock

Figure 5 given above shows the graphical representation of training time for proposed OSODR-IDT and two existing methods, multi-kernel [1] and AttBiLSTM [2] for two different stocks, ACC and ASIANPAINT. From the above graphical representation two inferences are made. First an increase in the sample size does not have negative influence on the training time and in other words increasing sample size do not increases the training time. This is confirmed from the sample simulation where the training time using 400000 samples was found to be 125 sec [using proposed method] whereas for 500000 samples was found to be 108 sec [using proposed method]. Second the training time consumed to predict stock market trends using ASIANPAINT was found to be lesser than to predict stock market trends using ACC. Third the training time consumed to predict stock market trends when applied with the proposed OSODR-IDT method was found to be comparatively lesser than [1] and [2]. This is confirmed for 100000 samples for both ACC and ASIANPAINT data with training time of proposed OSODR-IDT method being 115 sec and 95 sec respectively whereas for [1] and [2] it was found to be 145 sec, 185 sec and 104 sec, 118 sec respectively. The reason behind the training time improvement was due to the optimal technical indicator identification to update their positioning by taking into consideration the historic price/volume toward the prey (i.e. optimal features or technical indicators) to forecast financial or stock market prediction. This in turn aided in overall reduction of training time using proposed OSODR-IDT method by 21%, 36% compared to [1] and [2] for ACC stock and 13%, 26% upon comparison to [1] and [2] for ASIANPAINT stock.

Table 6 given below provides the tabulation result of precision by substituting the samples in equation (19) for two different stocks, namely, ACC and ASIANPAINT.

Table 6 Comparative analysis of precision for ACC stock and ASIANPAINT stock

Samples	Precision –ACC stock			Precision – ASIANPAINT stock		
	OSODR-IDT	multi-kernel [1]	AttBiLSTM [2]	OSODR-IDT	multi-kernel [1]	AttBiLSTM [2]
100000	0.94	0.92	0.91	0.9	0.88	0.87
200000	0.91	0.88	0.85	0.85	0.82	0.77
300000	0.88	0.85	0.82	0.8	0.75	0.7
400000	0.85	0.81	0.78	0.78	0.7	0.68
500000	0.87	0.83	0.8	0.83	0.72	0.7

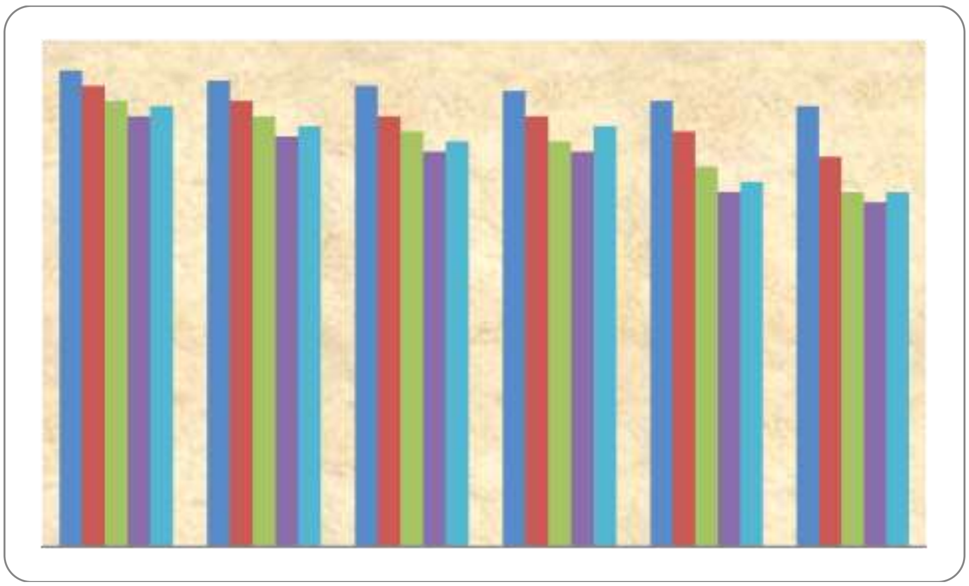

Figure 6 Precision versus samples for ACC and ASIANPAINT stock

Figure 6 given above illustrates the precision results analysis for ACC and ASIANPAINT stock using the proposed OSODR-IDT method and two existing methods, multi-kernel [1] and AttBiLSTM [2]. From the above graphical representation analysis of precision using the two different stocks, though decreasing trend was observed for the first four iterations, however in the fifth iteration the precision using all the three methods for two different company stocks were improved, therefore corroborating the objective. Also the precision rate of ACC stock when applied with the proposed OSODR-IDT method was comparably better than when applied with the ASIANPAINT stock. From the simulation performed for 100000 samples, the true positive rate of the three methods for ACC stock was observed to be 90000, 88000 and 87000, therefore observing an overall precision of 0.94 using proposed OSODR-IDT method, 0.92 and 0.91 using [1] and [2]. The reason behind the improvement was due to the application of Incremental Decision Tree model. By applying this model for each incoming sample instance of the training set (i.e. stock market data along with optimal technical indicators) increases the decision tree until a leaf is reached, in which the object is stored as a class (i.e. buy/sell/hold the stock) finally. This in turn improves the overall precision using the proposed OSODR-IDT method by 4% compared to [1] and 7% compared to [2] for ACC stock. In addition for each sample instance, dual statistical entities, i.e. entropy and information gain are measured that in turn improves the precision by 8% and 12% compared to [1] and [2] respectively.

Table 7 given below provides the tabulation result of classification error by substituting the samples in equation (19) for two different stocks, namely, ACC and ASIANPAINT.

Table 7 Comparative analysis of classification error for ACC stock and ASIANPAINT stock

Samples	Classification error (%) – ACC stock			Classification error (%) – ASIANPAINT stock		
	OSODR-IDT	multi-kernel [1]	AttBiLSTM [2]	OSODR-IDT	multi-kernel [1]	AttBiLSTM [2]
100000	0.05	0.07	0.09	0.03	0.05	0.08
200000	0.07	0.09	0.16	0.06	0.09	0.11
300000	0.08	0.15	0.2	0.09	0.12	0.14
400000	0.15	0.18	0.24	0.14	0.15	0.19
500000	0.09	0.11	0.2	0.11	0.13	0.17

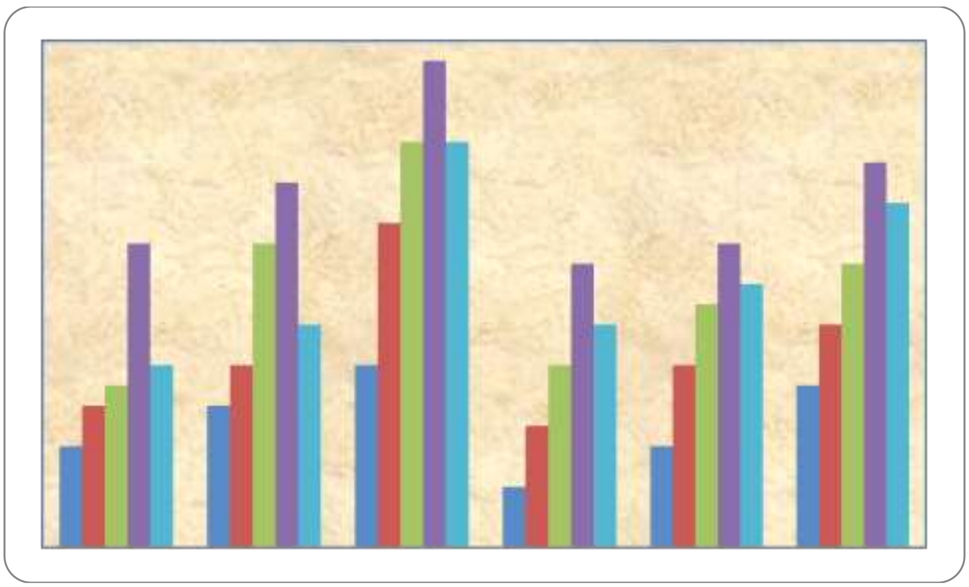

Figure 7 Classification errors versus samples for ACC and ASIANPAINT stock

Finally figure 7 given above shows the classification error using the three methods for two different stocks, namely, ACC and ASIANPAINT respectively. From the above figure the classification error of ASIANPAINT stock was found to be comparatively lesser than the classification error of ACC stock for all the three methods. Also increasing the data samples the classification error using all the three methods was not increased, therefore corroborating the objective of stock market prediction both accurately and precisely. Moreover, with the simulation of 100000 data, the classification using the proposed method for ACC and ASIANPAINT stock was observed to be 0.05 and 0.03 whereas using the [1] method for ACC and ASIANPAINT stock was found to be 0.07 and 0.05 and using [2] method for ACC and ASIANPAINT stock it was 0.09

and 0.08 respectively. With this the overall classification error using the proposed method was found to be lesser than [1] and [2] for two stock samples. The reason behind the improvement was due to the application of Information Gain (IG) for each attribute (i.e. optimal technical indicator) measures the anticipated minimization in entropy. To be more specific, the higher the IG more is the anticipated minimization in entropy. Moreover, the IG measures how well a given attribute (i.e. optimal technical indicator) separates training samples (i.e. stock) according to their target classification (i.e. buy/sell/hold the stock), therefore minimizing the classification error of the OSODR-IDT method by 26%, 51% compared to [1] and [2] for ACC stock and reduced by 24%, 41% compared to [1] and [2] for ASIANPAINT stock respectively.

7. Conclusion

In this work, an efficient method combining nature inspired optimization and deep convolution learning called Owl Search Optimized Deming Regression and Incremental Decision Tree (OSODR-IDT) for stock market prediction based on Stock Market Data - Nifty 100 Stocks (1 min) and 2 indices (Nifty 50 and Nifty Bank indices) data has been proposed, which employs Owl Search Optimized Deming Regression in the first hidden layer (i.e. pooling) and Incremental Decision Tree-based trading model (i.e. fully connected layer) in the second hidden layer of the Deep convolution learning. In this regard, two hidden layers were created for deep convolution learning via pooling and fully connected layer. The first hidden layer was based on Owl Search Optimization function and Deming Regression analysis that by employing historic price/volume obtains optimal technical indicators for further stock market prediction. Through the Incremental Decision Tree, the proposed OSODR-IDT method permits for exploiting the potentiality of stock market trading to generate class results of buying or selling accurately and precisely. By incorporating these features into information gain function, excellent classification accuracy was achieved than the previous methods. Experiments were conducted on stock market data to test the performance of the proposed method. Experimental results show that the proposed OSODR-IDT method achieved high accuracy and precision levels with minimum error and training time upon comparison to the state-of-the-art methods.

References

[1] Hei-Chia Wang, Wei-Ching Hsiao and Ru-Siang Liou, “Integrating technical indicators, chip factors and stock news for enhanced stock price predictions: A multi-kernel approach”, Asia Pacific Management Review, Elsevier, October 2023, Pages 1-15 [multi-kernel]

[2] Ming-Che Lee, Jia-Wei Chang, Sheng-Cheng Yeh, Tsorng-Lin Chia, Jie-Shan Liao and Xu-Ming Chen, “Applying attention-based BiLSTM and technical indicators in the design and performance analysis of stock trading strategies”, Neural Computer Applications, Volume 34, Issue 16, 2022, Pages 13267-13279 [attention-based BiLSTM (AttBiLSTM)]

[3] Agus Tri Haryono, Riyanarto Sarno and Kelly Rossa Sungkono, “Transformer-Gated Recurrent Unit Method for Predicting Stock Price Based on News Sentiments and Technical Indicators”, IEEE Access, Volume 11, 2023, Pages 77132 - 77146

[4] Chun-Hao Chen, Ping Shih, Gautam Srivastava, Shih-Ting Hung and Jerry Chun-Wei Lin, “Evolutionary Trading Signal Prediction Model Optimization Based on Chinese News and Technical Indicators in the Internet of Things”, IEEE Internet of Things Journal, Volume 10, Issue 3, 01 February 2023, Pages 2162 – 2173

[5] Saima Latif, Nadeem Javaid, Faheem Aslam, Abdulaziz Aldegheishem, Nabil Alrajeh, Safdar Hussain Bouk, "Enhanced prediction of stock markets using a novel deep learning model PLSTM-TAL in urbanized smart cities", Heliyon, Elsevier, Vol. 10, Mar 2024
[6] Burak Gülmez, "Stock price prediction with optimized deep LSTM network with artificial rabbits optimization algorithm", Expert Systems With Applications, Elsevier, Vol. 227, Oct 2023
[7] Hum Nath Bhandari, Binod Rimal, Nawa Raj Pokhrel, Ramchandra Rimal, Keshab R. Dahal, Rajendra K.C. Khatri, "Predicting stock market index using LSTM", Elsevier, Vol. 9, Sep 2022
[8] Xuan Ji, Jiachen Wang and Zhijun Yan, "A stock price prediction method based on deep learning technology", International Journal of Crowd Science", Vol. 5, Apr 2021
[9] Guangyu Mu, Nan Gao, Yuhan Wang, Li Dai, "A Stock Price Prediction Model Based on Investor Sentiment and Optimized Deep Learning", IEEE Access, Vol. 11, Jun 2023
[10] David Olumuyiwa Sunday, "Application of Long Short-Term Memory (LSTM) in Stock Price Prediction", International Journal of Development and Economic Sustainability, Vol. 12, Jun 2024
[11] Wuzhida Bao, Yuting Cao, Yin Yang, Hangjun Che, Junjian Huang, Shiping Wen, "Data-driven stock forecasting models based on neural networks: A review", Information Fusion, Elsevier, Vol. 112, Dec 2024
[12] Jaimin Shah, Darsh Vaidya, Manan Shah, "A comprehensive review on multiple hybrid deep learning approaches for stock prediction", Elsevier, Vol. 16, Nov 2022
[13] Kenniy Olorunnimbe, Herna Viktor, "Deep learning in the stock market—a systematic survey of practice, backtesting, and applications", Artificial Intelligence Review, Springer, Vol. 56, Jun 2022
[14] Audeliano Wolian Li, Guilherme Sousa Bastos, "Stock Market Forecasting Using Deep Learning and Technical Analysis: A Systematic Review", IEEE Access, Vol. 8, Oct 2020
[15] Somenath Mukherjee, Bikash Sadhukhan, Nairita Sarkar, Debajyoti Roy, Soumil De, "Stock market prediction using deep learning algorithms", - CAAI Transactions on Intelligence Technology, Wiley, Feb 2022
[16] Khorshed Alam, Mahbubul Haq Bhuiyan, InjamamUl Haque, Md Fahad Monir, Tarem Ahmed, "Enhancing Stock Market Prediction: A Robust LSTM-DNN Model Analysis on 26 Real-Life Datasets", IEEE Access, Vol. 12, Jul 2024
[17] M. Nabipour, P. Nayyeri, H. Jabani, A. Mosavi, E. Salwana, Shahab S, "Deep Learning for Stock Market Prediction", Entropy, MDPI, Dec 2020
[18] Yingying Yan, Daguang Yang, "A Stock Trend Forecast Algorithm Based on Deep Neural Networks", Scientific Programming, Hindawi, Jul 2021
[19] Keerthi Sagiraju, Prof. Shashi Mogalla, "Deployment of Deep Reinforcement Learning and Market Sentiment Aware Strategies in Automated Stock Market Prediction", International Journal of Engineering Trends and Technology, Vol. 70, Jan 2022
[20] Omid Boroumand, "Developing a Stock Market Prediction Model by Deep Learning Algorithms", Journal of Information Technology Management, Vol. 16, Jan 2024
[21] Pinyu Chen, Zois Boukouvalas, Roberto Corizzo, "A deep fusion model for stock market prediction with news headlines and time series data", Neural Computing and Applications, Springer, Aug 2024
[22] Warda M. Shaban, Eman Ashraf, Ahmed Elsaid Slama, "SMP-DL: a novel stock market prediction approach based on deep learning for effective trend forecasting", Neural Computing and Applications, Springer, Vol. 36, Jan 2024

[23] Riya Kalra, Tinku Singh, Suryanshi Mishra, Satakshi, Naveen Kumar, Taehong Kim, Manish Kumar, "An efficient hybrid approach for forecasting real-time stock market indices", Journal of King Saud University - Computer and Information Sciences, Elsevier, Vol. 6, Oct 2024
[24] Dost Muhammad, Iftikhar Ahmed, Khwaja Naveed, Malika Bendechache, "An explainable deep learning approach for stock market trend prediction", Heliyon, Elsevier, Vol. 10, Nov 2024
[25] Xavier Martínez-Barbero, Roberto Cervelló-Royo, Javier Ribal, "Portfolio Optimization with Prediction-Based Return Using Long Short-Term Memory Neural Networks: Testing on Upward and Downward European Markets", Computational Economics, Springer, May 2024
[26] Jingyi Shen, M. Omair Shafq, "Short-term stock market price trend prediction using a comprehensive deep learning system", Journal of Big Data, Springer, Aug 2020
[27] Armin Lawi, Hendra Mesra, Supri Amir, "Implementation of Long Short-Term Memory and Gated Recurrent Units on grouped time-series data to predict stock prices accurately", Journal of Big Data, Springer, Jul 2022
[28] Qi Li, Norshaliza Kamaruddin, Siti Sophiayati Yuhaniz, Hamdan Amer Ali Al-Jaif, "Forecasting stock prices changes using long-short term memory neural network with symbolic genetic programming", Scientific Reports, Jan 2024
[29] Jayaraman Kumarappan, Elakkiya Rajasekar, Subramaniyaswamy Vairavasundaram, Ketan Kotecha, Ambarish Kulkarni, "Federated Learning Enhanced MLP–LSTM Modeling in an Integrated Deep Learning Pipeline for Stock Market Prediction", International Journal of Computational Intelligence Systems, Springer, Oct 2024

[30] Isaac Kof Nti, Adebayo Felix Adekoya and Benjamin Asubam Weyor, "A systematic review of fundamental and technical analysis of stock market predictions", Artificial Intelligence Review, Springer, 2019, Pages 1-51