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ARTICLE

MATHEMATICAL APPROACH TOWARDS RECENT INNOVATION IN COMPUTATION AND ENGINEERING SYSTEM (MATRICS)

AN EFFECTIVE STOCK MARKET DIRECTION PREDICTION MODEL USING WATER WAVE OPTIMIZATION WITH MULTI-KERNEL EXTREME LEARNING MACHINE

Mohan Jeyakarthic[1*], Sachithanantham Punitha[2]
[1]Tamil Virtual Academy, Chennai, Tamil Nadu, INDIA
[2]Dept. of Computer Science, DGGA College for Women, Tamil Nadu, INDIA

ABSTRACT

Presently, forecasting of stock market return is commonly considered as a prediction problem. The intrinsic volatile characteristic of stock market all over the globe makes the forecasting procedure a difficult process. The reduction in predictive error rate would considerably decrease the risks in investment processes. This paper introduces a new hybridization of water wave optimization with multi-kernel extreme learning machine (WWO-MKELM) for stock market return prediction. The presented WWO-MKELM model comprises three major steps namely preprocessing, feature extraction and classification. At first, preprocessing is carried out by the use of exponential smoothing technique. Subsequently, the features will be extracted from the preprocessed dataset. Next, WWO-MKELM based model is employed to predict the stock prices. The presented WWO-MKELM model has the ability to predict whether the stock prices will be raised or reduced in advance. The WWO-MKELM technique is simulated by the use of Apple (APPL) and Facebook (FB) stocks. The attained experimental results defined that the WWO-MKELM model has provided better performance over the compared methods.

KEY WORDS
Stock market, Prediction, Classification, WWO algorithm, Machine learning

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***Corresponding Author**
Email:
jeya_karthic@yahoo.com

INTRODUCTION

In last decades, the effective differences in stock prices cannot be detected in previous days. Random Walk [1], as well as Efficient Market Hypothesis (EMH) revealed that a market would be considered as robust and efficient on the basis of recent information, if it is not feasible to detect the market flow due to the randomness of stock prices, then it is similar to the risks which can be recovered, economical gain cannot be enhanced. The task of stock market price detection is highly complex and it provides a maximum return from increasing measure for risk prediction. Followed by, the Wisdom of Crowd strategy pointed that diverse individuals can provide accurate estimation of information has been recovered appropriately. Still it becomes unknown and it is not applicable to detect the result of stock market; regardless, some of the individuals and organizational shareholders are capable of striking the market to make better profits. An incomplete detection is simplified due to diverse irregularities present and because of the presence of massive parameters that influences the market value per day. Consequently, stock markets are highly vulnerable for differences for prominent for making random conflicts in stock prices.

Various economical as well as statistical professionals have invoked to refer that the stock market prices could be predicted partially. Followed by, a novel economical expert has pointed the mental and behavioral elements of stock-price computation as well as volatility [2]. Followed by, only few professionals have stated the determining patterns would enable the shareholder to accomplish maximum gain from risk-based values. Recently, stock market detection methods are deployed using Machine Learning (ML) as well as Data Mining (DM) methodologies. Some of the related works are defined in the following. Predictive approaches have been applied to forecast the future patterns in stock market operations that offer a method to improve the determining capabilities and predefine efficient market strategy as well as diffusion schemes [3]. ML, besides, which is set of present approaches. Finally, diverse methods are applied to forecast stock prices such as Support Vector Machine (SVM), Deep Neural Network (DNN) [4], Random Forest (RF), naïve bayes (NB), and so on to accomplish the method of predictability with maximum efficiency. Simultaneously, DM methods are highly employed with regular stock data.

Generally, Autoregressive Integrated Moving Average (ARIMA) framework [5] has been applied for finding and identifying differences in time series. In Dai and Zhang, 2013 [6], closing prices were employed for analyzing the firm of 3M that have data from the interval of September 2008-August 2013. Massive methods have been used for detective approaches and applied for forecasting the dimension of stocks on effective day's data sample. It is also capable of predicting the amount for future n days. It is stated that US stock market is partially robust, which denotes technical as well as fundamental analysis cannot be employed and attain higher gain. However, the prolonged predictive model offers best accuracy that had surpassed if the time window is 44 days. Then, SVM has reached optimal accuracy.

In Di, 2014 [7], collection of 3 stocks has been applied with the help of symptoms like RSI, on balance volume, Williams's %R, and so forth. Over these features, highly randomized tree model, as defined by Geurts and Louppe, 2011 [8], for Feature Selection (FS) that is provided to SVM with Radial Basis Function (RBF) for training a method. It is identical which the stock market price values are highly non-static, non-parametric, chaotic and noisy by default that provides in threatening investment. Followed by, the trends of stock market prices are considered as a random task with alterations that is important shortly. It is essential to reveal the latest aspects of upcoming stock price trends should help in limiting the risk. Dealers are extremely a stock in current time periods with the values in future days. Moreover, it is pointed that the exact detection of movements in stock market prices would enhance the profit as well as to limit the loss. Hence, it is essential to deploy a new method that detects the direction of trends in stock prices.

Devi et al., 2015 [9] projected a hybridization of Cuckoo Search (CS) with SVM approaches in which CS method is employed for tuning the SVM parameters. Giacomel et al., 2015 [10] projected a trading agent with the application of Neural Network (NN) ensemble which detects the particle stock when it is minimum or maximum. Boonpeng and Jeatrakul, 2016 [11] applied a one-against all (OAA-NN) and one-against-one neural network (OAO-NN) to classify the purchasing, capturing or selling data and they are compared with the outcomes provided by conventional NN. In Qiu and Song, 2016 [12], an optimized ANN by applying Genetic Algorithm (GA) is used to predict the stock market prices identically.

Alrasheedi and Alghamdi, 2014 [13] used diverse classes of classification methods for SPP in Saudi stock exchange from 2006-2013. Dow Jones dataset has been utilized with 5-fold cross validation method. Milosevic, 2016 [14] presented a ML scheme for investigating the security of future cost for longer period. It is highly applicable in finding exact improvement in organizational measures in last decades. The main aim of applying ML model is to train the previous data that is suitable for predicting the stock price and to search the trends for certain time period. Here, diverse classification approaches are related for SPP. Once the comparison is completed, RF accomplished better results interms of Precision, F-score and recall.

Leung et al., 2014 [15] employed a structural SVM (SSVM) to predict the SSP. Hence, the developed model activates SSVM for learning predictive approach while complicated graph input such as massive edges of nodes. Therefore, results of SPP have positive and negative class labels that represented the enhancement as well as minimization in stock prices. Additionally, it is used under 3-fold cross validation to explore original measure as well as SSVM feature C is set as. Finally, it accomplished the maximum accuracy that has ensured that this model undergoes training with no application of over-fitting. Thus, the working principle of ML approach is highly applicable in detecting the stock prices.

Qiu and Song, 2016 [16] introduced an Artificial Neural Network (ANN) for SPP in Japanese stock exchange. It focuses in identifying the upcoming stock prices. To improve the classification accuracy, ANN is integrated with GA that generates a GA-ANN approach for attaining efficient SPP. In this model, GA is elected to enhance the accuracy of ANN and to eliminate the converging issues from back-propagation (BP) method. Hence, processing analysis is allocated as hybrid GA-ANN that assists to attain a better hit value which has to be higher than earlier model. Guo et al., 2015 [17] Implemented a hybrid approach which combined 2-D Principal Component Analysis (2D) (PCA) and RBF NN for SPP at Shanghai stock market. It has been selected with 36 stock market attributes as input values, in which a sliding window is used for retrieving input data. Besides, 2D-PCA is suitable to limit the dimensions of data and filter of intrinsic parameters. Consequently, RBFNN applies the data processed using 2D-PCA for detecting the upcoming stock price. Therefore, the simulation outcome represented that the applied method performs quite-well than MLP model.

Alkhatib et al., 2013 [18] applied k-Nearest Neighbor (KNN) technique as well as non-linear regression scheme for SPP in major organizations that is listed in Jordanian stock exchange which is applicable for users and suppliers in effective decision making operation. Based on the attained result, kNN approach should be effective and applicable to reach the lower error while forecasting the outcome that is corresponding to actual stock prices. Guo et al., 2014 [19] developed an SPP scheme using PCA, canonical correlation analysis (CCA) and SVM methodologies. First, 2 parameters have been filtered from previous closing cost as well as 39 scientific features retrieved from independent component analysis. As a result, SVM is applied to detect upcoming stock price.

This paper introduces a new hybridization of water wave optimization with multi-kernel extreme learning machine (WWO-MKELM) for stock market return prediction. The presented WWO-MKELM model comprises three major steps namely preprocessing, feature extraction and classification. At first, preprocessing is carried out by the use of exponential smoothing technique. Subsequently, the features will be extracted from the preprocessed dataset. Next, WWO-MKELM based model is employed to forecast the stock prices. The presented WWO-MKELM model has the ability to predict whether the stock prices will be raised or reduced in advance. The WWO-MKELM technique is simulated by the use of Apple (APPL) and Facebook (FB) stocks. The attained experimental results defined that the WWO-MKELM model has provided better performance over the compared methods.

MATERIALS AND METHODS

The entire task of the projected WWO-MKELM approach is showcased in [Fig. 1]. The presented approach is enclosed with pre-processing, feature extraction, as well as classification. The above mentioned sub processes are defined in the upcoming sections.The entire task of the projected WWO-MKELM approach is showcased in [Fig. 1]. The presented approach is enclosed with pre-processing, feature extraction, as well as classification. The above mentioned subprocesses are defined in the upcoming sections.

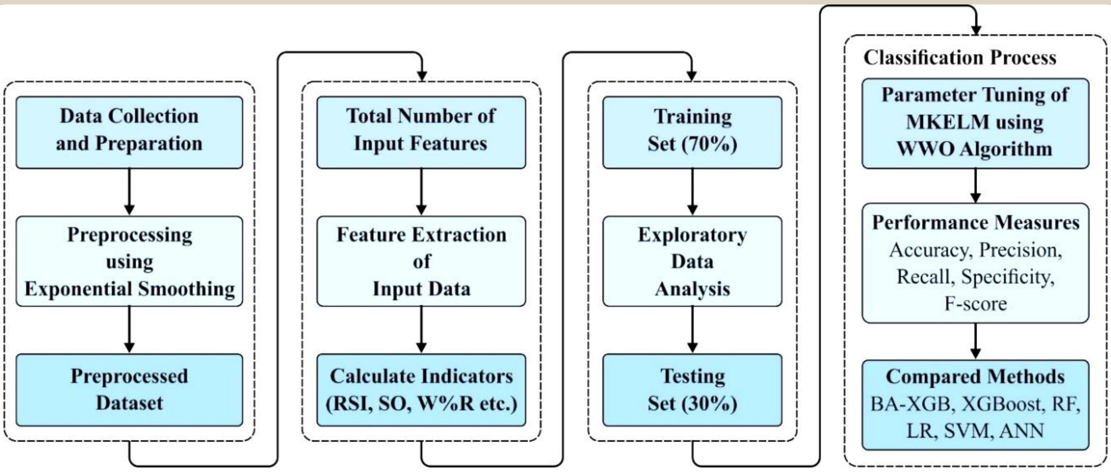

Fig. 1: Block diagram of WWO-MKELM Model.

Preprocessing: The upgraded smoothing offers maximum weights for recent observations and limited as same as existing observation. The statistic sequence of Y is determined in recursive manner using:

$$S_0 = Y_0$$

for $z > 0, S_z = \alpha * Y_z + (1\text{-}\alpha) * S_z\text{-}1$ (1)

where α refers the smoothing factor and $0 < \alpha < 1$. Higher value of α is applicable to reduce the smoothing phase. When $\alpha = 1$, smoothed statistic is same as actual processing. In addition, smoothed statistic S_z is determined rapidly as prominent observations are suitable. Hence, the smoothing assists in avoiding random variations from historical data by activating the model for discovering a prolonged stock price.

The technical detecting is determined from exponentially smoothed time period which is developed as feature matrix. Additionally, target is detected in u^{th} day that determines using the given below:

$$targ_u = sign(close_{u+d} - close_u) \quad (2)$$

where d implies value of days. When the value of $targ_u$ is $+1$, it represents the existence of positive shift in price in advanced d days; while -1 denotes the presence of negative shift after d days, which provides clear definition for corresponding stock price. Additionally, $targ_u$ measures are allocated as labels for uth row in feature matrix.

Feature extraction process: Here, the closing price of stock is considered and collect these metrics in past decades. Hence, input data is described as $(date, price_{closing})$. Therefore, data is composed of some detectors which are determined [20].

Relative strength index (RSI)

In general, a stock is overbought while there is demand enhanced the money. Therefore, it interprets the stock overvalue and reduced price correspondingly. In addition, it is meant as oversold at the time of there is a limitation of price under a positive value. The result is projected due to the panic sold task.

Stochastic oscillator (SO)

SO utilizes the trend of price. Based on this strategy, momentum is changed. It determines the density of closing price which is related to minimum to maximum range over a specific time limit.

Williams percentage range (W%R)

It is named as Williams %R is a secondary momentum predictor, which is similar to SO. It shows the markets closing price level in combination of higher amount for look-back time period. Such value from -100 to 0. When the measure is higher than -20, it is a sell point while it belongs to -80.

Moving average convergence divergence (MACD)

It is described as a momentum predictor which combines 2 moving averages of stock. Primary average is around 26-day Exponential Moving Average (EMA) and then moving average is 12-day EMA.

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Price rate of change (PROC)

It is referred as a scientific predictor which represents the ratio of modification in price between recently fixed price and existing price that is monitored for certain time period.

On balance volume (OBV)

It uses the alteration in quantity to estimate the modification in stock prices. The technical indicator is utilized for finding buying and selling moments of a stock, by considering the aggregating volume: as it encloses the volumes for days when the price is enhanced, and reduce the quantity of the price is limited, and correlated with the existing day price correspondingly.

WWO-MKELM based Classification Model: ELM is a single-hidden layer of feedforward neural network (FF-NN). It defines the input weights as well as biases in random manner and explanatory calculates the resultant weights in spite of tuning regularly. The ELM has incoming weights ω, bias b, hidden nodes L, and output weights α.

An effective ELM is represented in mathematical format as given in the following:

$$H\alpha = T \quad (3)$$

$$H = \begin{bmatrix} h_1(x_1) & \cdots & h_L(x_1) \\ \vdots & \vdots & \vdots \\ h_1(x_n) & & h_L(x_n) \end{bmatrix} \quad (4)$$

$$= \begin{bmatrix} G_1(\omega_{111}x + b_1) & \cdots & G_L(\omega_{1L} \cdot x_1 + b_L) \\ \vdots & \vdots & \vdots \\ G_1(\omega_{n1} \cdot x_n + b_1) & & G_L(\omega_{n1} \cdot x_n + b_L) \end{bmatrix}$$

where Himplies the hidden layer output matrix, α represents the final output weight matrix, Tdefines the matrix of target output, and $G_L$signifies the activation function applied in all hidden neurons. The final weight $(\alpha)$is attained by resolving the Eq. (3) under the application of Moore-Penrose normalized inverse of H:

$$\alpha = H^{\dagger}T \quad (5)$$

In order to enhance the ability of ELM, it reformed into (5) as:

$$\alpha = H^T\left(\frac{1}{C} + HH^T\right)^{-1} T \quad (6)$$

where C defines the regularization variable, and resultant function of ELM is provided in the following:

$$y = h(x)\alpha = h(x)H^T\left(\frac{1}{C} + HH^T\right)^{-1} T \quad (7)$$

The ELM function is enhanced under the application of sum of diverse activation functions and kernel functions.

A KELM is defined as an ELM with kernel functions from hidden layer nodes. A kernel function has been applied for data matching for high-dimensional feature space and transforms a nonlinear into linear issues. The kernel function is described under the application of Mercer's constraints for unstable feature mapping $h(x)$:

$$k(x_i, x_j) = h(x_i) \cdot h(x_j) \quad (8)$$

$$K = HH^T$$

where $k(x_i, x_j)$ defines the kernel function as well as K describes the kernel matrix. The resultant function of KELM is attained by replacing Eq. (8) into Eq. (7):

$$y = h(x)\alpha = \begin{bmatrix} k(x, x_1) \\ \vdots \\ k(x, x_n) \end{bmatrix} \left(\frac{1}{C} + K\right)^{-1} T \quad (9)$$

The normalization function as well as learning capability of KELM is based on the class of kernel function employed in hidden layer nodes. It is also composed of massive kernel functions that are classified as 2 major classes such as Global and Local. Initially, Global kernel functions like linear and polynomial kernel

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functions contains massive generalization function; however, a vulnerable for learning ability and influenced by instances away from one another whereas local kernel functions like Gaussian and wavelet kernel functions are composed of robust learning capability, hence, the lower normalization function is influenced by samples nearby one another.

A linear integration of diverse kernel functions offers a multi-kernel function which meets the Mercer's conditions. An MKELM is attained by applying multi-kernel function from hidden nodes of KELM. It is present with a managing attribute (λ) among diverse kernels are represented as given below:

$$k(x_i, x_j) = \sum_{n=1}^{N} \lambda_n k_n(x_i, x_j) \qquad (10)$$

Here, it has been examined with the efficiency of MKELM for categorization as well as position of error in under the application of 2 kernel functions like, wavelet and polynomial:

$$k(x_i, x_j) = \lambda k_1(x_i, x_j) + (1 - \lambda)k_2(x_i, x_j) \qquad (11)$$

$0 \leq \lambda \leq 1$

where $k_1(x_i, x_j)$ defines the Morlet wavelet kernel function that is provided below:

$$k_1(x_i, x_j) = \cos\left(1.75\left(\frac{x_i - x_j}{\gamma}\right)\right) e^{-\frac{(x_i - x_j)^2}{2\gamma^2}} \qquad (12)$$

and $k_2(x_i, x_j)$ refers the polynomial kernel function that is represented as:

$$k_2(x_i, x_j) = (1 + x_i \cdot x_j)^d \qquad (13)$$

Where, γ and d implies the dilation of wavelet kernel as well as polynomial degree, correspondingly. Such attributes should be normalized for MKELM by WWO algorithm to accomplish best function.

WWO algorithm is developed from shallow water wave techniques for solving optimization problems [21].

RESULTS

Dataset used: For experimentation, data from 2 firms such as Facebook (FB) and Apple (APPL) as well as other accessible data has been applied. These organizations are tested in random manner, without adverse considerations from the background or financial impact which offered in public. It is emphasized that the diversity of these firms are chosen for analyzing stock prices which is important to ensure the efficiency of this model. The actual values are obtained from data that has been attained from entry of data, closing price, volume, and so forth. From the actual format, size of parallel data to stocks of diverse organizations are varied from 10 kB to700 kB, under the application of rows which corresponds to closing prices and changes from 1180 and 10,700 [20].

Results Analysis: [Table 1] shows the results analysis of the WWO-MKELM model interms of distinct methods under different trading window sizes.

Table 1: Results of classification using WWO-MKELM

Company Name	Trading Window	Accuracy	Recall	Precision	Specificity	F-Score
AAPL Stock	3	67.90	74.00	70.00	60.00	70.00
	5	75.76	82.00	76.00	59.00	77.00
	10	80.15	85.00	85.00	79.00	84.00
	15	84.90	87.00	86.00	80.00	86.00
	30	87.83	90.00	89.00	83.00	89.00
	60	92.48	96.00	94.00	89.00	95.00
	90	96.23	98.00	96.00	93.00	96.00
FB Stock	3	69.44	76.00	70.00	66.00	75.00
	5	76.40	88.00	72.00	64.00	80.00

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	10	83.50	94.00	84.00	72.00	87.00
	15	88.22	93.00	93.00	84.00	92.00
	30	90.47	98.00	95.00	85.00	96.00
	60	90.27	99.00	92.00	63.00	97.00
	90	97.14	99.00	99.00	75.00	99.00

DISCUSSION

A comparative analysis of the WWO-MKELM model with existing models [20] interms of accuracy is made, and the outcome is tabulated in [Table 2] and [Fig. 2]. The table values defined that the LR and SVM models have demonstrated ineffective prediction results, which has resulted to a minimum accuracy of 55% and 58%.

Table 2: Comparisons of Proposed with Existing Methods

Methods	Accuracy
WWO-MKELM	97.14
BA-XGB	96.42
XGBOOST	83.00
RF	92.00
LR	55.00
SVM	58.00
ANN	72.00

On the other side, the ANN model leads to a slightly higher accuracy value of 72%. Along with that, the XGBoost model has exhibited a moderate classifier accuracy of 83%. In line with that, the RF model has demonstrated somewhat higher accuracy of 92%. Furthermore, the competitive predictive accuracy of 96.42% has been achieved by the BA-XGB model whereas the maximum accuracy of 97.14% has been obtained by the presented WWO-MKELM model.

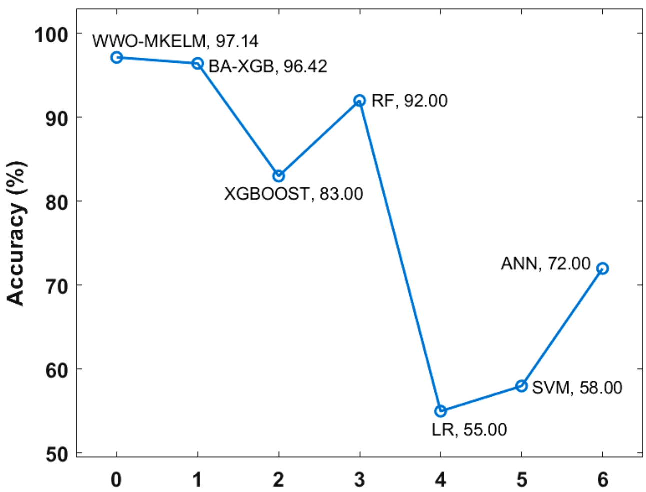

Fig. 2: Accuracy analysis ofWWO-MKELM model with existing models

CONCLUSION

This paper has developed a new WWO-MKELM model for stock market return prediction. The presented WWO-MKELM model initially performs preprocessing using exponential smoothing technique. Next, the features will be extracted from the preprocessed dataset. Afterwards, WWO-MKELM based model is employed to detect the stock prices. The presented WWO-MKELM model has the ability to predict whether the stock prices will be raised or reduced in advance. The WWO-MKELM technique is simulated by the use of APPL and FB stocks. The simulation results attained that the WWO-MKELM model has showcased effective outcome with the maximum accuracy of 97.14%. Then, the function of WWO-MKELM model has been increased by the use of outlier detection techniques.

CONFLICT OF INTEREST

There is no conflict of interest.

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None

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