Journal of Theoretical and Applied Information Technology
15th May 2023. Vol.101. No 9

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

AN INTELLIGENT SOFT COMPUTING FRAMEWORK FOR FORECASTING STOCK MOVEMENT DIRECTION IN INTERNATIONAL STOCK MARKETS

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ABSTRACT

Every investment in the stock market aims to maximize profit and minimize risk, which is the key to a thriving economy. In today's economy, stock market data prediction and analysis play a crucial role. The non-linear nature of stock market data makes it challenging to analyze. Several studies have been published recently that propose using soft computing techniques to predict stock trades. Predicting consistent outperformance in the stock market has always been a challenge because of the interaction of many factors. In this study, we present an intelligent soft computing framework for forecasting stock movement direction based on efficient feature optimization and hybrid detection technique. First, we introduce an improved Ebola optimization (IEO) algorithm for data preprocessing which filters the noise and irregular patterns from the gathered data. As part of the recursive feature selection, the selection of underlying model hyperparameters is critical. A Chaotic Farmland Fertility (CFF)algorithm is suggested for the feature optimization process which effectively improves the convergence speed for high-dimensional optimization problems. Next, a hybrid Spiking-Quantum Neural Network (hybrid SQNN) framework is present to forecast stock movement direction which ensures avoidance of false prediction rates. Following that, we validate our framework using international benchmark datasetslike the Australian stock market, U.S. stock market and China's wind economy. The simulations have demonstrated the effectiveness of our framework over existing frameworks in terms of error and quality metrics.

Keywords: *Soft Computing, International Stock Markets, Data Preprocessing, Feature Optimization, Stock Movement Forecasting*

1. INTRODUCTION

Many investors in the current world dislike keeping money in savings accounts. To obtain the best returns, they are interested in making investments in global markets [1]. Building a stronger financial investment is easy and quick when done through global market investing. The battle between computerized and traditional investors is heating up as they develop cutting-edge research, models, and tactics to forecast asset prices. The global economic markets [2][3] are becoming more systematic. The quantity of knowledge is available and the computers' insatiable greedy for analysis are remarkable. A financial revolution is currently being led by data, technology, and mathematics. In financial trading, pattern recognition and market forecasting are frequently employed to assess the futures market and commodities market [4]. The primary goal of financial forecasting is to identify significant variations or returns from trading. There are many ways to create models for variables influencing trading markets using historical data [5][6], including applying current systems, fusing economic theory with mathematical and statistical hypotheses, and materializing artificial intelligence technologies. Additionally, a link between futures and futures fundamental currency trading was established, and primary rates are mostly impacted

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

by futures prices. Additionally, the findings of the trial show the amazing relationship between telesales and the communication of pricing information. The stock prices of international stock markets fell sharply as a result of both events, which started in the US and quickly spread to other nations [7]. The crisis amply show that financial events occurring in one market are not confined to that market alone, but also can spread across national boundaries. In order to analyze the South Korean stock market's one day return stock forecast, we merged the data from the two markets and used the South Korean and US stock markets [8]. The markets combination is particularly intriguing, because the long-term upward trend is used by US markets while the South Korean markets don't[9]. Therefore, there may be connections between them that go beyond the continuous global economic boom.

Financial markets and economic growth are positively correlated, according to theoretical and empirical research. Giving financial markets' importance of predicting financial returns plays a key role for making decisions in investments. [10]. Due to complexity, dynamism and volatility, stock markets are differentiated. Macroeconomic forces, global events, and behavioural markets among others all have an impact on stock market movements [11]. Consequently, predicting stock returns can be difficult. How successful investments are in stock markets is significantly impacted by how predictable stock movement is. If market direction is correctly forecasted by a forecasting model, decrease of uncertainty and investment risk can be seen. This enables regulators, policymakers generate the necessary markets and put absolute measures and boost stock market investment flows. According to the study's conclusions, stock market forecasting does have a predictable component inSwitzerland, Sweden, Netherlands, Norway, Spain, Italy, Ireland, Iceland, Germany, France and Austria, even though there is evidence of volatility persistence and non-normality in returns series for the studied nations [12].

Nowadays, predicting future financial market patterns is more impressive, especially in light of the current global financial crisis [13]–[20]. An intelligent multi-agent technique for predicting stock price is BNNMAS (bat-neural network multi-agent system) [13]. Over an eight-year period, it makes quarterly predictions for the DAX stock price using a four-layer multi-agent system. An Artificial Neural Network (ANN) was used to forecast the Japanese Nikkei 225 index's return [14]. The local convergence issue of the BP approach is fixed by using global search methods like the GA (Genetic Algorithm) and SA (Simulated Annealing) to increase the ANN's prediction accuracy. To effectively predict stock market indices, a hybridized framework that combines the feature-weighted support vector machine (SVM) [15] and feature-weightedK-nearest neighbour (k-NN) has been developed. To forecast stock market indices for training MLP models, an ACRNN (Artificial Chemical Reaction Neural Network) is utilized [16]. The stock markets' fluctuating efficiency over time is shown by the Multiracial Detruded Fluctuation Analysis (MF-DFA) [17]. The revaluation of stock prices in China during a liberalization event was impacted by risk-sharing and other factors [18]. The reform's firm-specific information is priced into equities more effectively the more liquid the market is, how clear the information is, and how smart traders are.. Using the ModAugNet framework [19] and the LSTM module for overfitting avoidance and prediction, a data augmentation technique is employed to forecast stock market indexes. HyS3 (hybrid supervised semi-supervised model) [20] is created to give movement predictionwith direction using ConKruG (Continuous Kruskal-based graph construction) technique. Individual and institutional investors can greatly improve their trading decisions and market stability with the help of stock market prediction. For dealing with the problem of stock market forecasting, numerous tactics have lately been released. It remains difficult to combine different features and auxiliary data and efficiently extract temporal information and correlations from multivariate time series of market data, even if there is still opportunity for progress in the ability to anticipate the direction of the stock market.

Our contributions: An intelligent soft computing framework is suggested as a future improvement for predicting the direction of stock movement utilizing feature optimization and forecasting. The following is a summary of the key contributions of our suggested framework:

1. For data preprocessing, an Improved Ebola Optimization (IEO) algorithm is employed to filter the noise and irregular patterns from the collected data.
2. The chaotic farmland fertility algorithm (CFF), which significantly improves convergence speed for high-dimensional optimization problems, is introduced for the feature optimization process.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

3. To prevent false prediction rates, a hybrid spiking-quantum neural network (hybrid SQNN) framework is employed to forecast stock movement direction.
4. We used worldwide benchmark datasets, including those from China's wind economy, the Australian stock market, and the U.S. stock market, to validate our system.

The paper's rest is sectioned by: Section 2 has current studies for international stock forecasting. The problems with the existing frameworks for forecasting are discussed in Section 3 along with a new approach for information investigation for stock price trading. Section 4 discusses a proposed approach for international stock forecasting. Section 5 deals with the findings and comparative analysis. Section 6 serves as the paper's conclusion.

2. Related works

Throughout the world, numerous studies on international stock price forecasting employing intelligent soft computing have been conducted in recent years. Table 1 provides a summary of key parts of the literature.

By allowing consumers to visually comprehend the key variables that the stock price prediction model has learned, DeepClue [21] aims to bridge the gap between text-based deep learning algorithms and end users. To evaluate data and extract pertinent prediction elements, deep neural networks' architecture is applied. By analyzing hierarchies over extracted elements and displaying these factors in an interactive, hierarchical visualization interface, they give light on how to effectively communicate the interpreted model to end users. The interpretation separates the predictable from the unpredictable for stock prediction using the intercept model parameters and a risk visualization scheme. The integrated visualization system was then evaluated using two case studies in order to forecast the stock price using online financial news and social media tweets about the company.

The ACFLN [22] is an artificial functional link network built on chemical reaction optimization for stock market forecasting. The efficacy of this strategy was assessed by forecasting the values of five actual stock markets, including the FTSE BSE, DJIA, NASDAQ and TAIEX.

WANFIS in conjunction with a time series prediction model of closing price are used [23]. The fusion forecasting model dissects the financial time series data using the DWT. Detailed coefficients and resultant approximation are used as input variables in ANFIS for predicting stocks.

To predict future stock price, the Firefly technique with evolutionary framework-based feature reduction via transformation model for OSELM was utilized [24]. Two factors—statistically based feature reduction and optimized feature reduction—were the emphasis of the feature reduction. While Firefly, GA, and the Firefly algorithm with an evolutionary framework are used to decrease features with the appropriate optimization technique, PCA and FA are assessed for statistically based feature reduction. All feature reduction techniques can reduce features in the hopes of getting a better result, but the recommended Firefly algorithm with evolutionary framework has a very high potential and performs exceptionally well for the OSELM prediction model.

The accuracy of stock market predictions made by machine learning algorithms was examined by the authors of [25] in relation to public and political opinion. The authors also found relationships between several stocks. The writers found that there is little influence of public opinion on a firm. Either sentiment has no impact on a company's stock, or the current methods for sentiment analysis do not offer enough details on the relationship between a company's stock and a sentiment. They discovered that the impact varied between 0% and 3%. Additionally, the sentiment characteristic increased machine learning systems' prediction accuracy by about 2%. Additionally, seven days after a trade is made, it is possible to forecast stock market movements with the highest degree of accuracy.

CNNs with multiple channels used in deep learning allowed for the prediction of stock index fluctuations. The model's performance is improved by tuning CNN's network design. In order to create an ideal model that can effectively learn data patterns, CNN has a number of hyper-parameters that must be adjusted. Concentrate on improving CNN's feature extraction process because it is the most important component of its computational strategy. A method is used to methodically optimize CNN model parameters using genetic algorithms (GA). The CNN-GA model [26] outperformed the ANN model in accuracy, achieving a score of 73.74 percent.

The data set [27] is optimized using a variety of deep learning techniques to produce more accurate results. The TF-IDF model produces a prediction of about 85% using a deep learning architecture. The market patterns are the same for high and low stock prices. High frequency trading algorithms may help the results even more.

For a hybrid GA-XGBoost prediction system, a better feature engineering procedure was proposed [28] that integrates feature set growth, data preparation, and optimal feature set selection using the hybrid GA-XGBoost algorithm. It is possible to verify the effectiveness of the feature engineering process in predicting the trend of stock prices by comparing the created feature sets to the original dataset. Additionally, prediction performance can be enhanced to outperform benchmark models. The large increase in accuracy is due to the addition of 67 technical indicators to the original historical stock price data. The GA-XGBoost technique is used in this work to build a minimal optimal feature set that can achieve the necessary performance with significantly less features.

The graph-structured link between enterprises is included into time-series forecasting tasks using VAE-GCN-LSTM [29]. For determining a more meaningful distance between businesses, a Variation Auto Encoder (VAE) learned the lower-dimensional latent features of the main variables of the enterprises. The development of the graph network benefited from this. a hybrid deep neural network (GCN-LSTM) that combines a long-short term memory network with a graph convolutional network to simulate both the interactions between stocks that are arranged in a graph and the changes in stock price over time. Within the VAE-GCN-LSTM modelling paradigm, more real-world time-series applications with potential spatial dependence should be investigated.

Ahybrid deep neural network architecture (IKN-ConvLSTM) [30] was used to make a multisource information-fusion stock price prediction. It is used to combine information about stocks from six different sources. The Ghana Stock Exchange's stock information was examined using IKN-ConvLSTM (GSE). The analysis revealed that the merged dataset outperformed the separate dataset in terms of prediction.

Table 1 Summary of Research Gaps

Ref.	Methodology	Technique	Improvement	Remarks
[21]	Text-based deep stock prediction	DeepClue	Prediction accuracy	Don't consider the nonlinear nature of financial time series data
[22]	Prediction of stock market index	ACFLN	MAPE, ARV, POCID	Not suitable for nonlinear modeling capability
[23]	Stock market prediction	WANFIS	MAPE, R^2, accuracy	Higher fault tolerance capability
[24]	Stock market prediction	OSELM	Prediction accuracy	Functional expansion increases the number of dimensions
[25]	Stock prediction using public, political situation	SMO	accuracy	Quite noisy, changing, not linear, complicated, and not measurable
[26]	Stock market prediction	CNN-GA	Prediction accuracy	Not give good results for a nonlinear time series
[27]	Stock market prediction	EDLF-DP	Prediction accuracy	Lack of solving computational and dynamic complexity
[28]	Stock price prediction	GA-XGBoost	Prediction accuracy	Need more number of hidden layers
[29]	Stock market prediction	GCN-LSTM	Accuracy, F-Score, Recall, Precision	High computational cost caused by high dimensionality
[30]	Stock market prediction	IKN-ConvLSTM	Accuracy, F-Score, Recall	Data's ubiquitousness makes effective information fusion

3. PROBLEM METHODOLOGY AND SYSTEM DESIGN

3.1 Problem methodology

For stock price forecasting, an LSTM (Long-Short Term Memory) and IPSO (Improved Particle Swarm Optimization) hybrid model is used. To avoid premature convergence to a local optimum, an adaptive mutation factor was used as a parameter for model optimization. For optimizing the hyperparameters of the LSTM after a nonlinear approach using the IPSO model is then used to increase the inertia weight of particle swarm optimization [31].Sentiment analysis is used to transform unstructured textual documents into daily sentiment indexes. Eastmoney and Sina Finance are two popular financial websites chosen as test platforms to collect a corpus of financial

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

evaluation data. SSE 50 Index, China's most significant index, is then predicted using SVM using a realistic rolling window approach and fivefold cross validation [32]. As a result of the addition of emotion variables, accuracy has increased by 18.6%, reaching 89.93%. Due to the influence of economic crises, however, prices on the global market are highly volatile. Consequently, low-risk price judgments by future prediction and comparison lead traders. Forecasting stock market indices is an enticing topic. An appropriate analysis of such a topic will assist investors, traders, and policymakers in the attractive stock markets with significant insights.

In a short amount of time, the prices of instruments on the international stock market change a lot. There is a high risk because there are changes that can't be predicted. If you know what causes prices to change, you can predict how prices will change in the future. In a bullish situation, the main variable of concern, geopolitical price risk, shows significant results for both securities. Because the stock market is so volatile in stock prediction, it's important to know how to evaluate the role of outside factors. To predict the stock market by looking at information from social media and financial news which changes how investors act, Machine Learning is used. Also, the international stock market's global exchange rate and global interest rate move in the same direction. Because of uncertainty, the usual ways of making predictions can't be used to make predictions about the global market. The returns on these financial instruments on the global market are different. Risk can be reduced by figuring out what the future looks like and how it will behave. Most of the time, the statistical methods have been used to talk about the results. They are time series analysis, correlation analysis and descriptive statistical techniques. These models were used to build the model and figure out what would predict on the market in the future. But because the stock market isn't always the same and has a lot of moving parts, it's hard to predict the stock price accurately. To overcome above gathered research gaps, we introducean intelligent soft computing framework for forecasting stock movement direction. The main aim of our proposed framework is summarized as follows:

1. We examine how price shocks and global cases affect the stock markets.
2. Analysts improve managerial learning from stock prices by increasing price movement
3. To introduce optimization algorithm for feature optimization which reduces data dimensionality issues to select best and optimal features
4. Results confirm proposed soft computing framework is effective for volatility of stock price data.

3.2 System model of proposed intelligent soft computing framework

The system design of proposed intelligent soft computing framework is shown in Fig. 1, which used for the forecasting stock movement direction. In this proposed framework, we first use IEO algorithm for data preprocessing which filters the noise and irregular patterns from the raw data. Then, we applied CFF algorithm for feature optimization which improves the convergence speed for high-dimensional optimization problems. Next, a hybrid SQNN framework is presentedfor forecast stock movement direction which ensures avoidance of false prediction rates.Finally, we proved the effectiveness of our proposed hybrid SQNN framework using the standard assessment metrics such as error metrics (correlation coefficient (R), MAPE (mean absolute percentage error), root mean square error (RMSE)), quality metrics (F-measure, Recall, precision and accuracy).

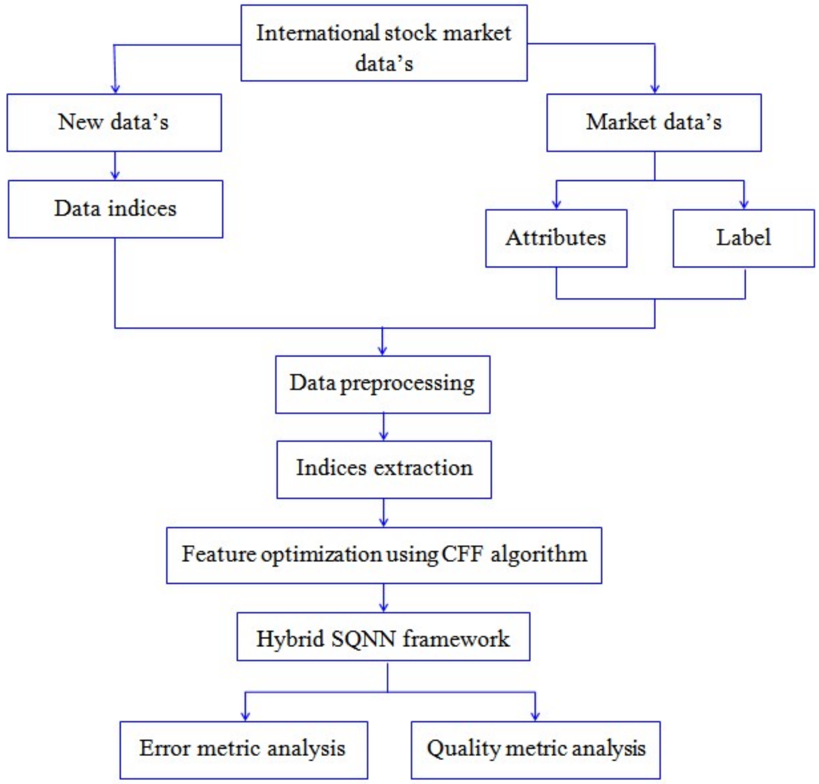

Figure. 1 System design of our proposed framework

4. PROPOSED METHODOLOGY

We describe the detailed working process of proposed intelligent soft computing framework for forecasting stock movement direction in this section. The proposed framework is consists set of process such as (1) data preprocessing (2) feature optimization and (3) stock movement direction forecasting.

4.1 Data preprocessing

Data cleaning is the process of eliminating or changing data that is inaccurate, lacking, unnecessary, duplicated, or formatted incorrectly in order to prepare it for analysis. It is more complicated than just rearranging certain rows or deleting data to create room for fresh information. In fact, we present an Improved Ebola optimization (IEO) technique that removes noise and erratic patterns from the collected data during data pre-processing. Ebola is one of the most lethal and contagious viruses that spreads rapidly and has a substantial effect on the population. The Ebola virus (EboV) causes a severe viral hemorrhagic fever in addition to other symptoms such as nausea, anorexia, stomach pain, headache, myalgia, and sore throat. It spreads through contact with an infected individual. Extensive use of mathematical and network models has been made in the monitoring and early prevention of this terrible disease. The temporal route length indicates the rate at which an EboV can travel from an infected user to another user on a network. EboV transmits more rapidly as the temporal path length decreases. It represents the average temporal distance between every pair of nodes.

$$l = \frac{1}{n(n-1)} \sum_{ji} D_{ji} \tag{1}$$

Where,the length of the temporal shortest path from node j to node I are denoted by D_{ji}. The collection of nodes are denoted by $n = \{1, 2, \ldots, n\}$.

This section describes how the infection rate β which is the value of the crucial parameter determined. This model is more straightforward than our "numerical spread" model since data are readily available and the differential equation system model is solvable. Here are the specifics of the simplified model:

$$\frac{dt}{ds} = -\beta t \frac{I}{n} \tag{2}$$

$$\frac{dt}{ds} = \beta t \frac{I}{n} - \sigma e \tag{3}$$

Compute the time-varying graph for temporal global efficiency by:

$$l = \frac{1}{n(n-1)} \sum_{ji} \frac{1}{D_{ji}} \quad (4)$$

It will assist the authorities in isolating the region and prohibiting travel there. In the proposed approach, the Temporal Correlation Coefficient (TCC) is employed to evaluate the likelihood that clusters would form. It is determined by:

$$tcc = \frac{1}{n} \sum_{j} c_j = \frac{1}{n} \sum_{j} \frac{1}{m-1} \sum_{m=1}^{m-1} c_j (s_m, s_{m+1}) \quad (5)$$

Where, the neighbourhood of infected user j's topological overlap $c_j(s_m, s_{m+1})$ in the time period $[s_m, s_{m+1}]$ is given by:

$$c_j(s_m, s_{m+1}) = \frac{\sum_i b_{ji}(s_m) b_{ji}(s_m+1)}{\sqrt{\left[\sum_i b_{ji}(s_m)\right]\left[b_{ji}(s_m+1)\right]}} \quad (6)$$

The first parameters ((β, γ and σvalues are known), the differential equation system model can be solved numerically. To ascertain the value of β, the grid search technique is used. The algorithm's main goal is achieved by the given function:

$$Min_{\beta} \sum_{j=1}^{N} (F_j - D_j)^2 \quad (7)$$

A very helpful indicator for figuring out how much each infected user is contributing to the outbreak is the temporal between's centrality. A user who is unwell and has a big number of neighbours in close proximity will hasten the spread of the disease. TCB (Temporal Between's Centrality) is the fraction of the temporal shortest path that travels through node j.

$$tc_j^A = \sum_{i \in V} \sum_{K \in V, K \neq i} \frac{\sigma_{iK}(j)}{\sigma_{iK}} \quad (8)$$

Where σ_{iK} indicates how many temporal shortest routes pass via an infected user j, $\sigma_{iK}(j)$ is the number of these temporal shortest routes connecting users j and K. Even when they are not in direct contact with the patient themselves, users occasionally know another user who had direct contact with an Ebola-infected patient. Each user's proximity centrality expresses how close they are to other users, infected or not. It can be determined using the average temporal shortest path length between users j and i

$$tc_j^c = \frac{n-1}{\sum_i D_{ji}} \quad (9)$$

Where user i from from user jhas the length D_{ji} of the temporal shortest path.Algorithm 1 describes the working function of data pre-processing using IEO algorithm.
The operation of the IEO algorithm's data pre-processing is described in Algorithm 1.

Algorithm 1 Data preprocessing using IEO

Input: Data related to different Ebola cases
Output: Ebola users database

1. Initialize the random population
2. Average temporal distance through all node pairs $l = \frac{1}{n(n-1)} \sum_{ji} D_{ji}$
3. If i=0, j=1
4. **While Do**
5. Identify the cluster formation probability $tcc = \frac{1}{n} \sum_{j} c_j = \frac{1}{n} \sum_{j} \frac{1}{m-1} \sum_{m=1}^{m-1} c_j (s_m, s_{m+1})$
6 Define objective function $Min_{\beta} \sum_{j=1}^{N} (F_j - D_j)^2$
7. Discard the record
8. Determine the mean duration of the temporal shortest path from users to user i

$$tc_j^c = \frac{n-1}{\sum_i D_{ji}}$$

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

9. Add the new user
10. **End if**
11. End

4.2 Feature optimization

Generally feature selection is part of the pipeline necessary to explore and prepare your dataset for some classification algorithm. Sometimes depending on the data set, data type etc dealing with a lot of variables since multivariate data is inherently difficult. Principal components analysis can be used to compress a large number of associated variables into a smaller set of composite variables, whereas factor analysis is a collection of approaches for revealing the latent structure underlying a set of variables. The recursive feature selection includes the selection of critical model hyperparameters. A Chaotic Farmland Fertility (CFF) algorithm is suggested for the feature optimization process which effectively improves the convergence speed for high-dimensional optimization problems.

A metaheuristic optimization method is Farmland Fertility Algorithm that mimics the natural process of Farmland Fertility (FF). It divides the farmland into various groups according on the quality of the soil. In order to effectively optimize each part, both internal and external forms of memory are used. Farmers also have a sufficient understanding of the number of sections on their farmland and the corresponding soil quality of each sector. The type and quantity of elements used to change and improve the soil in each area of agriculture are decided by the farmers. A collection of memory units is also situated next to each section of farmland. Local memory is the name of the memory quality that stores the best characteristics of soil. Only the top answers from prior visits to each section are saved in the local memory. Using a network of memories known as the global memory, the ideal value of soil quality is recorded in each area of farmland. The global memory contains the best solutions that have been found thus far across all visits for all sections. To construct the initial population, random numbers are generated between the higher and lower borders. All feasible solutions ought to materialize at this point. Currently, the number of farming parts and the corresponding solutions define the starting population size. The formula is used to determine the initial population size.

$$n = K * N \tag{10}$$

Where, K computes the number of parts for the optimization problem, n is the population size. The entire search space is consequently split into (K) sections, each of which has a predetermined number of solutions. N is the total number of possible solutions for each farmland section. The following is how the search space's random population is created:

$$Y_{ji} = l_i + rand(0,1) \times (u_i - l_i) \tag{11}$$

The design variable (Y)'s lower and upper bounds are shown here as and, respectively l_i and u_i .FFO takes its cues from how farmers assess the Soil Quality (SQ) of each plot of farmland.Differences in SQ are mostly brought on by the composition and addition of specific chemicals.As a result, farmers use unique compounds to improve SQ in their agricultural areas.Actually, adding these materials to the soil has the potential to improve or deteriorate SQ.The best solutions for all sections are maintained in the global memory, while the best solutions for each portion are kept in the associated regional memory in multiples. According to (19) and (20), in that order, the number of solutions in the universal memory m_{univ} and the number of solutions in the regional memory (m) Reg

$$m_{reg} = round(s \cdot n),\ 0.1 < s < 1 \tag{12}$$

$$m_{univ} = round(s \cdot n_{pop}),\ 0.1 < s < 1 \tag{13}$$

These memories are implanted with solutions based on their suitability and appropriateness. The best and worst parts were identified when the update of both memories was completed at this stage. The updating of memories is followed at this point by the classification of the best and worst parts. The quality of solutions for each farmland section can be mathematically represented as followers.

$$fit\_section_t = mean(Allfit(y_{ij}) in\ section_t) \tag{14}$$

In order to improve the quality of the solutions in each part, all possible solutions are integrated with the best ones rather than being limited by the local memory or at this stage, as indicated in

$$G = \begin{cases} Y_{new} = Y_{ji} + \omega_1 \cdot (Y_{ji} - finest_{univ}(a)),\ \forall\ P > rand \\ Y_{new} = Y_{ji} + rand(Y_{ji} - finest_{reg}(a)),\ \forall\ P \le rand \end{cases} \tag{15}$$

Where Q represents an FFO parameter that is originally set between 0 and 1 and designates the number of solutions that are incorporated with $finest_{univ}$. And 1 represents a parameter of the FFO that is initially modified and gradually reduced as a result of multiplying by a factor r_v based on the algorithm's repetition, as mentioned in

$$\omega_1 = \omega_1 \cdot r_v,\ 0 < r_v < 1 \quad (16)$$

Levy flights was used as a modified version of the random walk method. This random procedure entails performing a string of subsequent random steps. However, exploitation and exploration greatly benefit from randomness. It is possible to express the changed equations as followers.

$$g = \alpha \times levy(n_{\text{var}}) \quad (17)$$

$$g = \beta \times levy(n_{\text{var}}) \quad (18)$$

Levy flights are used to improve algorithm's global and search capacities during the exploitation and exploration phases, respectively. This is how the Levy flight can be computed.

$$levy(n_{\text{var}}) = 0.01 \times \frac{RR_1 \times \delta}{|RR_2|^{1/\beta}} \quad (19)$$

Where RR_1 and RR_2 are two evenly spaced random numbers between [0, 1]. The feature optimization using the in algorithm 2 showing CFF algorithm.

Algorithm 2 Feature optimization using CFF algorithm

Input: N and K parameters

Output: ω_1 final value

1. Initialize the random population
2. Create the search space's random population as follows: $Y_{ji} = l_i + rand(0,1) \times (u_i - l_i)$
3. If I >0
4. **While fit_sec Do**
5. The quality of solutions can be represented mathematically as followers
$$fit\_section_t = mean(Allfit(y_{ij})in\,section_t)$$
6. Rely the factor r_v on algorithmrepetition is stated in
$\omega_1 = \omega_1 \cdot r_v,\ 0 < r_v < 1$
7. Else
8. Define Levy flight rule $levy(n_{\text{var}}) = 0.01 \times \frac{RR_1 \times \delta}{|RR_2|^{1/\beta}}$ (
9. Update the final values
10. End

4.3 Stock movement direction forecasting

The most exciting and difficult task for academics, data scientists, and econometricians has continued to be anticipating the stock market index and its direction because of its prediction. Despite the fact that many studies have been conducted to predict stock price indices using various econometric models, there are few studies on the prediction of its direction movement. However, this area of research has attracted significant attention in recent years, particularly with the rise of machine and deep learning techniques. For the creation of exact and trustworthy market planning, it is essential to accurately estimate the direction of the movement of the stock price index. This study employs a hybrid spiking-quantum neural network (hybrid SQNN) framework to forecast stock movement direction while reducing the likelihood of inaccurate predictions.

The Spiking Quantum Neural Network (SQNN) model is employed in this study and is based on the Hopfield model that Natschlager and Ruff developed. This model employs a large number of synapses to convert input patterns into time-delayed pulses and output neurons that are intended to act as either spike response model (SRM) neurons or radial basis function (RBF) neurons, respectively. The data encoding technique is based on the best quantum-based encoding approach described by Bohte, where attributes are encoded into a large number of firings that are out of phase in time using superimposed out-of-phase Gaussian functions. The input patterns are encoded into out-of-phase pulses using the population's encoding as a base.

Through the use of overlapping Gaussian functions, continuous data can be converted into a train of pulses using this type of encoding. According to hybrid SQNN, the jth neuron recording the variable n computes the Gaussians' centre (Ci) and width (σ) as follows:

$$\mu = I_{Min}^{N} + (2 * j - 3)/2 * (I_{Max}^{N} - I_{Min}^{N})/(m-2), \quad M > 2 \tag{20}$$

$$\sigma = 1/\gamma(I_{Max}^{N} - I_{Min}^{N})/(m-2), \quad 1 \le \gamma \le 2 \tag{21}$$

For an input variable N with a range of n: $[I_{Max}^{N}, I_{Min}^{N}]]$, where I_{Max} and I_{Min} represent the maximum and minimum values that the variable is assuming respectively, and m Gaussian is employed. Following is a description of the RBF neuron model with auxiliary after-spike resetting:

$$\frac{Dv}{Dt} = 0.04V^2 + 5V + 140 - U + I \tag{22}$$

$$\frac{Dv}{Dt} = b(aV - U) \tag{23}$$

$$if\ V \ge 30mV, then \begin{cases} V \leftarrow C \\ U \leftarrow U + D \end{cases} \tag{24}$$

Where neuron's membrane potential is denoted by V, the input current is denoted by I (discussed later in this section), the membrane recovery variable is denoted by U, its decay rate (b=0.015 or 0.05), a is its sensitivity to membrane potential 'u' below a threshold (a = 0.15 or 0.7), The membrane potential's reset value after a spike is (C = 65), the variable's reset value after a spike is (D = 8). The winning output layer neuron is the one that fires first. The weights of the synaptic connections between the neurons in the input and output layers are modified by this learning rule using a temporal version of the Hebbian learning rule.

$$\Delta w_{ji}^{K} = \eta l(\Delta s) = \eta(1-a)E^{-((\Delta s - c)^2/\beta^2} - a \tag{25}$$

where, the interval between a corresponding neuron's firing and pulse's reception is denoted by Δs, the width of the learning curve's positive portion is denoted by β, the location of the learning curve's centre is established by 'c', the amount by which synaptic weights are decreased and increased are denoted by 'a', the rate of variation of the weight of the K-th link between neurons j and I is denoted by Δw_{ji}^{K}, the Hebbian function is denoted by L,the learning rate is denoted by η. The weight and conductance of the synapse can be used to compute the pre-synaptic total current I of a particular neuron as follows:

$$I_j = \sum_{K=1}^{m} h(s)_K \cdot t_{K,j} \tag{26}$$

It is possible to monitor the generation of classical individuals using a binary quantum chromosome, which is represented as a series of pairs of numbers. A general description of a person having Mqbits is as follows:

$$\begin{bmatrix} \alpha_1 & \alpha_2 \cdots & \alpha_M \\ \beta_1 & \beta_2 \cdots & \beta_M \end{bmatrix} \tag{27}$$

Each evolutionary stage updates the qbit of a quantum individual to converge to a maximum probability of 1. The rotation operator is used to calculate the new values α and β and as illustrated below.

$$\begin{bmatrix} \cos(\Delta\theta_j) & -\sin(\Delta\theta_j) \\ \sin(\Delta\theta_j) & \cos(\Delta\theta_j) \end{bmatrix} \begin{bmatrix} \alpha_j \\ \beta_j \end{bmatrix} \tag{28}$$

Rotation matrix can change the values of and since the values of $\Delta\theta_j$ and are defined using a table, increasing the likelihood that the best people will be observed. Additional critical SNN configuration parameters will be represented as numerical genes in the real region of the chromosome. Since the random variable must now be continuous rather than discrete, a representation based on real numbers is necessary. Hypothetical three-factor experiment can help arrange the observations.

$$y_j = \frac{F - (f_{low} + f_{high})/2}{(f_{high} - (f_{low})/2} \tag{29}$$

Finding the primary effects of each element and their interactions, as well as identifying whether of these effects are inconsequential or not, are the goals of this analysis. The following is how the quantum person is expressed:

$$p_j = [h_{j1} = q_{j1}(y), h_{j2} = q_{j2}(y), \ldots. h_{jH} = q_{jH}(y)] \tag{30}$$

Because PDF is used to generate values for the genes of the typical human, the function q_{ji} must be integrable in the domain region where the variables to be optimized can take on value. Workings of the hybrid SQNN framework used to forecast the direction of stock movement are described in algorithm 3.

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Algorithm 3 Stock movement direction forecastusing hybrid SQNNframework

Input: Optimal features from recent data and market data
Output: Forecast results

1. Initiate the Population
2. Evaluate the Neuron values
3. If j=0 and i=1
4. **While Do**
5. Define auxiliary after-spike resetting $\frac{Dv}{Dt}=0.04V^2+5V+140-U+I$
6. Define Hebbian learning rule $\Delta w_{ji}^{K}=\eta l(\Delta s)=\eta(1-a)E^{-((\Delta s-c)^2/\beta^2}-a$
7. Compute α and β using the rotation operator $\begin{bmatrix}\cos(\Delta\theta_j) & -\sin(\Delta\theta_j)\\ \sin(\Delta\theta_j) & \cos(\Delta\theta_j)\end{bmatrix}\begin{bmatrix}\alpha_j\\ \beta_j\end{bmatrix}$
8. Define quantum individual $p_j=[h_{j1}=q_{j1}(y),h_{j2}=q_{j2}(y),....h_{jH}=$
9. Update the quantum values
10. End

.

5. RESULTS AND DISCUSSION

The U.S. stock market, the Australian stock market, and China's wind economy are some examples of common international benchmark datasets that we use in this section to validate and assess our proposed methodology. The proposed stock movement direction forecast framework was developed using Spider simulation environment with the python programming language.The simulation results have demonstrated the effectiveness of our hybrid SQNN framework over existing frameworks in terms of error and quality metrics.

5.1 Data Description

5.1.1 U.S. stock market

If we evaluate the relationships between the firms, the total number of samples falls to 100 from 1000 if we analyze the firms independently. We employ minute-level stock data of 87 businesses from the S&P-100 composite in 2010 to obtain sufficient sample sizes due to the availability of data. The total number of minute observations is 97 890, and using a sliding window, we divided the entire dataset into batches. The sample sizes for the training, validation, and testing sets for a five minute interval are 16384, 2944, and 2944, respectively. The testing phase for data at the minute-level follows the training period by a month. For instance, if testing takes place in February 2010, training data would be from January 2010. Dec. 2010 marks the end of the testing phase. We observe that the months in 2010 span a variety of market conditions, including uptrends (such as March), downtrends (such as August), and mixed conditions (such as June). As a result, minute-level data from 2010 are sufficient for model validation and serve as a good representation of various market scenarios.

5.1.2 Australian stock market (ASM)

The ASM-S&P/ASX200 index, which is based on the 200 largest ASX listed stocks, serves as the industry standard. The market for ASM is established, booming, and profitable. Since 1900, the ASM has produced a yearly average return of more than 13%. The average return on investment is larger than it is in other well-known stock markets like the New York Stock Exchange, NASDAQ, and Tokyo Stock Exchange. The experimental dataset is the 10-year historical daily data from 1 September 2010 to 31 August 2020. All data were obtained from Yahoo! Finance.

5.1.3 China's wind economy

In addition to stock market data, we also plan to use news articles on the SSE 50 Index and its constituent parts to investigate the trend of this significant index in China. The top 50 most liquid and representative blue-chip stocks on the Shanghai Stock Exchange make up the Shanghai Stock Exchange 50 Index (SSE 50 Index). Common time series data include the opening price, closing price, high for the day, low for the day, trading volume expressed in shares, trading volume expressed in RMB, and change in percentage. The wind economic database, which leads the Chinese market for financial information services, is where we get the data on the SSE-50 Index and its 50 constituents. Therefore, over the span of 485 trading days, from June 17, 2014, to June 7, 2016, we employed a web crawler we designed to retrieve all of the postings and documents for the 51 shares from the East money stock forum and Sina. In China, the two forums are well-known for having active, long-standing communities. Each stock has an average of 37855 reviews, with high of 23236 and troughs of 7797. The total number of reviews on Sina and the East

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

money stock forum within the given time is 1930592 after filtering and denoising.

5.2 Comparative analysis for U.S. stock market

We test the effectiveness of our proposed hybrid SQNN structure in this example using data from the U.S. stock market. The state-of-the-art frameworks that are compared with our proposed hybrid SQNN framework in terms of simulation results include Long-Short Term Memory (LSTM), Linear Regression (LR), Fully Connected Neural Network (FCNN), Euclidean distance based ST-Trader (ecldn ST-Trader), industry based ST-Trader (idsty ST-Trader), and VAR ST-Trader (vae ST-Trader) [29]. Table 2 offers the error metrics comparative study of planned and existing stock market forecasting methods for the U.S. stock market dataset.

Table 2 Error analysis for U.S. stock market dataset

Stock forecast frameworks	Error metrics		
	RMSE	MAPE (%)	R^2
LR	158.23	0.2188	0.352
FCNN	123.47	0.1995	0.458
LSTM	114.26	0.201	0.547
ecldn_ST-Trader	98.56	0.1802	0.612
idsty_STTrader	95.23	0.1419	0.754
vae_ST-Trader	90.23	0.1358	0.897
SQNN	87.23	0.1124	0.947

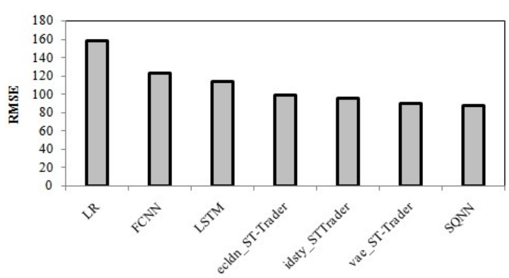

Figure. 2 RMSE analysis for U.S. stock market dataset

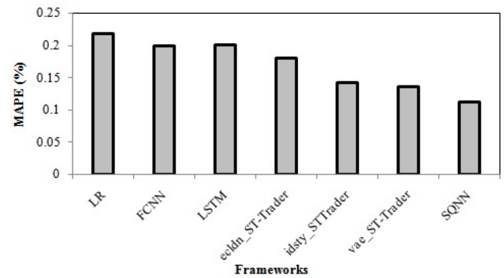

Figure. 3 MAPE analysis for U.S. stock market dataset

Fig. 2 shows the RMSE value of our proposed and existing stock market forecasting frameworks. The figure clearly depicts that the RMSE value of our proposed hybrid SQNN framework is 81.394%, 41.545%, 30.987%, 12.989%, 9.171% and 3.439% efficient than the existing state-of-art LR, FCNN, LSTM, ecldn_ST-Trader, idsty_STTrader and vae_ST-Trader frameworks respectively. MAPE value of proposed and existing stock market forecasting frameworks are shown in Fig. 3. The figure clearly depicts that the MAPE value of our proposed hybrid SQNN framework is 94.662%, 77.491%, 78.826%, 60.32%, 26.246%, and 20.819% efficient than the existing state-of-art LR, FCNN, LSTM, ecldn_ST-Trader, idsty_STTrader and vae_ST-Trader frameworks respectively. The R^2 value of proposed and existing stock market forecasting frameworks is shown in Fig. 4. From the figure, R^2 value of proposed hybrid SQNN framework is 62.83%, 51.64%, 42.29%, 35.38%, 20.38% and 5.28% efficient than the existing state-of-art LR, FCNN, LSTM, ecldn_ST-Trader, idsty_STTrader and vae_ST-Trader frameworks respectively.

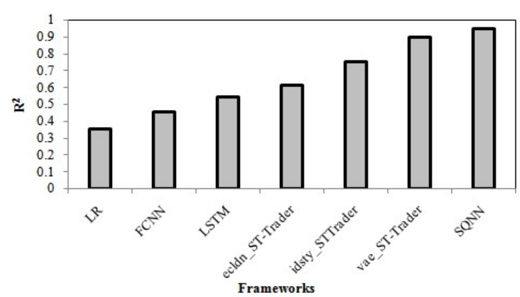

Figure. 4: R2 analysis for U.S. stock market dataset

Journal of Theoretical and Applied Information Technology
15th May 2023. Vol.101. No 9

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 3 Quality analysis for U.S. stock market dataset

Stock forecast frameworks	Quality metrics (%)			
	Accuracy	Precision	Recall	F-measure
LR	41.119	31.319	46.319	35.556
FCNN	49.679	39.879	54.879	44.243
LSTM	55.576	45.776	60.776	50.202
ecldn_ST-Trader	56.033	46.233	61.233	50.663
idsty_STTrader	56.490	46.690	61.690	51.125
vae_ST-Trader	56.700	46.900	61.900	51.336
SQNN	95.2	92.56	93.54	93.861

Table 3 describes the quality metrics comparative analysis of proposed and existing stock market forecasting frameworks for U.S. stock market dataset.The accuracy of existing and proposed stock market forecasting frameworks is shown in Fig. 5. The figure clearly depicts that the accuracy of our proposed hybrid SQNN framework is 56.808%, 47.816%, 41.622%, 41.142%, 40.662% and 40.441% higher than the state-of-art LR, FCNN, LSTM, ecldn_ST-Trader, idsty_STTrader and vae_ST-Trader frameworks respectively.Fig. 6 shows the precision of proposed and existing stock market forecasting frameworks. The figure clearly depicts that the precision of proposed hybrid SQNN framework is 66.164%, 56.916%, 50.545%, 50.051%, 49.557% and 49.330% higher than the existing state-of-art LR, FCNN, LSTM, ecldn_ST-Trader, idsty_STTrader and vae_ST-Trader frameworks.

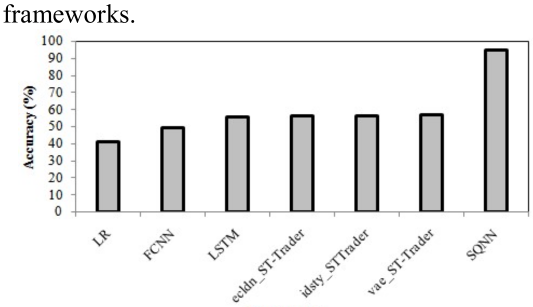

Figure. 5 Accuracy analysis for U.S. stock market dataset

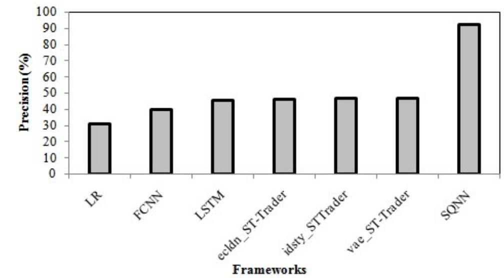

Figure. 6 Precision analysis for U.S. stock market dataset

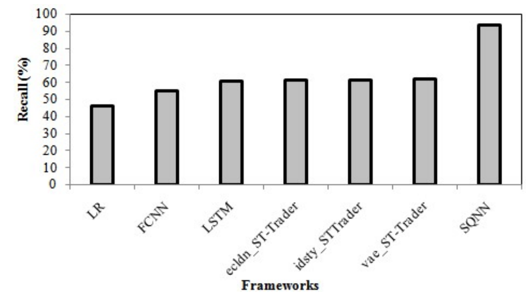

Figure. 7 Recall analysis for U.S. stock market dataset

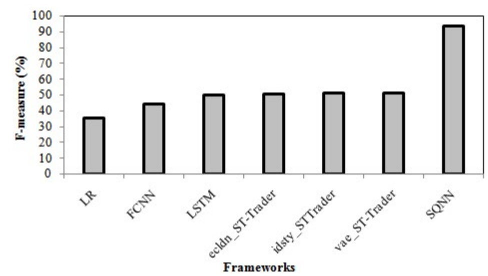

Figure. 8 F-measure analysis for U.S. stock market dataset

Recall of existing and proposed stock market forecasting frameworks is shown in Fig. 7. Figure clearly depicts that the Recall of our proposed hybrid SQNN framework is 50.48%, 41.33%, 35.03%, 34.54%, 34.05% and 33.85% higher than existing state-of-art LR, FCNN, LSTM, ecldn_ST-Trader, idsty_STTrader and vae_ST-Trader frameworks respectively. F-measure of our existing and proposed stock market forecasting frameworks is shown in Fig. 8. The figure clearly depicts that the F-measure of proposed hybrid SQNN framework is 62.119%, 52.86%, 46.52%, 46.02%, 45.53% and 45.31% higher than the existing LR, FCNN, LSTM, ecldn_ST-Trader, idsty_STTrader and vae_ST-Trader frameworks respectively.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 4 Error analysis for Australian stock market (ASM) dataset

Stock forecast frameworks	RMSE Vs look-back days					
	5	10	15	20	30	60
SVR	271.015	166.200	151.808	159.915	172.660	193.430
LSTM	151.139	197.370	205.943	142.105	189.850	176.460
PSO-LSTM	68.890	75.770	88.019	84.722	69.950	106.110
IPSO-LSTM	87.283	71.142	75.407	69.950	68.164	72.520
SQNN	65.230	60.120	59.870	56.230	54.230	56.450
	MAPE Vs look-back days					
	5	10	15	20	30	60
SVR	4.129	2.325	1.769	1.893	2.094	2.371
LSTM	1.844	2.361	2.534	1.612	2.334	2.243
PSO-LSTM	0.736	0.929	1.169	1.032	0.759	1.468
IPSO-LSTM	1.154	0.753	0.898	0.723	0.793	0.865
SQNN	0.523	0.512	0.513	0.546	0.532	0.556
	R^2 Vs look-back days					
	5	10	15	20	30	60
SVR	0.610	0.853	0.878	0.864	0.842	0.801
LSTM	0.879	0.794	0.776	0.893	0.809	0.835
PSO-LSTM	0.975	0.970	0.959	0.962	0.974	0.940
IPSO-LSTM	0.960	0.973	0.970	0.976	0.975	0.972
SQNN	0.985	0.978	0.985	0.982	0.984	0.979

5.3 Comparative analysis for Australian stock market (ASM)

Using data from the Australian stock market (ASM), we validate the effectiveness of our suggested hybrid SQNN system in this case. When compared to other state-of-the-art frameworks, like LSTM (Long-Short Term Memory), SVR (Support Vector Regression), particle swarm optimization LSTM (PSO-LSTM), and improved PSO-LSTM (IPSO-LSTM) [31], the simulation results of our proposed hybrid SQNN framework perform better. For the Australian Stock Market (ASM) dataset, Table 4 provides an error metrics comparison of our proposed and existing stock market forecasting systems.

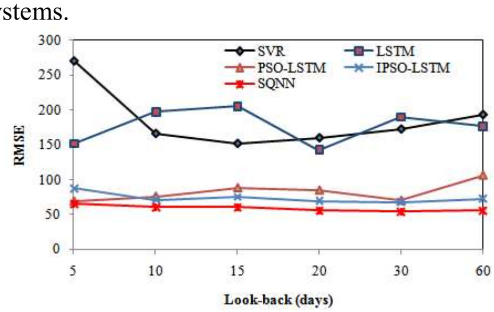

Figure. 9 RMSE analysis for Australian stock market (ASM) dataset

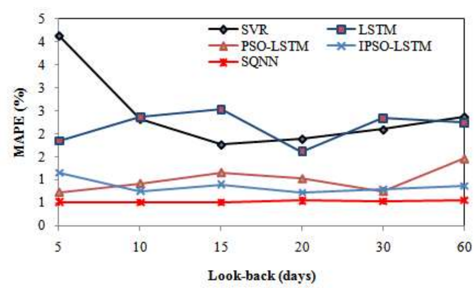

Figure. 10 MAPE analysis for Australian stock market (ASM) dataset

RMSE value of our proposed and existing stock market forecasting frameworks is shown in Fig. 9. From the fig, the RMSE value of our proposed hybrid SQNN framework is 68.42%, 66.87%, 28.641% and 20.775% efficient than the existing state-of-art SVR, LSTM, PSO-LSTM and IPSO-LSTM frameworks respectively. MAPE value of existing and proposed stock market forecasting frameworks is shown in Fig. 10. From the fig, the MAPE value of our proposed hybrid SQNN framework is 78.177%, 75.386%, 47.775% and 38.647% efficient than the existing state-of-art SVR, LSTM, PSO-LSTM and IPSO-LSTM frameworks respectively. Fig. 11 shows the R^2 value of proposed and existing stock market forecasting frameworks. The figure clearly depicts that the R^2 value of our proposed hybrid SQNN framework is 17.725%, 15.392%, 1.93% and 1.139% efficient than the existing state-of-art SVR,

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LSTM, PSO-LSTM and IPSO-LSTM frameworks respectively.

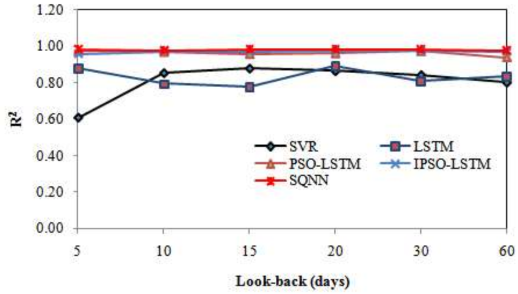

Figure. 11 R2 analysis for Australian stock market (ASM) dataset

Table 5 describes the quality metrics comparative analysis of proposed and existing stock market forecasting frameworks for Australian stock market (ASM) dataset. Fig. 12 shows the accuracy of proposed and existing stock market forecasting frameworks. The figure clearly depicts that the accuracy of our proposed hybrid SQNN framework is 56.808%, 47.816%, 41.622%, 41.142%, 40.662% and 40.441% higher than the existing state-of-art SVR, LSTM, PSO-LSTM and IPSO-LSTM frameworks respectively. The precision of proposed and existing stock market forecasting frameworks is shown in Fig. 13 shows. From the fig, the precision of proposed hybrid SQNN framework is 66.164%, 56.916%, 50.545%, 50.051%, 49.557% and 49.330% higher than the existing state-of-art SVR, LSTM, PSO-LSTM and IPSO-LSTM frameworks respectively.

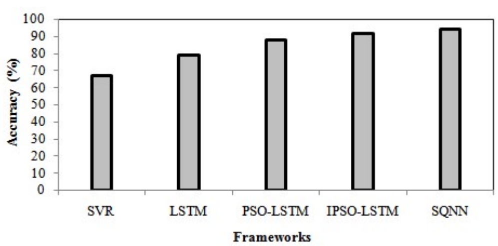

Figure. 12 Accuracy analysis for Australian stock market (ASM) dataset

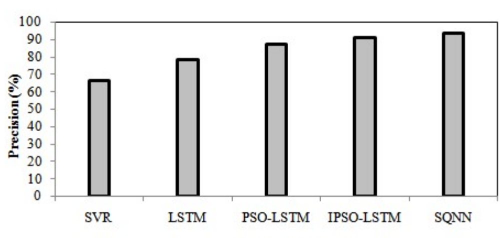

Figure. 13 Precision analysis for Australian stock market (ASM) dataset

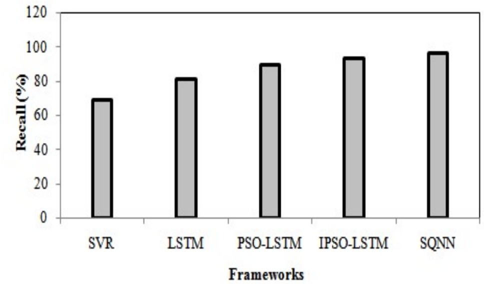

Figure. 14 Recall analysis for Australian stock market (ASM) dataset

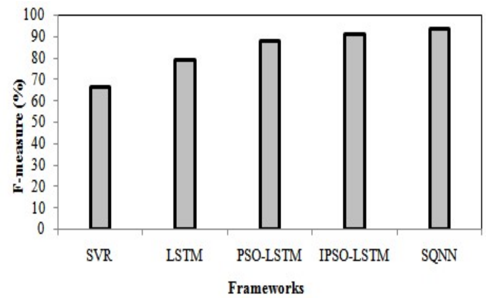

Figure. 15 F-measure analysis for Australian stock market (ASM) dataset

Table 5 Quality analysis for Australian stock market (ASM) dataset

Stock forecast frameworks	Quality metrics (%)			
	Accuracy	Precision	Recall	F-measure
SVR	66.942	66.182	68.742	66.55983
LSTM	79.302	78.542	81.102	78.92017
PSO-LSTM	88.192	87.432	89.992	87.81036
IPSO-LSTM	91.76	91	93.56	91.37842
SQNN	94.32	93.56	96.12	93.93846

The Recall of suggested and existing stock market forecasting frameworks is shown in Fig. 14. The figure clearly shows that compared to current state-of-the-art SVR, LSTM, PSO-LSTM, and IPSO-LSTM frameworks, the proposed hybrid SQNN framework's recall is 50.48 percent, 41.33 percent, 35.03 percent, 34.54 percent, 34.05 percent, and 33.85 percent higher. The F-measure of our suggested and existing stock market forecasting frameworks is shown in Fig. 15. The figure clearly shows that the proposed hybrid SQNN framework's F-measure is greater than the current state-of-the-art SVR, LSTM, PSO-LSTM, and IPSO-LSTM frameworks, respectively, by

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62.119 percent, 52.86 percent, 46.52 percent, 46.02 percent, 45.53 percent, and 45.31 percent.

5.4 Comparative analysis for China's wind economy

Using data from China's wind sector, we verify the effectiveness of our suggested hybrid SQNN structure in this case. Support vector machine (SVM), SVM with rolling windows, and logistic regression (LR) are the current state-of-the-art frameworks with which the simulation results of our proposed hybrid SQNN framework are compared [32]. Table 6 describes the error metrics analysis of our proposed and existing stock market forecasting frameworks for Australian stock market dataset.

Table 6 Error analysis for China's wind economy dataset

Stock forecast frameworks	Error metrics		
	RMSE	MAPE (%)	R
SVM	144.790	0.452	0.758
SVM-with rolling windows	122.450	0.321	0.798
LR	106.810	0.314	0.854
SQNN	96.560	0.302	0.897

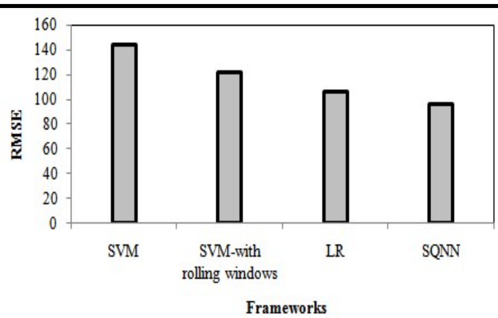

Figure. 16 RMSE analysis for China's wind economy dataset

The RMSE value of proposed and current stock market forecasting frameworks is displayed in Fig. 16. The figure clearly shows that the suggested hybrid SQNN framework's RMSE value is 33.31 percent, 21.143 percent, and 9.596 percent more efficient than the current state-of-the-art SVM, SVM-with-rolling-windows, and LR frameworks, respectively. The MAPE value of proposed and existing stock market forecasting frameworks is displayed in Fig. 17. The figure makes it evident that the MAPE value of the suggested hybrid SQNN framework is, respectively, 33.186 percent, 5.919 percent, and 3.822 percent more efficient than the state-of-the-art SVM, SVM-with-rolling-windows, and LR frameworks. The R2 value of proposed and existing stock market forecasting frameworks is displayed in Fig. 18. The figure makes it evident that our suggested hybrid SQNN framework is 15.497 percent, 11.07 percent, and 4.79 percent more efficient than the best-in-class SVM, SVM-with-rolling-windows, and LR frameworks, respectively, than their current state-of-the-art counterparts.

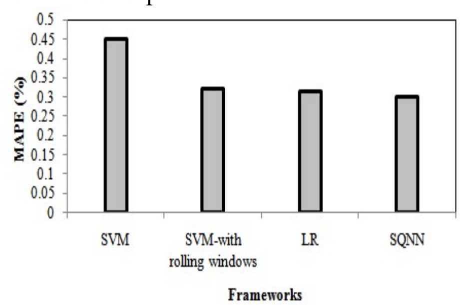

Figure. 17 MAPE analysis for China's wind economy dataset

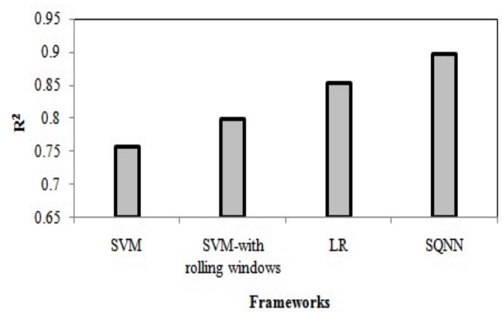

Figure. 18 R2 analysis for China's wind economy dataset

Table 7 describes the quality metrics comparative analysis of proposed and existing stock market forecasting frameworks for China's wind economy dataset. The accuracy of our proposed and existing stock market forecasting frameworks is shown in Fig. 19. From the fig, the accuracy of our proposed hybrid SQNN framework is 30.288%, 29.799% and 29.575% higher than the existing state-of-art SVM, SVM-with rolling windows and LR frameworks respectively. The precision of proposed and existing stock market forecasting frameworks is shown in Fig. 20. From the fig, the precision of our proposed hybrid SQNN framework is 45.471%, 44.987% and 44.765% higher than the existing state-of-art SVM, SVM-with rolling windows and LR frameworks respectively.

Journal of Theoretical and Applied Information Technology
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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 7 Quality analysis for China's wind economy dataset

Stock forecast frameworks	Quality metrics (%)			
	Accuracy	Precision	Recall	F-measure
SVR	66.942	66.182	68.742	66.55983
LSTM	79.302	78.542	81.102	78.92017
PSO-LSTM	88.192	87.432	89.992	87.81036
SQNN	94.32	93.56	96.12	93.93846

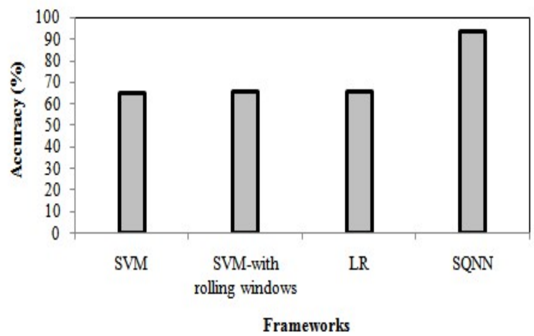

Figure. 19 Accuracy analysis for China's wind economy dataset

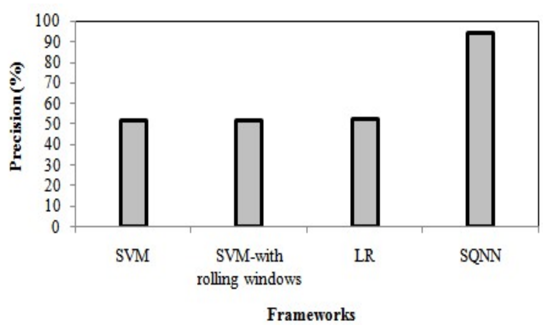

Figure. 20 Precision analysis for China's wind economy dataset

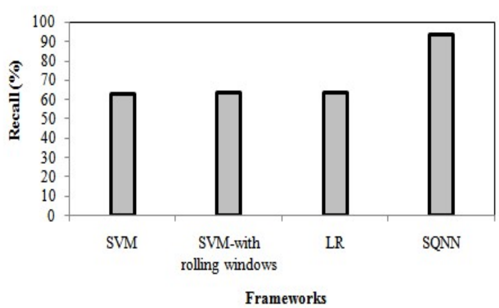

Figure. 21 Recall analysis for China's wind economy dataset

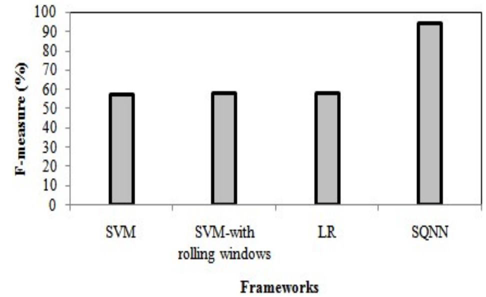

Figure. 22 F-measure analysis for China's wind economy dataset

Recall of our proposed and existing stock market forecasting frameworks is shown in Fig. 21. From the fig, the Recall of proposed hybrid SQNN framework is 32.742%, 32.254% and 32.029% higher than existing state-of-art SVM, SVM-with rolling windows and LR frameworks respectively. The F-measure of our proposed and existing stock market forecasting frameworks is shown in Fig. 22. From the fig, the F-measure of proposed hybrid SQNN framework is 38.767%, 38.275% and 38.048% higher than the existing state-of-art SVM, SVM-with rolling windows and LR frameworks respectively.

6. CONCLUSION

We have proposed an intelligent soft computing framework for international stock movement direction forecasting framework. The proposed framework is consists set of stages (1) improved Ebola optimization (IEO) algorithm is used for data preprocessing which filters the noise and irregular patterns from the gathered data (2) chaotic farmland fertility algorithm (CFF) is used for the feature optimization process which effectively improves the convergence speed for high-dimensional optimization problemsand (3) hybrid SQNN framework is used for international stock movement direction forecasting which ensures avoidance of false prediction rates.Finally, we have validated our proposed framework using international benchmark datasets such as U.S. stock market, the Australian stock market, and China's wind economy. From simulation results, we proved that the effectiveness of our proposed hybrid SQNN framework perform very well in terms of both error and quality metrics.Finally, we observed that the forecasting accuracy of our proposed hybrid SQNN framework is achieved as 95.2%, 94.32% and 93.56% for U.S. stock market, the Australian stock market, and China's wind economy datasets respectively.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

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