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STOCK PRICE PREDICTION USING QUANTUM NEURAL NETWORK

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Abstract - Quantum Neural Network (QNN) can improve upon the inadequacies of the classical neural network (CNN). The CNN requires a huge memory and needs more computational power. A new field of computation is emerging which integrates quantum computation with CNN. A quantum inspired hybrid model of quantum neurons and classical neurons is proposed. This paper details an approach, perhaps the first attempt; towards stock price prediction using this concept is evolved. The stock price prediction initiates the use of QNN in financial engineering applications.
Key words - Quantum neural network (QNN), commodities price prediction, QNN in financial engineering applications, quantum back propagation, quantum computation, stock price prediction.

I. INTRODUCTION

Significant work is being done in the field of quantum computation. Benioff and Feynman[1,2] has proposed the concept of quantum computation. Quantum algorithms by P. W. Shor and L.K. Grover[3,4] has received a lot of attraction. The idea of QNN can take leverage from quantum computation in the field of artificial intelligence,. Many prototypes for QNN similar to classical neural networks have been proposed. Kak[5] was first to present concept of QNN. Gupta and Gia[6] has shown that QNN has almost the same computational power as CNN. Menneer and Narayan[7,8] has laid some foundation of basic concepts inspired by quantum theory for use in neural networks design, development and implementation.

Quantum computers has inbuilt parallelism and large memories. Visualizing these potential for quantum computers, it is considered that the QNN shall be the next natural step in the evolution of neuro-computing system. Ezonov and Ventura[8] have introduced the possibilities of combining the unique computational capabilities of CNN and quantum computation. This combination can produce a computational paradigm of incredible potential. Xiao and Cao[9] have proposed a QNN model based on quantum and classical neurons. Miszczak[10] has proposed ways for preparing initial quantum state based on probabilities.

Earlier Eznov et. al [11] has proposed concepts of QNN and Nielsen et. al [12] has given concepts of quantum computation.

Since last two decades, a great attention is visualized in the efforts of researcher on the idea of time series prediction. They have studied these fluctuations through the use of CNN. Various prediction strategies can be applied for improving accuracy of prediction. A classical feed forward back propagation neural network has been successively applied and tested in this paper to the time series of one previous prediction using multiple stocks data using sliding window.

This paper has proposed and applied, a hybrid three layer feed forward back propagation quantum inspired neural network for stock price prediction. The input layer is classical, the hidden layer is quantum neuron, and the output layer is classical. The output calculation is based on classical computation.

The predicted output from classical and quantum neural networks are compared and discussed with respect to actual.

The section II deals with the hybrid quantum inspired neural network, section III deals with learning in quantum neural network, section IV deals with algorithm for hybrid quantum inspired back propagation, section V deals with stock price prediction, section VI presents results and discussion followed by conclusion in section VII.

II. HYBRID QUANTUM INSPIRED NEURAL NETWORK

The QNN is based on the techniques of quantum computation. Qubit is defined as the smallest unit of information in quantum computation which is a probabilistic representation. A qubit may either be in the "1" or "0" or in any superposition of the two[9].

Figure 1 and 2 represent the concept of hybrid quantum neural network.

The state of the qubit can be represented as:

$|\psi\rangle = \alpha\,|0\rangle + \beta\,|1\rangle$ …………………..(i)

Where α and β are the numbers that indicate the amplitude of the corresponding states such that:

$|\alpha|^2+|\beta|^2=1$

A qubit is defined as smallest unit of information in quantum computation. It is defined as a pair of numbers $\begin{bmatrix}\alpha\\ \beta\end{bmatrix}$.

Angle θ, in a more geometrical aspects is defined such that

$cos(\theta) = |\alpha|$ and $sin(\theta) = |\beta|$;

Quantum gates may be applied for modifying the probabilities as a result of weight updating,. One such rotation gate can be :

$U(\Delta\theta) = \begin{bmatrix}\cos(\Delta\theta) & -\sin(\Delta\theta)\\ \sin(\Delta\theta) & \cos(\Delta\theta)\end{bmatrix}$ ………….(ii)

A state of qubit can be updated by applying the above quantum gate. Application of rotation gate on a qubit can be represented as:

$\begin{bmatrix}\alpha'\\ \beta'\end{bmatrix}=\begin{bmatrix}\cos(\Delta\theta) & -\sin(\Delta\theta)\\ \sin(\Delta\theta) & \cos(\Delta\theta)\end{bmatrix}\begin{bmatrix}\alpha\\ \beta\end{bmatrix}$………….(iii)

The following hybrid quantum inspired neural network is proposed for the stock's price prediction.

- Initialize

  a. Quantum hidden neuron:

  Start from state $|0\rangle$, prepare the superposition :

  $\sqrt{p}\,|0\rangle + \sqrt{1-p}\,|1\rangle$ with $0\le|p|\le1$;

  Where p represents random probability of initializing the system in the state $|0\rangle$.

The desired state can be reached by using rotation gate R:

$\mathbf{R}(\theta) = \begin{bmatrix}\cos(\theta) & -\sin(\theta)\\ \sin(\theta) & \cos(\theta)\end{bmatrix}$;

$\tan(\theta)= \sqrt{\dfrac{p}{1-p}}$;

$\theta = \arctan\sqrt{\dfrac{p}{1-p}}$;

$R(\epsilon) = \begin{vmatrix}\sqrt{1-p} & -\sqrt{p}\\ \sqrt{p} & \sqrt{1-p}\end{vmatrix}$;

$\begin{bmatrix}\alpha\\ \beta\end{bmatrix} = \begin{bmatrix}\sqrt{1-p} & -\sqrt{p}\\ \sqrt{p} & \sqrt{1-p}\end{bmatrix}\begin{bmatrix}1\\ 0\end{bmatrix}$

b. Classical neurons:

Initialize classical neurons by random number generation.

- Output from quantum neuron:

  $v_j=f(\sum_{i=1}^{n}|\psi_{ji}\rangle * x_i)$ …………………………...(iv)

  Where f is a problem dependent sigmoid or Gaussian function

- Output from the network:

  $y_k = f(\sum_{j=1}^{l} w_{jk} * v_j)$.................................... (v)

- The desired output is o_k

  the corresponding squared error is:

  $E_k^2=|\ y_k - o_k\ |^2$……………………………..(vi)

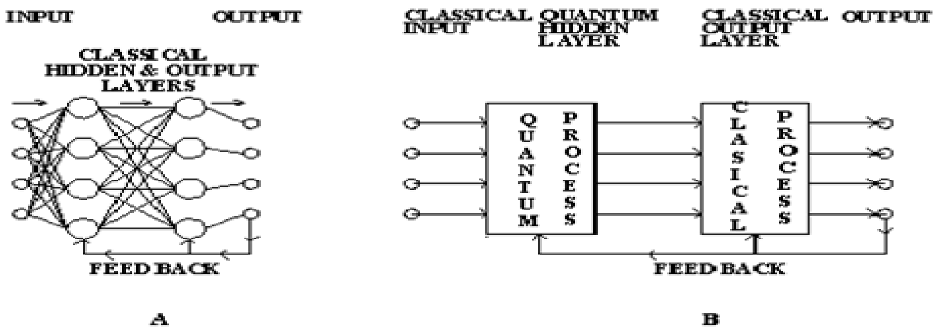

Figure 1. (A) Classical and (B) Hybrid Quantum Neural Network Learning by Feed Back

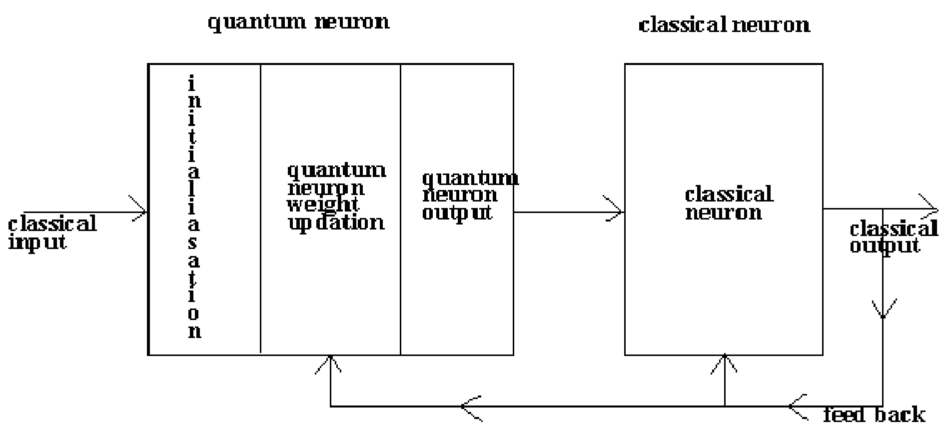

Figure 2. Hybrid Quantum Neural Network

III. LEARNING IN QUANTUM NEURAL NETWORK

The learning follows the rules of feed forward back propagation algorithm

- Updation of output layer weight
  $\Delta w_{jk} = \eta e_k f' v_j$……………………….(vii)
- Updation of quantum hidden layer weight

  in quantum BP algorithm the weights are updated by quantum gate according to equation (iii), in this case the equation shall be

  $$\begin{bmatrix}\alpha_{ij}' \\ \beta_{ij}'\end{bmatrix} = \begin{bmatrix}\cos(\Delta\theta_{ij}) & -\sin(\Delta\theta_{ij}) \\ \sin(\Delta\theta_{ij}) & \cos(\Delta\theta_{ij})\end{bmatrix}\begin{bmatrix}\alpha_{ij} \\ \beta_{ij}\end{bmatrix} \text{..(viii)}$$

where $\Delta\theta_{ij} = -\frac{\partial E}{\partial \theta_{ij}}$;

$= -\frac{\partial E}{\partial y_k}\frac{\partial y_k}{\partial v_j}\frac{\partial v_j}{\partial \theta_{ij}}$ by chain rule

$= -E_k f' w_{jk} v_j x_i (\cos(\gamma_{ij}) - \sin(\gamma_{ij}))$

where γ_{ij} is a phase of $|\psi_{ij}\rangle$ such that

$|\psi_{ij}\rangle = \begin{bmatrix}\cos(\gamma_{ij}) \\ \sin(\gamma_{ij})\end{bmatrix}$;

for γ_{ij} updation shall be:

$\gamma_{ij}' = \gamma_{ij} + \eta\Delta\theta_{ij}$; η is learning rate

IV. ALGORITHM: QUANTUM INSPIRED HYBRID BACK PROPAGATION

Start with randomly chosen weights for classical output neurons and initialize quantum hidden neuron

While mean squared error is unsatisfactory and computational bounds not exceeded

Do

For each input array $x_1, \ldots\ldots\ldots, x_n;$

Compute hidden node output

Compute the network output

Compute the output error

Modify weights between hidden and output node

Apply quantum gate and modify hidden node weights

End For

End Do

End while

End

V. STOCK PRICE PREDICTION

The succession of values in a time series is usually influenced by a number of external information. When this information are not available only past value of the series itself can be used to build a prediction model.

$X_{t+1}= f(x_1,\ldots\ldots..,x_n)$; where x_{t+1} is estimated next value based on current and past values of x.

Efficient market hypothesis (EMH) emphasizes that if statistically significant serial dependencies exist within time series of stock prices, the community of business analyst will immediately exploit it. Stock price changes can therefore be only be explained by arrival of new information, which by definition cannot be forecasted. EMH is only true when linear models are applied. It has been generally established that by use of non-linear models like neural networks, the results challenge the EMH hypothesis.

The data used for stock price prediction are monthly closing prices of 10 stocks. A total of 7 years (2003-2010) daily data were considered [13]. The figure 3(3.1 to 3.4) illustrates the price behavior of these stocks and illustrates the prediction performance of each stock while comparing classical neural network stock price prediction with that of quantum neural network.

VI. RESULTS AND DISCUSSION

The hybrid quantum back propagation model uses 30 quantum hidden neurons and 30 classical output neurons. The performance of the hybrid quantum model has been compared with classical back propagation neural network model having the same number of hidden and output neurons, parameters and data.

The ability of neural networks to discover nonlinear relationships in input data makes them ideal for modeling nonlinear dynamic systems of the stock market has been established. It has been found that the average error using lots of data is smaller than that using less amount of data. That is, the more data for training the neural network, the better prediction it gives. If the training error is low, predicted predictive stock prices are close to the real values.

The back propagation network has performed and predicted stock price trends and thus challenges the EMH. Since, if a neural network can outperform the market consistently or predict its direction with reasonable accuracy, the validity of the EMH is questionable.

The objective of this study was to establish the fact that quantum neural network can perform with almost the same accuracy as the classical ones. Even though, our hybrid quantum model uses quantum hidden neurons containing

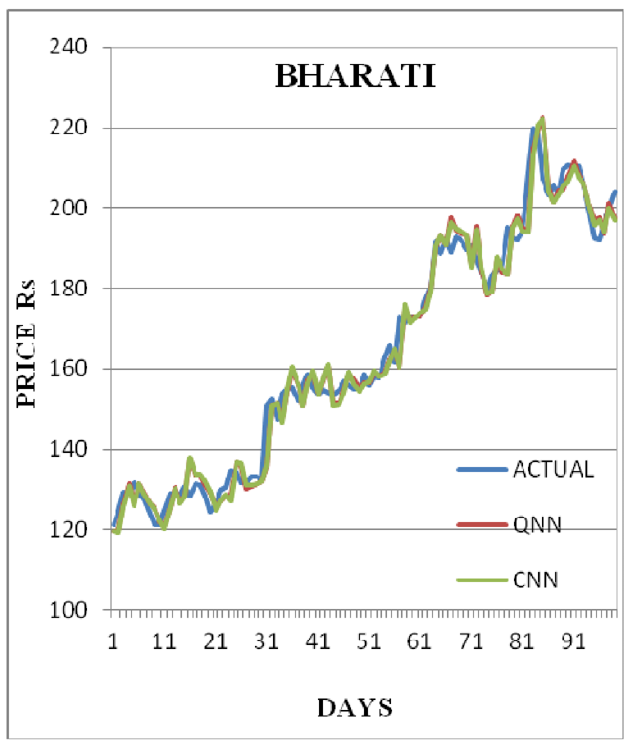

Figure 3.1 Comparison of CNN and hybrid QNN for BHARATI

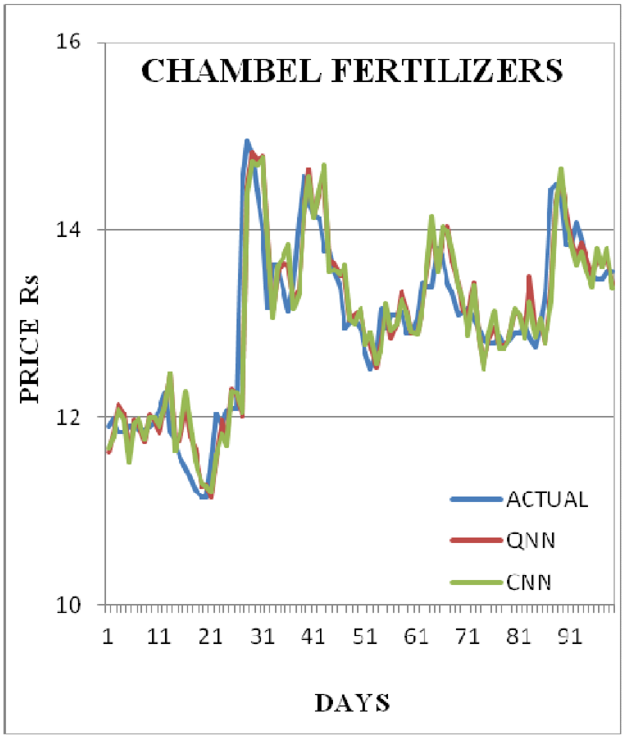

Figure 3.2 Comparison of CNN and hybrid QNN for CHAMBAL FERTILIZERS

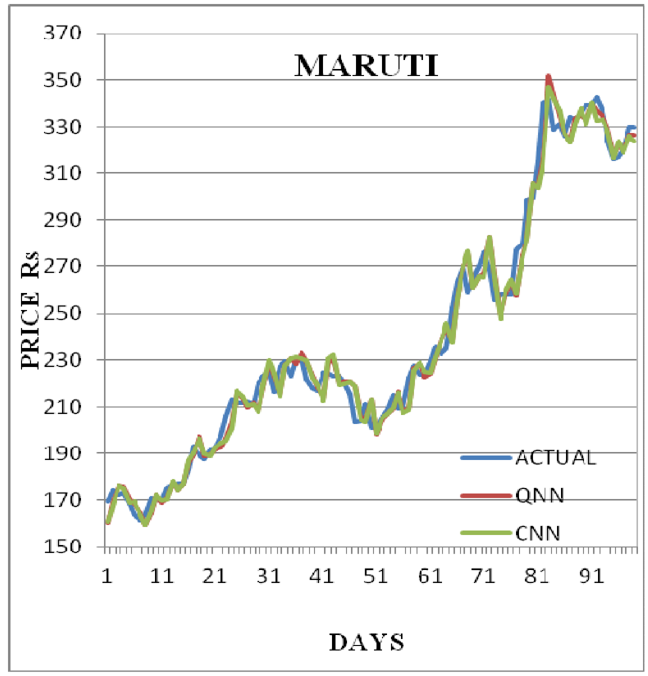

Figure 3.4 Comparison of CNN and hybrid QNN for MARUTI UDHYOG LTD.

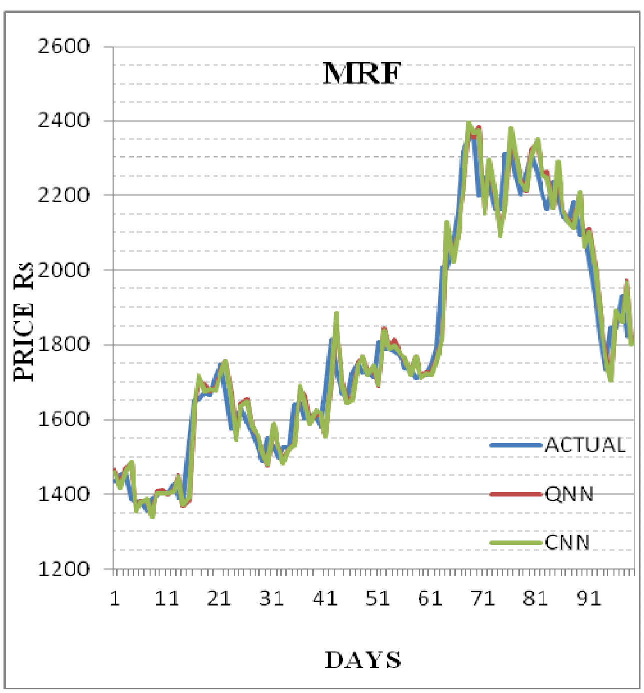

Figure 3.3 Comparison of CNN and hybrid QNN for MRF

FIGURE 3. PREIDCTION OF STOCK PRICES USING CNN AND HYBRID QNN

single qubit registers and interfaces with its classical component. All the results, in the figure. 3 for four stocks show that there is a close matching of results in both the cases with slight improvements (around 4 %) using QNN.

It can be further concluded that the processing time in quantum neural networks shall be very small due to the inbuilt capacity of the quantum computers to process the data in parallel. It is evident from the structure of the neural network that the calculations in all the neurons of the layer can be performed concurrently. Quantum computers can have huge memories associated with them and thus the future quantum neural network shall be able to handle large neural networks, thus ensuring the coverage of a wide range of stocks across all corners of stock markets globally.

Finally it is observed that:

- The prices move in a close range with an improvement of about 4% using QNN over CNN.
- Processing time will reduce due to quantum parallelism
- Availability of huge memory will ensure coverage for a wide range of stocks.

The comparison of results between classical and quantum neural networks has revealed that the results match closely and QNN results are better.

VII. CONCLUSION

The development and application of stock price prediction with both classical and hybrid quantum neural network has revealed that hybrid QNN can produce slightly better results around 4%. The QNN result has established that classical algorithms can be successfully replaced by hybrid QNN when quantum computers become a reality with improved performance and enhanced speed. It can be further concluded that the processing time in quantum neural networks shall be very small due to the inbuilt capacity of the quantum computers to process the data in parallel. It is evident from the structure of the neural network that the calculations in all the neurons of the layer can be performed concurrently. The advantage of quantum computing can be exploited by extending the quantum computation concepts to recurrent Hopfield nets and stochastic Boltzmann neural networks. The extension so achieved can be applied to the solution of combinatorial problems in financial engineering.

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