Rainfall Forecasting with Hourly Surface Data of Humidity, Pressure and Temperature using Artificial Neural Network

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***Abstract*— To forecast daily Rainfall, in this study a system is designed and developed in MATLAB 7.10 using Multi-layer Feed Forward Neural Network with Back-Propagation. The Network is trained using Delta Learning Rule. A dataset of 31488 samples were collected from Nungambakkam Meteorological Station, Chennai for the period of 2005 to 2015 by registering with India Meteorological Department (IMD), Pune. The data was organized into day-wise hourly recordings as well as day-wise maximum, minimum, average data of Relative Humidity (RH), Temperature and Pressure along with Rainfall data. The collected dataset were pre-processed and normalized with Min-Max Linear Scaling method and are used for both training and for testing the data. The developed system gives more accuracy of 95.5443% when the training data set is 50% and the testing data set is 50% with least Mean Squared Error (MSE) value 0.011555. Again to validate the accuracy rate obtained from this neural network model, Heidke Skill Score (HSS) has been computed.**

***Index Terms*—About Rainfall Forecast, Backpropagation Neural Networks, Delta Learning Rule, Heidke Skill Score (HSS).**

1. INTRODUCTION

Forecasting of rainfall is a tedious and complicated process, timely forecasting and the accuracy of forecasting is the need of the hour. More rains leads to floods and other natural calamities whereas less rainfall leads to drought. Forecasting of rainfall helps in agriculture, aqua farming and other water resource management. Based on rainfall forecasting, farmers are able to choose which crop to raise, to reap maximum agricultural products. Many of the existing forecasting methods were able to forecast seasonal monsoons like southwest monsoon, northeast monsoon, summer, winter monsoons etc.

The existing methods were forecasting rainfall over large regions such as state-level, zone levels but not over smaller regions In addition, existing methods uses advanced climatology indices such as Southern Oscillation Index (SOI), El Nino Southern Oscillation (ENSO), East Atlantic (EA), North Atlantic Oscillation (NAO), Inter-decadal Pacific Oscillation (IPO) to extract the data which are more difficult and expensive. Artificial Neural Networks (ANNs) have become very popular and most widely used technique for rainfall forecasting.

In this study, a system is designed and developed in MATLAB 7.10 using Backpropagation neural network with 2 hidden layers to forecast daily rainfall. The Neural Network is trained using Delta Learning rule. In this study, the surface data of relative humidity, pressure, temperature are taken as input parameters and occurrence of rainfall is taken as output parameter. The developed system gives more accuracy when comparing with other existing methods.

2. DATA AND METHODOLOGY

Data and Collection:

The data used in this study are the surface data of daily-wise hourly rainfall data. The surface data consist of Relative Humidity (RH), Temperature, Pressure and Wind Speed along with Rainfall. The required data is collected by registration with India Meteorological Department (IMD), Pune. Data collected for this study contains samples of 31488 related to Nungambakkam Meteorological Station (Station Index No. 43278), Chennai, for the period 2005 to 2015. The data was organized into day-wise hourly recordings as well as day-wise maximum, minimum, average data. In this study to forecast rain fall, Relative Humidity, Temperature, Pressure and wind speed are considered as input parameter and occurrence of rainfall as target parameter. Based on the correlation coefficients between input and output parameters, after omitting the data related to the input parameter wind speed, the input data file obtained for forecasting of rainfall is shown in Fig 1.

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68,1016,25.6,0
60,1016,27.2,0
56,1015.5,28.5,0
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95,1012.2,21.9,0
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84,1014.8,24,0
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70,1014.7,26.8,0
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Fig 1: Input Data File with Relative Humidity, Temperature, Pressure and Target Rainfall data

In Fig 1, the first three columns represents relative humidity (RH), pressure and temperature, 4^{th} column consist of rainfall data (target data). When only three input parameters (Relative Humidity, Pressure and Temperature) are considered for forecasting, total number of records obtained after data pre-processing are 38064 for the period 2005 to 2015 of the same Nungambakkam Weather Station with station index No. 43278.

Methodology:

The computational changes have brought growth to new technologies. Artificial Intelligence is proven to be an emerging technology to solve complex real world problems which require expertise & decision making. Artificial Intelligence (AI) is a human endeavor to create a non-organic machine-based entity that has the abilities like to think, to imagine, to create, to memorize, to understand, to recognize patterns, to make choices, to adapt change and to learn from experience. The two basic approaches to Artificial Intelligence are bottom-up and top-down approaches. The bottom-up approach believes the best way to achieve Artificial Intelligence to build electronic replicas of complex network neurons of the human brain, while the top-down approach attempts to mimic the brain's behavior with computer programs.

One of the bottom-up approaches of Artificial Intelligence is Artificial Neural Networks (ANNs). Artificial Neural Network is an information processing paradigm that is inspired by the biological nervous system. Artificial Neural Networks allow the systems to recognize the input patterns by learning from past experiences or examples of information. Moreover ANNs do not require separate memory locations to store the outcome data with its associated probabilities. The major tasks of Artificial Neural Networks are Function Approximation, Classification, Clustering, Decision Support Systems, etc.

Architecture of Neural Network consists of a set of neurons arranged in some sort of order and forms a *Layer*. Layers can be classified into three categories based on the behaviour of neurons: *Input Layer (input units)* - which contains a set of neurons that receive the signals from the external world as input and sends these signals to other neurons. *Output Layer (Output units)* - consists a set of neurons that receive the signals from input layer, calculates the net input and produces the response by applying the activation functions. *Hidden Layer (Hidden units)* - is a layer that acts as neither an input layer nor an output layer. The Hidden Layer is used to increase the performance of the network. Neural Network Architectures can be classified into either a single layer or multilayer Neural Networks based on the number layers present in the network. While determining the number of layers in the network, the input layer is not counted as a layer, because they perform no computation. Therefore, the number of layers in the network can be defined as the number of layers of weighted interconnected links between the levels of neurons.

A Single Layer Neural Network has one layer of connection weights. That is, there exists one input layer, one output layer and one weighted connection links between them. The architecture of a Single Layer Neural Network is shown in Fig 2(a). The input units (X_1, X_2, . . . , X_n) receive the signals as input and sends these signals to other neurons. The output units (Y_1,Y_2, . . . ,Y_m) receive the input signals (x_1, x_2 , . . . , x_n) from input units through the weighted communications links (w_1, w_2, . . . , w_n), calculates the net input (y_{in}) as the sum of the product of the input signal and weights $\sum x_i\ w_i$ and produces the output (y) of the network by applying the activation functions $f(y_{in})$.

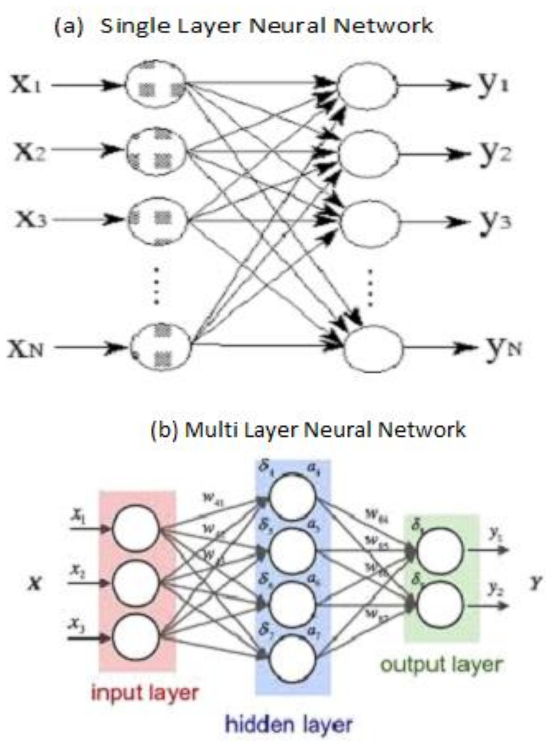


Fig 2: (a) Single Layer Neural Network and (b) Multilayer Neural Network

In Multi-layer Neural Network there exists one or more than one layer of connection weights between the input and hidden layers and between the hidden and output layers. The function of hidden neurons is to intervene between the external input and the network output in some useful manner. The architecture of a Multilayer Neural Network is shown in the Fig 2(b). Like in Single Layer Neural Networks, the input units (X_1, X_2, . . . , X_n) receive the signals from outside world and sends these signals to the hidden layer. The hidden layer (∂_1, ∂_2, . . . , ∂_P) receives these signals (x_1, x_2 , . . . , x_n) through a weighted connection links (v_{11},v_{12}, . . . , v_{np}), calculates the net input z_{inj} as the sum of the product of the input signal and weights i.e., $\sum x_i\ v_i$, produces the output (z_j) of the network by applying the activation functions i.e., $f(x_{ij})$ and sends these output to the output unit. The output unit (Y_1,Y_2, . . . ,Y_m) receives the signals (∂_1, ∂_2, . . . , ∂_n) from hidden units through the weighted connection links (w_{11},w_{12}, . . . ,w_{pm}), calculates the net input (y_{ink}) as the sum of the product of the input signals and weights i.e., $\sum z_j\ w_{jk}$ and produces the output (y_k) . If the response of the produced output neurons is not equal to the target value then the weights between input and hidden layers, weights between hidden and output layers are modified by learning. This process is continued until the network produces the desired output. Multilayer Neural Networks can be used to solve more complicated problems but the training process is difficult for Multilayer Neural Networks when comparing to the Single Layer Neural Networks

Backpropagation Neural Network is a Multilayer Feed Forward Neural Network which uses the extended gradient-descent based delta learning rule and also known as backpropagation (of errors) rule for training. Backpropagation rule provides a computationally efficient method for changing the weights in a Feed Forward Network with differentiable activation function units to learn a training set of input-output examples. Being a gradient descent method it minimizes the total squared error of the output computed by the net. The network is trained by supervised learning method. The aim of this network is to train the net to achieve the balance between the ability to respond correctly to the input patterns that are used for training and ability to provide good responses to the input that are similar.

In this study, to forecast daily rainfall using surface data, a multi-layer Feed Forward Neural Network model with Back Propagation algorithm is implemented. The system is designed, developed and implemented using MATLAB 7.10 application. The Network is trained using Delta Learning Rule. Pre-processed surface data of relative humidity (RH), pressure and temperature are taken as input parameters and the occurrence of rainfall as target parameter to train and test the developed neural network model.

3. EXPERIMENTS AND RESULTS

By using the developed system different types experiments are performed to forecast hourly rainfall data. In all the experiments the surface data of Relative Humidity, Pressure and Temperature are taken as three input parameters and the occurrence of the rainfall is taken as the target parameter. From the collected data, some of the data are taken for training and some of the data for testing. All the experiments performed along with results obtained are shown in the following. Again to validate the accuracy rate obtained from this neural network model, Heidke Skill Score (HSS) has been computed.

EXPERIMENT *A*:

This experiment is implemented with the developed neural network model with two hidden layers by taking hourly data of three input parameters namely Relative Humidity, Pressure, Temperature and forecasting result as target parameter. In this experiment, 90% of the dataset were used for training and 10% for testing data as shown in Fig 3.

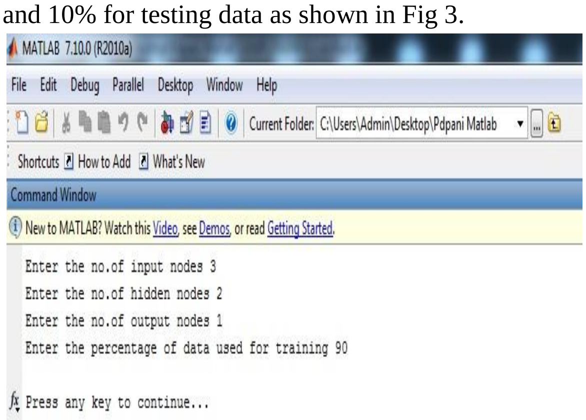


Fig 3: User Interactive to input parameter size to neural network

The results obtained from this experiment A is depicted in Fig 4. The accuracy achieved through this experiment is 94.6663%. The least Mean Squared Error (MSE) value achieved at epoch 6 is 0.011347. The graph between MSE Values and epoch numbers is shown in Fig 5. The output data file which was forecasted by this neural network model is shown in Fig 6.

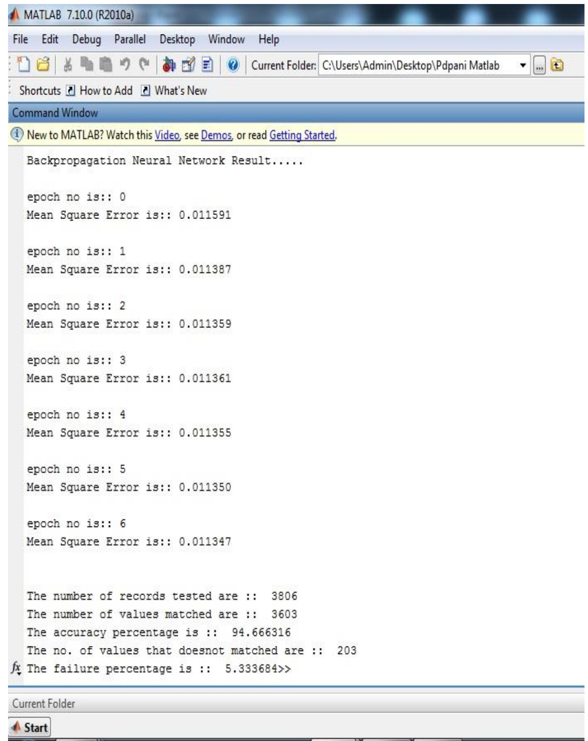
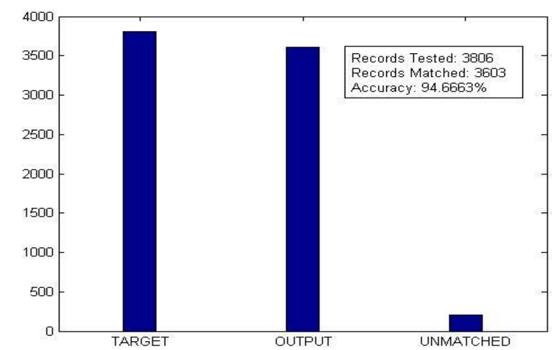


Fig 4: Result from NN with 90% Training Dataset and 10% target data



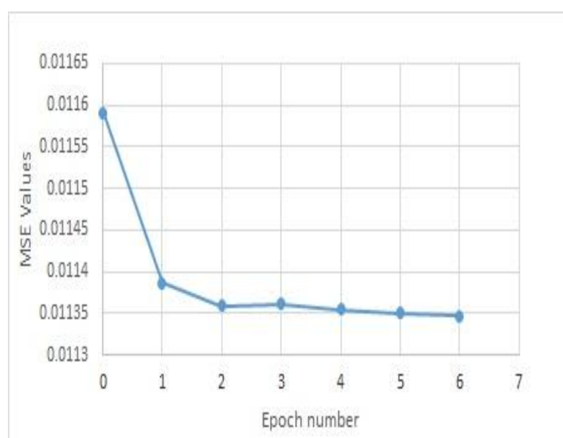
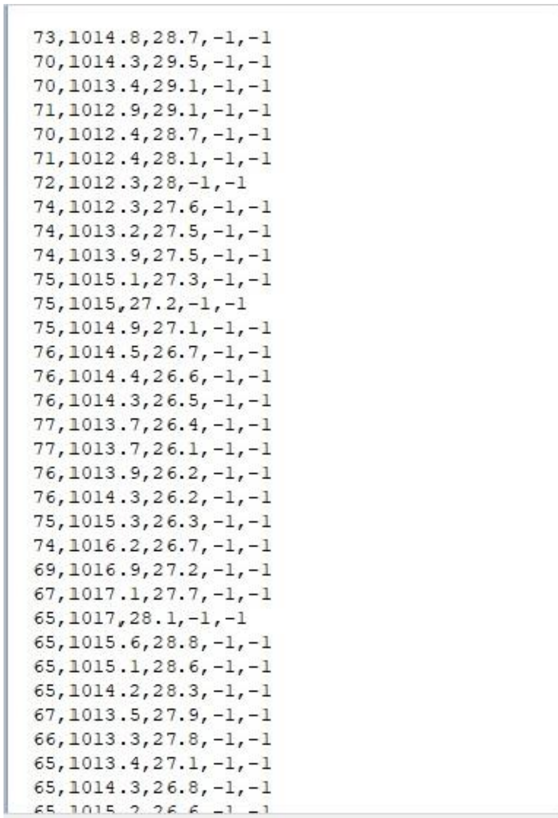


Fig 5: Graphical Representation of Result with 90% Training Dataset



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67,1017.1,27.7,-1,-1
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66,1013.3,27.8,-1,-1
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Fig 6: Output Data file of Rainfall Forecasting

To validate the accuracy of this forecasting, Heidke Skill Score (HSS) is computed for this experiment. The results of this experiment to compute HSS score is tabulated in Table 1.

Rainfall Forecasted	Rainfall Occurred		
	Yes	No	∑Occurred
Yes	3603	183	3786
No	203	2522	2725
∑ Forecasted	3806	2705	6511

Table 1: Result (with 3 Input Hourly Data, 2 Hidden Neurons, 90% Training Data)

In this experiment, out of 3806 total records tested, 3603 records were matched and 203 records were unmatched as in Table 1. The Heidke Skill Score computed for this experiment with 3 input parameters and 90% training dataset is 0.87807.

EXPERIMENT *B:*

In this experiment the developed neural network model was tested by taking three input parameters and one target parameter. 80% of the data were used to train the network and 20% were used to test the data.

The result obtained through this experiment is shown in Fig 7. The accuracy achieved through this experiment is 93.2212%. The least Mean Squared Error (MSE) value achieved at epoch 6 is 0.010167. The graph between MSE Values and epoch numbers is shown in Fig 8.

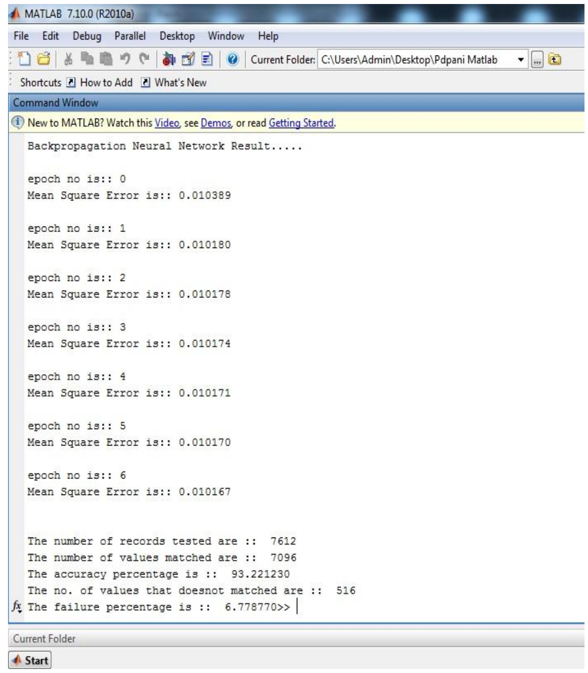
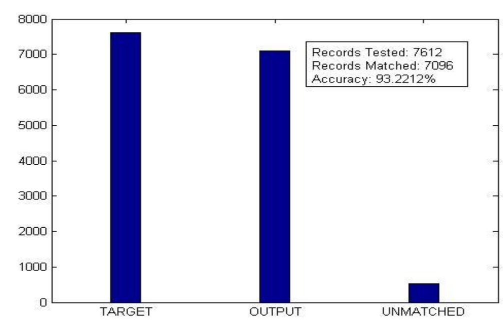


Fig 7: Result with 3 Input Parameters and 80% Training Dataset



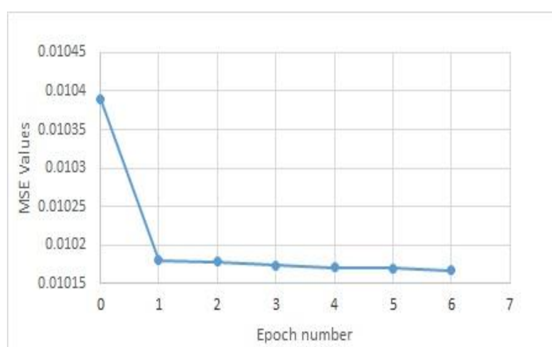


Fig 8: Graphical Representation of Result with 80% Training Dataset

To compute Heidke Skill Score for this experiment to forecast daily rainfall, the results of this neural network model with 80% training dataset are represented in Table 2.

Rainfall Forecasted	Rainfall Occurred		
	Yes	No	∑Occurred
Yes	7096	464	7560
No	516	4967	5483
∑ Forecasted	7612	5431	13043

Table 2 : Result (with 3 Input Hourly Data, 2 Hidden Neurons, 80% Training Data)

As in Table 2, in this experiment, 7612 records were taken for testing of this neural network, 7096 records were matched and 516 records were unmatched. The Heidke Skill Score for this experiment of rainfall forecasting, computed is 0.84562.

EXPERIMENT *C*:

The developed neural network model was implemented in this experiment for rainfall forecasting of hourly data with three input parameters and one target parameter. 70% of the data were used to train the neural network and 30% to test the data as shown in Fig 9 and the accuracy of forecasting along with graph between MSE values and epoch numbers were represented in Fig 10.

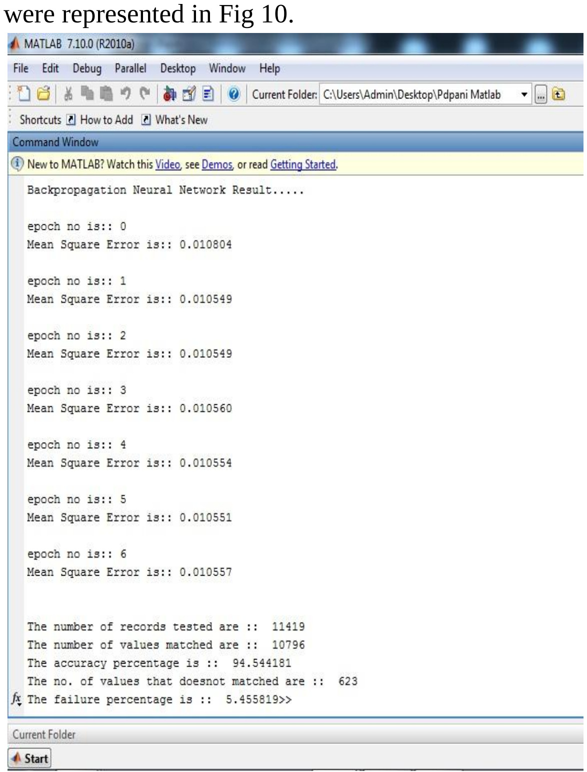


Fig 9: Result from NN with 3 Input Parameters, 70% Training Dataset

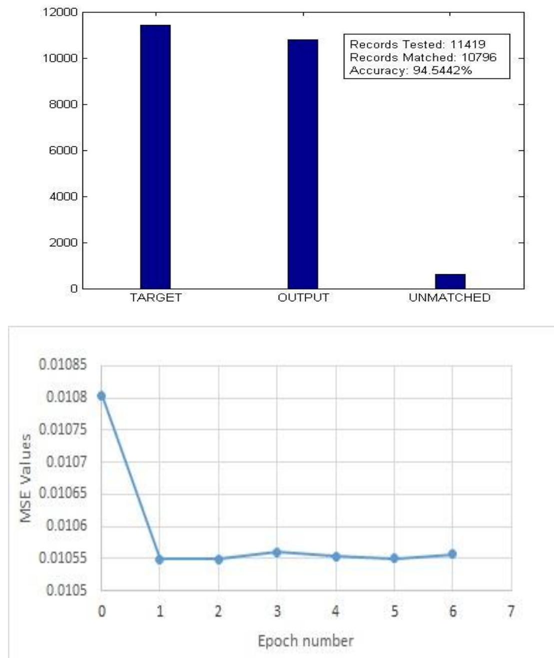


Fig 10: Graphical Representation of Result with 70% Training Dataset

From Fig 9, it is observed that the rainfall forecasting accuracy achieved in this experiment is 94.5442%. As in Fig 10, the least MSE is attained at epoch 2 and its value is 0.010549.

To support the accuracy rate attained in this experiment, Heidke Skill Score test is conducted. The results of this network were tabulated in Table 3 to compute HSS score of this experiment C.

Rainfall Forecasted	Rainfall Occurred		
	Yes	No	∑Occurred
Yes	10796	561	11357
No	623	7557	8180
∑ Forecasted	11419	8118	19537

Table 3 : Result (with 3 Input Hourly Data, 2 Hidden Neurons, 70% Training Data)

As in Table 3, this neural network is tested with 11419 records, 10796 records were matched between forecasted and target rainfall data and 623 records were unmatched. The Heidke Skill Score (HSS) computed for this experiment with 3 input variables, 2 hidden neurons and 70% training dataset is 0.87537.

EXPERIMENT *D*:

This neural network model is again experimented with the same three input variables and two hidden layer neurons but with 60% of training dataset to forecast rainfall. The outcome of this experiment is represented in Fig 11 and the graphical representation of the result was shown in Fig 12.

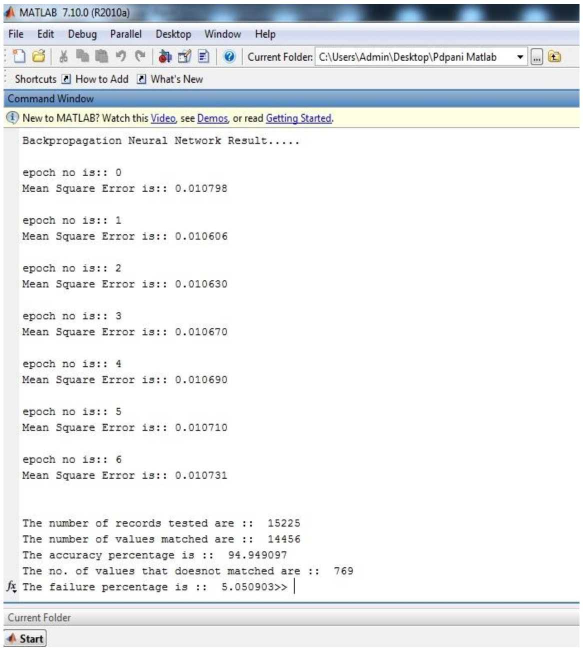


Fig 11: *Result of NN with 3 Input Parameters and 60% Training Dataset*

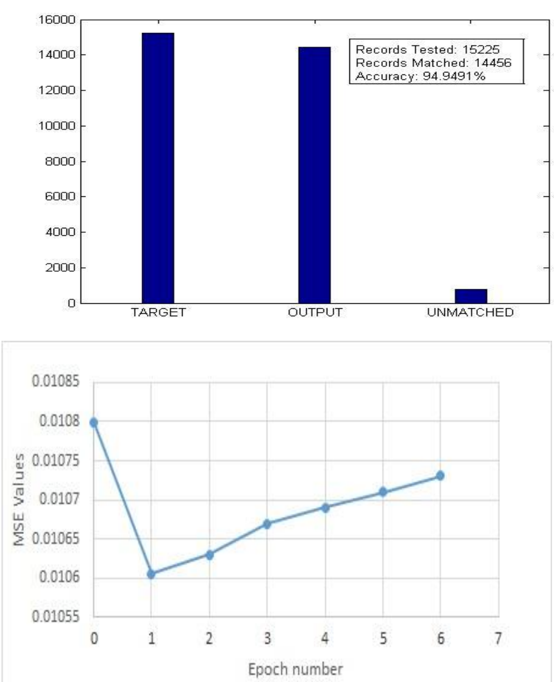


Fig 12: Graphical Representation of Result with 60% Training Dataset

From the result of this experiment as in Fig 11, the accuracy rate of forecasting observed is 94.9491. The least MSE value achieved is 0.010606 which is attained at 1st epoch as shown in Fig 12.

Validation of this accuracy of rainfall forecasting is done by computing Heidke Skill Score for this experiment. The results of this experiment (D) were represented in Table 4 to compute HSS Score of this experiment.

Rainfall Forecasted	Rainfall Occurred		
	Yes	No	∑Occurred
Yes	14456	692	15148
No	769	10119	10888
∑ Forecasted	15225	10811	26036

***Table 4**: Result (with 3 Input Hourly Data, 2 Hidden Neurons, 60% Training Data)*

Here, total records of 15225 were tested by this neural network, out of 15225 records, 14456 records were matched between forecasted and target rainfall data and 769 records were unmatched. The HSS Score computed for this forecast using neural network model is 0.88457.

EXPERIMENT *E*:

The developed neural network model for forecasting of daily rainfall is again experimented with three input variables (hourly data of relative humidity, pressure and temperature), two hidden neurons and with 55% training dataset (45% dataset for testing the network) and the outcome of this experiment were represented in Fig 13 and the graph between MSE values and epoch number is represented in Fig 14

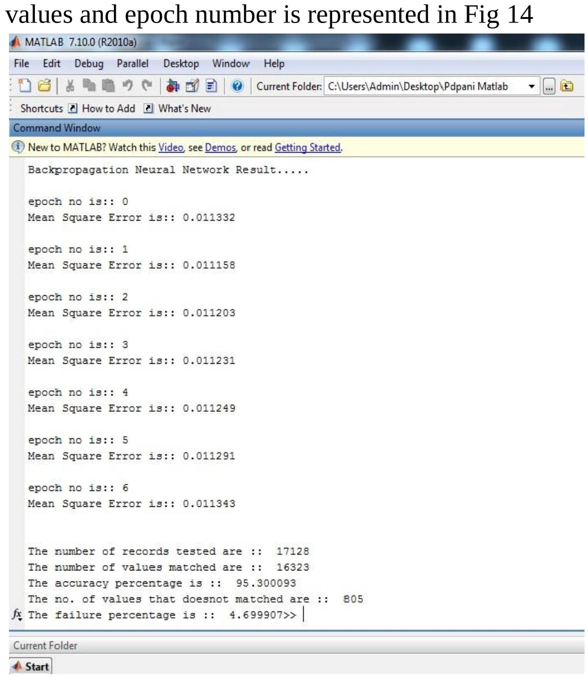
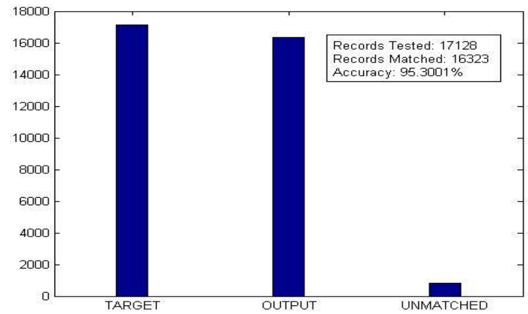


Fig 13: Result of NN with 3 Input Parameters and 55% Training Dataset



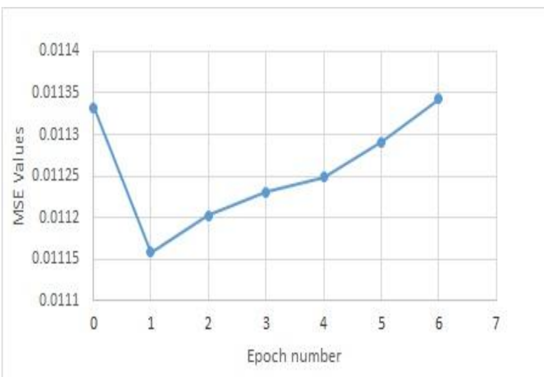


Fig 14: Graphical Representation of Result with 55% Training Dataset

As in Fig 13, the rate of accuracy of rainfall forecasting attained by this neural network model with 55% of training dataset is 95.3001%. The least MSE value obtained in this experiment is 0.011158 which is attained at epoch 1, thereafter, the MSE values are increasing which indicates that the network is over trained or over fitting.

To compute the HSS score of this forecasting, the results of this experiment (E) implemented with this neural network model are represented in Table 5.

Rainfall Forecasted	Rainfall Occurred		
	Yes	No	∑Occurred
Yes	16323	725	17048
No	805	11426	12231
∑ Forecasted	17128	12151	29279

Table 5: Result (with 3 Input Hourly Data, 2 Hidden Neurons, 55% Training Data)

As in Table 5, this neural network model has tested with 17128 records, 16323 records target data were matched with forecasted rainfall and 805 records were unmatched. The Heidke Skill Score (HSS) of this forecast is computed as 0.89248.

EXPERIMENT F:

Finally, this neural network model is implemented with 50% of training dataset, three input variables and two hidden layer neurons to forecast daily rainfall and the results obtained from this neural network is represented in Fig 15, the graph between MSE values and Epoch number in Fig 16.

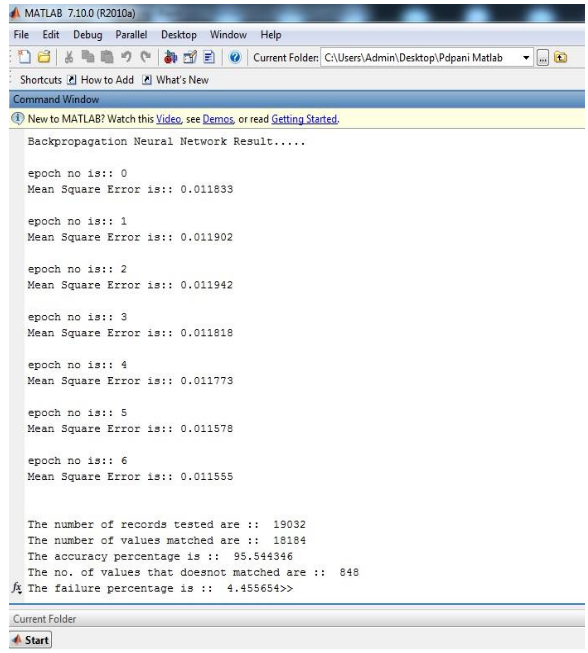
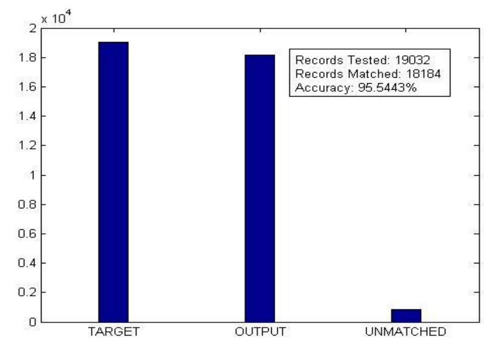


Fig 15: Result of NN with 3 Input Variables and 50% Training Dataset



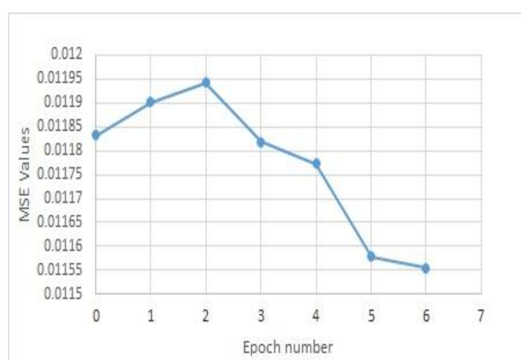


Fig 16: Graphical Representation of Result with 50% Training Dataset

From the Fig 15 and Fig 16, it is observed that the rainfall forecasting accuracy rate achieved as 95.5443% and the least MSE value achieved is 0.011555, which is attained at epoch 6. The accuracy of rainfall forecasting achieved in this experiment is better than that of previous experiments (A to E).
This experiment accuracy of forecasting is also validated with Heidke Skill Score and the results of this neural network are tabulated in Table 6 to compute HSS score of this forecast.

Rainfall Forecasted	Rainfall Occurred		
	Yes	No	∑Occurred
Yes	18184	763	18947
No	848	12729	13577
∑ Forecasted	19032	13492	32524

Table 6: Result (with 3 Input Hourly Data, 2 Hidden Neurons, 50% Training Data)

As in Table 6, this neural network was tested with 19032 records between target and forecasted rainfall data, out of 19032 records tested, 18184 records were matched and 848 records were unmatched in this experiment. The Heidke Skill Score (HSS) calculated for this forecast using backpropagation neural network model is 0.89807, which is significantly better than the earlier experiments (A to E).

4. ANALYSIS OF RESULTS OF RAINFALL FORECASTING USING HOURLY SURFACE DATA

A comparison study was made on the forecasting results obtained from the experiments A to F which are implemented based on the hourly surface data (relative humidity, pressure, temperature and wind speed) using Backpropagation Neural Network Model.
The values of Mean Squared Error (MSE) at each epoch number attained in the experiments A to F with varying size of training datasets obtained from the Neural Network implemented with three input parameters (hourly data of relative humidity, pressure and temperature) and two hidden layer neurons were represented in the graph Fig 17 and the least MSE of each experiment and its corresponding accuracy rate is represented in Table 7.

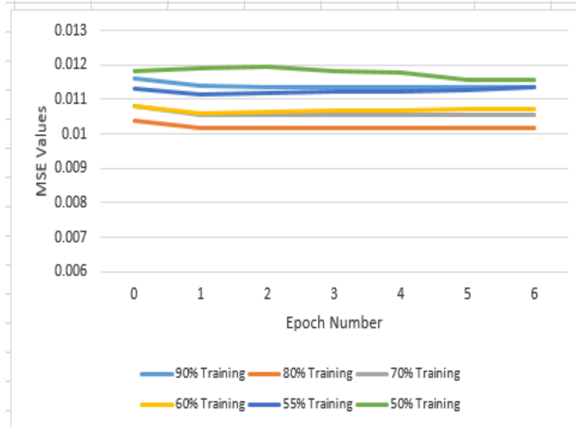


Fig 17: MSE Values with 3 Input Parameters and 2 neurons

Experiment No.	No. of Input Parameters	No. of Hidden Neurons	Training Dataset %	Mean Squared Error	Epoch No.	Accuracy %
A	3	2	90%	0.011347	6	94.6663
B	3	2	80%	0.010167	6	93.2212
C	3	2	70%	0.010549	2	94.5442
D	3	2	60%	0.010606	1	94.9491
E	3	2	55%	0.011158	1	95.3001
F	3	2	50%	0.011555	6	95.5443

Table 7: *MSE and Accuracy rate with 3 Input Parameters and 2 neurons*

With reference to the Table 7, it is observed that the developed backpropagation neural network model for the forecasting of daily rainfall performed better and the accuracy of forecasting is significantly improved. From the experiments A to F, the peak accuracy of forecasting is obtained in experiment F (implemented with 50% training dataset) as 95.5443% and its corresponding MSE value attained is 0.011555, which is attained at epoch 6. In the above experiments, least MSE value is attained in experiment B with value 0.010167 which was attained at epoch 6 with accuracy rate of forecasting as 93.2212%.
The Heidke Skill Scores obtained from the experiments A to F using backpropagation neural network for the forecasting of daily rainfall are represented in Fig 18.

Training Data Size	HSS Value
90% Training	0.87807
80% Training	0.84562
70% Training	0.87537
60% Training	0.88457
55% Training	0.89248
50% Training	0.89807

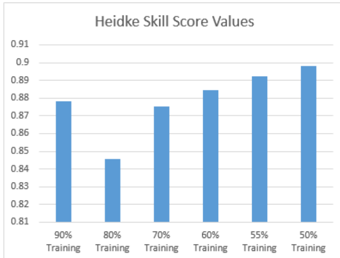


Fig 18: HSS Scores with 3 Input Variables & 2 Hidden Neurons.

From the Fig 18, it is also observed that the peak HSS score is obtained from the neural network model implemented with hourly data of three input parameters, two hidden layer neurons and 50% training dataset and the highest HSS score is 0.89807. Therefore HSS scores were also validated the performance efficiency of this neural network model.

5. CONCLUSION

In the present paper rainfall forecasting using hourly surface data using Backpropagation Neural Network has been presented. The experiments and results show that the Backpropagation Neural Network gives more accuracy and peak HSS score when the training data is 50% and the testing data is 50%. The Hourly surface data with three parameters produces much better accuracy in forecasting of rainfall when comparing with four parameters.

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