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Application of Back-Propagation Neural Network in Horoscope Prediction

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ABSTRACT
In this study a back-propagation neural network model is designed and its parameters are optimized for prediction of horoscope to identify a person type. Person type is a dynamic system based on the planet system. It is found that the back-propagation neural network is capable to predict the person type by learning planet dataset. The model is trained up to model error (i.e., mean square error) 1.2864E-04 and performs excellent during training and testing process.

Keywords
Neural Network, Prediction, Back-propagation, Horoscope

1. INTRODUCTION
System is defined as $y = f(x_1, x_2, x_3 \ldots, w_1, w_2, w_3 \ldots)$can be treated as non-linear dynamic system where different values of 'y' are dependent to different values of independent variablesx_1, x_2, x_3. The w_1, w_2, w_3 ... are the weights are to be adjusted to predict 'y' from inputted values of x_1, x_2, x_3. In other word x_1, x_2, x_3 are called predictors of the system y. here, y is dynamic and non-linear and depending on values ofx_1, x_2, x_3. Neural network and its training algorithm are basically used to define such system by adjustment of weights w_1, w_2, w_3 during training process. These weights are called trainable weights. In each epoch (iterations) the neural network may minimize the error between actual y's and its predicted values by adjustment of w_1, w_2, w_3 called training process. After training new values of x_1, x_2, x_3 may possibly be given to observe predicted value of y called validation or testing. It observed that weather datasets, stock datasets, financial datasets etc are dynamic system always depending on their predictors (independent variables). And neural network may identify the relationship between depending and independent variables. Thus in recent year many contributors are utilizing neural network for prediction of such system. It is observed that the Back-propagation neural network is sufficiently suitable for prediction of dynamic system as mentioned in the following Table 1, wherein, 17 different models have been depicted with their contributors. Thus in this study back-propagation neural network is applied for horoscope prediction as well.

Table 1. Neural network models for non-linear dynamic system

No.	Contributor	Application	Year	ANN Model
1	Tarsauliya et al.,	Financial forecasting	2010	Back-propagation and redial basis function
2	Peralta et al.,	Time series forecasting	2010	Back-propagation and genetic algorithm
3	Akintola et al.,	Stock market forecasting	2011	Back propagation
4	Juan José Montaño Moreno et al.,	Time series forecasting	2011	Multilayer Perceptron, Radial Base Function, Generalized Regression ANN, Recurrent Neural Network.
5	Khan et al,	Share Market forecasting	2011	Back-propagation
6	Vrabe et al	Prediction of surface roughness	2012	Back-propagation
7	Devi et al.,	Temperature forecasting	2012	Back-propagation
8	Donate et al.,	Time series forecasting	2013	Back-propagation with genetic algorithm
9	Sa et al.,	Forest forecasting	2013	Multilayer perceptron
10	Vieira	prices movements of oil and gas companies listed in stock exchanges	2013	Multilayer Perceptron models with logistic activation functions
11	Tamizharasi et al.,	Prediction the long range energy consumption for a country	2014	Back-propagation
12	Malik et al.,	Weather forecasting	2014	Back-propagation
13	Patel et al.,	Stock price prediction	2014	Back-propagation
14	Rao et al.,	Stock forecasting	2014	Back-propagation
15	Kuna,	Time series forecasting	2015	Recurrent neural networks

16	Enyindah et al.,	Financial forecasting	2016	Back-propagation
17	Shah et al.,	Stock market prediction	2016	Back-propagation, Multilayer perceptron, Redial basis function

A horoscope prediction system can be defined as

$$Type = f(Asce, Sun, Moon, Mars, Mercury, Jupiter, Venus, Saturn, Rahu, Ketu, Urenus, Nep, Pluto)$$

Here, Type may be Sportsman (2), Lawyer (4), Politician (5), Actor (8), scientist (8), astrologer (9), singer (6). Asce, Sun, Moon, Mars, Mercury, Jupiter, Venus, Saturn, Rahu, Ketu, Urenus, Neptune, Pluto are the predictor are to be inputted to the system to observed type as target.

The paper has been constructed with different sections. Section 2 used to describe dataset of horoscope, In section 3, the back-propagation neural network architecture is optimized to establish relationship between independent variables Asce, Sun, Moon, Mars, Mercury, Jupiter, Venus, Saturn, Rahu, Ketu, Urenus, Neptune, Pluto with the type. Section 4 represented for performance of the neural network, Result and discussion is explained in section 5, and concluded the paper in section 6.

2. DATA & PRE-PROCESSING

1200 record of different types and their corresponding planet values (i.e., Asce, Sun, Moon, Mars, Mercury, Jupiter, Venus, Saturn, Rahu, Ketu, Urenus, Neptune, Pluto) are used in this study. Out of 1200, 1993 records of different types (i.e., Sportsman (2), Lawyer (4), Politician (5), Actor (8), scientist (8), astrologer (9), singer (6)) and their planets are used for neural network system development (i.e., training) and one record of each type are used for testing as depicted in the following Table 2. Dataset are normalized within the closed interval [0 1] for neural network modelling.

Asc	Sun	Moo	$Mars$	Mer	Jup	Ven	Sat	Rah	Ket	Ure	Nep	Plu	$Type$
1	1	9	3	1	9	1	3	9	3	3	7	6	2
1	5	11	6	5	8	7	10	12	6	2	4	3	4
4	6	8	6	6	4	6	2	5	11	2	6	4	5
8	9	12	5	9	9	8	9	8	2	8	3	2	8
5	2	4	5	2	3	3	5	6	12	7	8	6	3
3	8	8	7	9	5	9	8	8	2	4	7	5	9
9	10	2	9	9	9	11	2	12	6	10	4	3	6

3. NEURAL NETWORK MODELLING

The structural design of Neural Network includes its primary parameters i.e., Number of input vectors in input layer (n), Number of neurons in hidden layers (p), Learning rate (α), Momentum factor (μ), and sets of biases and learning weights (i.e., w and v) as shown in following Fig. 1. It is known that, these parameters are dynamic based on input and targeted variables of the network. The identification of optimum values of parameters like n, p, α, and μ is an effort. at the same time as it is known that, without optimization of these parameters, might be reason of the unfortunate presentation. In this section the selection of these parameters and their optimization are discussed in this case. The architecture is shown.

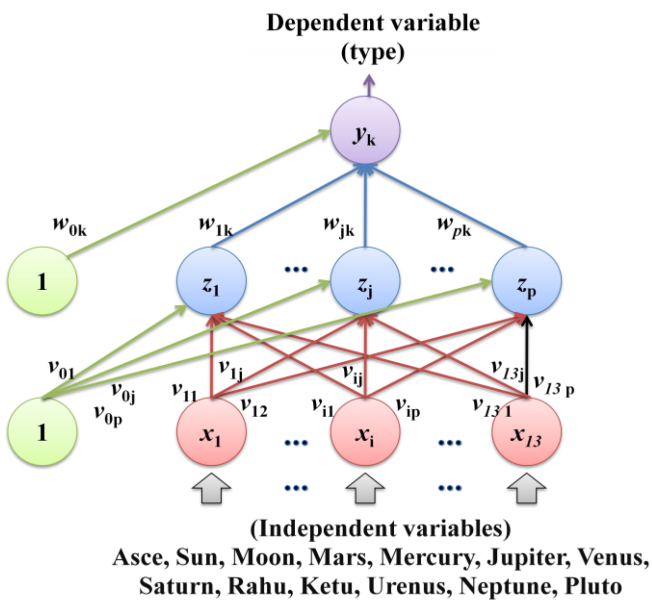

Fig. 1. Architecture of Neural Network for Spatial Interpolation

3.1 Optimization of Parameters

3.1.1 Number of input vectors in input layer (n)

Input of the model are 13 in this case i.e., Asce, Sun, Moon, Mars, Mercury, Jupiter, Venus, Saturn, Rahu, Ketu, Urenus, Neptune, Pluto. Look at the Fig. 1. In this case n =13.

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3.1.2 Number of output neurons (y)

Single output neuron is used to observe targeted value i.e., type (i.e., Sportsman (2), Lawyer (4), Politician (5), Actor (8), scientist (8), astrologer (9), singer (6))

3.1.3 Number of hidden layer

For nearly all problems, one hidden layer is enough. Using two hidden layers hardly ever advances the model, and it may introduce a greater hazard of converging to a local minima. There is no theoretical reason for using more than two hidden layers.

3.1.4 Number of neurons in hidden layers (p)

To obtain optimum value of '*p*' experiment have been accomplished. Experiment is done with initial weights and biases and with 100 epochs. The minimization of error (i.e., mean square error 'MSE') is observed and tried to identify the minimum mean square error (MSE) with corresponding parameter '*p*'. The minimization of error during training period of the system with their corresponding '*p*' is given in the following Table 2 and Fig 2. Wherein, it is clear that 30 neurons is optimum in this dataset for which the network error MSE = 3.3237443368085606E-4 is less therefore p = 30 is selected for this study.

Table.2. MSE corresponding to the number of neurons in hidden layer

Number of neurons in hidden layer (*p*)	MSE
2	0.001638729377750392
3	0.001638729377750392
4	0.001115547257976215
5	0.001010576885637086
6	8.835130957905274E-4
7	8.075992623893731E-4
8	7.759794687476993E-4
9	7.133125805921601E-4
10	6.694183869879488E-4
11	6.218868396468241E-4
12	5.920673410781053E-4
13	5.583996878601329E-4
14	5.419979904455619E-4
15	5.015120082000626E-4
16	4.888934797089644E-4
17	4.637275279312396E-4
18	4.381587423248476E-4
19	4.3605970407206533E-4
20	4.226594474728315E-4
21	4.067383031635331E-4
22	3.9361198686128815E-4
23	3.8158927065329415E-4
24	3.78634287524848E-4
25	3.605971241822392E-
26	0.28026419620770426
27	0.280256517557533
28	3.429787497471353E-4
29	0.28026627908467705
30	**3.3237443368085606E-4**

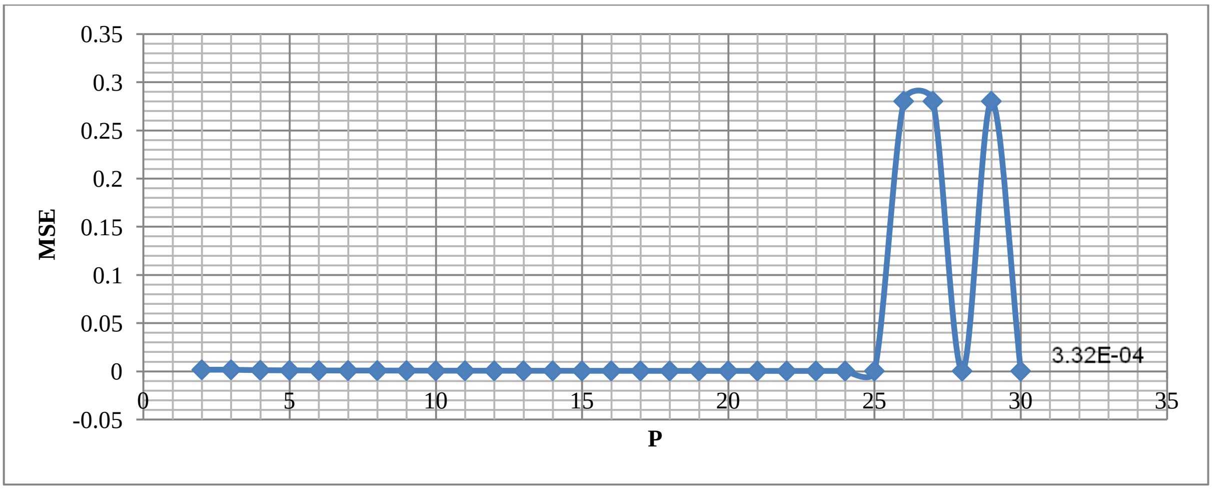

Fig. 2. MSE Corresponding to the Number of Neurons in Hidden Layer

3.1.5 Learning rate (α)

This parameter is highly significance for speeding up the training process and minimization of MSE by upgrading the trainable weights and biases. It is found that, a high 'α' leads to rapid learning but the weights may oscillate, while a lower value of α leads to slower learning process. Identification of an suitable value of α preserving a higher learning process needs special attention of the researchers in this area. It is tried to identify most favourable value of 'α' through the experiments where value of 'α' is considered in the close interval [0 1]. The values of 'α' and corresponding MSE through 100 epochs and p = 30 of learning is given in the following Fig 2 and Table 2. It is clear that α = 0.62 is optimum.

Table 2. MSE Corresponding to learning rate (α)

Momentum factor	0.1	0.2	0.3	0.4	0.5	0.6	0.6	0.8	0.9
1	0.280	0.280	3.14E-4	2.34E-4	0.28	2.32E-4	2.5E-4	2.58E-4	2.7E-4
Recommend ed Learning Facto	0.61	**0.62**	0.63	0.64	0.65	0.66	0.67	0.68	0.69
0.6	0.28	2.32E-04	2.328E-04	0.28	2.34E-4	0.29	2.32E-4	2.33E-4	0.28

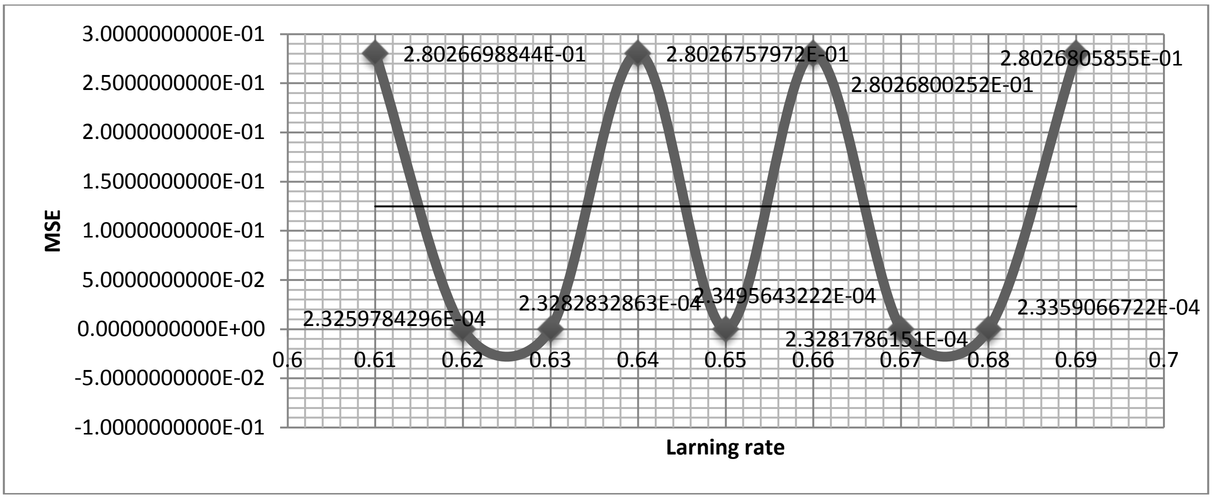

Fig. 3. MSE Corresponding to learning rate (α)

3.1.6 Momentum factor (μ)

The main purpose of the momentum factor (μ) is to accelerate the convergence of error during the training period in the equations (Karmakar et al., 2014). It is very important to know its optimum value between close interval [0 1]. The values of 'μ' and corresponding MSE's are obtained by 100 epochs of learning α = 0.62 and p = 30 is given in the following Fig 4 and Table 3. It is clear that μ = 0.96 is optimum.

Table 3. MSE Corresponding Momentum factor (μ)

Learning rate	0.1	0.2	0.3	0.4	0.5	0.6	0.6	0.8	0.9
0.62	0.28	0.28	0.28	0.28	3.04E-4	0.28	2.57E-4	2.42E-4	2.39E-4
Recommend momentum factor	0.91	0.92	0.93	0.94	0.95	0.96	0.97	0.98	0.99
0.6	2.36E-4	2.34E-4	0.28	2.34E-4	2.37E-4	**2.33E-4**	2.34E-4	2.33E-4	0.28

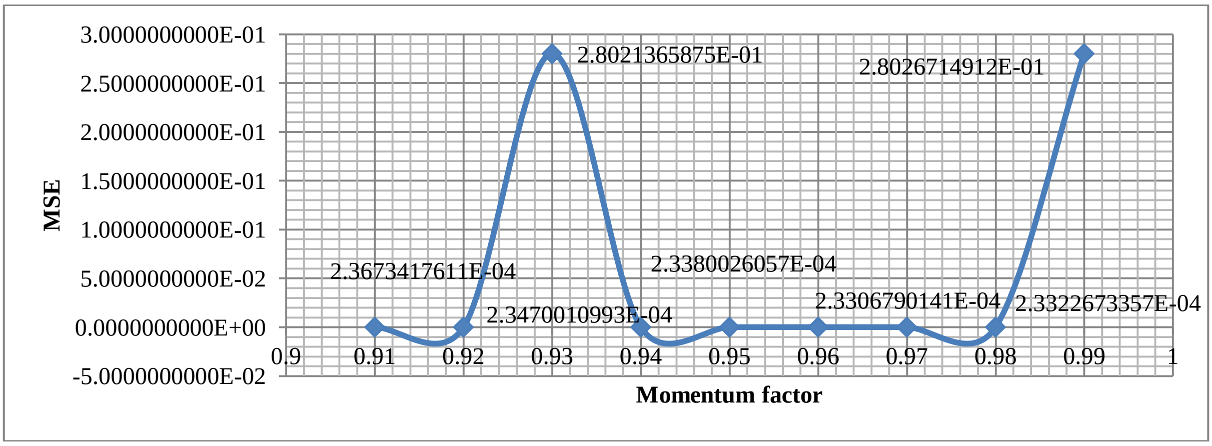

Fig. 4. MSE Corresponding Momentum factor (μ)

4. TRAINING

As per the discussion of section 3, it is found that parameters of Neural Network based on the experiment 5 are extremely suitable wherein, n = 13, p=30, α= 0.62, μ= 0.96 is optimum. The datasets of 1200 records are divided into two subset i.e., training and testing period. 1193 records are used for the training process and out of 1200 stations 7 records are randomly selected and used for the testing process. The initial weight and biases are selected randomly selected from close interval [0 1]. Then In each epoch the model minimizes MSE between actual targeted value and model predicted values as depicted in the following Fig.5. The training process minimized the model error MSE between actual and predicted values upto MSE = 1.2864E-04.

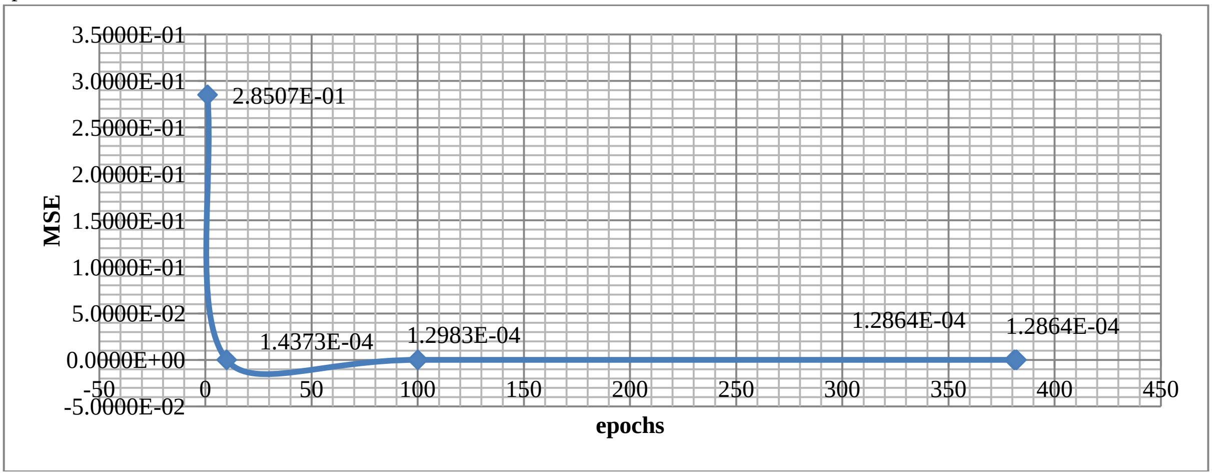

Fig. 5. Minimization of error during training process

4.1 Trained model

At MSE_G = 4.76E-04 might be considered as optimum and model might be assumed as fully trained. In this point the model has shown maximum performance. During the training process the trainable weights and biases are updated. At global minima $MSE_{G,}$ the updated weights and biases are shown in the following Table. In point of fact, it might be considered as a trained model and it is ready to suggest future values as target by inputted new independent values. In our case, now geo-coordinates (i.e., latitude, longitude, and altitude) unknown station may be inputted to interpolate the mean rainfall.

4.2 Performance in training

The performance of the model is training period is depicted in the following Fig 6. It is also visible that the absolute deviation between actual and predicted values are exceptionally small as depicted in the Fig. 7 As a result the model is accepted.

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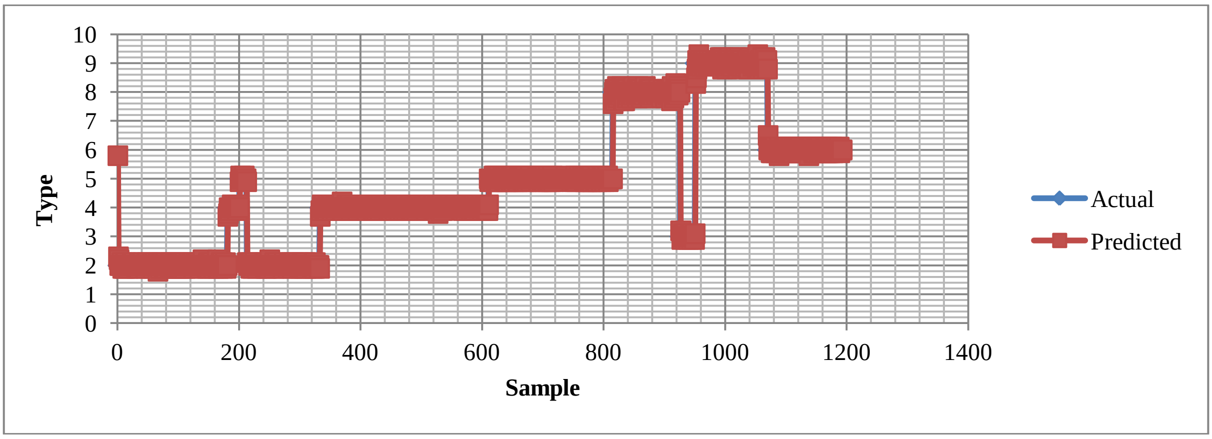

Fig. 6. Performance in Training Process

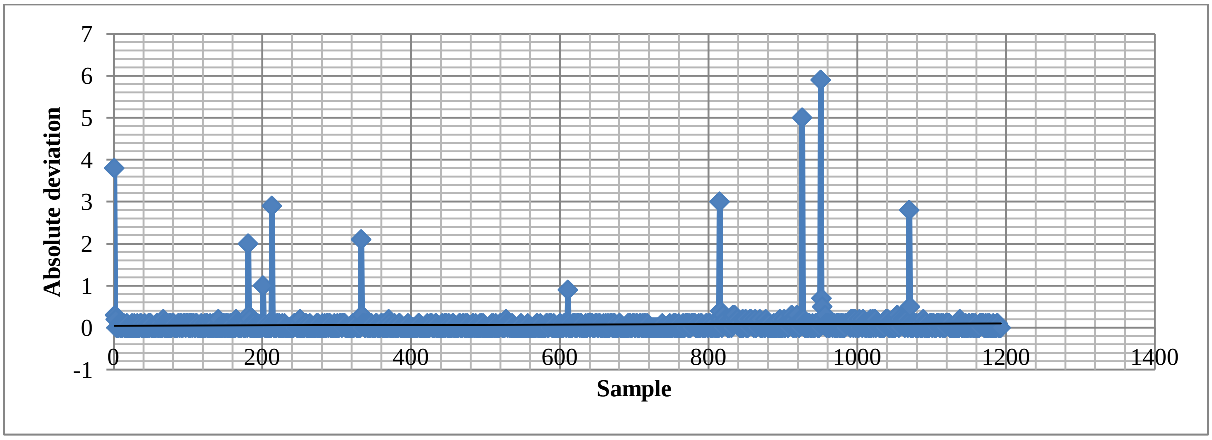

Fig. 7. Absolute Deviation between Actual and Predicted Values

5. TESTING

The performance of the model in training period is depicted in the following Table 8 and Fig 8. It is also visible that the mean absolute deviation is exceptionally small(Fig 9). Thus model is.

Table. 8. Performance in Testing Process

No	Actual	Predicted	Deviation
1	2	1.9	0.1
6	4	4	0
8	5	4.8	0.2
14	8	7.6	0.4
19	3	3.1	0.1
22	9	9.2	0.2
27	6	6.1	0.1

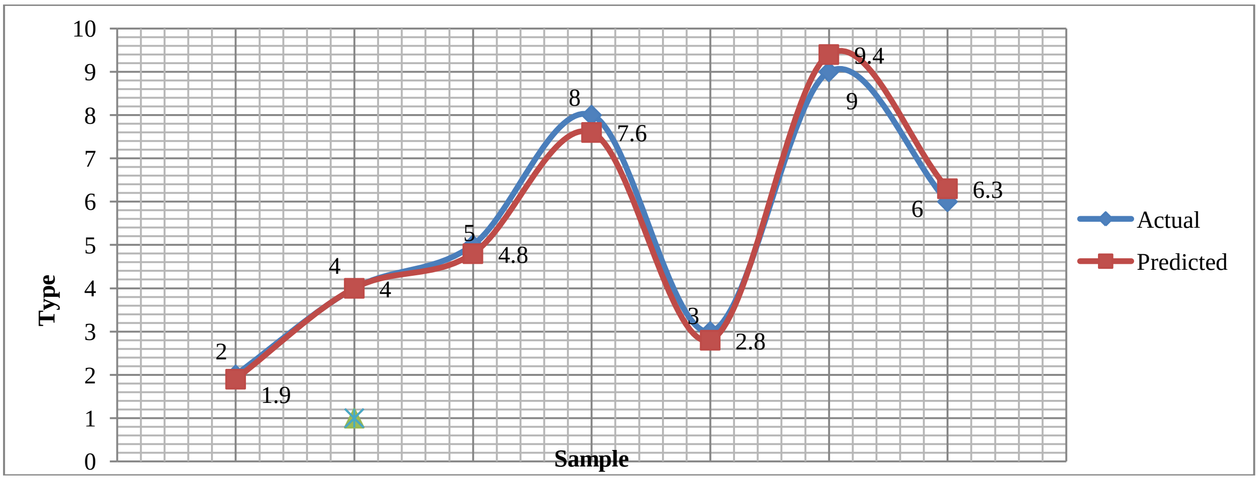

Fig. 8. Performance in Training Process

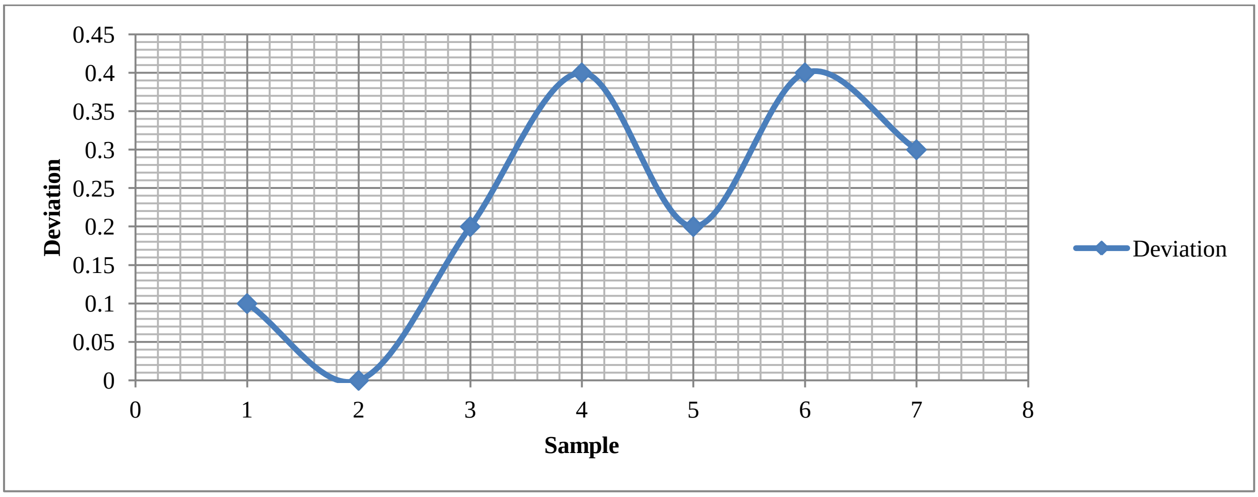

Fig 9. Absolute Deviation between Actual and Predicted Values in Testing Period

6. RESULTS AND DISCUSSIONS

In this study Neural Network model was developed for prediction of horoscope in which, 1200 records of different horoscope type were under study. Out of 1200 record type, 1193 records are selected for training and 7 records are selected randomly for testing of the model and following significance results have been found the Identification of architecture of neural network for prediction is complex and some time is sequential nervousness and also absolutely vibrant based on the inputted and independent parameters. In this study we observed that back-propagation neural network is suitable however its architecture is optimized as $n = 13$, p=30, α= 0.62, μ= 0.96. And found the optimum result with less deviation between actual and predicted values. Model is trained up to the minimal model error MSE = 1.2864E-04. Finally it is also observed that the model is performed well in testing period with minimum absolute deviation between actual and predicted values. Thus as a result it is found that neural network is suitable for horoscope prediction like other dynamic system as well.

7. CONCLUSIONS

It is concluded that, neural network is significance for constructing a relationship between planet dataset and horoscope type of a person. However, it is necessity that the neural network must be properly designed and. The proper model in this case have been found e.g., in this case, $n = 13$, p=30, α= 0.62, μ= 0.96. The training process is minimized model error up to MSE = 1.2864E-04 that were achieved by 281 epoch only and produced excellent result. Finally it is concluded that the back-propagation neural network is a appropriate tool for horoscope prediction as well.

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