VIT®

Vellore Institute of Technology

(Deemed to be University under section 3 of UGC Act, 1956)

School of Computer Science and Engineering

CSE3999 – Technical Answers for Real World Problems (TARP)

Forecasting trends In Indian Summer Monsoon Rainfall By Varying Architecture of Artificial Neural Networks(ANN)

A project submitted
in partial fulfillment of the requirements for the degree of
Bachelor of Technology (CSE)

By

Abhilasha Jha (15BCE0867)

Course Instructor

Dr. Anthoniraj A

Associate Professor

April-2018

UNDERTAKING

This is to declare that the project entitled "Forecasting trends In Indian Summer Monsoon Rainfall Using Artificial Neural Networks And Principal Component Analysis and ANN Hybrid" is an original work done by undersigned, as a part of CSE3999-Technical Answers for Real Time Problems (TARP) at School of Computer Science and Engineering, Vellore Institute of Technology.

All the analysis, design and system development have been accomplished by the undersigned. Moreover, this project has not been submitted to any other college or university.

Abhilasha Jha

ABSTRACT

Accurate forecasting of rainfall is not only the most important issue in the hydrological research but also challenging because of the non-linear data pattern followed by the rainfall data. There has been immense research in the area of precipitation pattern detection and there have been several models, but none of them has been very successful. Among several global monsoons distributed geographically lies the monsoon of South Asia which affects the Indian subcontinent, and happens to be one of the oldest and most anticipated weather phenomena and a pattern fundamental to India's economy. Indian Monsoon Summer Rainfall(ISMR) strikes India every year from June through September, but it is only partly understood and notoriously difficult to predict. Through this project, the intention is to predict the poignant problem of prediction of precipitation pattern during Indian Summer Monsoon using artificial neural networks.

Table of Contents

1. Introduction

Monsoon is actually a wind regime operating at a level of 20 km from the earth's surface. It is characterised by seasonal reversal of wind direction at regular intervals. Although the monsoon is a global phenomenon influenced by a variety of factors not yet completely understood, the real monsoon rains cover mainly the South Asian region, represented by India, Myanmar, Sri Lanka, Bangladesh, Bhutan and parts of Southeast Asia. Besides the monsoons, the Indian climate is influenced substantially by two more factors. The Himalayas contribute a continental nature to the climate, recognised by land winds, dry air, large diurnal range and scanty rainfall. The Indian Ocean, on the other hand, contributes a tropical character to the Indian climate characterised by uniformity of temperature throughout the year, short diurnal range, damp air, and frequent rainfall.

The monsoon system of the Indian subcontinent differs considerably from that of the rest of Asia. The centres of action, air masses involved, and the mechanism of precipitation of the Indian monsoon are altogether different from other monsoon systems.

Hence, unanticipated cyclones, flash floods and droughts are common phenomena in India, an issue we intend to tackle through the given project.

2. Literature Survey

The prediction of Indian Monsoon is a very niche area on which getting hold of previously done work is hard, though there have been several papers on prediction of rainfall using machine learning.

Studies of rainfall quantitative prediction are carried out using some numerical models by Bustamante et al. [1] and Olson et al. [2] and physical models by Georgakakos and Bras [3],. However, they are not successful enough in forecasting precipitation [2] due to inaccurate initial conditions, parameterization schemes of subscale phenomena, and limited spatial resolution . Using a numeric weather model, rainfall prediction is in general dependent highly on grid point values. However, it is quite difficult for rainfall as it is variable both in space and time.

Prediction of Indian Monsoon is impossible without knowing how it behaves. Paper by Gadgil[3] serves as an excellent review for those who intend to read or brush up their concepts on Indian Monsoon. The author discusses how the monsoon has over 300 years been viewed as a gigantic land-sea breeze, and puts forth the evidence and results to show that satellite and conventional observations support an alternative hypothesis, that is the monsoon as a manifestation of seasonal migration of the intertropical convergence zone (ITCZ) and why is it difficult to simulate the Indian Monsoon. The paper gives us an insight on what data(satellite/conventional) is most important in the prediction of Indian monsoon and what features are to be used(namely active-weak cycles, breaks, air pressure, zone of latitudinal belt). The author discusses about the Intraseasonal variation of TCZ.

Work by Kumar et. al[4] was instrumental in bridging the understanding the seasonal reversal of meridional temperature and pressure gradients and the associated wind circulations which constitute the summer and winter monsoons. They also present us with the fact the interannual variability of rainfall is high over low rainfall areas and vice versa. These trends, however, have been manually been observed, something which we intend to automate.

Now moving on to the works which describe methods of predicting natural phenomena using existing data and knowledge using machine learning. The most useful previously done work obtained was the one by Saha et al.[5], which employs deep learning techniques to predict monsoon over regions that are homogeneous. They state that Indian monsoon is a varying phenomena, and changes with regions and one learning algorithm cannot suffice for all regions. Hence, predicting rainfall at national level cannot suffice for all regions. They use the stacked autoencoder to automatically identify climatic factors that are capable of predicting the rainfall over the homogeneous regions of India. The process of monsoon prediction takes place using climatic predictors through an ensemble regression tree model.

Similar approach can be observed in work by Han et al. [6] that describes the application of SVM in flood forecasting. They state that like artificial neural network models, SVM also suffers from overfitting and underfitting problems and the overfitting is more damaging than underfitting. Their paper brings into focus that an optimum selection among a large number of various input combinations and parameters is a real challenge for any modellers in using SVMs. They make comparisons with some benchmarking models i.e. Transfer Function, Trend and Naive models. Their paper shows that linear and nonlinear kernel functions (i.e. RBF) can yield superior performances against each other under different circumstances in the same catchment.

Their study is also instrumental in understanding the SVM response to different rainfall inputs, where lighter rainfalls would generate very different responses to heavier ones, thus proves very useful way to reveal the behaviour of a SVM model.

Hong[7] in his paper puts forth some more points in relatively less explored area of rainfall forecasting using machine learning models. The author puts forth his own ideas while also giving a comprehensive review of other techniques used in the same field, enunciating that, Recurrent artificial neural networks (RNNS) have played a crucial role in forecasting rainfall data.

Meanwhile, support vector machines (SVMs) have been successfully employed to solve nonlinear regression and time series problems. The author uses hybrid model of RNNs and SVMs, namely RSVR, to forecast rainfall depth values. Moreover,they use chaotic particle swarm optimization algorithm (CPSO) for choosing parameters for their SVR model.

Cimen and Kisi[8] use wavelet-support vector machine conjunction model for daily precipitation forecast in their paper. They use the daily precipitation data from Izmir and Afyon stations in Turkey. They use the root mean square errors (RMSE), mean absolute errors (MAE), and correlation coefficient (R) statistics for the comparing criteria. Their comparison results indicate that the conjunction method could increase the forecast accuracy and perform better than the single support vector machine.

The major learning algorithms observed through our current literature survey is the hybrid of wavelet and support vector machine, smoothened support vector machine over GCM, hybrid of recurrent neural networks and SVM and Deep learning methods.

3.Methodology

Artificial Neural Networks, Support Vector Machines as well as Neuro-fuzzy Systems and data driven models are popular tools for predicting answers to Water Resources related research problems. Genetic Programming has been used by several researchers for modeling complex systems like in the fields of Hydraulics and Fluid Mechanics.

The problem of predicting meteorological phenomena such as rainfall over a region happens to more complex than any other general scientific problem reason being the extreme instability of the atmosphere. The systems that create what we are trying to predict, the clouds or monsoon depressions (in which thousands of clouds are embedded) are the resultants of several instabilities like nonlinear interaction between different spatial scales from kilometers (as in a single cloud) to hundreds of kilometers (as in a monsoon depression or a hurricane).

It is mathematically challenging to use climate signals for the prediction of rainfall due to the instabilities involved. The difficulties in modeling such complex systems can be considerably reduced by using the modern Artificial Intelligence(AI) tools like Artificial Neural Networks (ANNs), Genetic Algorithm (GA) and Genetic Programming (GP). Hence such AI tools are tried nowadays for modeling complex systems.

3.1 The dataset

All India (India taken as a single unit) summer monsoon rainfall data for the period 1871–2016 for June, July, August, September and the whole season is taken from Indian Institute of Tropical Meteorology[11]. The data-set is prepared by area-weighting 306 well-distributed non-hilly stations. A glimpse of the dataset can be viewed as follows:

ALL-INDIA MONTHLY, SEASONAL AND ANNUAL RAINFALL SERIES FOR THE PERIOD 1813-2006. THE RAINFALL FIGURES ARE IN MM.

YEAR	J	F	M	A	M	J	JU	A	S	O	N	D	ANN	JF	MAM	JJAS	OND
1813	10.0	14.2	20.1	25.6	52.0	190.8	274.1	222.6	153.0	64.2	78.3	13.7	1118.6	24.1	97.7	840.6	156.2
1814	9.0	12.3	14.2	22.5	44.3	133.1	242.4	246.1	215.8	55.8	16.2	9.7	1021.4	21.3	81.1	837.3	81.7
1815	18.5	14.7	16.5	26.1	51.4	149.8	373.0	215.9	156.7	71.4	92.6	15.7	1202.5	33.2	94.1	895.5	179.7
1816	8.5	16.0	14.1	22.2	44.8	134.6	297.5	244.2	217.9	54.6	27.7	6.2	1088.5	24.5	81.2	894.2	88.6
1817	10.5	12.8	14.7	23.2	46.7	242.3	269.9	226.0	238.2	103.9	56.7	15.5	1260.4	23.2	84.6	976.6	176.0
1818	10.0	14.2	16.2	30.4	50.5	187.3	319.1	340.3	189.5	115.4	65.2	20.0	1357.9	24.1	97.1	1036.1	200.5
1819	8.5	12.1	13.5	38.1	42.0	135.8	287.6	244.0	197.5	38.5	28.1	5.8	1051.5	20.7	93.6	864.9	72.3
1820	9.4	13.4	71.3	27.0	134.3	163.1	310.4	275.7	163.0	84.3	14.3	43.9	1310.0	22.7	232.6	912.2	142.5
1821	25.1	13.2	16.5	33.7	43.6	140.5	254.5	286.6	205.8	75.4	27.6	11.7	1134.3	38.3	93.9	887.3	114.7
1822	18.5	12.6	13.9	26.1	43.2	186.7	266.0	310.1	197.6	99.7	46.3	9.3	1230.1	31.1	83.2	960.4	155.3
1823	15.1	12.7	21.3	22.0	44.7	163.8	242.6	254.0	135.1	57.1	4.7	3.9	976.9	27.8	88.0	795.4	65.8
1824	16.9	15.0	16.9	26.7	52.9	115.9	242.7	285.3	126.3	91.7	28.7	12.6	1031.4	31.8	96.4	770.2	132.9
1825	10.3	13.5	15.9	25.1	72.9	186.6	297.5	269.2	167.6	98.0	28.4	17.9	1202.8	23.8	113.9	920.9	144.3
1826	17.8	10.6	11.8	21.5	66.5	220.2	303.7	276.0	178.8	41.4	74.7	27.2	1250.3	28.4	99.8	978.8	143.4
1827	55.5	14.2	39.3	21.6	143.4	278.5	257.7	234.9	206.1	87.2	57.4	15.1	1410.9	69.7	204.2	977.3	159.8
1828	12.7	13.7	34.7	19.6	46.1	146.4	311.5	233.5	200.0	8.3	1.0	0.6	1106.8	26.4	100.4	891.5	88.5
1829	7.8	22.0	21.2	19.7	51.5	211.3	253.4	228.1	124.6	84.1	15.7	17.6	1057.0	29.8	92.4	817.5	117.3
1830	6.8	7.3	21.4	44.3	78.4	175.9	277.6	211.9	113.7	76.4	9.1	11.2	1033.9	14.1	144.1	779.0	96.6
1831	6.3	20.2	14.7	38.7	34.5	209.1	235.1	295.3	222.8	85.7	35.5	18.0	1216.0	26.5	88.0	962.3	139.1
1832	7.4	15.1	28.8	22.9	45.2	112.5	295.9	213.6	153.1	48.7	2.6	2.2	948.0	22.5	96.8	775.1	53.5
1833	8.1	9.9	7.5	35.7	80.3	115.0	257.8	248.9	197.6	61.3	23.5	15.3	1060.8	18.0	123.5	819.3	100.0
1834	8.0	11.2	17.9	41.1	47.3	166.7	269.3	280.7	166.0	86.4	15.9	5.7	1116.2	19.2	106.3	882.7	108.0
1835	8.3	9.0	17.9	45.4	105.9	151.5	267.0	334.7	200.9	74.4	32.1	6.5	1253.7	17.3	169.2	954.2	112.9
1836	7.2	18.0	12.6	23.1	41.2	145.3	260.4	305.9	136.8	50.5	43.8	8.2	1053.1	25.3	76.9	848.4	102.5
1837	11.7	12.4	11.0	20.8	59.5	143.8	246.4	279.4	135.1	83.3	75.9	13.3	1092.7	24.1	91.2	804.8	172.5
1838	7.0	11.4	16.9	22.3	26.5	166.5	185.4	205.9	139.7	42.5	36.1	8.5	868.8	18.3	65.7	697.6	87.2
1839	22.0	9.7	13.4	23.4	58.7	154.1	301.4	256.1	171.1	39.4	37.3	6.6	1093.2	31.7	95.5	882.7	83.3
1840	6.8	7.0	15.1	17.9	51.2	167.1	254.5	223.5	128.7	55.8	41.7	2.8	972.2	13.8	84.2	773.8	100.3
1841	16.1	7.7	16.4	29.9	57.3	179.3	263.6	279.2	180.1	118.5	20.4	4.7	1173.5	23.9	103.7	902.2	143.7
1842	21.8	8.6	16.6	18.3	60.3	180.4	263.3	297.9	189.5	45.6	18.9	4.1	1125.3	30.5	95.1	931.2	68.6
1843	47.9	8.0	26.6	34.4	95.1	158.7	266.5	219.2	163.4	87.4	2.4	33.2	1142.6	55.9	156.1	807.7	122.9
1844	10.3	12.5	14.9	20.5	74.8	141.2	285.2	248.5	112.8	56.1	9.4	28.0	1014.2	22.8	110.2	787.6	93.5
1845	9.3	37.5	23.5	23.1	60.4	189.2	325.4	235.7	97.1	47.1	12.2	22.8	1083.3	46.8	107.0	847.4	82.1
1846	4.8	11.2	13.5	14.1	68.1	279.2	309.3	182.2	168.3	78.6	24.5	9.7	1163.5	16.0	95.6	939.1	112.8
1847	16.7	20.8	10.3	31.1	70.7	192.6	271.4	244.2	139.0	101.2	76.7	16.8	1191.6	37.5	112.1	847.2	194.7
1848	4.0	9.2	8.3	30.9	80.0	166.5	203.7	197.9	119.9	75.9	17.7	12.7	926.6	13.2	119.1	688.0	106.3
1849	36.3	10.0	11.8	30.8	53.4	179.5	210.2	239.4	169.1	101.0	25.7	18.0	1085.2	46.2	96.0	798.3	144.7
1850	30.5	28.3	13.3	30.0	30.3	174.8	240.3	260.1	188.3	76.5	31.5	11.6	1115.4	58.8	73.5	863.4	119.6
1851	33.1	26.9	9.8	28.0	49.8	153.7	297.5	173.3	119.5	93.6	38.9	5.5	1029.7	60.0	87.6	744.0	138.1
1852	5.8	7.0	58.3	26.0	93.1	203.6	300.5	219.7	156.9	61.1	29.4	21.0	1182.3	12.7	177.4	880.6	111.5
1853	32.3	8.6	27.5	25.1	41.6	203.5	308.0	170.3	118.5	90.4	17.6	1.3	1042.2	40.9	94.2	800.3	106.7
1854	7.2	18.4	4.4	28.0	30.7	212.9	236.4	303.2	183.8	102.4	41.2	10.5	1179.1	25.6	63.1	936.3	154.1
1855	9.4	13.2	32.9	38.5	32.5	142.6	290.2	133.9	178.7	50.8	1.2	11.8	935.7	22.6	103.9	745.4	63.8
1856	11.5	5.2	17.1	32.2	109.9	207.4	303.7	274.5	114.0	84.3	26.1	12.6	1198.4	16.7	159.2	899.5	123.0
1857	25.0	15.6	7.5	29.9	103.2	166.0	244.4	249.8	170.4	90.9	25.9	1.8	1130.5	40.6	140.6	830.7	118.7
1858	15.1	12.2	7.5	20.7	103.8	123.5	308.0	208.2	173.8	17.5	4.0	1.0	1118.1	27.3	132.0	813.5	145.3
1859	14.7	17.8	31.7	64.7	39.9	194.8	259.9	285.0	173.1	68.1	31.2	13.4	1194.4	32.5	136.4	912.8	112.7
1860	9.0	17.1	10.7	22.1	46.2	126.1	266.2	195.0	145.8	79.3	5.9	4.6	927.9	26.1	79.0	733.1	89.7
1861	16.1	2.7	17.3	26.2	70.7	245.8	363.6	279.9	161.9	79.5	30.5	6.5	1300.9	18.8	114.3	1051.2	116.6
1862	11.8	5.8	21.9	27.5	42.1	190.7	298.6	260.6	216.2	132.5	22.7	6.6	1237.0	17.6	91.5	966.1	161.9
1863	14.4	5.4	22.5	37.0	43.8	240.1	328.0	238.9	134.2	89.5	15.6	18.0	1187.4	19.8	103.3	941.2	123.1
1864	8.4	14.9	8.4	28.5	62.9	146.8	262.6	213.7	124.5	45.0	27.0	7.1	949.9	23.3	99.9	747.6	79.1
1865	10.7	27.3	33.2	43.8	85.2	128.7	265.4	297.2	129.8	41.8	21.5	13.6	1098.1	38.0	162.1	821.0	76.9

Fig 1. ALL-INDIA MONTHLY, SEASONAL AND ANNUAL RAINFALL SERIES FOR THE PERIOD 1813-2006. THE RAINFALL FIGURES ARE IN MM

3.2 Descriptive Statistics

Since we predict the Indian Monsoons, the relevant months are June, July, August and September. The Pearson's correlation values between the four months (June to September) are depicted in Table 1, which reflect that rainfall are not pairwise correlated. The correlation values for pair June–July , June–August , June–September, July–August , July–September and August–September are very small, which also suggested that the relationships are not linear.

Table 1: Correlation analyzes of ISMR data for the period 1871–2016

Correlation	June	July	August	September
June	1	-0.0176	-0.0159	-0.0810
July	-0.0176	1	0.1234	0.2747
August	-0.0159	0.1234	1	0.2601
September	-0.0810	0.2747	0.2601	1

The nonlinearity evident from the above statistics enable us to see the significance of designing ANN based model for advance prediction of rainfall . In this paper, we use ANN based model with varying outputs and varying layers to predict ISMR of a given year using the observed time series data of the four months.

The model is developed based on supervised multilayer feed forward neural network algorithm where the learning process aims to minimize the error rate between predicted output and the actual observation.

The performance of the model is assessed using various statistical parameters. Large number of input patterns may lead to overfitting of a model[10], and suitable predictor parameters to use for Indian Summer Monsoon Rainfall(ISMR) are not possible yet as far as existing literatures are concerned, so we intend to predict ISMR based on the monthly time series rainfall values.

3.3 Using Artificial Neural Networks(ANNs)

Before moving into the nitty gritty of the architecture let's view as to why we use the Multilayer Feed-Forward Neural Network:

1. A multi-layer feed-forward neural network with a nonlinear activation function can classify the data very efficiently. Therefore, we use the neural network of this kind for the development of our architecture.

2. A multi-layer feed-forward neural network with more than three layers can generate arbitrarily complex decision regions. Therefore, one or more hidden layer with one input layer and one output layer are considered in designing the architecture.

3. A large number of neurons in hidden layer can make the training process of multi-layer feed-forward neural network more complex, because weight of each interconnection link needs to be adjusted at each iteration of the training process. Therefore, the proposed neural network is designed with minimum number of neurons in hidden layer. During the training process, each time an error is calculated while adjusting the weights.

3.3.1 Architecture I : Hidden layer neurons are varied as per the number of neurons in the input layer

The network designed for the present study consists of comparison of several layers input, output (5-9 neurons, the next year value from any one of the time series under consideration, based upon time series in consideration) and hidden (6-10 neurons). Networks are trained separately for seasonal, June, July, August and September mean time series.

The rainfall data is normalized before putting in ANN. The years chosen from the data for co-validation and testing are random.

Table 2. Description of the neural networks employed(Varying Hidden layer nodes, Single Hidden layer)

Network ID	Input Layer nodes (How many years under consideration)	Hidden Layer nodes	Output layer nodes
ANN 1.1	5	6	1
ANN 1.2	6	7	1
ANN 1.3	7	8	1
ANN 1.4	8	9	1
ANN 1.5	9	10	1

3.3.1 Architecture II: Hidden layers are varied keeping input layer and hidden layer nodes constant

The network designed for the another of our ANN architecture consisted of five layers input (Previous five year values from each time series of monthly mean ISMR values of June, July, August and September and the seasonal mean), output (1 neuron, the next year value from any one of the time series under consideration) and six hidden neurons and variation in layers for comparison.

Both the architectures use the Rectifier Linear Unit(ReLu) as the activation function. The optimizer used is *Adam*. In simple words, we use *Adam's* update rule for the manipulation of weights due to it's important property of careful choice of stepsizes.

Table 3. Description of the neural networks employed(Varying Hidden layers,keeping hidden layer nodes constant)

Network ID	Input Layer nodes (How many years under consideration)	Hidden Layers	Number of nodes in each hidden layer	Output layer nodes
ANN 2.1	5	1	6	1
ANN 2.2	5	2	6	1
ANN 2.3	5	3	6	1
ANN 2.4	5	4	6	1
ANN 2.5	5	5	6	1

4. Results

4.1 Architecture I : Results

We covered the time series considering past 5 to 9 years for each of the months in ISMR and the following results were obtained:

Table 4. Root Mean Square Errors for Different Number of Years Used for Prediction of ISMR months (10000 epochs, Rainfall has been normalized to reduce time)

Months/ Years covered	June	July	August	September
5	0.126	0.0840	0.0751	0.172
6	0.162	0.0801	0.083	0.163
7	0.139	0.0664	0.1058	0.142
8	0.129	0.1009	0.1296	0.173
9	0.157	0.0933	0.0980	0.175

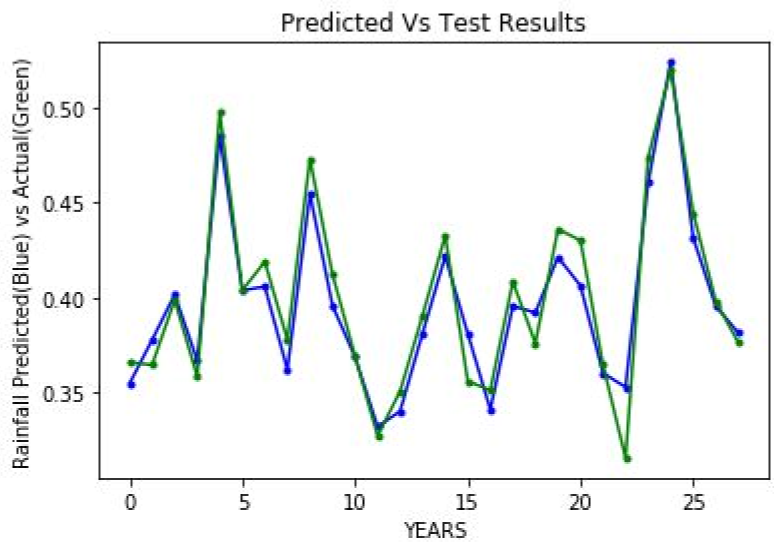

Fig 1. Rainfall Predicted Vs Actual for input layer =5 for the month of August

4.2 Architecture II : Results

Table 4. Root Mean Square Errors for Different Number of Layers Used for Prediction of ISMR months (10000 epochs, Rainfall has been normalized to reduce time, Input Layer has 5 neurons)

Months/ Layers Within MLFF network	JUNE	JULY	AUG	SEP
1	0.4973	0.0838	0.0748	0.4385
2	0.1251	0.0928	0.0737	0.1750
3	0.1257	0.0875	0.0757	0.1725
4	0.1279	0.2648	0.0837	0.1663
5	0.4974	0.0865	0.0742	0.1680

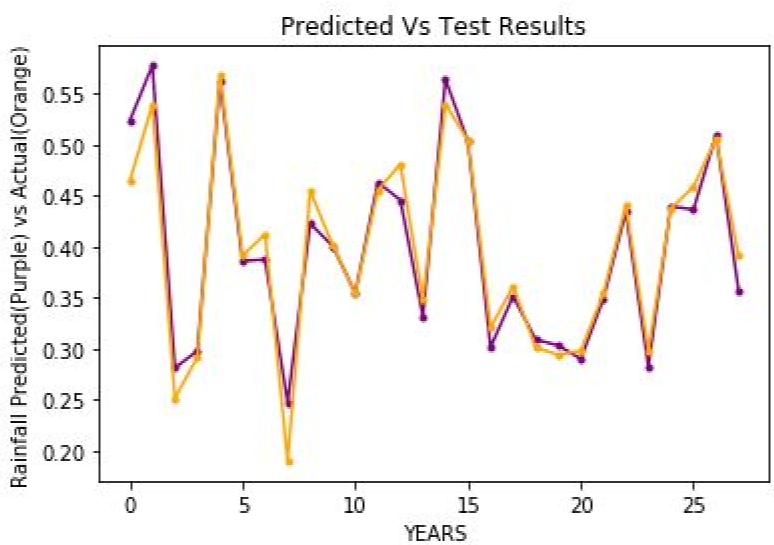

Fig 1. Rainfall Predicted Vs Actual for 2 layered MLFF for the month of June

5. Discussion and Conclusion

It was observed in both the architectures that the number of epochs increases the accuracy of the model that is reduces the root mean squared error. When the number of epochs defined is less or equal to 1000, the variance in the values of mse is relatively higher than when the number of epochs are increased.

In Table I, no clear pattern in root mean square errors can be observed. In Table II,the mean squared error stays consistent for all the months whatever the number of layers might be,however, an occasional large value of mean squared error is observed in case of June for the layers 1 and 5, in case of August for layer 4 and in case of September layer 1 . This makes us conclude that if the value of the number of epochs is sufficiently large, the number of layers of ANN plays little role in accuracy for the prediction of ISMR.

Hence, the best way to predict rainfall would to keep the number of inputs constant and vary the layers, and use mean of the values to come to a conclusion for each month.

References

1. Bustamante, J., Gomes, J., Chou, S., Rozante, J., 1999. Evaluation of April 1999 Rainfall Forecasts over South America Using the ETA Model. INPE, Cachoeira Paulista, Sp, Brasil
2. Olson, D.A., Junker, N.W., Korty, 1995. Evaluation 33 years of quantitative precipitation forecasting at NMC. Weather Forecast. 10, 498–511
3. Gadgil, S. (2003). The Indian monsoon and its variability. Annual Review of Earth and Planetary Sciences, 31(1), 429-467.
4. Rao, R. R., & Sivakumar, R. (2003). Seasonal variability of sea surface salinity and salt budget of the mixed layer of the north Indian Ocean. Journal of Geophysical Research: Oceans, 108(C1).

5. Saha, M., Mitra, P., & Nanjundiah, R. S. (2017). Deep learning for predicting the monsoon over the homogeneous regions of India. Journal of Earth System Science, 126(4), 54.
6. Han, D., Chan, L., & Zhu, N. (2007). Flood forecasting using support vector machines. Journal of hydroinformatics, 9(4), 267-276.
7. Hong, W. C. (2008). Rainfall forecasting by technological machine learning models. Applied Mathematics and Computation, 200(1), 41-57.
8. Kisi, O., & Cimen, M. (2012). Precipitation forecasting by using wavelet-support vector machine conjunction model. Engineering Applications of Artificial Intelligence, 25(4), 783-792.
9. http://www.tropmet.res.in/Data%20Archival-51-Page
10. Krishnamurti, T.N., Xue, J., Bedi, H.S., Ingles, K. and Oosterhof, D., 1991. Physical initialization for numerical weather prediction over the tropics. Tellus A: Dynamic Meteorology and Oceanography, 43(4), pp.53-81.