Turkish Online Journal of Qualitative Inquiry (TOJQI)

Volume 12, Issue 5, June 2021: 1272– 1287

Research Article

An Efficient Rainfall Prediction Scheme based on Sliding Window Algorithm with Effective Distance Metric Measure

M. Vijaya Chitra[1], Dr. Grasha Jacob[2]

Abstract

Rainfall prediction is essential for the planning and management of water resources and farming. Accurate prediction of rainfall is a difficult task due to the chaotic nature of atmosphere. This paper presents an approach for rainfall prediction using Sliding Window concept with various distance metric measures algorithm. The Sliding Window Algorithm (SWA) observes the data during the same period in a previous year and predicts rainfall in the following year. Various distance metrics are used and compared to improve the performance. Using Sliding Window Algorithm with Effective Distance metric measure (SWA-ED), month wise results are being computed. Based on this algorithm, the rainfall prediction test was conducted for Tirunelveli District, Tamil Nadu, India using the rainfall data for five-year period.

***Keywords* -** Rainfall prediction, Sliding window, Euclidean distance, Hamming distance, Chebyshev distance

I. INTRODUCTION

India is predominantly an agricultural country. Water is the most important resource for the existence of life and agriculture. Rainfall and ground water are the vital sources of water. Rainfall prediction is needed to conserve water and to prevent devastations. It is well known fact that execution is as well important as planning. If you fail to plan, we plan to fail. Predicting rainfall, the availability of water resources help utilize the water sparingly and effectively. As such undoubtedly predicting the rainfall which in turn helps sustain the water resources. For example, Rain Water Harvesting may be taken to store water, which may be used during lean periods. As far ground water recharge is concerned, the future availability of water should not get evaporated and its path to irrigate the fields.

[1]Research Scholar, Register Number : 18121172162001
[1]Manonmaniam Sundaranar University, Abishekapatti, Tirunelveli 627 012, Tamil Nadu, India
[2] Associate Professor, [1, 2] Dept of Computer Science Rani Anna Govt College for Women ,Tirunelveli 627 008, Tamil Nadu, India. grasha.viji@gmail.com

Nearly 80 to 84 percent of water is consumed in irrigation, whereas the remaining 20 percent is used for drinking and cleaning purposes. So it goes without saying rainfall prediction is essential. Climate forecasting has been a standout amongst the most deductively and mechanically difficult issues in the world over the most recent century. Since the most established human progress, people have endeavored to anticipate the climate casually. Presently, climate estimating is made through the use of science and innovation. It is made by collecting quantitative data about the current state of the atmosphere through weather station and interprets by meteorologist (Lee & Sohn, 2005). The forecast of climate condition is fundamental for different applications. Some of them are atmosphere observing, dry spell identification, extreme climate forecast, agribusiness and generation, contamination dispersal, etc. The country is, essentially, subject to the sensibly exact expectation of the aggregate sum of precipitation from the earliest starting point of June as far as possible September e.g. precise precipitation estimating will offer exact and convenient projection of stream determining in the waterway bowls.

Climate forecast (Divya and Jawahar, 2014) is the use of science and innovation to anticipate the condition of the environment for a given area. It is ending up progressively indispensable for researchers, agriculturists, farmers, global food security, disaster management and related associations to comprehend the regular wonders to design and be set up for the future. The art of weather prediction began with early civilizations using re occurring astronomical and meteorological events to help them monitor seasonal changes in the weather.

Precipitation is a complex environmental procedure, which relies on many climate related highlights. Precise and opportune precipitation expectation can be useful from numerous points of view, for example, arranging the water, issuance of early flood alerts, dealing with the flight tasks and restricting the vehicle and development exercises. Exact precipitation expectation is progressively mind-boggling today because of atmosphere varieties. Researchers reliably have been attempting to anticipate precipitation with greatest exactness by streamlining and incorporating information mining procedures.

In the past, rainfall was predicted by farmers on the basis of experience. Basically there are two approaches to calculate rainfall. They are Empirical and Dynamical Methods. The Empirical method is based on the analysis of past historical data of weather and its relationship to a variety of atmospheric variables. In dynamical approach, predictions are generated by physical models based on a system of equations that predict the future rainfall (Hirani & Mishra, 2016).

Since the art of weather predictions beginning with the early civilizations, its evolution, its volatility, points its fingers to the above empirical and dynamical methods, it is incumbent upon us to forecast the rainfall.

Figure 1 demonstrates the rainfall forecasting.

The Rest of this paper is organized as follows. The next section narrates the literature review of various techniques used for predicting weather. Then followed by study area and data. And then discussion about the Proposed Work. Next section shows the experimental results. Finally, the paper is concluded.

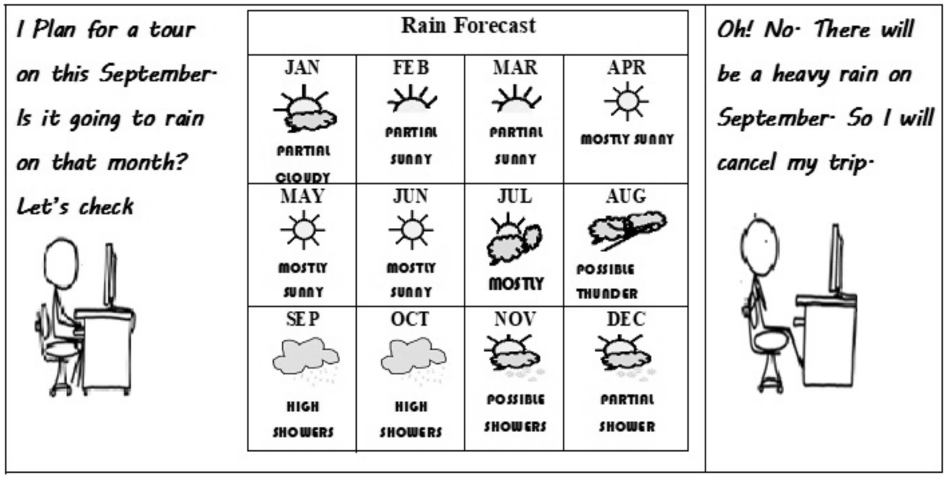

Fig 1. Rainfall Forecasting diagram

II. LITERATURE REVIEW

Many researchers have proposed rainfall forecasting models. Datar, Motwani, et.al (2002) introduced a model of estimating specifically sliding window that is setting for information streams, in which measurements are figured over a "sliding window" of the N, a large portion of things in the information stream. Various outcomes exhibited on evaluating capacities over a sliding window for a solitary stream were obtained.

Gedeon et al. (2003) divided the data into sub-population and hopefully reduce the complexity of the whole data. They compared their method with an established method which uses radial basis function networks and orographic effect. However, they proved that their method has the advantage over other methods.

Gabella et al. (2004) observed that the prediction of rainfall rate based on weather radar measurements using the neural SOM and the statistical KNN classifier.

In 2005 Chen et al. wenting for neural network with two hidden layers to forecast typhoon rainfall

The prediction model of Guhathakurta (2006) was found to be better since he developed the Artificial Neural Network model for Long-Range Monsoon Rainfall Prediction.

Agrawal et al. (2006) followed the statistical method based on autoregressive integrated moving average (ARIMA) and the emerging computationally powerful techniques based on ANN. They concluded that ANN model would be an appropriate forecasting tool which outperforms the ARIMA model.

By using Artificial Neural Networks based on feed-forward back-propagation architecture, Kumarasiri & Sonnadara (2006) incorporated the physical aspects of the atmosphere; three models were born out of that. Despite, their accuracies were found by decreasing they attempted to present the success rates confined to Monsoon seasons.

In 2007 Mathur et al. followed the artificial neural networks (ANNs) with back propagation for supervised learning. It was used to forecast the future weather conditions and the results were very positive.

Chattopadhyay (2007) adapted the feed forward Artificial Neural Network model. He proved that the supremacy of the ANN over the other models since he made elaborate comparisons.

By employing Artificial Neural Networks process Maity et al. (2007) followed an methodology. It could be utilized in handling the highly non-linear and complex behavior of the climatic variables. Genetic Optimizer (GO) was used by them to optimize the ANN architecture.

Manojit et al. (2007) presented ANN model again. They compared the performance of neural net model with conventional processes and the Neural Net stood out better in the Multi Layer Perceptron.

Chattopadhyay and Chattopadhyay (2008) skillfully followed nineteen neural network models. Elaborate comparison was also made. Finally they proposed that eleven hidden- nodes three-layered neural network came out better than asymptotic regression.

Tripathi et al. (2008) developed an Artificial Neural Network model. They also applied the developed ANN model in predicting the rainfall and flood management.

Since Cuimei et al. (2009) developed a new model based on empirical mode decomposition (EMD) and the RBF neural network (RBFN) for forecasting the rainfall, it showed high accuracy rate.

Guhathakurta et al. (2009) attempted to prove the probabilistic forecast was better one over deterministic forecast.

In the same year, Karim (2009) presented the Artificial Neural Network method is conductive rather than classical regression model.

In 2010 Santosh and Shareef developed back propagation neural network. They created the training data from more than 200. His methodology was able to determine non-linear relationship having with historical data provided to the system.

Again Ravikanth et al. (2010) followed the back propagation neural network model. They have used 70 percent of the data for training and 30 percent for testing. It goes without doubt their accuracy rate was between 94.28% and 99.79%.

Patil and Ghatol (2010) followed different artificial neural network topologies and proved that the topologies were found be right for the prediction.

Sarthak et al. (2012) focused on ANN model. They tested three algorithms in multi-layer architecture. They found out that Back Propagation Algorithm out performed than Layer Recurrent Network (LRN) and Cascaded Back-Propagation (CBP).

Gao, Wang, et al (2012) suggested a seasonal ARIMA (Autoregressive Integrated Moving Average) model for the prediction of monthly rainfall in Yantai, China. They first analyzed the stability and correlation of the time series and then predicted the monthly precipitation for three years.

Wu & Chau et al. (2013) dealt with several soft computing approaches. Two aspects were taken into considerations. They are data-preprocessing procedure and adopting a modular modeling method. They also used ANN in their presentation. Moving average showed better results to the other processes.

Indrabayu, Achmad, et.al (2013) discussed the potential of statistical approach in predicting rainfall using Adaptive Splines Threshold Autoregressive (ASTAR) and Auto-

Regressive Integrated Moving Average (ARIMA), and they suggested that the ASTAR method had a better prediction compared to ARIMA.

Kapoor and Bedi (2013) had proposed a Sliding Window Algorithm (SWA) to anticipate climatic conditions. They registered the month wise results for a long time to check the exactness. In their investigation they concluded their calculation by distinguishing the anticipated variety "V" that would add to the past precipitation information to deliver extreme precipitation estimation.

Nazim and Ajith (2015) developed a Neuro-Fuzzy Inference System (ANFIS) model for rainfall prediction using date, minimum temperatures, humidity and wind direction as predictors. This model was able to capture the dynamic behavior of the rainfall data and it helped in long term rainfall prediction.

Azahari, Othman and Saian (2017) had executed the sliding window idea that was proposed by Kapoor and Sarabjeet keeping in mind the end goal to deliver acceptable exactness precipitation anticipating result. The outcome demonstrates that the upgrade sliding window estimation is profoundly exact, contrasted with past sliding window calculation, in the light of the consequence of model approval utilizing Mean Square Error (MSE) and relative Geometric Root Mean Square Error (GRMSE). They utilized Euclidean separation metric in SWA so as to enhance its execution.

The above references invariably show the Artificial Neural Network method was profusely used. Though different models came out with different results, the data, the study, the methodology had as effect over all models including ANN. But my model is an entirely different one that is sliding window model.

III. STUDY AREA AND DATA

In this study the data set belongs to Tirunelveli District, Tamil Nadu in India. Tirunelveli is a coastal district where agriculture is the primary vocation. Both food crops and commercial crops are grown in the district. Rainfall is important for the persistent growth of crops and hence the rainfall in this district is analyzed for forecasting. Not only in Tirunelveli district but also the whole India two seasons that is Kar season and Pishanam season act on the cropping pattern. This is essentially because India is a sub tropical country and its agriculture is based on monsoon. So my study is confined to particular periods, say June to January.

The data used here for testing were collected from the Joint Director Office, Tirunelveli, Tamilnadu. The data covers the period of 40 months, that is, June 2012 to January 2018.

The data set contains three attributes, their data type and description as shown in Table 1.

Table 1. Attributes of the rainfall dataset

Attribute	Type	Description
Year	Numerical	Year Considered
Month	Numerical	Month Considered
Total	Numerical	Total annual rainfall

IV. PROPOSED WORK

In this study, the sliding window concept augmented the forecasting result by defining the average monthly rainfall, from June 2012 to January 2018. Using Sliding Window Algorithm with Effective Distance metrics measure (SWA-ED), month wise results are being computed to check the accuracy.

A. Methodology

In this study Euclidean distance metric is employed in Sliding Window Algorithm. Apart from Euclidean Distance, Chebyshev distance and Hamming distance metrics have been added tentatively. This is to give some impetus to effective distance metric measure. Besides, the results are elaborately compared in order to arrive at the accuracy level. This accuracy level helps estimate the right prediction of rainfall.

However weather conditions have to be taken into account. As such the past two years and the current one year weather conditions prevailing were taken. This augments to predict the future rainfall accurately.

The study is further divided into twelve months wherein the weather parameters which have a toll on monthly rainfall have been taken to predict the rainfall accurately.

Figure 2 exhibits the block diagram of methodology. In brief the rainfall data during the year 2015 and 2016 was used by sliding window. Besides 2017 data was also combined. All these helped this study to arrive the rainfall prediction using distance metrics.

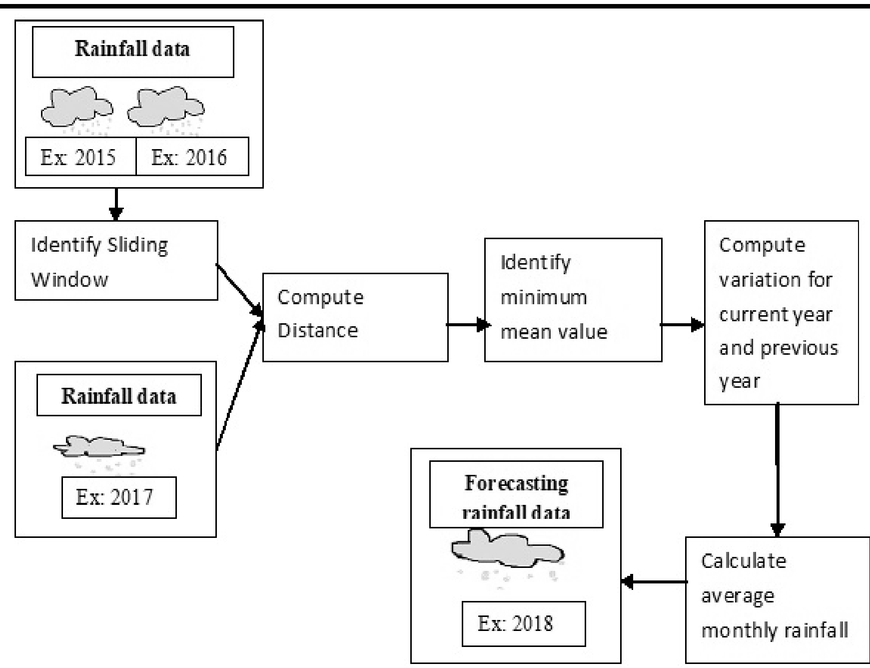

Fig 2. Block diagram of the methodology

B. Sliding Window

In this work only one weather parameter will be taken into consideration, that is, monthly Rainfall. Hence the size of the variation of the current year will be represented by a matrix of size 8 × 1 for the months June to January. Similarly for the past two years, the matrix size would be 16 × 1. Now, the first step is to divide the matrix of size 16×1 into the sliding windows.

Figure 3 demonstrates the concept of sliding window. W1 represents window1, w2 represents window2. Hence, 9 sliding windows can be made of size 16×1 each.

C. Distance Metrics

In this study different types of distances (Pandit & Gupta, 2011) are used to calculate and compare the data. They are Euclidean, Chebyshev and Hamming distances. These distances and Root Mean Square error are explained in Table 2.

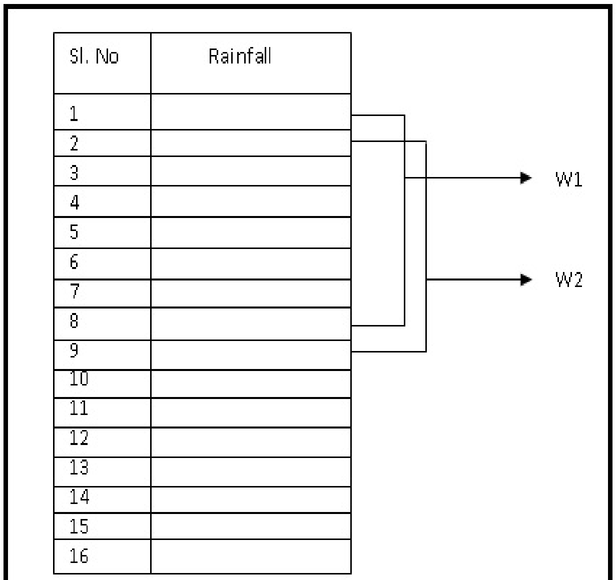

Fig 3. Sliding Window for 16 months

Table 2. Distance Metrics Used

Distance	**Meaning**	**Formula**
Euclidean distance	It is the straight distance. It calculates the metrics between two points.	$\sqrt{\sum_{i=1}^{m}(x_i - y_i)^2}$
Chebyshev distance	It computes the difference between two points. It offers the highest distance between the points in any single dimension.	$max_k\lvert x_{ik} - y_{ik}\rvert$

Hamming distance	It estimates the distance between two variables is the number of positions at which the corresponding variable is different	$\sum_{i=1}^{m} \lvert x_i - y_i \rvert \; x = y \rightarrow D = 0 \; x \neq y \rightarrow D = 1$
Root Mean Square Error	Root-mean-square error is a frequently used measure of the differences between the predicted value and the values actually observed.	$\sqrt{\frac{\sum_{i=1}^{m}(x_i - y_i)^2}{n}}$

D. Statistical Measures

The following statistical measures are used for rainfall prediction:

1) Mean: Mean is the average of the sum of the weather data of all the years considered.

2) Variation: Variation gives the difference between the previous year's weather and current year's weather.

E. Performance Metrics

A two-dimensional table exhibits the discrete joint appropriation of figures and perceptions as far as cell checks. For dichotomous downright estimates having just two conceivable results (Yes or No), the accompanying (2x2) possibility contingency table is characterized in Table 3. Table 4 gives the verification metrics obtained from the contingency table.

Table 3. Contingency table

		Observed		
		YES	**NO**	
Forecast	**YES**	**HITS p**	**FALSE ALARMS Q**	**Total event Forecast p+q**
	NO	**MISSED EVENTS R**	**CORRECT NEGATIVES S**	**Total non-event Forecast r+s**
		Total event Observed p+r	**Total non-event Observed q+s**	**Sample Size a=p+q+r+s**

Table 4. Verification Metrics

Metrics	Description	Formula
Hit Rate HR	It refers to the number of hits separated by the total number of events observed.	$\frac{p}{p+r}$
False alarm rate FA	It explains the number of false alarms separated by the total number of non-events observed.	$\frac{q}{(q+s)}$
Hanssen-Kuiper Score KSS	It measures the skill of the forecast to distinguish between events and non-events	HR-FA
Base Rate BR	It identifies the complete frequency of an event observed normalized by the whole number of events.	$\frac{(p+r)}{a}$
Relative Frequency of forecasted events RF	It relates to the complete frequency of an event forecast normalized by the whole number of events.	$\frac{(p+q)}{a}$
False alarm ratio FAR	It pertains to the quantity of false alarms separated by the total number of events forecast	$\frac{q}{p+q}$
Post Agreement PAG	It suggests the quantity of hits separated by the total number of events forecast	$\frac{p}{p+q}$
BIAS	The variation shown between the mean of the forecasts and the mean of the observations	$\frac{p+q}{p+r}$
Critical Success Index CSI	It is found sensitive to both false alarms and missed events; a more balanced measure than either POD or FAR	$\frac{p}{p+q+r}$
Equitable Threat score ETS	It measures the fraction of observed or forecast events that were accurately predicted, adjusted for the frequency of hits that would be required to occur simply by random chance.	$\frac{p-\frac{(p+q)(p+r)}{a}}{p+q+r-\frac{(p+q)(p+r)}{a}}$
Heidke Skill Score HSS	It is based on Accuracy corrected by the number of hits that would be expected by chance.	$\frac{(p+s)-\frac{(p+q)(p+r)+(r+s)(q+s)}{a}}{a-\frac{(p+q)(p+r)+(r+s)(q+s)}{a}}$

F. Sliding Window Algorithm-Effective Distance Metric Measure (SWA-ED)

The first step of this algorithm is to construct the current year matrix and previous year matrix. Eight months for current year (CYR) and sixteen months for previous year(PYR) are taken. The size of the matrix is 8X1 and 16X1. In the next step, it is identified nine sliding window from the previous year matrix (PYR). Now the size of the previous year matrix is 8X1. In the third step, computing all the distances such as Euclidean, Chebyshev and Hamming using the equations has been done. The mean value is found for all the distances. In the next step, sliding window with the minimum mean value is scrupulously followed. Next, in order to arrive at the variation for the previous year (MPV) from the minimum distance computation is pursued. The above computation is also adhered to for current year (MCV). Now the predicted variation using MCV and MPV is proceeded. In the next step, the average monthly rainfall (AMRF) for all the years in the data set is estimated. At last the forecast rainfall using predicted variation (PV) and average monthly rainfall (AMRF) are estimated. The sliding window algorithm with Effective Distance metric used for predicting the rainfall is shown in Algorithm 1.

Algorithm 1: Sliding Window Algorithm with Effective Distance metric

Step 1: Construct a matrix size of 8x1 for current year, **CYR** and 16x1 for previous year, **PYR**.
Step 2: Identify 9 sliding windows from matrix **PYR**.
Step 3: Compute various distances (Euclidean, Chebyshev and Hamming), for sliding window. Find mean of distances.
Step 4: Select the minimum mean value of all distance, from sliding window.
Step 5: Compute variation for minimum distance, and rename as mean previous variation (MPV)

$$\mathbf{MPV=AMRF_t\text{-}AMRF_{t-1}}$$

Step 6: Compute variation of current year, CYR and rename as mean current variation Current (MCV).
Step 7: Determine the predicted variation, PV.
Predicted Variation, $\mathbf{PV=\frac{MCV+MPV}{2}}$
Step 8: Calculate average monthly rainfall, AMRF.

$$\mathbf{AMRF=\frac{\sum Monthly\ rainfall\ for\ n\ years}{n}}$$

Step 9: Forecast rainfall

$$\mathbf{FRF = PV+AMRF}$$

V. DATASET DESCRIPTION

In this work, the Tirunelveli District precipitation information from the year 2012 to 2017 was pondered. To begin with, 2016 was considered as a present year, whereas 2014 and 2015 were earlier years. From these figures the outcomes for the year 2017, were identified. Next, the outcomes and the information from the Tirunelveli District precipitation information were contrasted. The separations and contrast were seen to be precise. To arrive at the above conclusion 2017 as the present year, 2015 and 2016 as earlier years were thought of. This, in turn paves way for the month to month precipitation from June to Dec 2018 and January 2019.

VI. EXPERIMENTAL RESULTS

A. Prediction Results for the year 2017

The following Table 5 demonstrates the analysis results obtained in millimeter and Root Mean Square Error for the year 2017 using various distance metric measures.

Table 5. 2017 Prediction results

Distance/ Month	Original	Euclidean Distance	Chebyshev Distance	Hamming Distance

June	46.68	54.7628571428571	54.7628571428571	58.3978571428571
July	24.92	18.9568571428571	18.9568571428571	22.5918571428571
August	40.39	27.4788571428572	27.4788571428572	31.1138571428572
September	64.48	44.4028571428572	44.4028571428572	48.0378571428572
October	282.98	262.006857142857	262.006857142857	265.641857142857
November	334.41	278.908857142857	278.908857142857	282.543857142857
December	231.36	194.606857142857	194.606857142857	198.241857142857
January	62.51	32.3388571428571	32.3388571428571	35.9738571428571
RMSE		28.3989	28.3989	25.7167

Figure 4 demonstrates the 2017 Prediction results. From the above outcome, it is conceivable that the hamming distance offers the exact outcome. Comparing to Euclidean and Chebyshev distances Root-Mean-Square error is minimum in hamming distances. So using this distance the precipitation information for the year 2018 is calculated.

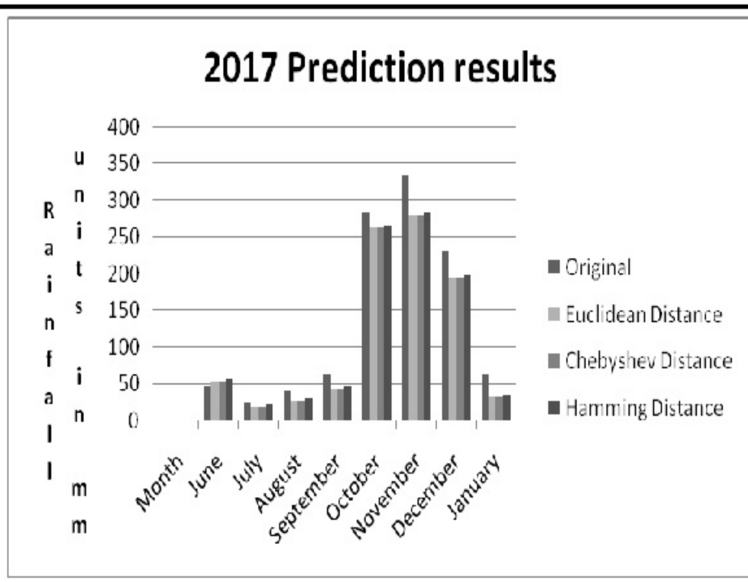

Fig 4. 2017 Prediction results

Figure 5 demonstrates the Root Mean Square Error.

B. Performance Analysis

Performance metrics are evaluated for the variety of distances such as Euclidean distance, Hamming distance and Chebyshev distance. Table 6 exhibits the performance metrics analysis for the above distances.

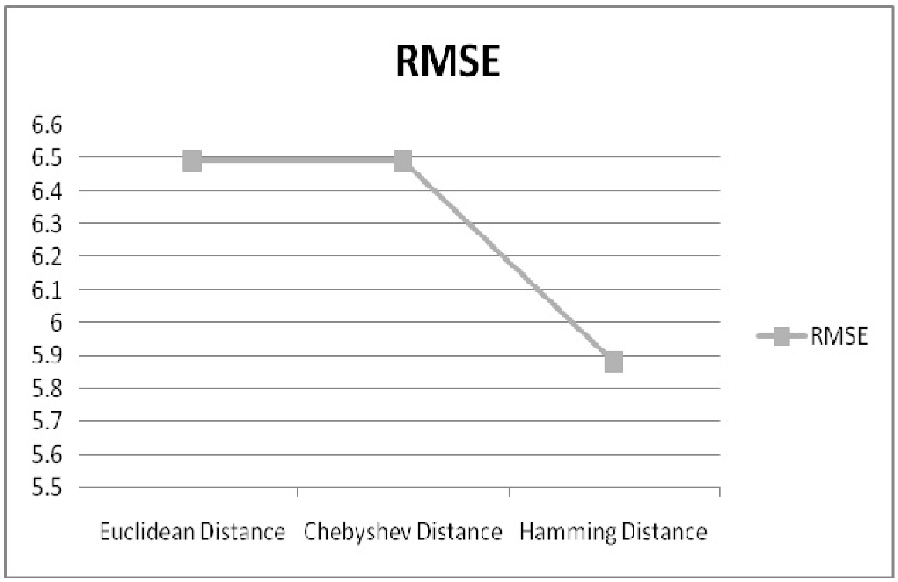

Fig 5. Root Mean Square Error

Table 6. 2017 Performance Metrics Analysis Results

Distance/ Metrics	**Euclidean Distance**	**Chebyshev Distance**	**Hamming Distance**
POD (or) HR	1	1	1
FA	0	0	0
KSS	1	1	1
BR	0.3750	0.3750	0.3750
RF	0.3750	0.3750	0.3750
FAR	0	0	0
PAG	1	1	1
BIAS	1	1	1
CSI	1	1	1
ETS	1	1	1

HSS	1	1	1

Table 7 exhibits the prediction results in millimeter for the month June to December of the year 2018 and January 2019.

Figure 6 demonstrates the 2018 Prediction results.

Table 7. 2018 Prediction results

JUN	JUL	AUG	SEP	OCT	NOV	DEC	JAN
57.68142 85714286	23.10714 28571429	31.59714 28571429	45.91285 71428572	274.9742 85714286	289.2314 28571429	186.2685 71428571	38.49000 00000000

Based on the results of this study, the hamming distance produced lower RMSE (25.7167) value when compared with the rainfall predictions using Euclidean and chebyshev distances (28.3989).

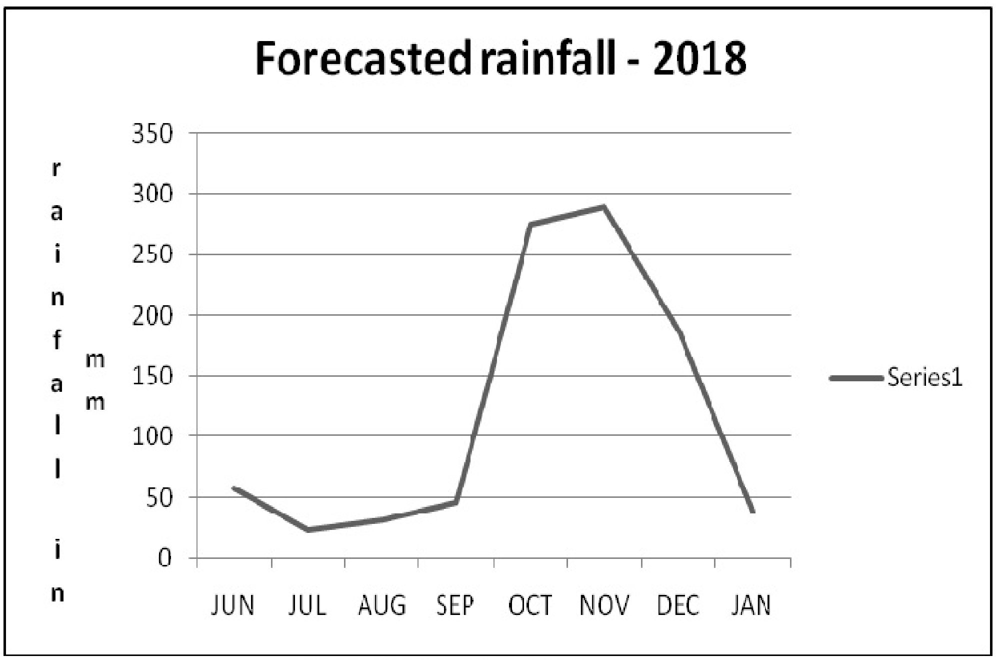

Fig 6. 2018 Prediction results

VII. CONCLUSION

In this study the simplest and the most effective technique - Sliding Window Algorithm with Effective Distance metric (SWA-ED) has been used. It has been observed that Artificial Neural Network (ANN) study, Autoregressive Integrated Moving Average (ARIA) model, Adaptive Splines Threshold Autoregressive (ASTAR) model have been employed by various great researchers. This sliding window methodology focuses on month-on-month basis for two such long years and the current year. This model comprises 9 steps which begins with the matrix current year CYR and previous year PYR from average monthly rainfall AMRF. The result of this process may be built up by increasing the window size to a limited period. It is highly possible that the results will enhance. Farmers in Tirunelveli District, Tamilnadu follow various crop patterns. Each crop pattern requires different amount of rainfall. So this paper helps them not only follow the existing crop patterns but also to sow/plant different crops. In essence the study helps the farming community to utilize even the lean period for their crops.

VIII. REFERENCES

1. Chattopadhyay. S.(2007). Feed Forward Artificial Neural Network model to predict the average summer moonsoon rainfall in India. *Acta Geophysica* 55 (3), 369-382.

2. Chattopadhyay. S & Manojit Chattopadhyay.(2007). A Soft Computing technique in rainfall forecasting. *International Conference on IT, HIT*, March19-21.

3. Chattopadhyay. S & Chattopadhyay. G. (2008). Identification of the best hidden layer size for threelayered neural net in predicting monsoon rainfall in India. *J. Hydroinformatics* 10 (2), 181–188.

4. Christodoulou. C.I, Michaelides. S.C, Gabella. M & Pattichis. C.S.(2004). Prediction of rainfall rate based on weather radar measurements. *IEEE, vol. 2*, 1393-1396.

5. Datar. M, Gionis. A, Indyk. P, & Motwani. R. (2002). Maintaining Stream Statistics over Sliding Windows. *SIAM Journal on Computing,31*(6),1794 - 1813.

6. Dhawal Hirani & Nitin Mishra. (2016). A Survey on Rainfall Prediction Techniques. *International Journal of Computer Application*, *6*(2), 28-42.

7. Divya Chauhan & Jawahar Thakur. (2014). Data Mining Techniques for Weather Prediction: a Review, *International Journal on Recent and Innovation Trends in Computing and Communication,vol. 2, issue 8*, 2184-2189.

8. Enireddy. Vamsidhar, Varma. K.V.S.R.P, Sankara Rao. P & Ravikanth satapati. (2010). Prediction of Rainfall Using Back propagation Neural Network Model. *International Journal on Computer Science and Engineering*, Vol. 02, No. 04, pp. 1119-1121.

9. Fathihah Azahari, Mahmod Othman & Rizauddin Saian. (2017). An enhancement of Sliding window Algorithm for rainfall forecasting. *Proceedings of the 6th International Conference on Computing and Informatics*, 25-27.

10. Guhathakurta. P. (2006). Long-Range Monsoon Rainfall Prediction of 2005 for the Districts and Sub-Division Kerala with Artificial Neural Network. *Current Science, 90 (6)*, pp-773-779.

11. Gwo-Fong Lin and Lu-Hsien Chen. (2005). Application of an artificial neural network to typhoon rainfall forecasting. *Hydrological Processes, 19*, pp. 1825–1837.

12. Hung. N. Q, Babel. M. S, Weesakul. S & Tripathi. N. K. (2008). An artificial neural network model for rainfall forecasting in Bangkok, Thailand. *Hydrology and Earth System Sciences,* vol. 5, pp. 183–218.

13. Indrabayu, Nadjamuddin Harun, M. Saleh Pallu & Andani Achmad. (2013). Numerical Statistic Approach for Expert System in Rainfall Prediction Based On Data Series. *International Journal of Computational Engineering Research,3*(4), 81-87.

14. Karim Solaimani. (2009). Rainfall-runoff Prediction Based on Artificial Neural Network (A Case Study: Jarahi Watershed). *American-Eurasian J. Agric. & Environ.* Sci., vol. 5(6), pp. 856-865.

15. Karmakar. S, Kowar. M.K & Guhathakurta. P. (2009). LongRange Monsoon Rainfall Pattern Recognition and Prediction for the Subdivision 'EPMB' Chhattisgarh Using Deterministic and Probabilistic Neural Network . *ICAPR*, 367-370.

16. Kumar. D.N, Reddy. M.J & Maity. R. (2007). Regional Rainfall Forecasting using Large Scale Climate Teleconnections and Artificial Intelligence Techniques. *Journal of Intelligent System,* Vol. 16, No. 4.

17. Kumar Abhishek, Abhay Kumar, Rajeev Ranjan & Sarthak Kumar. (2012). A Rainfall Prediction Model using Artificial Neural Network. *IEEE Control and System Graduate Research Colloquium.*

18. Kumarasiri. A.D & Sonnadara. D.U.J. (2006). Rainfall Forecasting: An Artificial Neural Network Approach. *Proceedings of the Technical Sessions*, vol 22, pp. 1-13.

19. Liu Xinia, Zhang Anbing, Shi Cuimei & Wang Haifeng. (2009). Filtering and Multi-Scale RBF Prediction Model of Rainfall Based on EMD Method. *ICISE*, 3785 – 3788.

20. Nazim & Abraham Ajith. (2015). Using Adaptive Neuro-Fuzzy Inference System (ANFIS) to Improve the Long-term Rainfall Forecasting. *Journal of Network and Innovative Computing,3*. 146-158.

21. Paras, Sanjay Mathur, Avinash Kumar & Mahesh Chandra. (2007). A feature based Neural Network Model for Weather Forecasting. *Internation Journal of Computational Intelligence, Volume 4(3).*

22. Patil. C.Y & Ghatol. A.A. (2010). Rainfall forecasting using local parameters over a meteorological station: an artificial neural network approach. *International J. of Engg. Research & Indoor,* Appls, Vol.3, No. II, pp 341- 356.

23. Piyush Kapoor & Sarabjeet Singh Bedi. (2013). Weather Forecasting Using Sliding Window Algorithm. *Hindawi Publishing Corporation, ISRN Signal Processing, Vol. 2013,* Article ID 156540.

24. Santosh Baboo. S & Khadar Shareef. I. (2010). An efficient Weather Forecasting Model using Artificial Neural Network. *International Journal of Environmental Science and Development*, Vol. 1, No. 4.

25. Shraddha Pandit & Suchita Gupta. (2011). A Comparative Study On Distance Measuring approaches For Clustering. *International Journal of Research in Computer Science,2*(1), 29-31.

26. Sohn.T, Lee. J. H, Lee. S. H & Ryu. C. S. (2005). Statistical Prediction of Heavy Rain in South

27. Korea. *Advances in Atmospheric Sciences*, Vol. 22, No. 5, pp.703-710.

28. Somvanshi. V.K, Pandey. O.P, Agrawal. P.K, Kalanker1. N.V, Ravi Prakash. M & Ramesh Chand. (2006). Modeling and prediction of rainfall using artificial neural network and ARIMA techniques. *J. Ind. Geophys. Union, Vol.10, No.2*, pp.141-151.

29. Wong. K.W, Wong. P.M, Gedeon. T. D & Fung. C. C. (2003). Rainfall Prediction Using Soft Computing Technique. *Soft Computing 7,* 434 – 438.

30. Wu. C.L & Chau K.W. (2013). Prediction of rainfall time series using modular soft computing methods. *Engineering Application of Artificial Intelligence* 26 ,997- 1007.

31. Xinghua Chang, Meng Gao, Yan Wang & Xiyong Hou. (2012). Seasonal Autoregressive Integrated Moving Average Model for Precipitation Time Series. *Journal of Mathematics and Statistics*,*8*(4), 500-505.