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EXAMINING AND INVESTIGATING DIFFERENT APPROACHES TO FORECAST RAINFALL

C.Vijayalakshmi Research Scholar PG & Research Department of Computer Science Quaid-E-Millath Government College for Women. vijiglory@qmgcw.edu.in
Dr.M.Pushpa, Research Supervisor, Department of Computer Science Quaid-E-Millath Government College for Women.

Abstract: Anticipating the onset of precipitation is an important problem that is gaining increased attention worldwide. Rain has major effects on a number of aspects of human life, including transportation, health, agriculture, and other areas of social and economic life. Overabundance of rain causes disasters like floods and landslides. Because rainfall has so many implications on human existence, and analyzed a number of models to understand and forecast rain, enabling early warning systems in a range of industries, such as agriculture and transportation. After being categorized according to various approaches, the research papers are reviewed. ANN, DNN, fuzzy, optimization, and machine learning (ML) are among the techniques that are based on artificial neural networks (ANN), machine learning (ML), and deep neural networks (DNN).
Keywords : Machine Learning, Artificial Neural Network, Deep Neural Network, Fuzzy, Optimization based Techniques.

I. Introduction

Earth's natural phenomena can be classified into many different categories, such as hydrological phenomena (such as storm waves and groundwater), biological phenomena (such as forest growth), atmospheric phenomena (such as thunderstorms and rainfall), human phenomena (such as urban development), and geological phenomena (such as earthquakes).

The goal of the science of physical geography is to better understand how different features and parameters that characterize the Earth's surface and interior structure are distributed by looking at the processes that shape the planet. The term "geophysical parameters" has been used in the literature to describe these characteristics or variables [1].

Rainfall is a key geophysical component that is essential to many applications in the management of water resources, especially in the agricultural sector. Rainfall forecasts can be used to make decisions about many important jobs, such as agricultural planting, traffic management, sewer system operation, and controlling natural calamities like droughts and floods [2]. The agricultural sector is a major contributor to the economic stability and food security of many countries, including Malaysia and India [2, 3]. In order to handle operations like those mentioned above and to make wiser judgments in the future, it is vital to estimate rainfall accurately. Predicting rainfall is one of the most difficult aspects of the hydrological cycle [4, 5]. This results from the dynamic nature of environmental factors and their erratic changes over time and space [3]. In order to find patterns in the data to predict rainfall, a number of machine learning (ML) technologies, including artificial neural networks (ANN), Fuzzy, etc., are used in the literature. This paper summarizes past research that looked at the application of ML models to rainfall forecasting. The process used by the authors in [6] to review publications that used machine learning to predict floods is quite similar to that used to predict rainfall. The authors in [7] concentrated primarily on the use of ML for generic spatiotemporal sequence forecasting. Finally, the authors of [8] conducted a survey on the use of machine learning (ML) for rainfall prediction.

II. Literature survey :

Several rainfall techniques is reviewed and described in this section. Figure 1 demonstrates the classification of typical rainfall forecasting techniques. The models and techniques are ARIMA model, SVM, Fuzzy, ML, Optimization, ANN, and DNN.

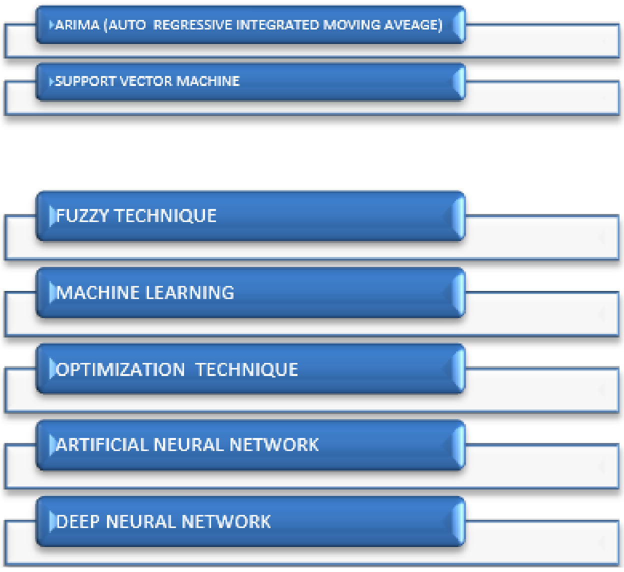

Fig1:various Rainfall Frecasting Techniques

III. ARIMA (AutoRegressive Integrated Moving Average)

Time series forecasting, analysis, and prediction are applications of this model. It is suggested by Box and Jenkins and consists of four approaches in fig 2. The ARIMA model employs the following four phases.

Step I: Using the statement "IDENTIFY," a series of replies is identified and utilized to calculate time series and autocorrelations.

Step II: Using the statement ESTIMATE, the parameters are estimated in this stage along with the previously specified variables.

Step III:

This step involves performing a diagnostic check on the variables and parameters that were gathered previously.

Step IV:

Stage 4: Using the ARCAIMA model and the FORECAST statement, future values are predicted for the time series predicting values in this stage. The variables in this model are denoted by the letters p,d, and q, which stand for the number of lag observations (p), the degree of differencing (q), and the moving average order (l).

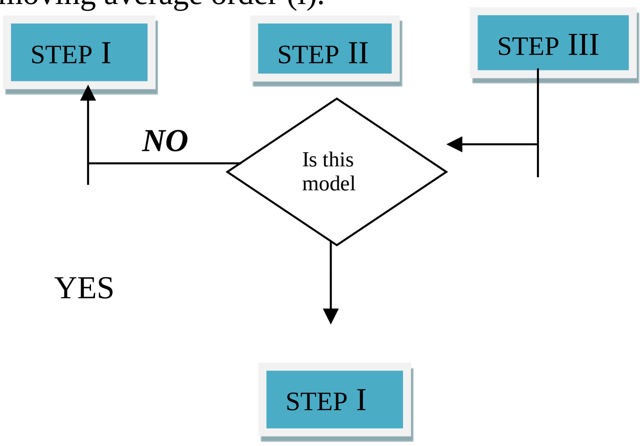

Fig2:ARIMA(Auto Regressive Integrated moving Average)

IV. SVM(Support Vector Machine)

In Rainfall forecasting, the job forecast model's projected memory and experience based on various weather kinds are still utilized.

It takes time to build up forecasting skills, and it is challenging to characterize forecasting information due to the complexity and nonlinearity of climate evolution. The conditional combinations of specific meteorological elements lead to the evolution of any climate or meteorological variable, and these combinations are diverse and intricate. With the development of sophisticated computer technology and smart retail machines, machine recognition skills have been refined to convey intricate nonlinear correlations between meteorological factors in real time and location, solving numerous machine learning challenges. SVM is frequently used for a wide range of machine learning issues. The main multi-layer feed-forward network classification is found in SVM. Support vector machines are employed for pattern recognition and non-linear regression, much like multi-layer perceptrons and radial function networks. The following tasks are carried out by the SVM:

- Greater generalization capability compared to other NN models.
- The same, effective SVM solution is absent from local minima.
- employed with non-vectorial data

This approach has only been employed by a small number of scientists to forecast rainfall, and the outcomes are acknowledged.

V. Fuzzy Logic:

He, S., et al.[9] devised a technique named modified ANFlS (MANFlS) structure for improving rainfall forecasting. Here, MANFlS was trained by the hybrid learning algorithm, integrating the least square method and the backpropagation gradient descent method.

Chang, F.J.,[10] describes how the fuzzy inference model for rainfall prediction has been improved. This work uses a fuzzy rule-based system to forecast rainfall. The process of mapping a given set of input and output through a series of fuzzy systems is known as fuzzy inference. On the fuzzy logic model, the fuzzification and defuzzification operations were carried out. Two input variables and one output variable are being obtained for this research work. The amount of predictable rainfall is the output variable, and the input variables are the temperature and wind speed at a specific moment in time. The selection of temperature and wind speed is based on their primary influence on the frequency of rainfall.

VI.Artificial Neural Network

Soft computing uses approximate models to produce approximate findings or solutions. Artificial Neural Networks (ANN), Genetic Algorithms (GA) and Fuzzy Logic(FL), are the three fundamental components of soft computing. When examining rainfall prediction, scientists frequently use ANN. A tremendously complex, parallel, nonlinear system makes up the human brain. information processing system (computer). The biological neuron system is condensed into cognitive networks. the nervous Basic processing units make up a network, a massively parallel distributed processor that naturally tends to preserve and make use of practical experience [11]. Synthetic neurons resembling real neurons in the human brain make up the main processing element of an ANN. Fig 3 shows that, it has the capacity to receive inputs, process them, and produce useful data. A network of neurons is formed when neurons join together at synapses, which may have one or more layers. A multilayer ANN is made up of neurons in an input layer, neurons in the output layer, and neurons in the hidden layer. Prior to transferring the input to the final layer, the hidden layer enables important computations. Using an application, inputs, and the associated targets train a network until it is able to connect a particular input with a respectable result. Once a network had been formed for a certain task. The minimal amount of weight change that can be obtained during a training cycle is the best moment to start training a network. value. After the network has been adequately trained, it is crucial to evaluate its ability to produce accurate outputs. Large multi-layered networks with numerous layers can have many nodes in each layer because of the vast quantity of synaptic weights and memory available on such a network. As a result, a network's ability to provide exact outputs is not supported by delivering correct outcomes, when it comes to the input vectors employed during the training process.

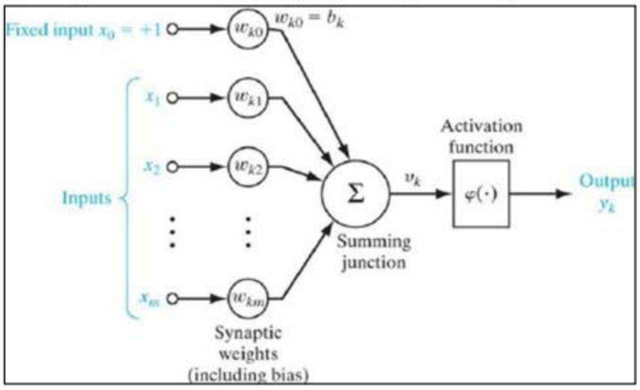

Fig 3:Artificial Neural Network

VII. Machine Learning Techniques:

The Machine learning (ML) approaches can be split into two main categories: i) Classical techniques and ii) Contemporary deep learning techniques. The Classical techniques like multivariate linear regression (MLR), KNN ANNs, SVMs, and RF; and contemporary deep learning methods like CNNs and Long-Short-Term Memory (LSTM). It was found that traditional ML models typically worked with 1D data from meteorological stations, such as in [12, 13,14, 15, 16, 17] for short-term data and [18, 19] for long-term data. Some studies employ hybrid models, which integrate two or more strategies. Combining ML with optimization technologies like genomics and particle swarm optimization to maximize hyper-parameters is a common hybrid strategy [20]. In [21, 22], multiple ML methods are coupled, while in [16], ML and ARIMA are employed.

VIII. Deep Learning Neural Network

Deep learning models are popular among short-term data sets, especially those that use 2D data, because they typically require enormous datasets to avoid over fitting on the data [23, 24]. Authors must use automated feature reduction techniques like CNNs since 2D data, in particular, has a large feature space [25, 26]. Many studies attempt to modify time series models like LSTMs for 1D data in [27, 28] in order to incorporate the time dimension in the data. ConvLSTMs models, which combine CNNs and LSTMs for 2D data, were originally employed in [23] in 2015; since then, various versions have been deployed [24, 29].

XI. Genetic Algorithms

A. Haidar and B. Verma [30] presented a hybrid GA approach that combines the standard reproduction with PSO to choose the optimal input characteristics and network components for every month.
[31] Genetic algorithm (GA) was applied to find the equation that best fits the rainfall data in one part of the dataset,
Using two distinct approaches—univariate (forecasting all-India summer (JJA) rainfall in terms of its past values) and multivariate (forecasting all-India summer (JJA) rainfall in terms of past values of rainfalls over five homogeneous zones during the months of June, July, and August—we generated several prediction equations for various values of m in order to comprehend the dependence of performance of the employed algorithm on lag (m). An identical initial random population of 800 equations was used to start the evolution process, which took 1000 generations for each iteration. A sufficiently significant number of terms could be present in the final equation. The algorithm's performance was assessed for every iteration utilizing the statistical standard error criteria (SE =

$[\sum(R_{fitted} - R_{actual})^2/N]^{1/2}$), where R_{fitted} and R_{actual} represent the predicted and observed rainfall, and N denotes the length of the training data set.

X. Conclusion:

This research presents an in-depth analysis of rain forecasts made using entirely distinct methodologies. According to the survey, almost all of the researchers employed machine learning techniques to predict the weather. this survey paper should be very helpful to machine learning researchers in their efforts to reliably predict future rainfall.

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