Comparative Analysis of Backpropagation and Radial Basis Function Neural Network on Monthly Rainfall Prediction

Thesis submitted in partial fulfillment of the requirements for the award of degree of

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Certificate

I hereby certify that the work which is being presented in the thesis entitled—**"Comparative Analysis Of Backpropagation and Radial Basis Function Neural Network On Monthly Rainfall Prediction"**, in partial fulfillment of the requirements for the award of degree of Master of Engineering submitted in Computer Science and Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of **Dr. Ajay Kumar** and refers other researcher's work which are duly listed in the reference section.

The matter presented in the thesis has not been submitted for the award of any other degree of this or any other University.

Nikita.

Signature:

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This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

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Abstract

Rainfall plays an essential role in the overall growth of any country. It is very crucial to forecasting the rainfall accurately and on time due to the highly erratic nature of weather conditions. Its accurate and predetermined forecast can prevent many natural hazards and is helpful to the tourists for traveling beautiful destinations of the world.

Artificial Neural Network is functionally analogous to the human brain. Earlier, due to its innate capability of performing highly complex calculations, researchers began to develop an interest in designing a computer model which can work in a way similar to the human brain. Under this study, we have applied the two commonly known techniques of artificial neural network backpropagation and radial basis function neural network for predicting rainfall. Furthermore, mean square error (training and testing) and accuracy are the performance indices used for the comparative analysis of the two models.

The motive of this thesis is to outline the working of these two approaches for accurate prediction of rainfall and advantages of using these methods over the other ANN techniques. In this study, we have also analyzed the prediction results of the two algorithms and determined which of the two is better regarding performance results. Further, the ideas are suggested to improve the prediction by combining the ANN methods with several other algorithms. A GUI software has been created in MATLAB for easy prediction of future rainfall data.

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Abbreviations

1.	ANN	Artificial Neural Network
2.	BPNN	Backpropagation Neural Network
3.	RBFNN	Radial Basis Function Neural Network
4.	PDP	Parallel Distributes Processing
5.	INNS	International Neural Network Society
6.	K-NN	K-Nearest Neighbour
7.	MSE	Mean Square Error
8.	MLC	Maximum Likelihood Classification
9.	ARIMA	Auto Regressive Moving Average
10.	MA	Moving Average
11.	MLC	Maximum Likelihood Classification
12.	MLFN	Multi-Layer Feedforward Neural Network
13.	TDNN	Time Delay Neural Network
14.	SSA	Singular Spectrum Analysis
15.	SVR	Support Vector Regression
16.	GA	Genetic Algorithm
17.	GUI	Graphical User Interface

Chapter-1

Introduction

1.1 What is Artificial Neural Network?

Artificial Neural Network (ANN) is a computing model which is functionally similar to the human brain. The human brain has an innate capability of performing highly complex computations and is believed to be a network interlinked by billions of neurons. It has been applied in the several fields of medicine, hydrology, engineering, etc. The first step into the innovation of artificial neural network came into the fact when in 1943, McCulloch, a neurophysiologist, and Pitts, introduced the concept of neurons that work in a way similar to the human brain [1]. ANN is represented as a computing model consisting of some neurons linked to each other and can derive outputs from the given input units.

Fig 1.1 below shows the structure of ANN model.

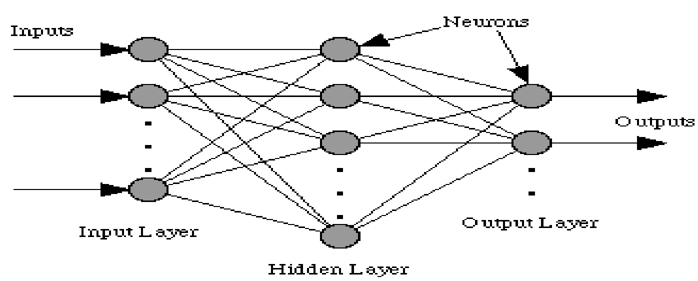

Fig 1.1: Simple Structure of ANN [2]

In 1943, McCulloch and Pitts [1] concluded that this system of neurons could be able to implement any complex function consisting of a system of neurons interconnected by the synaptic weights. Also, it was concluded that due to the highly parallel nature of ANN, computations could be performed simultaneously. Nowadays, ANN is represented as a cluster of neurons which represents several layers of ANN. It is the work of research analysts of the field to decide how the connection will be formed between these layers. There is no doubt that the field of ANN is the most interesting and rewarding field of research these days. ANN is also based on an optimization theory. As stated above, the structure of ANN is encouraged by the structure of the human brain and is capable of solving both machine learning and pattern recognition problems. Therefore, neural networks have an immense capability of analyzing highly complex tasks that are far too difficult for the human brain to analyze.

1.2 History of Artificial Neural Network

In 1943, McCulloch and Pitts [1] were the first to introduce the concept of artificial neurons. Their research work revealed that even the simple class of network can perform and analyze highly complex problems. Several other researchers like Weiner and Neumann [3] suggested that this research into the brain like model will be significant. In 1949, Hebb [4] revealed the fact that the neural connections are made stronger each time they are acknowledged. He also argued that if two neurons strike at the same time, then the connection between them is strengthened. Also, this was the era of the invention of the first neurocomputer (Snark) discovered by Minsky in 1951 [5], but the model failed to establish any remarkable achievement into the field of neural computing.

In 1950's as the use of computers became revolutionized. Therefore it was possible for scientists to implement a neural network model practically. Rochester [6], a researcher at IBM Research Laboratories took the first initiative towards this but failed to do so. In 1957, Rosenblatt made a remarkable contribution in the field by introducing the technique called perceptron [7]. The perceptron consists of fixed three-layered structure with middle layer known as an association layer. The model could produce random output unit based on the given input.

In 1959, Widrow and Hoff from Stanford proposed two techniques called "ADALINE" and "MADALINE" [8]. The typical name comes from Stanford's love for the acronym Multiple Adaptive Linear Elements. ADALINE was built to analyze pattern read from the phone line and could also predict the next bit pattern. The first real life model was MADALINE, which used a dynamic filter that eradicates echoes from the phone lines [8]. Although, above research rewarded a major contribution in the field of neurodynamics but scientists faced the two major devastating problems. First, the majority of the above research was proposed considering the experimental point of view. As a result, many researchers and analysts of the field could not apply the techniques practically. Second, a large number of neural network analysts were driven away by their way of writing and statements. As an example, there were many published assumptions that the artificial brain is just a few steps away from its evolution. However, in reality, no major practical evolution in the field was done. Therefore, the period of mid-90s suffered from the lack of good ideas.

During this final period of the 1960s, a campaign was initiated by Minsky and Papert [9] to vilify the groundwork in the field of neural network and contribute the funding into the field of "Artificial Intelligence" [10]. The perceptron model suffered a dire flaw that is the incapability of perceptron model to perform certain essential predicates such as XOR. To resolve this, researchers proposed several refinements to the perceptrons model but failed to do so. At last, it was concluded that the field of neural network research has come to a dead end.

Despite Minsky and Papert's argument of the restraints to the perceptron model, research in the field continued. Most of the areas advanced under the name of the neural network as adaptive signal processing, bio-neurological modeling and pattern recognition. Also, many of the veterans began to develop an interest in the field of neural networks. Among these include Amari [11], Fukushima [12], Grossberg [13], etc. However, the future researchers who appeared in the next thirteen years were the major contributors in the field who totally revolutionized the field of ANN.

During the early 1980s, many neural computation scientists proposed the solutions to the problems existing in the neural network techniques. During 1983-1986, Hopfield [14], a renowned physicist became highly interested in the field of neural computation. Later, he also introduced a network known as Hopfield Network. This network is a type of recurrent artificial neural network. The model works by setting a network to specific values initially. Then a number of iterations were applied synchronously or asynchronously. Then the network is stopped for some time and is read out to see which pattern exists in the network. The main idea behind its working is that patterns are stored in a weighted matrix. This weighted matrix storage is also known as Content Addressable Memory (CAM). Therefore, this work influenced many researchers, scientists, and technologists to accompany the revolutionary world of neural networks.

1.3 Architecture of Artificial Neural Network

As explained earlier, ANN is influenced by the highly complex structure of the human brain. It is believed to be a network consisting of billions of interlinked neurons. The Fig 1.2 below shows the neural network structure in human brain.

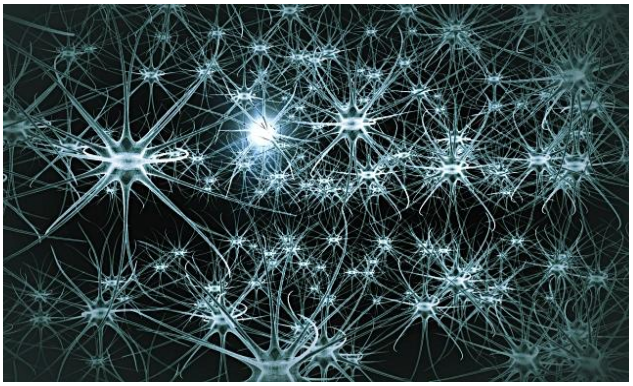

Fig 1.2: Structure of Neural Network in Human Brain [5]

A neuron is a special biological cell which processes information from one part of the brain to another through some chemical change or electrical signal. It consists of a cell body and two types of outreaching branches called the axons and the dendrites. The hereditary traits are contained in the nucleus of a cell body. It contains the molecular ingredients needed by the brain. The human neuron structure is shown in Fig 1.3 below.

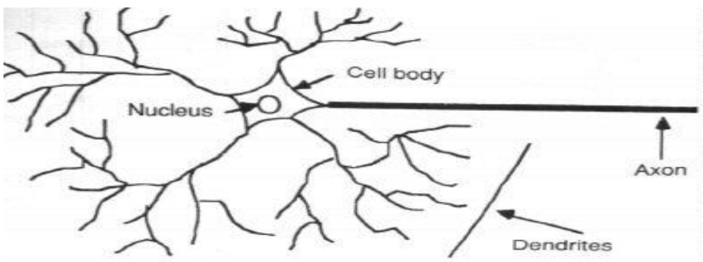

Fig 1.3: Structure of a Human Neuron [5]

The whole process is done in a manner in which the input signal is received by a neuron and is transmitted from one neuron to another through the dendrites. A neuron sends information at the spike of an electrical signal through a long thin stance called axon and the axon spreads this signal through the synaptic weight and transmits it to other neuron cells [5].

ANN is a practical model of biological neurons. It accepts many input signals and generates only one output signal. It consists of simple computational units interlinked to each other and are structured in layered form. The Fig 1.4 below shows a structure of an artificial neuron.

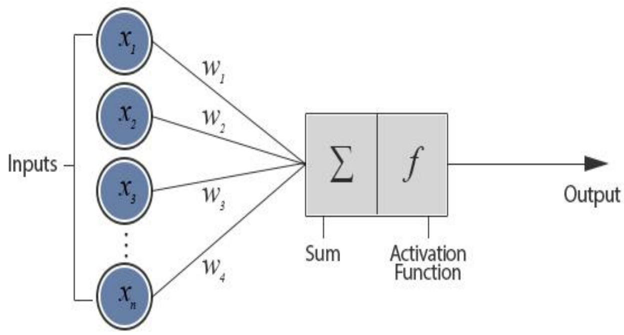

Fig 1.4: Structure of an Artificial Neuron [17]

ANN is organized into layers of interconnected neurons which are connected through the synaptic weights. Input, hidden and output is the three layers of ANN. The input signal is received through the input neurons. Then, the input units are weighted and added. Finally, the input is transformed into an output unit through the transfer function. Sigmoid function is used as a transfer function [17]. The function of an artificial neuron is shown in Fig 1.5 below.

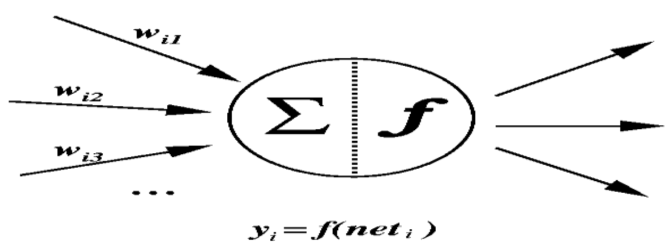

Fig 1.5: Functions of an Artificial Neuron [18]

1.3.1 Transfer Functions Used in ANN

The transfer function is also known as an activation function. It sends a signal from one neuron to another to update its weight. There are four kinds of transfer functions- Threshold, Piecewise Linear, Sigmoid function and Gaussian function [21]. Fig 1.6, 1.7, 1.8 and 1.9 below represents four types of transfer functions.

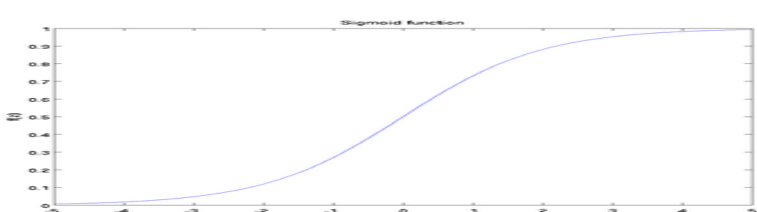

Fig 1.6: Sigmoid transfer function [21]

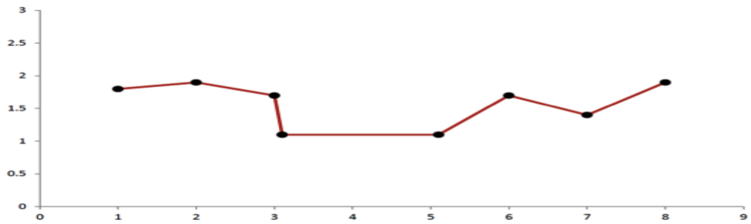

Fig 1.7: Piecewise Linear Transfer Function [21]

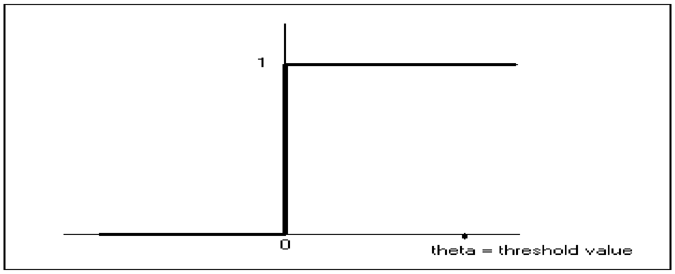

Fig 1.8: Threshold Transfer Function [21]

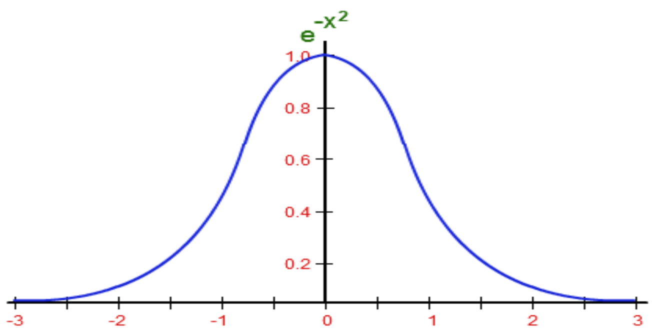

Fig 1.9: Gaussian Transfer Function [21]

1.3.2 Structure of Basic ANN

The two types of ANN structures are recurrent structures and non-recurrent structures. The Recurrent structures are also known as Auto-associative or Feedback structures. Non-recurrent structures are also known as Associative or Feed-forward structures [19]. In a feed-forward network, signals propagate unidirectionally in the forward direction. In a feed-backward network, signals propagate bi-directionally in both forward as well as backward direction introducing loops in the network. The structure of both the networks is shown in Fig 1.10 and 1.11 below.

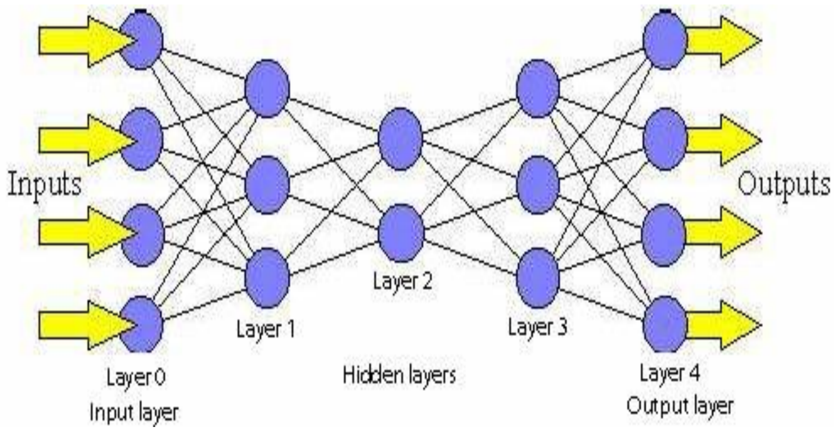

Fig 1.10: Structure of Feed-forward Neural Network [20]

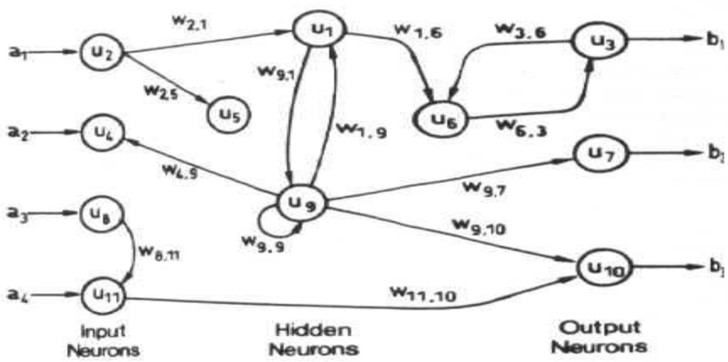

Fig 1.11: Structure of Feed-backward Neural Network [20]

1.3.3 Comparative Study of Modern Neural Network and Biological Neural Network

Modern Neural Network is similar to Artificial Neural Network which has been inspired by Biological Neural Network and is capable of performing intensive calculations based on the given input unit. In this sub-section, modern neural networks, and biological neural networks have been compared regarding their structure, working, the speed of processing and reliability parameters.

- Modern Neural Network contains fewer processing units which are complex in structure but faster in speed where as the biological neural network is simple in structure but slow in speed.
- Modern Neural Networks have a confined memory distinct from processors whereas biological neural networks have a distributed memory embedded in the human brain.

- In Modern Neural Networks, computation is done in a serial and centralized manner using stored procedures and programs, whereas in biological neural networks it is done through self-learning with a high level of parallelism.
- Modern Neural Network is very sensitive regarding reliability, whereas the biological neural network is highly resilient regarding reliability.
- Modern Neural Networks have very well defined and limited environment where as biological neural networks do not have very well defined and limited environment.

1.3.4 Characteristics of ANN

Nowadays, ANN performs an essential role in most of the fields like classification, pattern recognition, forecasting, etc. It is widely popular due to its compelling characteristics which have been discussed below:

- **Parallel Processing:** Parallelism in human brain design is a highly complex task but in ANN it is made simpler by the use of several techniques like matrix computations.
- **Distributive Memory:** Information is stored in pattern format as long-term distributed memory.
- **Fault Tolerance:** ANN is highly fault-tolerant. Therefore, it is assured that if one part of the network fails, the whole network does not stop working.
- **Collaborative Solution:** The outcome of a network is a weighted sum of all input units. The partial answer is useless in the neural network.
- **Fast Learning:** The network trains itself to adapt to the changing rules and weights. Supervised, Unsupervised and Reinforcement are the various learning methods [21]. The Fig 1.12 below shows several characteristics of ANN. Also, further classification of ANN is shown in Fig 1.13 below.

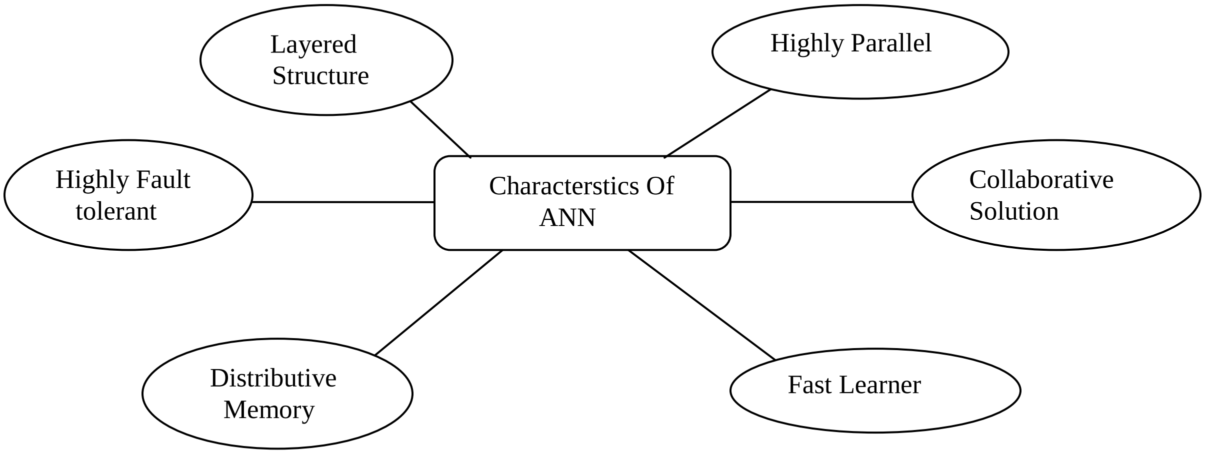

Fig 1.12: Characteristics of ANN [18]

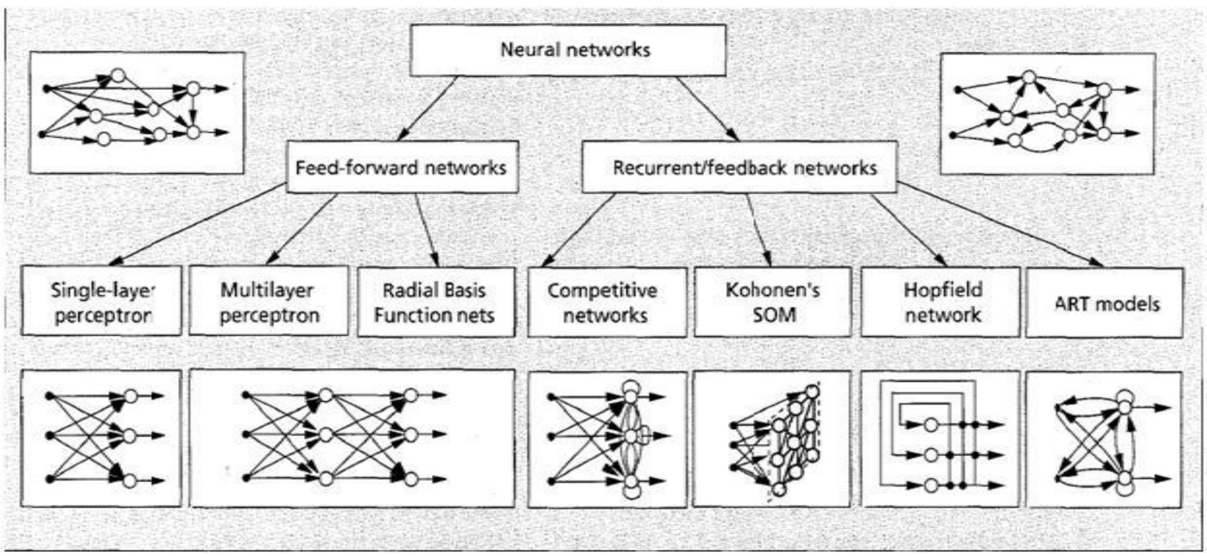

Fig 1.13: Classification of ANN [22]

1.4 Main Application Areas of ANN

ANN is a well developed and widely used technology. It has been used in several applications like accounting information, finance, human resource, marketing, and hydrology. It has been applied in several areas of prediction like human disease prediction, traffic prediction, stock market prediction. Some of its general application areas and current trends in application areas of ANN are discussed below:

1.4.1 General Application Areas of ANN

In this sub-section, some of the general applications of ANN in the fields like accounts, finance, human resource and hydrology have been mentioned. ANN is applied in these areas for prediction. These application areas are briefly discussed below:

1. **Accounting Information:** ANNs are widely employed in managing predictions about debt and equity securities. These are also used for credit granting. Example of this includes-GMAC's Credit Advisor, which grants instant credit for automobile loans. ANN also enhances inspection by finding pattern irregularities and had been used in several pattern recognition systems.

2. **Finance:** ANNs have been proved to be useful in the field of finance like forecasting foreign exchange rate, estimating country risk rate, predicting bankruptcy, fraud detection, forecasting economic crisis, loan approvals, risk management, mortgage risk assessment, etc.

3. **Human Resource:** In 2013, Akinyede and Daramola [23] applied an ANN technique for designing a Human Resource Management System Model. The model was designed to ensure that the organization hires and keeps good employees. The model collects data from applicants and matches it with jobs available. It will avoid the job dissatisfaction among the employees and will also remove the traditional method of interviewing employees for hiring. The model solved the previous problem in research that is the inability to handle employment planning, salaries, emoluments, reports, etc. At last, the model proved to be a promising one in human resource management.

4. **Marketing:** ANNs are widely employed in marketing as Market Segmentation. Market Segmentation is a method of segregating the large market into smaller groups or clusters of customers. The customer behavior is determined within each cluster. It improves the customer-company relationship. Therefore, a company can design a new product with specific needs of a particular group.

5. **Hydrology:** ANNs have proved to be very useful methods in the field of hydrology. It has been applied in several fields like weather forecasting, rainfall forecasting, precipitation level forecast, flood forecast, etc.

1.4.2 Current Trends in Application Areas of ANN

Nowadays, ANN is applied in almost all areas of prediction. Its current trends in application areas include bankruptcy prediction, credit/fraud prediction, application of ANN in stock market prediction, financial auditing, etc. Some of these application areas are briefly discussed below:

1. **Application of ANN technique in Bankruptcy:** Research area of ANN in bankruptcy prediction is active since the 1990s. Nowadays, many of the loan approval prediction systems are based on ANN technique. In the surveys of Savings and Loan Association, Tam and Kiang [18] demonstrated that ANNs are better predictive models than several other techniques like Discriminant Analysis, K-nearest neighbor and Decision tree method [18]. Fig 1.14 below shows the image of typical bankruptcy prediction system.

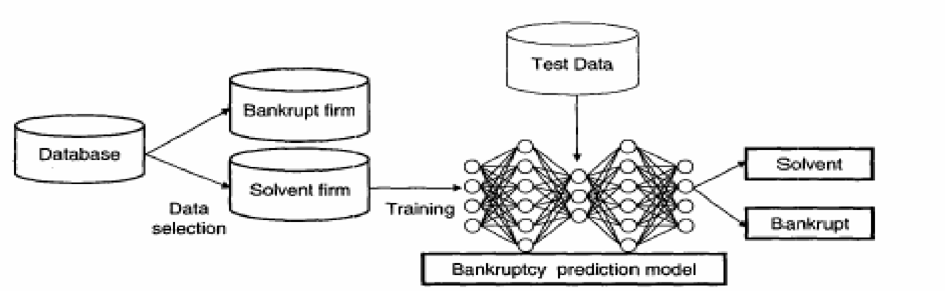

Fig 1.14: Bankruptcy Prediction System Using ANN [18]

2. **Application of ANN in Credit/Fraud Detection:** Credit fraud may be depicted as a simple theft, application fraud and theft using counterfeit cards. The straightforward way of credit fraud is the use of stolen card. Another form of credit theft occurs when transactions are done remotely; only card details are required, customer signature and card imprints are not required at the time of purchase.

3. **Application of ANN in Stock Market:** Neural Networks are useful in predicting stock price prediction. In paper [24], methodologies of ANN on stock market prediction is described. Some of the general classification methods used were Feed-forward Network, Time series method, and recurrent neural network.

4. **Application of ANN in financial auditing:** Main prospects of ANN in financial auditing are authentication errors, fraud management, and initiative for backing

control decisions. ANNs have been proved to be useful in the audit fee, control risk management, and financial distress problem [25].

1.5 Thesis Outline

The following thesis is arranged into seven chapters. Chapter 1 represents the formal introduction of the Artificial Neural Network, its history, architecture and several applications. Chapter 2 describes the background aspects of the Backpropagation Neural Network, its architecture, working and applications. Chapter 3 describes background details of the Radial Basis Function Neural Network, its architecture, working and applications. Chapter 4 represents literature review of several techniques used for rainfall prediction like time series methods used for rainfall prediction, statistical methods for rainfall prediction, ANN methods used for rainfall prediction and at last we compared these previously used techniques. Chapter 5 states the problem description, main objective, research methodologies and contribution to the field of the work done. Chapter 6 describes the implementation and experimental outcomes. Implementation details like MATLAB software and its features, working and design of BPNN and RBFNN model for rainfall prediction, comparative study of both the models on rainfall prediction. Also, in this chapter general steps for rainfall prediction like data collection, data normalization, network creation and output analysis were described. Lastly, in this chapter, comparative study of the results and how the values of accuracy, MSE (training and testing) were determined are explained. In Chapter 7 we conclude the topic and suggested further future scope.

Chapter-2
Backpropagation Neural Network

2.1 Background

Perceptron model is a kind of ANN model with only single neuron. It was first introduced by Rosenblatt in 1957. During 1959, it was suggested that the perceptron model is limited in its capability as it cannot learn non-linear decision boundary problem such as XOR problem. In 1969, Minsky and Papert [8], both argued that “if you had hidden units, you could compute any Boolean function. However no learning rule exists for such multi-layered networks, and we will not think that the one will ever be discovered”. However, in contrary, Backpropagation, one such mechanism was found. In 1961, Frank Rosenblatt introduced the concept of “Backpropagation” but was unsuccessful in his attempt [6]. In 1974, Werbos [26] introduced a new backpropagation algorithm, but it was overlooked by the scientific community till the 1980s. In 1985, Parker and Lecun [15] reinvented it, but it was Rummelhart, Hinton and Williams who popularized the algorithm in 1986 [15]. Since then the Backpropagation is a widely known technique applied mainly in the fields like classification, function approximation and forecasting.

2.2 Architecture and Working of BPNN

BPNN is a supervised learning algorithm. In general, its workings include forwarding of output to input layer in changing weights. The BPNN is a three layered architecture consisting of an input, hidden and the output layer. The Fig 2.1 below shows the structure of BPNN network.

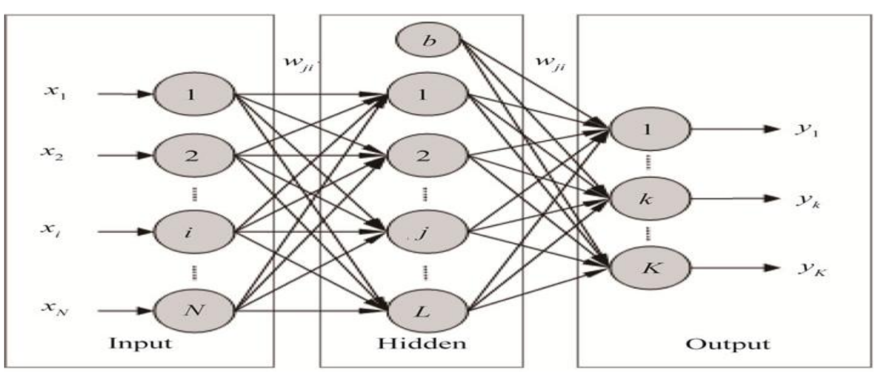

Fig 2.1: Structure of BPNN Network [27]

BPNN algorithm is a two-phase technique [27]:

Forward phase: An activation function is applied to the net input, and then propagating it forward to the output layer. Backward Phase: It is also known as weight correction phase. The error between the actual and the forecasted values is propagated backward into the hidden layer to modify weight and bias values.

Basic Steps in the BPNN algorithm as designed by Rummelhart [16] and used by several researchers for prediction [2, 27] are described as below:

$BPNN(I_i, O_i)$

Begin

Input: Rainfall Data I_i (1979-2002)

Output: Rainfall data O_i (2003-2006)

Step 1: Assign the weights to the network randomly.

Step 2: Run the network forward with I_i to get O_i.

Step 3 [16] : For $\forall O_i$ do,

$\delta_k = O_k(1-O_k)(O_k-t_k)$ Where,

δ_k : Error corresponding to output node

O_k : Net output of the output layer

t_k : target output

Step 4: If stopping criteria≠1, go to steps 5-7.

Step 5 [16] : $\forall h_j$, compute δ_j based on δ_k.

$$\delta_j = O_j(1-O_j)\sum_{k=K} \delta_k W_{jk}$$ Where,

O_j : net output at hidden layer

W_{jk} : weight propagated from hidden to output node

δ_k : Error propagated from output node

h_j : Hidden layer node

Step 6 [16]: Update weight and bias:

Given, $\Delta w = \eta \delta_l O_{l-1}$ Where,

η : Learning rate

δ_l : Error at layer l

O_{l-1} : Output from layer l-1

$\Delta\theta = \eta\delta_l$ (change in bias term)

Step 7 [16]: Update weight and bias terms

$w \leftarrow w + \Delta w$

$\theta \leftarrow \theta + \Delta\theta$ Where *w* represents weight.

End

2.3 Main Applications of BPNN

Main application areas of BPNN include classification, forecasting and function approximation. Few of these applied techniques are discussed below:

1. **Classification of IRIS-1D images by Aria et al. [28]:** In this application, the BPNN algorithm is applied for the classification of remote sensing images. Three steps are involved in this method. In the first step, features are extracted. In the second step, feature classification is done. In the third step, features are classified using BPNN method and then these are compared with results of Maximum Likelihood Classification (MLC) method. When the two algorithms were compared, it was found BPNN was more accurate in classification.

2. **Use of harmony search and BPNN to classify Breast Cancer data [29]:** The two algorithms-Harmony search and BPNN were used to classify breast cancer data. When the results were compared, it was found that BPNN was a better model for classification. BPNN is used in several other areas like network traffic prediction, weather forecasting, and flood prediction, etc. It has been proved to be an accurate model for such predictions.

3. **Prediction of Whiplash Associated Disorders (WAD) by the classification of neck movement patterns [22]:** Grip et al. proposed a technique for predicting Whiplash-Associated Disorders (WAD) by classifying neck movement patterns. The prediction was made using the novel approach of backpropagation neural network (BPNN). WAD is the diagnosis done after severe neck trauma, which can occur during the rear-end car accidents. In this research, BPNN technique showed correct results for almost 89 percent of WAD cases which indicate that BPNN is an appropriate technique for predicting motion characteristics.

Chapter-3

Radial Basis Function Neural Network

3.1 Background

Broomhead and Lowe first introduced Radial Basis Function Neural Network (RBFNN) method in 1988 [30]. It consists of three types of layers-Input, hidden and an output layer. This algorithm is conceptually similar to k-nearest neighbor algorithm [31]. Each neural unit in the input layer corresponds to each predictor variable. The number of units in the hidden layer are same as the number of clusters chosen. A number of clusters is a design parameter. RBFNN has a non-linear structure from input to the hidden layer and a linear structure from hidden to the output layer (also known as Gaussian function). Both supervised as well as unsupervised techniques exist for RBFNN training method [32]. RBFNN structure is shown in Fig 3.1 below.

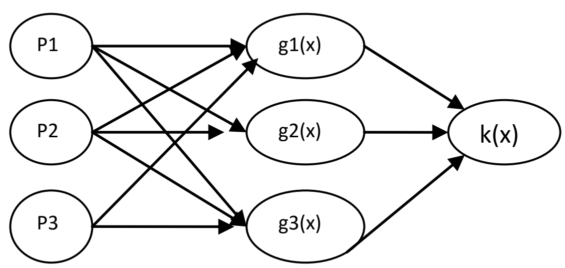

Fig 3.1: Structure of RBFNN Network [32]

3.2 Architecture and Working of RBFNN Algorithm

Basic steps involved in the RBFNN algorithm as designed by Broomhead and Lowe [33] and used by several researchers for prediction are described below [27, 31, 34]:

RBFNN (I_i, O_i)

Begin

Input: Rainfall Data I_i (1979-2002)

Output: Rainfall Data O_i (2003-2006)

Step 1: For each c_i , do

Initialize c_i to a randomly selected value.

Where, c_i **:** centre of a cluster.

Step 2: Compute the Euclidean distance between c_i and t_i

Where, Unit width (r): $r_j = \sqrt{\sum_{i=1}^{k} \frac{\left(c_j - c_i\right)^2}{k}}$

i: neighbouring cluster

j: current cluster

$$D(m,n) = \sum_{i=1}^{v} (m_i - n_i)^2$$

$$h(d) = \exp\left(\frac{-(d-c)^2}{r^2}\right)$$

h(d): radial function or Gaussian function

Step 3: For each c_i ,do

Assign t_i to c_i based on min(D(m,n)) value.

Step 4: For each c_i do

Compute $avg(c_i)$

Assign $new\_c_i = avg(c_i)$

Step 5: Repeat steps 2-4, until c_i do not change.

End

3.3 Main Applications of RBFNN

RBFNN Algorithm has been applied in various fields of classification, function approximation and prediction. Some of the case studies are discussed below:

1. Mary and Raj [35] proposed an idea to classify the sales data using the neural classifier and RBFNN with Data Reducing using Hierarchical Clustering. The record of sales was classified into “high sales car”, “moderate sales car” and “low

sales car”. Total of 1200 samples were used, among them (720 sample) 60% were used for training purpose and the remaining 480 (40%) samples were used for testing purpose. Results showed that the RBFNN neural network achieved its best result with an accuracy of above 91%.

2. Venkatasen and Anitha [36] proposed an idea for diagnosis of diabetes mellitus using the RBFNN neural network model. Out of the total of 1200 cases, 600 (50%) were chosen for training, 300 (25%) were selected for validation, and the rest 300 were chosen for the testing purpose. Root Mean Square using the best center approximation was found to be 0.3213, and the percentage of correct prediction was found to be 97%. Therefore, the results depicted that the RBFNN method proved to be an accurate and good model for diabetes prediction.

3. Hussein et al. [37] proposed the RBFNN technique for “Gold price prediction.” The main aim of the research work is to help gold investors to decide when to buy or sell gold in future. The data was collected from London Bullion Market Association (LBMA). In this research, data of 1000 days was used for training, 300 days of data was used for the testing purpose and 14 days of data was set for validation purpose. Further, it was concluded that the RBFNN model performed more effectively than the Auto-regressive model with the sum of square error (SSE) of value 114.05.

4. Usman and Alaba [38] proposed an RBFNN technique for predicting electricity consumption. The data of 26 years (1964-1989) was collected from CBN annual bulletin. 65 percent of data was used for training, 15 percent for validation and 20 percent of the remaining data was used for testing purpose. Furthermore, techniques of BPNN and RBFNN were applied for the time-series electricity consumption prediction. Results showed that RBFNN overweighed BPNN method regarding smaller sum of square error (SSE) and higher coefficient of correlation (R) value.

Chapter-4
Literature Review

4.1 Time Series Methods for Rainfall Prediction

4.1.1 Time Series Rainfall Forecast Models

Time series methods of prediction were the first methods used to predict rainfall. Some of these methods are ARMA, Auto-Regressive Moving Average, Moving Average. These methods are briefly discussed below:

ARIMA Model: ARIMA model [42] is a further extension of autoregressive moving average (ARMA) model. The basic difference between the two is that ARIMA model includes an autoregressive and moving average techniques for differencing time series where as ARMA model does not include any parameter for differencing the time series. Both the techniques are applied to fit the data for time-series prediction.

Auto-Regressive Model: The data items of a time series are serially dependent on each other in a sense that one can estimate next series of data based on the specific, time-lagged (previous) data items. The Auto-regressive model [43] is taken into consideration when a value from the time series is linearly dependent on a value from the same time series.

Moving Average Model: It is a general method to model univariate time series. Moving average model [43] determines that the output unit linearly depends on its previous stochastic term. Each data item in the time-series component can also be affected by the previous errors that are not encountered using Auto-Regressive model, but these are taken into consideration in Moving Average techniques.

4.1.2 Techniques of Time-Series Applied in Rainfall Prediction

Earlier, many efforts were made by several researchers for forecasting accurate rainfall using Time-series techniques. Among these were-Gorman and Taman [39], Salas et al. [39], Lall and Bosworth [39], Hsu et al. [39], Davidson et al. [39.Time Series consists of several non-identifiable components which make it difficult to analyze the pattern. Several advancements have been made in this approach of time-series rainfall forecast. Some of these approaches have been mentioned below:

Chiew et al. [40] preformed comparative study of six rainfall-runoff modeling techniques to predict daily, monthly and annual flows in the eight unregulated catchment areas. They deducted that the time-series methods can provide accurate predictions of monthly and annual water yield of catchments.

Khan et al. [41] predicted the yield of winter rice by rainfall distribution using the techniques of multiple regression analysis. Based on the experimental results, it was found that the root means square for the model to be more than 70%, and the results of prediction results indicated that the regression techniques provide good results for rice prediction.

Mohammadi et al. [42], used three different techniques of ANN, ARIMA time series, and regression to forecast spring inflows. Twenty-five years of analyzed data was used for training purpose and the rest five years was used for testing purpose. In the following research, ANN model found to be the best model for forecasting of spring inflows.

Wang et al. [43] used the techniques of autoregressive moving average (ARMA), artificial neural network (ANN), Genetic programming (GP), support vector machine (SVM) and adaptive neural-based fuzzy inference system (ANFIS) to analyze the patterns of monthly river flow discharges. The coefficient of correlation (R) and mean square error (MSE) were the performance indices used for comparative analysis. Based on the analysis, it was concluded that ANFIS and SVM model proved to be the best models for analysis of monthly river discharge patterns.

Chattopadhyay and Chattopadhyay [44] used ARIMA model to forecast Indian Summer Monsoon Rainfall (ISMR).The dataset was collected from Indian Institute of Tropical Meteorology, Pune. In this technique, backpropagation with the scaled conjugate gradient descent algorithm was used for prediction. ANN model was trained thrice to achieve a good result. After three iterations, it was found that the high prediction yield is possible.

Mahsin et al. [45] forecasted the monthly rainfall in Dhaka, Bangladesh region for 1981-2010 by using a Box-Jenkins technique to build a Seasonal Autoregressive Moving Average Model (SARIMA) model. In this research, SARIMA was found to be an acceptable model to forecast rainfall for the next two years. This helped analysts to establish policies for the water demand management.

Ramana et al. [46] proposed a technique for monthly rainfall forecast using wavelet neural network method. The monthly data was collected from Darjeeling station. Results indicated that the performance of wavelet neural network model was more efficient than the ANN model.

4.2 Statistical Methods for Rainfall Prediction

Statistical methods are mathematical models used to collect, analyze, summarize and predict variable numerical data. There are two types of statistical methods for rainfall prediction. These are discussed below. Further statistical techniques applied in rainfall prediction are briefly discussed in the section 4.2.2 below.

4.2.1 Types of Statistical Methods Used in Rainfall Prediction

Empirical methods and dynamic methods are the commonly used statistical methods for rainfall prediction these days. These methods have been briefly discussed below:

Empirical Method: In the empirical approach, the analysis is done on the historical data of rainfall and its relationship with other hydrological variables is taken into consideration. The well-known empirical techniques used for rainfall prediction are- ANN, Fuzzy logic, stochastic and collective methods of data handling.

Dynamic Approach: In the dynamic approach, physical models generate predictions based on the system of equations. Numerical weather forecasting methods are used to implement the dynamic methods. The record of some of the work using these empirical and dynamic approaches is mentioned below. Also, the empirical statistical technique of Regression is widely employed in the field of business, biological sciences, climate forecast, behavioral sciences, etc.

4.2.2 Statistical techniques applied in Rainfall Prediction

This sub-section provides a literature review of the statistical techniques applied in the area of rainfall prediction. Some of the case studies have been briefly discussed below:

Sen [47] applied an 8-parameter powered regression technique on long-range summer monsoon forecast. The parameters used were- Model parameters (months), EI Nino (previous year data), Eurasian snow cover (December) [47], North West Europe temperature (January) [47], Europe pressure gradient (January) [47], 50 hp wind pattern, Arabian Sea SST, East Asia Pressure, South Indian Ocean Temperature. Based on the experimental results, the model error was found to be below 5 percent and was found to be a suitable method for monsoon forecast.

Rajeevan et al. [48], devised the new statistical techniques of ensemble multiple linear regression (EMR) and projection pursuit regression (PPR) to predict the data collected from India Meteorological Department (IMD). The performance evaluation was done from a period of 1981-2004 using the sliding window model with a window length of 23 years. The root mean square error for the two models was found to be 0.00456 and 0.00675. The results of the models were found to be appropriate for forecasting the data of the year 2005.

Singhrattna et al. [49], developed a statistical method for seasonal forecasting of summer monsoon rainfall in Thailand region. Predictors identified for Thailand summer monsoon rainfall were: sea-surface temperature and sea-level pressure. The two methods used for forecasting are traditional linear regression and local polynomial based non-parametric methods. Furthermore, it was concluded that the non-parametric method is a better forecast model with a minimum predictive standard error.

4.3 ANN techniques used in Rainfall Prediction

Nowadays, ANN is a widely applied technology in the area of rainfall prediction. Some of its case studies have been briefly discussed below:

Hu [50] embarked a major contribution of ANN method in rainfall prediction He applied an adaptive system called Adaline for pattern classification. From this research, he concluded that the adaptive systems are capable of performing useful hydrological predictions without going into the complete knowledge of the dynamics or physical parameters involved.

French et al did an important research in the field of rainfall prediction using an ANN method [51], in which they used a neural network for forecasting the two-dimensional rainfall, one hour in advance. The ANN model used rainfall data as an input which was generated by a simulation model. However, there were several limitations to the proposed research- there was a mismatch between preprocessing and training time, which could not be easily balanced and the number of hidden nodes and layers were not sufficient about the number of input and output nodes. Notwithstanding, all these limitations, the model is still considered to be a significant contribution in the field of rainfall prediction using ANN.

Zhang and Scofield [52] introduced the ANN technique for the heavy rainfall prediction and cloud merger recognition from the satellite data. The above methodology lead to the following achievements-automatic prediction of cloud mergers, efficient prediction rate which is ten times faster than the previously applied techniques [52] and also the model error became significantly reduced.

Michaelides et al. [53] compared the two techniques of ANN and Multiple Linear Regression for computing missing data over the Cyprus region, south of Turkey. The ANN technique was applied on the data collected from neighboring regions of Cyprus that had sufficiently long and complete archive of data. In this way, the model can be used to fill the missing data. Based on the analysis, an ANN model proved to be a better model in predicting the missing rainfall data.

Lee et al. [54] used ANN technique for rainfall prediction by dividing the available data into equal subpopulations. They used a divide and conquer technique where the whole region was divided into four sub-regions, and each sub-region is modeled with distinct technique. RBFNN was used as a prediction model for the two larger regions, and Simple Linear Regression model was used for the two smaller sub-regions. The results depicted that the RBFNN approach generated good prediction results than the Simple Linear Regression models.

Toth et al. [55] compared the rainfall forecasting models with the real time flood forecasting approach. They used three-time series techniques-autoregressive moving average (ARMA), ANN and K-NN for predicting rainfall accruing in Sieve River Basin, Italy. The data collected was from 1992-1996. Results indicated that the ANN proved to be a better model for rainfall prediction.

Luk et al. [56] compared and modeled three techniques for rainfall prediction-Multilayer Feed Forward Network (MLFN), Elman partial neural network (Elman) and Time Delay neural network (TDNN). In this research work, 87 years of data were collected for prediction from Kerala region. Furthermore, it was concluded that the MLFN outperformed all the three models regarding prediction.

Wong et al. [57] used soft computing techniques of ANN and Fuzzy logic for rainfall prediction. The data was divided into the homogeneous sub-population using a Self-Organizing Map (SOM) technique. Then, the BPNN technique was applied to learn the characteristics inherent within each cluster. Afterward, fuzzy rules were extracted from each cluster. The fuzzy rule base is then applied in the prediction. The research provided a way to the future researchers to analyze the data regarding soft computing techniques.

Kumarasiri et al. [58] used feed-forward neural network approach for rainfall prediction. The impetus was made on predicting the rainfall using available data rather than using the physical aspects of the atmosphere. They have also described the change in rainfall trends with the changing monsoon season. Chattopadhyay [59] designed a feed-forward ANN to predict the average summer-monsoon rainfall in India. In this methodology, the three-layered network was created using sigmoid as a transfer function. He compared the performance of ANN and Multiple Linear Regression results, and it was concluded that the ANN method overrides other approaches regarding rainfall prediction.

Xinia et al. [60] designed a model consisting of Empirical Mode Decomposition (EMD) and RBFNN for rainfall prediction. The research concluded that the hybrid method is highly efficient and accurate in doing rainfall prediction. In 2012, Abhishek et al. designed [61] an ANN model to predict the average monthly rainfall in Udupi district of Karnataka, India. The comparative analysis was done between the three algorithms- BPNN, Layer Recurrent Network (LRN) and Cascaded BPNN (CBP) [61].At last, it was concluded that BPNN proved to be a better model for rainfall prediction based on its lower mean square error value.

Chau et al. [62] applied several soft computing techniques for rainfall prediction. Two methodologies were used to increase the accuracy of rainfall prediction- data preprocessing technique and modular modeling technique. The preprocessing techniques used were-Moving Average (MA) and Singular Spectrum Analysis (SSA). Local Support Vector Regression (SVR) and ANN models were used as modular models. Finally, it was concluded that the Moving Average (MA) model was better than the SSA model when coupled with ANN.

4.4 Comparative Study of Traditional ANN and RBFNN techniques

Traditional ANN and RBFNN are commonly used techniques and are considered to be the backbone of the artificial neural network. Section 4.4.1 demonstrates these techniques briefly. Section 4.4.2 illustrates the difference between these two techniques.

4.4.1 Traditional ANN and RBFNN techniques

Artificial Neural Network possesses very absolute power of computational intelligence. Few of the ANN method include Backpropagation Neural Networks [24], Radial Basis

Function Neural Networks [20], Counterpropagation Neural networks [63], Kohonen networks [63], etc and these are widely used for data classification, pattern recognition, and function approximation.

Traditional Neural Networks have to undergo rigorous training before being applied. Training is done directly where the network inputs are applied, and the network weights are adjusted iteratively according to the values of the error. The most popular form of traditional neural network is Multi-Layer Perceptron (MLP) network [63]. RBFNNs have a fixed three layered architecture consisting of input, hidden and an output layer. Inputs are taken from an input layer; hidden layer maps the input data to make it linearly separable, and an output layer provides the linear separation.

4.4.2 Difference between Traditional ANNs and RBFNNs

Traditional ANNs and RBFNNs widely differ from each other regarding network topology, function approximation, weight initialization and classification methods. Some of these differences have been briefly discussed below:

1. MLP networks can involve more than three layers but is not the case with RBFNNs, so training is faster in RBFNNs.

2. RBF network follows the concept of Local Approximation, as certain hidden units decide the output in the confined local receptive field but MLP networks are global in nature where output is determined collectively by all neurons.

3. It is necessary for RBFNNs to set the correct initial weights but in MLP networks these are adjusted randomly.

4. The classification method for the two networks is also different as RBFNN clusters are separated by hyperspheres but in MLP networks, there are arbitrarily shaped hyper-surfaces used for separation.

The Table 4.1 below shows the literature review of the some of the work done in the area of rainfall prediction.

Table 4.1: Literature Review of the work done in Rainfall Prediction

S.No	Authors	Techniques Used	Key Findings
1	Khan et al. (1995) [41]	Multiple Linear Regression techniques	• They predicted the yield of winter rice by rainfall distribution. • It was found root mean square error for the model to be more than 70% and regression technique provided accurate results of prediction.
2	Mohammadi et al. (2005) [42]	ANN, ARIMA, and Regression	• To forecast spring inflows, 25 years of data was used for training and five years for testing purpose. • Based on the analysis, they concluded ANN to be a better model having minimum mean square error values.
3	Wong et al. (2009) [43]	ARMA, ANN, Genetic Programming, Support Vector Machine and Adaptive Neural Based Fuzzy Inference System (ANFIS)	• They analyzed the patterns of monthly river-flow discharges. • ANFIS and SVM proved to be better models based on higher correlation (R) and lower mean square error values.
4	Chattopadhyay and Chattopadhyay (2010) [44]	ARIMA, Moving Average	• They used Backpropagation with conjugate gradient descent algorithm for prediction of summer monsoon rainfall. • Based on the analysis, ANN proved to be a better model which achieved better results of prediction after three iterations.
5	Mahsin et al. (2012) [45]	Box-Jenkins technique of Seasonal Autoregressive Moving Average Model (SARIMA)	• They predicted monthly rainfall in Dhaka, Bangladesh region. • SARIMA proved to be an acceptable model to forecast rainfall for the next two years.

6	Ramana et al. (2013) [46]	Wavelet Neural Network and ANN method	• They forecasted monthly rainfall in Darjeeling station. • Wavelet method provided more accurate results than ANN and hence proved to be a better model for prediction.
7	Sen (2003)[47]	Eight parameters powered regression technique	• To forecast long-range summer monsoon. • Based on the experimental results, the model error was found to be below 5% and proved to be a suitable method for monsoon forecast.
8	Rajeevan et al. (2006) [48]	Ensemble Multiple Linear Regression (EMR) and Projection Pursuit Regression (PPR)	• To forecast rainfall data collected from India Meteorological Department (IMD). • The evaluation was done from years 1981-2004 using sliding window with a window length of 23 years. • EMR proved to be a better model with root mean square error of value 0.00456.
9	Singhrattna et al. (2005) [49]	Traditional Linear Regrefssion and Local Polynomial based Non-parametric methods	• To forecast summer monsoon rainfall in Thailand region. • The non-parametric method proved to be a better model with a minimum predictive standard error.
10	Hu (1964) [50]	Adaptive technique of ADALINE	• He performed pattern classification of rainfall data. • He further concluded that adaptive system is capable of performing hydrological predictions.
11	French et al. (1992) [51]	ANN	• To forecast two-dimensional rainfall, one hour in advance. • ANN provided accurate results for two-dimensional rainfall prediction.
12	Zhang and Scofield (1994) [52]	ANN	• They performed heavy rainfall prediction and cloud merger recognition from satellite data. • Based on the analysis, following achievements have been made- accurate prediction of cloud merger, efficient prediction rate and model error was reduced significantly.

13	Michaelides et al. (1995) [53]	ANN and Multiple Linear Regression	• To compute missing data over Cyprus region, South of Turkey. • ANN proved to be a better model in predicting missing rainfall data.
14	Lee et al. (1998) [54]	RBFNN, Simple Linear Regression technique	• They divided complete data into four sub-regions. • RBFNN was used for prediction on two larger sub-regions and SLR was used for prediction on two smaller sub-regions. • RBFNN approach generated good prediction results than SLR.
15	Tooth et al. (2000) [55]	ARMA, ANN, and K-NN	• To forecast rainfall from 1992-1996. • Based on the experiment, ANN provided better results than the other two methods.
16	Luk et al. (2001) [56]	Multilayer Feed Forward Network (MLFN), Elman partial Neural Network (Elman) and Time Delay Neural Network (TDNN)	• To forecast rainfall in Kerala region. • Based on the results, it was concluded that MLFN outperformed all three models regarding accurate prediction values.
17	Wong et al. (2003) [57]	ANN, Fuzzy Logic	• They divided whole data was into smaller clusters using Self-Organizing Map (SOM) technique. • Then BPNN was applied to learn characteristics of each cluster. • Afterward, Fuzzy rules were extracted from each cluster. • The research provided a way for future researchers to analyze the data regarding soft computing techniques.
18	Chattopadhyay (2007) [59]	Feed Forward Neural Network, Multiple Linear Regression	• To predict rainfall in tropical regions of India. • Based on the results, it was concluded ANN outperformed MLR regarding accurate prediction results.

19	Abhishek et al. (2012) [61]	BPNN, Layer Recurrent Network (LRN) and Cascaded BPNN (CBP)	• To predict average monthly rainfall in Udupi district of Karnataka, India. • Based on the results, it was found BPNN proved to be a better model based on its lower mean square value.
20	Chau et al. (2013) [62]	Preprocessing techniques- Moving average (MA) and Singular Spectrum Analysis (SSA). Modular techniques- Local Support Vector Regression (SVR) and ANN Models.	• To predict monthly rainfall using soft computing techniques. • Based on the results, it was concluded Moving Average proved to be a better model than SSA when coupled with ANN.

Chapter-5
Problem Outline

5.1 Problem Description

Rainfall plays an integral role in the socio-economic as well as moral well-being of any country. The problem statement is to predict the future rainfall data from the years (2003-2006) based on the previous year's collected data from Coonoor region in Nilgiri district (Tamil Nadu). To perform this forecast, two well-known techniques of ANN-backpropagation and radial basis function neural network were deployed. Furthermore, two models are compared based on their mean square error and accuracy values. Earlier, RBFNN and BPNN techniques were applied separately to the rainfall prediction, but we have used both the RBFNN and BPNN techniques for the comparative study. Similar approach was used previously by Purnawansyah and Haviluddin [27] for monthly network traffic prediction.

5.2 Main Objective

Based on exhaustive literature survey, following are the objectives of the Thesis work :

1. Analysis of various Artificial Neural Network techniques used in the area of rainfall prediction.
2. To apply the techniques of Backpropagation Neural Network and Radial Basis Function Neural Network on rainfall data (1979-2002) for future prediction of rainfall data (2003-2012).
3. To design a GUI based application in MATLAB for rainfall prediction.
4. To compare BPNN and RBFNN models.

5.3 Research Methodology

Backpropagation and Radial Basis Function Neural Network techniques were applied in the area of rainfall prediction. Section 5.3.1 provides brief details about these techniques. Section 5.3.2 demonstrates stepwise research methodology used in the following research work.

5.3.1 Applied Techniques

In this section techniques of backpropagation and radial basis function neural network are explained.

Backpropagation Neural Network: Backpropagation Neural Network is one of the most powerful algorithms of ANN, which is applied for minimizing the error through a multi-layer network. It was first introduced by Rummelhart and McCelland in 1986. BPNN algorithm employs a Delta rule [5] for calculating the error in the output layer. The error is propagated backward into the previous layer at each subsequent iteration. Its learning process involves:

1. **Forward propagation:** The input signal is propagated from an input to output layer via hidden layer. During this forward propagation, weight and bias valued are kept constant, and each neuron of the current layer will only exert an effect on the neuron of next layer.
2. **Backward propagation:** The difference between actual output and network output is known as an error signal. During this phase, the error is propagated backward into the input layer in a layer-by-layer manner. Also, the weights and bias are adjusted by the error propagating values. The process continues until the network output becomes closer to the actual output [27]. The Fig 5.1 below represents error propagation through the artificial neural network. Flowchart for the stepwise methodology applied in BPNN algorithm is shown in Fig 5.2 below.

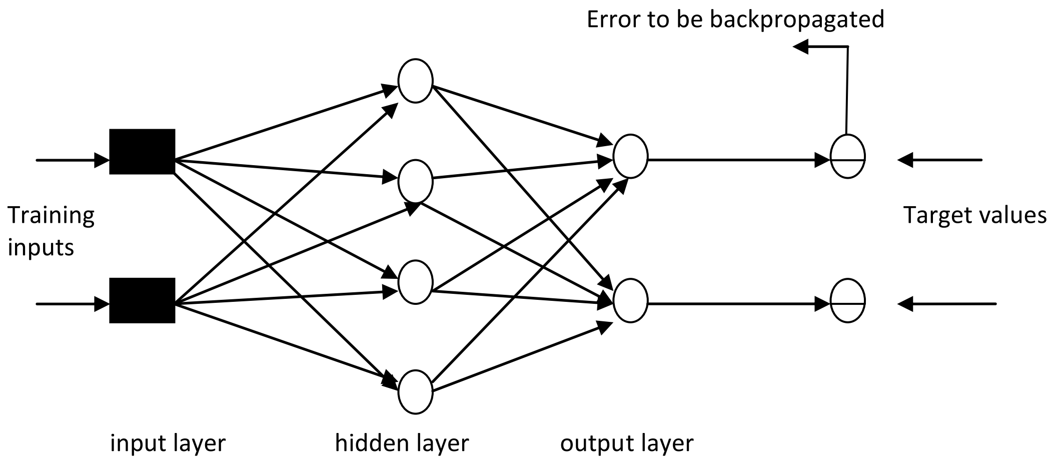

Fig 5.1: Error Propagation through Backpropagation Neural Network [27]

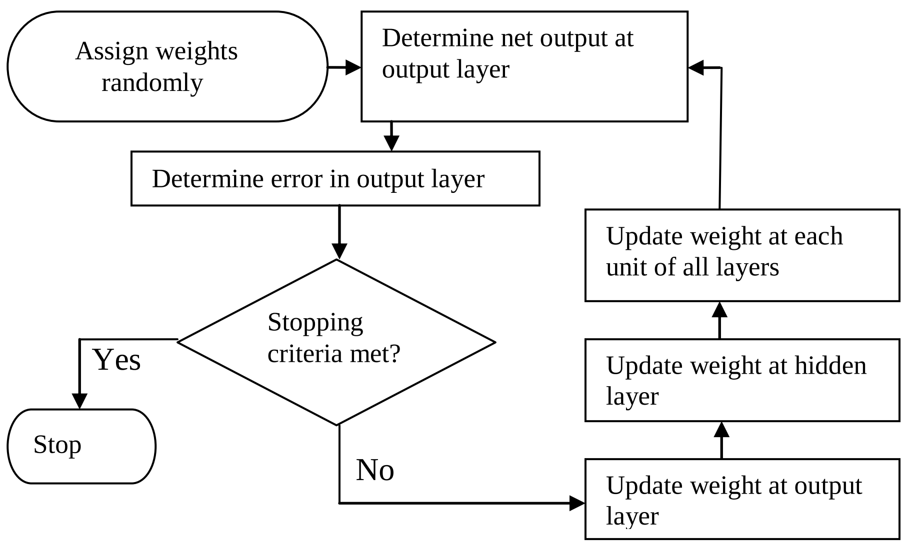

Fig 5.2: Flowchart of BPNN algorithm [27]

2. **Radial Basis Function Neural Network:** Radial Basis Function Neural Networks are the simple class of functions. These can be applied to any linear or non-linear data. The learning technique of this method involves both supervised and unsupervised learning methods. Broomhead and Lowe first introduced this technique in 1988 [33]. The RBFNN method is a fixed three-layered structure. The RBFNN method is similar to working as K-Nearest Neighbor algorithm. The Fig 5.3 below shows the structure of RBFNN network. Also, the flowchart of the RBFNN algorithm is shown in Fig 5.4 below.

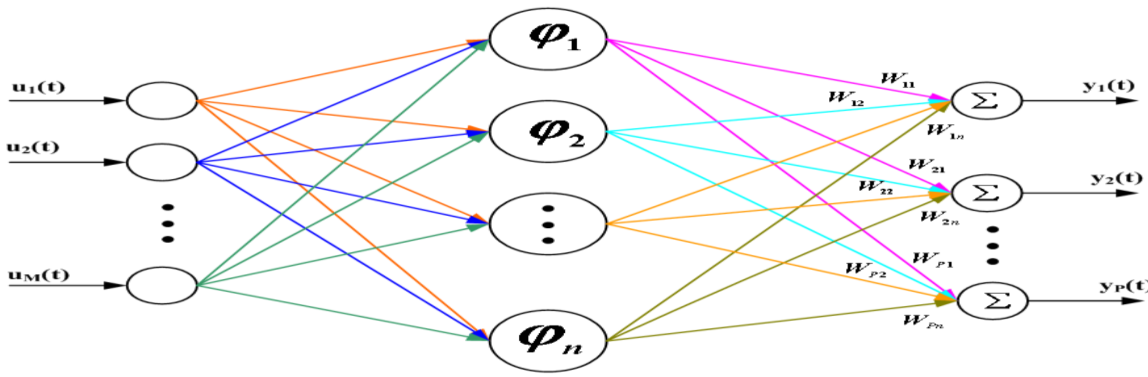

Fig 5.3: Structure of RBFNN Neural Network [27]

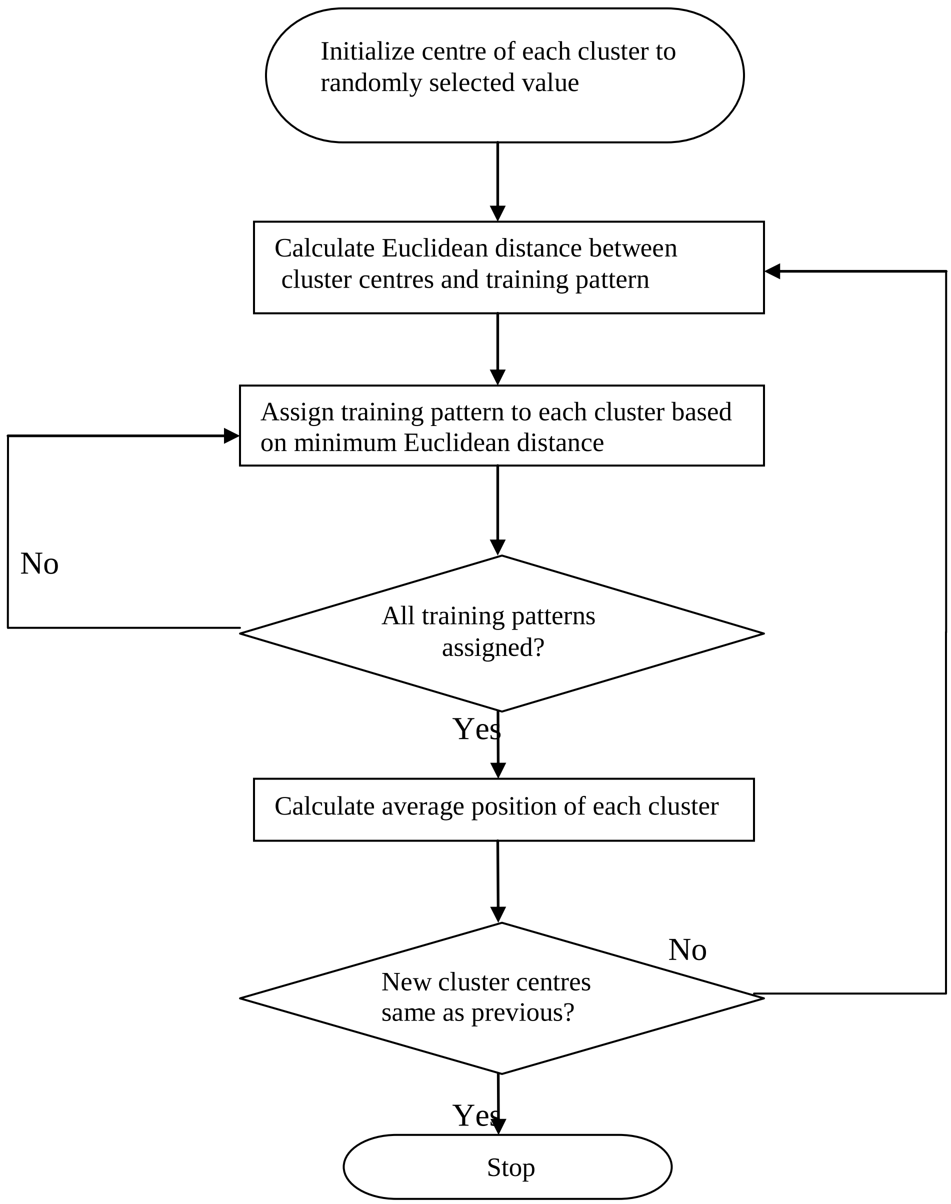

Fig 5.4: Flowchart of RBFNN algorithm [27]

5.3.2 Methodology

Following steps are used to achieve the desired objective:

1. Input data is collected from http://nilgiriswaterportal.in/analysis-of-time-series-data-on-rainfall-for-coonoor from years 1979-2002.

2. Data preprocessing and normalization of data is done to prepare the data in a way to make it suitable for training using ANN methods. Data preprocessing is done to identify any missing data and remove any non-numeric value from the data. Data normalization is done to make the data uniform and in a smaller range of values.

3. Divide the data in the ratio of training and testing.

4. Create the BPNN and RBFNN networks using the inbuilt functions available in MATLAB.

5. Predict the future values using BPNN and RBFNN techniques based on the training and testing results.

6. Compute the accuracy and mean square error values.

7. Compare and analyze the above results. Also, a better model for the rainfall prediction is suggested based on the values of above results.

Block Diagram for the applied research methodology is shown in Fig 5.5 below:

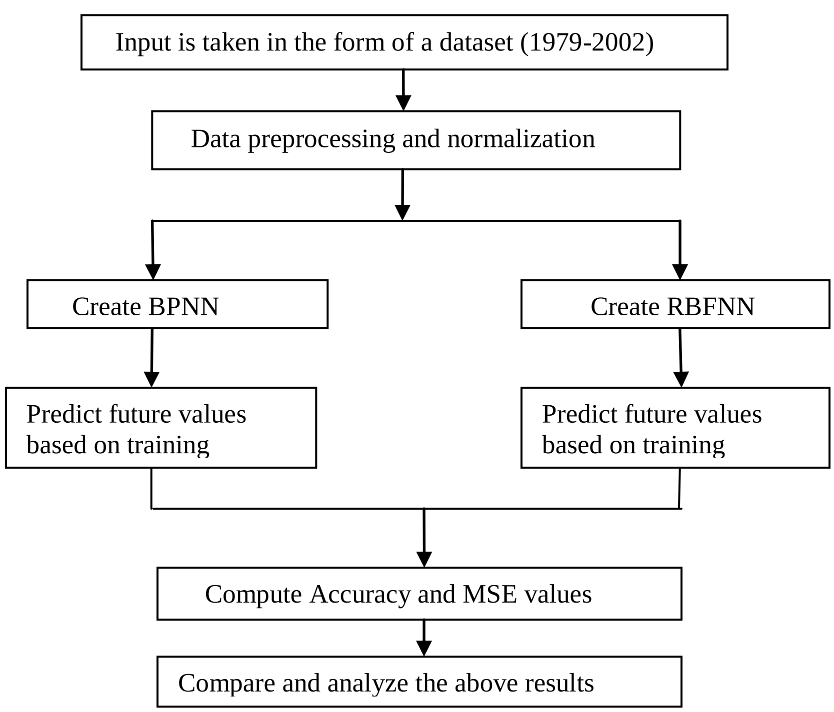

Fig. 5.5: Block Diagram of the Applied Research Methodology

5.4 Contribution

As discussed earlier, rainfall plays a significant role in the socio-economic growth of every country. Therefore, an accurate and predetermined forecast of rainfall is indispensable for the welfare of every country. The current research work will help tourists, farmers, native people of the region, weather forecasters, etc. It would also be helpful to the tourist population visiting the Coonoor region of Nilgiri district (Tamil Nadu) as it belongs to a hilly area and is the beautiful tourist location. If tourists would know the exact prediction of rainfall, it would be easier for such people to enjoy the beauty of the region timely and comfortably. Farmers can also well plan the time of growing and harvesting the crops. Therefore, considering all these points in mind, it gave me inspiration to do some research in the field of rainfall prediction as it will be beneficial to the society.

Chapter-6

Implementation and Experimental Outcomes

6.1 An Introduction to MATLAB

We have implemented the above algorithms of BPNN and RBFNN using MATLAB 2015a software.

Brief Overview of MATLAB [64]: The term “MATLAB” stands for Matrix Laboratory. Earlier MATLAB was written to provide easy understanding and working with matrix software developed by LINPACK (Linear System Package) and EISPACK (Eigen System Package) projects. This language is mainly used for high performance technical computations. It is an integration of computation, visualization and programming environment. It contains advanced data structures, has its built-in editing and debugging tools and integrates the power of object oriented methodologies. These features make MATLAB a powerful tool for development and research. The software tool is available since 1984 and is used worldwide these days in universities and industries. It has built-in routines to perform a wide range of computations. The Toolbox contains a collection of applications called packages. There are many available toolboxes for signal processing, symbolic computation, simulation, optimization, neural network and many other modern tools and techniques. Fig 6.1 below shows a graphical interface of the MATLAB workspace.

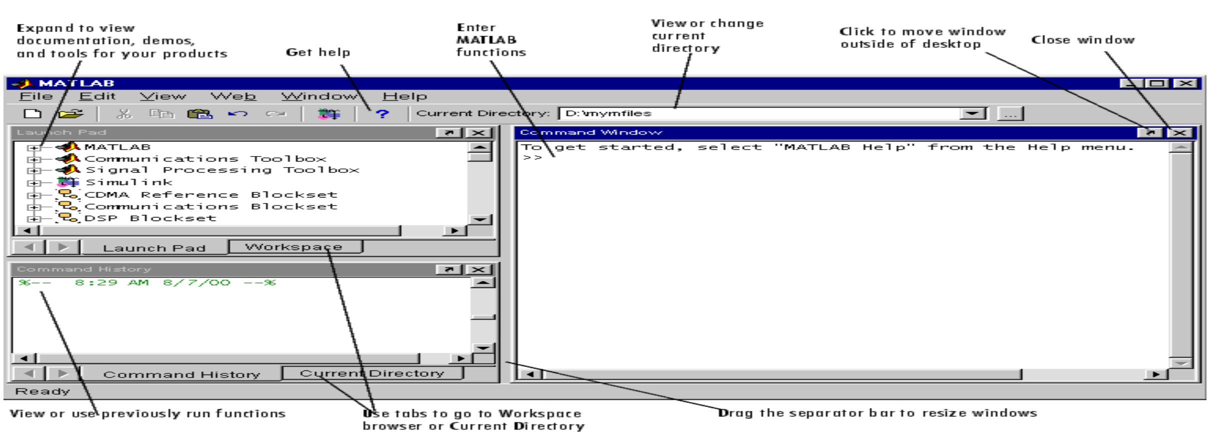

Fig 6.1: Graphical Interface of MATLAB Workspace [64]

6.2 Implementation Steps

We have used following steps in designing and programming BPNN and RBFNN model in MATLAB. These steps are briefly discussed below:

1. A collection of data.
2. Preprocessing and Normalization of data.
3. Network Creation.
4. Train the model.
5. Test the model.
6. Perform prediction of data.
7. Compute the performance parameters-MSE and Accuracy.
8. Compare the results.

1. **A collection of data:** The data (1979-2002) was collected from the water portal "http://nilgiriswaterportal.in/analysis-of-time-series-data-on-rainfall-for coonoor" of Coonoor region based in Nilgiri district of Tamil Nadu from years 1979-2002. Table and plot for the same are shown in Table 6.1 and Fig 6.2 below:

6.1: Table of Rainfall Data (1979-2002)

	Jan	Feb	Mar	...	Nov	Dec
1979	7	178	157	...	1348	281
1980	0	2	59	...	534	34
1981	43	0	94	...	123	174
1982	8	0	2	...	339	31
1983	35	0	8	...	91	482
1984	298	285	395	...	150	142
1985	118.8	0	0.1	...	249.6	309.1
1986	74.8	224.2	99.8	...	112.9	315.9
1987	56.4	36.1	55.5	...	340.3	536.4
1988	16.6	24.3	26.4	...	193.3	192.9
1989	16.6	0	204.6	...	292	171.8
1990	233	0	70.4	...	375.1	125.7
1991	124.4	5.3	61.4	...	536.3	21.3
1992	47.1	0	0	...	936.4	65.1
1993	0	0	82.8	...	1060.2	265.3
1994	52.5	86	31.2	...	593.2	54.3
1995	193.1	11.1	195.4	...	179	8
1996	8.1	99.4	49.1	...	255.3	553.6
1997	119.2	0	39	...	528	279.6
1998	51.2	11.7	3.2	...	214.4	667.5
1999	1.9	264.1	11.1	...	431	150.8
2000	47.9	243.7	0	...	419.9	153.1
2001	54.1	8.6	6	...	502	372.9
2002	41.9	19.2	14.2	...	547.7	51.8

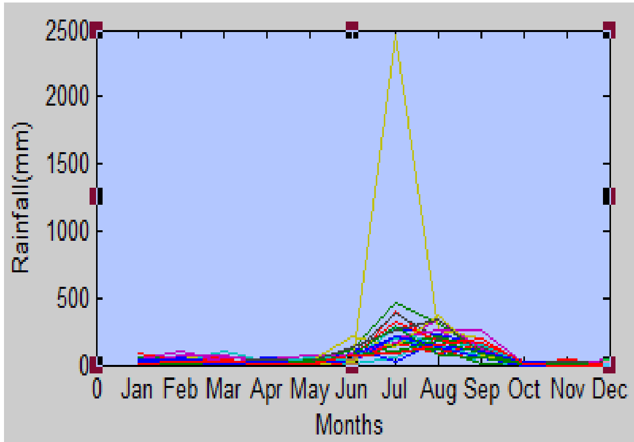

Fig 6.2: Plot of Real Data

2. **Data preprocessing and normalization:** Data preprocessing is done because of the three reasons: to find the missing data, to normalize the data and to randomize the data. Normalization is done so as to make the data uniform. Rainfall values of low magnitude are ignored in comparison to the rainfall values of high magnitude. Therefore, it becomes crucial to take into account all the values uniformly. Normalization is performed in excel sheet using an equation defined below:

$$p' = \frac{p - q'}{q - q'} \quad [23]$$

Where p, q' and q denotes original, minimum and maximum values in dataset respectively.

3. **Network Creation:** During this stage, the programmer specifies the type of network, number of hidden layers, the number of hidden neurons, training method, learning method, number of epochs and gradient descent of the network. We have used the BPNN and RBFNN functionalities of the neural network to do the same.

   Designing BPNN network in MATLAB

   Training_data=xlsread(‘D:\matlab\bin\training’)

   net =newff(Training_data',T,20)

   Training_data→Data used for training purpose

   T→Target data

   Number of neurons in hidden layer = 20

net.trainparam.epochs=50

net.trainFcn=LM (Sets the type of training function, here Levenberg-Marquardt is used as a learning function)

net.trainParam.lr=0.4 (Sets the learning rate of a network)

Designing RBFNN network in MATLAB

net=newrb(Training_data',T,20)

Training data→Data used for training purpose

T→Target data

Here, we have used number of neurons in hidden layer as 20

4. **Network training:** During the training process, weight and bias values are adjusted to make predicted results (output) close to the actual values. The figure of training process using BPNN algorithm is shown in Fig 6.3 below:

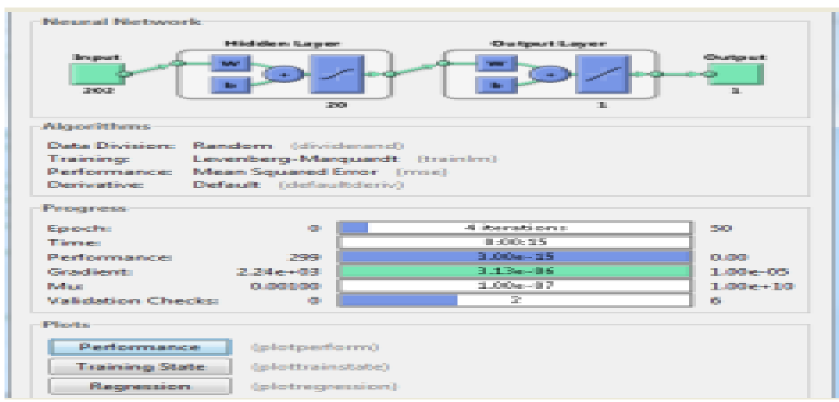

Fig 6.3: Training using BPNN network

5. **Test the model:** As the data was divided into the ratio of 70% (training) and 30% (testing). Therefore, the next step is to test the data using an unseen test data.

6. **Prediction of data:** After the training and testing procedures, values of rainfall from years 2003-2006 are determined. The table and plot for the predictions using BPNN and RBFNN are shown below:

Table 6.2: Results of prediction using RBFNN

	2003	2004	2005	2006
Jan	23.92	23.97	23.99	23.96
Feb	12.94	12.58	12.93	12.90
Mar	23.99	23.84	23.98	23.81
Apr	12.97	12.86	12.97	12.68
May	37.95	37.84	37.79	37.67
Jun	13.92	13.89	13.82	13.94
Jul	35.91	35.85	35.88	35.67
Aug	33.98	33.84	33.79	33.68
Sep	43.91	43.88	43.77	43.72
Oct	25.92	25.87	25.96	25.72
Nov	11.95	11.87	11.77	11.69
Dec	14.93	14.93	14.84	14.95

Table 6.3: Results of Prediction Using BPNN

	2003	2004	2005	2006
Jan	23.91	23.83	23.75	23.76
Feb	12.86	12.85	12.89	12.89
Mar	23.97	23.60	23.86	23.67
Apr	12.91	12.83	12.54	12.67
May	37.51	37.83	37.75	37.89
Jun	13.88	13.83	13.60	13.65
Jul	35.46	35.83	35.42	35.44
Aug	33.91	33.83	33.75	33.67
Sep	43.80	43.88	43.72	43.67
Oct	25.91	25.85	25.35	25.80
Nov	11.88	11.94	11.65	11.76
Dec	14.91	14.83	14.32	14.67

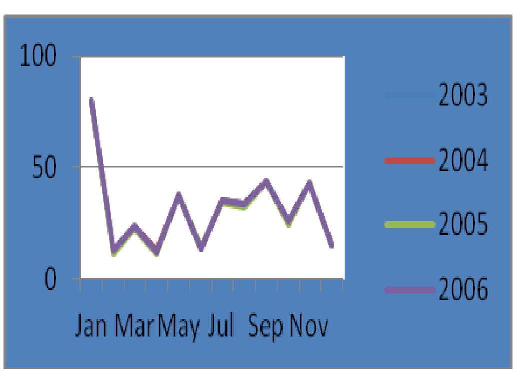

Fig 6.4: Plot of prediction using RBFNN

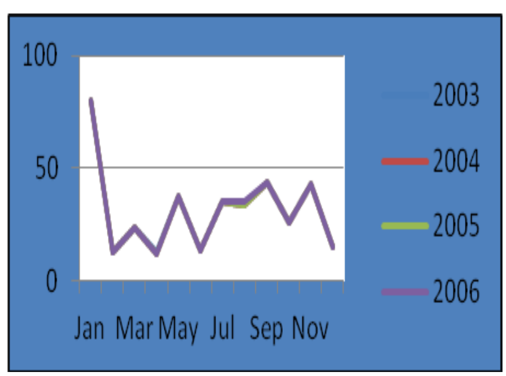

Fig 6.5: Plot of prediction using BPNN

The table of prediction indicates the monthwise rainfall values from years 2003-2006. The above values show that there will be heavy rainfall during the months of May and September. Therefore, such rainfall prediction is helpful in a region where weather conditions are very unstable. The GUI for the above rainfall prediction is designed using MATLAB 2015a software. It takes rainfall dataset as input (1979-2002), it can plot rainfall graphs for a specific year and month; it displays training and testing results. Prediction values for a particular year from (2003-2012) for a particular month can be easily determined using this GUI application. It can also be applied to new dataset for the rainfall prediction. GUI creating techniques can be easily seen by typing GUIDE command on MATLAB interface. The GUI for the above work is shown in Fig 6.6 below:

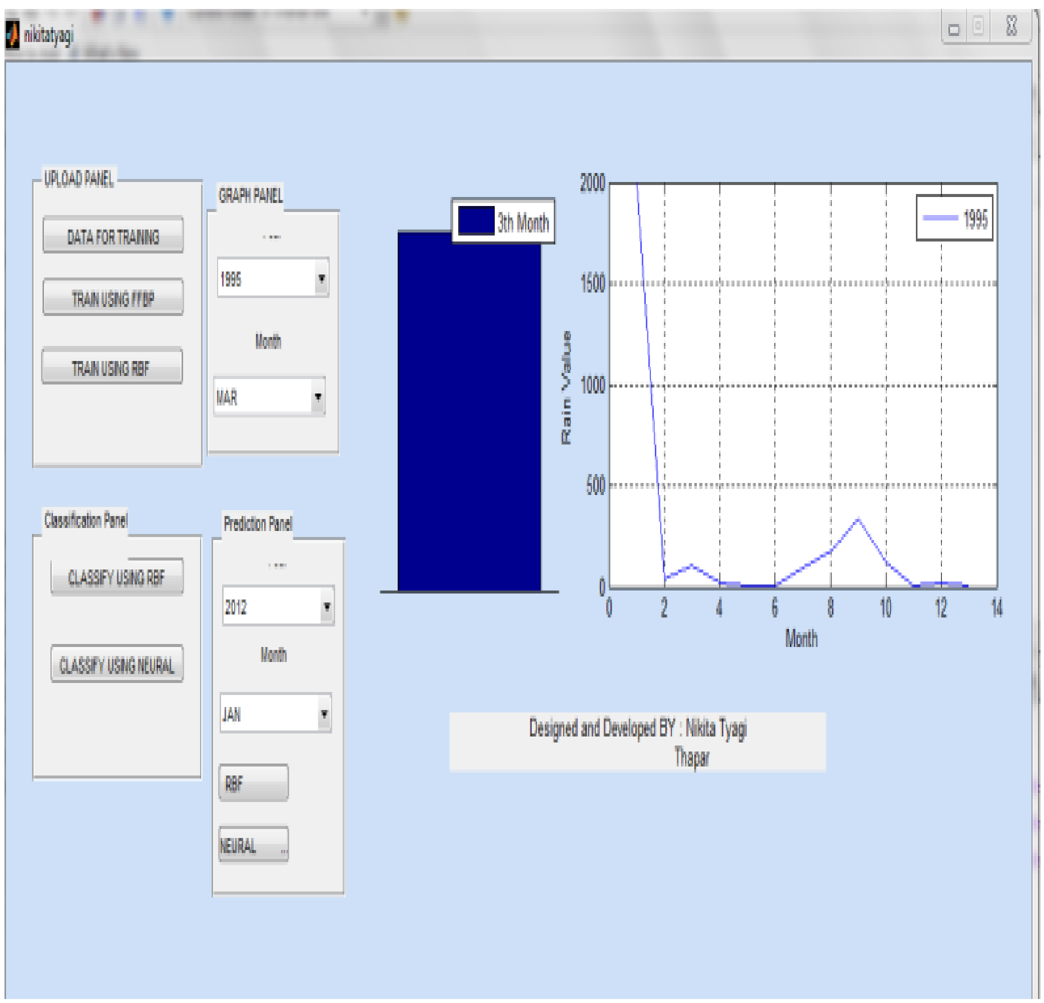

Fig 6.6: GUI for Rainfall Prediction

6.3 Experimental Outcomes

In this section, experimental outcomes of the research work are outlined. Subsection 6.3.1 demonstrates how the values of mean square error and accuracy were estimated. Subsection 6.3.2 determines comparative study of the results.

6.3.1 Estimation of Mean Square Error (Training, Testing) and Accuracy

Following are the criterion for measuring performance of backpropagation and radial basis function neural network in rainfall prediction:

1. **Mean Square Error (MSE):** MSE measures the square of the errors or deviations i.e. the difference between actual and the predicted results. Equation used to calculate MSE is shown below:

$$MSE = \frac{1}{n}\sum_{j=1}^{n}\left(z' - z\right)^2 \quad [28]$$

where z and z' represents actual and predicted data

2. **Training means square error (MSE):** This is an error which occurs when the model is applied to the training data. In our research work, we have used 70% of data (194 samples) as the training data.
3. **Testing mean square error (MSE):** This is an error which occurs when the model is tested on the unseen dataset. This error determines how well a model can perform on future unseen data.
4. **Accuracy:** Accuracy is usually the performance parameter used to measure the quality of a prediction model. It is the rate of a total number of correct predictions to the total cases being evaluated. The equation used for the same is shown below:

$$Accuracy = \frac{(Actual - Forecast)}{Actual} \times 100 \quad [28]$$

6.3.2 Comparative Study of the Results

Based on the experiment, it was found that the RBFNN model outperformed the BPNN model regarding its higher accuracy value of 67.30% and lower mean square error (testing) value of 0.013761. Table 6.4 below shows the performance results:

Table 6.4: Performance Results

	Training Error	Testing Error	Accuracy
RBFNN	0.003172	0.013761	67.30
BPNN	0.024478	0.015659	63.50

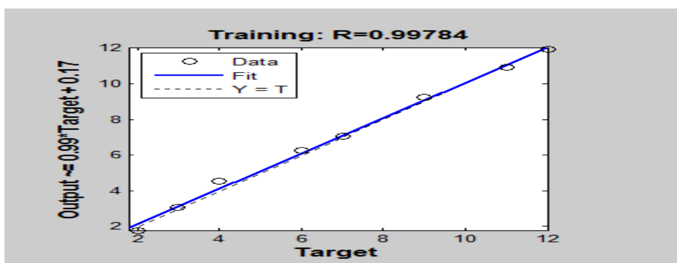

Fig 6.7: Plot of Regression using BPNN

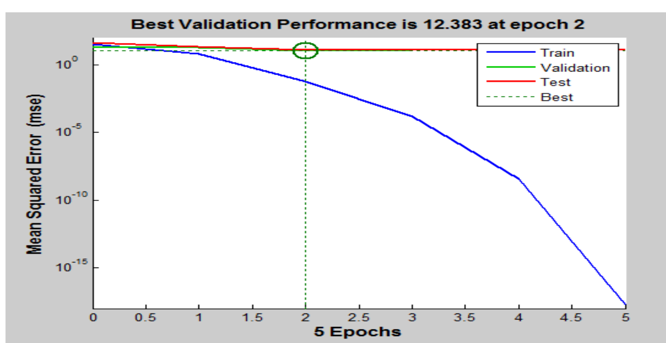

Fig 6.8: Plot of performance using BPNN

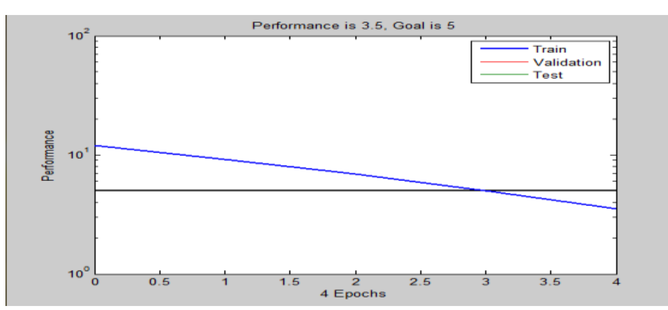

Fig 6.9: Plot of performance using RBFNN

The plot of prediction for the years (2003-2006) indicate that the values of current year prediction are much similar to the values of the previous year. The plot of regression shows that how close are the output values to the actual target values with the coefficient of linear regression (R) of value 0.99784. The performance plot shows how many minimum numbers of iterations or epochs are required to achieve the best performance results. The result of the performance graph for the BPNN training indicates that the best validation performance is 12.383 and is achieved at epoch 2. The result of the performance graph for the RBFNN training indicates that the best validation performance is 3.6 and is achieved at epoch 6. The training models are efficient in prediction as the curves of testing and validation overlap in the performance graph of both the algorithms.

Chapter-7
Conclusion and Future Scope

7.1 Conclusion

In this research work, rainfall prediction is applied on the data collected from Coonoor region in the Nilgiri district (Tamil Nadu) using the two commonly known techniques of backpropagation and radial basis function neural network. The prediction results showed that there would be heavy rainfall in the months of May and September. Therefore, the above prediction results can be used to determine the type of rainfall season of any particular region. Furthermore, the values of mean square error (MSE) for RBFNN and BPNN found to be 0.013761 and 0.015659 which indicate that RBFNN outperforms BPNN regarding lower mean square error (MSE) value. Also, the results of accuracy using RBFNN and BPNN are found to be 67.30 and 65.30 which shows that RBFNN is a better model regarding higher accuracy values. Therefore, by analyzing the overall results, it is concluded that the RBFNN is a better model than the BPNN model for the prediction of current rainfall data.

7.2 Future Work

- As the RBFNN proved to be a better model than the BPNN model for rainfall prediction, therefore, future work is suggested to use Backpropagation Neural Network algorithm with some other techniques like fuzzy logic, which is a rule-based mechanism and can help in improving the accuracy rate of BPNN.
- Several other algorithms can be used with BPNN like Genetic Algorithm (GA) which can be helpful in improving the efficiency of BPNN results.
- Time series methods like autoregressive moving average (ARIMA), moving average (MA) and autoregressive (AR) can also be used together with BPNN technique to improve the rainfall prediction accuracy.

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1. Nikita Tyagi and Ajay Kumar, ”Comparative Analysis of Backpropagation and Radial basis Function Neural Network on Rainfall Prediction”, International Conference on Inventive Computation Technologies (ICICT), IEEE Explore, 2016. [ACCEPTED]

Video Link

https://www.youtube.com/channel/UCsgko6qbOBeqFF4dVvgIA9g