Chapter 4
Application of Artificial Neural Networks in Short-Term Rainfall Forecasting

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Abstract Short-term rainfall is important in agriculture, industry, the energy sector, and any other water-dependent activities where profitability depends on climatic conditions. The scarcity of reliable prediction models encouraged the authors of the present study to develop a modeling platform using a neurogenetic model to estimate rainfall occurrence within a short-term duration. The data on both the quantity and the probability of occurrence of rainfall based on the previous 1–5 days were used to predict the quantity and occurrence of rainfall 1–4 days hence. The potential of neurogenetic models to predict short-term rainfall on the basis of such a small-scale data set was analyzed with the aim of developing a software platform for laypeople and to help related professionals maintain the profitability of their organization by reducing the likelihood of wastage resulting from large-scale prediction errors, which are common with the available linear models. The results indicate that neurogenetic models can reliably predict rainfall 1, 3, and 4 days in advance, but not 2 and 5 days, if the models are trained with a suitable algorithm. The subpar performance of the 2- and 5-day rainfall prediction models was attributed to the choice of training algorithms and length of time, although the reliable prediction of rainfall even 1 day in advance warrants pursuing further development of the present investigation.

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4.1 Introduction

The prediction of short-term rainfall (STR) involves the estimation of the intensity and/or frequency of rainfall events within a span of 5 days. Rainfall impacts the production efficiency of the essential services (like water, electricity, and gas), agriculture, stock exchanges, and various other water-dependent industries. Laypeople also are affected by rainfall events.

Rainfall can impact daily water supplies from the water treatment plant (WTP) of any city because of the increase in suspended solids and pollutants in surface water. The chemical dozing pattern must be adjusted to prevent any excess of toxicity from affecting the quality of the treated water. If a rainfall event could be predicted within the next 24–48 h, then compensatory measures could be taken to maintain the quality of treated water.

Demand for electricity depends on temperature and humidity. After a rainfall event both temperature and humidity decreases, which leads to a reduction in the demand for electricity. Because demand is reduced, production of electricity will need to be adjusted to prevent wastage. If the occurrence of rainfall events within a short span of time could be predicted, then a sufficient amount of electrical energy could be conserved; this would also reduce the release of greenhouse gases into the atmosphere.

The demand on natural gas also varies with the frequency and intensity of rainfall events. Because of the impact of extreme events, electrical transmission or distribution networks can be damaged. The absence of electricity induces increased demand on liquefied petroleum gas and compressed natural gas.

That is why there is a need for a reliable prediction model that can estimate both probability and magnitude of rainfall at least 24–48 h before its occurrence. The absence of a large-scale data set have decreased the availability of reliable prediction models for solving such problems. The absence of a regular pattern in the related parameters within such short time domain has forced modelers to apply stochastic modeling to predict short-term rainfall patterns.

Stochastic models have fewer requirements when it comes to data but are extremely vulnerable to uncertainty due to the unstable nature of the interrelationships of the variables. Due to the complexity and uncertainty involved in such models, linear methods often fail to deliver effective estimations, as can be concluded from the references given in Table 4.1.

4.1.1 Earlier Studies on the Prediction of Short-Term Rainfall

Short-term rainfall is a popular topic of research due to its importance in industry and the agricultural output of a country. Table 4.1 shows the application of different types of mathematical and statistical models in the prediction of short-term rainfall. The accuracy achieved and drawbacks identified are also explained.

Table 4.1 Studies on the estimation of short-duration rainfall

References	Model type	Input requirement	Accuracy level	Remarks
Kisi and Cimen (2012)	Wavelet-support vector machine conjunction model	Daily rainfall data	Combined model was found to perform better than when applied separately	Prediction of rainfall 1 day in advance conducted with two types of model: combined wavelet-support vector machine model and support vector regression used separately. According to performance metrics (wavelet-support vector machine conjunction model) the latter was outperformed by former model's accuracy level
Papalexiou et al. (2011)	Stochastic model developed using scaling behavior of both time and state change of catchments	5–10 s rainfall data	Study recommended use of stochastic models; power-type distribution tails and autocorrelation functions were found to be indicators of better performance from such models	Stochastic models involve assumptions and are highly linear in nature. But in the present study the model uses scaling information of time and state to differentiate domains of solution space
Kottegoda et al. (2003)	Beta and geometric distribution for reducing parameters from daily to hourly values	Daily rainfall	The results from the distribution models were found to predict the statistical extremes satisfactorily	The study tried to disaggregate daily rainfall into hourly values with the help of beta distributions. Wet and dry season daily rainfall was found to follow a geometric distribution. From the disaggregation results it was found that the hourly rainfall also follows a geometric distribution but is conditioned on total daily rainfall values
Sugimoto et al. (2001)	Stochastic model where Kalman filter was used for incrementing time domain	Rainfall from radar data	Developed model was compared with deterministic physical model created for same purpose. Comparison result shows higher level accuracy for stochastic model with respect to deterministic modeling framework	Data from radar were converted and fed as input to a physical mesoscale climate model developed on concept of water balance and thermodynamics. Extended Kalman filter was utilized for state update. Data generated were compared with deterministic model for validation

(continued)

Table 4.1 (continued)

References	Model type	Input requirement	Accuracy level	Remarks
Thielen et al. (2000)	Conceptual, simple mass balance model of water within air columns	Surface rainfall and vertically integrated liquid water content (VIL)	Model was evaluated with numeric data generated from a mesoscale meteorological model and results encouraged further development of the model	Developed model of present study was conceptual in nature and involves simple balancing of water mass in air columns and spatial advection within variables. The result was found to be better than the simple advection routines for specific time frames
Burlando et al. (1993)	Autoregressive moving average (ARMA) model	Hourly rainfall	It was assumed that hourly rainfall follows an autoregressive moving average process; with the help of this assumption hourly rainfall was predicted for both event-based and normal time domain. Predictions were found to be more reliable for the latter with respect to the former	Assumption that hourly rainfall follows an ARMA process was used to predict short-term rainfall. But model was not compared with other models developed for same purpose
French et al. (1992)	Monte Carlo Stochastic State-space model	Hourly rainfall	Generation of hourly data on both time and space scales was found to improve its accuracy when high-density primary data were used as input	This study generates hourly rainfall data from a state-space model iterated by Monte Carlo simulation where effect of sample network density on model reliability was also analyzed. The results clearly show advantage of using high-density sampling network for such forecasting procedures

4.1.2 Neural Network for Short-Term Rainfall Prediction

The ability of neural networks to map the nonlinear and inherently complex interrelationship between a set of input variables and an output variable is well established and supported by many studies on different topics in science and engineering. Table 4.2 shows the application of neural networks in solving various types of problems. Table 4.3 presents earlier applications of neural networks, both individually and in combination with other algorithms in predicting short-term rainfall with respect to different regional conditions.

4.1.3 Neurogenetic Algorithms

In the development of neural network models, network topology, weights assigned to input variables, and the type of activation function are the three important parameters that affect the accuracy and reliability of a neural network model. Because there are no predetermined methodologies for identifying the optimal values of these parameters, various studies have applied different statistical methods, including nature-based algorithms, to determining an ideal value for these three parameters.

When genetic algorithms are used to search for optimal values of these parameters, the models are jointly referred to as neurogenetic models.

From Table 4.3 it is clear that there is a substantial lack of research studies involving stochastic neural network models and short-term rainfall. The table also shows that such models have already been developed to perform effectively in predicting hourly to monthly rainfall intensities and occurrence. The table also demonstrates that in the case of occurrence, neural networks generally prefers categorized data rather than numerical data sets (Olsson et al. 2001).

4.1.4 Objective

The main objective of the present investigation will be to analyze the capability of neurogenetic models in estimating short-duration rainfall patterns. The study involves the prediction of both the quantity and occurrence probability of rainfall within the next 5 days based on the rainfall records of the previous 5 days. A stochastic modeling approach was used, keeping in mind the scarcity of adequate data sets and the level of uncertainty included in such prediction problems.

4.1.5 Brief Methodology

In case of the neural network models the probability of occurrence and amount of rainfall in the previous 5 days were considered as input variables. In total, five

Table 4.2 Examples of application of neural network in different prediction and classification problems

References	Model type	Input-output	Success
Piotrowski et al. (2012)	Noise-injected multilayer perceptron neural networks	Longitudinal dispersion coefficient was predicted to test a novel approach for avoiding "convergence to local minima" and "inability to optimize nondifferentiable data set" errors involved in gradient-based training algorithms by introduction of evolutionary computation	The result of the noise-injected MLP neural network was compared with many evolutionary computation techniques (like distributed DE with explorative–exploitative population families, self-adaptive DE, DE with global and local neighbors, grouping DE, JADE, comprehensive learning particle swarm optimization, efficient population utilization strategy particle swarm optimization, and covariance matrix adaptation –evolutionary strategy) to find the best EC for optimal prediction. The results show that an extended differential evolutionary algorithm performs much better than the other training algorithms in use
Khashei et al. (2012)	Multilinear regression model coupled with multilayered perceptron neural network model	This model was developed to create more accurate but general two classes as well as multiclass classification algorithm. The business credit data of Japan, Indian diabetes data, forensic glass data, and a set of Fisher Iris data were used for classification with the developed model	Yes [the investigation compared the combined model with linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), K-nearest neighbor (KNN), and support vector machines (SVMs)] and concluded that the present model was more effective in classifying the test data sets than the compared models
Lekouch et al. (2012)	Artificial neural network	Air and dew point temperature or relative humidity, wind speed and wind direction, and cloud cover were used to develop the model for prediction of dew yield	Yes (the model was used to extrapolate output for 15 cities in and around the test cities situated in coastal regions of southwest Morocco)

Kisi et al. (2012)	Back propagation neural network coupled with artificial bee colony algorithm (ANN-ABC)	Streamflow from two gauge stations was used to predict sediment load of same	Yes (according to results from performance metrics like mean square error and coefficient s, the ANN-ABC model performed better compared to ANN-fuzzy, neural differential evolution and rating curve models. The logarithm of the inputs was found to increase the model efficiency with respect to the normal data set)
Zhao et al. (2012)	Multilayered (three in the present investigation) neural network model	The first transverse cracking of ice cover was the output and different hydrometric and meteorological data were used as input	Yes (when compared with multilinear regression models the ANN model was found to be more efficient and effective than the former model, at least in cases of river breakup prediction)
Alvisi and Franchini (2012)	Gray neural network (a neural network model whose parameters are represented by gray numbers) (NNs)	The uncertainty level or the difference between the predicted and actual values of the river level was taken as output	Yes (the NNs were compared with a Bayesian neural network and according to the predictions from both models, estimation from NNs was far narrower than the latter neural network model, showing the accuracy level of the NN model)
Kim and Pachepsky (2010)	Regression tree (RT) coupled neural network	Missing precipitation data were the output and available rainfall data from the station were the input	Yes (better than RT when applied separately)
Jain and Kumar (2007)	Conceptual model coupled to neural network	Monthly stream flow data	Yes (four conventional time series models of autoregressive type and four neural network models were used successfully in predicting monthly stream flow of Colorado River, California)
Gautam et al. (2004)	Feedforward neural network	Groundwater level of interconnected wells of a floodplain as input and electrical conductivity was treated as output	Yes (effect of bridge construction was successfully identified by observing changes in electrical conductivity in groundwater compared to preconstruction period benchmarks)
Bodri and Cermak (2000)	Back-propagation-trained neural network	Monthly rainfall data of 38 years were used to predict rainfall for next month and next summer	Yes

Table 4.3 Examples of stochastic neural network for estimation of short-term rainfall

Type of model in prediction of short-term rainfall	Study area	Lead time	Problem solved	References
Neuroclassifier followed by neuropredictor model	Friuli Venezia Giulia region (henceforth FVG, NE Italy)	6 h	The problem of de-classification was mitigated by introduction of a regression-type neural network model	Manzato (2007)
Dynamic recurrent neural network	Wu Tu Watershed, Taiwan	3 h	Absence of link between physical concept and neural networks was overcome with introduction of unit hydrograph model	Pan and Wang (2004)
Serially connected neural network	Chikugo River basin, Kyushu Island, southern Japan	12 h	Problems of zero value, which are generally present in training data set of short time duration	Olsson et al. (2001)
Backpropagation neural networks	Moravia, eastern part of Czech Republic	1 month	Heavy rainfall followed by occurrence of an extreme event cause flooding. Prediction of next-month extreme rainfall performed by neural network; good fit was achieved, which can help professionals in the field with preplanning of compensatory and preventive measures	Bodri and Čermák (2000)

neurogenetic models were prepared, each having two submodels. The occurrence probability and quantity of rainfall for the next 5 days were considered as model outputs for the present study. As stated earlier, each model has two submodels predicting the quantity and occurrence of rainfall in different time domains (one to five).

The models were trained with the help of a data matrix that contains every possible combination between input and output variables if their data values are converted into nine categories representing nine different degrees of intensity of the variables. Table 4.4 shows the input and output variables considered for the five different models. In Table 4.5 are shown the variables and categories into which all are divided based on the intensity of the magnitude.

Because the data matrix contains all possible situations, the model can learn the inherent relationship between the input and output variables for all possible combinations, ensuring the reliability of the model output.

All the developed models were evaluated based on selected performance metrics like the kappa index of agreement, precision, sensitivity, and specificity. The metrics will help to identify the best model among the five models developed. The selection will also indicate the range within which the functionality of the neurogenetics models will be optimized.

4.2 Methodology

In the present investigation the objective is to identify the range within which neurogenetic models will efficiently predict output with the desired level of accuracy and reliability. At first, five neurogenetic models are prepared with the help of common model parameters. Each model has two submodels predicting the quantity and probability of occurrence within different time domains starting from 1 to 5 days in advance of the rainfall.

The input and output variables of all models are given in Table 4.4. Table 4.6 shows the common model parameters adopted for all the neurogenetic models so that a uniform decision can be made.

Before the models are developed, the data to train the models are preprocessed as described in the next section.

4.2.1 Data Preprocessing

All the neurogenetic models considered for the present study have ten input variables. If the data of the input variables are represented as a percentage of the maximum, then all the variables can be encoded in nine categories based on the percentage value of the variables because categorized data were found to perform more efficiently than normal sets. Table 4.5 shows the input variables and the nine categories in which the data values of the variables are grouped.

Table 4.4 Input and output variables of neurogenetic models developed

Input	Output
STRFM1	
Occurrence probability of rainfall, same day (P_t)	Occurrence probability of rainfall, 1 day before (P_{t+1})
Occurrence probability of rainfall, 1 day before (P_{t-1})	Quantity of rainfall, 1 day before (Q_{t+1})
Occurrence probability of rainfall, 2 days before (P_{t-2})	
Occurrence probability of rainfall, 3 days before (P_{t-3})	
Occurrence probability of rainfall, 4 days before (P_{t-4})	
Quantity of rainfall, same day (Q_t)	
Quantity of rainfall, 1 day before (Q_{t-1})	
Quantity of rainfall, 2 days before (Q_{t-2})	
Quantity of rainfall, 3 days before (Q_{t-3})	
Quantity of rainfall, 4 days before (Q_{t-4})	
STRFM2	
Occurrence probability of rainfall, same day (P_t)	Occurrence probability of rainfall, 2 days before (P_{t+2})
Occurrence probability of rainfall, 1 day before (P_{t-1})	Quantity of rainfall, 2 days before (Q_{t+2})
Occurrence probability of rainfall, 2 days before (P_{t-2})	
Occurrence probability of rainfall, 3 days before (P_{t-3})	
Occurrence probability of rainfall, 4 days before (P_{t-4})	
Quantity of rainfall, same day (Q_t)	
Quantity of rainfall, 1 day before (Q_{t-1})	
Quantity of rainfall, 2 days before (Q_{t-2})	
Quantity of rainfall, 3 days before (Q_{t-3})	
Quantity of rainfall, 4 days before (Q_{t-4})	
STRFM3	
Occurrence probability of rainfall, same day (P_t)	Occurrence probability of rainfall, 3 days before (P_{t+3})
Occurrence probability of rainfall, 1 day before (P_{t-1})	Quantity of rainfall, 3 days before (Q_{t+3})
Occurrence probability of rainfall, 2 days before (P_{t-2})	
Occurrence probability of rainfall, 3 days before (P_{t-3})	
Occurrence probability of rainfall, 4 days before (P_{t-4})	
Quantity of rainfall, same day (Q_t)	
Quantity of rainfall, 1 day before (Q_{t-1})	
Quantity of rainfall, 2 days before (Q_{t-2})	
Quantity of rainfall, 3 days before (Q_{t-3})	
Quantity of rainfall, 4 days before (Q_{t-4})	
STRFM4	
Occurrence probability of rainfall, same day (P_t)	Occurrence probability of rainfall, 4 days before (P_{t+4})
Occurrence probability of rainfall, 1 day before (P_{t-1})	Quantity of rainfall, 4 days before (Q_{t+4})
Occurrence probability of rainfall, 2 days before (P_{t-2})	
Occurrence probability of rainfall, 3 days before (P_{t-3})	
Occurrence probability of rainfall, 4 days before (P_{t-4})	
Quantity of rainfall, same day (Q_t)	
Quantity of rainfall, 1 day before (Q_{t-1})	
Quantity of rainfall, 2 days before (Q_{t-2})	

(continued)

Table 4.4 (continued)

Input	Output
Quantity of rainfall, 3 days before (Q_{t-3})	
Quantity of rainfall, 4 days before (Q_{t-4})	
STRFM5	
Occurrence probability of rainfall, same day (P_t)	Occurrence probability of rainfall, 5 day before (P_{t+5})
Occurrence probability of rainfall, 1 day before (P_{t-1})	Quantity of rainfall, 5 day before (Q_{t+5})
Occurrence probability of rainfall, 2 days before (P_{t-2})	
Occurrence probability of rainfall, 3 days before (P_{t-3})	
Occurrence probability of rainfall, 4 days before (P_{t-4})	
Quantity of rainfall, same day (Q_t)	
Quantity of rainfall, 1 day before (Q_{t-1})	
Quantity of rainfall, 2 days before (Q_{t-2})	
Quantity of rainfall, 3 days before (Q_{t-3})	
Quantity of rainfall, 4 days before (Q_{t-4})	

Table 4.5 Input variables and categories of neurogenetic models

Input variable	Category considered
Occurrence probability of rainfall, 1 day before (P_t)	Extremely High (EH), Very High (VH), Semi High (SH), High (H), Normal (N), Low (L), Semi Low (SL), Very Low (VL), and Extremely Low (EL)
Occurrence probability of rainfall, 2 days before (P_{t-1})	Extremely High (EH), Very High (VH), Semi High (SH), High (H), Normal (N), Low (L), Semi Low (SL), Very Low (VL), and Extremely Low (EL)
Occurrence probability of rainfall, 3 days before (P_{t-2})	Extremely High (EH), Very High (VH), Semi High (SH), High (H), Normal (N), Low (L), Semi Low (SL), Very Low (VL), and Extremely Low (EL)
Occurrence probability of rainfall, 4 days before (P_{t-3})	Extremely High (EH), Very High (VH), Semi High (SH), High (H), Normal (N), Low (L), Semi Low (SL), Very Low (VL), and Extremely Low (EL)
Occurrence probability of rainfall, 5 days before (P_{t-4})	Extremely High (EH), Very High (VH), Semi High (SH), High (H), Normal (N), Low (L), Semi Low (SL), Very Low (VL), and Extremely Low (EL)
Quantity of rainfall, 1 day before (Q_t)	Extremely High (EH), Very High (VH), Semi High (SH), High (H), Normal (N), Low (L), Semi Low (SL), Very Low (VL), and Extremely Low (EL)
Quantity of rainfall, 2 days before (Q_{t-1})	Extremely High (EH), Very High (VH), Semi High (SH), High (H), Normal (N), Low (L), Semi Low (SL), Very Low (VL), and Extremely Low (EL)
Quantity of rainfall, 3 days before (Q_{t-2})	Extremely High (EH), Very High (VH), Semi High (SH), High (H), Normal (N), Low (L), Semi Low (SL), Very Low (VL), and Extremely Low (EL)
Quantity of rainfall, 4 days before (Q_{t-3})	Extremely High (EH), Very High (VH), Semi High (SH), High (H), Normal (N), Low (L), Semi Low (SL), Very Low (VL), and Extremely Low (EL)
Quantity of rainfall, 5 days before (Q_{t-4})	Extremely High (EH), Very High (VH), Semi High (SH), High (H), Normal (N), Low (L),Semi Low (SL), Very Low (VL), and Extremely Low (EL)

Table 4.6 Characteristics of model parameters and adopted performance metrics

Model parameter	Value
Genetic algorithm parameters	
Population size	60
Number of generations	50
Crossover rate	0.80
Mutation rate	0.20
Neural network parameters	
Network topology	10-8-2
Network weight	88
Training algorithm selected	Quick propagation (QP) and conjugate gradient Descent
Quick propagation coefficient	1.75
Learning rate	0.20
Generalization loss allowed	50.00%
Correct classification rate (CCR) desired	98.00%
Number of training iterations allowed	1,000,000
Number of retrains	10
Performance metrics of STRM1	
Training CCR of STRM1-QP	99.95%
Testing CCR of STRM1-QP	99.95%
Training CCR of STRM1- CGD	99.95%
Testing CCR of STRM1-CGD	99.95%
Kappa index of agreement of STRM1 -QP	99.95%
Precision of STRM1-QP	99.95%
Sensitivity of STRM1-QP	99.95%
Specificity of STRM1-QP	99.95%
Kappa index of agreement of STRM1 -CGD	99.95%
Precision of STRM1-CGD	99.95%
Sensitivity of STRM1-CGD	99.95%
Specificity of STRM1-CGD	99.95%
Performance metrics of STRM2	
Training CCR of STRM2- QP	99.95%
Testing CCR of STRM2-QP	99.95%
Training CCR of STRM2- CGD	90.91%
Testing CCR of STRM2-CGD	100%
Kappa index of agreement of STRM2 -QP	99.95%
Precision of STRM2-QP	99.95%
Sensitivity of STRM2-QP	99.95%
Specificity of STRM2-QP	99.95%
Kappa index of agreement of STRM2 -CGD	94.76%
Precision of STRM2-CGD	95.55%
Sensitivity of STRM2-CGD	96.04%
Specificity of STRM2-CGD	95.06%
Performance metrics of STRM3	
Training CCR of STRM3- QP	99.95%
Testing CCR of STRM3-QP	99.95%
Training CCR of STRM3-CGD	99.95%

(continued)

Table 4.6 (continued)

Model parameter	Value
Testing CCR of STRM3-CGD	99.95%
Kappa index of agreement of STRM3 -QP	99.95%
Precision of STRM3-QP	99.95%
Sensitivity of STRM3-QP	99.95%
Specificity of STRM3-QP	99.95%
Kappa index of agreement of STRM3 -CGD	99.95%
Precision of STRM3-CGD	99.95%
Sensitivity of STRM3-CGD	99.95%
Specificity of STRM3-CGD	99.95%
Performance metrics of STRM4	
Training CCR of STRM4- QP	99.95%
Testing CCR of STRM4 – QP	99.95%
Training CCR of STRM4- CGD	99.95%
Testing CCR of STRM4 – CGD	99.95%
Kappa index of agreement of STRM4 -QP	99.95%
Precision of STRM4-QP	99.95%
Sensitivity of STRM4-QP	99.95%
Specificity of STRM4-QP	99.95%
Kappa index of agreement of STRM4 -CGD	99.95%
Precision of STRM4-CGD	99.95%
Sensitivity of STRM4-CGD	99.95%
Specificity of STRM4-CGD	99.95%
Performance metrics of STRM5	
Training CCR of STRM5- QP	99.95%
Testing CCR of STRM5-QP	99.95%
Training CCR of STRM5-CGD	99.09%
Testing CCR of STRM5-CGD	100%
Kappa index of agreement of STRM5-QP	99.95%
Precision of STRM5-QP	99.95%
Sensitivity of STRM5-QP	99.95%
Specificity of STRM5-QP	99.95%
Kappa index of agreement of STRM5-CGD	99.37%
Precision of STRM5-CGD	99.41%
Sensitivity of STRM5-CGD	99.44%
Specificity of STRM5-CGD	99.38%

The rule for categorizing the data values of both input and output variables are given below:

```
If {
V < 15%,
Then ( V = EL,
Else,
If (
16% < V < 30%,
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Then ( V = VL,
Else,
If (
31% < V < 40%
Then ( V = SL
Else,
If (
41% < V < 50%,
Then ( V = L,
Else,
If (
51% < V < 60%,
Then ( V = N,
Else,
If (
61% < V < 70%,
Then (V = H,
Else,
If (
71% < V < 80%,
Then (V = SH,
Else,
If (
81% < V < 90%,
Then ( V = VH,
Else,
V = EH )
)
)
)
)
)
)
)
)}
```

4.2.2 Model Training, Testing, and Validation

A combinatorial data matrix is used to train all the neurogenetic models. Quick propagation (QP) and conjugate gradient descent (CGD) are selected as the training algorithms. Performance metrics like the kappa index of agreement, precision, sensitivity, and specificity were used to select the best model from among the five models considered.

4.3 Results and Discussion

As explained in the previous section, Table 4.6 shows the values of the model parameters selected for this study. The models' performance metrics are also shown in the table.

The results from the performance metrics indicate that, except for STRM2-CGD and STRM5-CGD, all the models performed satisfactorily. Because the models were validated using a small set of data randomly selected from the training data set, the metrics results were found to be near 100. Even then, also the kappa index of agreement, precision, sensitivity, and specificity for STRM2-CGD was found to be 94.76, 95.55, 96.04, and 95.06%, respectively, whereas the same for model STRM5-CGD were determined to be equal to 99.37, 99.41, 99.44, and 99.38%, although the STRM5-CGD model when compared to STRM2-CGD was concluded to be preferable to the latter.

4.4 Conclusion

The present investigation tried to estimate short-term rainfall using neurogenetic models and 1–5-days lagged rainfall data. In total, five models were prepared predicting both the occurrence and magnitude of next five days. The network topology of the models was selected using a genetic algorithm, and both QP and CGD were selected for training. The data set of the input and output variables was converted into nine categories, each representing a different level of magnitude and probability. According to the model results, it was found that only the 2- and 5-day rainfall prediction models trained with a CGD algorithm did not perform on par with the other models. This subpar performance can be attributed to the incompatibility of the CGD algorithm and the length of the time domain. If the prediction is made using real-life data of a study area, then the actual reasons for the subpar performance of the STRM2-CGD and STRM5-CGD can be properly analyzed. This approach of predicting short-term rainfall may help to predict extreme events even if data availability is scarce.

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