

Original article

Comparative Evaluation of Artificial Neural Network and Adaptive Neuro-Fuzzy Inference System Models for Monthly Rainfall Prediction: A Case Study in Benghazi, Libya

Fayiz Alkareemi[✉], Asma Muhmed[✉], Sarah Mohamed[✉], Aryn Abdulali[✉], Faysl Hasheem[✉]

Department of Civil Engineering, Tobruk University, Tobruk, Libya

Corresponding Email. fayiez.moftah@tu.edu.ly

Abstract

This study investigates the application of machine learning techniques, namely Artificial Neural Networks (ANNs) and Adaptive Neuro-Fuzzy Inference Systems (ANFISs), to monthly rainfall prediction in Benghazi (Benina region), Libya. Due to increasing rainfall variability under climate change, accurate forecasting is crucial for water resource management, infrastructure planning, and disaster mitigation in semi-arid regions. Historical meteorological data from 1970 to 2020, including rainfall, temperature, relative humidity, and wind speed, were obtained from the Benina Meteorological Station. Model performance was evaluated using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). The results demonstrate that both models capture rainfall patterns; however, the ANN exhibited superior prediction accuracy and generalization performance compared to ANFIS. Model accuracy was constrained by several factors, including the use of monthly data, missing records, and the exclusion of key climate variables such as sea surface temperature, cloud cover, and atmospheric pressure. The findings highlight the potential of machine learning in rainfall prediction while emphasizing the need for high-resolution, multi-variable datasets to improve reliability and support sustainable water and climate adaptation strategies in Benghazi and similar arid regions.

Keywords. Rainfall Prediction, Machine Learning, ANN, ANFIS.

Introduction

Rainfall is a critical climatic variable that significantly influences human activities, water resources management, and economic development. In the context of climate change and increasing weather variability, accurate rainfall prediction has become essential for mitigating floods, managing water supplies, and protecting lives and infrastructure. Recent advances have highlighted the effectiveness of machine learning techniques in rainfall forecasting due to their ability to model complex, non-linear relationships within climatic data [1-9]. Among machine learning methods, Artificial Neural Networks (ANN) have been widely applied in rainfall prediction because of their capacity to capture the non-linear nature of atmospheric processes governing precipitation. In parallel, Adaptive Neuro-Fuzzy Inference Systems (ANFIS) integrate neural networks with fuzzy logic to enhance pattern recognition, classification, and regression performance, enabling more flexible and accurate prediction by assigning new data to the most appropriate categories based on similarity [1,5].

Improving rainfall prediction accuracy is of great importance for sustainable water resource management and disaster risk reduction. Reliable rainfall forecasts support policymakers, engineers, and planners in making informed decisions related to infrastructure design and maintenance, including dams, drainage systems, and flood control structures. Moreover, advanced climate modeling contributes to sustainable economic growth by providing insights into climate-related risks and supporting effective decision-making in water and environmental management [9,4]. Despite technological advancements, accurate prediction of heavy rainfall remains a major challenge due to climatic variability, regional differences, and the complexity of meteorological processes.

Inadequate rainfall forecasting can lead to inefficient water resource management and increased vulnerability to floods and droughts. While ANN and ANFIS models have shown strong potential in extracting hidden patterns from historical climatic data, achieving high prediction accuracy across diverse geographical conditions remains difficult [1,8]. This study aims to address these challenges by investigating the application of ANN and ANFIS models for rainfall prediction, particularly in regions with limited or incomplete historical data. The research focuses on developing and evaluating both models, comparing their performance in terms of accuracy, robustness, and computational efficiency, and providing recommendations for improving rainfall forecasting systems based on the obtained results.

Methodology

Study Area

This research is based on the second-largest Libyan city of Benghazi, which is a seacoast town in the northeastern part of the country along the Mediterranean Sea and is situated at approximately 32.0505°N latitude and 20.1618°E longitude. The study location is set around the Benina meteorological station, which is situated in Benina International Airport, at an altitude of 129 meters above sea level. Benghazi features a semi-arid Mediterranean with 250-300 mm of rain every year, most of which occurs between

the time of October and March, constituting the wet season. The region experiences significant climatic variation, with February winter temperatures of 7°C and July summer temperatures of 35°C, relative humidity ranging from 34% to 97%, and northwesterly winds between 6 and 13 knots [6]. The flat topography near the sea with a gentle inland slope towards Jabal al Akhdar (Green Mountain), 100 km eastward, is responsible for rainfall variations. Benghazi's climate and recent extreme rainfall events (e.g., the Daniel flood in 2023) make it a critical case study for developing advanced rainfall forecasting models to support water resource management, agriculture, and flood mitigation.

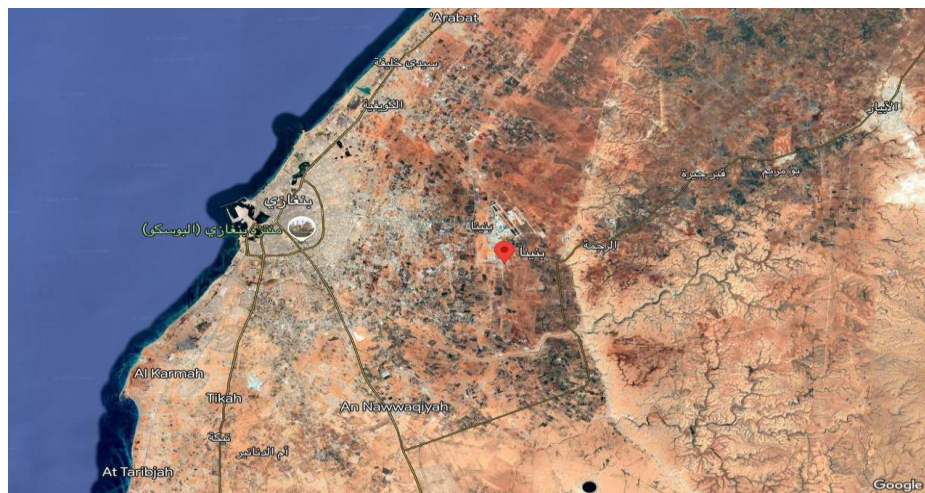


Figure 1. Benina in Benghazi, Libya (Google Earth, 2025)

Data Collection

The city of Benghazi was selected for this study based on a number of criteria. The study area is located on the coast of Libya. By thoroughly examining different coastal locations, researchers utilize the study area to track rainfall trends. Machine learning models may be trained with proven historical data from these locations' long-term rainfall data records. Because scientists can track changes in Libya's coastal regions, Benghazi, the primary research city, improves our understanding of rainfall patterns. Since artificial neural networks (ANNs) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) function in distinct coastal settings, the evaluation method, which encompasses several coastal locations, aids in improving the models' generalizability.

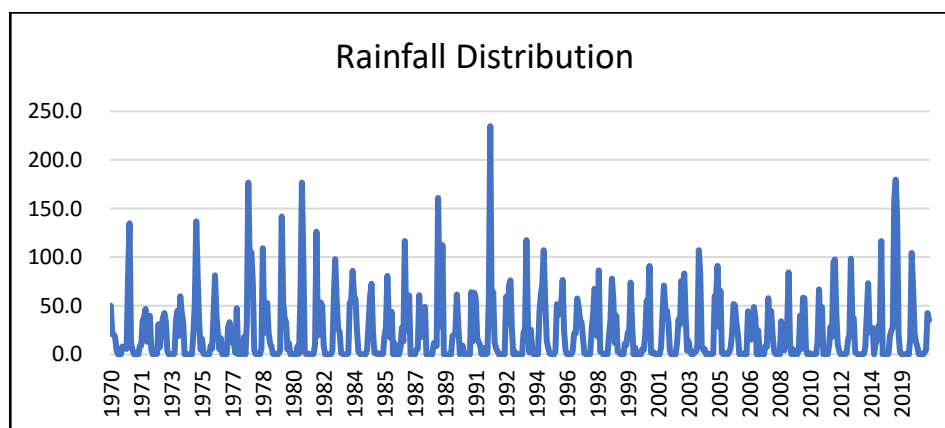


Figure 2. Rainfall Distribution for Benghazi 1970-2020 (LNMC)

Data Sources

This study utilizes a long-term dataset covering a 51-year period from 1970 to 2020, obtained from the Benina meteorological station of the Libyan National Meteorological Centre (LNMC). The dataset consists of monthly observations of key meteorological variables relevant to rainfall forecasting, including rainfall (mm), maximum and minimum temperature (°C), relative humidity (%), and wind speed (knots). Out of a total of 612 monthly records, approximately 46 months (7.51%) contained missing data. Consequently, 566 complete monthly observations were used for training and testing the Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models. The availability of this extensive historical dataset supports the development of robust machine learning models for rainfall prediction in Benghazi.

Data Normalization

In this study, data normalization was applied as a preprocessing step to enhance the performance of the Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models. Specifically, the input data were normalized to range between -1 and 1, where the maximum value in the dataset was scaled to 1, the minimum to -1, and all other values were proportionally transformed within this range [2]. The following normalization formula was used to scale the data to the [-1, 1] range:

$$X_{\text{normalized}} = 2 * \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} - 1$$

Development of an ANN Model

An Artificial Neural Network (ANN) based on a feedforward Multilayer Perceptron (MLP) architecture was developed for monthly rainfall prediction. This architecture was selected due to its proven capability in modeling complex nonlinear relationships between meteorological variables and rainfall. The optimal network structure was determined through a systematic trial-and-error process aimed at achieving high predictive accuracy while avoiding overfitting. Several configurations with hidden neurons ranging from 1 to 100 were tested. The final ANN architecture consisted of four input neurons representing maximum temperature, minimum temperature, relative humidity, and wind speed, one hidden layer with 39 neurons (corresponding to 195 connection weights), and a single output neuron representing monthly rainfall (mm).

ANN Model Implementation

The artificial neural network (ANN) model was implemented using the Neural Network Fitting Tool (nftool) within the MATLAB toolbox. The dataset was first imported from an Excel (.xlsx) file and subjected to preprocessing to ensure consistency and readiness for analysis. Subsequently, the data was divided into training, validation, and testing subsets in proportions of 80%, 10%, and 10%, respectively, to facilitate robust model development and evaluation. A feedforward neural network architecture was designed, and the Levenberg–Marquardt (LM) algorithm was selected as the training function due to its efficiency in handling nonlinear optimization problems. The training process was closely monitored using performance indicators such as mean squared error (MSE) and regression plots to assess convergence and predictive accuracy. Model performance was further evaluated using the coefficient of determination (R^2) and MSE on both validation and testing datasets to confirm generalizability. The final ANN model, structured as 4–39–1 and trained with the LM algorithm, demonstrated reliable predictive performance. Detailed results and interpretation of this model's outputs are presented in the following subsections.

ANFIS Model Development

An Adaptive Neuro-Fuzzy Inference System (ANFIS) was developed to combine the learning capability of neural networks with the interpretability of fuzzy logic. To ensure a fair comparison with the ANN model, the same four meteorological input variables (maximum temperature, minimum temperature, relative humidity, and wind speed) were used. Gaussian membership functions were selected for all input variables due to their smoothness and suitability for continuous data. The optimal number of membership functions per input was determined through experimental testing, ranging from two to five functions. Depending on the selected configuration, the number of generated fuzzy rules varied from 16 to 625, following a Takagi–Sugeno fuzzy inference structure with linear output functions.

ANFIS Model Implementation

The Adaptive Neuro-Fuzzy Inference System (ANFIS) model was implemented using the MATLAB Fuzzy Logic Toolbox. The dataset was prepared and loaded, then divided into training and testing sets using three different ratios (80/20, 70/30, and 60/40) to evaluate the robustness of the model under varying data distributions. An initial Sugeno-type fuzzy inference system was generated with the *genfis* function, employing Gaussian membership functions to define input–output relationships. Model training was carried out using a hybrid learning algorithm that combined least squares estimation with backpropagation, thereby optimizing both the premise and consequent parameters. Fuzzy rules were automatically generated based on the number of membership functions and input variables, ensuring systematic coverage of the input space. Performance evaluation was conducted using root mean squared error (RMSE), the coefficient of determination (R^2), and training time, with careful monitoring for signs of overfitting or underfitting. This methodological framework provided a reliable basis for assessing the predictive capacity and efficiency of the ANFIS model.

ANFIS Model Performance

The performance of the ANFIS model was evaluated through multiple experimental configurations. Three different training–testing data splits (80/20, 70/30, and 60/40) were examined. For each data split, Gaussian membership functions were applied with varying numbers of membership functions per input, resulting in different levels of model complexity and corresponding fuzzy rule bases. This systematic evaluation enabled an objective assessment of the ANFIS model's predictive capability under different

configurations and facilitated a direct comparison with the ANN model in terms of accuracy, generalization, and computational efficiency.

Results and Discussion

ANN Model Performance

Table 1. Performance Metrics for 80% Training (452 months), 10% Testing (57 months), and 10% Validation (57 months) – ANN

Group	MSE	R	R ²
Training	0.0223	0.8463	0.7162
Validation	0.0243	0.8862	0.7853
Test	0.0230	0.8669	0.7515

Overall Analysis

The 4-39-1 architecture ANN result demonstrates strong predictive capability in modeling monthly rainfall in the Benghazi Benina region. As shown in (Table 1), the network achieved Mean Squared Error (MSE) values of 0.0223 for training, 0.0243 for validation, and 0.0230 for testing, indicating a consistent level of prediction accuracy across all data subsets. The Coefficient of Determination (R²) was also relatively good, with values of 0.7162 (training), 0.7853 (validation), and 0.7515 (test), reflecting a strong linear relationship between the predicted and actual rainfall values. These values are further reinforced by the corresponding R² metrics, all above 0.71, confirming the model's ability to capture a significant proportion of the data variance.

Visualizations

1. R Scatter Plots

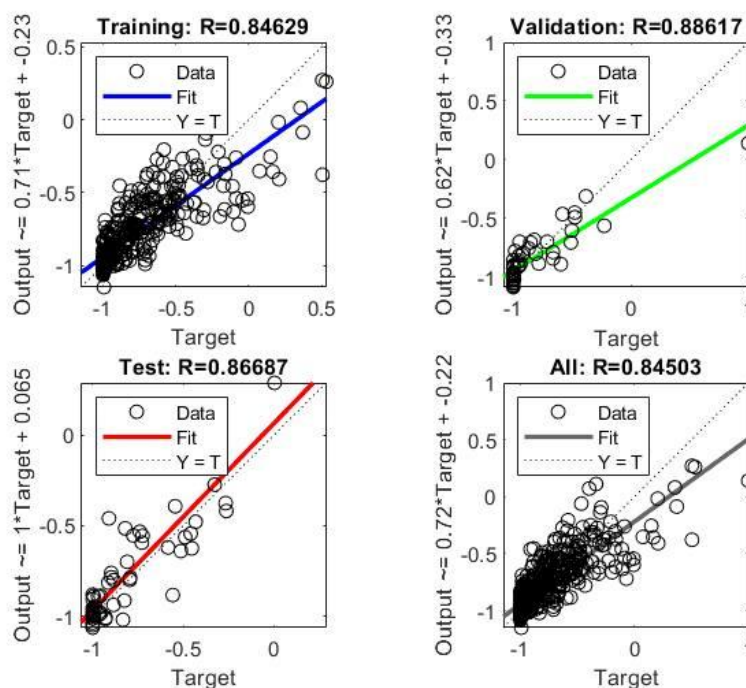


Figure 3. R Plots of ANN (author)

The training process of the ANN model, as shown in (Figure 4) the epoch -mean squared error (MSE) plot, demonstrates a typical learning behavior. During the initial epochs (0–5), the model experiences a rapid decrease in MSE for all three subsets: training, validation, and test, indicating effective early learning and parameter adjustment. At around epoch 17, the best validation performance is achieved, with an MSE value of 0.024322, as highlighted by the green marker. This point represents the model's optimal generalization capability, where it has learned the underlying pattern without overfitting. Beyond epoch 17, a noticeable increase in the test error (red curve) is observed, while the training error (blue curve) continues to decline. This divergence between the training and test/validation errors suggests the onset of overfitting, where the model becomes too specialized to the training data and loses its ability to generalize to unseen data. The relatively flat and stable validation curve (green) around the optimal epoch indicates that the model maintained a balanced performance over several iterations, reinforcing the robustness of the selected stopping point. The training was automatically halted at epoch 23 based on early stopping criteria to prevent further overfitting.

2. Epoch Scatter Plots

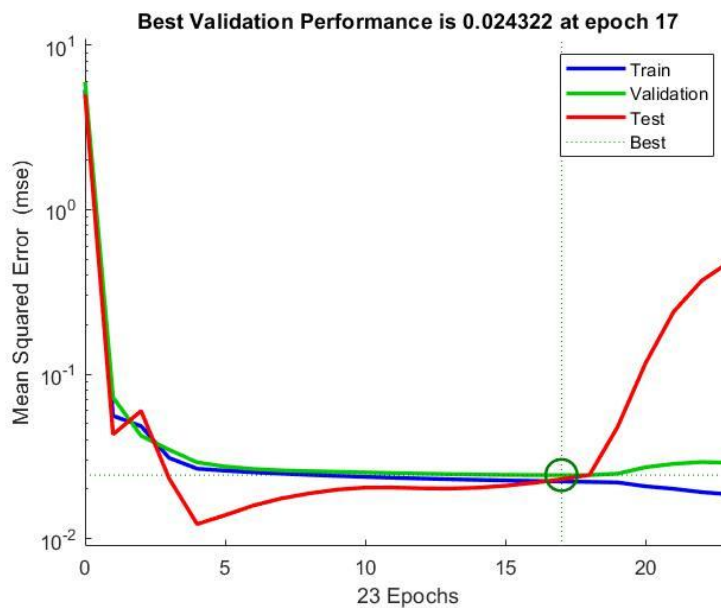


Figure 4. Epoch plot (author)

The following results show the model's performance under each case, highlighting its adaptability and predictive accuracy:

Case 1. 80% Training / 20% Testing

Table 2. Performance Metrics for 80% Training (452 months) and 20% Testing (114 months)

Mfs	2	3	4	5
Rules	16	27	256	625
R ² train	65.45	73.76	83.84	95.18
R ² test	48.46	5.69	4.59	0.8
RMSE train	0.1628	0.12	0.11137	0.060837
RMSE test	0.2158	0.85	0.86761	1.2974
Epochs	200	62	60	128
Time min	4	10	25	40

Full Analysis

It is observed that although increasing the number of MSFs enhances training accuracy (R² reaches 95.18 with MSF = 5), it significantly deteriorates testing performance (R² = 0.80), indicating overfitting. The 2-MF with 16 rules trained with R² = 65.45% and tested with R² = 48.46%, RMSE = 0.1628 (training) and 0.2158 (testing). The moderate performance indicates a good fit to the training data but an extreme loss of generalizability, which will be a result of too few rules available (16) to capture the whole scope of relationship nonlinearity in rain data. The rise in the RMSE during training to test (32.5%) demonstrates that the model would not be capable of providing for inter-year variability up to a point, particularly in those instances of extreme rainfalls. 3-MF configuration (81 rules) increased training R² to 73.76% but decreased test R² to 5.69%, increasing RMSE to 0.85. This kind of huge difference is an indicator of severe overfitting, where the model learned the training data by heart but could not generalize to novel test data. Increased rule complexity (81 rules) likely resulted in over-parameterization, capturing noise rather than underlying patterns. The 4-MF (256 rules) and 5-MF (625 rules) configurations only aggravated the overfitting issue. Train R² was 83.84% and 95.18%, respectively, with a tremendous fit in the training set. The Test R² dropped to 4.59% and 0.8%, respectively, with attendant RMSEs of 0.86761 and 1.2974, respectively. These results show an easy trade-off: although higher MFs increase training accuracy, they severely compromise the model's ability for generalization, rendering higher MF configurations infeasible for practical uses. Computer time increased exponentially as the number of MFs was increased, e.g., 4 minutes when there were 2 MFs and 40 minutes when there were 5 MFs. This is consistent with the increased computation requirement needed to compute additional rules and to learn additional parameters (e.g., Gaussian MF means, variances, rule weights).

Case 2. 70% Training / 30% Testing**Table 3. Performance Metrics for 70% Training (396 months) and 30% Testing (170 months)**

Mfs	2	3
Rules	16	81
R ² Train	64.25	73.14
R ² Test	65.75	34.36
RMSE Train	0.16889	0.14641
RMSE Test	0.16553	0.24752
Epochs	200	80
Time (min)	2	1

With a 70/30 split, the model with MSF = 2 achieved the highest R² for testing (65.75) and a relatively low RMSE (0.16553), indicating that this configuration offers the most robust generalization performance among all experiments.

Case 3. 60% Training / 40% Testing**Table 4: Performance Metrics for 60% Training (340 months) and 40% Testing (226 months)**

Mfs	2	3
Rules	16	27
R ² train	65.35	77.85
R ² test	61.25	3.45
RMSE train	0.17176	0.13746
RMSE test	0.16809	0.83903
Epochs	126	76
Time min	4	2

Full analysis

In this configuration, MSF = 2 yields the best generalization ability, with R² = 61.25 for testing, and RMSE = 0.16809, suggesting a well-balanced model. The 2-MF model (16 rules) achieved training R² = 65.35% and test R² = 61.25%, with RMSE = 0.17176 (training) and RMSE = 0.16809 (testing). The comparable correspondence between training and test statistics (R² difference of 4.1%) indicates good generalization, due to the larger test set size (226 months) offering a better representative sample of rainfall variability. The 3-MF configuration (81 rules) trained with R² = 77.85% but tested with only 3.45%, and RMSE went up to 0.83903. This is a repeat of overfitting in the 80%/20% split, where the model overfitted the smaller training set (340 months). The reduced training time (2 minutes) compared to the 80%/20% split (10 minutes for 3 MFs) is due to the smaller size of the training set, but at the cost of accuracy in predictions.

Recommended Results

Based on the comparative analysis of all configurations, the most effective ANFIS model for rainfall prediction is 70%/30% split, which is the larger test set provided, a stricter test, which reflected the strength of the 2-MF model. The balanced performance (R² > 60% on test data) makes this configuration a candidate for deployment in operations.

Table 5. Performance Metrics for ANFIS recommended result

Mfs	2
Rules	16
R ² Train	64.25
R ² Test	65.75
RMSE Train	0.16889
RMSE Test	0.16553
Epochs	200
Time (min)	2

This setup provides the best compromise between prediction accuracy and model generalization without the risk of overfitting.

Visualizations

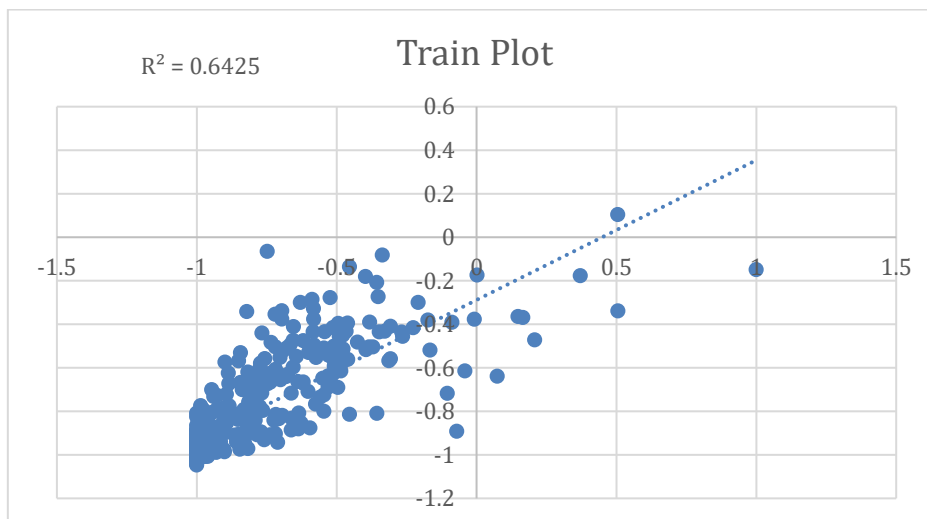


Figure 5. R^2 Plot of ANFIS train (author)

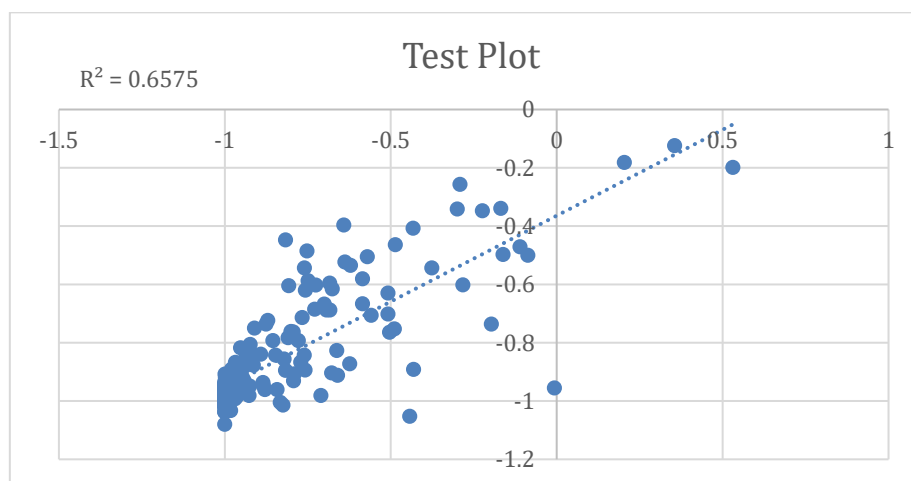


Figure 6. R^2 Plot of ANFIS test (author)

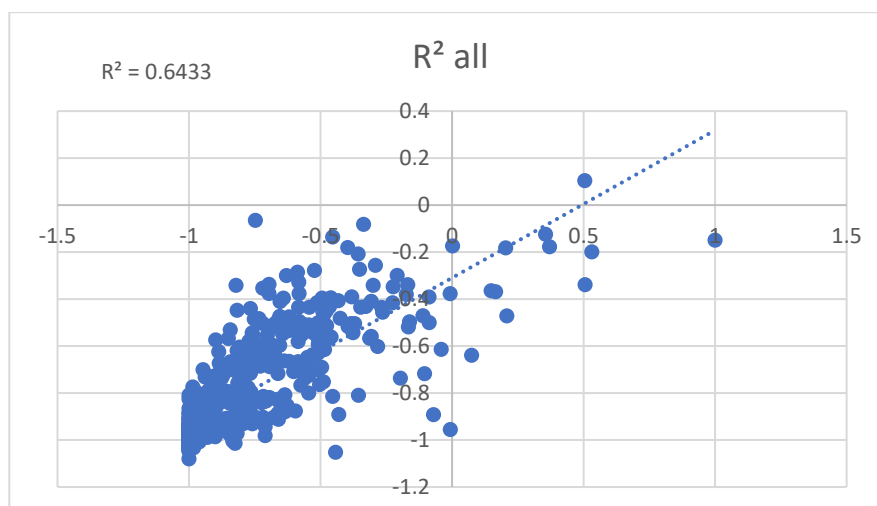


Figure 7. R^2 all Plot of ANFIS (author)

Discussion

The ANN model showed consistently strong performance across all phases. The R values indicate good correlation between predicted and actual rainfall, particularly in the test phase ($R = 0.7515$), suggesting effective generalization. The MSE values were also relatively low and stable, further confirming the reliability of the model's output. In ANFIS, the results reveal a clear trend: increasing the number of MSFs improves training accuracy but often leads to overfitting, as seen from the degraded test performance. The

optimal balance between model complexity and generalization was achieved in the 70/30 split with MSF = 2 (16 rules), where the model attained an R^2 of 65.75 on the test set.

Comparative Analysis ANFIS vs. ANN

1. Accuracy (R^2 Score)

The coefficient of determination (R^2) for the ANN model is 71.62%, significantly higher than that of the ANFIS model, 64.33%. This indicates that ANN has a better ability to explain the variance in the dataset, making it more accurate for prediction in the Benghazi climate.

2. Error Rate (Mean Squared Error - MSE)

The MSE value of ANN (0.0232) is lower than that of ANFIS (0.0285), which further confirms that ANN produces more accurate predictions with less error. Lower MSE values are critical when high precision is required in regression tasks.

3. Training Efficiency (Epochs and Time)

The comparative analysis between the artificial neural network (ANN) and the adaptive neuro-fuzzy inference system (ANFIS) highlights clear differences in computational efficiency and predictive accuracy. The ANN model required only 17 epochs and approximately three seconds of training time, whereas the ANFIS model demanded 200 epochs and nearly two minutes, underscoring the faster convergence and lower computational cost of the ANN. In terms of performance, ANN consistently outperformed ANFIS, achieving higher coefficients of determination (R^2), lower mean squared error (MSE), and superior training efficiency. While ANFIS offers the advantage of interpretability through fuzzy logic and the incorporation of expert knowledge, these benefits were offset in this case by significantly greater computational demands and inferior predictive accuracy. For applications where prediction accuracy and computational efficiency are paramount, ANN represents the recommended approach. ANFIS may still be valuable in contexts where model transparency and rule-based interpretability are prioritized, but in this study, ANN demonstrated clear superiority for practical deployment.

Table 6. Comparative Analysis ANFIS vs. ANN

metric	ANN	ANFIS
R^2 all	71.62%	64.33%
MSE	0.0232	0.0285
Epoch	17	200
time	3 Sec	2 min

Conclusion

This research confirms that accurate rainfall prediction is a critical component in supporting sustainable structural design, agricultural planning, and environmental risk management. Rainfall forecasting is not merely a technical task, but a societal necessity that contributes to enhancing safety, infrastructure resilience, and effective water resource management. A comparative analysis between Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) was conducted to evaluate their effectiveness in rainfall prediction. The results demonstrated that ANN outperformed ANFIS, achieving a coefficient of determination of $R^2 = 71.62\%$ and exhibiting stable performance across training, validation, and testing phases. ANN showed strong capability in modeling complex nonlinear relationships while maintaining satisfactory generalization with a moderately sized dataset.

In contrast, although ANFIS achieved high accuracy during the training phase (R^2 up to 95.18%), its performance deteriorated significantly during testing. This limitation was primarily attributed to the limited dataset size (566 monthly observations) and overfitting resulting from increased model complexity, which reduced the model's ability to generalize unseen data. Despite the acceptable performance of the ANN, several constraints limited further improvement in predictive accuracy. These include the coarse temporal resolution of monthly data, missing records (approximately 7.51%), and the restricted set of meteorological input variables. The absence of key climatic factors such as wind direction, sea surface temperature, and cloud cover constrained the models' ability to fully capture rainfall dynamics.

Additionally, the nonlinear and chaotic nature of atmospheric processes, compounded by the growing impact of climate change, poses further challenges to rainfall prediction based solely on historical data. Overall, the findings highlight the importance of aligning model selection with data availability and quality. While ANFIS offers theoretical interpretability advantages, ANN demonstrated greater practical robustness and reliability under data-limited conditions.

Conflict of interest. Nil

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