Artificial neural network for predicting cashew nut (*Anacardium occidentale* L) productivity under climate variability

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Abstract. Cashew production is affected by environmental dynamics and climate change. This study aimed to predict cashew productivity using an Artificial Neural Network (ANN) based on climate variables. The dataset comprised cashew productivity records from Selogiri Sub-district, Wonogiri, Central Java (1990–2020), along with annual rainfall, air temperature, and humidity over the same period. The analytical procedures included data collection, normalization, reprocessing, determination of network architecture using Mean Squared Error (MSE), parameter setting, training, denormalization, testing, and K-Fold cross-validation with Mean Absolute Percentage Error (MAPE). The optimal network architecture was 3:14:1, consisting of three input neurons (humidity, temperature, rainfall), 14 neurons in one hidden layer, and one output neuron (cashew productivity). This architecture yielded the lowest MSE of 0.0005. Validation using K-Fold produced an average MAPE of 40% with an accuracy of 60%. According to the MAPE criteria (20–50%), the forecasting model is categorized as fair or acceptable for predicting cashew productivity. These findings demonstrate the potential of ANN to support agricultural yield prediction under climate variability.

1 Introduction

Cashew (*Anacardium occidentale* L.), a long-lived perennial crop of the Anacardiaceae family, is highly sensitive to climate change, particularly to increasing temperature extremes and altered rainfall patterns during the flowering and fruit development stages that critically determine yield [1,2]. In Indonesia, cashew is cultivated on approximately 420,970 ha across 22 provinces, with East Nusa Tenggara serving as the main production region and covering about 154,000 ha. This region is characterized by a prolonged dry season and high vulnerability to climate-related stresses, making cashew production particularly susceptible to climate variability [3]. These conditions highlight the urgent need for climate-adaptive cultivation strategies to ensure yield stability and sustain farmer livelihoods.

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From a practical perspective, climate information such as forecasts of dry-season intensity and elevated temperatures is essential for supporting adaptive management decisions in cashew cultivation. The use of such information enables the timely implementation of adaptive technologies, including the selection of drought-tolerant varieties and the application of flowering- and fruit-setting enhancement techniques, such as pollination induction, to reduce the risk of yield losses under variable climatic conditions [4,5]. However, the effectiveness of these strategies strongly depends on the availability of reliable yield forecasting methods capable of translating climate signals into actionable production estimates.

Given the strong dependence of cashew productivity on climatic variability and environmental factors, robust forecasting approaches are required to support sustainable production planning. Recent advances in data-driven modeling have enabled the use of Artificial Neural Networks (ANNs), which are capable of capturing complex and nonlinear relationships between climate parameters and crop responses. As information-processing systems inspired by biological neural structures, ANNs can process data through parallel computation, extensive interconnections, and strong error tolerance, resulting in more accurate forecasts than conventional statistical methods due to their iterative learning processes [6,7].

Among various ANN techniques, the backpropagation algorithm is one of the most widely used learning methods [8]. This algorithm is typically implemented in multilayer network architectures consisting of an input layer, one or more hidden layers, and an output layer, with the final network output generated from the last hidden layer [9,10]. In this study, the backpropagation method is applied to predict cashew productivity by integrating rainfall, air temperature, and humidity as key climatic predictors. The novelty of this study lies in the application of a multi-climatic input, backpropagation-based ANN model for cashew, a perennial crop that has received limited attention in climate-driven yield forecasting studies. By leveraging nonlinear learning behavior and multiple climate variables, the proposed approach is expected to improve prediction accuracy, enhance decision-support tools for climate-sensitive commodities, and contribute to climate-resilient management and sustainable agricultural planning.

2 Materials and methods

The materials used in this study consisted of cashew productivity data from Selogiri District, Wonogiri, Central Java, Indonesia covering the period from 1990 to 2020 (Wonogiri in Figures 1991–2021). Climate data, including annual rainfall, air temperature, and humidity for the same 30-year period, were obtained from the Selogiri Meteorological Station in Wonogiri. The research methodology involved data preprocessing, development of an Artificial Neural Network model using the backpropagation algorithm, model training and validation, and evaluation of prediction performance.The methods used in this study included the following steps, including data normalization as expressed in Equation (1).

1. Data collection
2. Data normalization using the equation

$$New\ value = \frac{original\ value - minimum\ value}{maximum\ value - minimum\ value} \quad (1)$$

3. Data preprocessing
   The data were divided into two groups: training data and testing data. Subsequently, the input variables and output (target) variables were identified.

4. Determining the network architecture
   The relationships between neurons, commonly referred to as the network architecture, are organized into layers known as neuron layers. An ANN typically consists of three main layers: (a) the input layer, which contains units that receive external input patterns representing the problem; (b) the hidden layer, which consists of units whose output values cannot be directly observed; and (c) the output layer, which contains units that represent the ANN's predicted solution. The optimal network architecture is selected based on the smallest Mean Squared Error (MSE), calculated using the following equation:

$$MSE = \frac{\sum_{i=i}^{n}(Yi-\hat{Y}i)^2}{n} \quad (2)$$

   where:
   MSE = Mean Squared Error
   n = number of data
   Yi = data obtained from observations
   Ŷi = target data

5. Determining training parameters
   The training parameters were determined before the data training process. These parameters included: **a.** training the network using the MSE performance function, **b.** an epoch value of 1000, **c.** a target error of 0.001, **d.** a momentum value of 0.95, and **e.** a display interval of 20 iterations.
6. Data training
   Data training is conducted to determine the optimal output weights, which will later be used as calculation weights during the testing phase.
7. Data denormalization
   The training results are then denormalized and compared with the original target data using the following equation:

$$Original\ value = (maxsimum\ valuae - minimum\ value) \times new\ value + minimum\ value \quad (3)$$

8. Data testing
   Data testing is carried out using the output weights obtained from the training phase.
9. K-Fold cross validation
   The prediction accuracy is calculated using K-Fold cross-validation. This study uses 32 K-Folds because the initial data allocation for forecasting consists of 33.33% testing data and 66.66% training data. The dataset is divided into three folds, with each fold containing 12 test data points and the remaining data used for training. Each box represents 12 months of data, where the blue box indicates testing data and the yellow box indicates training data. The average accuracy obtained from all K-Folds represents the overall prediction accuracy produced by the backpropagation ANN method. Before determining the accuracy value, the Mean Absolute Percentage Error (MAPE) is calculated for each fold. The MAPE formula is as follows [9]:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{x-y}{y}\right] \times 100\% \quad (4)$$

   where:
   MAPE = Mean Absolute Percentage Error
   n = number of data
   x = original test data
   y = forecast test data

The MAPE value is interpreted according to the following criteria Rinjani [10]: a. MAPE < 10% indicates very good forecasting ability; b. 10% ≤ MAPE < 20% indicates good forecasting ability; c. 20% ≤ MAPE < 50% indicates fair forecasting ability; and d. MAPE ≥ 50% indicates poor forecasting ability. Once the MAPE value is obtained, forecasting accuracy is calculated using the formula 100 − MAPE.

3 Results and discussion

3.1. Data collection

The results of data collection on air humidity, air temperature, rainfall, and cashew productivity in Selogiri, Wonogiri are presented in Table 1. These data describe the key environmental conditions influencing cashew growth and production in the study area. In addition, the information provides an overview of cashew productivity levels during the observation period, which serves as a basis for further analysis.

Table 1. Data on air humidity, air temperature, rainfall, and cashew productivity in Selogiri, Wonogiri, over 31 years (1990–2020)

Year	Relative Humidity (%)	Temperature (°C)	Rainfall (mm)	Productivity (kg/ha)
1990	77.08	27.17	1587	271
1991	75.83	26.83	1587	237
1992	80.58	26.50	2481	201
1993	79.08	27.00	1944	212
1994	74.25	26.42	1714	225
1995	80.42	26.50	2358	228
1996	79.00	26.92	1750	161
1997	76.00	26.67	1434	254
1998	85.75	26.75	2160	161
1999	83.67	25.92	1896	287
2000	84.67	26.08	1559	959
2001	85.75	26.17	1418	202
2002	84.08	26.50	1018	959
2003	85.17	26.17	1510	962
2004	85.50	27.00	1469	766
2005	87.17	26.42	1693	766
2006	85.67	27.17	1333	766
2007	86.42	30.25	1540	377
2008	87.58	27.08	2152	438
2009	87.83	27.67	1840	377
2010	84.92	26.83	2738	185
2011	84.30	27.67	1899	730
2012	90.13	27.60	1933	950

2013	86.54	27.33	2696	850
2014	90.34	27.26	1787	850
2015	84.79	27.50	1965	615
2016	87.72	28.69	3030	444
2017	85.85	26.99	2213	305
2018	85.31	27.27	1488	310
2019	87.44	27.16	1105	659
2020	85.04	26.96	2305	827

Climate conditions and cashew productivity in Selogiri, Wonogiri from 1990 to 2020 show substantial interannual variation. Relative humidity fluctuated between 74 and 90 percent, whereas air temperature was generally stable within the range of 26 to 28 degrees Celsius, except for a notable anomaly in 2007 when it peaked at 30.25 degrees Celsius. Annual rainfall also exhibited wide variability, ranging from 1018 to 3030 mm, with several years characterized by exceptionally high precipitation. Such conditions warrant careful attention, as excessive rainfall can accelerate erosion processes in vegetated areas and consequently influence crop growth and development [11]. Accordingly, the adoption of appropriate cultivation mitigation measures to address extreme rainfall events and climate anomalies, particularly El Niño, is crucial for sustaining cashew productivity [12].

Cashew yield trends do not consistently correspond with climatic variations. The lowest yields were observed in 1996 and 1998 at 161 kg ha^{-1}, while the highest yields were recorded between 2000 and 2003, reaching 959 to 962 kg ha^{-1}. These results suggest that although climatic variability has a significant influence on cashew production, additional factors including soil characteristics, management practices, and the effectiveness of climate adaptation strategies also play a vital role in ensuring yield stability and long-term sustainability [12].

3.2. Data normalization

Data normalization was performed to scale all input variables within a range of zero to one, thereby ensuring compatibility with the binary sigmoid activation function. This process helps improve model stability and learning efficiency by reducing the influence of differing data scales. The normalized dataset resulting from this procedure is presented in Table 2.

Table 2. Data normalization results

Year	Relative Humidity	Temperature	Rainfall	Productivity
1990	0.175886	0.288684	0.282803	0.137328
1991	0.098198	0.210162	0.282803	0.094881
1992	0.393412	0.133949	0.727137	0.049938
1993	0.300186	0.249423	0.460239	0.06367
1994	0	0.115473	0.345924	0.0799
1995	0.383468	0.133949	0.666004	0.083645
1996	0.295214	0.230947	0.363817	0
1997	0.108763	0.17321	0.206759	0.116105
1998	0.71473	0.191686	0.567594	0

1999	0.585457	0	0.436382	0.157303
2000	0.647607	0.036952	0.268887	0.996255
2001	0.71473	0.057737	0.198807	0.051186
2002	0.610938	0.133949	0	0.996255
2003	0.678682	0.057737	0.244533	1
2004	0.699192	0.249423	0.224155	0.755306
2005	0.802983	0.115473	0.335487	0.755306
2006	0.709758	0.288684	0.156561	0.755306
2007	0.75637	1	0.259443	0.269663
2008	0.828465	0.267898	0.563618	0.345818
2009	0.844002	0.404157	0.408549	0.269663
2010	0.663145	0.210162	0.854871	0.029963
2011	0.624612	0.404157	0.437873	0.710362
2012	0.986948	0.387991	0.454771	0.985019
2013	0.763828	0.325635	0.833996	0.860175
2014	1	0.309469	0.382207	0.860175
2015	0.655065	0.364896	0.470676	0.566792
2016	0.837166	0.639723	1	0.353308
2017	0.720945	0.247113	0.593936	0.179775
2018	0.687383	0.311778	0.233598	0.186017
2019	0.819764	0.286374	0.043241	0.621723
2020	0.670603	0.240185	0.639662	0.831461

3.3. Data preprocessing

A total of 31 data sets were employed in this study and subsequently partitioned into training, testing, and validation groups to support the modeling process. This division ensures that the model is trained effectively while maintaining an unbiased evaluation of its performance. The preprocessing step also helps improve data quality and prepares the inputs for optimal learning.

3.4. Determining network architecture

Training to obtain the best network architecture was conducted several times using trial-and-error experiments on the number of neurons in the hidden layer. A good architecture is characterized by high accuracy, a small number of epochs, and the lowest MSE value.

The optimal network was achieved using a 3-14-1 architecture, consisting of three input neurons (air humidity, air temperature, rainfall), fourteen hidden-layer neurons, and one output neuron (cashew productivity), with the lowest MSE of 0.0005 (Table 3). Based on the training process, the best configuration—namely the 3-14-1 network used for forecasting—is illustrated in Figure 1.

Table 3. MSE training values for several network architectures

Network Architecture	MSE Training
3-6-1	0.012
3-8-1	0.0377
3-10-1	0.0311
3-12-1	0.0415
3-14-1	**0.0005**

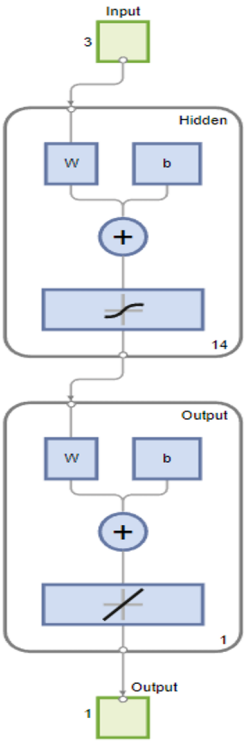

Fig. 1. Artificial neural network model 3-14-1

3.5. Data training

Based on Table 4, the 3-14-1 network model produced an MSE value of 0.0005 with an epoch count of 22. The training correlation (R) reached 0.9983, while the testing correlation was 0.9942. These values indicate a strong agreement between the network output and the target, as both correlation coefficients are close to 1.

Table 4. Characteristics of the 3-14-1 network architecture

Network Architecture	Epoch	MSE Training	R Training	R Test
3-14-1	22	**0.0005**	0.9983	0.9942

The performance graph of the 3-14-1 network architecture training can be seen in Figure 2. It illustrates the convergence of the network and the reduction of the MSE over the training epochs.

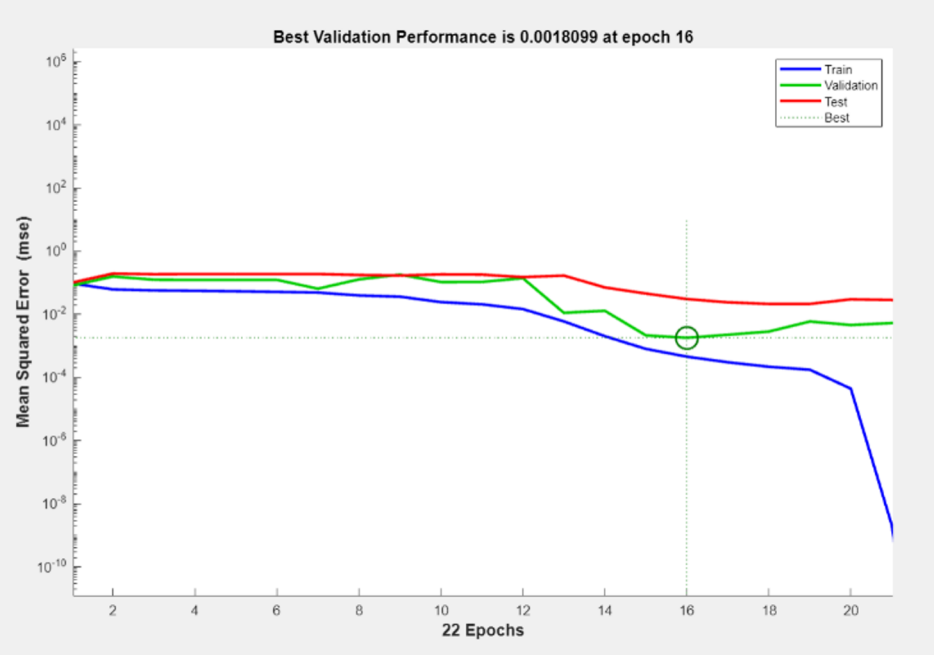

Fig. 2. Performance of 3-14-1 network 6architecture

Figure 2 shows the comparison graph of training, validation, and testing, with the best performance value of 0.0018099 occurring at epoch 16, which represents the smallest and optimal goal value in the network. The goal is a parameter that sets a limit on the MSE value, causing the iteration to stop once it is reached. In this study, the goal parameter was set at 0.001 for the MSE limit. When the performance or MSE goal is achieved, the network architecture is considered acceptable, and the desired MSE has been reached. This prediction resulted in a Mean Squared Error (MSE) of 0.00727. The prediction was based on historical production data and did not incorporate other factors in forecasting cashew production [8].

Epoch (iteration) is a parameter in ANN that specifies the maximum number of training iterations. In this study, the iteration limit was set to 1000 to achieve satisfactory results. Determining the appropriate iteration value requires trial and error. If the value is too high, training will require longer computation time; if it is too low, the network may not reach its maximum training performance, known as the "maximum epoch reached." In such cases, the number of iterations must be increased to achieve the desired results.

Commonly used stopping conditions are either the maximum number of iterations (epochs) or the minimum error. If the error falls below the tolerance limit, the iteration is stopped. However, if the error exceeds the limit, the weights of each connection in the network are adjusted to reduce the error. The stopping condition is met when the error produced by the network is less than or equal to the target error, or when the predetermined maximum number of iterations (epochs) is reached. In practice, researchers commonly set the maximum number of iterations at 1,000 epochs.

The regression plot showing the relationship between the target and the output of the 3-14-1 network architecture is presented in Figure 3. This plot demonstrates how closely the network predictions align with the actual target values, indicating the accuracy of the model.

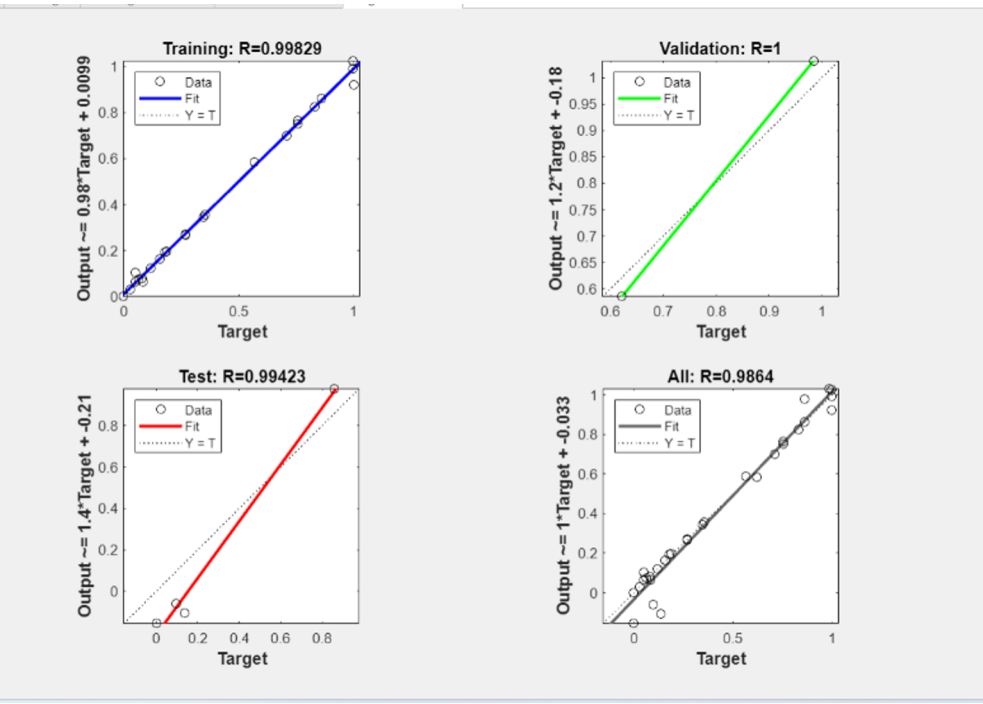

Fig. 3. Relationship between target and output in network architecture 3-14-1

Based on this regression plot, the network's performance can be validated by assessing whether the output deviates significantly from the target. Figure 3 shows the blue line representing the training data versus the target, the green line representing the validation data versus the target, the red line representing the test data versus the target, and the black line representing all data combined. The correlation values for the training, test, validation, and overall data are 0.99829, 0.99423, 1.0, and 0.9864, respectively.

3.6. Cashew productivity prediction results using ANN

The results of cashew productivity prediction using the 3–14–1 network architecture, with the training data regression equation (Output = 0.98 × Target + 0.0099), are presented in Table 5. The regression results indicate a strong linear relationship between the predicted and actual productivity values. This finding confirms the high accuracy and reliability of the model.

Table 5. Cashew productivity prediction for the 3-14-1 network architecture

Year	Cashew Productivity (Target) (kg/ha)	Cashew Productivity Prediction (output)) (kg/ha)
1990	0.137328	0.144482
1991	0.094881	0.102884
1992	0.049938	0.058839
1993	0.06367	0.072297
1994	0.0799	0.088202
1995	0.083645	0.091873

1996	0	0.0099
1997	0.116105	0.123683
1998	0	0.0099
1999	0.157303	0.164057
2000	0.996255	0.98623
2001	0.051186	0.060062
2002	0.996255	0.98623
2003	1	0.9899
2004	0.755306	0.7501
2005	0.755306	0.7501
2006	0.755306	0.7501
2007	0.269663	0.27417
2008	0.345818	0.348801
2009	0.269663	0.27417
2010	0.029963	0.039263
2011	0.710362	0.706055
2012	0.985019	0.975218
2013	0.860175	0.852871
2014	0.860175	0.852871
2015	0.566792	0.565356
2016	0.353308	0.356142
2017	0.179775	0.18608
2018	0.186017	0.192197
2019	0.621723	0.619188
2020	0.831461	0.814831

Data denormalization was performed to convert the test results into a scale comparable to the original data. The results of the denormalization process are presented in Table 6. This step enables a clear interpretation and evaluation of the model outputs.

Table 6. Denormalization results of cashew productivity predictions in network architecture 3-14-1

Year	Cashew Productivity (kg/ha)	Cashew Productivity Prediction (kg/ha)	Error
1990	271	277	-2.11435
1991	237	243	-2.70460
1992	201	208	-3.54721
1993	212	219	-3.25939
1994	225	232	-2.95551
1995	228	235	-2.89031
1996	161	169	-4.92540
1997	254	260	-2.38972
1998	161	169	-4.92540

1999	287	292	-1.88498
2000	959	951	0.83734
2001	202	209	-3.51975
2002	959	951	0.83734
2003	962	954	0.84097
2004	766	762	0.54440
2005	766	762	0.54440
2006	766	762	0.54440
2007	377	381	-0.95753
2008	438	440	-0.54564
2009	377	381	-0.95753
2010	185	192	-4.02697
2011	730	727	0.47262
2012	950	942	0.82633
2013	850	844	0.68825
2014	850	844	0.68825
2015	615	614	0.18701
2016	444	446	-0.51124
2017	305	310	-1.65570
2018	310	315	-1.59674
2019	659	657	0.30806
2020	827	814	1.61064

Table 6 shows that the predicted cashew productivity varies widely, with the highest value reaching 954 kg/ha in 2003 and the lowest at 169 kg/ha in 1996 and 1998. These predictions were then compared with the observed data to assess their accuracy. Based on Table 6, the predicted values tended to overestimate actual productivity, particularly in the years 2000, 2002–2006, 2011–2015, and 2019–2020.

3.7. K-Fold cross validation

Table 7 presents the MAPE values and accuracy for each fold of the 3-14-1 network architecture, with each fold consisting of different combinations of training, validation, and test data. This information highlights the model's prediction performance across the various data splits.

Table 7. Results of the K-Fold cross validation process for the 3-14-1 network architecture

Fold		Amount of Data	MAPE (%)	Accuracy (%)
K1	Training	26	69	31
	Validation	2		
	Test	3		
K2	Training	24	2	98
	Validation	2		
	Test	5		

K3	Training	23	41	59
	Validation	2		
	Test	6		
K4	Training	22	47	53
	Validation	2		
	Test	7		
Rata-rata			40	60

The average MAPE of 40% obtained from the K-Fold cross-validation results (Table 7) indicates a moderate level of prediction error in the backpropagation ANN, with a system accuracy of 60%. According to Rinjani [13], this MAPE value falls within the satisfactory range of 20–50%. Although the model has some limitations, the predictions can still support the production and development of perennial crops, as demonstrated in studies on nutmeg [14,15], where early growth, physiological traits, and seed quality were effectively monitored and managed. Such predictive tools can assist in achieving production targets while also supporting mitigation strategies in response to climate variability.

4 Conclusion

The best-performing network architecture was the 3–14–1 model, consisting of three input neurons (air humidity, air temperature, and rainfall), fourteen neurons in the hidden layer, and one output neuron representing cashew productivity. This architecture produced the lowest MSE value of 0.0005, indicating strong model performance. Network validation using the K-fold cross-validation method resulted in an average MAPE of 40% and an average accuracy of 60%. Because the MAPE value falls within the 20–50% range, the forecasting model is classified as adequate and feasible for predicting cashew productivity.

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