INTERNATIONAL JOURNAL OF ADVANCED RESEARCH
International Peer-Reviewed Research Journal
ISSN (Online): 3106-7980 | ISSN (Print): 3106-7972
Volume 3 • Issue 7 • November 2026

DETECTION AND MODELLING OF FOG USING ARTIFICIAL NEURAL NETWORK: A CASE STUDY OF LAHORE

Naeem Sadiq[*1], Fozia Hanif[2], Syed Inayatullah[3]

[*1]*Institute of Space Science and Technology, University of Karachi, Pakistan*
[2,3] *Department of Mathematics, University of Karachi, Pakistan*

[*1]nsadiq@uok.edu.pk, [2]ms_khans2011@hotmail.com, [3]inayat@uok.edu.pk

DOI: https://doi.org/10.5281/zenodo.24131912

Keywords
Fog; artificial neural network; visibility; Lahore; fog occurrence; Pakistan

Article History
Received: 05 August 2026
Accepted: 19 October 2026
Published: 11 November 2026

Copyright © The Author(s)
Corresponding Author: * Naeem Sadiq

Abstract
This study develops an artificial neural network (ANN) model to estimate fog occurrence in Lahore using daily records of day, month, minimum temperature, dew point, relative humidity, wind speed, and visibility for the November–March seasons from 2014 to 2017. The dataset was divided equally into training and testing subsets (50% each), and a randomly selected 40% of the data were also used for validation. The ANN architecture comprised seven input variables, a single hidden layer with 10 neurons, and one output representing fog occurrence. Model estimates were compared with observed fog-occurrence values using an absolute-difference threshold of 0.05. The comparisons indicate that the model reproduces most of the observed values reasonably well. These findings suggest that an ANN can be a useful approach for estimating fog occurrence in Lahore.

1. Introduction

Fog is a stratus cloud at ground level that reduces horizontal visibility to less than 1,000 m. It forms when water vapour condenses into tiny water droplets suspended in the air near the ground. Fog can disrupt road and air transport. Road accidents and flight cancellations associated with fog can have serious socioeconomic consequences (Edwards, 1996; Kulkarni et al., 2019).

High-resolution numerical weather prediction (NWP) models are widely used for fog prediction (Bartok et al., 2012; Payra & Mohan, 2014; Singh et al., 2018). However, local fog prediction remains challenging because the complex processes controlling fog formation are not always adequately represented by NWP models (van der Velde et al., 2010).

Several statistical and machine-learning approaches have been applied to fog and visibility prediction. Decision-tree methods have been combined with NWP output for fog forecasting (Bartoková et al., 2015). Regression approaches, including wavelet-based models, multilayer perceptron (MLP), support vector regression (SVR), and Gaussian process regression, have been used to predict visibility (Cornejo-Bueno et al., 2017). Deep-learning methods have also been applied to airport visibility forecasting (Zhu et al., 2017). Artificial neural networks have been used to forecast fog at Canberra International Airport (Fabbian et al., 2007) and for weather forecasting more generally (Abhishek et al., 2012). Negishi and Kusaka (2022) identified precipitation, mean night-time wind speed, minimum night-time

INTERNATIONAL JOURNAL OF ADVANCED RESEARCH
International Peer-Reviewed Research Journal
ISSN (Online): 3106-7980 | ISSN (Print): 3106-7972
Volume 3 • Issue 7 • November 2026

temperature, the temperature decrease during the night, minimum humidity on the preceding day, and visibility at 18:00 as predictors of radiation fog. Gharekhan et al. (2022) used ANN models with radiative-transfer computations to estimate downwelling longwave radiation under foggy-sky conditions; their results concern longwave-radiation estimation, not fog-occurrence prediction.

Image-based studies have also examined visibility detection in foggy images and fog removal in aerial images (Yan et al., 2022; Xia et al., 2022; Li et al., 2022), although their focus differs from meteorological fog-occurrence modelling. The objective of the present study is to develop an ANN model to estimate fog occurrence in Lahore using daily meteorological and calendar variables.

2. Data and Methodology

Daily fog-occurrence and meteorological data for Lahore, the provincial capital of Punjab, were used for the November–March fog seasons from 2014 to 2017. This seasonal period follows the period considered by Muslehuddin et al. (2004). All data were obtained from the archives of the Pakistan Meteorological Department.

2.1 Artificial Neural Network

An artificial neural network (ANN) is a computational approach used to model relationships between input and output variables. In the network used here, the input layer is connected to the hidden layer through weights and bias terms. Each hidden neuron forms a weighted sum of the input variables and a bias term, as expressed in Eq. (1).

$$p_{hidden} = \sum_{i=1}^{z} w_i p_i + C_{input} \qquad (1)$$

Here, p_i (i = 1, ..., z) denote the input variables, w_i (i = 1, ..., z) denote the corresponding weights, and C_{input} is the input bias. A nonlinear activation function is then applied to the weighted sum in Eq. (1). In this study, the logistic sigmoid activation function is given in Eq. (2).

$$f(p_{hidden}) = \frac{1}{1+e^{-p_{hidden}}} \qquad (2)$$

The hidden layer is connected to the output layer, and the hidden neurons pass their outputs to it. The observed data are compared with the network output to estimate the error. If the error does not meet the convergence criterion, the weights are updated iteratively through backpropagation to minimise the difference between the observed and estimated values. The proposed network architecture is shown in Fig. 1.

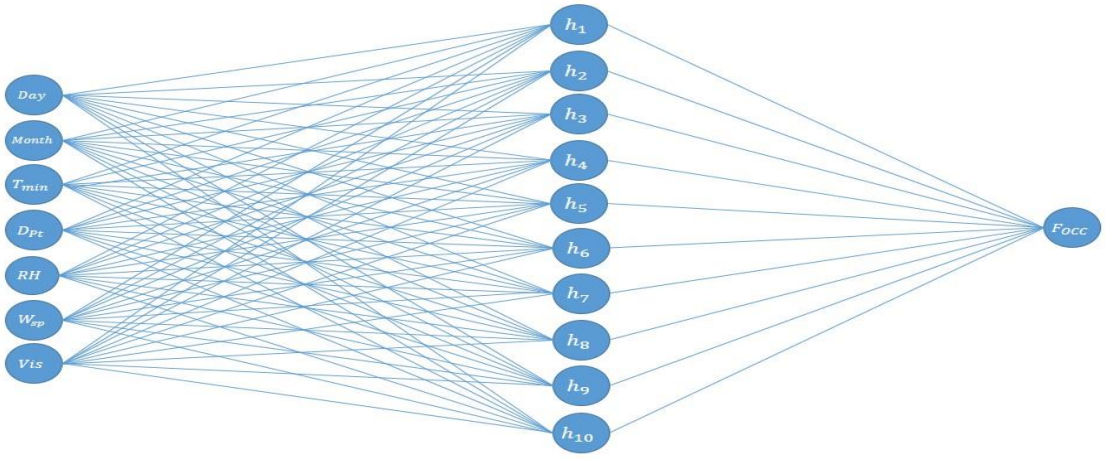


Fig. 1. ANN architecture used to estimate fog occurrence in Lahore.

3. Results and Discussion

Fog occurrence was estimated using seven input variables: day of the month, month of the year, minimum temperature (Tmin), dew point (Dpt), relative humidity (RH), wind speed (Wsp), and visibility (Vis). These variables formed the input layer of the ANN. The hidden layer consisted of 10 neurons, each connected to the input variables through weights listed in Table 1. The output layer represented fog occurrence and was connected to the hidden-layer neurons through the output weights (w2).

The dataset was divided into two equal parts: 50% for training and 50% for testing. A randomly selected 40% of the data were also used for validation. Model performance was assessed by comparing the observed and ANN-estimated fog-occurrence values. The absolute difference is the absolute value of the difference between an observed value and its corresponding estimated value. The figures show that only a small number of points in the training, testing, and validation sets have an absolute difference greater than 0.05 (Figs. 2–4, respectively).

Fog occurrence was represented numerically: 0.1 for no fog and 0.2 for fog. The midpoint between these values is 0.15, and each value is 0.05 away from this midpoint. An ANN estimate with an absolute difference below 0.05 falls on the same side of the midpoint as the corresponding observed value and is therefore treated as an acceptable estimate. Overall, the plotted results indicate reasonable agreement between the observed and estimated fog-occurrence values.

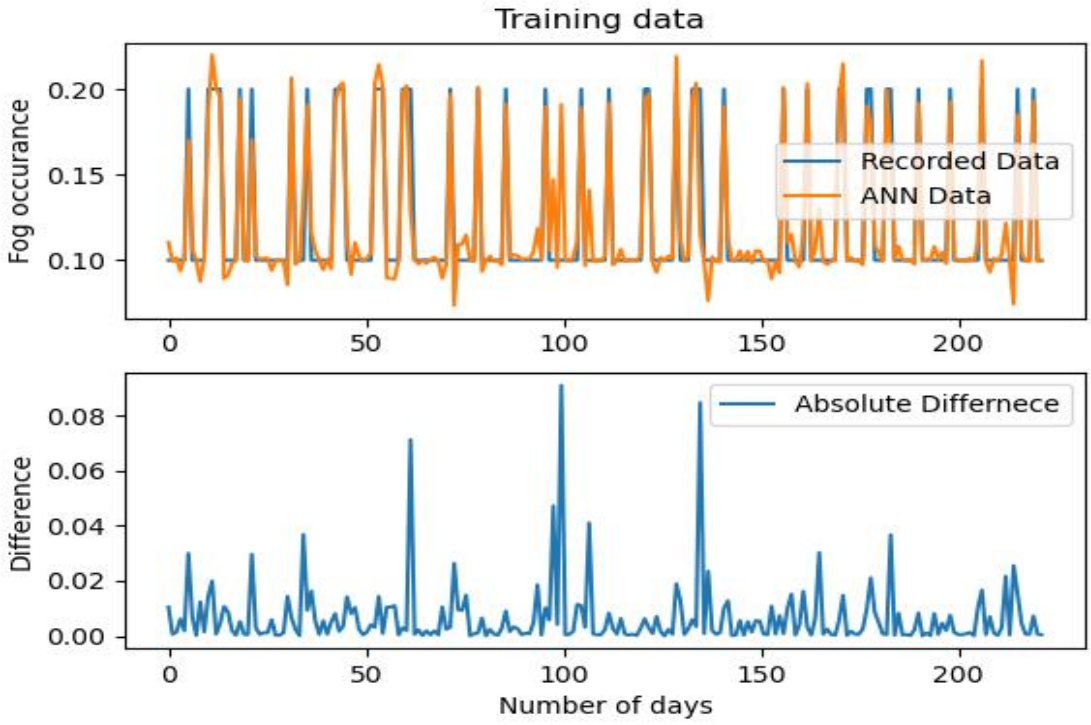


Fig. 2. Training data and absolute differences between observed and ANN-estimated fog occurrence.

INTERNATIONAL JOURNAL OF ADVANCED RESEARCH
International Peer-Reviewed Research Journal
ISSN (Online): 3106-7980 | ISSN (Print): 3106-7972
Volume 3 • Issue 7 • November 2026

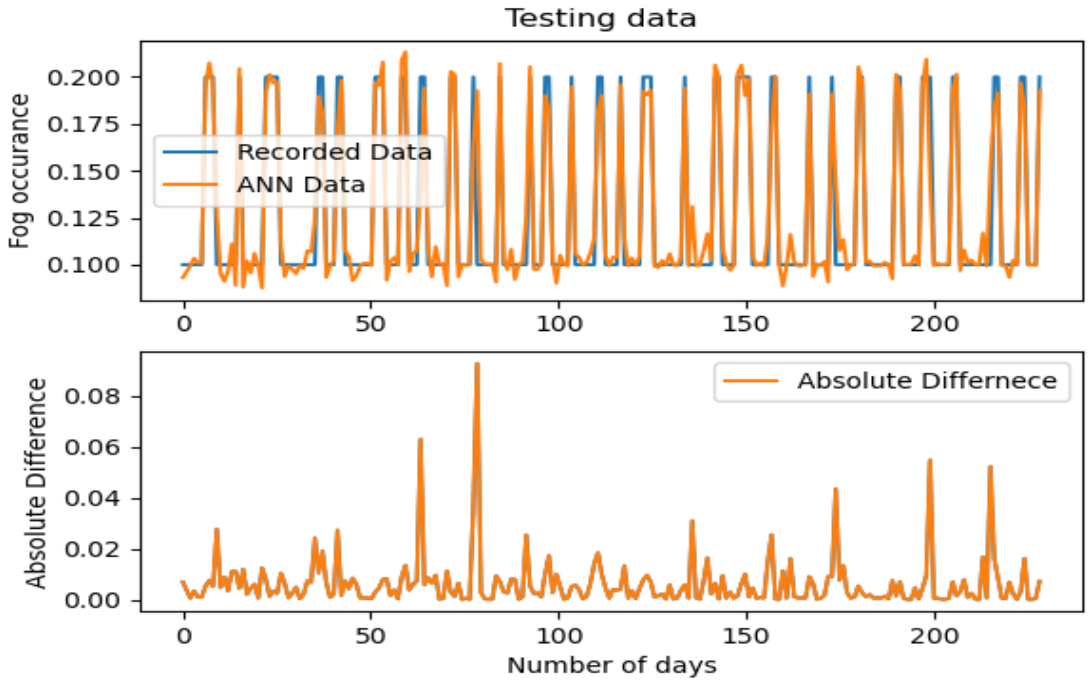


Fig. 3. Testing data and absolute differences between observed and ANN-estimated fog occurrence.

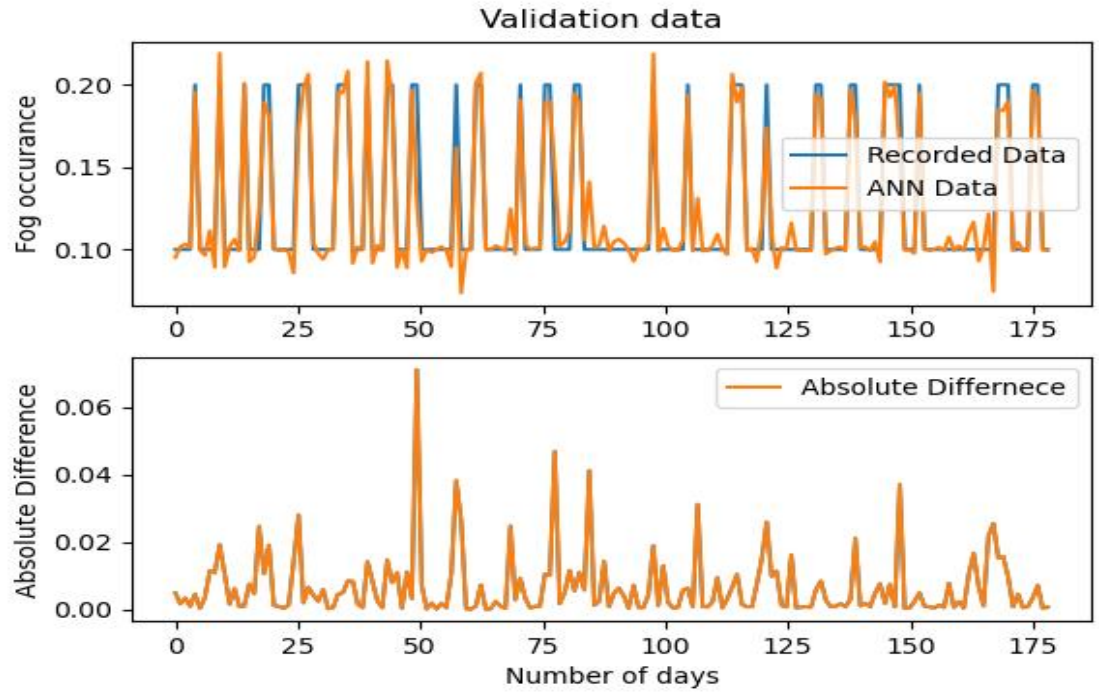


Fig. 4. Validation data and absolute differences between observed and ANN-estimated fog occurrence.

Table 1. Weights of the ANN for the estimation of fog occurrence

w_{11}	w_{12}	w_{13}	w_{14}	w_{15}	w_{16}	w_{17}	w_2
-1.6628	-43.9633	8.6460	2.9931	-2.4040	5.8814	109.4986	1.2788
3.7822	-21.5187	7.3638	8.7464	-0.8782	-7.8106	29.1877	-10.0196
8.4458	69.1660	-177.8681	-61.4152	149.1250	-186.6078	-181.1289	-4.5137
-8.2648	0.0045	-45.9317	-49.9196	59.7171	-212.6041	-64.8148	3.3919
12.7037	-29.1836	13.5593	23.6288	-3.0139	-58.3022	7.7476	12.7089
65.0696	-43.9531	51.6620	25.7901	-18.2832	-187.2059	-66.0441	8.0633
42.3853	-136.2680	66.6942	-117.9640	-23.3708	-78.8299	-7.4228	0.1249
-2.6314	-30.7989	105.6366	36.4653	-91.9075	164.6388	107.7312	-5.3486
49.2222	-37.4484	34.8538	25.9993	-11.7396	-142.8843	-48.2111	-9.0117
-12.6115	-5.6978	-50.7473	-60.5128	66.1092	-217.1310	-69.2117	-3.4765

4. Conclusions

This study applied an ANN with seven input variables (day, month, minimum temperature, dew point, relative humidity, wind speed, and visibility) to estimate fog occurrence in Lahore. The network contained a single hidden layer with 10 neurons and an output layer representing fog occurrence. The dataset was divided into 50% training and 50% testing subsets, while a randomly selected 40% of the data were used for validation. The comparison plots show that most ANN estimates were within 0.05 of the observed encoded values, indicating reasonable agreement for the data examined. The results suggest that ANN modelling can be useful for estimating fog occurrence using the selected daily variables.

REFERENCES

[1] Edwards, J.B., 1996. Weather-related road accidents in England and Wales: a spatial analysis. Journal of transport geography, 4(3), pp.201-212.

[2] Kulkarni, R., Jenamani, R.K., Pithani, P., Konwar, M., Nigam, N. and Ghude, S.D., 2019. Loss to aviation economy due to winter fog in New Delhi during the winter of 2011–2016. Atmosphere, 10(4), p.198.

[3] Bartok, J., Bott, A. and Gera, M., 2012. Fog prediction for road traffic safety in a coastal desert region. Boundary-layer meteorology, 145(3), pp.485-506.

[4] Payra, S. and Mohan, M., 2014. Multirule based diagnostic approach for the fog predictions using WRF modelling tool. Advances in Meteorology, 2014. 1–11.

[5] Singh, A., George, J.P. and Iyengar, G.R., 2018. Prediction of fog/visibility over India using NWP Model. Journal of Earth System Science, 127(2), pp.1-13.

[6] van der Velde, I.R., Steeneveld, G.J., Schreur, B.W. and Holtslag, A.A.M., 2010. Modeling and forecasting the onset and duration of a fog event during frost conditions. Paper presented at the 5th International Conference on Fog, Fog Collection and Dew (Münster, 25–30 July 2010).

[7] Abhishek, K., Singh, M.P., Ghosh, S. and Anand, A., 2012. Weather forecasting model using artificial neural network. Procedia Technology, 4, pp. 311–318.

[8] Fabbian, D., De Dear, R. and Lellyett, S., 2007. Application of artificial neural network forecasts to predict fog at Canberra International Airport. Weather and forecasting, 22(2), pp.372-381.

[9] Bartoková, I., Bott, A., Bartok, J. and Gera, M., 2015. Fog prediction for road traffic safety in a coastal desert region: Improvement of nowcasting skills by the machine-learning approach. Boundary-layer meteorology, 157(3), pp.501-516.

[10] Cornejo-Bueno, L., Casanova-Mateo, C., Sanz-Justo, J., Cerro-Prada, E. and Salcedo-Sanz, S., 2017. Efficient prediction of low-visibility events at airports using machine-learning regression. Boundary-layer meteorology, 165(2), pp.349-370.

[11] Zhu, L., Zhu, G., Han, L. and Wang, N., 2017. The application of deep learning in airport visibility forecast. Atmospheric and Climate Sciences, 7(03), p.314-322

[12] Muslehuddin, M., Mir, H. and Faisal, N., 2004. Recent occurrence of fog over Pakistan (1997 to 2000). Pakistan Journal of Meteorology Vol, 1(2).

[13] Negishi, M. and Kusaka, H., 2022. Development of statistical and machine learning models to predict the occurrence of radiation fog in Japan. Meteorological Applications, 29(2), p.e2048.

[14] Gharekhan, D., Bhattacharya, B.K., Desai, D. and Patel, P.R., 2022. Modelling of downwelling longwave radiation over multiple agro-climate settings of India under foggy sky conditions–A neural network approach. Remote Sensing Applications: Society and Environment, 25, p.100684.

[15] Yan, M., Chen, J., Xu, J. and Xiang, L., 2022, May. Visibility detection of single image in foggy days based on Fourier transform and convolutional neural network. In 2nd International Conference on Applied Mathematics, Modelling, and Intelligent Computing (CAMMIC 2022) (Vol. 12259, pp. 1440-1445). SPIE.

[16] Xia, F., Song, H. and Dou, H., 2022. Fog removal and enhancement method for UAV aerial images based on dark channel prior. Journal of Control and Decision, pp.1-10.

[17] Li, L., Yang, B. and Chen, S., 2022. Detection of agglomerate fog based on a shallow convolutional neural network. Multimedia Tools and Applications, 81(2), pp.2841-2857.