SSRG International Journal of Civil Engineering
ISSN: 2348-8352/ https://doi.org/10.14445/23488352/IJCE-V12I8P108

Volume 12 Issue 8, 97-104, August 2025

Original Article

Optimizing Geographical Weather Data Structures Using IoT and Discriminant Models

D. Menaka[1], Vijay Kumar Gowda B N[2], Rahul S G[3], Dasari Naga Vinod[4]

[1]*Department of Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai, Tamil Nadu, India.*
[2]*Department of Electronics and Communication Engineering, Faculty of Engineering Management and Technology, BGS Institute of Technology, Adichunchanagiri University, B G Nagar, Mandya, Karnataka, India.*
[3]*Department of Electronics and Communication Engineering, Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Chennai, Tamil Nadu, India.*
[4]*Department of Electronics and Communication Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu, India.*

[4]*Corresponding Author : dasaarinagavinod@gmail.com*

Received: 04 June 2025 Revised: 08 July 2025 Accepted: 07 August 2025 Published: 29 August 2025

***Abstract** - Developing climate forecasting models is region-specific and based on data from discriminant analysis. Using a discriminant approach, the study demonstrates that understanding this pattern probably aids in the organization and production of businesses and crops. To predict the weather, this paper uses the Internet of Things (IoT) to connect numerous sensors as well as controllers. As a result, this study takes into account climate data for ten years across various locations. Temperature, Precipitation, Humidity, and wind variations in tropical regions are investigated, as are the causes of these variations in parameters. Canonical correlation, Wilks' Lambda, and general characterization all play a role in determining the outcomes. The Structure Matrix and Standardized Discriminant function were also used to identify the parameters of interest. The Precipitation variable is primarily responsible for distinguishing between the two locations. According to the classification matrix, 98.9% of the original as well as cross-validated clusters are correctly classified. The developed mechanism is found to be useful for weather forecasting as well.*

***Keywords** - Canonical correlation, Classification matrix, Eigen value, IoT, Linear discriminant function.*

1. Introduction

IoT has discovered its applications in a few zones, for example, associated industries, smart energy, smart cities [1, 2], smart homes, associated vehicles, Intelligent horticulture [3], as well as intelligent weather forecasting, associated building, and grounds, human services [4], coordination [5], among different spaces.

IoT intends to incorporate the physical world into the virtual world by utilizing the Web as the medium to impart as well as trade data [6].

IoT has been characterized as an arrangement of correlated computing gadgets, mechanical as well as objects, creatures, or individuals, advanced machines, that obtain remarkable identifiers as well as the capacity to transfer information through a network without the need for human-to-PC or human-to-human collaboration.

With the quick advancement of the economy, substantial mechanical park development and generation action are increasingly prevalent, increasing the likelihood of natural contamination mishaps, mainly air contamination mishaps.

Influenced by meteorological and topographical conditions, air contamination will be profoundly grouped in a short time after occurring, causing incredible damage or even complete obliteration to both humans and the environment. So, it is incredibly essential to set up a continuous air contamination checking framework [7].

IoT is a developing communication technology [8, 9] with sensors, actuators, and smart devices regularly associated with the internet [10]. IoT incorporates the capacity to detect and transmit information and to make decisions based on the collected data. Subsequently, it can be utilized in various applications like ecological checking, well-being observing, yield observing, and other applications [11].

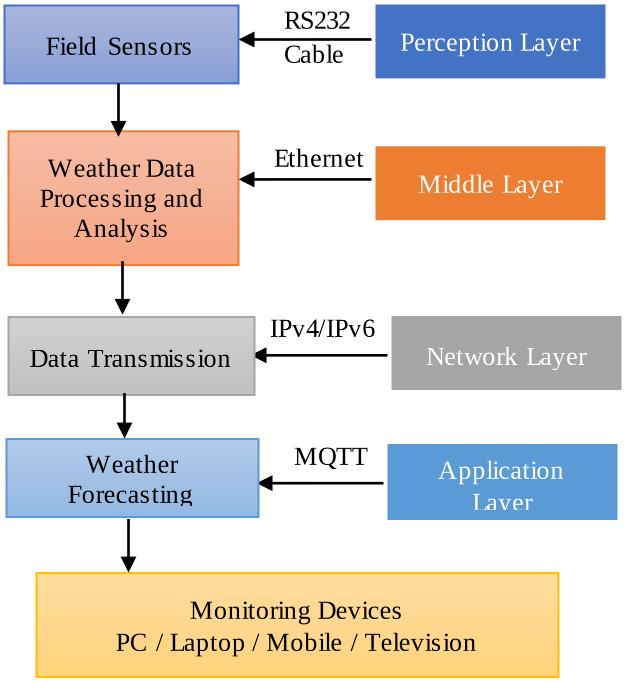

Fig. 1 Climate observing and determining framework with IoT layered illustration [12]

Atmosphere observation is vital in any place. Its pressure, Temperature, dampness, wind speed, and delicacy estimations are utilized in various farming, military, and entertainment applications. There are multiple answers for climate checking, the most widely recognized being at least one static climate station. These stations calculate information and send it by wire to a focal station. The portrayed arrangement requires explicit developments for the climate stations, and the checking goals are low since the number of stations has decreased for financial reasons [13].

IoT illustration includes the Perception layer, the Middle layer, the Network layer, and the Application layer. The Climate forecasting framework structure with the IoT layered determination is represented in Figure 1.

Climate estimating is an expectation of what the climate will resemble in the near future. In the online world, climate determination is significant for various reasons, viz, saving of lives and natural disasters (floods, tornadoes, tropical storms, etc.). Climate anticipation can predict natural disasters in the future. The climate can influence day-to-day lives. If the climate were at the ideal time, it would be in a challenging situation. It can control sports, outside exercises, cultivating, routes, transportation, and so on. The above aspects motivated the authors of this research to enhance IoT applications in real-life systems further further. The contributions of this paper are the following:

- Comparison of two important geographical locations in India with the proposed discriminant analysis.
- Geospatial aspects are entirely different for the two cities, and identified parameters of interest based on the Standardized Discriminant function as well as the Structure Matrix.
- Models developed are new, comparisons can be made with distinctive features, and they obtained 98.9% group classification.

The rest of the article is described as ensuing: Section II illustrates the literature survey. Discriminant function-related aspects are indicated in section III. The data structure for the present study is given in Section IV. Section V contains the analysis as well as the results of the investigation. The conclusions are drawn in section VI.

2. Literature Survey

2.1. IoT Applications in General

IoT applications are certain to bring enormous benefits to people's lives. With more advanced remote networks, prevalent sensor systems, and dynamic registering capacities, the Web of Things may be the next advancement in the race for a large portion of the wallet [14, 15]. Consider a smart device, such as a traffic camera. The camera can scan the streets for traffic jams, mishaps, and weather conditions and transmit this data to a standard door. This section also collects data from other types of cameras and sends it to a city-wide traffic monitoring system [16, 17].

2.2. IoT-Related Studies Concerning Metrological Studies

Determining climate utilizing time-series examination, A.I., and artificial neural systems with sensible exactness was done [18]. They neglected to anticipate significant parameters like Precipitation, Humidity, and Wind. Researchers just thought of predicting two essential climate parameters, for example, maximum and minimum temperatures.
Numerous researchers have considered climate determination in time series analysis. They have considered an answer for a time series investigation concentrating on climate forecasting [19, 20].

Researchers in [21-23] attempted to study an intelligent weather grid as a significant part of the smart city. The strength of the shrewd climate network will directly influence the health of the smart city. Researchers have examined an effective and precise forecast about air quality levels, which can give a dependable premise to cultural choices, safety for intelligent transportation, and climate-related disaster preparedness.

2.3. Development of IoT in Recent Years

Authors [24] examined an endeavour to make use of discriminant work examination of meteorological parameters for creating a reasonable factual technique to predict rice harvest for the Faizabad area of eastern Uttar Pradesh. Their work does not concentrate on the everyday date of harvest season, but rather on the meteorological parameters that have been measured. The technique for assessing climate gauges using satellite inactive millimetre-wave perceptions and tropical climate conjecture assessment for a climate forecasting framework. This work finds that the climate estimates in the tropics will be considerably improved if storm areas can be precisely adjusted by utilizing satellite passive millimetre-wave perceptions.

2.4. IoT Applications in Metrological Studies: A Current Scenario

Authors in [26] address the orderly plan of a "multistage artificial neural system-based short-term load forecaster" (ANNSTLF). The created ANNSTLF engine has been used in a simple utility framework. They discovered the examination of estimating precision because this upgrade is broken down.

An incorporated estimating technique makes it hard to pursue load variety and climate diversity throughout the region in a mass power framework covering an enormous land region. An appropriate burden forecasting technique is dependent on neighborhood climate data [27, 28]. Another work in [29] proposes calculations to control the yield of P.V. frameworks dependent on climate conditions and support vector machines. Simultaneously, the weather circumstances are categorized into four parts: clear sky, shady day, foggy day, and stormy day.

3. Materials and Methods

3.1. Definition

An element of a few variables is used to allocate things into one of at least two groups. The capacity for a specific arrangement of things is acquired from estimations of the variates of things that belong to a known group.

3.2. Description of the function

This examination was finished utilizing the IBM SPSS software tool. This chore plans to discover which season is best for segregating between gatherings, assuming the massive job in summer, winter, and rainy weather. The information here is isolated consistently for ten years of data.

The accompanying area clarifies the means associated with the investigation and its outcomes regarding the data.

3.2.1. Model

The discriminant investigation model is of the structure:

$$M = d_0 + d_1 Y_1 + d_2 Y_2 + \cdots + d_z d_z \qquad (1)$$

Where M = Dependent factors and the arranged variable

d_z = Coefficients of free factors

Y_z = An indicator of the free factors, in this informational index, is 'singular parameters'.

3.2.2. Descriptive Measurements

The normal estimation of an irregular network is the grid that comprises every component's normal analysis.

$$Q(Ƶ) = \begin{pmatrix} Q(Z_{11}) & \cdots & Q(Z_{1q}) \\ \vdots & \ddots & \vdots \\ Q(Z_{l1}) & \cdots & Q(Z_{lq}) \end{pmatrix} \qquad (2)$$

Where **Ƶ** is the irregular network of size l x q

Assume Ƶ * = $[Z_1, Z_2, \ldots . Z_q]$ is a q x1 irregular vector. At that point, each component of Ƶ is an arbitrary variable with its very own peripheral probability appropriation. The peripheral mean

$\mu_j = Q(Z_j)$ and Variance $\sigma_j^2 = Q(Z_j - \mu_j)^2$ where j = 1,2,…q, respectively.

$\mu_j = \sum_{all\ zj} Z_j\, q_j\, (Z_j)$, if z_j is a discrete random variable with probability function $q_j(z_j)$

$\sigma_j^2 = \sum_{all\ zj} \left(Z_j - \mu_j\right)^2 q_j\, (Z_j)$ If z_j is a discrete random variable with a probability function $q_j\, (Z_j)$.

3.3. Data Gathering Aspects

The intelligent weather forecasting system is discussed in Figure 2. Initially, weather data is available in the cloud database, and then the data is directed to the IBM SPSS statistical platform to forecast the variables. After that, substituting the string data with numerical data, like Chennai is represented as 0, and Delhi is represented as 1. After that, the Discriminant technique was used to examine the data. Finally, evaluating as well as predicting the parameters, viz., Precipitation, Temperature, Wind, and Humidity.

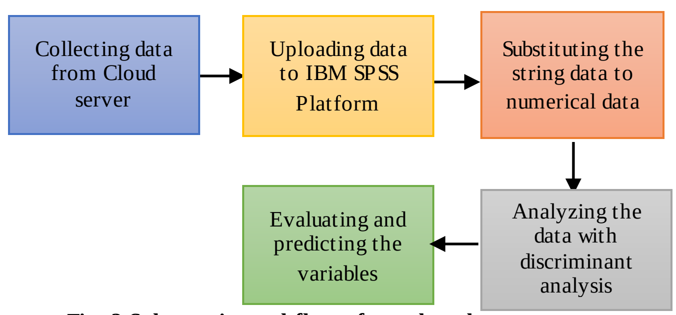

Fig. 2 Schematic workflow of weather data structure

3.4. Data structure with parameter description

Contemplating the utilization example of individual parameters in climate determination can help arrange and create undertakings/crops. Seasons produced during the year have various parameters, for instance, Temperature (*°C), Precipitation (%), Humidity (%), wind (km/h), and readings are taken for each day. Numerous examinations have been conducted concerning the time arrangement investigation. The following procedure can locate the various temperatures utilized by most planning and generating vendors for endeavours and farmers for cultivating.

3.5. Framing of the Data, Constructing the Discriminant Model

The informational collection utilized in this work contains regular readings of various parameters in two different geographical locations, for example, Chennai and Delhi in India. This examination is finished by taking the information of Chennai and Delhi from the ordinary climate estimating database. The current data is pre-processed to locate the number of parameters that the season was utilized in the year. The information is isolated as Chennai, which is signified as 0, and Delhi, signified as 1.

3.6. Associated Results

The means as well as the covariance of qx1, an arbitrary vector **Ƶ,** can be depicted as matrices.

$$\mathrm{P}(Ƶ) = \begin{pmatrix} P(Z_1) \\ P(Z_2) \\ \vdots \\ P(Z_q) \end{pmatrix} = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \cdot \\ \mu_q \end{pmatrix} = \mu \tag{3}$$

Variance-Covariance matrix,

$$\mathbf{\Sigma}=\mathrm{P}(\mathbf{Z}-\mu)(\mathbf{Z}-\mu)^{*}= \mathrm{Cov}(\mathbf{Z})=\begin{pmatrix} \sigma_{11} & \cdots & \sigma_{1q} \\ \vdots & \ddots & \vdots \\ \sigma_{q1} & \cdots & \sigma_{qq} \end{pmatrix} \tag{4}$$

Where μ**:** vector

Σ**:** matrix.

The population correlation coefficient ρ_{js} was characterized into covariance σ_{js} as well as variances σ_{jj} & σ_{ss}.

$$\rho_{js} = \frac{\sigma js}{\sqrt{\sigma jj}\sqrt{\sigma ss}} \tag{5}$$

$$\boldsymbol{\rho} = \begin{pmatrix} 1 & \dots & \rho_{1q} \\ \vdots & \ddots & \vdots \\ \rho_{q1} & \dots & 1 \end{pmatrix} \tag{6}$$

Consider the q x q standard deviation matrix to be

$$\mathrm{D}^{1/2} = \begin{pmatrix} \sqrt{\sigma_{11}} & 0\dots. & 0 \\ 0 & \sqrt{\sigma_{22}} & \vdots \\ 0 & \dots. & \sqrt{\sigma_{22}} \end{pmatrix} \tag{7}$$

Σ can be gotten from $\mathrm{D}^{1/2}$ and ρ

ρ can be gotten from Σ.

4. Results and Discussion

The accompanying segment subtleties the consequences of the discriminant investigation for intelligent climate prediction for finding the parameters of the vast job.

4.1. Basic Statistics

The standard deviation and the mean of the independent variables are given in Table 1 for the two metropolitan cities, Chennai and Delhi.

Significant variation concerning Precipitation (%) and wind (km/hr) between Chennai and Delhi was observed.

Table 1. Group statistics

Location	Parameters	Mean	SD
0 (Chennai)	Tempt (^{O}C)	.56	.496
	Precipitation (%)	24.75	7.220
	Humidity (%)	72.13	12.279
	Wind (Km\hr)	18.60	4.140
1 (Delhi)	Tempt (^{O}C)	.55	.498
	Precipitation (%)	2.18	1.676
	Humidity (%)	61.56	12.139
	Wind (Km\hr)	40.94	16.933

The variation in the Humidity (%) and Temperature (%) is not significant between Chennai and Delhi. Chennai is a tropical zone city on the coast. It is humid and uncomfortable for half a year, from April to September. Delhi is dry on most days of the year. Chennai is a seaside city on the coast and is humid for most of the year, while Delhi has an extraordinary summer that is excessively sweltering, and winter is freezing. Winter is lovely in Chennai, but Delhi is excessively cold. In Delhi, air contamination likewise differs from Chennai in terms of the number of vehicles and crop consumption in the field from surrounding states, as well as the brown haze enveloping Delhi.

4.2. Test for Equality of Group Means

One-way Variance investigation has been used to recognize the predicted variables/ explanatory variables that exhibit a difference in means between Chennai and Delhi. Figure 3 shows the test of the equality of group means concerning Wilks' lambda. There exists a significant difference in means among Chennai and Delhi with respect to the predictor variables, which are Precipitation (%), Humidity (%), and Wind (Km/hr).

The p-values for these predictor variables are <0.05, the expected level of significance. There is no significant difference in the mean Temperature among Chennai and Delhi, as the p-value is more than 0.05.

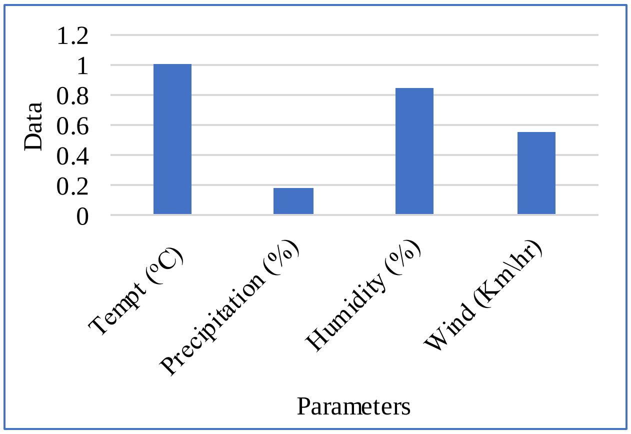

Fig. 3 Test of equality in terms of Wilks' Lambda

4.3. Correlation Matrix

The correlation matrix in Table 2 between the predictor variables was presented. The correlation coefficient among any parameter of the forecaster variables does not exceed 0.75. This does not raise the problem of multicollinearity.

Table 2. Correlation matrix

Parameters	Tempt (^{O}C)	Precipitation (%)	Humidity (%)	Wind (Km\hr)
Tempt (^{O}C)	1.000	-.159	-.008	.042
Precipitation (%)	-.159	1.000	-.112	.015
Humidity (%)	-.008	.112	1.000	-.029
Wind (Km\hr)	.042	.015	-.029	1.000

The unstandardized discriminant function was constructed to maximize the Variance between the two cities relative to the city.

4.4. Unstandardized Discriminant Function Model

The unstandardized discriminant function is followed by

Y=0.348*(tempt)+0.178*(precipitation)+0.022*(humidity)-0.031*(wind)-3.152 (8)

Given the Temperature, Precipitation, Humidity, and wind values of the discriminant score for each day.

4.5. Eigen Value and Wilk's Lambda

The Eigenvalue for the discriminant function above is 6.123, as shown in Table 3, with 100% Variance elucidated. The value of the canonical correlation coefficient is 0.927, and its squared value is 85.93. This exhibits that the discriminant technique describes 85.93% of the variation between the two cities.

Table 3. Eigen values

Test of Function (s)	Eigen Value	% of Variance	Cumulative %	Canonical Correlation
1	6.123	100.0	100.0	.927

Table 4. Wilk's Lambda

Test of Function (s)	Wilks' Lambda	Chi-square	Df	Sig.
1	.140	14332.206	4	.000

Wilks' lambda indicates the significance of the discriminant function constructed. The value of Wilks' Lambda is 0.140 as exhibited in Table 4. The Chi-square statistic is 14332.206 with 4 degrees of freedom, and the p-value is 0.000. As the value of $p < 0.05$, the discriminant function is significant.

4.6. Standardized Discriminant Function as well as Structure Matrix

The standardized discriminant function is given by

Y=0.173*(tempt)+0.934*(precipitation)+0.270*(humidity)-0.380*(wind) (9)

The variables of the normalized discriminant function are unit-independent. The absolute value of the standardized discriminant function coefficient indicates the relative contribution of the factors in distinguishing between Chennai and Delhi. Precipitation is the most important predictor variable, and it distinguishes between Chennai and Delhi in a significant way, followed by wind, Humidity, and Temperature.

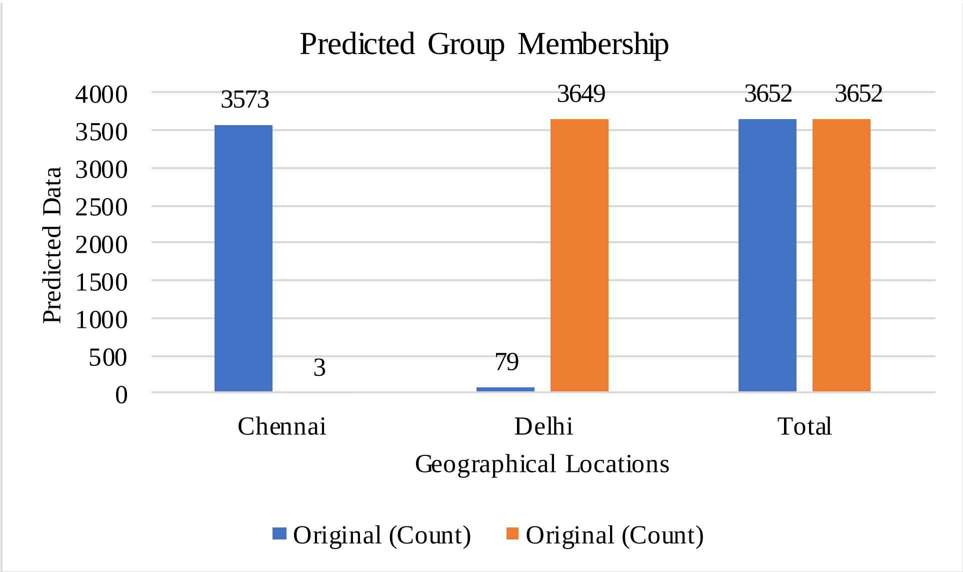

Fig. 4 Predicted group membership

Table 5. Classification Results

Parameters		Location	Predicted Group Membership		Total
			0 (Chennai)	1 (Delhi)	
Original	Count	0 (Chennai)	3573	79	3652
		1 (Delhi)	3	3649	3652
	%	0	97.8	2.2	100.0
		1	.1	99.9	100.0
Cross-validated	Count	0	3573	79	3652
		1	3	3649	3652
	%	0	97.8	2.2	100.0
		1	.1	99.9	100.0

Figure 4 represents the predicted group membership across two geographical locations, such as Chennai and Delhi. Based on the developed discriminant model, a classification matrix was created that encapsulates the correct and incorrect categorization of observations (days) in both metropolitan cities. These findings are presented in Table 5, and they represent the performance assessment procured through simulation analysis. The original and cross-validated groups are correctly predicted as 98.9%.

Table 6 depicts the comparison of the existing mechanisms with the proposed mechanism with respect to performance.

Table 6. Contrast of the existing mechanisms

Reference	Algorithm	Performance (%)
Ref. [29]	SVM	73.12%
Ref. [29]	RF	95.7%
Ref. [30]	XGB	97.6%
Ref. [31]	Time Series	87.5%
Proposed	**Discriminant Model**	**98.9%**

5. Conclusion

In the present work, the construction of a discriminant technique for weather data structure in two geographical regions is observed with the Internet of Things usage. The Weather data, viz., Temperature (oC), Precipitation (%), Humidity (%), as well as Wind (Km/hr), were obtained for ten years and analyzed employing the discriminant technique.

The developed model revealed no significant variation in Humidity and Temperature between the two cities due to geographical locations. It is also to be noted that there is a more substantial variation concerning Precipitation and Wind between Chennai and Delhi.

The results have shown that 85.93% of the divergence between the two cities in respect of predictor variables, viz., Temperature (oC), Precipitation (%), Humidity (%), and Wind (Km/hr). The Precipitation variable plays a primary role in discriminating between Chennai and Delhi.

The classification matrix indicates that 98.9% of the original and cross-validated groups are classified correctly. The values of the predictor variables using the discriminant model were created, and they obtained improved performance compared to the existing mechanisms.

Data Availability

Enquiries about data availability should be directed to the authors.

Acknowledgments

This work is supported by Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology.

References

[1] Andrea Zanella et al., “Internet of Things for Smart Cities,” *IEEE Internet of Things Journal*, vol. 1, no. 1, pp. 22-32, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[2] Luis Sanchez et al., “SmartSantander: IoT Experimentation Over a Smart City Testbed,” *Computer Networks*, vol. 61, pp. 217-238, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[3] Ibrahim Gad, and Doreswamy Hosahalli, “A Comparative Study of Prediction and Classification Models on NCDC Weather Data,” *International Journal of Computers and Applications*, vol. 44, no. 5, pp. 414-425, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[4] S.M. Riazul Islam et al., “The Internet of Things for Health Care: A Comprehensive Survey,” *IEEE Access*, vol. 3, pp. 678-708, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[5] Lin Li, “Application of the Internet of Thing in Green Agricultural Products Supply Chain Management,” *2011 Fourth International Conference on Intelligent Computation Technology and Automation*, Shenzhen, China, pp. 1022-1025, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[6] Ovidiu Vermesan, European Research Cluster on the Internet of Things - Outlook of IoT Activities in Europe, SINTEF. [Online]. Available: https://sintef.brage.unit.no/sintef-xmlui/handle/11250/2429910?locale-attribute=en

[7] P. Dayananda et al., “A Brief Study on Smart Medicine Dispensers,” *International Journal of Hyperconnectivity and the Internet of Things*, vol. 6, no. 1, pp. 1-7, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[8] R. Geetanjali et al., “Methodical Applications for Cybersecurity Using Deep Learning Techniques,” *Solid State Technology*, vol. 63, no. 6, pp. 7345-7359, 2020. [Google Scholar] [Publisher Link]

[9] M.B. Apsara, P. Dayananda, and C.N. Sowmyarani, “A Review on Secure Group Key Management Schemes for Data Gathering in Wireless Sensor Networks,” *Engineering, Technology and Applied Science Research*, vol. 10, no. 1, pp. 5108-5112, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[10] Bhargav Hegde et al., “Deep Learning Technique for Detecting NSCLC,” *International Journal of Recent Technology and Engineering*, vol. 8, no. 3, pp. 7841-7843, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[11] Ankush B. Pawar, and Shashikant Ghumbre, “A Survey on IoT Applications, Security Challenges and Counter Measures,” *2016 International Conference on Computing, Analytics and Security Trends*, Pune, India, pp. 294-299, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[12] Matheus S. Monteiro et al., “University Campus Microclimate Monitoring Using IoT,” *2019 Workshop on Communication Networks and Power Systems*, Brasilia, Brazil, pp. 1-5, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[13] S. Narasimha Swamy, and C.N. Sowmyarani, “Repeated Data Management Framework for IoT: A Case Study on Weather Monitoring and Forecasting,” *2018 4th International Conference on Recent Advances in Information Technology*, Dhanbad, India, pp. 1-7, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[14] Ravi Kishore Kodali, and Archana Sahu, “An IoT Based Weather Information Prototype Using WeMos,” *2016 2nd International Conference on Contemporary Computing and Informatics*, Greater Noida, India, pp. 612-616, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[15] Kalyani G. Gajbhiye, and Snehlata S. Dongre, “A Survey on Weather Monitoring System in Agriculture Zone Using Zigbee,” *International Journal of Science and Research*, vol. 2, no. 1, pp. 192-197, 2013. [Google Scholar]

[16] M. Sowjanya, and MD. Ameenuddin, “A Reconfigurable Smart Sensor Interface for Weather Monitoring with IOT Environment,” *IJESRT*, pp. 1339-1344, 2017. [Google Scholar] [Publisher Link]

[17] Medilla Kusriyanto, and Agusti Anggara Putra, “Weather Station Design Using IoT Platform Based On Arduino Mega,” *2018 International Symposium on Electronics and Smart Devices*, Bandung, Indonesia, pp. 1-4, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[18] Abhishek Agrawal et al., “An Application of Time Series Analysis for Weather Forecasting,” *International Journal of Engineering Research and Applications*, vol. 2, no. 2, pp. 974-980, 2012. [Google Scholar] [Publisher Link]

[19] J.M. Craddock, “The Analysis of Meteorological Time Series for Use in Forecasting,” *Journal of the Royal Statistical Society, Series D (The Statistician)*, vol. 15, no. 2, pp. 167-190, 1965. [CrossRef] [Google Scholar] [Publisher Link]

[20] Małgorzata Murat et al., “Forecasting Daily Meteorological Time Series Using ARIMA and Regression Models,” *International Agrophysics*, vol. 32, no. 2, pp. 253-264, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[21] Yuanni Wang, and Tao Kong, “Air Quality Predictive Modeling Based on an Improved Decision Tree in a Weather-Smart Grid,” *IEEE Access*, vol. 7, pp. 172892-172901, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[22] Piotr Mirowski et al., “Demand Forecasting in Smart Grids,” *Bell Labs Technical Journal*, vol. 18, no. 4, pp. 135-158, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[23] Federico Montori, Luca Bedogni, and Luciano Bononi, “A Collaborative Internet of Things Architecture for Smart Cities and Environmental Monitoring,” *IEEE Internet of Things Journal*, vol. 5, no. 2, pp. 592-605, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[24] B.V.S. Sisodia et al., “Forecasting of Pre-Harvest Crop Yield Using Discriminant Function Analysis of Meteorological Parameters,” *Journal of Agrometeorology*, vol. 16, no. 1, pp. 121-125, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[25] J.Y. Fan, and J.D. McDonald, “A Real-Time Implementation of Short-Term Load Forecasting for Distribution Power Systems,” *IEEE Transactions on Power Systems*, vol. 9, no. 2, pp. 988-994, 1994. [CrossRef] [Google Scholar] [Publisher Link]

[26] T.W.S. Chow, and C.T. Leung, “Neural Network Based Short-Term Load Forecasting Using Weather Compensation,” *IEEE Transactions on Power Systems*, vol. 11, no. 4, pp. 1736-1742, 1996. [CrossRef] [Google Scholar] [Publisher Link]

[27] Dunnan Liu et al., “A Distributed Short-Term Load Forecasting Method Based on Local Weather Information,” *IEEE Systems Journal*, vol. 12, no. 1, pp. 208-215, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[28] Jie Shi et al., “Forecasting Power Output of Photovoltaic Systems Based on Weather Classification and Support Vector Machines,” *IEEE Transactions on Industry Applications*, vol. 48, no. 3, pp. 1064-1069, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[29] Hassan Al Sukhni et al., “Data-DrivenWeather Prediction: Integrating Deep Learning and Ensemble Models for Robust Weather Forecasting,” *Journal of Cybersecurity and Information Management*, vol. 15, no. 2, pp. 260-284, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[30] Adela Bâra, Alin Gabriel Văduva, and Simona-Vasilica Oprea, “Anomaly Detection in Weather Phenomena: News and Numerical Data-Driven Insights into the Climate Change in Romania’s Historical Regions,” *International Journal of Computational Intelligence Systems*, vol. 17, pp. 1-26, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[31] K.K. Pandey, B.V.S. Sisodia, and V.N. Rai, “Forecasting By Discriminant Function Weather Based Analysis,” *International Journal of Environmental Sciences & Natural Resources*, vol. 4, no. 4, pp. 1-4, 2017. [CrossRef] [Google Scholar] [Publisher Link]