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Research Article

Weather Forecasting Method from Sensor Transmitted Data for Smart Cities Using IoT

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India experiences severe weather events around the year. Severe thunderstorms occur during the premonsoon season (March-May), cyclonic storms occur over the Bay of Bengal/Arabian Sea during the premonsoon and postmonsoon seasons (October-December), and heavy rainfall occurs during the monsoon season (June-September). It causes a lot of damage to property and the lives of humans. Smart urban areas aim to improve residents' personal satisfaction by utilizing data about urban scale procedures separated from heterogeneous information sources gathered on city-wide arrangements using sensors. The Internet of Things (IoT) is an empowering concept for forecasting weather situations on an urban scale. A multisource detecting framework influences IoT innovation to accomplish city-scale detection of climatic changes and forecasts them to citizens in a smart city. The existing models gather the data in an unstructured process that need to be structured. This is a complex task that needs to be reduced. The proposed model gathers data from various regions in a city and uses it to identify the weather regions. A novel approach is introduced to detect this climate information gathered by utilizing various sensors arranged in a city. The information gathered from the sensors is thoroughly examined to see if there is any inconsistency in weather reports in any of its key hubs, and cautions are activated to the city for prompt actions. In this proposed work, an efficient method for weather casting using an IoT mechanism is introduced, and the results state that the proposed method is effective in terms of accuracy and speed when contrasted with the traditional methodologies.

1. Introduction

The IoT comprises 3 layers: the perception layer, the network layer, and the application layer, as shown in Figure 1. The perception layer incorporates a gathering of Internet-empowered gadgets that can see, identify objects, accumulate data, and share data with different gadgets through the Internet association systems [1]. Radio-frequency identification devices (RFID), cameras, sensors, and the global positioning system (GPS) are a few instances of perception layer gadgets. Sending information to the application layer from the perception layer with the requirements of gadgets' capacities and some applications' imperatives will be carried out by the network layer [2]. Figure 2 shows the sensor to actuator flow. IoT frameworks utilize a mix of short-extend systems communication advancements. Since applications intend to make keen homes, smart urban areas, control framework checking, coordination of appropriate control storage, and a mix of sustainable power sources, that is, the application layer is the place where the data are prepared and then processed [3]. The climate information utilized in this investigation and the proposed examination are exhibited alongside how the climate information investigation issue is tackled utilizing the system. The proposed weather forecasting method in smart cities is more useful to the public in avoiding human loss and property damage with better knowledge regarding weather conditions to take necessary actions in saving human lives and reducing property loss. The key aspects of smart cities are depicted in Figure 3.

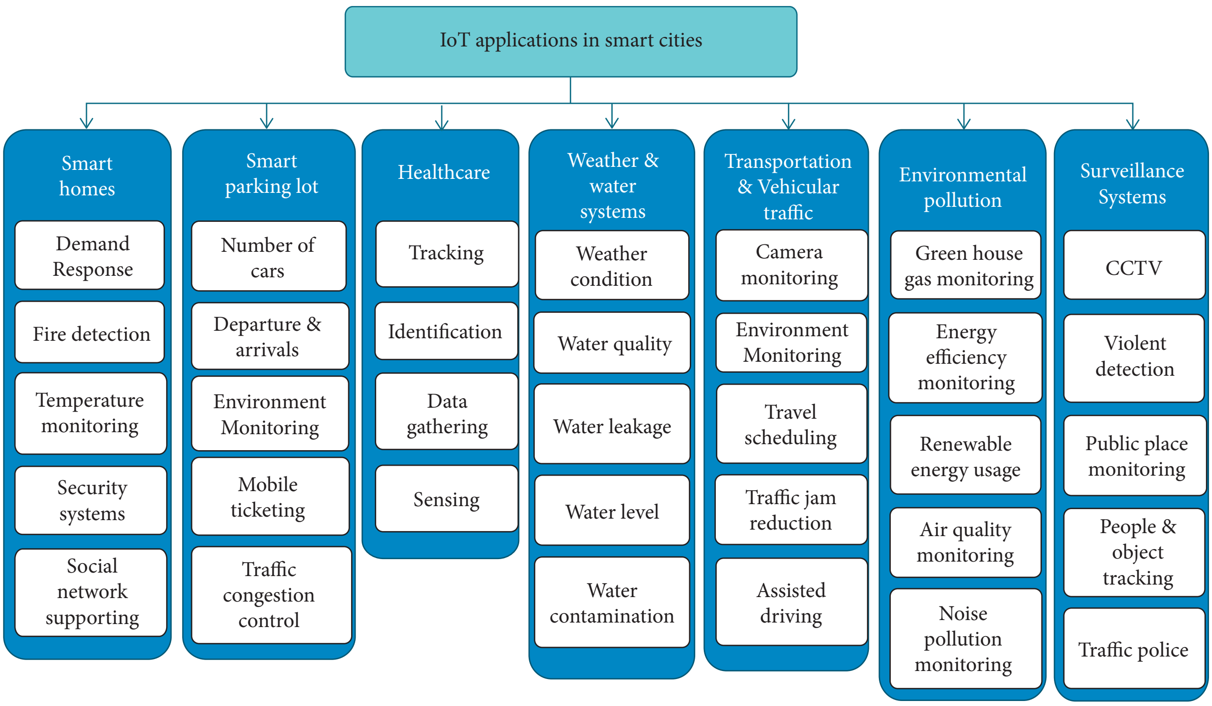

Figure 1: The main applications of the IoT.

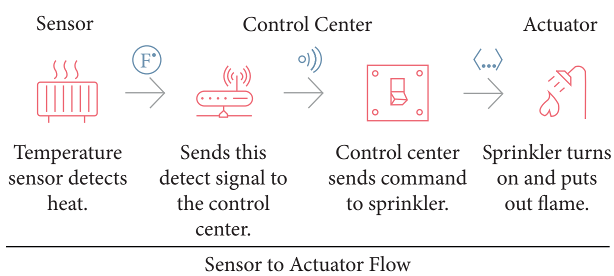

Figure 2: Sensor to actuator flow.

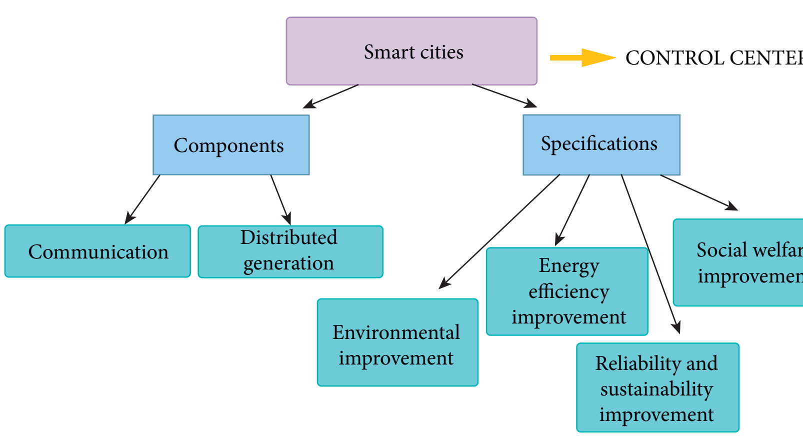

Figure 3: The key aspects of smart cities.

Weather forecasters have to monitor different weather conditions that cause severe weather hazards [4]. Weather hazards are the most dangerous, and their occurrence probabilities and ranges are to be observed and forecasted as quickly as possible. Cyclonic disturbances (CDs) are one of the most extraordinary climatic vortices [5], which create over-warm tropical seas, causing tremendous harm to life and property at the hour of intersection with the coast and resulting in the development of the land [6]. Weather-related information needs to be forecasted from different sensors in smart cities to the central weather forecasting authority for analyzing the data and forecasting relevant information to the public. Weather disturbances cause a lot of loss for the public and should be avoided. Present-day advancements in modernization mostly center around the controlling and examination of different gadgets remotely over the web with the end goal that the web goes about as a model for the association between each one of the gadgets [7]. The proposed work is mainly centered on the effective assessment and calculation of various circumstances based on data gathered from sensors. The unstructured data gathered from sensors have to be arranged in a structured manner and then analyzed. An effective framework is necessary to analyze and monitor climate conditions [8]. A lack of a set schema makes it difficult to transport unstructured data to a target system without proper tools, unlike structured data. It is the simplest way to deal with unstructured data, move it to a data warehouse, execute the data processing, and apply the ontology set to create the data structure.

A framework is considered as a keen framework when the gadget is outfitted with sensors, microcontrollers, and special programming applications that perform data structuring and analysis to improve the accuracy of the method [9]. In the proposed method, sensors are arranged in different locations of smart cities, and the sensors send the data to the central weather forecasting authority for arranging the unstructured data sent from the sensors in a structured way for better analyzing and predicting weather hazards [10]. Initially, sensors gather information and are arranged such that they recognize several parameters, such as temperature, humidity, radiation levels, and so on.

2. Literature Survey

Climate forecasting has been a noteworthy test from the early days; new approaches are grouped with regular ones. Existing methods have demonstrated that AI systems accomplish preferable execution over conventional measurable strategies. In IOT, several gadgets are linked up to establish communication among them. Existing climate observing frameworks that are utilized in the field by and large comprise unusual and vast hardware that comprises various moving parts that require steady support and should be physically observed and changed regularly. Power prerequisites are one of many real requirements as these instruments are by and large located a long way from the principal power supply. This adds to the expense of utilizing such instruments.

Wang et al. [1] introduced a system to discover exceptional and uncommon examples of climate data. To oblige the dynamic information, the authors proposed an adaptive Markov chain calculation model which uses an open number of conditions on the Markov chain. This method gathered the information with the tropical air sea which was created by the International Tropical Ocean Global Atmosphere program. The method time complexity levels are too high that impact the performance levels. Wan et al. [2] displayed an overview dependent on the meteorological information mining procedures. In this method, information mining procedures are utilized, for example, decision trees, fluffy artificial neural systems, rule-based methods, and some different strategies for the atmosphere of expectation. In this method, neural system-based calculations are performed well when contrasted with other information-mining procedures. The model proposed considers the limited-size dataset that impacts the accuracy levels. Ke et al. [3] displayed a way to deal with information on temperature and moistness esteems for the future by utilizing calculation procedures. In this method, they considered anomaly examination that is considered to distinguish the exceptions as for the information and clustering investigation, which is accustomed to dividing the information dependent on the comparability of the articles. The utilized KNN calculation is utilized to foresee the estimations of temperature and dampness parameters of the atmosphere.

Andrade and Bessa [4] set up a framework for occasional to between-yearly atmospheric expectations by utilizing an information mining strategy. The principal motivation behind this method is to utilize an information mining procedure using KNN and build a framework. It operates authentic numeric information to gauge the atmosphere of an explicit area, city, or nation months ahead. The method utilizes the sea surface temperature that is considered as a fundamental factor, and a relapse tree system is utilized to discover the predication of the atmosphere. Numerous researchers have examined tropical tornado development and force in subtleties taking different restrictions as information. The model time and the consistency of INSAT OLR information are dependent on a solitary radiometer, and the strategy of extraction has been talked about in detail by Yang et al. [5]. Shi et al. [6] contemplated the escalation and development of cyclonic tempests in the Bay of Bengal during the rainstorm season. They inferred that the direction of isotherms in the Bay of Bengal affected the course of movement of tropical tornadoes. Jiang et al. [7] have demonstrated that the tornado moves towards and crosses close to the station having moderately more extreme reduction of geopotential stature up to midtropospheric level, followed by an increment in geopotential stature [8].

Chinet al. [9] detailed the variety of TOC (Total Ozone Segment) previously, during and after when tropical twisters happened in prestorm and postrainstorm periods over the Bay of Bengal and the Arabian Sea. From investigation, it has been reasoned that TOC diminishes consistently previously, and during the development of violent wind and pretty much any expanding pattern, it is trailed by scattering of tornadoes [9]. Gyrard et al. [10] have demonstrated the connection between climate conditions and short-cycling activities by utilizing enormous amount of information gathered from IoT climate sensors. IoT sensors are utilized where there is a wide range of uses [11]. Climate observing and determining are a broadly utilized IoT application zone that can be additionally used in application regions such as traffic checking, farming and nourishment generation, travel arranging, keen urban communities and smart frameworks, public activity, and numerous zones of our everyday lives [12]. Prior methodologies used basic measurable techniques to anticipate, for instance, farming generation utilizing climate information; however, new research utilizes all the huger information arrangements and AI strategies for expectation utilizing climate and with data gathered from IoT sensors [13].

The IoT uses heterogeneous devices for establishing a link with other gadgets and communicates using the Internet [14]. All the gadgets are monitored, for instance, monitoring power usage, radiance organization, and the atmosphere control framework [15]. To get to this point, sensors can be connected in various locations and gathered for useful improvements in predicting hazards.

There are 2 segments in IoT gadgets; sensors and actuators that empower association with the physical world [16]. While the sensor tests and transmits data to the cloud as information input, the actuators receive a direction from the application or AI framework or modified in the edge itself to perform a specific activity in the case of identifying [17] an exemption to control the physical condition, for example, turning on a sprinkler in the recreation center at a specific time for a specific term in the underneath figure [18].

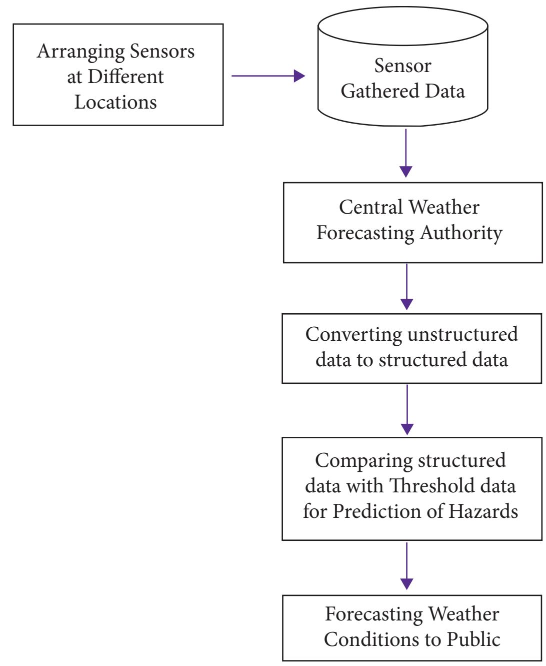

Figure 4: Proposed weather forecasting framework.

3. Proposed Method

An extended IoT framework includes a data collecting layer for collecting data from different location sensors. This layer is not responsible for analyzing data. In the wake of acquiring data, the data verifying layer passes on data to the extract transform load (ETL) layer [19]. The ETL layer analyzes the data and sends it to the sensor data description model (SDDM). The SDDM is used for prediction and forecasting [20].

The model uses a SQL database as a lot of information is gathered continuously from sensors. The proposed model is depicted in Figure 4.

Let sensors arranged in different locations of the city be $S_1, S_2, \ldots S_n$. Each sensor has to gather temperature, vibrations, wind direction, humidity levels, heat levels, pressure in water at sea, and so on. The sensors gathered data as

$$S\left(D_{(1\,.\,N)}\right) = S^{D}_{h,w,v,t,ht,p} * D^{\theta} \tag{1}$$

where D is the data and θ is the range of the values.

In the proposed model, the data verifying layer, sensor data, and threshold data are considered by methods for mass stacking strategy. By then, the picked-up data are honestly moved to the ETL layer for analysis [21]. Here, sensor data and recognition data are parsed with standard articulation, all features with their characteristics are accumulated by their time length, and a sorted-out file is made for further use [22]. The conceptual structure of the IoT model is depicted in Figure 5.

Datasets contain two sensor files that include linked sensor data and linked observation data. A variety of sensors are used to monitor weather and climate conditions such as temperature and humidity, wind speed, moisture, light intensity, UV radiation, and carbon monoxide levels in the air. Using these sensors, data are sent to a web page, where it is plotted as graphical statistics [23]. Also, every sensor file contains various bits of rundown of capacities. Associated sensor data are used to get sensor region, altitude, extension, and longitude. Linked observation data are used for procuring discernment data such as heat, wetness, temperature at sea levels, wind posture, wind impact, wind speed, and detectable quality [24].

sens-obs: point_3CLO3 a wgs84: Point:

wgs84: alt ″20″ˆxsd: float:

wgs84: alt ″46.22″ˆxsd: float;

wgs84: long ″-124.00″ˆxsd: float.

The pseudocode format is specified here.

(1) Consider the sample weather datasets where $N = \{L1, L2, \ldots LN\}$ where L1 to LN are the location weather representing variables.
(2) Initialize the parameters
(3) For
(4) Gather the data using sensors from different locations of smart cities.
(5) Perform probability estimation among the locations and sensors for deep weather analysis
(6) Calculate the error function at every location mode
(7) Identify the parameter set
(8) Perform weather status update
(9) If the error is less than threshold
(10) Update
(11) Else

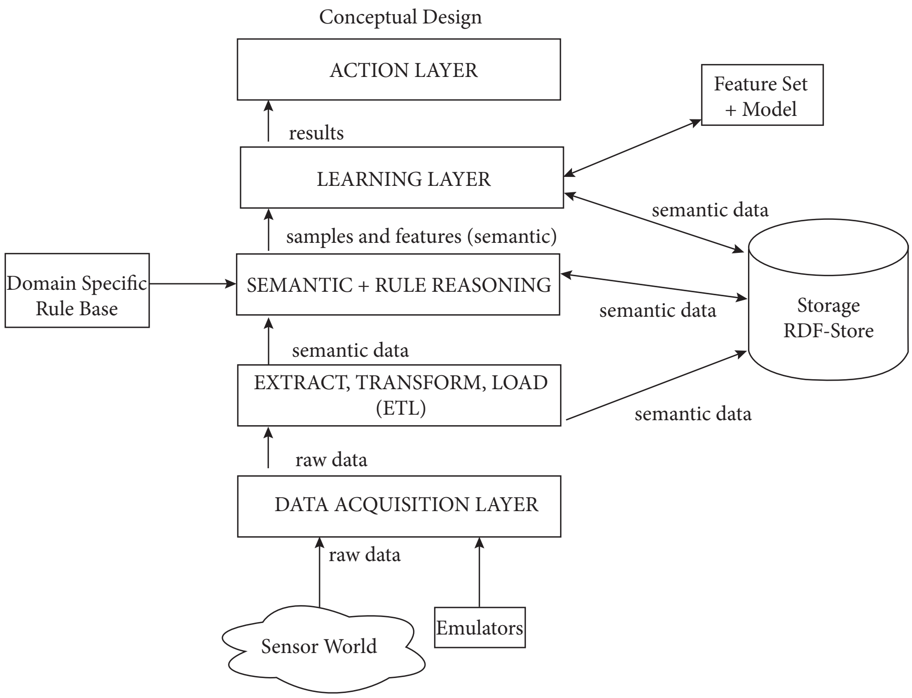

Figure 5: Conceptual structure of the IoT system.

(12) Go to step 3

(13) End

(14) End

The sensor data are inserted into the file as

$$\mathbf{P}(d_i|\boldsymbol{\theta}) = \sum_{j=1}^{|\mathbf{c}|} P(c_i|\theta)P(d_i|c_i;\theta). \quad (2)$$

Here, P is the probability of information being collected from dataset d and having a range θ. C is the cluster set generated from sensor data.

Sensor name, elevation, scope, and longitude esteems can be acquired effectively from this RDF documentation. Similarly, linked observation data utilize a similar documentation:

sens-obs:

MeasureData_WindSpeed_3CLO32005823_172000.

a om-owl: MeasureData;

om-owl: floatValue ″300.0″ˆxsd:float;

om-owl: Uom weather: degrees.

After forming a file having sensor gathered data and using IoT gadgets, the data are communicated to the central authority for analysis. The data at the central authority needs to be arranged in a structured order [25]. The probability estimations of weather hazards are calculated as

$$\boldsymbol{\theta}_{\mathbf{w_k}|\mathbf{c_j}} = \frac{1 + \sum_{\mathbf{i}=1}^{|\mathbf{v}|} N(w_k, d_i)P(c_j|d_i)}{|v| + \sum_{k=1}^{|\mathbf{v}|}\sum_{\mathbf{i}=1}^{|\mathbf{D}|} N(w_k, d_i)P(c_j|d_i)} + \ldots \quad (3)$$

Here, θ is the range of the values, and N is the hazard type such as rain, earthquake, and thunder. W is the weight of each value gathered by sensors from different locations of the city.

Each and every other component uses the same documentation. In this way, it might be considered adequately by RegEx that is used for parsing of data. During the learning stage, hidden data can be evacuated to get extra information [26]. The IoT framework model is depicted in Figure 6.

In our methodology, we utilized the expectation-maximization method to perform clustering of sensor data.

The level of the weather hazards and the distance range are calculated by the forecasting authority as

$$\mathbf{d}(\vec{\mathbf{x}}, \vec{\mathbf{y}}) = \sqrt{\sum_{n=1}^{\mathbf{N}} (x_n - y_n)^2} \quad (4)$$

Here, x and y are the starting parameters of the values gathered in one location from the sensor group.

The data are arranged in a structural format that is represented as

$$\begin{bmatrix} \mathbf{S}(1) & \mathbf{C}(0) & \mathbf{W}(0) \\ \mathbf{S}(2) & \mathbf{C}(1) & \mathbf{W}(1) \\ \vdots & \vdots & \vdots \\ \mathbf{S}(\mathbf{m}) & \mathbf{C}(\mathbf{m}-1) & \mathbf{W}(\mathbf{m}-1) \end{bmatrix} \quad (5)$$

Here, S is the sensor, C is the cluster set, and W is the weight of the values.

The probability set of weather conditions is identified as

$$\mathbf{P}(\mathbf{S}_{1..\mathbf{N}}) = \mathbf{E}\sum_{\mathbf{S}=0}^{\mathbf{N}} \left((\mathbf{x}(\mathbf{k}) - \mathbf{x_{ref}})^2 + \mathbf{u}(\mathbf{k})^2 + \mathbf{P}(\mathbf{k}) \right) \quad (6)$$

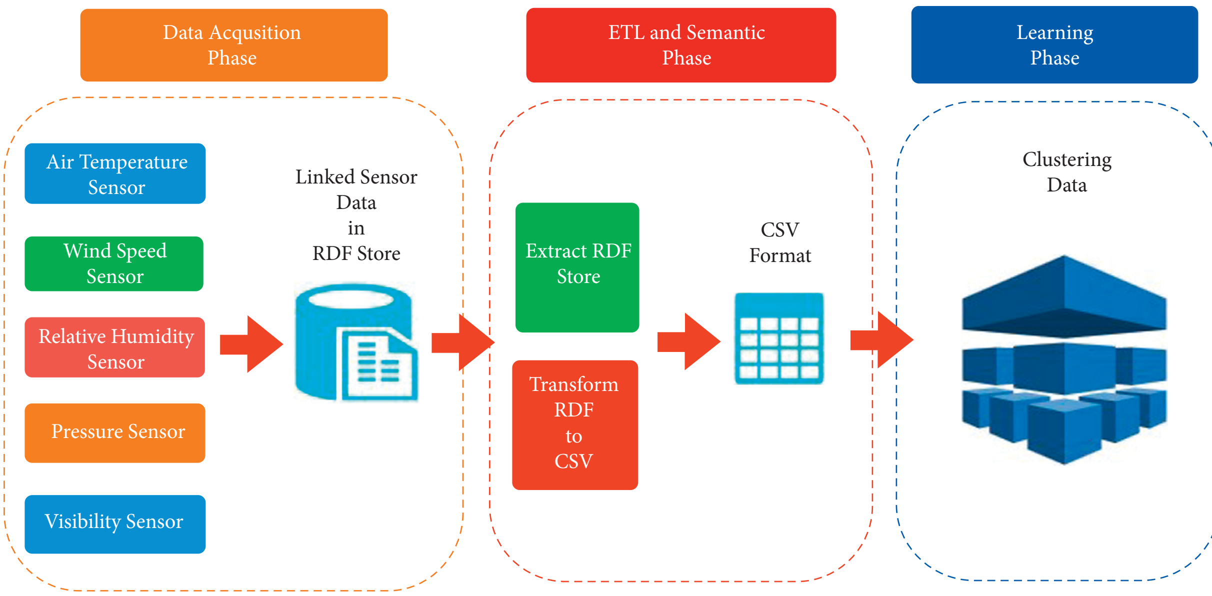

Figure 6: IoT framework model.

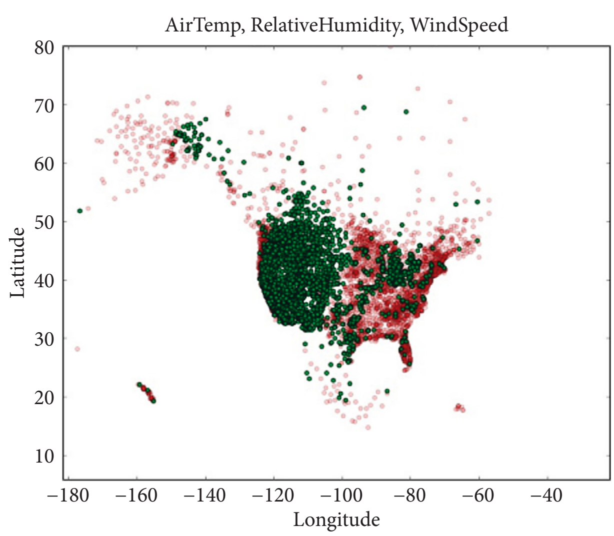

Figure 7: Air temperature, relative humidity, and wind speed cluster set.

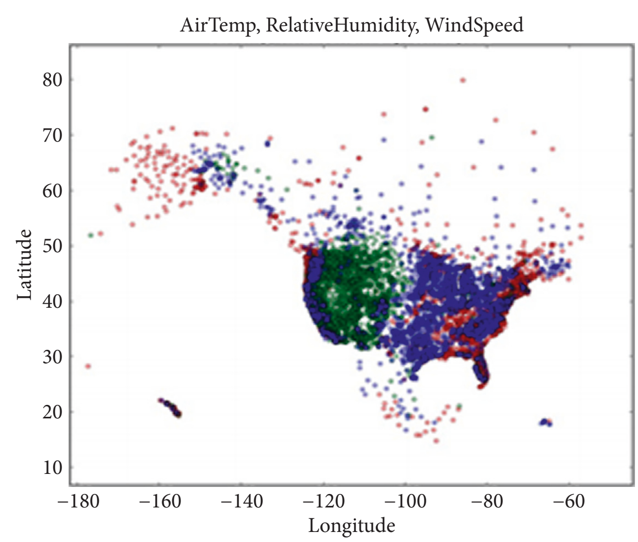

Figure 8: Overall cluster set.

Here, E is the threshold value, and u is the value gathered from the sensor. Based on the prediction set generated, the information is passed to the public with accurate predictions such that necessary actions are taken for saving human lives and reducing property loss during natural calamities.

4. Results

The proposed model is implemented in *Python* using the ANACONDA platform. Information grouping results speak to a straight qualification between the geological locales. The intriguing point is that the model makes right around 2 indistinguishable measured group squares. The sensor data cluster is used for the prediction of weather conditions [27]. The information is geologically isolated similarly as can be seen from Figure 7.

The most distinctive element by all accounts is the relative dampness; as a result, the temperature is generally8 degrees hotter, but the humidity is significantly lower, which improves temperature [28]. Utilizing 2 groups of sensor data, the results are clear. The overall cluster set is depicted in Figure 8.

The temperature levels are calculated by the sensor, and they are analyzed day-wise as indicated in Figure 9.

The cluster information consistency is additionally still flawless. This higher temperature locale, by and large, is pursued in an inclining way. The cluster set with different parameters is depicted in Table 1.

In order to forecast the weather in the future, one must look at the weather patterns of the past. As far as I can tell, it is quite unlikely that this year's weather will be exactly like last year's. It is, however, extremely likely that it will match during the next two weeks of the previous year's calendar

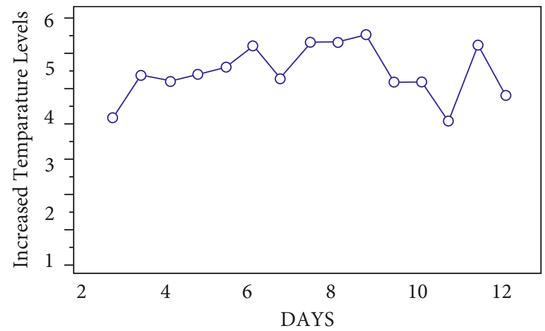

Figure 9: Temperature levels.

Table 1: Sensor gathered information type.

Sensor type	Cluster set	Color of cluster	Centroids average	Max range average	Min range average
Air temperature gathering	C0-Cn	Red Green Bule	85.26	163.0	−50.0
Pressure gathering	C0-Cn	Red Green Bule	74.22	33.0	45.0
Wind speed gathering	C0-Cn	Red Green Bule	64.85	120.0	3.0
Humidity level gathering	C0-Cn	Red Green Bule	74.85	695.0	54.0

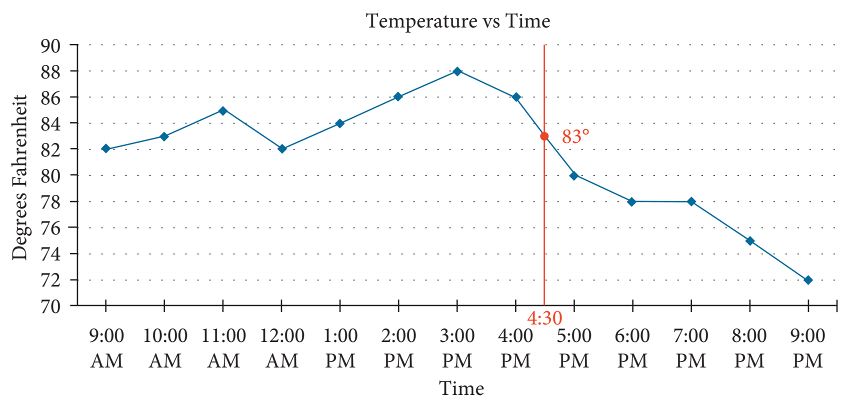

Figure 10: Air temperature clusters.

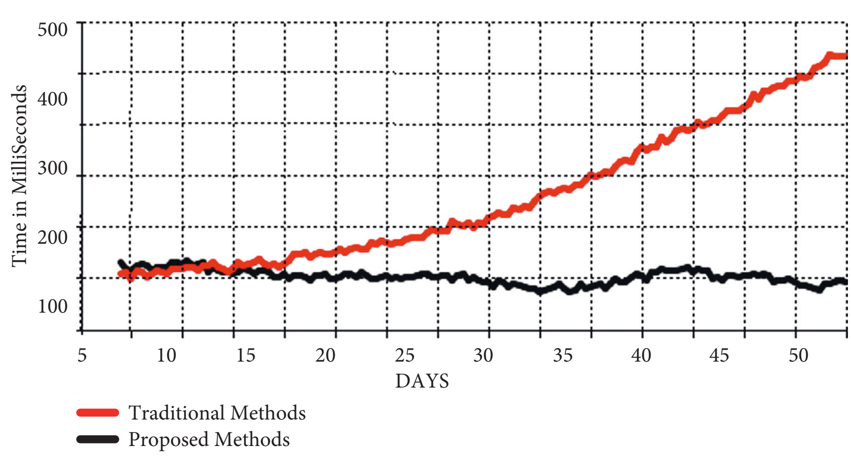

Figure 11: Time for prediction of weather hazards.

[29]. Consequently, a sliding window with a width comparable to a week is chosen for the two weeks considered in the preceding year. The current year's week is then compared to every week of the sliding Table 1 window. The window that is best suited for weather forecasting is designed to do so [30].

Figure 10 shows the air temperature clusters. Utilizing just air temperature as the component for grouping

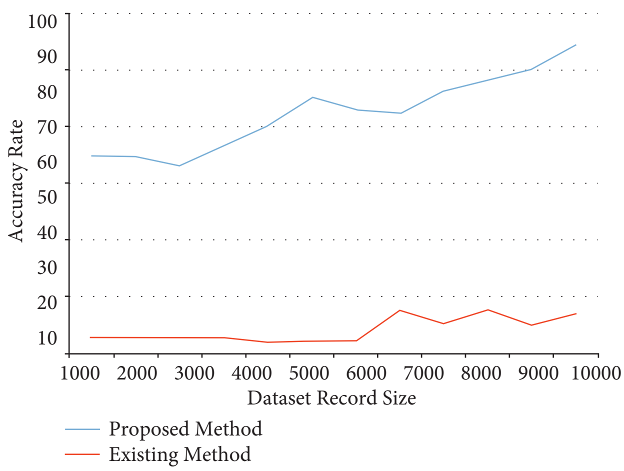

FIGURE 12: Accuracy rate.

brings about an intriguing result on the off chance such that the 2-group case information is considered [19]. Despite the fact that there are a few bunches of other groups of information, everything speaks to a total square. The bunching definitely changes for the 3-group portrayal.

The time for prediction of the weather is less in the proposed method when compared with the traditional method. Figure 11 illustrates the time levels in the identification of weather hazards.

Figure 12 shows the accuracy rate. The accuracy levels of the proposed method are high when contrasted with the traditional methods [20]. The results proved that the proposed method is more accurate in the prediction of hazards [21].

5. Conclusion

Applying IoT advances to the smart urban environment, observation is an amazing choice to gather the required datasets for identifying weather hazards and to discover them prior to saving human lives. By applying IoT advancements, carbon discharges can be reduced by 10–15%, water utilization can be brought down by 20–30%, and solid waste per capita can be reduced by 10–20%. In this proposed work, an all-encompassing IoT framework that coordinates the information recovery, preparation, and learning layers are given a utilization case on the climate information grouping examination. The conventional k-means calculation is connected, and the outcomes are exhibited. In the proposed work, the information grouping matches the geological arrangement of the stations. At the end of the day, a portion of the significant areas of climate group information is gathered and effectively separated from one another. Furthermore, conceivable sensor flaws and peculiarities are developed by utilizing the clustering technique. This utilization case enabled us to exhibit a case of how such an IoT framework can be utilized for such executions. The proposed work identifies the weather conditions and identifies the hazards that save human lives and properties by reducing loss. Future works intends to add more meteorological conditions into its forecasts and use a different categorization system to improve its accuracy.

Data Availability

The data used to support the conclusions of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

References

[1] Z. Wang, W. Wang, C. Liu, Z. Wang, and Y. Hou, "Probabilistic forecast for multiple wind farms based on regular vine copulas," *IEEE Transactions on Power Systems*, vol. 33, no. 1, pp. 578–589, 2018.

[2] C. Wan, J. Lin, J. Wang, Y. Song, and Z. Y. Dong, "Direct quantile regression for nonparametric probabilistic forecasting of wind power generation," *IEEE Transactions on Power Systems*, vol. 32, no. 4, pp. 2767–2778, 2017.

[3] D. Ke, C. Y. Chung, and Y. Sun, "A novel probabilistic optimal power flow model with uncertain wind power generation described by customized Gaussian mixture model," *IEEE Transactions on Sustainable Energy*, vol. 7, no. 1, pp. 200–212, 2016.

[4] J. R. Andrade and R. J. Bessa, "Improving renewable energy forecasting with a grid of numerical weather predictions," *IEEE Transactions on Sustainable Energy*, vol. 8, no. 4, pp. 1571–1580, 2017.

[5] M. Yang, Y. Lin, and X. Han, "Probabilistic wind generation forecast based on sparse bayesian classification and dempster–shafer theory," *IEEE Transactions on Industry Applications*, vol. 52, no. 3, pp. 1998–2005, 2016.

[6] E. Shi, L. I. Qian, G. U. Daquan, and Z. Zhao, "Weather Radar echo Extrapolation Method Based on Convolutional Neural networks," *Journal of Computer Applications*, vol. 10704, pp. 16–28, 2018.

[7] M. Jiang, M. Cui, and Dangyue, "Application of Radar combined Reflectance in precipitation data quality Control," (in Chinese).

[8] *Observation Technology and its Application in the 32nd Annual Meeting of China Meteorological Society*, 2015.

[9] J. Chin, V. Callaghan, and I. Lam, "Understanding and personalizing smart city services using machine learning, the internet-of-things and big data," in *Proceedings of the 2017 IEEE 26th International Symposium on Industrial Electronics (ISIE)*, pp. 2050–2055, IEEE, Edinburgh, UK, June 2017.

[10] A. Gyrard, P. Patel, A. Sheth, and M. Serrano, "Building the Web of Knowledge with Smart IoT Applications," *IEEE Intelligent Systems*, vol. 31, pp. 83–88, 2016.

[11] L. Natrayan, P. S. Sundaram, and J. Elumalai, "Analyzing the Uterine physiological with MMG Signals using SVM," *International journal of pharmaceutical research*, vol. 11, no. 2, pp. 165–170, 2019.

[12] M. A. Hayes and M. A. Capretz, "Contextual anomaly detection in big sensor data," in *Proceedings of the 2014 IEEE International Congress on Big Data*, pp. 64–71, IEEE, Anchorage, AK, USA, June 2014.

[13] K. Nagarajan, A. Rajagopalan, S. Angalaeswari, L. Natrayan, and W. D. Mammo, "Combined economic emission dispatch of microgrid with the incorporation of renewable energy sources using improved mayfly optimization algorithm," *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1–22, Article ID 6461690, 2022.

[14] S. S. Institute, *IoT Mind Map-Application Domains*, 2016.

[15] A. sendrayaperumal, S. Mahapatra, S. S. Parida et al., "Energy auditing for efficient planning and implementation in commercial and residential buildings," *Advances in Civil Engineering*, vol. 2021, pp. 1–10, Article ID 1908568, 2021.

[16] L. Liu, D. Liu, Y. Zhang, and Y. Peng, "Effective sensor selection and data anomaly detection for condition monitoring of aircraft engines," *Sensors*, vol. 16, no. 5, p. 623, 2016.

[17] P. Asha, L. Natrayan, B. T. Geetha et al., "IoT enabled environmental toxicology for air pollution monitoring using AI techniques," *Environmental research*, vol. 205, Article ID 112574, 2022.

[18] J. Mineraud, O. Mazhelis, X. Su, and S. Tarkoma, "A gap analysis of Internet-of-Things platforms," *Computer Communications*, vol. 89-90, no. 9, pp. 5–16, 2016.

[19] C. S. S. Anupama, L. Natrayan, E. L. Lydia et al., "Deep learning with backtracking search optimization-based skin lesion diagnosis model," *Computers, Materials & Continua*, vol. 70, no. 1, pp. 1297–1313, 2021.

[20] C. Perera, C. H. Liu, and S. Jayawardena, "The emerging internet of things marketplace from an industrial perspective: a survey," *IEEE Transactions on Emerging Topics in Computing*, vol. 3, no. 4, pp. 585–598, 2015.

[21] S. Magesh, V. R. Niveditha, P. S. Rajakumar, S. Radha RamMohan, and L. Natrayan, "Pervasive computing in the context of COVID-19 prediction with AI-based algorithms," *International Journal of Pervasive Computing and Communications*, vol. 16, no. 5, pp. 477–487, 2020.

[22] R. Anandan, S. Phani Kumar, K. Kalaivani, and P. Swaminathan, "A survey on big data analytics for enhanced security on cloud," *International Journal of Engineering & Technology*, vol. 7, no. 21, pp. 331–334, 2018.

[23] G. Kanimozhi, L. Natrayan, S. Angalaeswari, and P. Paramasivam, "An effective charger for plug-in hybrid electric vehicles (PHEV) with an enhanced PFC rectifier and ZVS-ZCS DC/DC high-frequency converter," *Journal of Advanced Transportation*, vol. 2022, Article ID 7840102, 2022.

[24] M. M. Rathore, A. Ahmad, A. Paul, and S. Rho, "Urban planning and building smart cities based on the internet of things using big data analytics," *Computer Networks*, vol. 101, pp. 63–80, 2016.

[25] K. R. Vaishali, S. R. Rammohan, L. Natrayan, D. Usha, and V. R. Niveditha, "Guided container selection for data streaming through neural learning in cloud," *International Journal of System Assurance Engineering and Management*, vol. 16, pp. 1–7, 2021.

[26] O. B. Sezer, E. Dogdu, M. Ozbayoglu, and A. Onal, "An extended iot framework with semantics, big data, and analytics," in *Proceedings of the 2016 IEEE International Conference on Big Data*, pp. 1849–1856, IEEE, Washington, DC, USA, December 2016.

[27] S. S. Sundaram, N. Basker, and L. Natrayan, "Smart clothes with bio-sensors for ECG monitoring," *International Journal of Innovative Technology and Exploring Engineering*, vol. 8, no. 4, pp. 298–301, 2019.

[28] M. M. Rathore, A. Ahmad, A. Paul, and S. Rho, "Urban planning and building smart cities based on the Internet of Things using Big Data analytics," *Computer Networks*, vol. 101, pp. 63–80, 2016.

[29] A. Botta, W. de Donato, V. Persico, and A. Pescapé, "Integration of cloud computing and internet of things: a survey," *Future Generation Computer Systems*, vol. 56, pp. 684–700, 2016.

[30] D. K. Jain, S. K. S. Tyagi, S. Neelakandan, M. Prakash, and L. Natrayan, "Metaheuristic optimization-based resource allocation technique for cybertwin-driven 6G on IoE environment," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 7, pp. 4884–4892, 2022.