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ORIGINAL ARTICLE

EFFECTIVE WEATHER PREDICTION FRAMEWORK FROM IOT SENSOR THROUGH MACHINE LEARNING

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Abstract

Precise weather forecasting is required in applications like agriculture, disaster management, intelligent cities, and in the planning of renewable energy. The mass use of Internet of Things (IoT) sensors has facilitated continuous acquisition of fine-grained meteorological data, which has presented novel chances of offering localized and real-time weather forecasting. Nevertheless, the conventional forecasting tools and standard statistical models are not always effective in taking advantage of heterogeneous data provided by the IoT because of noise, data sparsity and insufficient flexibility to adapt to the changing environmental factors. In a bid to overcome these issues, this paper will come up with a capable weather forecasting system, which combines IoT-based sensing and sophisticated machine learning algorithms. The framework involves systematic collection of data, strong preprocessing in order to deal with missing and noisy sensor values and intelligent feature learning to represent multidimensional nonlinear projections of weather variables. The main goal is to enhance the accuracy, scalability, and reliability of short-term weather forecasting. The outcomes of experiments show that the suggested approach has a high-predictive performance in contrast to the baseline models that generate correct and timely weather forecasts. In general, the framework mentions the possibility of utilizing IOT sensor networks together with machine learning to create effective data-driven weather prediction systems applicable to the real-world implementation.

Keywords: *big data; clustering; complex dataset; internet of things; machine learning*

1. Introduction

Two- or one-day forecasts are known as short-range weather reports. On these durations, one would wonder on the rate of arrival of a cold front or the formation and movement of certain thunderstorm formations. It is an intricate issue as such cloud platforms require extremely high levels of simulation using horizontally spaced geographical units of the order of 1 km [1-3]. This inevitably leads to short-range estimation methods being regionally based as opposed to a global approach to be available at processing capacities. These turbulent cloud structures are often a feature of updrafts which are too small to be adequately resolved, even at a lattice scale of 1 km and their development is highly reliant on the deposition of precipitation [4]. It is still problematic to model on these period and space scales. These have likely brought the largest substantial advances in capacity over the past few decades in medium-range projection, over time spans of a few days to a few weeks. The most characteristic event of the medium-range time scale is the baroclinic waves, and systems of numerically forecasting weather processes globally with grid time scales of the order of ten km are very good at unravelling its characteristic features [5]. Proper measurement of such durations in 20 years of baroclinic waves is also frequently possible. Sub seasonal prediction takes between 2 weeks and a season. The Madden Julian Oscillation is one of the major predictors in this timescale. This equatorially-constrained oscillation of the tropical winds, which has a period of 30 to 80 days and propagates eastwards, is related to either enhanced or suppressed structured precipitation [6-7]. This timeframe attracts a great deal of attention in recent times with the launch of the Sub seasonal to Seasonal Prediction Experiment. S2S projections of tactical and academic simulations are included in many large datasets tied to this program that can be helpful in the case of possible ML requests [8]. The related processes of the atmosphere and the ocean are essential to annual predictions, and the El Nino phenomenon in the Pacific Ocean equator is a classical example [9]. Connected ocean-atmospheric systems show expertise in El Nino prediction on seasonal time intervals. A frequency like this requires simulations to use grid distances of several tens of kilometers. Moreover, climate change forecasting deals with the development of meteorological data over the years and several years when the quantity of greenhouse gases in the atmosphere increases [10]. Once again in these time scales, the simulation techniques reveal quite high biases, the magnitudes of which are equally comparable to the climate change sign they forecast [11]. Suggestions of now-casting appear to be an appropriate starting point of Tough AI. Technical constraints such as conservation regulations can be ignored on such times as faults will not accumulate into a lot within just a few days. The information provided regarding the IoT is becoming more readily available and utilized in weather predictions, including in the format of cell phone information [12]. The integration of such information based on the standard approaches will be very complicated because of the many observations and the huge inaccuracies.

The introduction of the Internet of Things (IoT) has rapidly facilitated mass usage of cheap sensors that can constantly measure the environmental conditions including temperature level, humidity, atmospheric pressure, speed of wind, and rainfall. These IoT sensors produce real-time and high-frequency data that offers precious information about the changing weather conditions. Conventional weather forecasting systems have mostly depended on satellite images and numerical weather prediction models that tend to have large computational software requirements and fails to get localized microclimatic variations. Consequently, there is an increasing demand of smart and data-driven weather prediction systems capable of effectively using IoT sensor data to enhance the accuracy of the forecast at both the local and regional levels. Machine learning (ML) technologies have become highly effective at processing a large amount of diverse IoT data and finding complex nonlinear correlations between weather variables. In contrast to traditional statistical models, ML algorithms have the capability to adaptively aggregate patterns in past and real time sensor data, hence suitable to short-term and medium-term weather forecasting. Nevertheless, some of the current ML-based weather prediction methods have several weaknesses, including sensor readings that are noisy, missing data, scalability, and poor generalizability to different geographical areas. All these problems may severely harm prediction and reduce the feasibility of IoT-based forecasting systems. To address these issues, a good weather prediction framework should be developed that incorporates powerful data acquisition technology in IoT, clever preprocessing, and machine learning models optimization. A structure of this nature must provide robust data integration among distributed sensors, unpredictability and variability of environmental data, and provision of precise and timely weather forecasts. Thanks to the use of sophisticated ML technologies in a scalable and organized system, IoT-based weather prediction can be used to serve the important needs of smart agriculture, disaster management, renewable energy management, and smart urban infrastructure and ultimately lead to better decision-making and climate resilience.

2. Related Works

One of the primary issues that Hard AI has to cope with over the short and medium-term period is the lack of a high-quality training example [13]. Training systems to execute machine learning based on traditional methods may enhance the performance of high-performance computation. However, the precision of the predictions was not possible to be enhanced [14]. Predictive improvements are feasible should the system information be generated at a higher spatial resolution than the current system capability to execute within an active forecasting time frame, but the computational power required to generate such a trained model would have been large. Although there are several IoT platforms and applications that have been developed, challenges and capabilities that are required in this industry still exist. Such problems may include implementation of learning algorithms, gathering of huge data sets, and compatibility, among others, and may be solved [15]. The compatibility problem is solved with the help of Semantic Web technologies, such as the representation of data in the Resource Description System, Web Ontology Language standard, and the common data representation, such as Turtle, N3, and JSON-LD [16]. Literary also produces standardized terminologies of presenting information which are used to aid semantics. The semantic sensor network ontology has been developed to explain things and interactions that result in better accessibility rates [17]. Internet of Items ontologies are being studied and proposed to define and describe sensors, sensor features, and sensor results. Also, extended SSN Ontologies are used in numerous IOT Functional areas [18]. Machine learning techniques are well used in Iot networks. Most systems have elementary administration capacity. However, Iot systems can be made smarter with the help of machine learning algorithms [19]. These techniques can be of three main types reinforcement learning, unsupervised learning and a combination of the two. In case the information is labelled, a supervised learning may serve as a method of instruction. Another learning model which does not need labelled training data is unsupervised learning. Unsupervised learning methods are employed to cluster the information. Unsupervised learning methods have the advantage of grouping as far as the anomaly detection is concerned. Unsupervised learning methods that have been applied include K-means, fuzzy clustering, and DBSCAN. Unsupervised learning techniques can easily be used to solve sensor problem and outlier detection in the IoT paradigm. The third type of instructional strategies is reinforcement learning which is used in games, simulation-based controls, and other applications. It has a feedback channel to improve the performance of the model.

A number of studies have examined the application of IoT sensor networks in weather monitoring and prediction and have found that they can be able to capture fine-grained environmental variations. The initial IoT-based weather systems were mainly concerned with real-time data collection and visualization, and sensor nodes were used to determine temperature, humidity, pressure, and rainfall levels. These systems were used to prove the practicability of inexpensive, localized weather surveying, but this was at the cost of forecasting by threshold-based or statistical methods, which constrained their capacity to forecast and adjust to evolving climatic environments. As the amount of data expanded, machine learning methods started to take the key role in the predictions of weather driven by the IoT. The linear regression, support vector machines (SVM), decision trees, as well as the random forest models have been used by researchers to predict weather parameters based on historical sensor measurements. These methods performed better than the classical methods especially in short term forecasting. They were however frequently effective when a meticulous feature engineering was performed and they were not useful when complex temporal dependencies that are inherent in weather data are involved. To represent dynamics with time, various works used the time-series models and neural networks, such as the Artificial Neural Networks (ANNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks. These models were found to be better at sequential patterns on the streams of IoT sensors resulting in better prediction of temperature, rain and humidity. Although they have been successful, these deep learning methods can need huge labeled data sets and are computationally expensive, which means they are difficult to be deployed in real-time to resource-constrained IoT systems. Recent works examined hybrid and ensemble learning models to increase the strength of prediction and generalization. These methods can reduce noise and support lost sensor data and sensor faults by aggregating a number of ML models together, or by comparing signal processing methods with learning algorithms. Although hybrid models provide better accuracy, most of the existing solutions do not have a standardized structure of data preprocessing, model selection, and evaluation, which provide discrepancies in reported performance across datasets and environments. Also, current studies have concentrated on scalable, cloud-enabled and edge-based architectures of IoT-based weather prediction. Such frameworks use edge computing to do pre-processing data filtering and feature extraction, and cloud-based ML models are doing more intricate analytics and long-term forecasting. Though these architectures enhance the latency, scalability, the issues of data synchronization, model interpretability, and flexibility to different climatic areas are still open. There is therefore an obvious need to have a favorable and well-integrated weather prediction system that incorporates IoT sensors with streamlined machine learning solutions delivering precise, scalable and reliable prediction.

3. Proposed System

In this study, the analysis of gathered meteorological data is completed with the help of the following methods. Connected Sensor Technologies and Connected Observations Information are collected through bulk uploading method in the level of data processing. The information gathered is then instantly forwarded to ETL level where further operations are done. The regular expressions are used to process sensor information and observational statistical measures by the ETL level as illustrated in Figure 1. Once the file is created, Node server invokes a Python script that is specific to the clustering. Python programs are executed through the Python-shell. The Dataset production stage will change as the production continues. The item of data holding the results of the processing will be directly transmitted to the program rather than created in the form of a CSV.

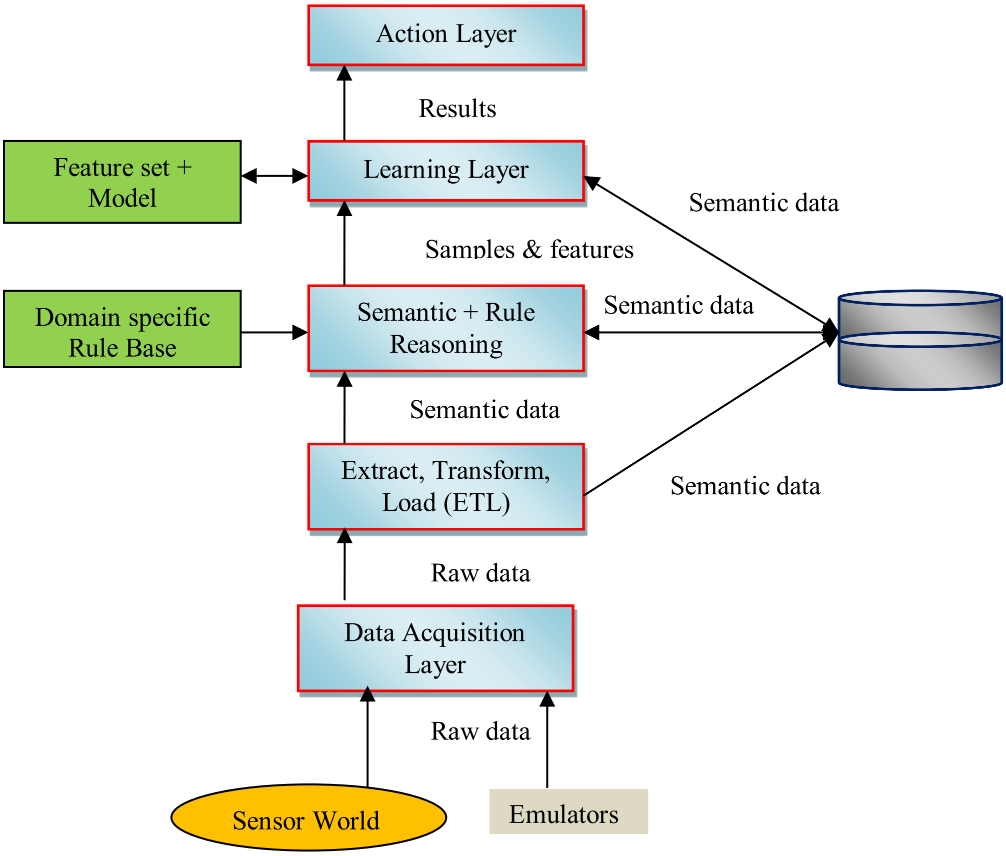

Figure 1: IoT conceptual framework

3.1 Dataset descriptions

The data utilized in this paper is gathered on an IoT sensor network that is distributed to provide twenty-four-hour weather observation. All sensor nodes are capable of reading important environment parameters, such as temperature, humidity, atmospheric pressure, wind speed, wind direction, rainfall, and solar radiation at constant intervals of time as indicated in Table 1. All these attributes are used to model the atmospheric and surface conditions and allow the short-term and local weather patterns to be modeled with accuracy. Each record is accompanied by meteorological measurements, a timestamp and a location identifier in order to maintain a temporal continuity and spatial context across several locations of sensing. Raw sensor readings are preprocessed to remove noise, missing values and outliers that are normally caused by sensor faults or environmental interference in order to provide data that is reliable. To line up the data streams sampled at varying rates, temporal alignment is used whereas the scale of the number features are brought to the same level so that the machine learning models can be trained effectively by using the normalization techniques. Supervised learning is based on the target variable obtained by way of observed trends or labeled historical records and is used to represent weather conditions or the forecasted variables.

The constructed and carefully maintained dataset can be beneficial in the creation of a successful machine learning-based weather prediction framework, as it allows effective learning of features and generalization. The fact that the model employs various meteorological properties enables it to address complex nonlinear relationships among the weather variables whereas the temporal and spatial tags improve the accuracy of prediction. In general, the data offers a holistic basis of assessing the performance, scaling and reliability of the IoT-based weather prediction models.

Attribute	**Description**	**Unit /**	**Sensor Type**	**Sampling Interval**

Name		**Type**		
Temperature	Measures ambient air temperature	°C	Digital Temperature Sensor	5–10 minutes
Humidity	Measures relative humidity of air	%	Capacitive Humidity Sensor	5–10 minutes
Atmospheric Pressure	Measures air pressure	hPa	Barometric Pressure Sensor	5–10 minutes
Wind Speed	Measures speed of wind flow	m/s	Anemometer	10 minutes
Wind Direction	Indicates wind flow direction	Degrees (°)	Wind Vane Sensor	10 minutes
Rainfall	Measures precipitation level	mm	Rain Gauge Sensor	Event-based / 10 minutes
Solar Radiation	Measures sunlight intensity	W/m^2	Pyranometer	10–15 minutes
Timestamp	Date and time of observation	Date-Time	System Generated	—
Location ID	Identifies sensor deployment location	Categorical	GPS / Static ID	—
Weather Condition (Label)	Target variable for prediction (e.g., Clear, Rainy, Cloudy)	Categorical	Derived	—

Table 1: Dataset description

Timestamp	Location ID	Temperature (°C)	Humidity (%)	Pressure (hPa)	Wind Speed (m/s)	Wind Direction (°)	Rainfall (mm)	Solar Radiation (W/m^2)	Weather Condition
2024-06-01 08:00	LOC-01	28.4	72	1008.5	3.2	180	0.0	520	Clear
2024-06-01 08:10	LOC-01	28.6	71	1008.2	3.5	190	0.0	540	Clear
2024-06-01 08:20	LOC-02	27.9	75	1007.8	2.8	165	0.4	410	Cloudy
2024-06-01 08:30	LOC-02	27.3	78	1007.1	2.4	160	1.2	300	Rainy
2024-06-01 08:40	LOC-03	29.1	68	1009.0	4.1	200	0.0	610	Clear

Table 2: Sample data

Every row of the sample dataset represents one observation of an IoT sensor node at a given time and place. The quantitative inputs of machine learning models are constant meteorological conditions like temperature, humidity, pressure, speed of wind, rain, and solar radiations; categorical ones include the location ID and weather condition illustrated in Table 2. This organized format allows effective preprocessing, feature extraction and machine learning algorithm training of weather predictions that can be accurate and scalable.

3.2 System Model

Figure 2 demonstrates the stages of information collection, ETL and semantic processing, and training. The Linked Sensor Technologies and Linked Data Collected are represented in two distinct n3 documents and they are contained in each data. Moreover, each sensor data possesses distinct set of features. Linked Sensor Information is applied in order to determine the position, height, longitude and meridian of sensors. Linked observation data retrieved is utilized to get the altitude, humidity levels, ambient temperature, relative humidity, prevailing winds, wind burst and wind direction and transparency. The relevant part of the information in a document is extracted through clustering methods since Linked Observation Data comprises of a lot of irrelevant information. The sensor information linked is then analyzed using the data structure and the relocation is saved in task specific map view. Each type of sensor has a subclass structure that will support all the sensor attributes and location services which are saved. Later, in another stage, related observation information is analyzed. In a similar fashion of the first step, the variables of observation are recalled and stored in the said class diagram. N/A stands for not existing features because every sensor data may include a different portion of the extracted features. In summary, translation script is constructed that may build a Dataset and offer sensors results for the chosen timespan, such as 06.00 PM–07.00 PM.

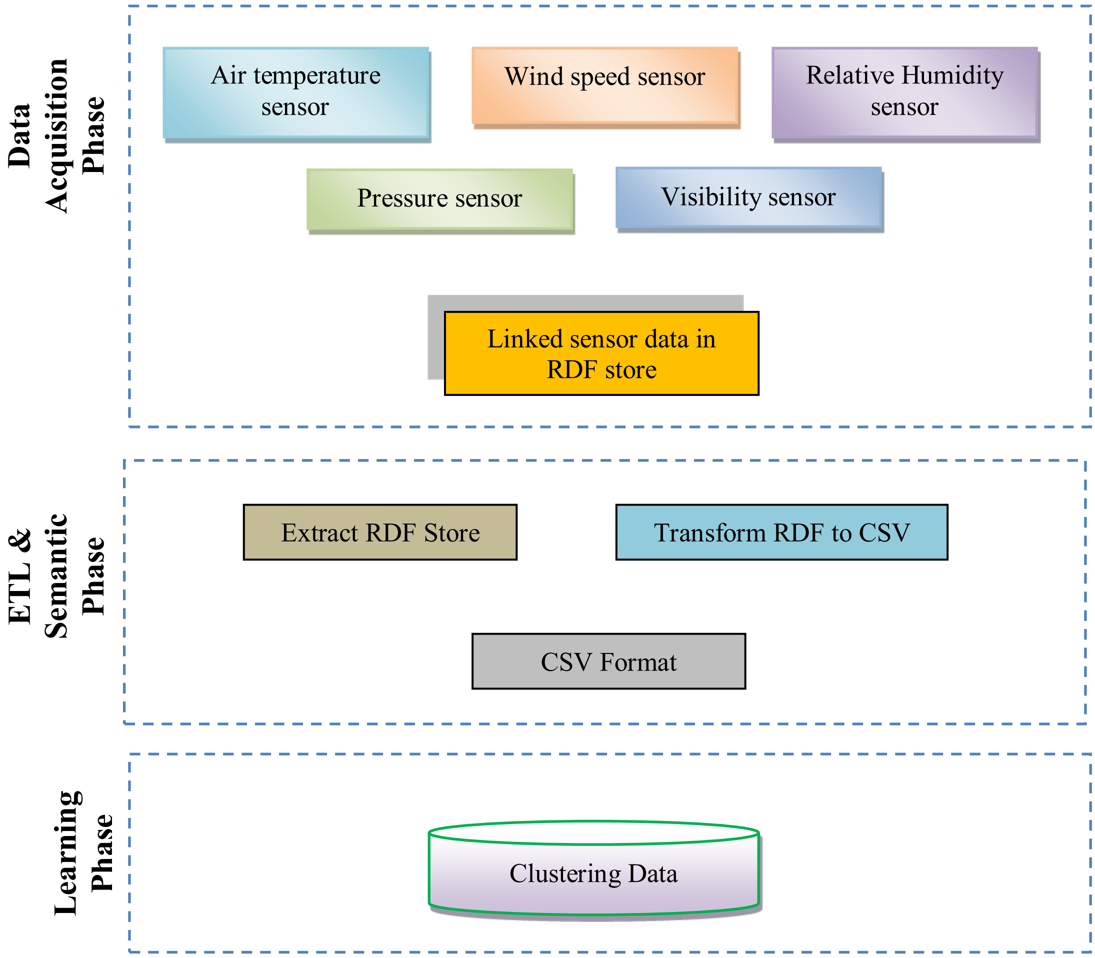

Figure 2: Use-case Scenario framework

It is simple to retrieve the sensor identification, elevation, longitude, and meridian data from this RDF syntax. Identical syntax is employed by Linked Observation Data:

```
sens-obs:
    MeasureData_windSpeed_3CLO32005823_172000
    a om-owl: Measure Data:
    om-owl: float Value “300.0”^^xsd: float:
    om-owl: uom weather: degrees
```

The characteristic description in this case is Measure Data, being recorded on August 23, 2022, at 05:20 PM. It has a 300 grade. The rest of the characteristics can be easily accessed since they share the same syntax with the use of regex, which we employed to do the parsing process. Stated data may be obtained at the learning stage, and methods of machine learning are used to obtain more detailed data. More data has to be obtained in this instance by processing weather sensors. Information is not recognized by the sensors. That is why; to identify the concealed data, we cluster the data. We used the K-Means clustering algorithm to find general trends in the data and sensor errors and anomalies. Plans are planned and algorithms of learning are applied. A generalized recommended supervised learning is presented in algorithm 1.

Algorithm 1: Generalized IoT Framework Algorithm

```
readLinkedObservationDataFileDirectory()
sensorValueList = createSensorValueList()
```

```
foreach(file)
uniqueTimeFrames = findUniqueTimeF1
createSensorValueList
foreach(uniqueTimeFrame)
sensorValueList.add(sensorValue)
createCsvFileFromSensorValueList()
Learning Phase:
dataFrame = pandas.readcsv('file.csv')
table = dataFrame.pivottable(index= ["Name"])
table = table.dropna()
if (numberOfSensorTypes == 1) :
no need to normalize sensor data
elif (numberOfSensorTypes == 2):
tableNormalized = normalize2values(table)
elif (numberOfSensorTypes == 3):
tableNormalized = normalize3values(table)
k= numberOfClusters
cluster sklearn.cluster.KMeans(nclusters = k)
if (numberOfSensor Types == 1):
table["Cluster"] = cluster.fitpredict(table[table.columns[:]])
Evaluation:
EvaluateResults()
```

4. Results and Discussions

We created a data clustering by using the above public data of weather that are freely available. To simplify the findings, we just incorporated 2, 3 and 4 groups. The areas still continued to decrease as we increased above 4 groups hence, we considered 4 as the largest value of k. The specific feature selections of the different grouping possibilities are elaborated on further in the sub categories below. The Himalaya Mountains clearly serve as a wonderful border between the two distinct weather information groups and information grouping outcomes indicate a reasonable division between the geographical regions of south Asia. Interesting is that the model produces group chunks which are practically exactly equal in size. As Figure 3(a) indicates, the information is generally distributed equally all over the world. In opposition to the south part of the Himalaya Mountains, the region further along the coast of the mountain ranges is a few temperatures warmer yet much drier. The closer feature seems to be the humidity level at which the conditions are usually 8 degrees higher in the West but the proportion of moisture is considerably lower and, thus, it can compensate the higher degree. It should also be taken into consideration that the temperature image was captured on August 29, which was one of the hottest days of the whole year.

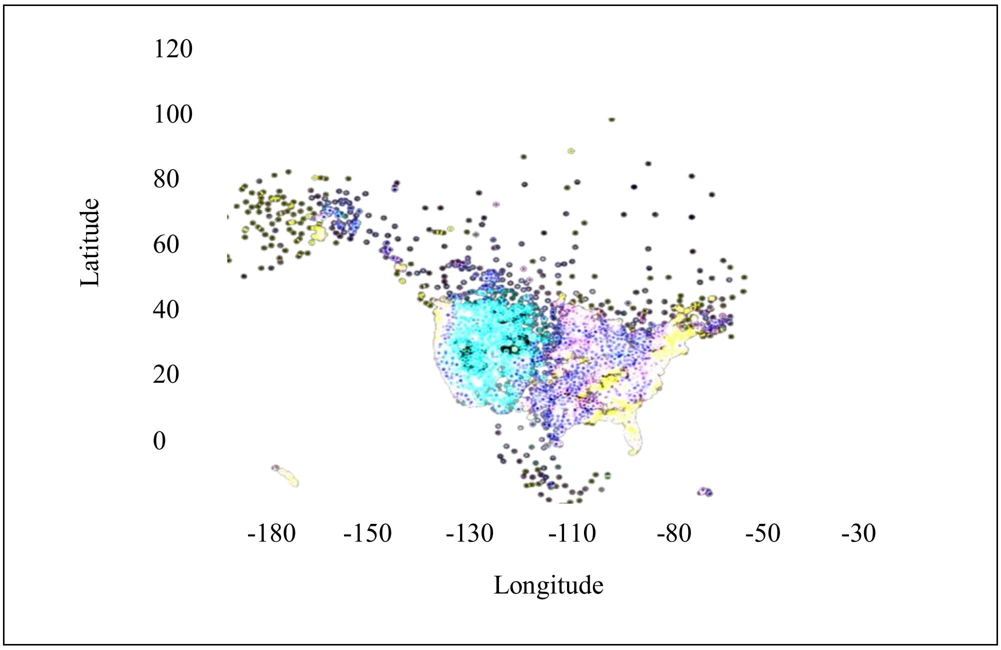

Figure 3 (a). AirTemp, Relative Humidity, WindSpeed 2 Clusters

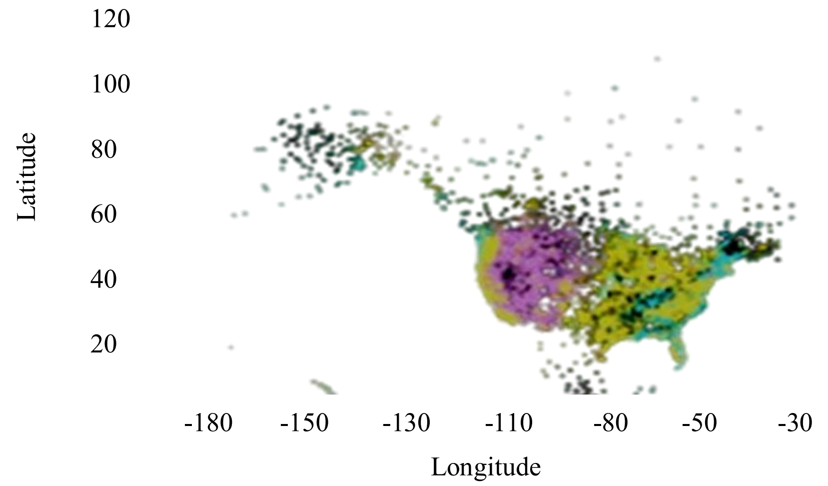

Figure 3(b). AirTemp, Relative Humidity, WindSpeed 3 Clusters

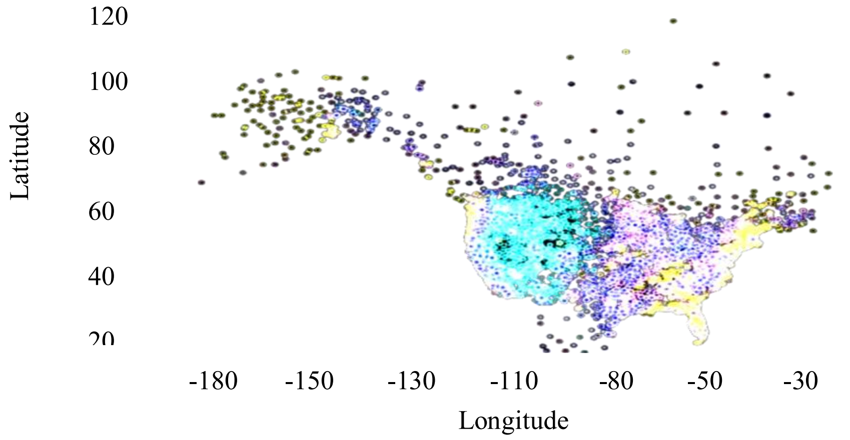

Figure 3(c). AirTemp, Relative Humidity, WindSpeed 4 Clusters

The geometrical difference can be observed with the help of the 2 groups (see Figure 3). In doing three grouping as in Figure 3(b) we also find interesting results, as of eastern and western-coast parts coming into relation, but still the mountainous plains between any Mountains and the western coast comes into view as a separate zone. However, as opposed to the Mountains and the Eastern Coast, the Tibetan Plateau and the Deserts are a transitional zone. The Asia and southeast Himalaya Mountains form a transferable area that can be compared to the Eastern Coast, there are also qualities that are common at the southern Coast that we are aware of. In this event, the transition zone possesses temperature and humidity values that are directly central to the two areas mentioned above and the variation between the degrees and humidity rates is the same as in the case of two clusters. It would again seem that when put in conjunction with the other climate variables wind speed does not have a big contribution. Also worth noting, as it was observed in the case of the two groups, the data distribution across all the groupings is mostly constant.

According to a 4- cluster probe Figure 3(c), no further interesting results are obtained. The results are not much different than the results of the three-group scenario; the southern Mountainous region and the western coast countries remain one segment portion, and the juxtapositions between the internal and coastal regions are also visible in the Figure 4. The homogeneity of the group information is also still present. The analysis of these two variables 2-3-4 cluster is very close to ambient temperature, precipitation and wind direction analysis. This owes to the fact that, humidity levels are the most important aspect of weather information. Aggregation has established geographical regions that share apparent parallels to the three- feature composite example.

Although it would be logical to assume that the geographical areas involved in this evaluation would have been the same as the ones used in the examination of the ambient temperature, moisture, and wind direction, the two sets of results have some notable differences. To begin with, the areas are not evenly distributed as it was in the previous case. Figure 4(b) indicates three cluster investigation which reflects some interesting trends. Though the fact that the results are similar to the 2-cluster example, the group which grew out to the Plain and the Munak Canal (see Figure 4) (a) represents lower temperature center, and the North and west, South-eastern, and Southern Valleys are larger temperature centers around the center. This is comparatively in line with the weather predictions during summers. This region of higher temperatures usually moves diagonally south-westward of Southern Asia via Telangana and to the Waterways. A similar horizontal formation is observable between the Mahanadi River valley on the South to the Arabian Sea.

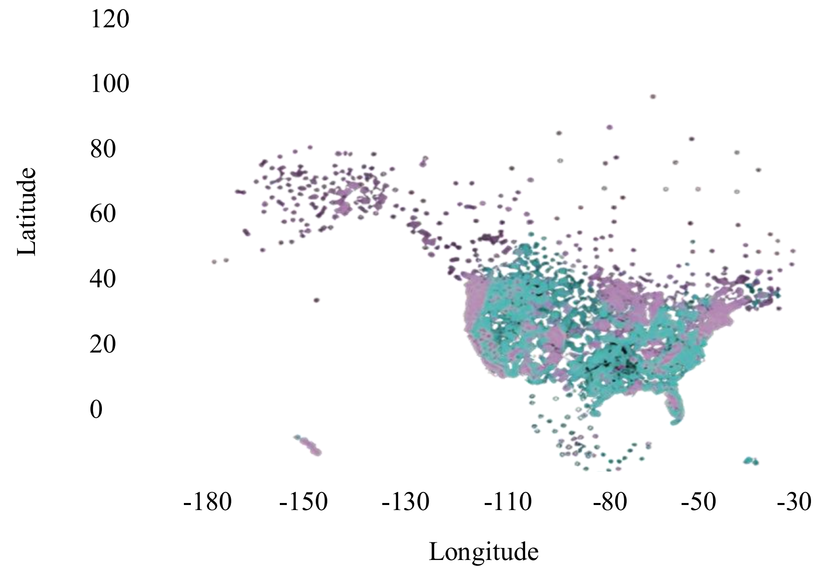

Figure 4(a) Air Temperature Relative Humidity 2 Clusters

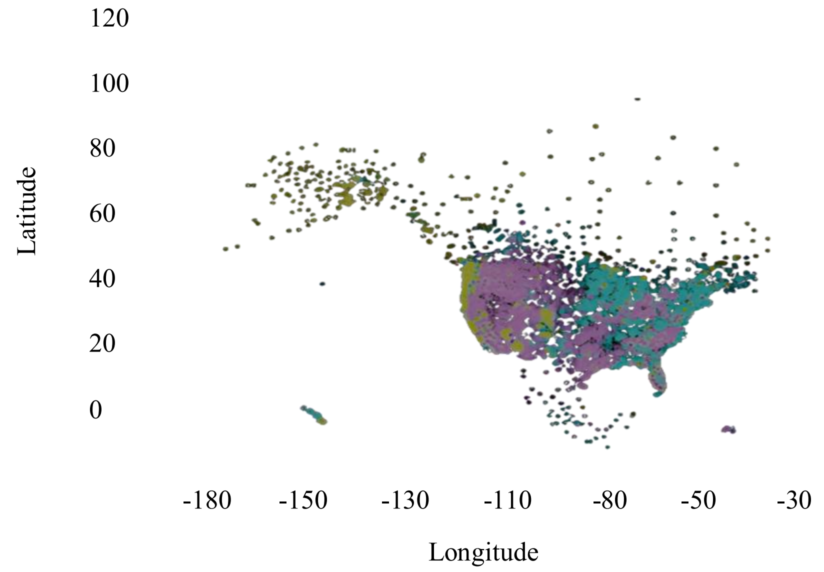

Figure. 4(b). Air Temperature Relative Humidity 3 Clusters

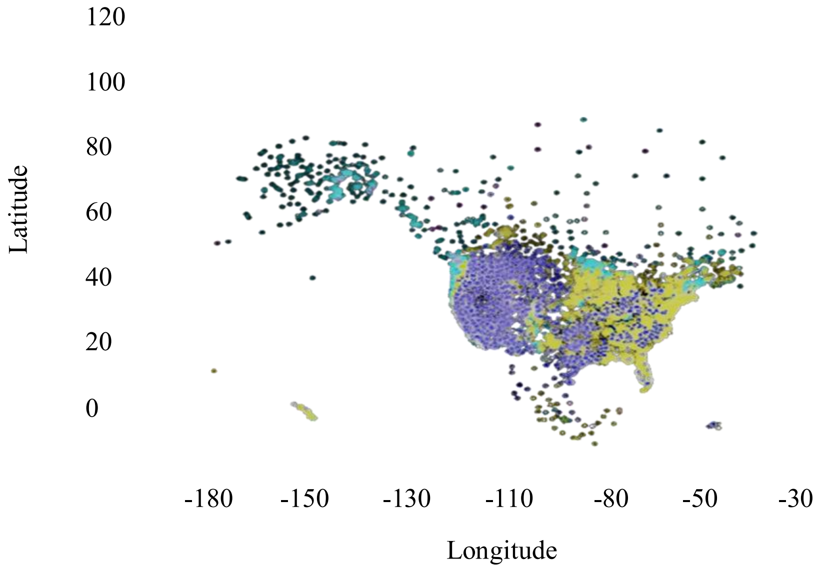

Figure 4(c) Air Temperature Relative Humidity 4 Clusters

Interestingly however, this is not evident when the data is broke into four categories. Figure 4 (c) This result emphasizes the importance of making the right number of clusters in the study. The variations in the 3 and the 4 clustering methods are very remarkable. We can observe that most of the sensor recorded partial data when we read the measured data and thus the analysis of the data became more difficult. The recent findings, though lacking in the information, however, are consistent with the geographical locations formed by the selection of other traits. Figure 5 indicates that there are only two clusters that are needed;

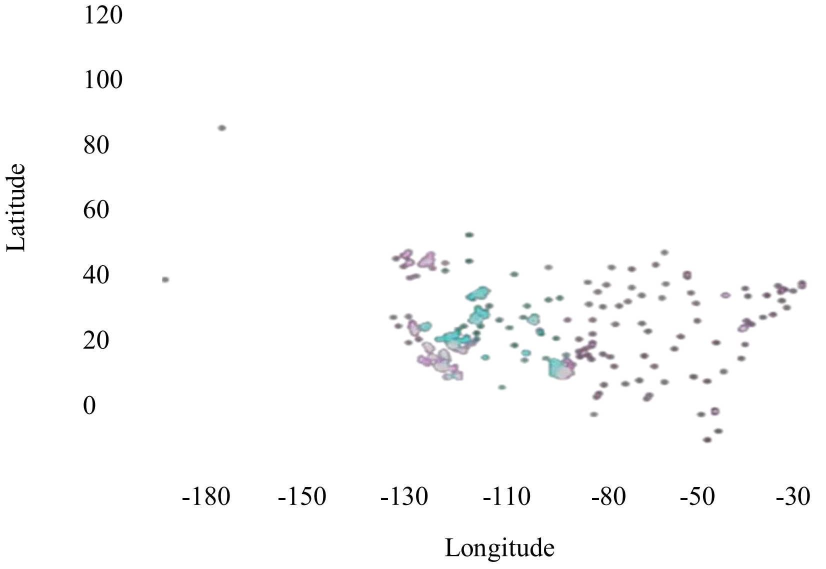

Figure 5: Pressure 2 Clusters

In case we examine the 2-cluster scenario in Figure 6 (a) wherein only air temperature is used as an indicator of grouping; an interesting conclusion is obtained. It divides India geographically in such a manner that it follows the borders between INDIA and Canada. Despite the existence of Fig. In the metropolitan INDIA group, Pressure 2 groups some isolated instances of data of other groups, but remains a whole block. Figure 6 (b) shows a tremendous shift in grouping between three clusters.

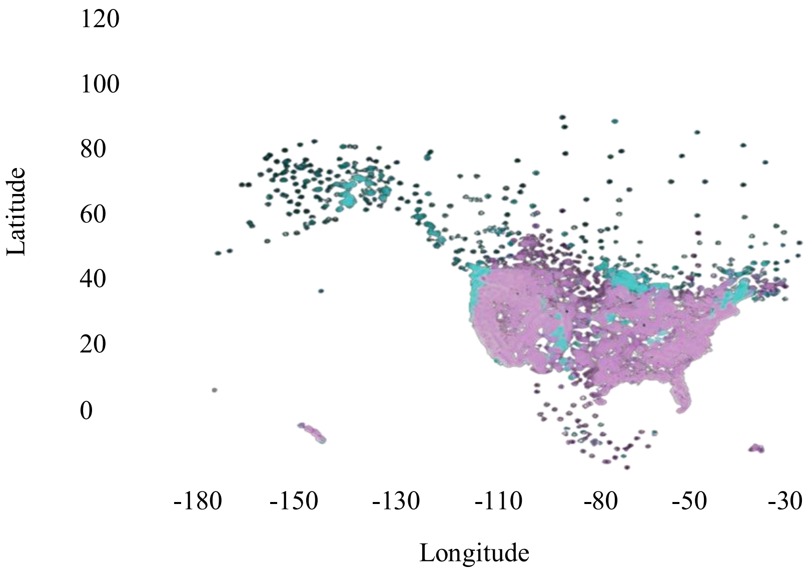

Figure. 6(a) Air Temperature 2 Clusters

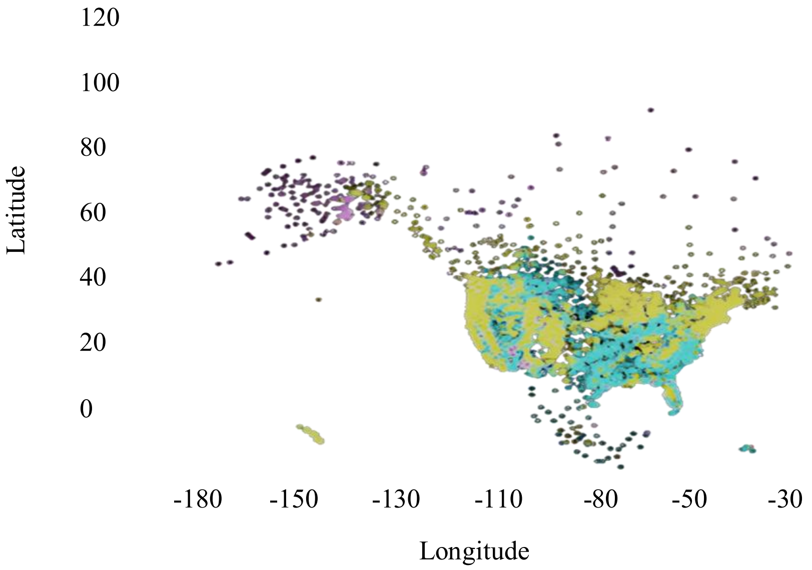

Figure. 6(b) Air Temperature 3 Clusters

Weather information grouping was also used in the case of inaccuracy sensor detection. Although we lost a level of generality, in the cases where we performed clustering analysis on wind direction and humidity levels separately, a number of sensor data outputs differed radically with their immediate surroundings. Consider Figures 7 and 8 to give an instance use case of the detectors that are damaged. In the given case, the faulty sensors are segregated and eliminated out of the other data sets. The number of clusters is mainly used as one of the crucial findings that exist in the case of these defective detectors.

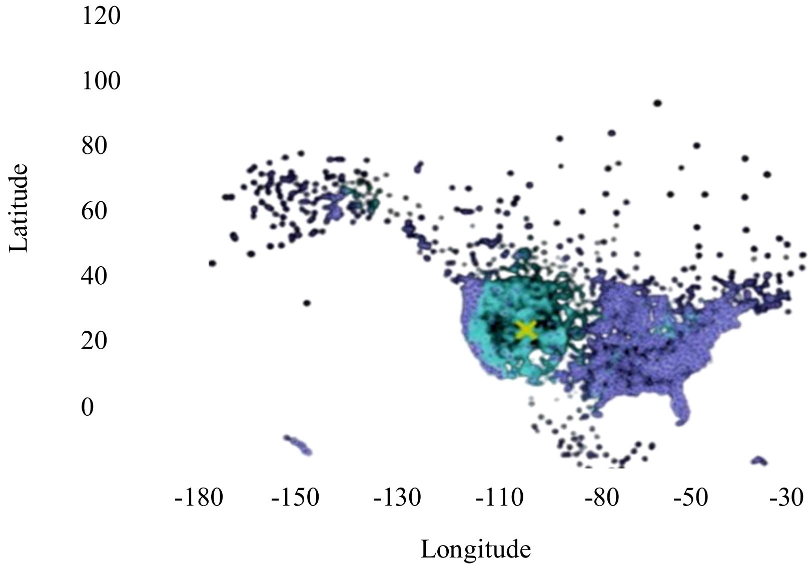

Figure 7: Relative Humidity 3 Clusters, Sensor Fault

Figure 8: Wind Speed 3 Clusters, Sensor Fault

Although we only used the attributes of wind direction and humidity levels to identify anomalies, other characteristics or a combination of factors may be used to identify malfunctioning sensors and anomalous information. To create a more comprehensive framework, additional research may be required.

5. Conclusion

This study explains the improved IoT - based system with an application example on meteorological information clustering algorithm that engages the retrieval of information, analyses, and learning tiers. To maximize the use of the large datasets that are related to this topic, we constructed a learning strategy by using the grouping unsupervised learning strategy when training the strategy. In India Using event logs, weather information which is derived based on 8000 distinct weather station area within India is accessed. This information is collected and analyzed using the Node.js calls. The submissions were done in three wind speed groups, device failure and period of training. Data regarding ambient temperature, wind direction, humidity, transparency and altitude is used in data processing of this particular study. The conventional k-means grouping algorithm is employed and the results are displayed. It is interesting to note that the coherence of the spatial distribution of the stations is represented by the clustering algorithm. To put it in other words, there are a few notable geographical points of the Indian continent which have distinct weather formations which can be easily differentiated. Also, the clustering process indicates possible sensor defects and anomalies. Through this use case, we could prove how the IoT Big Data architecture could be used in such deployments.

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