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Article

Service Oriented R-ANN Knowledge Model for Social Internet of Things

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Abstract: Increase in technologies around the world requires adding intelligence to the objects, and making it a smart object in an environment leads to the Social Internet of Things (SIoT). These social objects are uniquely identifiable, transferable and share information from user-to-objects and objects-to objects through interactions in a smart environment such as smart homes, smart cities and many more applications. SIoT faces certain challenges such as handling of heterogeneous objects, selection of generated data in objects, missing values in data. Therefore, the discovery and communication of meaningful patterns in data are more important for every application. Thus, the analysis of data is essential in smarter decisions and qualifies performance of data for various applications. In a smart environment, social networks of intelligent objects are increasing services and decreasing the relationship in a reliable and efficient way of sharing resources and services. Hence, this work proposed the feature selection method based on proposed semantic rules and established the relationships to classify the services using relationship artificial neural networks (R-ANN). R-ANN is an inversely proportional relationship to the objects based on certain rules and conditions between the objects to objects and users to objects. It provides the service oriented knowledge model to make decisions in the proposed R-ANN model that produces service to the users. The proposed R-ANN provides an accuracy of 89.62% for various services namely weather, air quality, parking, light status, and people presence respectively in the SIoT environment compared to the existing model.

Keywords: SIoT (Social Internet of Things); objects; ANN (Artificial Neural Network); AI (Artificial Intelligence); predictive modeling

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1. Introduction

The Social Internet of Things (SIoT) is a network of interconnected heterogeneous or homogeneous objects with social relationships as in humans. A network of interconnected heterogeneous objects that are uniquely identifiable which provide data transfer ability without the need for human-to-computer or vice-verse is called Internet of Things (IoT) [1–8]. The Social Internet of things (SIoT) is a mapping between social objects and users. The objects and users create a relationship among them based on similar features and characteristics, thus forming a social network. Typically, ten types of object relationships (OR) are identified, namely parent-OR, owner-OR, guardian-OR, social-OR, sibling-OR, guest-OR, service-OR, strange-OR, co-location-OR and co-work-OR. The description of the relationship types are shown in the Table 1 [9].

Every relationship has its own functionality based on the characteristics exhibited by an object in the SIoT environment. All these relationships provide services in a reliable and efficient way while sharing resources and services. For example, IoT objects such as sensors, smart-phones and actuators have distinct features, such as different operating systems, platforms, communication protocols and related standards. Therefore, each device needs to communicate with other devices around it to fulfill the needs of its users. Thus, different objects cooperate effectively and securely to gratify end-users desires to satisfy some main parameters such as reliability, safety, time, cost-effectiveness and availability. Social IoT provides a platform for interconnected objects to establish social relationships possessing common interests and providing better services for users [10].

Table 1. Description of relationship types.

Relationship Types	Definitions
Parent-OR	Objects that belong to the same manufacturer.
Ownert-OR	Objects belonging to the same owner.
Guardiant-OR	Between Child object and parent object association.
Socialt-OR	Closeness between objects either random in time or periodically.
Guestt-OR	Between objects that belong to the users in the guest role.
Siblingt-OR	Objects that belong to a group of friends or family members.
Servicet-OR	Objects coordinating in the same service composition.
Stranget-OR	Objects suddenly disappear in a public environment.
Co-locationt-OR	Objects share information at the same location.
Co-workt-OR	Group of objects shares common work done by them.

Figure 1 shows the sensors and devices such as tablet, fitbit, parking lot, smart watch, air conditioner (AC), traffic lights, laptop, road map, environmental monitoring and car used to generate data. The data are of two categories, namely environment activity and public activity having parameters namely devices, device brand, owner id, distance, protocol, device type, locations, air quality, temperature, pressure, humidity, weather description, people presence, parking location, traffic status and street light status. SIoT faces certain challenges such as handling of heterogeneous objects, the selection of generated data in objects and missing values in data. Therefore, the discovery and communication of meaningful patterns in data are more important in every application. Hence, the goal of this study is service discovery and communication between the objects. In the SIoT environment, data analysis is the harder task with respect to discovering meaningful patterns in data; in particular, analysis relies on both statistics and computer programming and also in quality performance. The goal of data analysis is to obtain actionable insights, making smarter decisions and better outcomes. Therefore, it has different techniques to analyze the large and diverse data such as predictive (forecasting), descriptive (datamining), prescriptive (optimization simulation) and diagnostic analysis. In predictive analysis, valuable, actionable information uses data to determine the probable outcome of an event or a likelihood of a situation occurring. It has a variety of statistical techniques from modeling, machine learning, and data mining techniques that analyze current and historical facts to make predictions about a future event such as linear-regression, time-series and forecasting techniques. In descriptive analysis, this method examines data and analyzes past events for insight as to how to approach future events. These analyses can be made using many techniques such as data queries generation, reports and statistics. Prescriptive analysis automatically synthesizes Big Data, and machine learning(ML) helps in making a prediction. These techniques allow us to predict future outcomes, benefit from the predictions and show the decision. However, there are many techniques for dealing with diagnostic analysis, namely data discovery, data mining and data correlations. Hence, based on these techniques, many objects will be available in the market, such as Google assistant, Amazon's Alexa and Apple's Siri. Similarly, using Web Search assistance such as Cortana, Bing will recommend users' needs based on the history of user data. These assistants that provide some recommendations to users, in the proposed work, attempt to help monitor the user, such as weather information, air quality of environment, traffic information and parking status recommendations [9,11]. According to Cisco, an IoT solution for a smart environment can be described with four general layers, namely street layers, city layers, data center layers and service layers. The street layer includes location sensors, traffic sensors and weather air quality sensors. The city layer includes alarms, communication route, locations and environment details. The data center layer includes protocols and energy of the sensors. In-service layers include public information, parking details, public infrastructure, garbage trucks, neighborhood device details, logistics and many more. Cisco IoT solutions for smart city layers proposed the work on the smart environment to the users objects using SIoT data. However, there exists no specific model that selects features based on the relationship between the devices. Hence, there is a need to propose a model that has to be applied on the data generated by various SIoT applications that help users to make decisions based on the services [12–19]. Thus, the following contribution are made in this work:

- Proposed semantic rule based feature selection method to the existing Artificial Neural Network (ANN) model called Relationship-ANN (R-ANN) for SIoT.
- Defined the ten types of relationships between the devices and evaluated the proposed R-ANN algorithm.
- Proposed service oriented Knowledge model to classify services in SIoT-based smart-city applications.

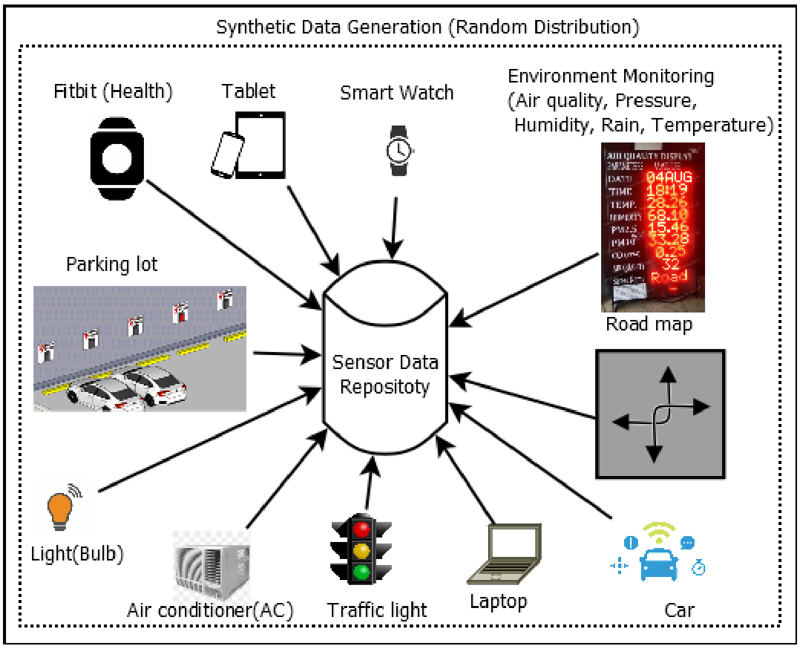

Figure 1. Input sensors (IoT Objects).

The organization of the proposed work is as follows: Section 2 presents the related work, Section 3 describes problem statement, Section 4 provides system model and problem formulations, Section 5 introduced the proposed relationships in artificial neural network models, Section 6 explains the algorithm, Section 7 discusses on dataset and results, Section 8 focuses on a comparative study , Section 9 provides pros and cons and Section 10 presents the conclusion and future directions of the work.

2. Related Work

This section describes the works conducted by several authors related to SIoT. Wang et al. (2015) worked on IoT on video data and prepared a literature survey on object detection, object tracking, face recognition, image classification and scene labeling using deep learning techniques [20]. Lau et al. (2019) worked on IoT on multiple data and prepared a literature survey on a multi-perspective classification of data fusion to evaluate smart city applications [21]. Lin et al. (2020), worked on IoT devices based on microcontroller units (MCU) and proposed a framework called MCUNet. The MCUNet has jointly designed the efficient neural architecture (TinyNAS) and the lightweight inference engine (TinyEngine) and enabled ImageNet-scale inference on microcontrollers with an accuracy of 70% on IoT devices that are smaller even than mobile phones types of MCU [22]. Le et al. (2019) worked on buildings that were investigated and simulators, namely Ecotect and four new artificial intelligence (AI), for heating load of buildings energy efficiency [23]. Mohammadi et al. (2017) worked on indoor localization based on BLE signal strength and semi-supervised deep reinforcement learning model for generalizing optimal policies. It produced results of a semi-supervised model that achieves 6% to 23% improvement for localization [24]. Verhelst et al. (2017) worked on IoT-based image recognition for the performance of the deep neural network processors [25]. Zamil et al. (2019) worked on four large audio-datasets of modalities in a smart city and proposed on deep learning(DL) methodology for classifying audio data and obtained the accuracy of 63.4%, 87.7%, 89.2% and 86.4% for city sounds, home appliances, household sounds and human audio, respectively [26]. Drewil et al. (2021) has worked on air pollution as a type of environmental challenge in smart cities, and prepared a literature survey worked on detecting and predicting air pollution using deep learning techniques [27]. Sotiriadis et al. (2014) proposed a simulator called SimIoT, which works on the Social Internet of Things. The SimIoT is used on dynamic and real-time development using the virtual machine as an interface that requestins messages in simIoT interactions occurring within the IoT-enabled health care context. Specifically, adding the IoT layer incorporates IoT devices, which generated data for private clouds [28]. Zeng et al. (2017) proposed a simulator called IOTSim, the IoTSim for analysing IoT applications, to improve the efficiency of cloud infrastructure using MapReduce model in cloud computing environments for Cloudsim. In real-time and low-latency requirements, stream processing is highly required and has been identified as an ideal platform for real time IoT applications [29]. Osterlind et al. (2016) proposed a simulator called COOJA. COOJA simulation is for the Contiki sensor node operating system. COOJA performs on simulation at the network level and operating system level [30]. Henderson et al. (2008) proposed a simulator called ns-3. In ns-3, the framework uses a callback-based design for protocol stacks and emit/consume network packets over real device drivers or VLANs [31]. Harshit Gupta et al. (2017) proposed a simulator called iFogSim. In iFogSim, it is based on the impact of resource management techniques in latency, network congestion, energy consumption and cost. This simulates IoT, Fog and Edge computing environments [32]. Han S. N et al. (2014) proposed a simulator called DPWSim. DPWSim used to build service-oriented and event-driven IoT applications on top of these devices [33]. Daniel et al. (2020) proposed a simulator called DANOS. DANOS enhances objects' profiles and their interaction behavior with intelligence based on specific human aspects such as full friendship and partial friendship [34]. Kasnesis P et al. (2016) proposed a simulator called ASSIST. ASSIST based semantic rules on agents basis of needs and services for SIoT applications [35]. Yang et al. (2017) has worked on dynamic traffic planning for smart city systems in real-time IoT and GIS data, which is processed using deep belief networks (DBN) and K-means to make the optimizing decision for transportation costs. The analysis of city traffic data is measured by using an accuracy obtained at 96.61% [36]. Chen J. F et al. (2016) worked on Taiwan Stock Index Futures dataset using a proposed framework of planar features on deep convolution neural networks (CNN) [37]. Rose et al. (2016), worked on identical token timing channels based on molecular communication for token payload [38]. Udmale et al. (2019) worked on kurtogram and sequence models (SM) for fault diagnosis on industrial systems [39]. Meghana J et al. (2021) worked on the performance analysis of social IoT objects using machine learning approaches [10].

State of the Art

The recent works on service-oriented knowledge model in SIoT applications proposed by researchers are summarized in Table 2.

Pillai et al. (2021) has worked on the IoT architecture for disaster prediction using MQ4, 4 MQ7 and force sensing resistors on the AWS(amazon web services) cloud platform [40]. Akhter et al. (2021) worked on smart agriculture to increase the quantity and quality of production [41]. Bhuiyan R. (2021) worked on the examination of air pollutant concentrations in Smart City Helsinki using data exploration and deep learning methods. It has long short term memory (LSTM), convolution neural network (CNN), recurrent neural network (RNN) and gated recurrent unit (GRU) network using all these methods to analyze the quality of air and achieved efficiency of mean absolute error (MAE) values of 0.09, 0.056, 0.096 and 0.114 for NO, NO_2, CO and O_3, respectively [42]. Alrahhal et al. (2022) has worked on Wireless Sensor Networks (WSNs) proposed to detect and isolate the malicious sensors from the data link for information and acknowledgments (ACKs) using protocol Tow-ACKs Trust (TAT) [43]. Al-Otaiby et al. (2022), worked on a trust management system inspired by an ant colony, proposed Ant Trust has a strong positive effect in terms of providing a more trustful environment by increasing the success rate of good peers [44]. From the literature review, it can be found that very few works are carried out for holding the architecture and thrust areas of SIoT. There exists a gap related to the service oriented classification of applications and establishing relationships between the devices that has to be filled by proposing a model using machine learning approaches.

Table 2. State of the art.

Authors	Applications	Methodology	Remarks
Pillai et al. [40]	Disasters prediction	Proposed the MQ4, MQ7 and force sensing resistoron AWS cloud.	It is confined only to IoT Architecture
Akhter et al. [41]	Smart Agriculture	ML approach in Apple disease analytics.	IoT in ML based agriculture analytic.
Bhuiyan et al. [42]	Smart City	Examine the air pollutant using LSTM CNN, RNN and GRU	Analyse the quality of air.
Alrahhal et al. [43]	Smart City Security	Tow-ACKs Trust (TAT) Routing protocol	Analyses network security based on trust.
Al-Otaiby et al. [44]	Smart City trust management system	AntTrust, a trust management system inspired by the ant colony	Analyze network trust between peers in P2P networks.

3. Problem Statement

SIoT relies on relationships between the objects within the SIoT environment and has some challenges namely, handling of heterogeneous objects, selection of generated data in objects, missing values in data. Therefore, it requires the discovery of meaningful patterns in data, which is more important in an SIoT environment. Thus, data have to be analyzed using the predictive modeling technique to provide the decision on services within objects. Hence, there is a need to develop better feature selection methods and a proper service oriented classification knowledge model for an SIoT environment application.

4. System Model

The SIoT system model SM has many objects N where it tries to form relationship R_s. The SIoT has many homogeneous object H_o and heterogeneous object H_t. Among independent objects, D is within the given set of networks N_x for the given set of objects in various distributions in space D_{N_x} possessing services S_r and applications A_p. Thus, each individual object has applications holding a set of services, which helps the user to obtain sensors S_n and data through it. The variables and its descriptions used to model the system are shown in Table 3.

Since the objects are distributed randomly in the network, the relationship is indirectly proportional to the object's service and applications. Hence, the system model is shown in Equation (1):

$$S_M = \lim_{H_o, H_t} R_s(D_{N_x}(D) : \forall(S_r, A_p)) = f\left(\frac{D_{N_x} D(S_r, A_p)}{R_s}\right) \quad (1)$$

where D_{N_x} has a set of independent objects D with homogeneous objects H_o and heterogeneous objects H_t for given services S_r and applications A_p. Independent objects D can be homogeneous or heterogeneous in nature, i.e., $D \approx H_o, H_t$. Then, the system model function has object network D_{N_x} and object D possessing services S_r and applications A_p are presented under relationships R_s.

Table 3. Variables and its descriptions.

Variables	Descriptions
S_M	*System model*
N	*Objects*
R_s	*Relationship*
H_o	*Homogeneous Object*
H_t	*Heterogeneous Object*
D	*Independent objects*
N_x	*Networks*
D_{N_x}	*Distribution in a space*
S_r	*Services*
A_p	*Applications*
S_n	*Sensors*
K_m	*Knowledge model*
Er_{inf}	*Environment information*
Pu_{inf}	*Public information*
Lc	*Locations status*
Aq	*Airquality status*
Tm	*Temperature status*
Ps	*Pressure status*
Hm	*Humidity status*
Wt	*Weather status*
Pp	*People presencestatus*
Pk	*Parking status*
Tf	*Traffic status*
St	*Street light status*

4.1. Problem Formulation

In SIoT, objects provide service with respect to time for an application forming a relationship among each object. The SIoT dataset has environment and public activities. In public activity and environment activity, data help make a decision for the user using a relationship-based artificial intelligence model (R-ANN). The artificial intelligence model provides the decision using service-oriented knowledge model K_m based on user environment information Er_{inf} and public information Pu_{inf} for a given application. Each public and environment information is represented to perform mathematical operations for analyzing the information such as locations status Lc, air quality status Aq, temperature status Tm, pressure status Ps, humidity status Hm, weather status Wt, people presence status Pp, parking status Pk, traffic status Tf and street light status St. The application's data are generated with respect to the SIoT environment by considering the activity of user participation in both environment data and public data. Therefore, the obtained data are analyzed by using predictive modeling techniques using artificial neural network (ANN) algorithm and proposed the relationship artificial neural network (R-ANN); hence, the objective function can be defined in Equation (2):

$$K_m = \lim_{H_o, H_t} D_{N_x}(\frac{1}{R_s}, S_r, A_p) = f\left(\frac{Er_{inf} + Pu_{inf}}{R_s}\right) \quad (2)$$

where knowledge model (K_m) helps make decisions for the user to find inverse relationship (R_s) in network (D_{N_x}) of all individual objects (D) for services(S_r) and applications(A_p) under homogeneous or heterogeneous objects possessing public (Pu_{inf}) and environment information Er_{inf}; this is shown in Equation (3).

$$K_m = \lim_{n\to\infty} \sum_{n=H_o}^{H_t} f\left(\frac{(Aq+Ps+Tm+Hm+Wt)+(Lc+Pp+Pk+Tf+St)}{R_s}\right) \quad (3)$$

Subject to public information, (Pu_{inf}) possesses location status Lc, people presence status Pp, parking status Pk, traffic status Tf and street light status (St), as shown in the Equation (4):

$$Pu_{inf} = (Lc + Pp + Pk + Tf + St) \tag{4}$$

and environment information Er_{inf} has air quality status Aq, temperature status Tm, pressure status Ps, humidity status Hm and weather status Wt, as shown in Equation (5).

$$Er_{inf} = (Aq + Ps + Tm + Hm + Wt) \tag{5}$$

Since there will be multiple services available within the network, the proposed knowledge model considers any services added to the network and groups the relevant services. Hence, in public information (Pu_{inf}) and an environment information Er_{inf}, they are used as parameters in the proposed knowledge model K_m.

5. Proposed Relationship Artificial Neural Network (R-ANN) Knowledge Model for Smart City Applications

5.1. Model Design

This section explains the proposed model design, the methodology followed and the working principle of the proposed model. The proposed work is carried out under the SIoT environment with request devices and response devices. It consists of 12 services, namely locations, NO_2, O_3, CO, NO_x, AQI, device moving, movement, pressure, humidity, POI and landmarks for six applications, namely traffic, air quality, weather, street light, parking and people presence status in a smart city environment. The proposed process diagram is shown in Figure 2; it shows two objects having twelve services and six application types that are connected using proposed semantic conditions that result in creating any one type of relationship between the objects. The proposed algorithm initiates semantic rule-based feature selection methods within the request device to search the necessary service out of available 12 services. The algorithm classifies applications based on the required services by finding the relationship between the request and response devices imposing proposed semantic rules.

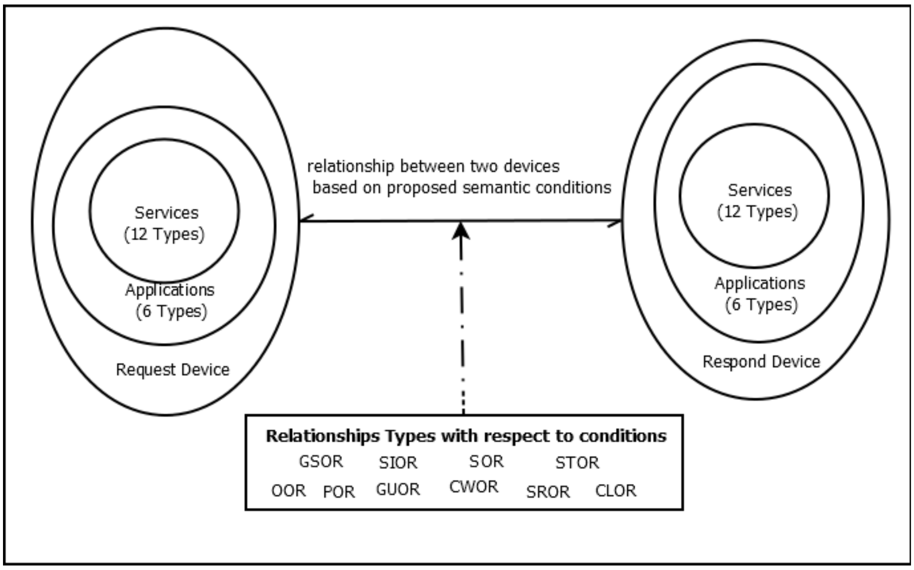

Figure 2. Proposed process diagram.

5.2. Methodology

This section explains the steps involved in the proposed R-ANN model. The working methodology of the proposed model is shown in Algorithm 1. First, input the smart city data and read the attributes of the dataset; then, select the features by defined semantic rule-based relationships in the environment. Then, predict the application status using an ANN classification model with the help of a relationship. The RANN model will provide the classified objects information to the user.

Algorithm 1 Proposed methodology of R-ANN knowledge model

```
Input: Smart city Data.
Output: Relationship based Services.
smart city Objects Data()
pre-processing Data()
identify Relationship Using Semantic Rules()
select Objects are in a Relationship()
i = 0
for i do
    n = i++
end for
while Artificial Neural Network(ANN) Model do
    Dense network = 200; Batch Size = 30; Epoch = 10;
    Input activation function = ReLu
    Output activation function = softmax
end while
```

5.3. Working Principle

To build a knowledge model for smart objects in the SIoT environment, the knowledge model is based on semantic rules for relationship establishment defined by considering object profiling where objects consist of protocols, device type and device brands and nature of objects. Every object consists of at least one of the protocols that are in some range for communication. Thus, Wifi, Bluetooth, Wifi-direct and zigbee are limited to 0–1000, 0–100, 0–200 and 0–100 m, respectively. Each SIoT object's device type can be the same or different, also the brand name varies from one device to another. The nature of the device can be private and public and located randomly in the SIoT environment as shown in Table 4. Considering this information, in this work, a semantic rule to establish the relationship between the user to object and objects to objects is proposed. The applications have environment information and public information of users, and these data can be preprocessed using the Gaussian technique, which helps to normalize data, as shown in the Figure 3.

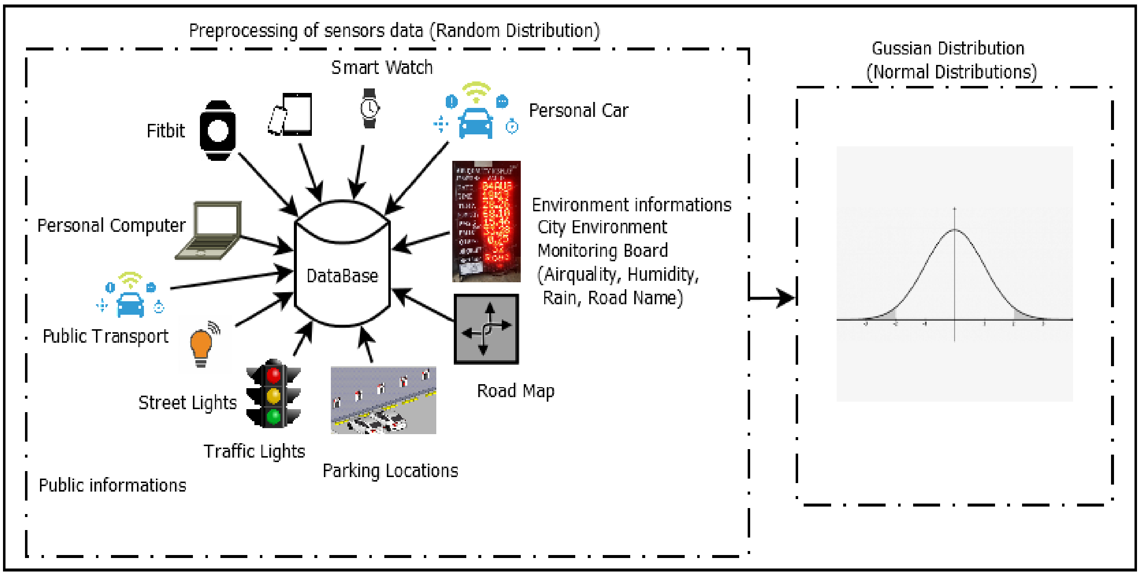

Figure 3. Sensor data–random to Gaussian distribution.

Table 4. Semantic rules for establishing relationship.

Relationship Types	Device Type	Distance	Conection Type	Communication Protocol	Device Brand
STOR	different	≤ 15 mt	public to private	zigbee	different
SROR	same	≤15 mt	public to private	wifi	different
GUOR	different	>50 mt <100 mt	private to private	wifi or bluetooth or wifi direct	different
CWOR	different	<10 mt	private to private	wifi or bluetooth or wifi direct	different
CLOR	same	>10 mt <50 mt	private to private	wifi or bluetooth or wifi direct	different
POR	same	<400 mt	private to private	wifi or bluetooth or wifi direct	same
GSOR	same	<10 mt	private to private	wifi or bluetooth or wifi direct	different
SIOR	different	<50 mt	private to private	wifi or bluetooth or wifi direct	different
SOR	different	>20 mt <50 mt	public to private	wifi or bluetooth or wifi direct	different
OOR	different	<20 mt	private to private	wifi or bluetooth or wifi direct	same

Figure 4 shows that the initial sensor generates various types of data that are grouped into public information and private information.

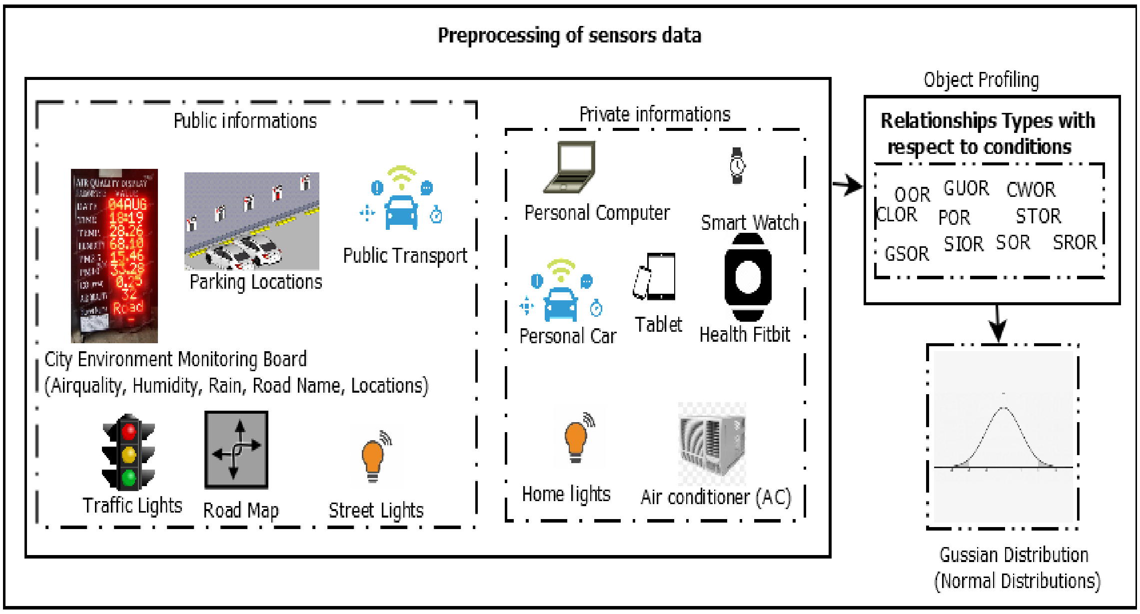

Figure 4. Sensor data preprocessing from random to Gaussian distribution.

The information for objects profiling contains device brands, device types, protocols, user ID, connection types service and applications that are randomly distributed in a space; in this work, these data need to be normalized using Gaussian techniques and by using Equation (6) for subsequent analysis:

$$\sigma = \sqrt[2]{\frac{\sum_{n=1}^{n} (x_i - \mu)^2}{n-1}} \tag{6}$$

where n is the number of samples in data, x_i is the values of the data and μ is the mean of x_i.

The data are selected based on device profiling conditions to extract information into the artificial neural network (ANN). Furthermore, under the concept of predictive modeling technique, the data are analyzed using an artificial neural network (ANN) that produces the corresponding information to the user, as shown in the Figure 5.

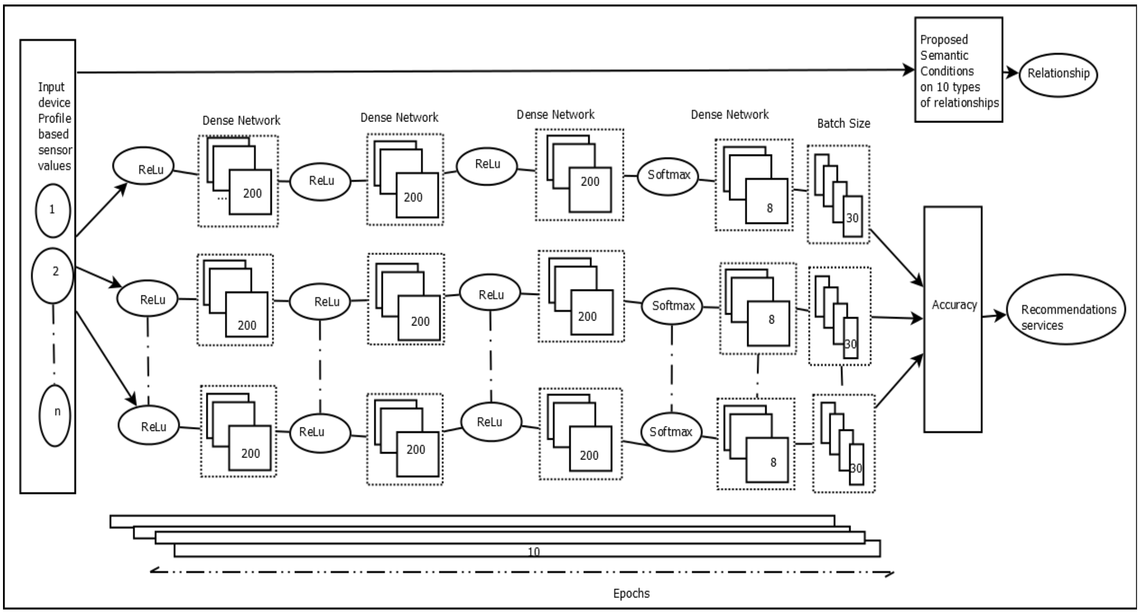

Figure 5. Proposed relationship artificial neural network (R-ANN) knowledge model.

The preprocessed sensor data are collected based on device profiling and given to the artificial neural network that classifies and predicts the most accurate services; the proposed semantic rules are used to predict the relationship type based on device profiling, as shown in Figure 5. Furthermore, the proposed the R-ANN model produces a relationship-based, service-oriented knowledge model used for pattern analysis. From Equation (1), it is known that the relationship is inversely proportional to service and application. Thus, the proposed R-ANN knowledge model is inversely proportional to the services and applications, which helps to make decisions according to users' requirement in a given SIoT environment. The design of the proposed R-ANN Knowledge model is shown in Figure 5, and the working principle of the R-ANN Knowledge model is derived in Section 5.2.

In the proposed solution, the relationships between the user and objects are established based on user profiling within the context and the semantic rules in an SIoT environment. The proposed R-ANN model uses neurons, back propagation and activation functions in the memory of the network similarly to ANN. It has inputs, an activation function and the net input is calculated as shown in Equation (7).

$$K_m = x_1.w_1 + x_2.w_2 + x_3.w_3 + ... + x_(n-1).w_(n-1) + x_n.w_n \tag{7}$$

$$\begin{aligned} K_m = {} & (Er_{inf} + Pu_{inf})1.w1 + (Er_{inf} + Pu_{inf})2.w2 + ... \\ & + (Er_{inf} + Pu_{inf})(n-1).w_(n-1) + (Er_{inf} + Pu_{inf})_n.w_n \end{aligned} \tag{8}$$

Equation (8), $(Er_{inf} + Pu_{inf})$ contains 25 service features as input and the ANN model has a three layer model for a 200 dense network that has a batch size of 30 and 10 epochs. The model has two layered Rectified Linear unit(ReLu) for the analysis of input sensor values and one layer of softmax that has to produce output sensor services.

Using Equation (3) in Equation (7), the proposed R-ANN knowledge model is defined and is shown in Equation (8). Thus, the output results have backtracking to identify corresponding devices and for calculating indirect proportional relationships between the devices using the semantic rules given by the user; it then recommends the service to users, as shown in the Equation (9).

$$\begin{aligned} K_m = {} & \frac{1}{R_s}((Er_{inf} + Pu_{inf})1.w1 + (Er_{inf} + Pu_{inf})2.w2 + \ldots\ldots \\ & + (Er_{inf} + Pu_{inf})(n-1).w_(n-1) + (Er_{inf} + Pu_{inf})_n.w_n) \end{aligned} \tag{9}$$

Therefore, the services and applications respect relationships. Using user-defined semantic rules, R-ANN is defined from ith to mth objects, where i = 0 to m number objects, and it is as shown in Equation (10).

$$K_m = \sum_{i=0}^{m} \frac{(Er_{inf} + Pu_{inf})_i . w_i}{R_s} \tag{10}$$

Here, the concept of smart environment information is analyzed and transmitted through hidden layers containing hidden neurons. In the hidden layers, data are analyzed and calculated by using weights. The biases are also estimated to ensure a balanced level of data for producing output. The relationship between the object is identified by using an R-ANN model for predicting user environment information and public information based on the conditions and rules to produce the corresponding services to the objects, as shown in the Table 4.

6. Algorithm

Algorithm 2 uses objects in network D_{N_x}, and public (Pu_{inf}) and environment information (Er_{inf}) to provide services and relationships, respectively, as shown in Equations (3). When the objects are within the network, they check the semantic rules and set relationship condition C_{Rs} to true or false.

Algorithm 2 Proposed R-ANN knowledge model (K_m)

Input: Objects in network D_{N_x}, Public informations Pub_{inf} , environment information Er_{inf} and Conditions on Relationships (C_{Rs}), Relationships R_s.
Output: Knowledge model K_m.
while Objects in D_{N_x} **do**
  if (C_{Rs} == True) **then**
    $C_{Rs} \leftarrow Pub_{inf} + Er_{inf}$
    $S_r, A_p = \sum_{i=0}^{m} \frac{(Er_{inf}+Pu_{inf})_i . w_i}{R_s}$
    $K_m = (R_s, S_r, A_p)$
  else
    Exit()
  end if
end while

7. Results and Discussion

7.1. Dataset

The SIoT dataset contains real IoT objects that are categorized into five data models such as object description, objects profile, private devices, public devices and adjacency matrices. The object description has a few categories, namely device ID, user ID, device type, device brand(ranging from 1 to 12) and device model (ranging from 1 to 24). It has a total of 16,216 devices, out of which 14,600 are generated from private users and 1616 from public services. The object's profile has a few categories, namely device type, service ID (ranging from 1 to 18) and application ID (ranging from 1 to 28). Private devices consist of smart-phone (mobile), car (mobile), tablet (mobile), smart watch (mobile), pc (static), printer (static) and home sensor(static). Moreover, it consists of private devices possessing 14,600 users and is simulated later with a user movements mobility model called small world in motion (SWIM) possessing 4000 users in perception radius 0.015 for 10 days with movement α as a 0.9 value. In public devices, there are a few categories called data models, namely point of interest (specific point of nine locations), environment and weather (10 weather stations), transportation(taxis or buses includes; total number: 11), indicator (display information: 12), garbage truck (waste products truck: 13), street light (14 lamps in roads), parking (location: 15) and alarms (traffic monitoring: 16). Total public and private devices includes both static and mobile devices. In static devices, they produce data based on a few parameters, namely ID user and x (coordinates) and y (coordinates), and mobile devices produce data that are based on a few parameters, namely time stamp start (beginning of the rest state), time stamp stop (end of the rest state), ID user and x(coordinates) and y(coordinates). Similarly, adjacency matrices are based on the relationship between the objects and a few categories of relationships, namely ownership object relationship, parental object relationship, co-location object relationship, social object relationship 1 and social object relationship 2. The ownership object relationship means objects owned by the same user with communication ranges for different technologies such as in LoRa (around 1500 m), Wi-Fi (around 400 m) and Bluetooth (around 40 m). The parental object relationship has the same type, model and brand only if their distance is greater than a two threshold of 2 or 2.5 km. The co-location object relationship has all static devices (public or private) and private mobile contacts numbering more than 13 (number of meetings). The social object relationships between private mobile devices include the following: the number of meetings (N = 3), the meeting duration (TM = 30 min) and the interval between two consecutive meetings (TI = 6 h). The social object relationship means the following: it is a relationship between public mobile devices and users mobile objects having N = 3, TM = 1 min and TI = 1 h [9].

7.2. Data Preparation

The attributes of environment activity and public activity are explained in this subsection. It has a few data models such as object description, object profile, private devices, public devices and relationships. The description of the sample dataset is shown in the Table 5 and smart city dataset descriptions as public and environment information are shown in the Table 6.

Table 5. Device profile dataset.

Attributes	Sample Descriptions
OwnerId	Owner IDs up to range of 1 to 100,000 users
Devices	Devices includes (smart phone, fitbit, tablet, car and smart watch)
DeviceBrands	Total four brands A, B, C and D for all devices.
Distance	0 to 500 m
Protocols	Blueetooth, WIFI, GSM and Zigbee
DeviceType	Private and Public
Locations	Device location Name

Table 6. Smart city dataset.

Attributes Types	Samples
People Presence$_{Public}$	People present in the public places.
AirQuality	Air quality of the public place
NO_2	Gaseous air pollutant comrpising nitrogen and oxygen
O_3	Ozone O_3 in Ground-level or the bad ozone
CO	Smoke and fumes contained in carbon monoxide are common air pollutants.
nox	Pollution is emitted by automobiles, trucks and various non-road vehicles.
AirQualityIndex	It is used by government agencies to communicate to the public (range 0 to 500)
DeviceMoving	Accelerometer in range of −270 to +270
Movement	Device movement yes or No
ParkingStatus	City location parking status yes or no
StreetlightStatus	Yes or no
Temperature	City location temperature range of −10 to 100
Pressure	City location pressure range of 0–100
Humidity	City location humidity range of 0–100
WeatherDescription	City location weather: sunny, cloudy, thunder, lightning and rainy
Point ofInterest	City location events range 1–50
LandMark	City landmark
TrafficStatus	City landmark or location traffic status (yes or no)

Object description has a few categories, namely device, owner ID (ranging from 1 to 100,000), device type (ranging from 1 to 5), device brand (range 1 to 4) and device protocol (ranging from 1 to 4). The device protocols are used to establish connections using wifi, wifi direct, Bluetooth and zigbee. In objects profile, it has a few categories, namely device type, ID service(ranging from 1 to 9), and ID application (ranging from 1 to 5). The services are used to make recommendations to the users, namely temperature status, weather status, traffic status, parking status and street light status. In private devices, there are a few categories, namely smart phone(mobile), car(mobile), tablet(mobile), smart watch(mobile) and smart fitbit(mobile).

In public devices, there are a few categories called data models, namely weather, air quality and temperature indicator. Weather has five classes, namely sunny, rainy, cloudy, thunder and lightning. Air quality is based on the chemical compositions of oxides and oxygen such as NO_2, O_3, CO, NO_x, air quality index (aqi) and humidity in different areas with respect to 100 numbers of locations. In temperature indicators, they are based on actuators around 20 locations.

In private devices, there are a few categories, namely 100 locations, street lights at 1000 on roads and 50 parking places. Traffic monitoring is around 200 across the environment. All information was combined in classes of each application status, namely air quality, people presence, parking, traffic, street light and weather; all objects are shown in Figures 6–11. Typically, all figures have a number of classes on the x axis and total samples count on the y axis, respectively.

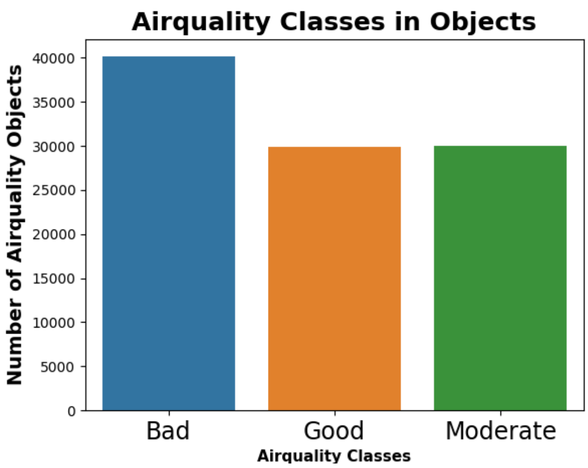

Figure 6. Air Quality Status Types.

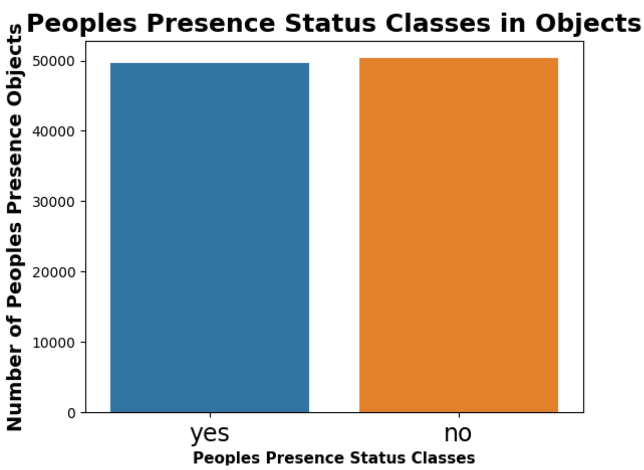

Figure 7. People Presence Status Types.

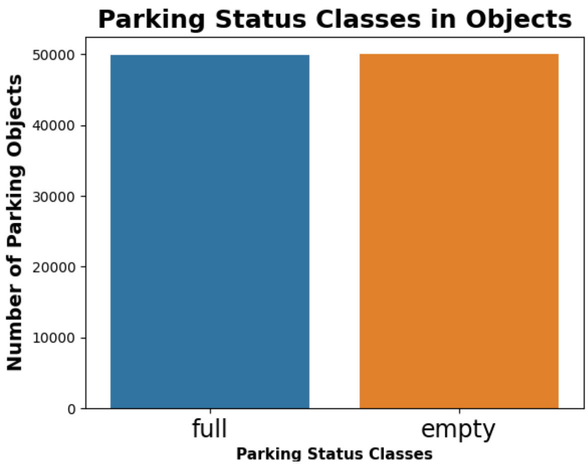

Figure 8. Parking Status Types.

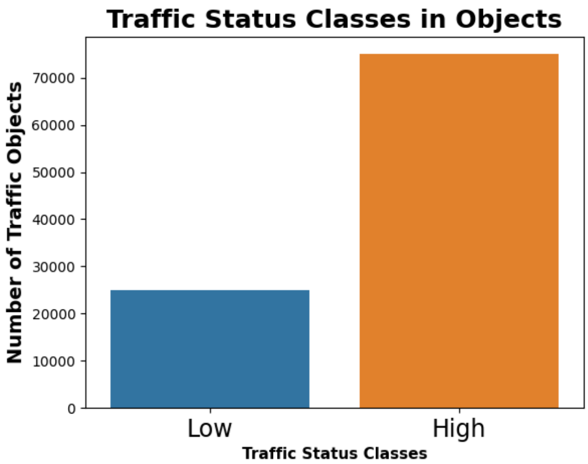

Figure 9. Traffic Status Types.

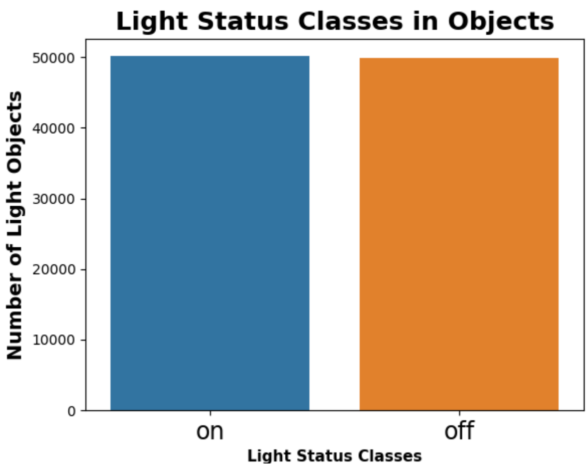

Figure 10. Street Light Status Types.

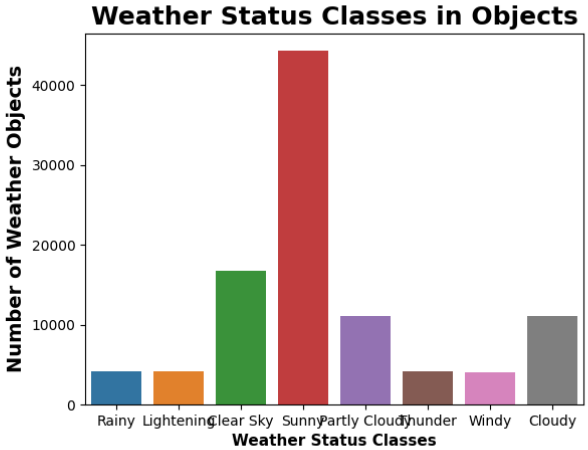

Figure 11. Weather Status Types.

The experimental dataset contains the attributes shown in Tables 5–7. The owner ID has up to of 1 to 100,000 users, devices for air quality, device brands for air quality, distance between air quality devices, protocol air quality and device type air quality. This further includes the people's presence in public places, air quality status, owner ID for weather, devices for weather status, device brands weather status, distance between weather status, protocols for weather, device types for weather status and weather locations. We also have parking status, street light status, temperature at locations, pressure at locations, humidity at locations, weather status at locations, point of interest at every location, nearby landmarks, people presence at landmarks and traffic status near landmarks. All these attributes have created relationships between objects in privates and public data model based on 10 types of relationships, namely parental (POR), Co-Location (CLOR), Ownership (OOR), Guardian (GUOR), Social (SOR), Guest (GSOR), Sibling (SIOR), Stranger (STOR), Service (SROR) and Co-Work (CWOR). These relationships are formed based on some conditions shown in Table 4. Environment activity and public activity possessing mobile devices produce data based on a few parameters, namely devices, device brand, owner ID, distance, protocol, device type, locations, NO_2, O_3, CO NO_x, aqi, air quality, temperature, pressure, humidity, weather description, people presence, parking location, traffic status and street light status. All these data are based on IoT object standards in order to obtain relationship-based decisions using the proposed R-ANN based on the knowledge model relative to the users.

Table 7. Services and corresponding applications.

Applications	Services
Air Quality	Location, Landmark, NO_2, CO and NO_x
Weather	Location, Landmark, Pressure, Humidity and Temperature
Traffic	Movement, Device Moving, Location and Landmark
Parking	Movement, Device Moving, Location and Landmark
Street Light	Movement, Device Moving, Location and Landmark
People Presence	Movement, Device Moving, Location and Landmark

7.3. Results

The proposed work aims to predict services using relationships between the objects of the SIoT environment. This experiment helps to find the relationship using the semantic rules shown in Figures 12–17. Based on services and relationships using an ANN model, the knowledge model was applied to the SIoT environment. The conventional ANN and proposed R-ANN methods are explored in this subsection. Firstly, ANN is used to analyze the sensor data that are encoded with the service and they are normalized using the Gaussian technique. The data are categorized into two types: target and features; the services are target class; and remaining data are features corresponding to sensor values. These classes and feature data are split into two phases such as 70% training data and % testing data . The neural network model has three ReLu activation function layers and one softmax activation function of the output layer for training the network. The output layer is compiled with the Adam optimizer with a loss function of cross entropy.

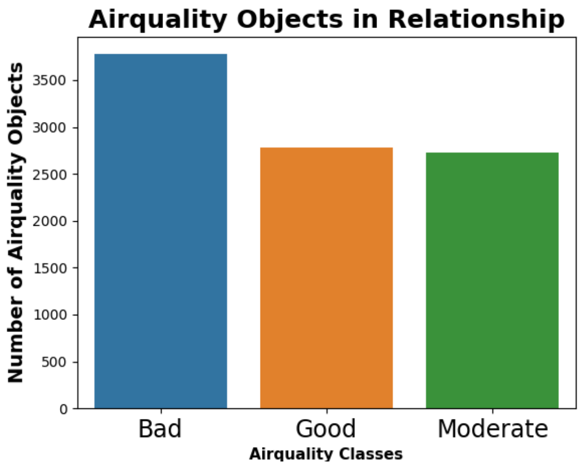

Figure 12. Air quality objects in relationship.

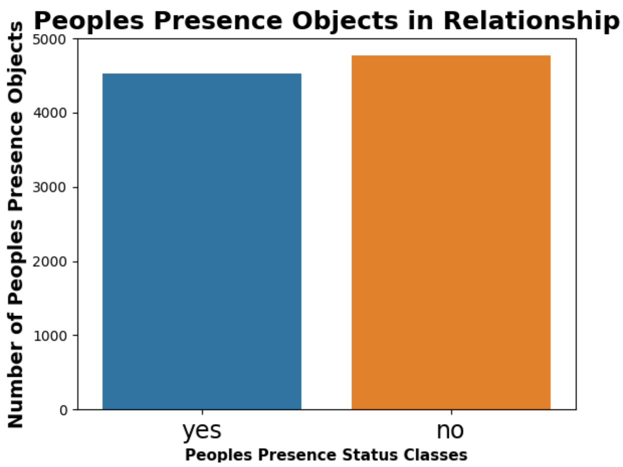

Figure 13. People presence objects in relationship.

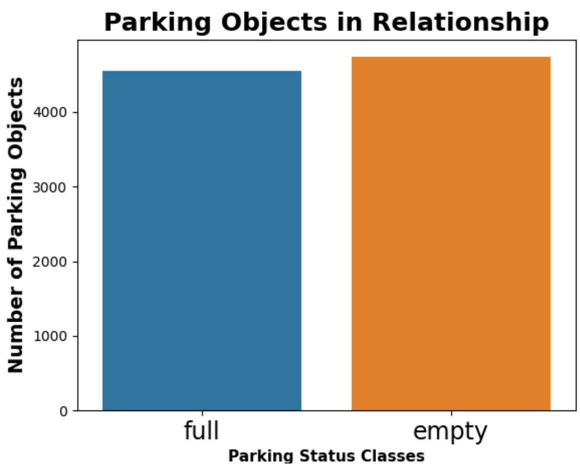

Figure 14. Parking objects in relationship.

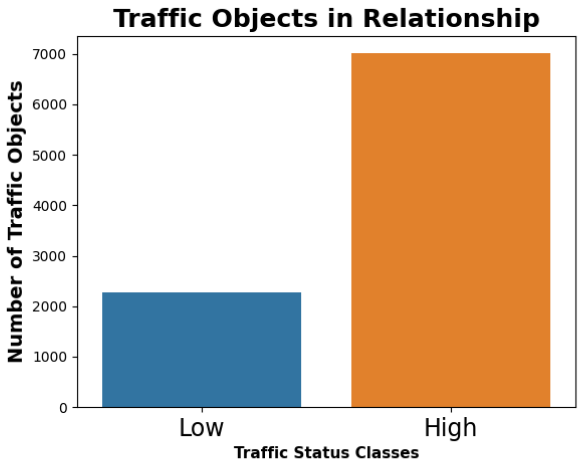

Figure 15. Traffic objects in relationship.

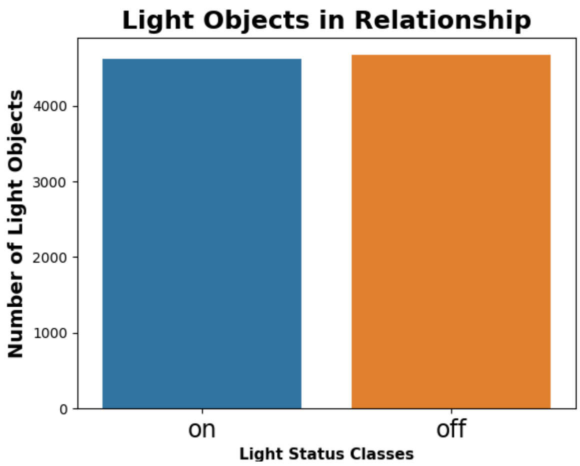

Figure 16. Street light objects in relationship.

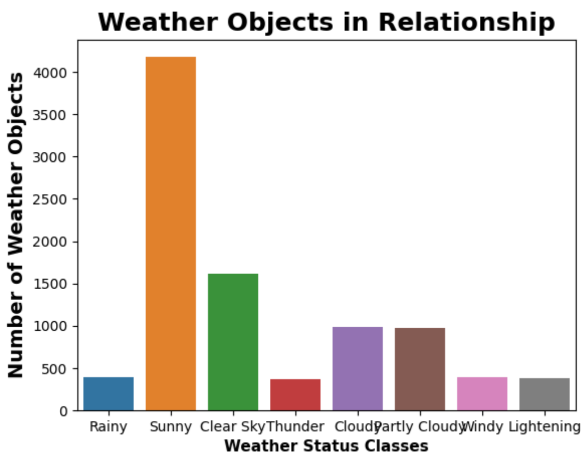

Figure 17. Weather objects in relationship.

Table 8 shows that the classification report of the existing ANN; it predicts the decision with an average of 78.82% for all applications where weather status, air quality status, traffic status, parking status, people presence status and light status provide accuracies of 74.89%, 96.08%, 94.00%, 66.50%, 66.50% and 75.00%, respectively.

The weather status has eight classes of input values on a total of 100,000 samples; rainy, lightning, thunder and windy classes have over 5000 sample counts and cloudy and partially cloud classes have 10,000 count samples. Moreover, clear sky class has 15,000 count samples. Compared to the other classes, Figure 11 shows sunny classes having 45,000 count samples, and it has more imbalanced data of the classes obtained with an accuracy of 74.89%, 66.50% and 66.50%. In traffic status, there are three classes with a sample count of 33,000 shown in Figure 6, obtained with a good accuracy of 96.08%; moreover, air quality status has three classes, namely good with a moderate sample count of 30,000 and bad class possessing 60,000 sample count, as shown in Figures 7 and 8, and they obtained the accuracies of 66.50% and 66.50%. In traffic status, there are three classes with a sample count of 33,000 shown in Figure 6, obtained with good accuracy of 96.08%, and air quality status has three classes, namely good with a moderate sample count of 30,000 and bad class possessing 60,000 sample counts, as shown in Figure 9; they obtained a good accuracy of 94%. Therefore, from the results, it is better to know that training the data in sequence into the artificial neural network algorithm produces better results, as shown in Table 8. However, all the accuracy of all trained data depend upon object support for precision and recall.

Table 8. Classification report of existing ANN.

Applications	Precision	Recall	F1 Score	Average Accuracy
Weather Status	0.94 0.51 0.30 0.10 0.25 0.97 0.25 0.15	0.93 0.96 0.05 0.25 0.05 1.00 0.92 0.80	0.93 0.66 0.08 0.14 0.08 0.99 0.39 0.25	74.89 %
Air quality Status	0.98 0.93 0.98	0.99 0.99 0.89	0.98 0.96 0.93	96.08%
Traffic Status	0.91 0.94 0.96	0.95 0.93 1.00	0.92 0.93 0.97	94.00%
Parking Status	0.50 0.55	1.00 0.85	0.67 0.66	66.50%
People Presence Status	0.65 0.50	0.75 1.00	0.66 0.67	66.50%
Light Status	0.97 0.35	1.00 0.99	0.99 0.51	75.00%
Average Accuracy of All Applications				78.83%

7.4. Experimental Setup

This subsection explains the experimental setup of the RANN model. Initially, it collects all data from air quality, weather, traffic, parking, people presence and light sensors. This sensor data are stored in comma separated value (csv) format in repositories that are randomly distributed because all sensors are in various distributions. These data are encoded into object profiling, such as device type, device brands, protocols, user ID, distance and connection types and services with applications. Object profiling was analyzed by using the proposed semantic rules to establish the relationships between the objects. These various distributed data have numerical and categorical data types, and all categorical data are encoded into numerical values. Therefore, numerical data are normalized by subtracting the mean μ of each feature and a division by the standard deviation σ that helps for the convergence of gradients in the environment. Normalized data have a target class of relationship types and features and attributes of services. Features data are split into two phases such as training 70% and testing 30%.

Therefore, input training features a sequential ANN model that has three layers of ReLu with a dense network size of 200 and one layer of softmax with a dense network size of 8 in the proposed R-ANN model. The proposed model is compiled with an Adam optimizer, and categorical cross entropy was used for loss function; the output results obtained 89% accuracy.

Hence, to visualize the results, test data are used as requesting devices and can find the corresponding class in the relationship types. Therefore, the model increased the visualization of the path between objects with relationships for classifications of services to users. Hence, a few samples of the service-oriented R-ANN Knowledge model are based on relationships between request and response devices, device brands, protocols, device types and device relationship types, and they are shown in Table 9.

Table 9. *Requestdevices* and *Responddevices*.

Request Device	Protocols	Repond Device	Service	Applications	Relation Identified
[SmartPhone]	[WiFi]	[Car]	Location	Traffic	SIBOR
[Tablet]	[Bluetooth]	[Car]	Location	Traffic	SIBOR
[SmartPhone]	[Bluetooth]	[Car]	Landmark	Weather	POR
[Tablet]	[Bluetooth]	[Car]	Pressure, Humidity	Weather	SIBOR
[Tablet]	[Bluetooth]	[Car]	CO, Nox	Air quality	POR
[SmartPhone]	[WiFi]	[Car]	CO, Nox	Air quality	GUOR
[SmartPhone]	[WiFi]	[Car]	CO, Nox	Air quality	POR
[SmartPhone]	[WiFi]	[Car]	Landmark	Weather	GUOR
[SmartPhone]	[Bluetooth]	[Car]	Movement, Device Moving, Location and Landmark	Traffic	SIBOR
[Tablet]	[Bluetooth]	[Car]	Landmark	Weather	SIBOR
[Tablet]	[Bluetooth]	[SmartPhone]	Landmark	Weather	SIBOR
[SmartPhone]	[Bluetooth]	[SmartPhone]	Landmark	Weather	POR
[Tablet]	[Bluetooth]	[SmartPhone]	Landmark	Weather	POR
[SmartPhone]	[Bluetooth]	[SmartPhone]	Movement, Device Moving, Location and Landmark	Traffic	SIBOR
[Tablet]	[Bluetooth]	[SmartPhone]	Landmark	Weather	SIBOR
[Tablet]	[Bluetooth]	[SmartPhone]	Landmark	Weather	CWOR
[Tablet]	[Bluetooth]	[SmartPhone]	Landmark	Weather	POR

To evaluate the performance of the proposed algorithm, the results are summarized in Table 9 and provide the relationship between requested and responding objects, respectively, for the corresponding services too. The classification report of the proposed R-ANN knowledge model has correct and incorrect predictions that are summarized by each class. The decisions on relationship conditions for all objects are used for all services in the SIoT environment. The correct classification of relationships is predicted and an f1-score of 93%, precision of 96% and recall of 90% are obtained for all relationships. Moreover, the correct classification of services is predicted and an f1-score 82%, precision of 76% and recall of 88% are obtained for all services. Hence, the overall accuracy of the R-ANN knowledge model is 89.62%, and it is shown in Table 10.

Table 10. Classification report of proposed R-ANN model.

	Precision	Recall	F1 Score
	0.96	0.90	0.93
	0.76	0.88	0.82
accuracy			0.90
macro avg	0.86	0.89	0.87
weighted avg	0.90	0.90	0.90
Overall Accuracy	89.62 %		

8. Comparative Study

This section presents a comparative study on different proposed models on different applications, as shown in Table 11.

Ghoneim et al. (2017) worked on CityPulse EU FP7 Project smart city data and a new deep learning-based ozone level prediction model. It has support vector machine (SVM), neural network (NN) and multilinear regression (GLM) models with efficiency of mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE) and coefficient determination of R square (R2) values of 0.08, 0.2, 0.2 and 0.9 for deep learning(DL) methods, respectively [45]. Alam et al. (2016) collected data from the three real IoT datasets used to understand and control complex environments around us. The dataset is examined by using data mining algorithms, which include deep learning artificial neural networks (DLANNs), and they can a feed forward multilayer artificial neural network (ANN) for modeling high-level data abstractions. The output result is measured by using the root mean square error (RMSE) and by calculating the residual difference between prediction and truth, obtaining an RMSE of 0.542 [46]. Subash R et al. (2021) worked on the Satisfactory Factor (SF) on a Grey Wolf Algorithm (GWA)-based User Object Affiliation mechanism by combining object predilection and object sociality analogous in SIoT [47]. Rahman et al. (2021) worked on the Internet of Health Things (IoHT) dataset using CNN and obtained a 95% accuracy [48]. Chen et al. (2022) worked on heart-beat detection on chips using convolution neural networks (CNN). It uses a dataset of MIT-BIH arrhythmia, and it obtained an accuracy of 96.3% [18].

Table 11. Comparative study.

Dataset		Model	Results				Accuracy
			MSE	RMSE	MAE	R^2	
PJM and Open Energy (Information)	[45]	CNN	–	0.542	–	–	–
		SVR	–	0.542	–	–	–
City Pluse EU FP7	[46]	SVM	0.08	–	–	0.9	–
		NN	–	0.02	–	0.9	–
		GLM	–	–	0.2	0.9	
CASAS Dataset MIT Dataset	[47]	SF + GWA + Ranking	–	1.816	1.585	–	–
IoHT data	[48]	CNN	–	–	–	–	80% to 94%
MIT-BIH arrhythmia Dataset	[18]	CNN	–	–	–	–	96.3%
Smart city Dataset for 6 applications (Air quality Weather Traffic Parking Street Light People Precence)		Proposed R-ANN	–	–	–	–	89.62%

The comparative study is based on the algorithm and dataset of IoT for many applications such as Internet of Things (IoT), energy and smart city applications. It is focused on algorithms such as Convolution Neural Network (CNN), Support Vector Machine (SVM), Neural Network (NN), Multi-Gaussian Linear Regression (GLM) models, Support Vector Regression (SVR) and Satisfactory Factor (SF) on Grey Wolf Algorithm (GWA) and the proposed Relationship Artificial Neural Network (R-ANN) Knowledge Model is shown in Table 11.

The error metrics such as RMSE, MSE, MAE and R^2 are used to evaluate the result based on the mportance of data for algorithms shown in Table 11. In error, metrics measure what is unbiased and follow a normal distribution of data where it does not reduce the effectiveness of data when observation data are averaged, and the error rate is measured only on input data. Therefore, the proposed work uses accuracy metrics to measure the closeness of objects using relationship conditions between objects for measured quantity value and a true quantity value of services. Thus, all objects satisfy the compatibility of the proposed relationship conditions into the objects, and the classification of data is measured based on closeness of classes. Hence, the proposed R-ANN resulted in an accuracy of

89.62% with respect to all relationship conditions; it measured closeness between the objects to predict the services in the SIoT environment.

9. Pros and Cons of Proposed Model

The proposed model develops an SIoT required for service based on the semantic rules of user objects. The proposed model has a few pros, such as facilitating the interaction between heterogeneous objects through relationships. Hence, every object in the network autonomously establishes various types of relationships and uses the resulting links to navigate the network. It shares information through relationships and provides information anywhere and anytime. Moreover, it also provides secured information by using relationship conditions. However, there are some cons in every technology, and in this work, it requires objects profiling to establish the relationships between objects.

10. Conclusions and Future Work

The proposed work carried out on public and private devices recommends using various services in personal activities and public activities. The conventional ANN model is used to predict accuracy in terms of the values each device obtains, such as closeness of classes in services such as air quality, weather, temperature, traffic, people presence and parking status within a smart city. The proposed R-ANN knowledge model uses feature selection based on semantic rules to establish relationships between request and response devices that provide services. It provides more information to the users about the services when using the ANN model within an SIoT environment. Thus, service-oriented R-ANN knowledge model produces an accuracy 89.62% for all services possessing relationships. Moreover, data enhance the concept of smart environment using smart objects data and create a decision to analyze the entire system of the SIoT environment. The limitation of the work is that the user can define any semantic rules to obtain the relationships between the objects. Hence, in future works, we will focus on the enhancement of results to predict services for the knowledge model for every object within an SIoT environment.

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