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Semantic Web of Things for pollution measurement and validation interoperability using AI Techniques

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Abstract

In response to the growing IoT device diversity, efforts are underway to better integrate data, applications, and services. The Semantic Web, known for its simplicity in integration, has the potential to improve data interpretation and interoperability. In this research, a pollution management model is used, combining the Semantic Web of Things (SWoT) and Artificial

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Intelligence (AI), to create smarter cities, providing real-time environmental information. The dataset has been sourced from Aarhus City, Denmark, and the study outlines Semantic Web Technologies (SWTs) in IoT frameworks, including common ontologies for IoT-based architecture. The dataset's relationship between various gases/pollutants is analyzed using correlation matrix. Machine learning methods like Multi-Layer Perceptron (MLP) with Sigmoid, ReLU, Tanh, Maxout, Swish hybrid activation functions are employed, with results assessed using Root Mean Squared Error (RMSE) and Mean Squared Error (MSE). A comparison of errors for different activation functions is also performed and the findings reveal good results when comparing actual and predicted values in the proposed model.

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Keywords: *Artificial intelligence, IoT, Semantics, Smart city, SWoT.*

1. Introduction

The Internet of Things (IoT) is a transformative technology connecting objects, enabling new services and applications. Smart cities, an emerging urban trend, offer citizens accessible services through various IoT-enabled devices. This connectivity empowers individuals to make informed decisions about their safety and health by increasing awareness of their environment [1]. Using the Web of Things (WoT), embedded sensors can easily monitor urban environmental factors like air quality, radiation, and electromagnetic fields. Semantic technologies are recognized as the most suitable tools for managing diverse IoT objects [2].

A root resource that can be accessed with an HTTP URL is necessary for the Web Thing Model to function as the portal for communicating with the Web Thing. In this case, an Internationalized Resource Identifier (IRI) is absent. An IRI serves two purposes: providing unique names for resources and indicating their location, while a URL only indicates location.

Figure 1 shows how an IRI identifies and represents a Thing on the Semantic Web. Here, Thing is defined as utilizing connections among its identifier and other resources once described on the semantic web.

RDF (Resource Description Framework) serves as a standard model for data exchange on the Web, utilizing RDF triples to describe web items [2]. RDF offers the ability to merge data even with differing schemas and supports schema evolution without requiring all data consumers to adapt. The RDF: type property establishes relationships between multiple construct levels [Figure 1], often defined using domain-specific schema and ontologies like RDFS (RDF Schema) and OWL (Web Ontology

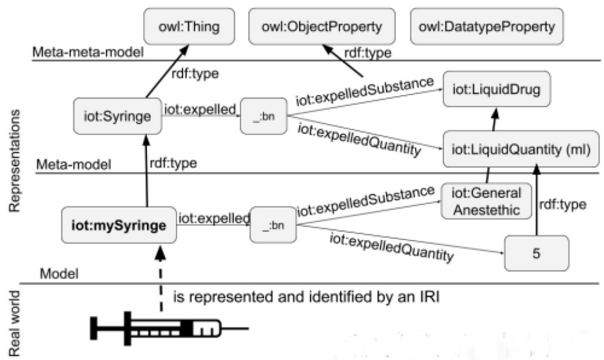

Figure 1

Semantic Web's depiction of the thing, adapted from [2]

Language). Ontologies and schemas are pivotal in the Semantic Web, with ontology referring to a detailed description of shared conceptualizations [3]. Ontologies consist of two critical components: the formal model and the common conceptualization, with description logic defining the formal aspect.

Deep Learning (DL) has excelled in various tasks such as computer vision, audio processing, and natural language processing, benefiting from vast datasets and sophisticated computational resources. Different deep neural networks (DNNs), including MLP (Multi-Layer Perceptron) [4], have been developed for various problems. Artificial Neural Networks (ANNs) have gained popularity as an effective approach in handling extensive, noisy data from non-linear, dynamic systems, particularly when only partial knowledge of essential physical connections is available [5].

The New Smart City-based system enhances urban livability for pedestrians and vehicles, employing the Social Internet of Things paradigm. It tracks all types of vehicles and pedestrians, integrating real-time air quality measurements from mobile and fixed sensors. A monitoring network on local public transportation enables real-time monitoring of environmentally sustainable and traffic-congested areas [6].

This paper explores the integration of Semantic Web, IoT, and Artificial Intelligence (AI) to create a SWoT (Semantic Web of Things)-AI model. The model is designed to assess pollution data in a smart city, using Aarhus, Denmark, as a case study. The fusion of SWoT and AI is pivotal for revolutionizing pollution management in smart cities. SWoT's semantic framework establishes standardized data representation for interoperability among diverse sources, while AI processes and analyzes this amalgamated data for profound insights. The synergy enables real-time monitoring and early warning systems, empowering proactive measures against potential pollution events. SWoT's semantic understanding, combined with AI's capacity to decipher complex data, facilitates decision support systems for informed policymaking. This collaborative approach optimizes resource allocation, ensuring efficient management of energy, transportation, and waste. Additionally, AI-driven predictive analytics forecast pollution trends, enabling proactive policies for environmental sustainability in smart cities, thereby fostering resilient and intelligent urban ecosystems.

1.1 *Research Problem*

In order to achieve long-term stability through pollution management, the primary implementation problems in wireless networks, AI, and intelligent sensors must be addressed. One complex issue with current IoT applications is that since their data relies on proprietary formats and they do not generally utilize standard terminology or vocabulary to express interoperable IoT data, devices are either not or are only partially interoperable with one another.

1.2 *Research Objectives*

- To analyze pollution measurement from the ready4smartcity database using ANN-IoT-based architecture. Using a correlation matrix, analyze the relationship between various gases/pollutants in the traffic pollution dataset considered.
- To calculate RMSE (Root mean squared error), MSE (Mean squared error) values in the proposed SWoT-AI model for validation and interoperability of pollution dataset.
- To perform comparison of errors for the different activation functions.

1.3 *Research Significance*

This paper contributes significantly to the Semantic Web of Things and its potential for improving data models in pollution measurement. The primary aim is to explore environmental pollution using an ANN-IoT framework, ensuring compatibility with different activation functions: Sigmoid, ReLU (Rectified Linear Unit), Tanh (Tangential Hyperbolic activation), Maxout and Swish hybrid. By identifying the relevant ontologies for enhancing energy efficiency in smart cities and understanding the rules and specifications governing data use (publication and exchange) according to these ontologies, available traffic sensors can offer more precise data. The study includes the MSE and RMSE values for a pollution dataset, specifically sourced from Ready4SmartCities in Aarhus city, Denmark, spanning across three months. This assessment of pollution data in smart cities, leveraging AI-SWoT, represents a significant aspect of this research.

2. Literature Review

The literature studies are selected based on relevancy to the research study, useful sources of information from journals and the information are evaluated and stated. The strategy of critical analysis is based on the initial tasks, data collection, and data analysis to carry out the research study. Most literature studies are relevant to IoT, SWoT, ANNs and data processing.

2.1 *IoT ontologies*

Various Web projects, including Schema.org [7], index ontologies and vocabularies are available to enhance the structured data on the Web. Schema.org is an initiative aimed towards cooperation, focussing on creating, preserving, and promoting schemas for structured web data. It is widely adopted, with over 10 million websites presently utilizing its diverse types, properties, and enumeration values. While Schema.org offers abstract classes suitable for SWoT systems, it lacks specialized IoT concepts like actuators and sensors. Ontology components typically encompass objects, occurrences, relationships, and traits, often using objects to describe something along with associated items [8].

The Open Knowledge Foundation gives users online access to reusable semantic vocabulary, including the LOV (Linked Open Vocabularies) database [9-10]. LOV simplifies vocabulary discovery for web content and is linked to the IoT via LOV4IoT [11]. The Web Thing Model describes Things using both static and dynamic properties. Static properties describe the core characteristics of a Thing, while dynamic properties capture contextual information such as location and service attributes [12].

The World Wide Web Consortium's (W3C) Semantic Sensor Network (SSN) Ontology [13] primarily addresses sensor concepts but lacks actuator concepts. SSN integrates various other ontologies, including the DOLCE (Descriptive Ontology for Linguistic and Cognitive Engineering) + DnS Ultra lite (DUL) ontology, W3C SSN ontology, Event Model-F ontology for meteorological sensors [14], and the SPITFIRE Ontology, which covers observations, sensors, and many other concepts. These ontologies collectively contribute to describing knowledge related to IoT entities and their interactions [14].

2.2 *IoT's semantic web stack*

IoT's semantic web stack displays the fundamental semantic web technologies (SWTs) applied at various IoT system levels. There are three primary levels of SWT incorporation into IoT systems. The modeling level offers a shared knowledge of the properties and capabilities of Things [15]. It leverages widely acknowledged and shared vocabularies and ontologies to make integrating data produced by many systems, such as sensor ontologies, easier. OWL semantics and Description logic are used at the "data processing level" to support data-driven reasoning and inference. The "IoT Services and Applications" level, which is the final level, makes use of specific descriptions and ontologies to facilitate the publication, discovery, composition, and modification of services [16].

2.2.1 Semantic web services discovery

Users should use, generate, and exchange knowledge in large-scale environments with various users, whether they are software agents, robots, intelligent gadgets, or people. To address this challenge, a standard language and framework for communicating knowledge are used [17-19]. For AI calculations, the standard metadata known as WSDL documents is complicated to understand on a semantic level. On this basis, semantic web administration disclosure has been put forth as a potential solution. Numerous methods have been used to replicate administration depictions to enhance Web administrations with machine-processable semantics, including Web Service Modeling Ontology [20], WSMO-lite and Lightweight semantic annotations for Web services [21].

2.2.2 Processing of data

An IoT system, inherently a distributed system, facilitates multiple levels of data processing. While local data may provide only basic insights and processing within its scope, more extensive analyses become feasible when data is aggregated, managed, and interconnected from various sources. Experts have proposed two approaches for handling and processing data: employing algorithms for big data analysis, including AI, and employing semantic reasoners [22].

Big Data and algorithms for machine learning (ML) – Reasons why semantic tools are a great choice for IoT structures are: i) they enable data exchange through schematics and ontologies, and ii) knowledge embedding in ontologies using depiction reasoning components. However, huge amounts of data mixed with ontologies with high expressiveness can limit the effectiveness of reasoners' inferences. IoT systems are typically used to track, identify, forecast, and suggest movements.

3. Methodology

The proposed model for validating and interoperability of pollution measurement using SWoT and Artificial intelligence is represented in Figure 2. The components of Figure 2 are: IoT system, which can compute and communicate, and can exchange data with other networked devices to coordinate its operations and to create data that will be utilized at an advanced stage of the application or service; OWL (The W3C Web

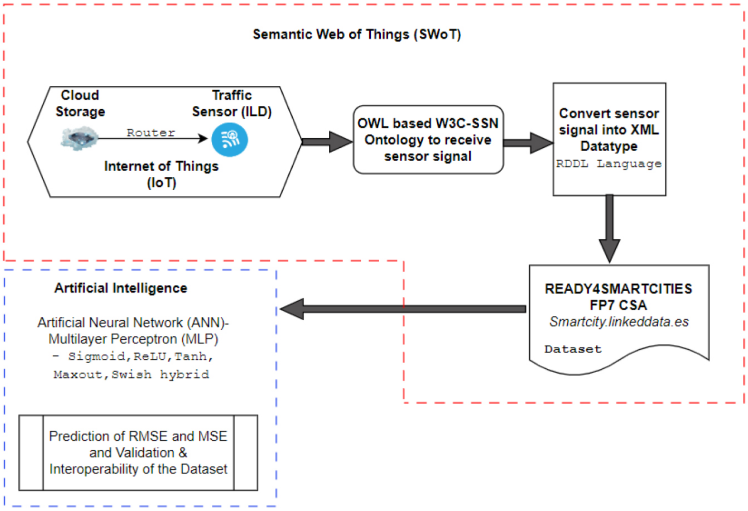

Figure 2

SWoT & AI based method for Validating & for Interoperability of Pollution data Measurement in Smart cities

Ontology Language) based W3C-SSN ontology, which is used to retrieve sensor signal, and the sensor signal is then converted into XML (eXtensible Markup Language) data type; Dataset (of smart city pollution) collected from Ready4smartcities is analyzed using AI-based ANN-MLP with activation functions of Sigmoid, ReLU, Tanh, Maxout and Swish hybrid.

3.1 *IoT Architecture*

While IoT systems can become highly complex, Figure 3 illustrates a simplified IoT system architecture. In this setup, a computationally and communicatively capable object can exchange data with other networked entities to coordinate their actions. It can also generate data that finds utility at higher levels of application and services, such as analytics and business decision-making.

Three primary capabilities define a Thing in an IoT system: connectivity, programmability (including data storage and processing), and sensing and actuation abilities. According to ITU, a "device" is an "equipment piece with optional capabilities for sensing, actuation, data acquisition, data storage, and data processing" [23]. Sensing and actuation abilities enable the Thing to communicate with its surroundings. Thing possess either sensing (e.g., a thermometer) or actuation (e.g., motors) capabilities, or both (e.g., thermostats). For instance, traffic sensors like ILD-Inductive Loop Detectors are employed for traffic monitoring. Sensing capabilities can be shared across various services as well as applications,

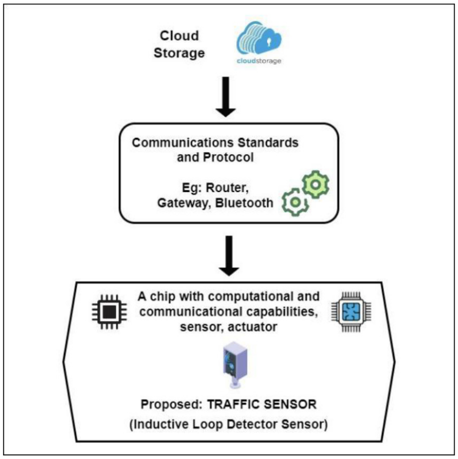

Figure 3

Architecture of IoT

enhancing the overall IoT value, while triggering capabilities are typically restricted and often require authorization [24].

3.2 *OWL-based W3C-SSN ontology*

OWL extends RDF (Resource Description Framework) schema and offers a technical syntax for ontology definition, adding more expressive concepts compared to RDF. OWL allows for logical expressions and contextual relationships like equality, property constraints, class intersections, cardinality, versioning, and property characteristics within the vocabulary, which includes terms like class, property type, subclass type, domain, and range.

The W3C Semantic Sensor Network (SSN) ontology, derived from Sensor ML, serves platforms, systems, sensors, and sensor data. It enables cross-domain concepts for sensors and annotates attributes like deployment, capabilities, and observations. SSN supports sensor deployment, maintenance, and discovery, forming the foundation of the SSN model [25]. Figure 2 illustrates the use of the W3C SSN ontology in retrieving traffic sensor signals, highlighting the role of Semantic Web Things (SWTs) in IoT.

However, the SSN ontology does not model parameters related to time, space, data representation, measurement units, control, actuation, network connections, and topology. It consists of ten components, encompassing 39 object properties and 41 concepts, all rooted in eleven DUL ideas and its fourteen object properties.

The SSN ontology merges sensor and observation topic information using the Stimulus-Sensor-Observation (SSO) ontology configuration. Key classes in SSN include device, sensing process, observation, feature of interest, deployment, measurement capability, and platform. SSN is modular in design, emphasizing the fundamental aspects of sensing rather than communication.

3.3 *XML Data Type and RDDL Language*

XML Schemas provide standard vocabularies enabling computers to adhere to human-defined rules, specifying the structure, content, and semantics of XML documents. On May 2, 2001, XML Schema 1.0 became a W3C recommendation, with a second edition released on October 28, 2004, addressing various errors. The W3C's XML Schema Working Group oversees this work, and the W3C XML Schema Interest Group discusses technical aspects related to XML Schema development [26].

Resource directories, created using the Resource Directory Description Language (RDDL), offer comprehensive information about objects, including human-readable textual descriptions and lists of relevant resources, each linked with information about the resource. RDDL was designed for describing XML namespaces, associating resources like schemas, style guides, and executable code with specific namespaces. When dereferencing a URI acting as a name for the XML namespace, the returned entity body is intended to be a Resource Directory, suitable for that purpose. XHTML Basic 1.0 is expanded into RDDL, including a resource element that acts as the resource's XLink. This XLink includes a machine-readable resource description and links explaining the link's purpose and the resource's attributes, with xlink:role indicating the resource type and xlink:arcrole specifying the link's goal [27]. Figure 2 in the methodology demonstrates the conversion of traffic sensor signals, retrieved through the SSN ontology, into XML format using RDDL.

3.4 *Dataset*

Data streams on pollution from Aarhus (Denmark) between August and October 2014 have been considered. This dataset contains simulation data for each traffic sensor at its precise position. Ozone (O_3) index, sulphur dioxide (SO_2), carbon monoxide (CO), nitrogen dioxide (NO_2), and particulate matter levels are all given pollution values. Air Quality Index (AQI) measures the data (450 total observation points).

This dataset was collected from Ready4SmartCities, comprising over 17000 data records. The CityPulse information model is used to provide the data in both its raw (CSV) and semantically annotated form (Turtle) [28]. A snapshot of the raw dataset is shown in Figure 4.

	ozone	particullate_matter	carbon_monoxide	sulfure_dioxide	nitrogen_dioxide	longitude	latitude	timestamp
0	44	69	57	67	83	10.189355	56.182102	2014-08-01 00:05:00
1	41	66	54	67	78	10.189355	56.182102	2014-08-01 00:10:00
2	46	62	59	68	80	10.189355	56.182102	2014-08-01 00:15:00
3	44	58	58	64	80	10.189355	56.182102	2014-08-01 00:20:00
4	48	55	63	59	82	10.189355	56.182102	2014-08-01 00:25:00
...	...	...	...	...	...	...	...	...
17563	79	170	164	158	73	10.189355	56.182102	2014-09-30 23:40:00
17564	81	166	166	153	74	10.189355	56.182102	2014-09-30 23:45:00
17565	83	170	163	157	74	10.189355	56.182102	2014-09-30 23:50:00
17566	84	165	161	162	69	10.189355	56.182102	2014-09-30 23:55:00
17567	79	165	157	160	69	10.189355	56.182102	2014-10-01 00:00:00

17568 rows × 8 columns

Figure 4

Snapshot of the raw dataset

The Ready4SmartCities project (http://www.ready4smartcities.eu/) aims to promote understanding and interoperability for the deployment of ICT (information and communication technologies) and semantic technologies in energy systems to achieve a reduction in consumption of energy and emission of CO_2 (carbon dioxide) at the level of smart cities' communities by innovatively relying on RTD (Resistance temperature detector) sensor and innovative thinking outcomes and ICT-based solutions.

3.5 *ANN – Multilayer perceptron, Activation functions*

An ANN can use a feedforward or feedback network topology. There are k input arcs that originate from nodes 1, 2, and k, each of which has associated input values and weights w_{1i},... x_{ki} and w_{1i},... w_{ki}, respectively. The values are being transmitted over the network. The y_i value displays the forecast. The input values are subjected to various activation functions (f_i) before flowing through the network, as shown in Figure 5 [29].

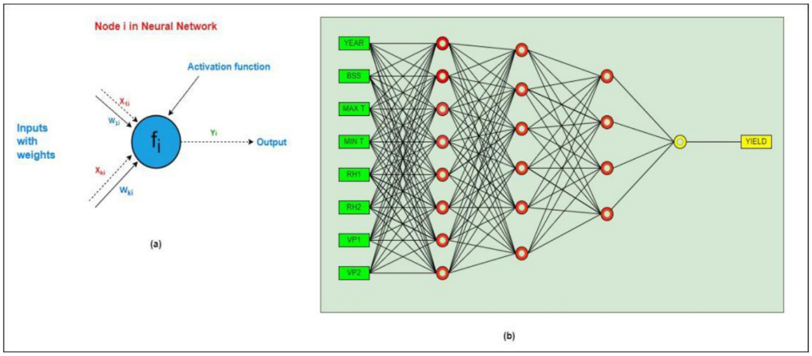

Figure 5

(a) Simple structure of a neural network node (b) Neural network with input, output and hidden layers [29]

3.5.1 Multilayer perceptron

The most popular neural network is MLP. Artificial neurons are used to create neural networks, each carrying a distinct weight. From 1 to n, where n (an integer value) denotes the total no. of inputs, a neuron can receive any number of inputs. The inputs are written as $x_1, x_2, x_3, \ldots x_n$ while the weights are written as $w_1, w_2, w_3, \ldots w_n$ and the output is written as $a = x_1w_1+x_2w_2+x_3w_3+x_nw_n$. We can employ neural networks both for classification and numerical prediction. The MLP algorithm is adapted from [29].

The network, which is a deep network, comprises of multiple hidden layers of several nodes. The input value from the layer before it is multiplied by the weights and biases before reaching unit j in the hidden layer. The nonlinear activation function *f* yields a single output for the hidden unit j using equation 1 [4].

$$O_j^i = F\sum_{K=1}^{K} w_{k_j} x_k + \theta_j \quad (1)$$

where, K= the no. of hidden units in each hidden layer, F = transfer function, and w and θ are the weights and biases that must be learned for unit j.

3.5.2 Activation functions

A processing element or squashing function are other names for an activation function. There are numerous activation functions, including sigmoid, threshold, and Gaussian. Equation 2, a sum of products, is generated when the activation function is applied to the input values; if bias exists, equation 3 is also formed. Each node in a neural network has an additional input called bias, which is an integer value. The swish activation function has been represented using equation 2 and 3, where W_{ij} stands for weight and X_{ij} for input values related to the input layer.

$$S_i = \sum_{j=1}^{k} (W_{ij} X_{ij}) \quad (2)$$

$$S_i = W_{0i} \sum_{k=1}^{k} (W_{ij} X_{ij}) \quad (3)$$

Scardapane et al. [30] proposed the Swish activation function, which was found favorable during experimentation, intercalating between a linear function and ReLU. However, the Swish activation function still faces the issue of gradient diminishment.

Tanh, a widely used activation function, shares properties with the sigmoid function but yields output values ranging from -1 to 1. Its non-linearity supports layer stacking and aids in preventing activation blow-up thanks to its -1 to 1 range. Tanh also boasts steeper derivatives than sigmoid, making it suitable when strong gradients are needed [4]. Nonetheless, both Tanh and sigmoid suffer from vanishing gradients in both positive and negative directions, especially when lower-layer gradients approach zero. Proper weight initialization is crucial to mitigate saturation issues during initial training. Equation 4 for the Tanh function can be formulated as follows:

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{4}$$

where, x= real-valued input, ranging between -1 to 1. In this work, hybrid is denoted as the composition of two activation functions (Tanh and Swish). Equation 5 shows the hybrid activation function (Tanh activation functions for the sigmoid plot).

$$\tanh(x) = \frac{2}{1+e^{-2x}} - 1, f'(x) = f(x)(1 - f(x)) \tag{5}$$

where, x is the input value of the Tanh function, and its range -1 to 1 which is better to map near negative and zero.

ReLU has become a popular choice in different applications including natural language processing, image identification, and numerous other ML tasks because of its simplicity and its effectiveness in mitigating the vanishing gradient problem. By passing through positive inputs and producing zero for negative inputs, it creates non-linearity, as shown in equation 6.

$$f(x) = \max(0, x) \tag{6}$$

Maxout is an activation function that generalizes ReLU by taking the maximum output of k linear combinations of input features, as shown in equation 7, allowing the model to learn more complex relationships by adapting multiple piecewise linear functions for different regions of the input space.

$$f(x) = \max(w_1^T x + b_1, w_2^T x + b_2, \ldots, w_k^T x + b_k) \tag{7}$$

4. Results and Discussions

The MLP model explained in the methodology has been implemented in Python.

4.1 *ANN-based Validation and Interoperability*

The methodology used for validating and interoperability of pollution data retrieved from SWoT regarding AI technology is to analyze it using a multi-criteria approach comprising different fitness values such as MSE and RMSE. Figure 6 shows a Python code snippet used to calculate MSE and RMSE.

```
from torchmetrics.regression import MeanSquaredError
mean_sq_er = MeanSquaredError()
print("MSE - ",mean_sq_er(test_pred,y_test))
print("RMSE - ",np.sqrt(mean_sq_er(test_pred,y_test)))
print("Error - \n",(test_pred-y_test))
```

```
MSE -  tensor(192.0002)
RMSE -  tensor(13.8564)
Error -
 tensor([[ 0.0701],
        [ 0.0025],
        [-0.0176],
        ...,
        [-0.0028],
        [ 0.0604],
        [-0.0124]])
```

Figure 6

Result output of MSE and RMSE calculation

Equation 8 and 9 show the formula for calculating MSE and RMSE, respectively.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{8}$$

where, n = data points number, Y_i = value which is observed, $\hat{Y}_i$ = value which is predicted

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}} \tag{9}$$

where, n = records number, P_i = predicted value, O_i = actual value

4.2 *Dataset*

In this work, the dataset, using random train-test data division, is split into training data sets and testing data sets maintaining a 80:20 ratio. It's crucial for the training set to be sufficiently large to adequately

```
(array([[ 70.        ,  43.        ,  76.        ,  60.        ,
          10.18935531,  56.18210218],
        [167.        , 188.        ,  78.        , 205.        ,
          10.18935531,  56.18210218],
        [ 43.        ,  38.        , 119.        ,  74.        ,
          10.18935531,  56.18210218],
        [ 60.        ,  22.        ,  94.        , 155.        ,
          10.18935531,  56.18210218],
        [189.        , 150.        ,  57.        ,  70.        ,
          10.18935531,  56.18210218]]),
        carbon_monoxide
 15010              144
 11069               99
 2528               142
 8181                99
 13574              198)
```

(a) X_train, Y_train (first 5 records)

```
(array([[-3.96529774e-01,  1.24979748e+00,  4.34154728e-01,
          1.46416244e-01,  0.00000000e+00,  7.10542736e-15],
        [-5.97964845e-01, -6.14234399e-01,  7.65092577e-02,
          1.08871225e+00,  0.00000000e+00,  7.10542736e-15],
        [-5.61340287e-01, -1.47846736e+00, -6.18912491e-01,
          1.85056860e+00,  0.00000000e+00,  7.10542736e-15],
        [ 2.26087720e-01, -1.59708757e+00, -3.01005406e-01,
         -9.16172872e-01,  0.00000000e+00,  7.10542736e-15],
        [ 3.17649116e-01,  7.58370893e-01,  3.34808764e-01,
          1.65008009e+00,  0.00000000e+00,  7.10542736e-15]]),
        carbon_monoxide
 12223              116
 15459               45
 8658                30
 3695                52
 11350              141)
```

(b) X_test, Y_test (first 5 records)

Figure 7

Snapshot of training and testing data

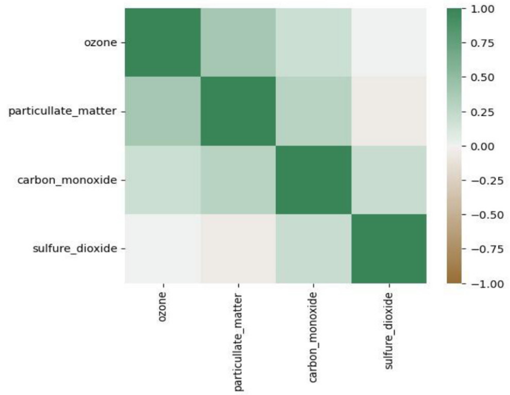

Figure 8

Correlation matrix for pollution index

represent the population, ensuring optimal solution capability in ANN modeling. Additionally, the testing set must be randomly selected to guarantee that its characteristics align with those of the training data. Figure 7 shows a snapshot of the first five records for training and testing dataset respectively.

Figure 8 displays a correlation matrix between atmospheric gases, indicating the strength of their relationships. The color gradient within each cell signifies the correlation between any two gases or pollutants, with values ranging from -1 to 1- stronger correlations result in larger magnitudes, and a positive value signifies a consistent correlation, while a negative value indicates an inverse correlation. The correlation matrix signifies the importance of gases and pollutants in the dataset, revealing how each of the five-O_3 index, SO_2, CO, NO_2, and particulate matter levels influence one another in the pollution index dataset. While this information can be valuable for feature selection, this dataset contains only a few columns (features), primarily consisting of five gases, potentially making feature selection more efficient.

4.3 *Comparison of Error*

The presented ANN modeling results, employing five activation functions, for various hidden nodes, have been showcased. The training and testing datasets in this finding are validated using RMSE and MSE. The effectiveness of activation functions in estimating pollution measurements is evident. Figure 9 presents a comparison of MSE and RMSE values for different activation functions-Sigmoid, ReLU, Tanh, Maxout and Swish hybrid, further showing minimal error value and highlighting the prediction accuracy for the SWoT ANN model using ReLU and Maxout activation functions.

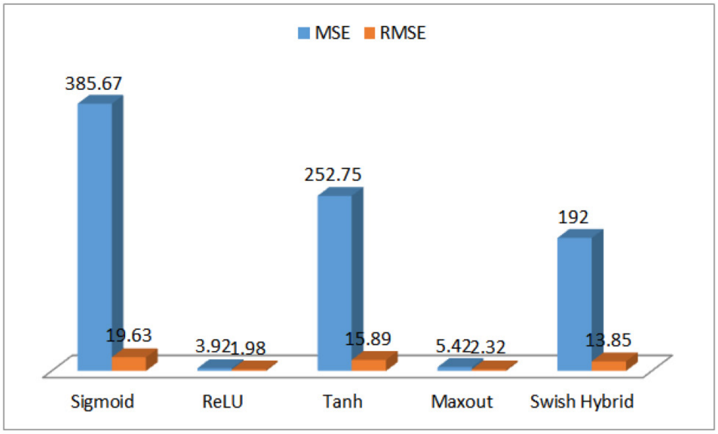

Figure 9

Comparison of MSE and RMSE for different Activation functions

Figure 10 shows a comparison between the actual value and predicted values, i.e. error, for the SWoT-AI model using ReLU activation function.

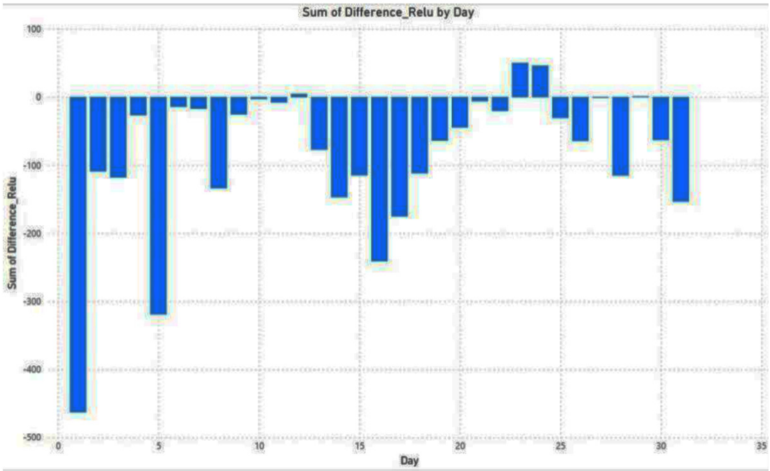

Figure 10

Differences in the Actual and Predicted Values of AQI by day

Figure 10 shows the results of the proposed SWoT and AI-based model for validation and interoperability. Spread over a total of 3500 samples, the difference or error between the actual value of the dataset and the predicted values is shown, implying that the results of this model do not vary greatly in comparison to the actual values for ReLU activation function, which in turn tells about the high accuracy of the model.

Figure 11 presents a comparative 3D view of the error values (sum of difference by day) on employing different activation functions, namely- Sigmoid, ReLU, Tanh, Maxout and Swish hybrid. It shows an overall stable state and minimum error in the proposed model using ReLU activation function as compared to other activation functions which produce higher varying error values.

It is therefore more accurate, with minor errors and promising results with many samples. This model can be suggested for precise environmental pollution measurement by checking the AQI due to greenhouse gases which cause global warming and ozone layer depletion. Pollution control is essential for Earth. Otherwise, it will be deadly, affecting us in the upcoming years. Ozone layer depletion leads to higher UV (ultraviolet) rays on Earth, and it directly harms the human skin, resulting in skin cancer and other harmful effects.

The model discussed in this paper stands out due to its utilization of ANN, which offers increased accuracy even with a relatively small dataset. The AI-based SWoT model enhances precision, accuracy, scalability, and adaptability for testing on larger datasets, making it a more intelligent and versatile choice compared to other models.

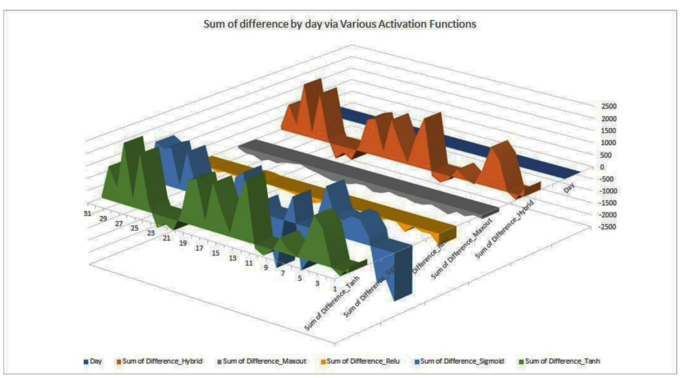

Figure 11

Comparison of Error (sum of difference by day) for different Activation functions

5. Conclusion and Future Scope

In conclusion, this research shows that the ANN model excels in both solution and pollution prediction. The hybrid activation function proves effective with minimal generalization error and high model accuracy in the proposed SWoT and AI-based model, particularly for monitoring air pollution indices in smart cities. IoT technologies are crucial for connecting urban sensors, enabling environmental monitoring.

Using pollution data from Aarhus, Denmark, sourced from Ready4SmartCities, this study emphasizes the significance of SWTs in IoT applications. The SWoT methodology, incorporating AI mechanisms, validates an IoT-based pollution dataset. Additionally, a correlation matrix illustrates relationships between various gases and pollutants. The ANN-MLP model, employing the ReLU activation function, exhibits the least RMSE and MSE, confirming data accuracy.

Looking forward, this research envisions an enhanced IoT system by merging semantic technologies and custom machine learning algorithms. Expanding to larger case studies in different cities aims to monitor a broader range of environmental factors, including dust, fog, water pollution, mist, radiation, noise, harmful chemicals, and heavy metals in food.

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