SMART-FCD: IOT DATA INTEROPERABILITY USING SENSOR BASED FUZZY LINKED RULES FOR CROSS DOMAIN APPLICATIONS

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ABSTRACT

Internet of Things (IoT) is connected everywhere and enables massive information exchange between objects and people. The unified global IoT must manage a massive amount of data generated by these connected smart which arises the interoperability challenges such as lack of communication protocols, device support, and accepted open standards in smart environments. To combat these issues, a novel Smart-Fuzzy linked rules for Cross Domain application (Smart-FCD) framework is proposed to ensure interoperability by enabling efficient communication and data exchange between multiple platforms and systems. Initially, the heterogenous data from the sensors such as temperature sensors and humidity sensors, and the descriptions are implemented according to the Sensor Measurement List (SenML) language. After composing, semantic modelling will occur which converts the relational data into Resource Description Framework (RDF) format. The Linked Open Vocabulary for the Internet of Things (LOV4IoT) dataset is used to extract interoperable domain knowledge, which is then fed into the related sensor-based fuzzy rules. The IoT preset semantic models which utilise interoperable datasets and domain instances, which are updated via fuzzy association rules. Semantic Web of Things (SWoT) is a technology that assists in creating semantic-based IoT applications, thus IoT developers may use it to create intelligent applications. The sensor data, RDF simulation, evolution time and latency are some of the parameters that are used to evaluate the effectiveness of the proposed Smart-FCD methodology.

Keywords: Semantic Interoperability; Internet of Things; Resource Description Framework; Fuzzy Inference SystemLinked Open Vocabularies for Internet of Things.

1.0 INTRODUCTION

IoT enables the data transfer between humans and physical items, which is carried out via IoT-based user activities' services and gadgets [1]. Using complimentary elements and Internet Protocol (IP), atmospheric bodies or objects actively participate in data sharing across wired or wireless networks[2]. Employing extra objects and facilities needed by heterogeneous objects to share data in an interoperable way to give understandable information and services. The semantic interoperability provides a high efficiency and a more comprehensive understanding of technological platforms and devices [3].Semantic interoperability of Internet of Things applications is critical to enabling decentralization and integration of personal health data, since it allows for the description of knowledge and information using ontologies and semantic languages. Semantic interoperability, on the other hand, creates a shared language that makes computer-to-computer communication precise and dependable. Efficient communication between machines relies on the capacity of various HIT systems to convert disparate ideas into a shared meaning or semantics. Semantic interoperability facilitates communication across devices and platforms [4].

They enable communication between devices and cloud-based platforms that process and evaluate the data produced by the devices. Complex applications can respond fast to changing conditions to this communication's real-time monitoring and control of equipment [5]. The system can respond because it is aware of the present situation to data collected by IoT devices and allows the system to grasp the context of that data [6]. Because IoT devices and data formats are so diverse, semantic interoperability in the IoT applications continues to be a major concern. The interconnection of devices from many distinct domains results in a challenging data exchange task with semantic heterogeneity [9]. The diversity of devices and the dynamic nature of their requirements and deployment circumstances make it more difficult to manage and configure them. These difficulties result from the absence of a separate, defined model for IoT devices, their data, and services [10]. To resolve these shortcomings, this paper proposed a novel Smart-Fuzzy linked rules for Cross-Domain application (Smart-FCD) which ensures interoperability by enabling efficient communication and data exchange between multiple platforms and systems. The major contributions of the proposed Smart-FCD approach is given as follows.

- Initially, the heterogenous data from the sensors such as temperature sensor and humidity sensors and the descriptions are implemented according to the SenML language. After composing, semantic modelling will occur which converts the relational data into RDF format.
- The Linked Open Vocabulary for the Internet of Things (LOV4IoT) dataset is used to extract interoperable domain knowledge, which is then fed into the related sensor-based fuzzy rules.
- The IoT preset semantic models which utilise interoperable datasets and domain instances, which are updated via fuzzy association rules.
- Semantic Web of Things (SWoT) is a technology that assists in creating semantic-based IoT applications, thus IoT developers may use it to create intelligent applications.
- The sensor data, RDF simulation, evolution time and latency are some of the parameters that are used to evaluate the effectiveness of the proposed Smart-FCD methodology.

The work described in this paper is organized as follows; Section II describes the related works on semantic interoperability. The detailed description of the proposed Smart-Fuzzy linked rules for Cross Domain application is described in Section III. The thorough explanation of the experimental findings and research discussions are described in Section IV. The conclusions and the future research of this research is described in Section V.

2.0 LITERATURE SURVEY

The development of the IoT paradigm has led to the creation of a number of fundamental ideas that offer deeper insights into actual IoT deployments in multi-domain applications. Some of the strategies are covered briefly in this section. In 2022 Famá, F., et al[11] suggested an interoperable IoT-based system for wireless organic tracking of patients using sensor patches. At the top level, numerous discrete low-power sensors are attached to the patient's body, the hospital bed, and the smart gateway. These sensors integrate with the hospital's current information systems via BLE-based EHR exchange, MQTT protocol, and FHIR standards. However, the suggested approach consist of lack of Security and privacy.

In 2022 Pathak, N., et al[12] suggested a semantic interoperability in the field of mobile electronic medical equipment. The suggested SemBox technique classifies the received data packets using three distinct fitness wearables and a Mamdani-based FIS with data preprocessing. The maximum classification accuracy of the suggested SemBox approach is 85.71%, and the maximum PDR is 1. However, the suggested SemBox approach suffers from security and privacy issues. In 2023 Calbimonte, J.P., et al[13] suggested a distributed semantics for feeds related to individual health. The suggested SemPryv framework facilitates the management of semantically enhanced streams of personal health data. An overall request success rate of 4% to 5% is achieved by the suggested SemPryv approach. However, processing massive volumes of data from the SemPryv method rapidly is challenging. In 2023 Thirumahal, R. and SudhaSadasivam, G.,[14] suggested a semantic integration of disparate fitness data ontology with a hybrid root. Expand the ontology version using SPARQL queries, which is based entirely on the database. A comparable highest accuracy of 99% is achieved by the suggested hybrid root LHR ontology. However, the reliability of the suggested approach is need to be enhanced.

In 2023 Kamalesh, S. and Muthukrishnan, A.,[15] suggested an IoT-based fully context-aware architecture with dictionary-based completely SRL designed for healthcare tracking. The DBSRL approach is used in the suggested procedure to categorize the patient's state as normal, irregular, or critical. When applied to OMNeT, the suggested DSRL-GJO-HD-CAA-IOT approach yields faster reaction times than 36%, 29.51% greater scalability, and 7.73% higher accuracy. In 2023 Singh, A. and Chatterjee, K.,[16] suggested an health monitoring framework based on Edge computing for electronic healthcare system. ABE focuses on robust biological signal records and steady accessibility, while the suggested SEOT technique uses clustering strategies to explore biological signal records for anomaly identification. The suggested SEOT approach offers improved profile security and a maximum accuracy of 98.5%. However, the robustness of the suggested SEoT approach is very low. From the related studies, various IoT-based cross-domain techniques were used for the smart environment. However, the scalability, discovery, interoperability, and data management of the aforementioned methods is low. The Smart-FCD technique is proposed as a solution to this issue since it enables complex programs to have the capability to respond quickly to changing conditions by allowing them to be monitored and managed in real-time.

3.0 SMART-FUZZY LINKED RULES FOR CROSS-DOMAIN APPLICATION METHODOLOGY

This paper proposes a novel Smart-Fuzzy linked rules for Cross Domain application (Smart-FCD) framework which is developed to ensures interoperability by Integrating platforms and systems to facilitate seamless data exchange and communication. Initially, the heterogenous data from the sensors such as temperature sensor and humidity sensors and the descriptions are implemented according to the SenML language. After composing Semantic modelling will occur which converts the relational data into RDF format. The Linked Open Vocabulary for the Internet of Things (LOV4IoT) dataset is used to extract interoperable domain knowledge, which is then fed into the related sensor-based fuzzy rules. The domain ontologies and the interoperable datasets used in the preconfigured semantic IoT templates are updated using fuzzy linked rules. The sensor-based fuzzy linked rules infer additional knowledge. The IoT preset semantic models which utilise interoperable datasets and domain instances, which are updated via fuzzy association rules. Semantic Web of Things (SWoT) is a technology that assists in creating semantic-based IoT applications, thus IoT developers may use it to create intelligent applications. The overall block diagram of the proposed method is depicted in Fig.1.

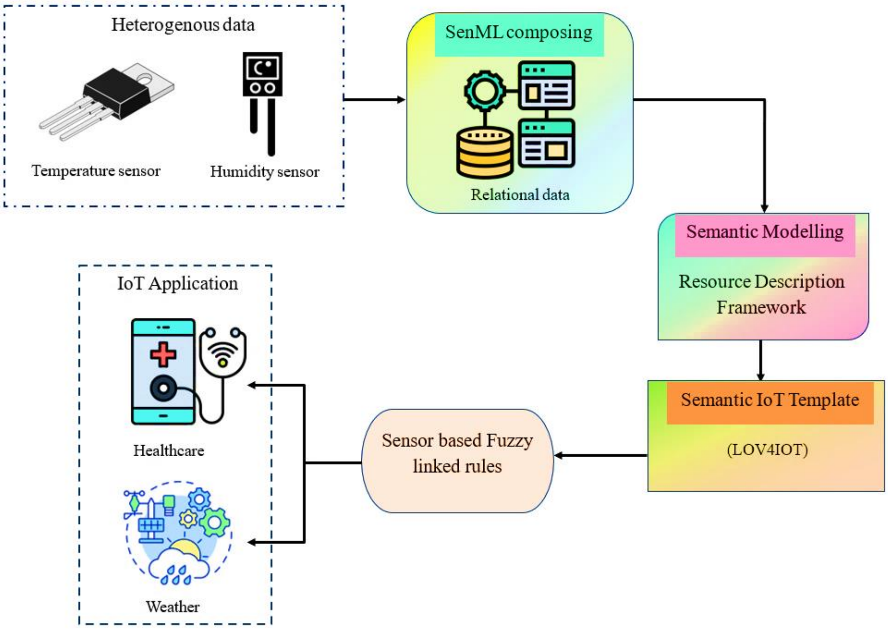

Fig. 1: Overall Block Diagram of the Smart-FCD Model

3.1 Heterogenous Data Colllection

Heterogenous sensors such as temperature and humidity sensors will collect heterogenous data from cross domains such as weather and health domains, which helps in improving interoperability. To successfully control sensors paired with IoT sensors and actuators, they can be connected to the cloud utilizing a variety of communication and transport techniques. This study gathers heterogeneous data using IoT-based temperature and humidity sensors.

(i) Temperature Sensor

The major purposes of temperature sensors are to regulate air conditioners, freezers, and other environmental control systems. The fields of meteorology and medicine currently employ them. With a tiny circuit board size and a digital output signal, these sensors offer precise temperature measurements. Temperature sensors can be included into medical equipment to track the temperature of the air entering respiratory systems, enhancing patient comfort.

(ii) Humidity Sensor

Humidity is the quantity of water vapor in an atmosphere or other gaseous mixture. The phrase "relative humidity" (RH) is the most frequently used. To manage heating, ventilation, and air conditioning systems, they are applied and used in both industrial and residential settings.

3.2 SenML Composing

SenML is a format for consistently documenting sensor measurements and metadata. It is suggested as a mechanism to uniformly describe sensor data in the Internet of Things environment. Each object may have different metadata, including the type of sensor used, the size unit, and the time the measurement was collected. This makes it simple for both humans and machines to understand recordings. One of SenML's important strengths is its capacity to aggregate many measurements into a single message, enabling for the sustainable transmission of sensor data and the correlation of results from several sensors. This feature shortens messages by avoiding the repetition of the same values across all dimensions. In addition, a variety of record codecs, including JSON, CBOR, XML, and Effective XML Interchange (EXI), are used to support SenML. These codecs can share a common SenML records model, allowing sensor data to be represented in an easy-to-understand and easy-to-create format.

3.3 Resource Description Framework(RDF)

The Resource Description Framework (RDF), a standardized data model for representing and connecting data on the Web created by the World Wide Web Consortium (W3C). It is a method of graphical data structure in which nodes stand in for resources like sensors, actuators, or objects, and edges signify connections between them. Due to its ability to integrate heterogeneous data from numerous sources, RDF is particularly beneficial for IoT applications. This is significant in the IoT, because data is frequently produced by various devices utilizing various protocols and file formats. Regardless of the source, data may be merged and queried consistently using RDF. Then, information is represented in triples in RDF. Subject, predicate, and object make up a triple. The resource statements are represented graphically by these three components:

i. ***Subject:*** The context is the source of the information that the message refers to. It can be represented by an empty node or a URI for a resource. The scenario, which describes the relevant usable resource, is typically the most important RDF.
ii. ***Predicate:*** An assertion concerning the subject's quality or connection is known as a predicate. It is represented by an attribute-specific URI. In an RDF triple, the predicate is often the second element.
iii. ***Object:*** The value of a relationship or asset is an object. This could be a real-world resource, or it could be something else. The object is usually the third element of an RDF triple.

It is also possible to represent this data model using turtle syntax or other data binding languages like XML or JSON-LD. Turtle syntax, RDF/XML, and RDF/JSON-LD are all suitable for some IoT applications, however these formats are too complex for devices with constrained capabilities.

3.4 Semantic IoT Template-LOV4IoT

The Linked Open Vocabulary for the Internet of Things (LOV4IoT) makes an effort to analyze data using subject-specific knowledge developed by professionals in the areas of weather and health. In order to quickly improve IoT data, S-LOR (Sensor-based Federated Open Rules) proposes to exchange and reuse interaction rules for Federated Open Data. Furthermore, it requires to reuse IoT LOV4 domain knowledge. Rules and datasets can interact by using ontologies. Useful data is produced by the weather and health sectors and is kept in a time-stamped data warehouse. The same ontology-based project can be integrated into both the weather and the health domains of a static HTML website. To prevent the same position from being done again in two different locations, a single table is no longer sufficient. The table is converted to an RDF dataset in order to provide details on the overall set of ontologies, the set of ontologies consistent with domain, and the set of ontologies consistent with society. When a user requests a portion of the LOV4IoT dataset, the RDF dataset automatically builds a table inside the HTML web page and filters ontology-based projects by society or ontology domain.

3.5 Sensor based Fuzzy Linked Rules

A collection of objects known as a fuzzy set has a membership function that ranges from 0 to 1. In this technique, linguistic factors such as high risk , moderate risk, and no risk are employed as variables. Term sets are the values used to represent linguistic variables and term sets are the collections of such values. Situations are assessed using fuzzy rules (IF-THEN). The outputs are created when the precise inputs are transformed into linguistic variables, fuzzy rules are applied to them, and outputs are generated. In the defuzzification stage, the linguistic values of the output are transformed into net values. Trapezoidal functions are employed to determine the high and low terms. The fuzzifier employs the Mamdani inference method and a region-centroid defuzzification strategy. Fuzzy sets are used by IF-THEN fuzzy rules in the inference system to produce output.

By offering the ability to make intelligent decisions, fuzzy systems can play a significant part in the composition of services in the IoT.

Fuzzification

This model uses trapezoidal membership functions in conjunction with Mamdani inference rules to fuzzify the equation (1). T_v in the equation stands for the trustworthiness of the user.

$$f(w,x,y,z,\mu) = \begin{cases} 0 \text{ when } T_v < w \text{ and } T_v > z \\ \dfrac{(w - T_v)\mu}{w - x} \text{when } w \leq T_v \leq x \\ \mu \text{ when } x \leq T_v \leq y \\ \dfrac{(z - T_v)\mu}{z - y} \text{ when } y \leq T_v \leq z \end{cases} \tag{1}$$

The inputs and outputs are estimates rather than precise quantities; these estimates establish general categories rather than hard, defined groupings. Inputs are divided into valid ranges to create classes. For eg, the temperature can range from "Very high" to "Very low". The humidity can range from "Very high" to "Very less". Fuzzy sets in three categories such as High Risk (HR), Moderate Risk (MR), and No Risk (NR) determines the output. How much a value falls within a category is indicated by a number between 0 and 1. Table 1 provides the range of the input and output variables.

Table 1: Variables with a variety of inputs and outputs

Fuzzification Input: Temperature		
Value	Notation	Range
Very Low	VL	0-0.15
Low	L	0.15-0.55
Medium	M	0.55-0.75
High	H	0.75-0.9
Very High	VH	0.9-1
Fuzzification Input: Humidity		
Value	Notation	Range
Very Less	VLs	0-0.3
Less	Ls	0.3-0.5
Average	A	0.5-0.7
High	H	0.7-0.8
Very High	VH	0.8-1
Output variable		
Value	Notation	Range
Low Risk	HR	0-0.3
Moderate Risk	MR	0.25-0.9
High Risk	LR	0.8-1

Rule Evaluation

Mamdani's system's inference engine, the findings of the assessment of the trust value, which makes use of a knowledge base with ten FIS, are displayed in table 2.

Table 2: Fuzzy Inference Rule

1.	(Temp = = VL) & (Humidity = = VLs) → (O = = NR)
2.	(Temp = = VH) & (Humidity = = VH) → (O = = HR)
3.	(Temp = = M) & (Humidity = = A) → (O = = MR)
4.	(Temp = = VH) & (Humidity = = VLs) → (O = = HR)

5.	(Temp = = VL) & (Humidity = = VH) → (O = = HR)
6.	(Temp = = L) & (Humidity = = Ls) → (O = = NR)
7.	(Temp = = M) & (Humidity = = Ls) → (O = = MR)
8.	(Temp = = L) & (Humidity = = A) → (O = = MR)

Defuzzification

The process involves turning the fuzzy sets into a crisp value. One of the most often utilised techniques in fuzzy mathematics, the centroid is used in the De-fuzzification method. Equation (2) has been used to select the TV's output crisp value.

$$\text{Trust value} = \frac{\sum_j x_j * \mu_{m\cdot}(x_j)}{\sum_j \mu_{m\cdot}(x_j)} \quad (2)$$

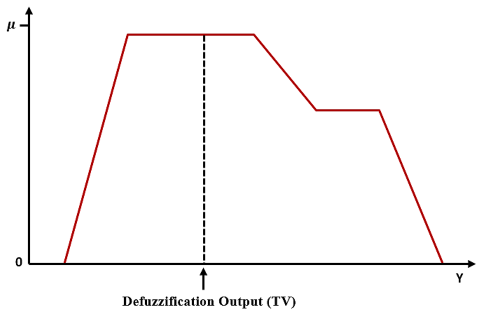

Fig.2 : COA Defuzzification

Whereas, the aggregated output's Membership function is represented by $\mu A(z)$. The 'n' fuzzy set's weighted average is depicted in Fig. 2.

4.0 RESULT AND DISCUSSIONS

The proposed semantic interoperability framework in the public domain cloud platform is provided by Cloud Simulator. Solve interoperability problems in healthcare and weather applications and measure framework performance using analytical evaluation and qualitative evaluation. These tests are performed by the Cloud platform, which must rely on the configuration of the IoT analytics cloud platform.

4.1 Performance Measures

Simulating and modeling large-scale virtualized data centers, and servers are provided by CloudSim. Policies may be tailored to reduce the power consumption of virtual machines and increase server processing power. Cloudsim, which was created using the GridSim simulator, has a multi-level architecture. Its four levels are the Simjava layer, the GridSim layer, the business layer, and the application layer. The Simjava class implements the fundamental functionality needed for higher level simulation. The GridSim layer includes high-level software components for simulating various grid infrastructures and supports the management layer that keeps track on servers, data centers, CPU sets, and virtual machines. Lastly, the Application class allows users to write code that configures the functionality of servers, virtual machines, apps, and broker scheduling policies. To facilitate semantic interoperability across diverse platforms, healthcare and weather applications must communicate effectively. The Sensor data, RDF simulation, Evolution time and latency are taken to evaluate performance.

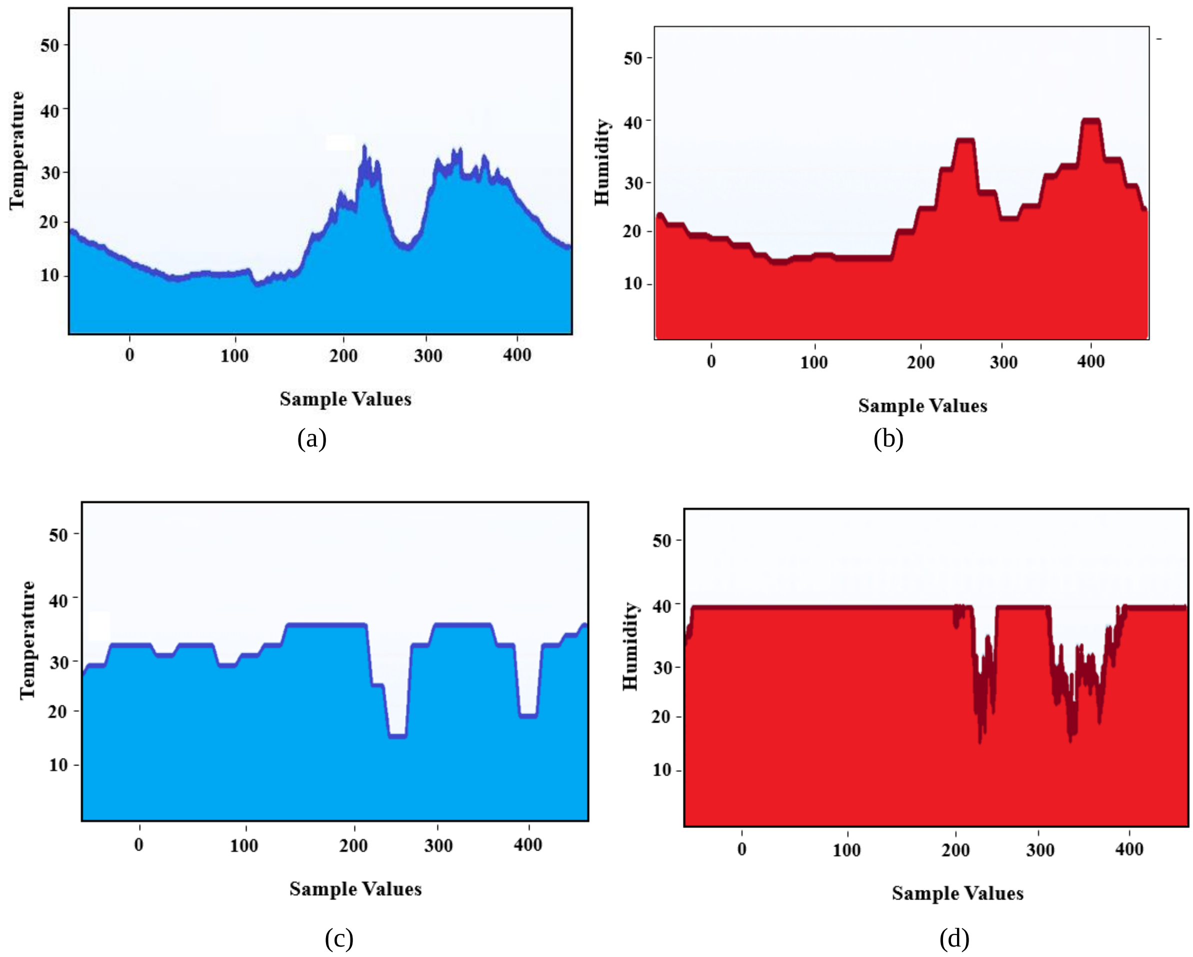

Fig. 3: Sensor data received from the temperature and humidity sensor

Fig.3 displays the temperature and humidity data that the sensors have gathered. A subset of 300 data points from the temperature measurements that were received every 60 seconds are shown in Fig.3. The simple and gradual variations in temperature and humidity over time make these data more stable. The transmission frequency of this data can be lowered to allow for the transfer of complicated and time-sensitive data. For the purpose of analyzing data skew and information loss. The standard deviation is a statistical measure used to analyze the dispersion of big data sets. This is denoted by sigma “r”. It has a correlation with the variance squared and is associated with the mean. This formula yields the sample's standard deviation, represented by “SD”.

$$SD = \sqrt{\frac{\sum(x-\bar{x})^2}{N}} \tag{3}$$

where x is the number of samples and $\bar{x}$ is the mean of the samples.

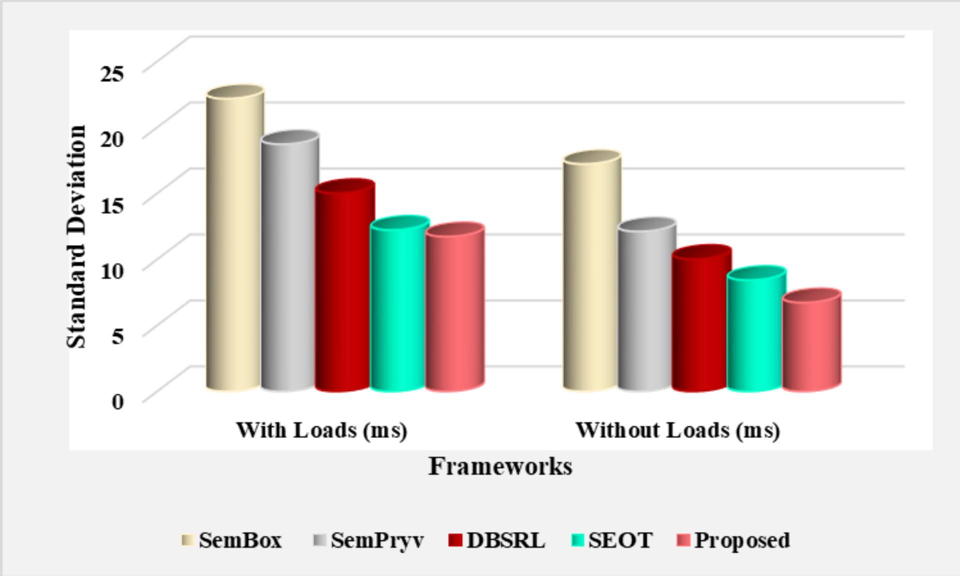

Fig.4: Standard Deviation Vs Frameworks

Fig. 4 displays the standard deviation time on several frames on the same cloud platform with and without load. The computations show that the standard deviation time is 2.17 ms in the absence of load and 7. 25 ms in the presence of load. Therefore, it can be concluded that the proposed structure is better appropriate for multi-domain applications after comparing these findings with those of the existing framework.

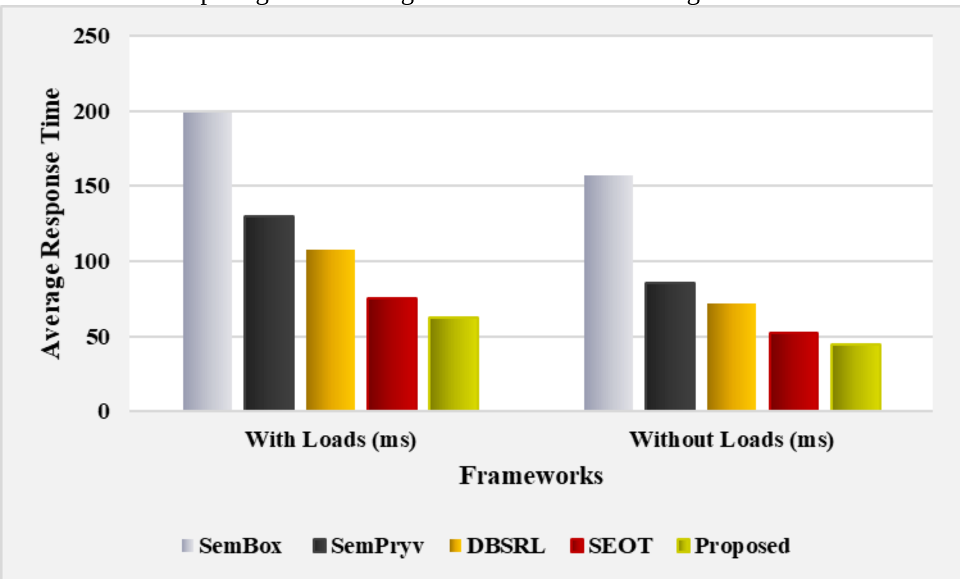

Fig.5: Average Response Time Vs Frameworks

Fig.5 displays the average response time on several cloud platforms on various frameworks, both with and without load. The average response time was determined to be 31.72 ms at idle and 44.14 ms under load. As a consequence, the proposed design is more appropriate for multi-domain applications as compared to the existing framework based on the comparison of these results. Fig.6 shows a simulation of an RDF graph using the user's database. Each attribute can be distinguished by a certain color. Using RDF triples, all fields are semantically tagged to show how one instance relates to other related instances. In order to guarantee interoperability between diverse IoT devices, the data is semantically machine-readable.

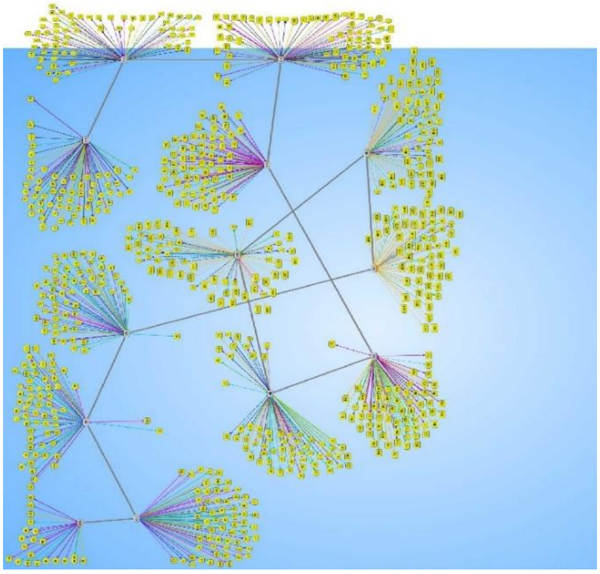

Fig.6: RDF graph for Semantic Interoperability in IoT

Every attribute has its own distinct tint. Every Info node in an RDF network is linked to a distinct Info table, which is a table that has semantic relationships with every instance. Semantically, all fields are annotated with RDF triples, which indicate the link between each instance and its associated instances. Different kinds of IoT devices can connect with each other via machine-readable patient weather records with semantics. Figure 4 illustrates the many ways in which a single node RDF network communicates with another node. An RDF graph is used to show how nodes interact with various dataset properties in Figure 4. RDF diagrams are used to semantically annotate all patient details, guaranteeing that significant provider details are deleted in a way that is both semantically and informationally consistent. Furthermore, for experimental validation, the patient data's are extracted from RDF graphs using text formatting.

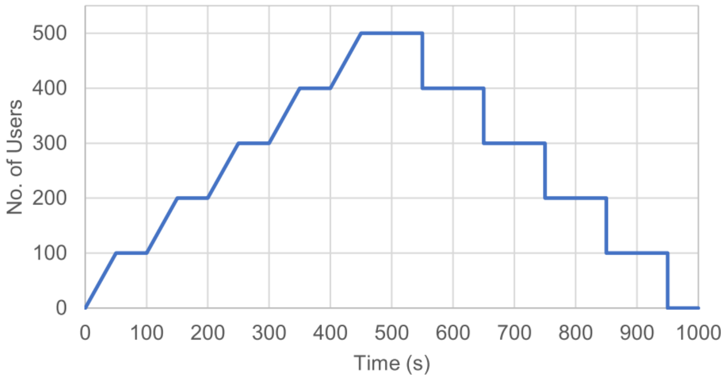

Fig.7: Concurrent user's evolution in time

Fig.7 depicts the development of concurrent consumers through time, with the number of customers escalating from 100 to 500 in a group. The user starts to taper off at a pace of 100 by 100 from time t = 550s until the trial's end. By transmitting random statistics, this arrangement lowers each consumer's latency and throughput size. The client delivers statistics and the framework responds with the requested statistics in an exchange of statistics. The following scenario tests the data read latency while increasing the number of concurrent users from 20 to 100 in increments of 20. In order to examine the impact on server read latency, the number of servers is increased. In Figure 8, the experimental outcomes are displayed. These charts display a box plot of the least latency, first quartile, median, third quartile, and maximum latency for each server 1, 3, 7, and 15. The test will be conducted for 600 seconds with each adjustment for each use case server (i.e. 20, 40, 60, 80, 100). For a set number of users, the latency value is roughly consistent across all servers.

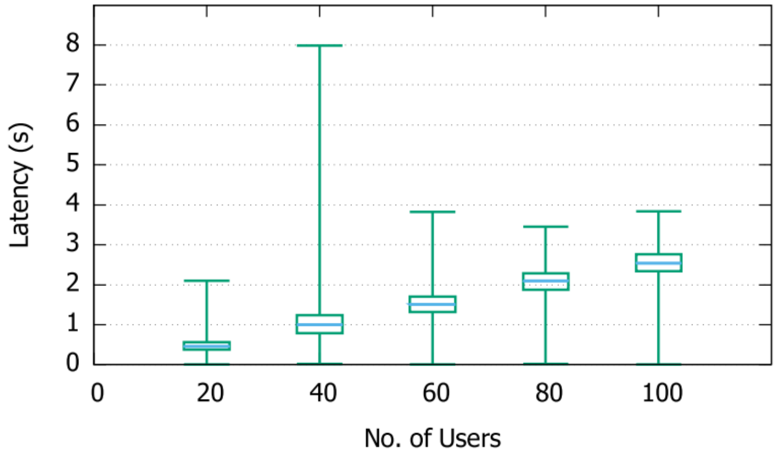

Fig.8: Latency Vs No. of Users

5.0 CONCLUSION

This paper proposed a novel Smart-Fuzzy linked rules for Cross Domain application (Smart-FCD) framework which is developed to ensure interoperability by enabling seamless communication and data exchange across different systems and platforms. Smart-FCD uses formal data presentation, contextual knowledge, and domain insights to make data sharing across systems or organizations easier and guarantee that all stakeholders can comprehend and evaluate the information. The proposed framework is validated by using Cloud Sim. The sensor data, RDF simulation, evolution time and latency are some of the parameters that are used to evaluate the effectiveness of the proposed Smart-FCD methodology. The evolution of the concurrent user count over time, with the number of users escalating from 100 to 500 over time. The number of users begins to decline at time t=550s and continues to do so at a pace of 100 to 100 until the trial is over. Future developments of the proposed Smart-FCD method may make syntactic interoperability amongst diverse IoT devices possible. Syntactic interoperability ensures that the information shared maintains its syntactic structure. Security is the latest major vulnerable when it comes to interoperability among heterogeneous IoT devices. This need to be a crucial component of any engagement strategy. Coming future, difficulties with syntax compatibility and security will be taken into account.

REFERENCES

[1] Fawzy, D., Moussa, S.M. and Badr, N.L., "An IoT-based resource utilization framework using data fusion for smart environments". *Internet of Things*, Vol. 21, 2023, pp.100645.

[2] Alomar, M.A., "An IOT based smart grid system for advanced cooperative transmission and communication". *Physical Communication*, 58, 2023, p.102069.

[3] Koo, J. and Kim, Y.G., "Resource identifier interoperability among heterogeneous IoT platforms". *Journal of King Saud University-Computer and Information Sciences*, Vol. 34, No. 7, 2022, pp. 4191-4208.

[4] Amara, F.Z., Hemam, M., Djezzar, M. and Maimour, M., "Semantic web technologies for internet of things semantic interoperability". *In Advances in Information, Communication and Cybersecurity: Proceedings of ICI2C'21*, Springer International Publishing. 2022.

[5] Rahman, H., Medhi, K. and Hussain, M.I., "DynO-IoT: a dynamic ontology for provisioning semantic interoperability in internet of things". *International Journal of Sensor Networks*, Vol. 41, No. 2, 2023, pp. 114-125.

[6] Yao, S., Lu, Y., Niu, K., Dai, J., Dong, C. and Zhang, P., "Semantic Information Processing for Interoperability in the Industrial Internet of Things". *Fundamental Research*. 2023.

[7] Maamar, Z., Faci, N., Elnaffar, S., Yahya, F., Boukadi, K. and Benslimane, D., "Semantic thingsourcing for the Internet of Things". *Concurrency and Computation: Practice and Experience*, Vol. 35, No. 11, 2023, pp. e6684.

[8] Benkhaled, S., Hemam, M., Djezzar, M. and Maimour, M., "An ontology–based contextual approach for cross-domain applications in internet of things". *Informatica*, Vol. 46, No. 5. 2022.

[9] Gong, B., Zheng, G., Waqas, M., Tu, S. and Chen, S., "LCDMA: Lightweight cross-domain mutual identity authentication scheme for Internet of Things". *IEEE Internet of Things Journal*. 2023.

[10] Alshudukhi, K.S., Khemakhem, M.A., Eassa, F.E. and Jambi, K.M., "An Interoperable Blockchain Security Frameworks Based on Microservices and Smart Contract in IoT Environment". *Electronics*, Vol. 12, No. 3, 2023, pp. 776.

[11] Famá, F., Faria, J.N. and Portugal, D., "An IoT-based interoperable architecture for wireless biomonitoring of patients with sensor patches". *Internet of Things*, Vol. 19, 2022, pp. 100547.

[12] Ahmed, Syed Thouheed, Vinoth Kumar, and JungYoon Kim. "AITel: eHealth Augmented Intelligence based Telemedicine Resource Recommendation Framework for IoT devices in Smart cities." *IEEE Internet of Things Journal*, 2023.

[13] Calbimonte, J.P., Aidonopoulos, O., Dubosson, F., Pocklington, B., Kebets, I., Legris, P.M. and Schumacher, M., "Decentralized semantic provision of personal health streams". *Journal of Web Semantics*, Vol. 76, 2023, pp. 100774.

[14] Thirumahal, R. and SudhaSadasivam, G., "Semantic integration of heterogeneous healthcare data based on hybrid root linked health record ontology". *Earth Science Informatics*, 2023, pp.1-14.

[15] Kamalesh, S. and Muthukrishnan, A., "Optimized Dictionary-based Sparse Regression Learning for Health Care Monitoring in IoT-based Context-Aware Architecture". *IETE Journal of Research*, 2023 pp.1-16.

[16] Al-Shammari, Naif Khalaf, T. H. Syed, and Muzamil Basha Syed. "An Edge–IoT framework and prototype based on blockchain for smart healthcare applications." *Engineering, Technology & Applied Science Research*, Vol. 11, No. 4, 2021, pp. 7326-7331.

[17] Liu, W. and Lu, B., "Semantic Association and Decision-Making for the Internet of Things Based on Partial Differential Fuzzy Unsupervised Models". *Mathematical Problems in Engineering*, 2022, pp.1-11.

[18] Jayender, P. and Kundu, G.K., "IoT Analytics and ERP Interoperability in Automotive SCM: ANN-Fuzzy Logic Technique for Designing Decision Support Systems". *International Journal of Fuzzy System Applications (IJFSA)*, Vol. 11, No.3, pp.1-19. 2022.

[19] Ghorbani, A., Davoodi, F. and Zamanifar, K., "Using type-2 fuzzy ontology to improve semantic interoperability for healthcare and diagnosis of depression". *Artificial Intelligence in Medicine*, Vol. 135, p.102452. 2023.

[20] Kumar, S. Sreedhar, et al. "Unstructured Oncological Image Cluster Identification Using Improved Unsupervised Clustering Techniques." *Computers, Materials & Continua* 72.1 (2022).