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Energy efficient distributed intelligence on cognitive IoT gateway using MQTT protocols

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ABSTRACT

Internet of things (IoT) facilitates communication between machines and devices which plays a crucial role in the conservation of energy. In large-scale multidomain environments securing the data exchange among various IoT devices and key sharing creates a significant challenge. However, the message queuing telemetry transport (MQTT) lacks functional security mechanisms as well as mutual authentication between brokers and clients. To address these issues, a novel cognitive IoT in Teroperability Recognition USing deep learning (CITRUS) framework is developed for real-time decision-making and sharing information among multiple IoT systems. Initially, the healthcare and weather data are collected remotely by using interoperable sensors which are then fed to the deep learning (DL) module for efficient decision-making. The MQTT module makes an energy-efficient IoT data communication over a resource-constrained network and the QoS1 introduces an acknowledgment and retransmission mechanism to ensure message delivery. The efficacy of the CITRUS model has been analyzed in terms of accuracy (AC), recall (RC), F1-score (F1S), sensitivity, packet delivery ratio (PDR), transmission speed, communication overhead, packet loss ratio (PLR) and delay. The experimental result shows that the CITRUS method achieves 89.89% of delay whereas, the IHPEC, SemBox, and Dyno-IoT methods achieve 161.63%, 128.99%, and 111.70% respectively for efficient data transmission.

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1. INTRODUCTION

An internet of things (IoT) platform is a constantly expanding network made up of numerous distinct components or items. IoT will offer an intuitive and secure method of communication and information sharing for individuals attempting to connect to the internet [1], [2]. The semantic web (SW) technology is required to provide effective solutions along with enhancing straightforward user interaction between IoT devices. SW technologies can be used to link disparate IoT components at various IoT infrastructure tiers [3], [4].

Numerous IoT models have been generated to manage objects and their metadata through the use of data models and semantic technologies. This has improved the knowledge representation for heterogeneous IoT items and offered recommendations to develop new IoT systems [5], [6]. Advances in IoT-specific semantic technologies, such as semantic code generation for device interfaces, search, and object identification briefly address the significance of semantic knowledge in the context of the IoT [7], [8]. Smart object applications and services, such as motion detectors, light sensors, and thermostats, are becoming more widely utilized in various settings such as healthcare, cities, and energy production [9]-[12]. The system needs to safeguard and uphold privacy among various nodes inside the IoT network [13], [14].

When IoT platforms are co-located in different domains, deploying identical sensors across various platforms in the same position may result in resource inefficiencies. The difficulty of managing and establishing an organization's complete end-to-end infrastructure, including servers, infrastructure, sensors, and gateways, further raises the financial hurdles for new entrants in several IoT domains [15], [16]. Consequently, IoT application developers will find it very challenging to integrate communication protocols [17], [18]. To resolve these shortcomings, a novel Cognitive IoT inTeroperability Recognition USing deep learning (CITRUS) framework is proposed which can communicate and exchange data securely among multiple IoT devices using different domains. The aim of the CITRUS approach is outlined as follows,

- Initially, the healthcare and weather data are collected remotely by using heterogenous sensors such as THS which are given to the DCNN module for efficient decision-making.
- The IoT MQTT module makes energy efficient IoT data communication over a resource-constrained network and the TCP socket routines enable reliable IP communication between the server and the client.
- The MQTT broker integrates the messages between the various users which receives and filters the message or identifies and sends the messages to each subscribed client.
- The AC, sensitivity, RC, F1S, precision, PDR, PLR, and delay are among the criteria used to assess the effectiveness of the developed CITRUS technique.

The remaining sections of the research is organized as follows: The literature review for Cross-domain interoperability are covered in Part II, and the developed CITRUS model is described in Part III. The results and discussions for the CITRUS framework are presented in Part IV and the Part V concludes the research with future enhancement.

2. LITERATURE SURVEY

Several fundamental ideas have emerged with the evolution of the IoT paradigm that provide a more comprehensive understanding of real-world IoT deployments in hybrid applications. This section briefly discusses a few of the strategies.

Nagarajan *et al*. [19] recommended a DL framework for organizing the internet of health things (IoHT) in intelligent cities. The developed DHNN with the task scheduling method achieves AC, precision, and sensitivity of 97.6%, 97.9%, and 94.9%, respectively, based on research carried out with real-time data. Abdel-Basset *et al.* [20] suggested a DL method for energy management in smart cities using IoT. The Energy-Net approach was assessed using the IHPEC and ISO-NE datasets, and the findings revealed root mean square errors (RMSE) of 0.535 and 0.354.

Pathak *et al.* [21] suggested an Electronic medical gadgets that are mobile are semantic and interactive. The suggested SemBox approach demonstrates the maximum PDR of 1 and 85.71% of accuracy respectively. Rahman *et al.* [22] suggested a dynamic ontology for IoT interoperability. The suggested method improves AC by 17% and decreases the response time by 35%, respectively.

Bao *et al.* [23] suggested a fine-grained and multi-scale learning for retrieval across domains. Using the Street2Shop and DeepFashion-C2S datasets, the suggested approach was evaluated which produced mAP and accuracy of 4.2% and 11.4%, respectively. Abad-Navarro and Martínez-Costa [24] suggested a framework for harmonizing information enabling the reuse of secondary data in knowledge graphs. To test the suggested approach, the Precision4Q H2020 European project dataset is utilized.

Gueddes and Mahjoub [25] suggested an approach to facilitate remote personal intervention based on probabilistic ontology. One such technique integrates probability statements into the ontological form of the definition through ontological enrichment based on Bayesian Networks (BN). The existing research on this topic supports the examination of security issues when using basic MQTT or traditional, less effective, or incomplete, lacking security mechanisms. The CITRUS approach is suggested as a remedy for this problem.

3. COGNITIVE IOT INTEROPERABILITY RECOGNITION USING DEEP LEARNING

In this section, a novel CITRUS framework is developed for real-time decision-making and sharing of information. Figure 1 displays the block diagram for the CITRUS architecture. Initially, the healthcare and weather data are collected remotely by using interoperable sensors such as THS and are fed to the DCNN module for efficient decision-making. The IoT MQTT module is implemented to transmit and receive data. After data transmission, the TCP socket routines enable reliable IP communication which makes a communication between the server and the client. Finally, QoS 1 adds an acknowledgment and retransmission mechanism to guarantee message delivery. The sender is required to retain the PUBLISH packet for possible retransmission up until that point.

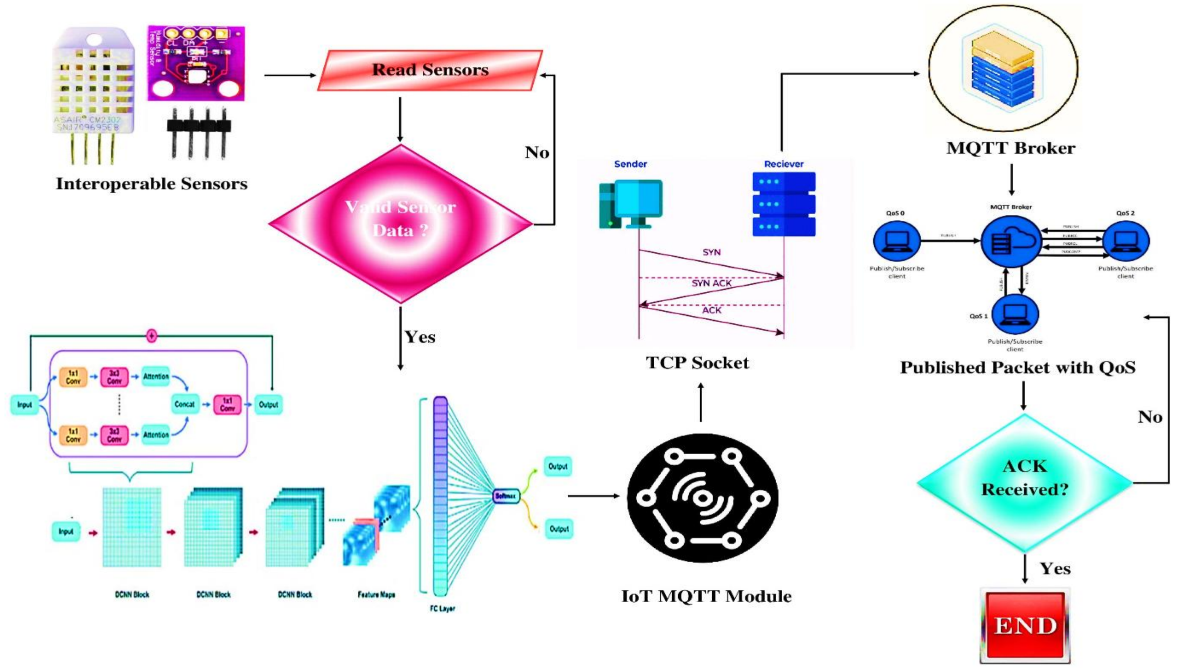


Figure 1. Proposed CITRUS framework

3.1. Data acquisition

Smart gadgets and IoT solutions are combined on the same target hardware. The DCNN module and MQTT IoT client are implemented using the microcontroller unit (MCU). Because of the hardware constraints and its successful integration, it runs on a real-time operating system (RTOS). After being validated, the sensor data will be forwarded to the RTOS task that handles the DCNN model. Figure 2 depicts the signal output (SO) from the heterogeneous sensors. Figure 2(a) depicts the SO of the humidity sensor for weather monitoring which measures and monitors the amount of water present in the surrounding air. Figure 2(b) depicts the SO of the humidity sensor for health monitoring which monitors humidity levels within respiratory devices, helping to prevent respiratory infections. Figure 2(c) depicts the SO of the temperature sensor which measures and records the temperature of a specific environment or process to control it. Finally, Figure 2(d) represents the temperature sensor which accurately measures the body temperature of a patient with a digital output signal. After data collection, the gathered data are given to the DCNN module to make a productive decision.

3.2. Deep convolutional neural networks model

In this research area, the DCNN module is implemented to make efficient decisions based on the collected sensor data.

a) The nonlinear activation functions

Rectified linear unit (ReLU) function liberally avoid gradient fading and maintain the ability to express the equation as an expression (1).

$$Out = ReLU(Net) = max(0, Net) \quad (1)$$

where max (.) is the procedure to reach the maximum value. In contrast, the input and output scalars of the classes under discussion are represented by the variables Net and Out.

b) The point-wise activation hypothesis

In (2) provides the basic equation for the DCNN convolutional layers, which implement the feature extraction function.

$$Net = w_1x_1 + L + w_dx_d + b = \sum_{i=1}^{d} w_i\, x_i + b = W^T X + b \quad (2)$$

where w and x are the weight vectors, respectively, that reflect the convolution kernel function and the local area of the feature map under consideration. For (2) to function, w and x's dimensions must be equal. In addition, scalar Net and b indicate the output and deviation terms.

$$ND = f(x) \tag{3}$$

$$f(x) = \frac{1}{\sqrt{2\pi\sigma}} exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{4}$$

More specifically, in (2) indicates that the ReLU function is frequently applied in DCNN. In (3) generates a positive result for normal distribution (ND) when the Net is positive and a zero result otherwise by utilizing the ReLU function. In (4) illustrates how to determine the Net variable for the convolutional layer by entering data at a certain position.

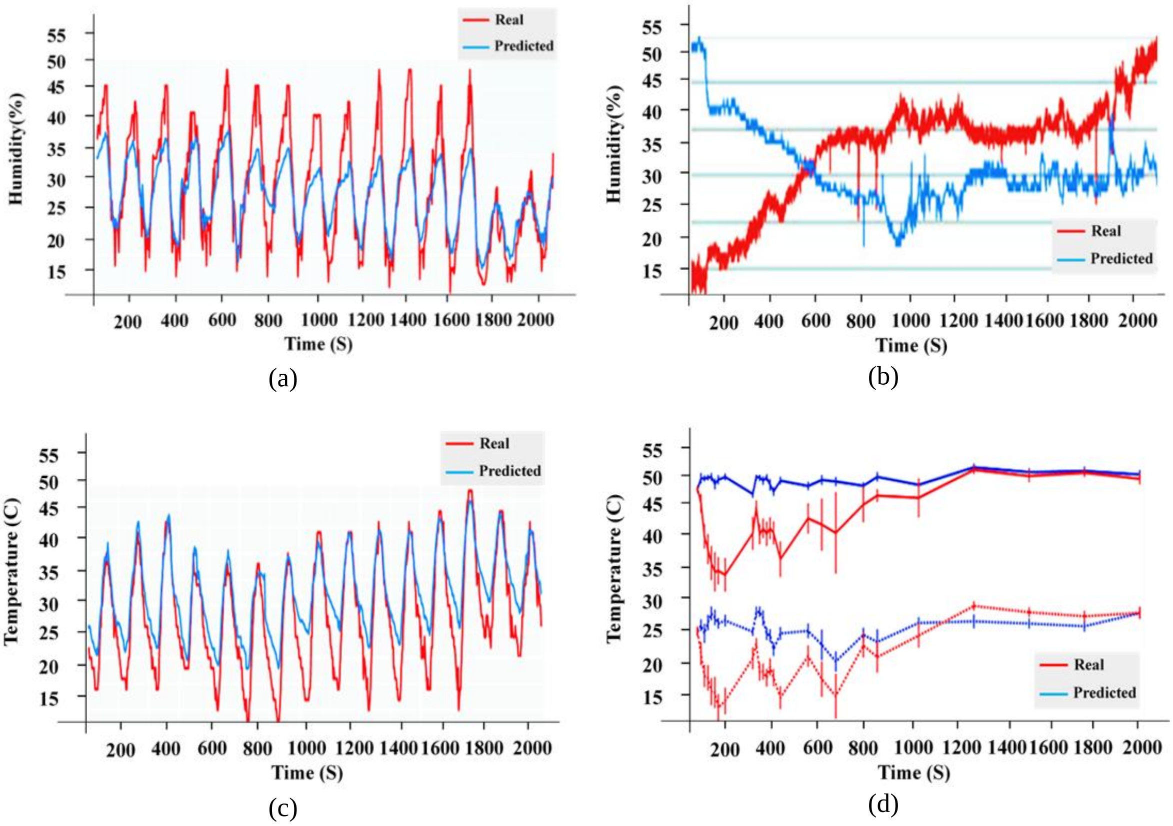


Figure 2. Signal output of the sensors: (a) humidity SO for weather monitoring, (b) humidity SO for health monitoring, (c) temperature SO for weather monitoring, and (d) temperature SO for weather monitoring

3.3. IoT data communication and packet publication

After decision-making, the IoT MQTT module is carried out to provide energy-efficient IoT data communication over a resource-constrained network. The outcomes of the DCNN phase in IoT will be released to the public following the implementation of the DCNN model in MCU. Using the domain name and port of the server, create a TCP connection with the MQTT broker as the initial step. The server that hosts the MQTT broker settings opens the TCP socket. Sending the MQTT CONNECT packet to create the connection is the next step. It contains connection-specific flags and parameters in addition to client identification data. The MCU turns into a MQTT client after the MQTT connection is established. Based on the designated topic, the DCNN model's output will be bundled into messages and sent to the maintenance center. Different quality of service (QoS) levels exist, that enable QoS0's send and forget, QoS1's at least one guaranteed message delivery, and QoS2's exactly guaranteed message delivery. To possibly retransmit the PUBLISH packet, the sender must ultimately retain it.

4. RESULT AND DISCUSSION

The particular applications of the developed approach and the outcomes will be thoroughly examined in this section. The effectiveness and accessibility of the proposed approach were put to the test to assess the measuring capability, sensitivity, specificity, accuracy, and accessibility of cross-domain collaboration.

4.1. Dataset description

The sensors and their measurements are described in the LOV4IoT dataset. Nearly 300 ontology-based works addressing sensors in 19 different domains such as weather, health care, smart energy, environment, IoT, smart city, sensor networks, agriculture, emotions, music, building automation, fire, food, security, travel, traffic, activity recognition, semantic sensor network (SSN), and so on are covered by the LOV4IoT framework.

4.2. Performance evaluation

The experimental data are used to evaluate the F1S, RC, AC, and precision. The statistical analysis of the parameters is shown below.

$$\text{Accuracy} = \frac{TP+TN}{Total\ no.of\ samples} \tag{5}$$

$$Recall = \frac{TP}{TP+FN} \tag{6}$$

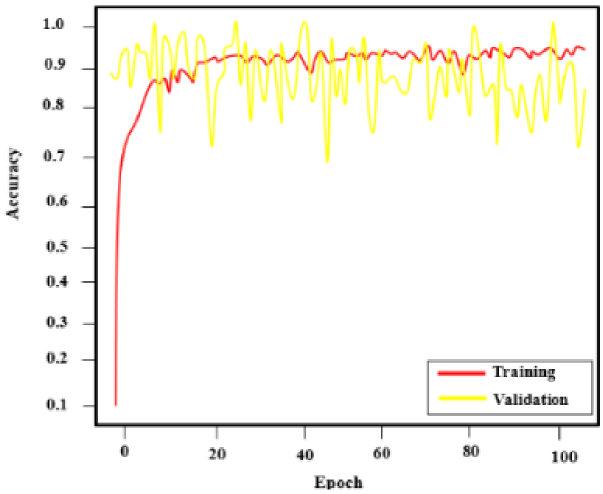
$$f1\ score = 2\left(\frac{precision*recall}{precision+recall}\right) \tag{7}$$

$$Sensistivity = \frac{TP}{TP+FP} \tag{8}$$

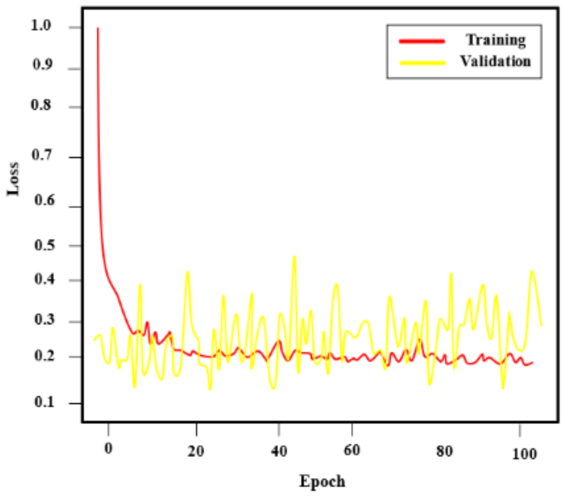
$$TRP = \frac{TP}{TP+FP} \tag{9}$$

The numbers of False Negatives is illustrated as F_N, False Positives is illustrated as F_P, True Negatives is illustrated as T_N, and True Positives are illustrated by T_P respectively. The Prediction performance is improved by raising the accuracy value.

Figures 3 demonstrate the AC and loss curve of the developed method. Figure 3(a) represents the great precision and Figure 3(b) represents the loss with which proposed procedures are applied during both training and testing. Sensitivity, accuracy, specificity, and recall serve as the foundation for the CITRUS efficacy. The result shows that the CITRUS model has a 99.92% classification accuracy rate.



(a)



(b)

Figure 3. Training and testing output for CITRUS model (a) accuracy curve and (b) loss curve

The DL models involving CNN, LSTM, and DHNN models are compared with the proposed DCNN technique. As overfitting occurs in CNN which is failed to find the difference between the categories of more decisions. LSTM model has considerable performance in the classification. The proposed DCNN has 98.72% accuracy, 92.32% sensitivity, 93.42% recall, and 95.72% specificity. The comparison of DL networks is presented in Figure 4.

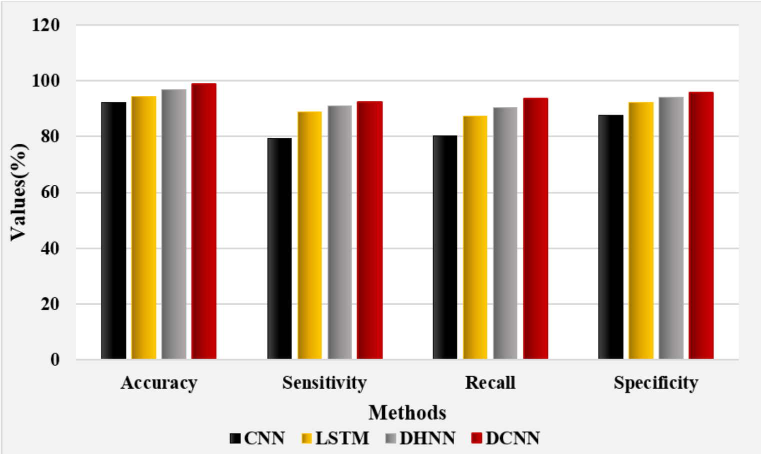


Figure 4. Comparison of DL networks

a) Packet delivery ratio

As time rises, the packet delivery speed is calculated which is illustrated in Figure 5. In comparison with existing methods, the proposed algorithm's packet delivery speed increases with time, as seen in the Figure 5. The proposed approach maximizes the amount of traffic that passes through the links as it increases over time.

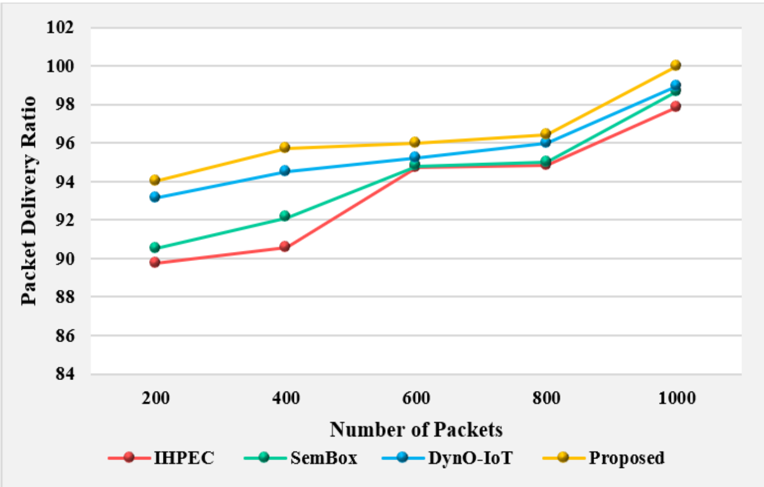


Figure 5. Comparison of PDR

b) Packet loss ratio

Figure 6 illustrates the association between the packet loss rate and the number of active nodes. In this scenario, every packet has a fixed length of 100 bytes. This is demonstrated as there are more active nodes in the system, more packets are sent, which raises the possibility of packet collisions and packet loss rates.

However, the system's communication protocol has an acknowledgment (ACK) mechanism that makes sure packets always arrive at the host or port as intended.

c) Transmission speed

Figure 7 displays the data transmission success rate relative to the packets. At a transmission speed of 30 m/s, the proposed method has a 34.72% data transfer success rate. Even at a transmission speed of 40 m/s, the proposed method manages to achieve a successful data transfer rate of 40.72%. Existing techniques will become far less successful when the transmission speed reaches 30 m/s. However, 53.72% of the data were successfully transferred using the proposed approach at a speed of 50 m/s.

d) Communication overhead

Communication overhead is the duration of time needed to deliver and receive data and is given by:

$$C = N * T(S_{dt}) \tag{10}$$

where N denotes the number of users, T denotes the required time for S_dt to send data securely, and C is the cost of communication. The time needed for secure data transfer is determined by using (10) about the quantity of extra data (K). The communication overhead encountered while sending data securely using three different methods is depicted in Figure 8. In comparison to IHPEC, SemBox, and Dyno-IoT, the proposed strategy therefore lowers the communication overhead for secure data transmission between users.

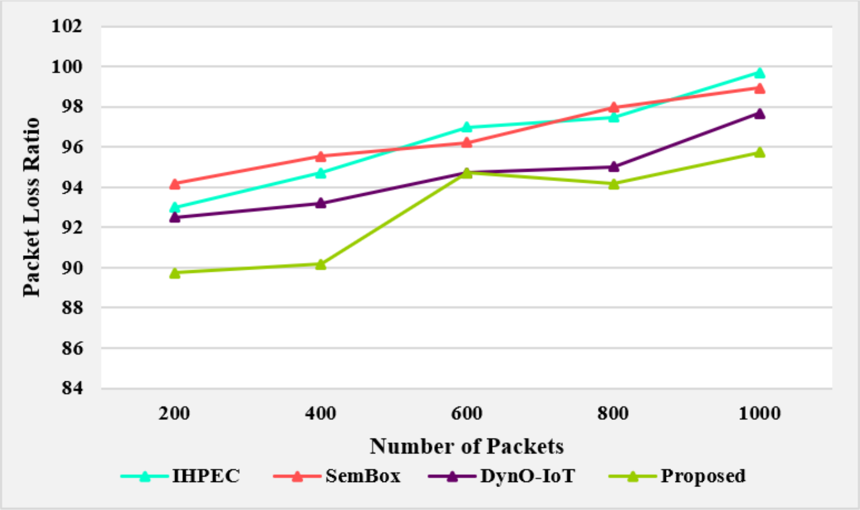


Figure 6. Comparison of PLR

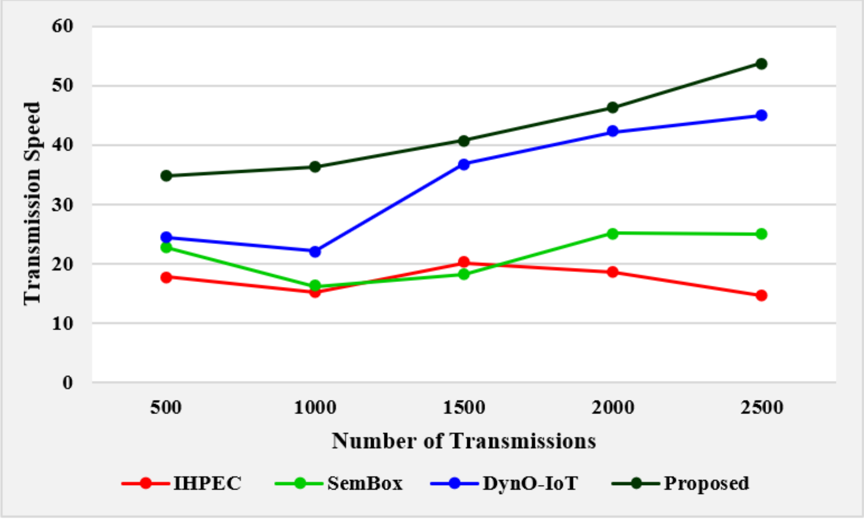


Figure 7. Comparison of transmission speed

e) Delay

The results displayed in Figure 9 demonstrate that the value of MQTT publishing is much more than the expense of data transfer between brokers. Since these tests are synthetic, very low levels of actual latency can be achieved. Results represents that the CITRUS approach attains 89.89% of delay whereas, the IHPEC, SemBox, and Dyno-IoT methods achieve 161.63%, 128.99%, and 111.70% respectively for efficient data transmission.

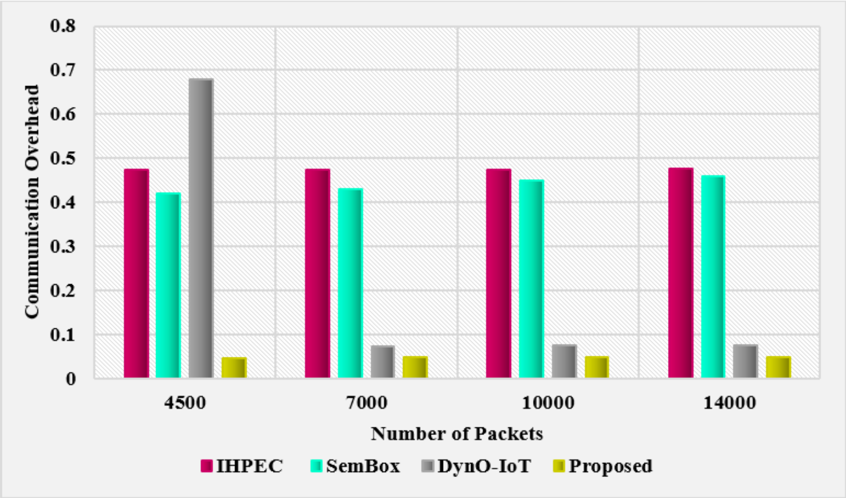


Figure 8. Comparison of communication overhead

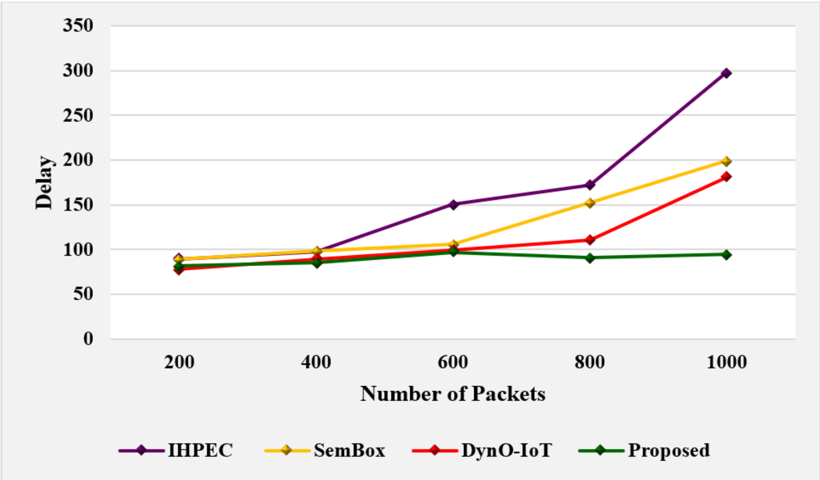


Figure 9. Comparison of delay

4.3. Discussion

In IoT paradigm several fundamental approaches have emerged with the evolution of IoT interoperability to provide a more comprehensive understanding about real-world IoT deployments in hybrid applications. However, the existing research on this topic supports the examination of security issues when using basic MQTT or traditional, less effective, or incomplete, lacking security mechanisms. To address these issues, a novel CITRUS framework is developed for real-time decision-making and sharing information among multiple IoT systems. The efficacy of the CITRUS approach is analyzed including AC, RC, F1S, sensitivity, PDR, transmission speed, communication overhead, PLR, and delay. In the proposed CITRUS model, the comparison of the DL model which is the DCNN networks is depicted in Figure 4 that are compared against the CNN, LSTM, and DHNN models. The proposed DCNN has 98.72% accuracy, 92.32% sensitivity, 93.42% recall, and 95.72% specificity. In Figure 5, the CITRUS framework enhances PDR by ensuring efficient message delivery through the MQTT and the QoS1 mechanism reduces the PLR with an acknowledgment and retransmission strategy which is presented in Figure 6. During data transmission, the CITRUS framework achieves 34.72%, 40.72%, and 53.72% of data are successfully transmitted with the transmission speed of 30 m/s, 40 m/s, and 50 m/s respectively. The communication overhead is represented in Figure 8, where the CITRUS framework is compared against the existing IHPEC, SemBox, and Dyno-IoT models which reduces the communication overhead for secure data transmission. The comparison of delay is displayed in Figure 9, which demonstrates that the CITRUS model achieves 89.89% of delay whereas, the IHPEC, SemBox, and Dyno-IoT methods achieve 161.63%, 128.99%, and 111.70% respectively for efficient data transmission. However, due to resource constraints, the CITRUS framework consists of limited scalability for large-scale IoT deployments. In the future, adaptive MQTT configurations are explored to enhance the scalability of the CITRUS framework. Based on these experimental analyses, the proposed CITRUS framework attains better AC, efficient PDR, transmission speed, and less communication overhead, PLR, and delay for potential cross-domain IoT interoperability.

5. CONCLUSION

This research introduced an innovative CITRUS architecture that allows many IoT devices to safely converse and share information. Cloud Sim is used to validate the suggested framework. The sensor data, accuracy, sensitivity, recall, F1 score, precision, PDR, PLR, and delay are among the criteria used to validate the efficacy of the developed CITRUS approach. The experimental results show that the developed CITRUS approach achieves 89.89% of delay whereas, the IHPEC, SemBox, and Dyno-IoT methods achieve 161.63%, 128.99%, and 111.70% respectively for efficient data transmission and the proposed DCNN has 98.72% accuracy, 92.32% sensitivity, 93.42% recall, and 95.72% specificity. However, due to resource constraints, the CITRUS framework consists of limited scalability for large-scale IoT deployments. In the future, adaptive MQTT configurations are explored to enhance the scalability of the CITRUS framework. Furthermore, the CITRUS framework will concentrate on advanced DL techniques to provide intelligent packet transmission scheduling capabilities under dynamic temporal channel state information in the IoT network. More investigation should concentrate on how various MQTT configurations affect the efficiency and reliability of MQTT via comparison analysis.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Muthu Kumar Balasubramanian		✓	✓	✓			✓		✓		✓	✓	✓	
Venkatesh Prasad Kadaba Srinivas Desikachar	✓	✓		✓	✓	✓			✓	✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

INFORMED CONSENT

We certify that we have explained the nature and purpose of this study to the above-named individual, and have discussed the potential benefits of this study participation. The questions the individual had about this study have been answered, and we will always be available to address future questions.

ETHICAL APPROVAL

My research guide reviewed and ethically approved this manuscript for publishing in this journal.

DATA AVAILABILITY

Data sharing not applicable to this article as no datasets we regenerated or analyzed during the current study.

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