Sensor cloud virtualisation systems for improving performance of IoT-based WSN

S. Senthil Kumaran* and
S.P. Balakannan

Department of Information Technology,
Kalasalingam Academy of Research and Technology,
Krishnankoil, Tamil Nadu, India
Email: sk@stylesen.org
Email: balakannansp@gmail.com
*Corresponding author

Abstract: A cloud is a new paradigm for IoT-based WSN that overcomes several limitations of traditional WSN and decouples the owners of the physical sensors from the network users. This paper proposes a cloud-based Internet of Medical Devices (IoMD), a novel architecture for the healthcare system to validate the efficiency of sensor-cloud virtualisation technique. IoT, cloud computing and fog are the three key technologies that make up the framework outlined in this paper. IoT and medical devices are integrated into our cloud-based architecture, and deep learning algorithms are used to process the collected data. A deep learning neural network method called Generative Adversarial Network (GAN) model that runs in both fog and cloud platforms and is capable of processing massive data in a fast and efficient manner. The suggested GAN is trained on a real-data set from the UCI Machine Learning Repository. Even yet, the results show that the GAN classifier can correctly categorise the medical data activities with a 99.16% accuracy rate. The proposed architecture for validation case study will ensure to benefit the sensor-cloud virtualisation paradigm for developing innovative applications in different sectors of the IoT system.

Keywords: cloud-based internet of medical device; cloud computing; wireless sensor network; sensor data and fog computing.

Reference to this paper should be made as follows: Kumaran, S.S. and Balakannan, S.P. (2023) 'Sensor cloud virtualisation systems for improving performance of IoT-based WSN', *Int. J. Wireless and Mobile Computing*, Vol. 24, No. 1, pp.38–47.

Biographical notes: S. Senthil Kumaran received his MS degree from Birla Institute of Technology and Science, Pilani in 2010. He also received his Bachelor's degree from the Department of Computer Science and Engineering, Thiagarajar College of Engineering, Madurai in the year 2006. He is a Committer and Project Management Committee (PMC) Member at Apache Software Foundation, Debian Maintainer and Apache Subversion Developer. Currently, he is a Research Scholar in the Department of Information Technology, Kalasalingam Academy of Research and Education, Tamil Nadu, India.

S.P. Balakannan received his PhD degree from the Department of Electronics and Information Engineering at Chonbuk National University, South Korea in 2010. He also received his Master's degree (5 years integrated) from the Department of Computer Science and Engineering, Bharathiar University, India in 2003. He has worked as a Project Assistant in Indian Institute of Technology (IIT), Kharagpur, India from 2003 to 2006. Currently, he is working as an Assistant Professor in the Department of Information Technology, Kalasalingam Academy of Research and Education, Tamil Nadu, India. His research interests include wireless network, network coding, cloud & green computing, cryptography and mobile communication.

1 Introduction

The significant advances in microelectronic-based system and wireless communication skill have facilitated the invention of low-energy and low-cost smart sensor devices that are dedicated to sense a variety of the environmental conditions such as humidity, temperature, pressure, pollutants, sound, vibration, motions and organise collected data at base station for further processing and analysing (Priyadarshi et al., 2020). In general, the sensor nodes are self-organised, dynamically configured, wirelessly communicated in short-range and collaboratively grouped to form WSN topology

(Saoud, 2021). Usually, WSN contains various heterogeneous sensor nodes that are randomly deployed in a target location to take various measurements which will be converted to useful information (Radhi, 2020). However, in recent years, WSN is implemented in real-life applications e.g. environment monitoring applications, health care applications, smart home applications (Kashani et al., 2021; Selvaraj and Sundaravaradhan, 2020; Ud Din et al., 2019). Several heterogeneous sensors have been adopted in IoT systems for measuring various aspects such as temperature, humidity, sound, light, etc. (Kim et al., 2020). IoT paradigm is an innovative technology that provides an intelligent communication between autonomous devices and ordinary physical objects. Recent advance in IoT technology has enabled various devices to integrate and cooperate automatically with each other in such a way that allows them to provide ubiquitous services. The words 'Internet' and 'Things' put together have introduced an immense innovation in the world of ICT. It is a paradigm where each device has a unique identification/address and is connected to the internet (Silva et al., 2018). It is a worldwide network of objects which are connected and can be referred, processed, stored and transferred the environmental data. It seems as a convergence of different visions as IoT has found its applications in major domains with application scenarios like healthcare domain (Tracking, Data Collection, Sensing). Figure 1 shows different visions namely Semantic, Things and Internet oriented visions which converges into one paradigm called IoT. In healthcare domain IoT can track objects and people, identify and authenticate people and automatically collect the data by sensing environments. Also, IoT can communicate in heterogeneous environment using different protocols and wired and wireless media. When IoT and cloud are viewed as a paradigm, it's called as Cloud IoT paradigm. It is pervasive and hence now your cloud architecture can sense the real-time data in client environments. In this approach the IoT device continuously senses the data and sends it to the cloud server and cloud server stores data, where it can be analysed for decision making or can be accessed by other users

Cloud computing is the internet-based computing, meant to provide any sort of computing on demand. The two models which make cloud accessible and feasible to end users are service model and deployment models (Sahmim and Gharsellaoui, 2017; Swathi and Prasad, 2018). New paradigm/architectural concept known as Fog Computing or Edge Processing provides limited computing, storage and network functions at the end user devices (Mutlag et al., 2019). Figure 2 shown in the diagram is a basic Fog Computing system design.

Figure 1 IoT role in various visions

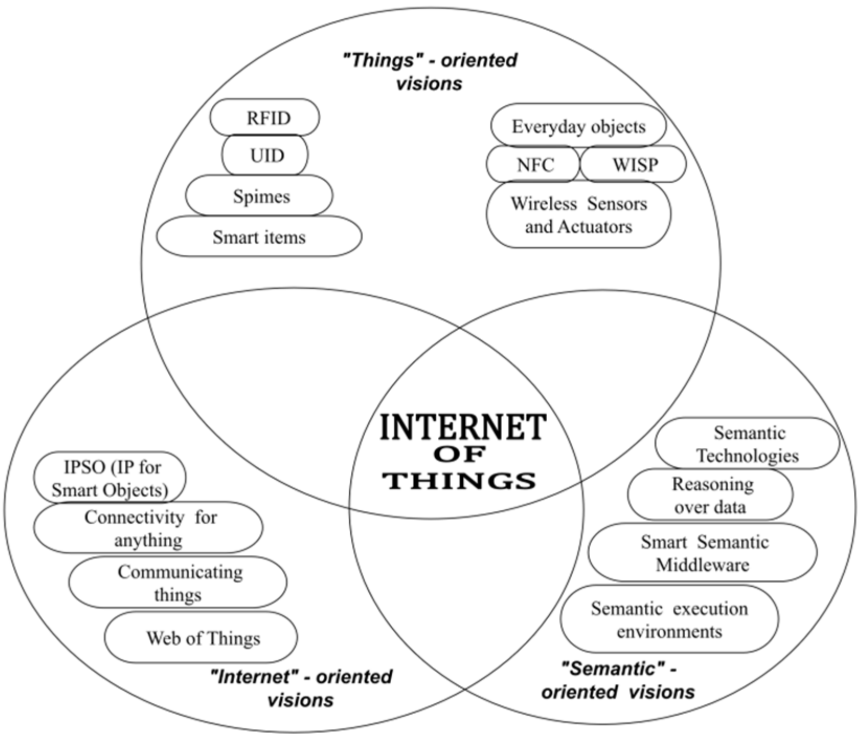
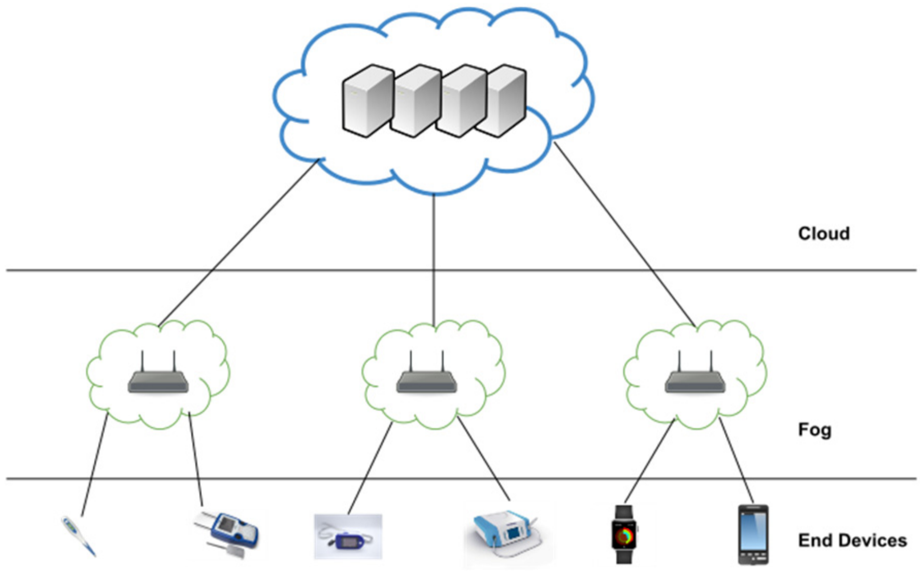


Figure 2 Fog computing architecture



Data stream volume and variety have grown exponentially in recent years as the IoT has grown at an astronomical rate. When it comes to the IoT (Fortino et al., 2014, 2016), it is a dynamic and global network architecture that connects items with unique identities for a variety of advanced applications. IoT's limited storage and processing capability prevents it from processing and storing vast amounts of data, despite its improved features. Virtual resources can be paid for on a pay-as-you-go basis, eliminating IoT's inconveniences by giving infinite processing and storage capacity. Cloud computing resources, services and applications are widely available, yet some of these resources are not fully realised because of worries about latency.

Sensing subsystem (Analogue-to-Digital Converter), processing subsystem (Digital Signal Processor), and communicating subsystem (Signal Transmission) as well as power supply subsystem which can be a battery power or solar energy (Puliafito et al., 2019). Moreover, there are secondary elements of these four major subsystems such as transducers, filters, amplifiers and comparators. The sensing unit performs sensing mechanism for the monitored environment. The processing unit is responsible for manipulation and aggregation of various data tasks; whereas, the communication unit handles data delivery to the base stations, and all units will be supplied with energy by power unit.

Sensor-Cloud is a consolidation of sensor networks and cloud computing that is extensively used in different sectors for supporting real-time sensing applications and providing remote monitoring (Dwivedi and Kumar, 2018). However, the major challenge in Sensor-Cloud paradigm is the survivability of the sensor nodes since they are energy-constrained devices and thereby must be optimised. Moreover, increasing the sensor nodes' lifetime is a demand to ensure network functionalities and process stability. The Sensor-Cloud virtualisation technique and its role in overcoming various limitations of traditional WSN. To validate this approach, a case study for one application must be presented. Consequently, we suggested a unique Cloud-based Internet of Medical Devices (IMD) architecture as a proof of concept. IoT, cloud computing and artificial intelligence are the three key technologies that make up the framework given for the development of innovative healthcare applications.

This paper starts with the introduction to IoT with WSN, along with cloud and fog computing. Section 2 describes literature review and details of prevailing research in the related area. Section 3 puts forth the proposed methodology explaining each of the individual components of the proposed model. In Section 4, we discuss about the results based on our proposed model and experiments carried out. We conclude the paper in Section 5 with the established goals as per our motivation.

1.1 Research objectives

Regardless of the existing works and survey conducted in the past few years, we have plan to introduce a novel Sensor-Cloud virtualisation technique for improving the performance of IoT-based WSN. Our first objective as a part of this research is to propose a novel classification for virtualisation methods in IoT-based WSN as this is considered as a key concept for exploring optimal solutions to implement virtualisation techniques on resource constrained network. In this research work we present a new architecture for the Sensor-Cloud virtualisation technique and to broadly discuss its key elements, basic principles and the process of initiating virtual sensors in the cloud infrastructure. Also, deep learning neural network based Generative Adversarial Network (GAN) model to handle large data sets in the cloud layer. Classification, that runs in both fog and cloud platforms and capable of processing massive data in a fast and efficient manner. The data classified into training data and testing data and these data are passed into the neural network for extracting features and make different predictions at each time step. We use a prediction method called Deep long short-term memory (LSTM) for sequence-to-sequence classification. The data set contains sensor data generated from smartphones worn on volunteers' bodies (30 people). The Deep LSTM network is trained to recognise the activity of the wearer given sequence data representing accelerometer readings in three different directions and each sequence has 561 features and differ in length. The physical activities are recognised by the Deep GAN and the classifications of each activity are transmitted to the application layer to take the decision by professional expert and necessary action is taking place. And, to validate the efficiency of the sensor-cloud virtualisation technique with real-life applications. An IoMD architecture is proposed to overcome the limitations of conventional healthcare systems.

2 Literature survey

Reyes et al. (2017) introduced an architecture for cloud-sensor using 'Service Oriented Computing' (SOC) and sensor virtualisation, to improve data management efficiency in heterogeneous WSNs and maintain QoS as well as higher levels of scalability. The proposed model contains four layers: Physical Layer, Virtualisation Layer, Service Layer and Application Layer. The authors utilise the concepts of 'Queue Message-Oriented Middleware' (MOM) to aggregate and standardise data from various sensors and cloud, store & process it, and make it shareable through W3C standard interface. They considered OpenStack in their implementation and evaluate the proposed solution in terms of response time using different data collection and traffic load scenarios.

Sensor-Clouds can support healthcare systems by employing several available wearable sensors such as smartphone sensors (accelerometer and gyroscope sensors), proximity sensors, ambient light sensors and temperature sensors. These wearable sensors must be internet enabled and support wireless connectivity (Bluetooth's wireless interface) to forward data to the internet gateway. The primary task of these wearable sensors is to collect patients' health data and track sleep patterns, physical activities, blood sugar levels, body temperature and so forth (Jo et al., 2021). The collected data are organised at the cloud platform for further processing and analysing and then the reported data is available to the doctors or experts who are assigned to the patient and better treatment is recommended.

A system that targets to enhance the functioning of a parallel multifrontal solver, MUMPS has been suggested by Guermouche and L'Excellent (2004) and this approach to scheduling is based on memory. The slaves and/or associates of a processor are selected based on memory constraints based on their memory availability, the slaves are selected. It targets to minimise the utilised stack size at run time. A paper that attempts to improve the effective utilisation of global memory has been suggested in Zhang et al. (2000). Strategies for distribution of jobs are constructed appropriately. Additional load migrates to associates with availability for sufficient memory when a node does not have requisite memory to accept jobs. Page faults occur on account of unbalanced memory allocations and thus, the aim is reduction of the same to improve efficiency. The performance of memory-bound jobs is enhanced by the suggested policy for load sharing. A paper with proper description of distributed systems is suggested in Shi et al. (2007).

Atlam et al. (2018) gave an outline of the concepts of Fog Computing and the Internet of Things. They talked through about various advantages of Fog Computing and how it is proficient of supporting many IoT applications to provide superior services to users. The challenges faced by the IoT devices such as scalability, complexity, dynamicity, heterogeneity, latency and security that needs to be overcome to have a successful development of fog architecture. The fog environment involves numerous Fog devices thus the computation is distributed and can be energy efficient as compared to the centralised cloud model of computation. Furthermore, the authors addressed several issues of using Fog Nodes with the IoT devices. This included communication of fog with the cloud, communication between fog servers, parallel computation.

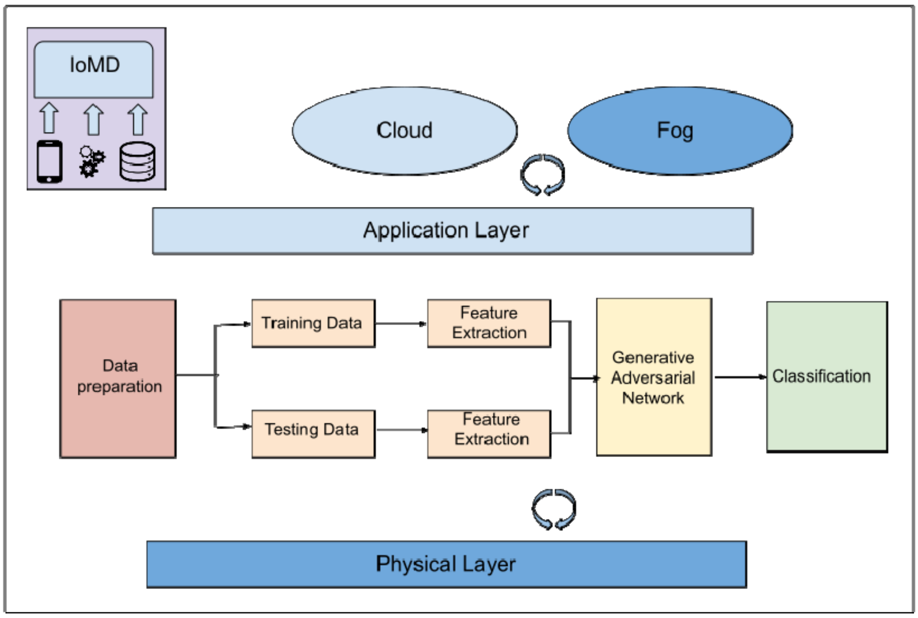
Usman et al. (2017) discussed about the need of security and privacy of data in IoT devices to build confidence among users and use IoT technology at a large scale. As IOT devices remain unsupervised for a long time it is extremely open to attacks. Also due to wireless transmission of data, attacks like eavesdropping become quite easy to execute. Furthermore, IOT devices have low processing capabilities and limited memory. Thus, the execution of traditional encryption algorithms like AES, DES which are computationally costly will hamper the proper functioning of such constrained devices that has limited resources.

3 Proposed methodology

In this section, we have introduced the Sensor-Cloud and fog virtualisation technique and its role in overcoming various limitations of traditional WSN. Figure 3 signifies the proposed Novel Cloud-based IoMD Architecture. To validate this approach, a case study for one application must be presented. Therefore, we proposed a novel Cloud-based IoMD architecture as a validation case study.

There are three key technologies that make up the framework presented: the Internet of Things (IoT), Cloud Computing (CLOUD) and fog Computing (FOG). In our cloud-based architecture, artificial intelligence algorithms are used to process the data collected from IoT-enabled medical equipment. We've looked at some of the daily routines of the elderly in order to evaluate the framework we've designed. For this reason, we introduced a neural network method called Deep GAN that runs on the cloud platform and is capable of processing enormous amounts of data quickly and efficiently. UCI Machine Learning Repository data is used to train the proposed Deep GAN for everyday activities recognition.

Figure 3 The proposed novel cloud-based IoMD architecture



3.1 Sensor-cloud for medical devices

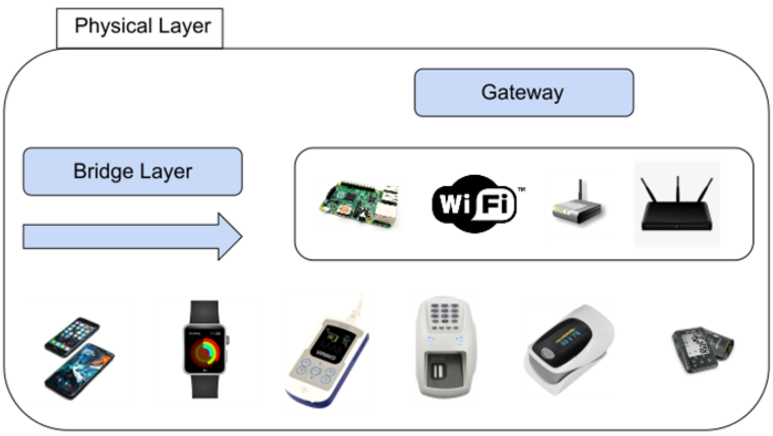
Cloud computing and Internet of Things (IoT) technologies have made it easier to design smart apps in several industries. As one of the most important applications of IoT-based WSN, Healthcare is a major focus for researchers and industry. In IoMT (Joyia et al., 2017), communications between smart sensors and medical devices can take place automatically without human intervention and data is forwarded to the cloud for further process and analysis. IoMT system allows doctors and caregivers to monitor patients' health conditions timely while they are at their homes and provide immediate support in case of emergency as well as recommend preferable treatment. Mainly, IoMT aims to improve patients' health management, increase the life quality of the elder population and enable hospitals and physician staff to deliver excellent healthcare services.

3.2 Physical/perception layer

The Physical/Perception Layer (also called as data realisation layer) is composed of the medical devices embedded with sensors that are capable of internet connectivity to transmit biomedical data to the access point. Our IoMD framework consists of various medical equipment and wearable sensors and smartphone sensors connected to the body of patient and start collecting biomedical data and transmit it to the Bridge Layer which in turn forward data to the cloud and fog platform. As shown in Figure 4, sensors are taking vital-sign measurements like ECG signal, heartbeat, blood pressure, oxygen level, temperature and various activities performed by patient and forward these signals in a real-time scenario to the cloud.

For implementation purpose and to validate our proposed IoMD framework we are considering smartphone data set to observe physical activities of the subject's movement. The smartphone tracks different physical activities such as marching, going upstairs, going downstairs, sitting down, stand up and relaxing. The embedded sensors in smartphones (accelerometer and gyroscope) were worn in the waist of the subject. The perceived data from smartphones is transmitted to the cloud layer through the Bridge Layer.

Figure 4 The cloud-based IoMD physical layer architecture



3.3 Cloud layer

Cloud is an infrastructure where physical resources can be virtualised and served to different users. Cloud provides various services such as storage, powerful processors, computing resource, networking and enables users to access and share information through the internet. In our IoMD architecture cloud is utilised to store patient's data collected from different medical devices, wearable sensors, and smartphones. Analysing techniques and pre-processing is applied to the data using efficient and intelligent algorithms and makes the analytical data available on time to the specialist like doctors and caregivers for decision making. We proposed a deep learning network to handle large data sets in the cloud layer.

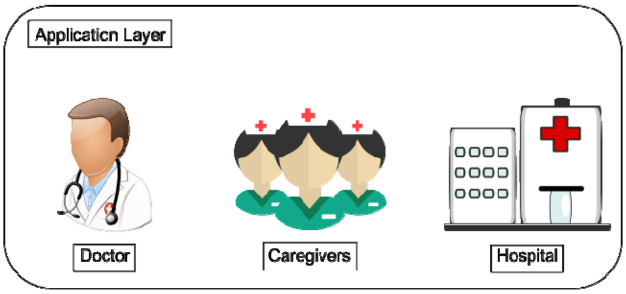
The purpose of our neural network is to recognise the physical activities performed by target subjects. The smartphone data set is further classified into training data and testing data and these data are passed into the neural network for extracting features and make different predictions at each time step. The physical activities are recognised by the Deep GAN and the classifications of each activity are transmitted to the application layer to take the decision by professional expert and necessary action is taking place. Using cloud computing technology, analysing results and diagnostics report are updated to the application layer periodically in an efficient and faster manner. Moreover, the cloud allows collaboration between many experts in the field to share and exchange knowledge and suggest more sophisticated treatment plans and then, enhancing users' experience quality and make the patients more comfortable.

3.4 Applications layer

The application layer is a data visualisation and user interface layer. Doctors, caregivers, and hospitals receiving records and sensory data regarding patients' status from the cloud and monitor patients remotely using their tablet or smartphone and recommend better treatment for the patients and take early action in emergency cases. In our proposed framework there are three types of application interfaces: Doctor Interface: In this interface, the expert doctor can track the status of assigned patients remotely and monitor the body activities and analyses the reports generated from the classifier method and takes the decision based on classification results.

Caregivers Interface: This interface consists of patient's relatives and nursing staff who are responsible for taking care of patients and providing appropriate treatment as recommended by the doctor. Caregivers will receive an alert email in case of emergencies to track patients' activities and stratify risks and initiate essential action plans. Hospital Interface: Hospital will provide 24/7 medical services to various patients such as ambulances, Medical Intensive Care Unit (MICU) and Surgical Intensive Care Unit (SICU) rooms, emergency physician and so on. In case of heart attacks or fall detection of the patient, the hospital will be notified by alert SMS messages to provide all the facilitates to rectify the risk and save patient's life.

Figure 5 The cloud-based IoMD application layer architecture



3.5 Generative adversarial network (GAN)

A GAN is derived from the Machine Learning (ML) frameworks. Based on noise contrastive estimation and the loss function employed in the current GAN. On top of that, it uses probabilistic representation for generative models to learn, and then generates its own data in this manner. If you have a contradictory circumstance, you can train a model there and then. Finally, the entire system can be trained utilising deep learning neural networks and artificial intelligence algorithms. Though they were originally designed for unsupervised ML approaches, GAN networks proven to be more effective for semi-supervised and reinforcement learning. GAN networks can provide complete solutions in a wide range of industries, including healthcare, mechanics, banking and more. The Discriminator and Generator reach their equilibrium after about 2000 steps, with the monitor completing training as soon as possible. The pseudo-code of GAN training is defined in Table 1 (Goodfellow, 2014).

$$D_{loss} = \frac{1}{m}\sum_{i=1}^{m}\left[logD\left(x^{(i)}\right) + log\left(1 - D\left(G\left(z^{(i)}\right)\right)\right)\right] \tag{1}$$

$$G_{loss} = \frac{1}{m}\sum_{i=1}^{m}log\left(1 - D\left(G\left(z^{(i)}\right)\right)\right) \tag{2}$$

In the above equations, D represents the discriminator and G represents the generator. D is trained to maximise the probability to assign the correct label to both training examples and sample from G. We train G simultaneously to minimise $log\left(1 - D\left(G\left(z^{(i)}\right)\right)\right)$.

Proposed GAN model hyperparameters that are used in the Generator and Discriminator are defined in Tables 2 and 3.

Table 1 A pseudo-code of GAN training

for number of training iterations **do**
  for k steps **do**
  • Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  • Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
  • Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right)\right].$$

  end for
  • Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  • Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

end for

Table 2 The generator hyperparameters

Generator hyperparameters					
Operation	*Kernel*	*Feature maps*	*Strides*	*Non-linearity*	*Dropout*
Gx(z) – 8 × 8 × 256 input	5X5	128	2X2	Leaky ReLU	0.4
Transposed convolution	5X5	32	2X2	Leaky ReLU	0.4
Transposed convolution	5X5	1	2X2	Leaky ReLU	0.4
Transposed convolution	5X5	64	2X2	Leaky ReLU	0.4

Table 3 The discriminator hyperparameters

Discriminator hyperparameters					
Operation	*Strides*	*Kernel*	*Feature maps*	*Non-linearity*	*Dropout*
Gx(z) – 32 × 32 × n input Transposed convolution	2X2	5X5	64	Leaky ReLU	0.4
Transposed convolution	2X2	5X5	128	Leaky ReLU	0.4
Transposed convolution	2X2	5X5	256	Leaky ReLU	0.4
Transposed convolution	1X1	5X5	512	Sigmoid	0.4

4 Results and discussion

The experiment is performed using the MATLAB environment with human activity data set from the UCI Repository as described earlier. We have trained our network with various hyper-parameters of GAN model. The structure data set contains certain activities performed by 30 people within the age of 19–48 years. The experiment is carried out by attaching a smartphone (embedded with sensors) on the waist of person and each one performs six different activities. Three are dynamic activities in the data set they are ‘WALKING, WALKING UPSTAIRS, WALKING DOWNSTAIRS’ and three are in the static postures ‘SITTING, STANDING, LAYING’ as shown in the Table 4. The accelerometer and gyroscope sensors capture 3-axial angular velocity and 3-axial linear acceleration at a constant rate of 50 Hz and sensor signals were prepossessed by applying noise filters with 0.3 Hz cut-off frequency and the sliding windows is 2.56 sec. and the data is labelled manually. The data set is partitioned into 70% for training and 30% for testing.

Table 4 Activities and label of data set

Activity	*Label*
SITTING	1
WALKING	2
WALKING UPSTAIRS	3
WALKING DOWNSTAIRS	4
STANDING	5
LAYING	6

4.1 Testing and validation

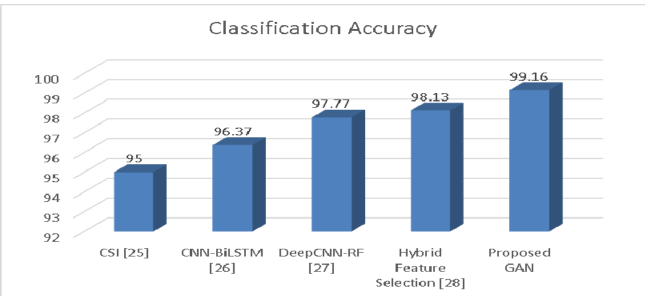
To test and validate our proposed IoMD architecture, we proceed with real-data set from ‘UCI Machine Learning Repository’. Details description of the data set and how the experiment was carried out is given below.

To validate our proposed framework, we develop deep learning neural method called Deep GAN. We trained a deep neural network using sequence-to-sequence classification. The proposed neural network can make different predictions for each individual time step of the sequence data. The data set contains sensor data generated from smartphones worn on volunteers' bodies (30 people). The Deep LSTM network is trained to recognise the activity of the wearer given sequence data representing accelerometer readings in three different directions and each sequence has 561 features and differ in length. The data set is divided into two sets first 70% is used for training purpose and the other 30% for testing.

4.2 Comparison with conventional methods

The comparison of our proposed method with related methods results on the same UCI data set in terms of accuracy is presented in Figure 6. The method, Channel State Information (CSI) as one of the characteristics of Wi-Fi signals, can be utilised to recognise different human activities (Parisa et al., 2021). Challa et al. (2021) classified the UCI data set based on a hybrid combination of Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) called multibranch CNN-BiLSTM network which does automatic feature extraction from the raw sensor data with minimal data pre-processing and achieved an accuracy of 96.37%. The Deep CNN-RF Method proposed in Ghate and Hemalatha (2021) achieved an accuracy of 97.77%. In Ahmed et al. (2020), a hybrid feature selection model which is a combination of Sequential Floating Forward Search (SFFS) based filter approach and Support Vector Machine (SVM) based wrapper approach fetched 98.13% accuracy. From details analysis and experiment results we found that our proposed Deep GAN method is achieving optimal accuracy of 99.16% in classifying physical activities in comparison to previous methods with respect to UCI HAR data sets.

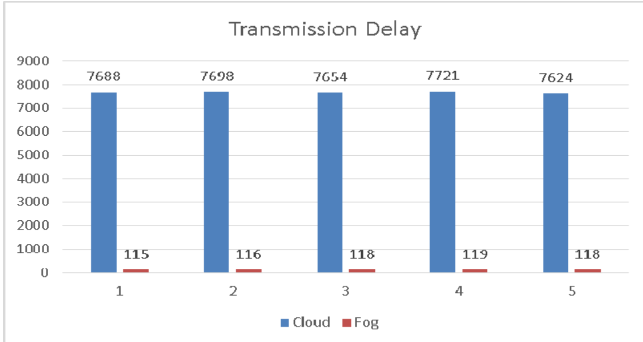
Figure 6 Graphical representation of proposed methods with existing technique



4.3 Transmission delay

There are various variables that affect transmission delay, including the number of hops between the source and the destination and the amount of bandwidth available on the network as well as the number of users. A three-file test of the suggested system is carried out. Figure 7 shows that for the same source and destination for various files, the transmission delay in Cloud and Fog Computing is nearly the same. In addition, Cloud Computing's transmission delay is far higher than Fog Computing's. In general, when the files must reach the Cloud there is more network overhead involved before it reaches the Cloud such as increased number of hops since the Cloud is far away from the source, similarly the network bandwidth can vary drastically due to the number of networks the files have to cross before reaching the cloud. These network overheads account for the huge transmission delay to reach the Cloud, rather than the Fog. In terms of Fog, the number of hops is lesser (compared to Cloud) and other factors as mentioned earlier account for a lower transmission delay.

Figure 7 Transmission delays of fog and cloud computing

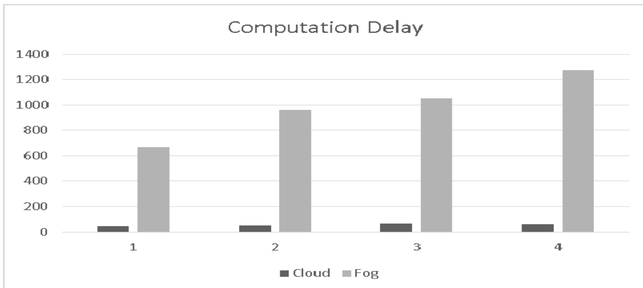


4.4 Computation delay

Depending on the device's hardware configuration, computing power can vary. How many cores and how much cache memory a processor has are all factors that affect performance.

Computing time is affected by several other factors, such as the design of the system, the number of parallel processes, refresh rate and so on, and the average value is depicted in Figure 8. The time-sensitive decision-making systems can't handle more stress on Fog.

Figure 8 Fog and cloud computing computation delay

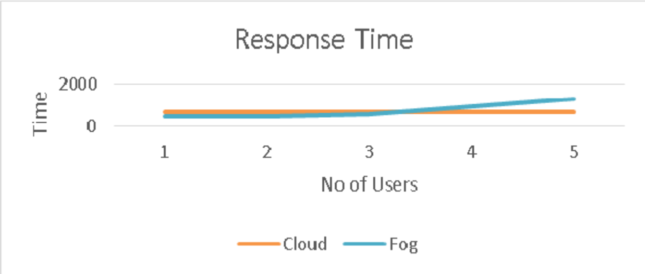


4.5 Response time

The response time is the whole time it takes for the system to perform. A normal or excessive time lag between the creation of the ECG signal and the generation of a response or decision is shown.

Figure 9 shows how the average reaction time can be calculated by altering the number of patients. Cloud design provides faster replies when there are many users, but only if there are no more than four of them. If the number of users is low, it reacts quickly. When it comes to Cloud Computing, response times are nearly identical. In cases when the number of end-users exceeds five, the suggested Fog Computing architecture will fall short of cloud computing.

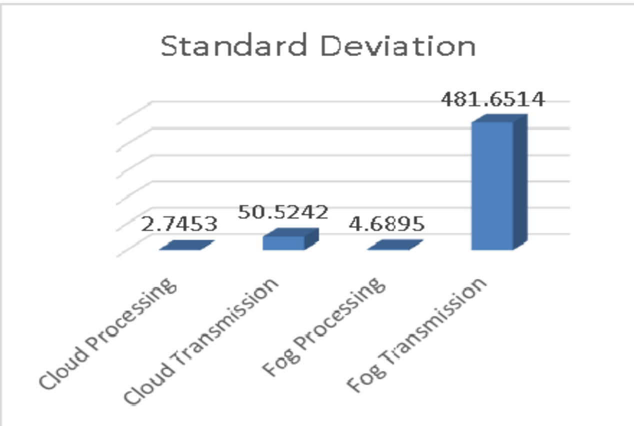
Figure 9 Response time of fog and cloud computing



4.6 *Standard deviation*

Data can be expressed in terms of standard deviations, which demonstrate how much data are spread out from their mean or expected value. The Fog processing time has the highest standard deviation when the various parameters like transmission time and calculation time for Fog and Cloud Computing are considered. The number of patients in the Fog Node has fluctuated, causing this discrepancy. Figure 10 depicts this.

Figure 10 Standard deviation of fog and cloud computing



5 Conclusions

We have developed a novel architecture for the IoMD system to monitor elder people in their homes. In the proposed framework, an intelligent method is introduced to handle massive data collected from the physical layer. This method called Deep GAN method is running in the cloud layer where rich resources are available on-demand, as well as the reported results, and are made available directly to the application layer through the internet. The detailed analysis presents that our method could classify the activities with high accuracy. Thus, the present case study has ensured benefits of the Sensor-Cloud virtualisation paradigm for developing innovative applications in different sectors of the IoT system.

A cloud-aided smart fog gateway for time-sensitive IoT-driven healthcare applications was introduced in this work. It ensures that the healthcare applications receive the service at a reasonable delay. Users can expect a quick response from this method. For critical healthcare applications, cloud computing-based IoT architecture is time-sensitive. It's possible to lessen the delay by using the LAN-based Fog Computing Processing method. Additionally, this method helps to limit the amount of data that must be stored on the Cloud. Additionally, Fog Computing must have memory, processing and compute capabilities, and Fog Nodes can be placed in either LAN or Gateway mode.

References

Ahmed, N., Rafiq, J. and Islam, R. (2020) 'Enhanced human activity recognition based on smartphone sensor data using hybrid feature selection model', *Sensors*, Vol. 20. Doi: 10.3390/s20010317.

Atlam, H.F., Walters, R.J. and Wills, G.B. (2018) 'Fog computing and the internet of things: a review', *Big Data and Cognitive Computing*. Doi: 10.3390/bdcc2020010.

Challa, S.K., Kumar, A. and Semwal, V.B. (2021) 'A multibranch CNN-BiLSTM model for human activity recognition using wearable sensor data', *The Visual Computer*. Doi: 10.1007/s00371-021-02283-3.

Dwivedi, R.K. and Kumar, R. (2018) 'Sensor cloud: integrating wireless sensor networks with cloud computing', *Proceedings of the 5th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON)*, pp.1–6.

Fortino, G., Guerrieri, A., Russo, W. and Savaglio, C. (2014) 'Integration of agent-based and cloud computing for the smart objects-oriented IoT', *Proceedings of the IEEE 18th International Conference on Computer Supported Cooperative Work in Design (CSCWD)*, IEEE, pp.493–498.

Fortino, G., Russo, W. and Savaglio, C. (2016) 'Simulation of agent-oriented internet of things systems', *CEUR Workshop Proceedings*, Vol. 1664, pp.8–13.

Ghate, V. and Hemalatha, C.S. (2021) 'Hybrid deep learning approaches for smartphone sensor-based human activity recognition', *Multimedia Tools and Applications*, Vol. 80, pp.35585–35604.

Goodfellow, I.J. et al. (2014) 'Generative adversarial networks', *arXiv 1406.2661*.

Guermouche, A. and L'Excellent, J. (2004) 'Memory-based scheduling for a parallel multifrontal solver', *Proceedings of the 18th International Parallel and Distributed Processing Symposium*, IEEE, Santa Fe, NM, USA.

Jo, T.H., Ma, J.H. and Cha, S.H. (2021) 'Elderly perception on the internet of things-based integrated smart-home system', *Sensors*, Vol. 21. Doi: 10.3390/s21041284.

Joyia, G.J., Liaqat, R.M., Farooq, A. and Rehman, S. (2017) 'Internet of medical things (IoMT): applications, benefits and future challenges in healthcare domain', *Journal of Communications*, Vol. 12, No. 4, pp.240–207.

Kashani, M.H., Madanipour, M., Nikravan, M., Asghari, P. and Mahdipour, E. (2021) 'A systematic review of IoT in healthcare: applications, techniques, and trends', *Journal of Network and Computer Applications*, Vol. 192. Doi: 10.1016/j.jnca.2021.103164.

Kim, W.S., Lee, W.S. and Kim, Y.J. (2020) 'A review of the applications of the internet of things (IoT) for agricultural automation', *Journal of Biosystems Engineering*, Vol. 45, pp.385–400.

Mutlag, A.A., AbdGhani, M.K., Arunkumar, N.A., Mohammed, M.A. and Mohd, O. (2019) 'Enabling technologies for fog computing in healthcare IoT systems', *Future Generation Computer Systems*, Vol. 90, pp.62–78.

Parisa, F.M. et al. (2021) 'A CSI-based human activity recognition using deep learning', *Sensors*, Basel, Switzerland, Vol. 21. Doi: 10.3390/s21217225.

Priyadarshi, R., Gupta, B. and Anurag, A. (2020) 'Deployment techniques in wireless sensor networks: a survey, classification, challenges, and future research issues', The Journal of Supercomputing, Vol. 76, No. 9, pp.7333–7373.

Puliafito, C., Mingozzi, E., Longo, F., Puliafito, A. and Rana, O. (2019) 'Fog computing for the internet of things: a survey', *ACM Transactions on Internet Technology (TOIT)*, Vol. 19, No. 2, pp.1–41.

Radhi, A.M. (2020) 'Framework for decision support based on hybrid of ad hoc intelligent dynamic system', *Journal of Computing and Information Technology*, Vol. 28, No. 1, pp.11–20.

Reyes, R.J.R., De Mendon¸ F.F. and Dias, K.L. (2017) 'A service-oriented architecture with data virtualization support for cloud-based wireless sensor networks', *Proceedings of the 7th Brazilian Symposium on Computing Systems Engineering (SBESC)*, pp.199–204.

Sahmim, S. and Gharsellaoui, H. (2017) 'Privacy and security in internet-based computing: cloud computing, internet of things, cloud of things: a review', *Procedia Computer Science*, Vol. 112, pp.1516–1522.

Saoud, B. (2021) 'Simulation and analysis of routing protocols in wireless sensor network', *Proceedings of the International Conference on Recent Advances in Mathematics and Informatics (ICRAMI)*, IEEE.

Selvaraj, S. and Sundaravaradhan, S. (2020) 'Challenges and opportunities in IoT healthcare systems: a systematic review', *SN Applied Sciences*, Vol. 2. Doi: 10.1007/s42452-019-1925-y.

Shi, L., Sun, Y. and Wei, L. (2007) 'Effect of scheduling discipline on CPU-MEM load sharing system', *Proceedings of the 6th International Conference on Grid and Cooperative Computing (GCC'07)*, Los Alamitos, CA, pp.242–249.

Silva, B.N., Khan, M. and Han, K. (2018) 'Internet of things: a comprehensive review of enabling technologies, architecture, and challenges', *IETE Technical Review*, Vol. 35, No. 2, pp.205–220.

Swathi, K. and Prasad, K.A.V. (2018) 'A review on privacy and security challenges in internet based computing: cloud computing, internet of things and COT', *International Journal of Emerging Technologies and Innovative Research*, Vol. 5, No. 6, pp.54–58.

Ud Din, I., Almogren, A., Guizani, M. and Zuair, M. (2019) 'A decade of internet of things: analysis in the light of healthcare applications', *IEEE Access*, Vol. 7, pp.89967–89979.

Usman, M., Ahmed, I., Aslam, M.I., Khan, S. and Shah, U.A. (2017) 'SIT: a lightweight encryption algorithm for secure internet of things', *International Journal of Advanced Computer Science and Applications*, Vol. 8, No. 1.

Zhang, X., Qu, Y. and Xiao, L. (2000) 'Improving distributed workload performance by sharing both CPU and memory resources', *Proceedings of the 20th IEEE International Conference on Distributed Computing Systems*, Taipei, Taiwan, pp.233–241.