

# Edge Computing: A study to improve latency and security of data in the health sector

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**ABSTRACT:** The rapid advancement of technology and the increasing number of devices being connected each day have led to the development of the Internet of Things (IoT). It has been used widely in the health sector. IoT-based healthcare technologies have allowed medical professionals to remotely monitor and track the patient's health and provide medical aid when necessary. To manage more substantial and intricate healthcare data in an IoT environment, cloud computing was developed to store, and access data and applications on remote servers that are hosted online. Integrating IoT with the cloud resulted in some major issues such as latency, bandwidth overuse, privacy, and protection. To solve this problem, the ideas of edge computing and fog computing were developed. In addition, it is critical for the health sector to have an intelligent system to identify certain diseases based on symptoms or patterns given by the devices for faster diagnosis without the need for human intervention. Most data in the health sector is large and requires high computational speed in terms of processing. Also, accurate results are required so that the diagnosis probability is true. In this article, we will propose an edge-computing architecture that can help improve the latency and security of data in the health sector.

**KEYWORDS:** Edge Computing, Security, Latency, Deep Learning, Machine Learning, Edge Intelligence, Healthcare.

## I. INTRODUCTION

The Internet today connects people from all over the world and makes it possible to participate in a global dialogue at any time and from anywhere. Things that were previously out of reach are now just a few clicks away. [1] Without a question, if the internet hadn't been created, the world would not be

what it is now. The Internet of Things is one of the innovations made possible by the internet (IoT). It is utilised in a variety of industries, including automation, smart grid, traffic management, smart homes, and smart cities.[2]

In the health sector, wearable and embedded smart IoT sensors have made remote monitoring possible. The amount of data generated by the devices is increasing dramatically as the IoT grows.[3] To manage data more efficiently, cloud computing was introduced where data can be stored, processed, and accessed over cloud-enabled platforms.[4] There have been several healthcare architectures proposed with most of them integrating IoT with cloud computing. However, it faces other difficulties, including transportation congestion, data delays, and the processing of enormous amounts of data. The installation of cloud servers far from IoT devices is the main cause of these problems.[5]

Edge computing can be utilised to address latency and data security challenges. It ensures that the computing and data storage facilities are situated closer to the topology's edge. The gadgets that communicate with the internet are referred to as the edge.[6] Edge computing can be used to process healthcare sensor data collaboratively and effectively with a number of edge devices and local servers. The field is moving toward intelligent healthcare frameworks with human-like intelligence and even cognitive intelligence, which will enable technology to uncover hidden patterns and track users in order to diagnose and warn about critical conditions. Edge intelligence has resulted from the use of machine learning or deep learning techniques at the edge layer.[7] Edge intelligent architectures can be taught wholly or in part at the edge level, with additional processing then being distributed

among edge and fog nodes or carried out in the cloud for computationally demanding applications.[8]

## II. RELATED WORK

	Author	Network Latency	Security
1	[9]	√	√
2	[10]	√	√
3	[11]	√	√

Table 1: Related work summary

[9]assessed that edge computing with its focus on proximity to users and better intelligence provides better user service. It makes the users get a very quick response and thus latency is improved.

[10] also analysed that because data is being processed at the edge this indeed provides low latency and can also be applicable for real-time applications.

[9]document that since data is being processed right where it is being collected and does not have to go to servers on the cloud. Security is enhanced because any security problems will be on the local device.

[10]proposed that a lightweight authentication mechanism should be placed on Edge Servers that can be used to authenticate edge devices as such enhancing the security on the Edge. And in situations where the processing is distributed between different servers then the trust of a device on one particular server is not transferred to another server. Each server will authenticate its devices.

Even though the data processing is brought to the proximity of where it is being collected other researchers argue that data being processed locally also brings a threat to security in that it is difficult to

handle data that is being processed locally by some vendors[8].

[9]propose different architectures that use deep learning on edge devices just to make sure that the processing of data is faster and makes proper use of the network bandwidth.

## III. METHODOLOGY

This section outlines the procedure for searching, retrieving and reviewing topic related literature. Fog computing, edge intelligence and deep learning were used as search terms on the Google Scholar search engine to find research papers related to the topic.The search filter was adjusted to display papers that were published after 2016 in order to get the latest information. Reading the keywords and abstract on the corresponding websites served as the basis for the initial selection. The most recent studies that were relevant were selected. After reviewing the key contributions and conclusion section of the paper, the second selection procedure was conducted. Here, only research that focused on using machine learning or deep learning techniques in the edge computing settings was selected.

### Proposed Edge Computing Architecture

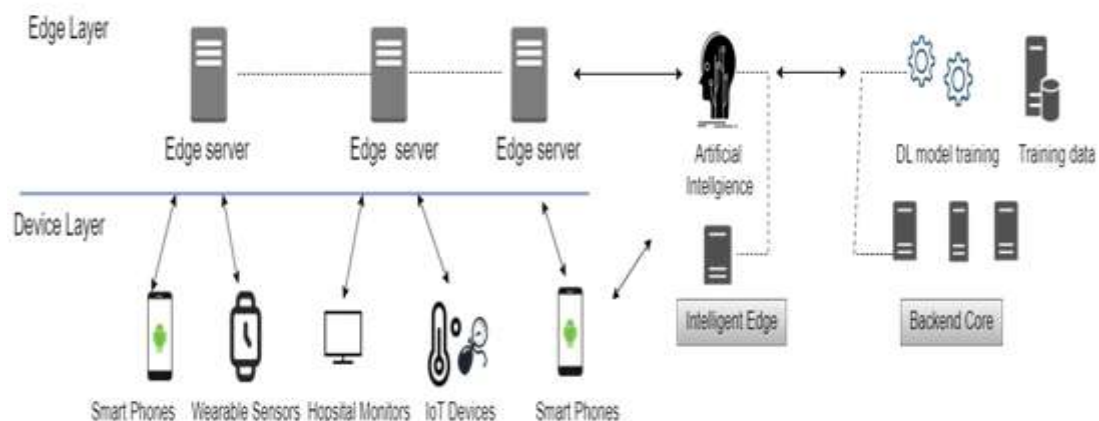


Figure 1: Edge Computing Architecture

The figure below illustrates the architecture of an edge-based health monitoring system. It comprises of two layers: device and edge.

#### A. Device Layer

Edge devices make up the device layer. These include wearables, tablets, smart phones, and health monitors. Clinicians may receive real-time data on patient vitals from wearables, including

#### B. Edge Layer

The top layer of the suggested architecture is made up of the edge layer. The data generated from the sensors is forwarded to different edge server. When devices send massive amounts of data to the server, it will analyze what is important. The important data will be stored while the irrelevant data will be deleted or kept for further analysis. To help the server distinguish between relevant and irrelevant data, deep learning can be used to make decisions and predictions. Aside from data filtering, the servers also perform real time data processing, data visualization and analytics. [12] Devices will be authenticated by different servers to enhance security. Once moved to another server it will also have to be authenticated by that server.[13]

#### C. Deep Learning

One may classify deep learning as a subset of machine learning. It relied on self-improvement and learning by studying computer algorithms. [14] Artificial neural networks used in deep learning are made to resemble human brain activity. Layers of

heart rate, pulse rate, blood pressure, and body temperature. The upper-level edge gadget processes the data once it has been collected to decide if the patient is in a critical condition or not. Health monitoring can help with remotecare and can prompt actions depending on patient data results.[11]

neurons make up an artificial neural network, which is the main processing unit that enables technology to do tasks likeface or image recognition, signature verification, visual surveillance, and medical diagnosis.[14] As shown in the edge computing architecture in figure 1, deep learning can used in the device and edge layer of various IoT devices to recognize objects and patterns.[9]

Neural network comprises of three layers: input, hidden and output.

- Input Layer: Images provide data to the input layer, often in the form of pixels. Each neuron in the first layer of neurons is fed one of these pixels (input layer). Neurons in one layer are linked to neurons in another layer through channels. Each of these channels is given a weight, which is a numerical value. The inputs are multiplied by the corresponding weights before their sum is given to the hidden layer neurons as input.[15]

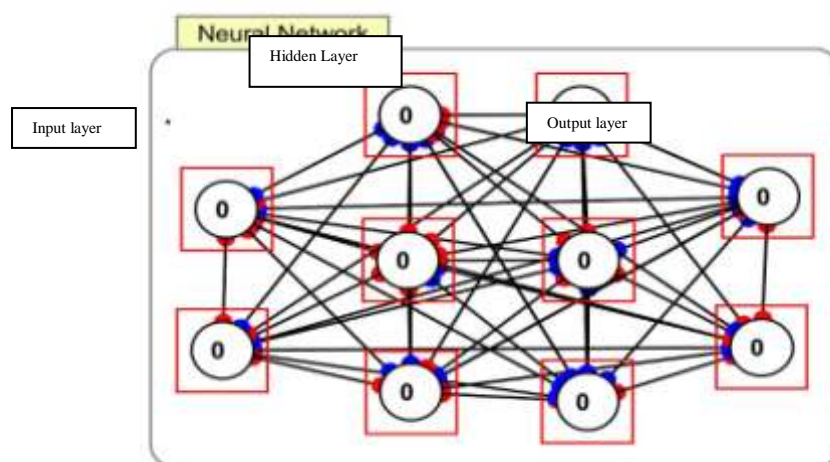


Figure 2: Neural Network Model

- Hidden Layer: The biases are then added to the input total once it receives its input from the input layer. Each of the neurons in the buried layer has a bias, which is a set of numerical

values. The activation function, a threshold function, is then applied to this number (AF). By generating a weighted sum and then including bias with it, AF will select whether

or not to activate a neuron. The activation function's objective is to add non-linearity to a neuron's output. The input is transformed nonlinearly by the activation function, enabling it to learn and carry out more difficult tasks.[16]

- **Output layer:** In this way, data is propagated across the network until it produces the output: activated neurons will transfer data to the neurons of the next layer over the channels. It is also known as a forward pass, forward propagation, or feed forward. The output is determined by the firing of the neurons with the highest value.[17] The values essentially represent a likelihood. The output will be determined by which likelihood is highest.

Once the output has been obtained, the error can be determined by subtracting the output value from the real value. This will guarantee that the model produces the desired results. If there is a mistake, it is sent back to each node along with its appropriate weight so that it can be changed in order to further minimise the error. Back-propagation utilising gradient descent is the name of this method. The feed forward and back propagation procedure continues for a number of iterations until the output has low error. This procedure, known as training, aids in developing a model that accurately predicts the outcome of unknowable facts. [18]

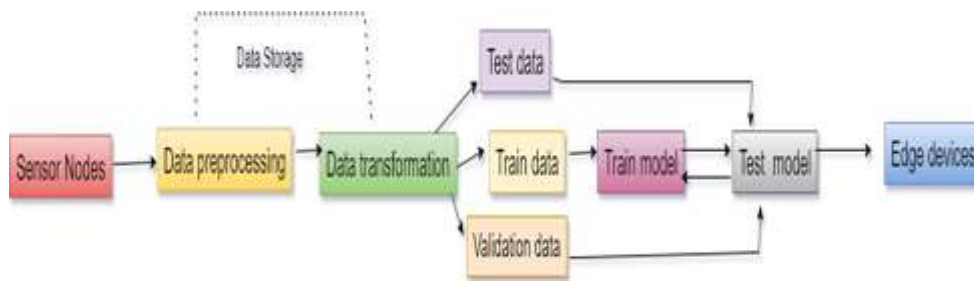


Figure 3: Deep Learning training process

Deep learning is used in various ways in the health sector as shown in the table given below.

Area	Applications	Input Data	Base Method	Reference
Medical Imaging	Tissue Classification Organ Segmentation	MRI/CT Images Endoscopy image	Convolutional Deep Belief Network	[19]
			Convolutional Neural Network	[20]
Medical Informatics	Prediction of disease Human behavior monitoring	Electronic health records Big medical dataset	Convolutional Neural Network	[21]
			Recurrent Neural Network	[12]
Public Health	Predicting demographic info Lifestyle disease	Social media data	Deep Auto Encoders	[22]
			Deep Belief Network	[23]

Table 2: Summary of the different deep learning methods by areas and applications in health informatics

#### IV. DISCUSSIONS

In this section, we go through how the suggested design performs in terms of latency and data security. Network latency is the term used to describe the delay in network communication. It shows how long it takes for data to move around

the network.[24] When edge applications get a flood of data and information, a centralised location that serves as the primary location for data processing and storage generally finds it difficult to handle the load and performance issues that result in excessive latency and disruptions.[24] Due to the

fact that data is processed and examined closer to the place where it is originated, edge computing can assist reduce the impact of latency.[9]

As a result, processing data does not need sending it across a network to a cloud or data centre. Multiple servers that process various user data kinds are part of the design. The servers will be located close to the data's original source of generation.[25] Because learning models are dispersed over the network and data is processed at the network edge, these machines will be equipped with deep learning algorithms, which will result in faster computing of data.[26] As a result, it can increase data processing efficiency and provide quicker predictions for medical diagnosis. Secondly, each server should be modelled with an authentication method that will help authenticate users. Authentication algorithm to be used that will authenticate users. RFID authentication method can be used. This will enhance security in that each server will authenticate the devices presented to it.[13]

## V. CONCLUSION

Edge Computing has proven to offer better solutions than cloud computing, especially in environments that require faster processing of data. The healthcare sector requires fast processing of data and using edge computing is better than cloud computing, particularly for this sector. The proposed architecture is one that facilitates fast processing but also enhances security because different users will be authenticated at different servers. If a user moves to another server they will have to be authenticated by that particular server as well. We appreciate that the proposed architecture might offer some costs but for further work the solution can be implement in a cost-effective approach.

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