Deep Learning Techniques in Mobile Edge Computing for Internet of Medical Things

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***Abstract*—The fast expansion of the Internet of Medical Things (IoMT) has resulted in a ubiquitous home health diagnostic network. High patient demand results in high costs, short latency, and communication overload. As a result, 6G is the next generation of IoT, IoMT, and cellular networks, intending to considerably improve the quality of smart healthcare services through high throughput and decreased latency. So far, adopting cloud computing for time-critical applications and decreasing access delays to resources is difficult. Deep learning has been extensively employed to extract characteristics from complicated networks as artificial intelligence technology has advanced. On the other hand, deep learning models are often run in cloud computing data centres with tremendous processing resources. Conventional cloud computing systems primarily rely on the network, which has significant latency and security and privacy issues. One of the successful solutions is the Mobile Edge Computing (MEC) paradigm, which brings cloud computing services closer to the edge network and uses available resources. Mobile edge computing places computer and storage nodes near mobile devices at the Internet's edge, leading to considerable savings in system operating time, memory cost, and power usage. Deep learning is used in mobile edge computing to forecast changes in demand based on daily patient behaviours. It also prepares the network by scaling up network resources as required. This study aims to discuss IoMT and identfy the problems in deep learning for mobile edge computing technology and its applications.**

Keywords- Deep learning, 6G, Internet of Medical Things, Mobile Edge cpomuting.

I. Introduction

The Internet of Medical Things (IoMT) refers to integrating connected devices, sensors, and software in healthcare. One of the key benefits of the IoMT is that it allows healthcare providers to use wireless and internet technologies to monitor, collect, and analyze patient data and health information in real time, even when they are not in the hospital [1]. This helps healthcare providers to detect potential health issues early and take action before they become serious problems. The IoMT is also reducing the cost of healthcare by enabling remote patient monitoring and reducing the need for hospitalization. Another important aspect of the IoMT is the ability to collect and analyze large amounts of health data, which can be used to improve the accuracy of diagnoses and treatments [2, 3].

With the growth of the IoMT, there is an increasing demand for more reliable and secure communication networks to support these devices. Therefore, 6G is the next generation of wireless communication technology that promises to bring new levels of speed, reliability, and low latency to the Internet of Things (IoT) [4, 5]. With the increased capabilities of 6G, the IoMT is poised to take a major leap forward in healthcare delivery and patient outcomes. 6G for the IoMT is its ability to support low latency, high-speed communications. The technology has latency levels as low as 1 millisecond, significantly lower than current 4G and 5G networks for patient monitoring. This low latency will allow healthcare providers to receive real-time information from patients' wearable devices, such as continuous glucose monitors, heart rate monitors, and sleep-tracking devices. 6G technology is expected to have the capacity to support millions of devices and sensors, enabling the widespread adoption of the IoMT in healthcare [6, 7].

Simultaneously, intelligence-oriented IoMT in 6G is increasingly researched to facilitate the fully connected world [1], especially for edge intelligence. It provides an emerging integrated communication network mobile edge computing (MEC) framework. Mobile Edge Computing (MEC) is an important technology that is expected to play a crucial role in the Internet of Medical Things (IoMT) for 6G [8, 9]. MEC refers to the deployment of computing and storage capabilities at the edge of the network, close to the end users and devices. By bringing computing and storage resources closer to the edge, MEC enables real-time processing of data and reduces latency. With the development of the processing capabilities of MEC, many applications that collect and utilize big data in IoMT have emerged. Examples include patient detection apps or real-time natural language processing [10, 6]. Deep learning algorithms can be deployed at the edge of the network to process medical data in real time, providing healthcare providers with critical insights about patient health.

Integrating deep Learning with Mobile Edge Computing (MEC) in the IoMT for 6G can revolutionize healthcare delivery and improve patient outcomes. Deep learning is a branch of artificial intelligence (AI) that has the potential to transform the Internet of Medical Things (IoMT) in 6G by enabling real-time analysis and interpretation of medical data at the edge of the network [11,12]. Furthermore, deep Learning in MEC for the IoMT in 6G has the potential to

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significantly reduce the latency and cost associated with medical data processing. By processing data at the edge of the network, deep learning algorithms can reduce the need to transmit large amounts of data to cloud computing, which can be costly and time-consuming. Additionally, the low latency capabilities of 6G technology will enable deep learning algorithms to process data in real-time, further reducing latency, improving the speed and accuracy of medical data analysis, and providing healthcare providers with more accurate and up-to-date information about patient health [7, 10, 11].

Following is a summary of this paper's contributions: It supplies a public definition for mobile edge computing at 6G-IoMT and its advantages. Additionally, it describes deep learning and applications of deep learning for mobile edge computing. Finally, this essay covered several issues with deep learning for mobile computing at the edge in 6G-IoMT.

The remaining sections of the article are organized as follows: Section II discusses mobile computing at the edge and its benefits. Section III describes deep learning and its uses for 6G-IoMT mobile computing at the edge. Section VI discusses the difficulties with deep learning for mobile computing at the edge of 6G-IoMT. Section V offers a conclusion to this article.

II. ADVANTAGES OF MOBILE EDGE COMPUTING

A. Mobile Edge Computing in 6G-IoMT

The European Telecommunications Standard Institute (ETSI) proposed mobile edge computing (MEC) 2014. At the edge of the cellular network, MEC is a network concept that offers cloud computing capabilities. The edge of a mobile network is referred to as "mobile edge computing". The seamless integration of cloud computing elements into mobile networks is made possible by mobile computing on the edge. It is a revolutionary architecture that extends cloud computing capabilities to the network's edge [13, 14]. MEC was recognized as a critical component for 6G system technologies in IoMT [4]. It comprises installing several small-scale servers at the network edge and spreading partial data storage, processes, and applications on those small-scale servers rather than transferring almost all data and processes to faraway cloud servers. Its primary argument is that processing jobs closer to the sick customer reduces network congestion and alleviates the issue of lengthy latencies [15,16]. It is distinguished by its low latency, closeness, high bandwidth, and agile mobile service. It offers pervasive and effective cloud services for Wearable mobile devices [17].

B. Advantages of Mobile Edge Computing

MEC can assist biometrics in providing high-quality biometric services. Wearable devices, mobile devices, edge servers, and cloud servers work together to fulfil MEC-aided biometric service architecture activities. To illustrate why MEC can help biometrics offer high-quality biometric services to service providers and customers [9].

a) Reliability: It is not unexpected that MEC provides excellent dependability, given its security benefits. Because IoMT mobile edge devices and data centres are positioned near end users, the likelihood of network failures in faraway places impacting local consumers is reduced. If the edge computing design is followed, IoMT edge computing devices will work correctly even if there is a problem with the adjacent data centres. When MEC architecture is implemented, it is observed that the entire service will never be totally disabled. The objective is to establish 'intimacy' with the consumer using new technology [18,19].

b) Speed: MEC makes it possible to reply to data practically instantly by removing delays. By locating data processing computers close to the source, internet traffic is lowered. Because the resources are accessible remotely, efficiency and cost are boosted. The patient data is not needed to be stored on the cloud, and the sensitive patient data remains secure. The most crucial benefit of MEC is its ability to improve network performance by battling latency [20, 21].

c) Security: The dispersed nature of the MEC architecture makes it simple to implement the security protocol that can isolate the attacked pieces without shutting down the entire healthcare network. IoMT, for example, has utilized facial recognition technology to verify the faces of those entering and departing facilities. This approach requires machine learning, natural language processing, neural networks, and other statistical computation. This technology, in particular, needs storage for the setting to be practical [22, 23].

III. DEEP LEARNING OF MOBILE EDGE COMPUTING AND ITS APPLICATIONS

A. Deep Learning

Deep learning becomes a machine learning method that employs a series of layers, each performing a non-linear change. Geoffrey Hinton pioneered deep learning in 2006, and his work has been swiftly followed by Yann LeCun and Yoshua Bengio. Deep learning has recently gained popularity due to its capacity to train complicated models and conduct representation learning [24, 25]. This sort of learning does learn through data representations rather than explicit data: data are converted into hierarchical abstract representations that allow learning of useful features, which are then utilized for ML tasks [11].

B. Applications of Deep Learning in Mobile Edge Computing

We now discuss various examples of applications where deep learning on mobile edge computing devices might be valuable and what "real-time" implies in each of these cases. Other deep learning applications exist in addition to the ones discussed below, as shown in Figure 1, in the MEC context for healthcare networks. The unifying thread in these applications is that they are complicated machine learning problems where deep learning has been proven to perform well. They must operate in real-time and/or have privacy issues, requiring inference and/or training on the MEC in IoMT.

a) Computer vision: Deep learning was already acknowledged as the nation for picture categorization and object recognition since its win in the ISLVRC computer vision competition in 2012 [26]. Image classification and object identification were essential computer vision tasks in various applications such as video surveillance, item counting, vehicle detection, and patient monitoring. This approach requires machine learning, natural language processing, neural networks, and other statistical computation. This technology, in particular, needs storage for the setting to be possible. For this, mobile edge computing offers critical storage for data processing [27].

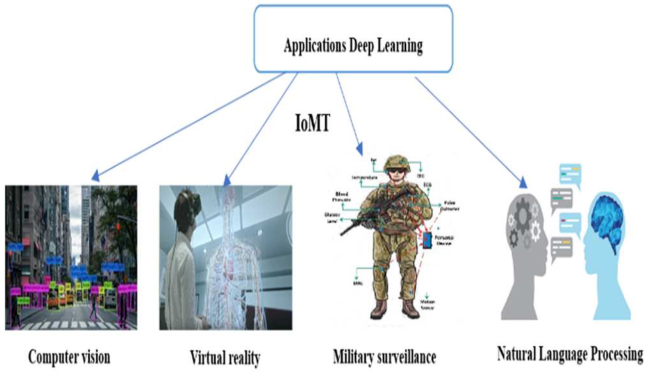

Fig. 1. Applications of Deep Learning in MEC based IoTM.

b) Virtual reality: Deep Learning has been suggested in 360 virtual reality to forecast the user's and physicians' field of vision in order to deliver immersive and engaging experiences for patients and healthcare professionals. In addition, MEC in IoMT significantly influences pain management, rehabilitation, mental health therapy, and virtual reality medical training (VR) [28, 29]. It enables the exchange of real-time patient data between clinicians and network edge. These predictions are utilized as a non-pharmacological pain management technique to determine or create a simulated environment for patients to perform physical therapy exercises of the 360 video. They should be computed in real-time to minimize stalls, maximize the quality of care, and improve patient outcomes in healthcare. Deep learning may be applied in virtual reality to identify things of interest in healthcare [12].

c) Military surveillance: Wearable and implantable sensors could be used to monitor armies and spy cameras in military healthcare. In IoMT, the edge sensor gives immediate data for the host server rather than the cloud data server to preserve soldiers' patients' data and concealment from suspicious acts in critical zones. Such data requires additional delay to be sent to the cloud data centre. In essence, data collection and processing on the MEC in the IoMT networks server gives a speedy response [30].

d) Natural Language Processing: NLP has been an intelligent technology that aids in the interaction between machines and people. Deep learning also gained traction in natural language processing applications, such as voice synthesis, named entity recognition (understanding distinct portions of a phrase), and machine translation (translating from one language to another) [31, 32]. NLP enables the MEC in healthcare networks to become more resilient and boosts the pace of data processing, allowing for considerably quicker output generation. NLP bridges the gap among machines and humans by using multiple codes, computation linguistics, and computer science to modify the human language and assist machines in producing more exact results. In contemporary healthcare network systems, the latency on the order of hundreds of milliseconds has been achieved for conversational AI [33]. This contributes to better data transport routes in networks. NLP aids in real-time analytics by increasing CPU demand. The key is to understand the sector of healthcare interest and market, as well as to analyze patient activities and create an appropriate design to support systems.

IV. CHALLENGES IN DEEP LEARNING FOR MOBILE EDGE COMPUTING AT 6G-IoMT

Deep learning and mobile edge computing integration in 6G-IoMT is still in its early stages. This section investigates the challenges connected with the combination of deep learning with mobile edge computing, as shown in Figure 2.

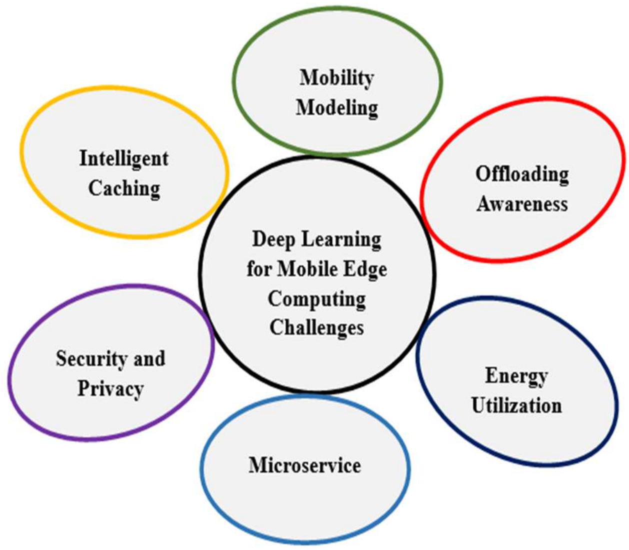

Fig. 2. Challenges of Deep Learning in MEC based IoTM.

A. *Offloading awareness in deep learning for mobile edge*

The MEC servers installed in 6G-IoMT networks capture the patient data supplied by mobile users. Multiple users communicating with the MEC servers at the same time may produce congestion, reducing the overall network's stability. Deep learning systems in MEC systems may be taught to reduce the cost of offloading tasks in healthcare networks and tiny wireless devices by employing immediate and long-term incentives during the training stage [34, 35]. However, additional resilience in delay and energy usage is still required. In addition, many wearable devices were linked to the edge network. However, in certain circumstances, the majority of edge servers do not allow several wearable devices to connect at the same time. Today, an edge-enabled smart city comprises a million IoMT device connections. When a significant number of devices offload duties for edge servers simultaneously, communication becomes difficult. Future studies should concentrate on offloading services using a load-balancing mechanism [36, 19].

B. *Mobility Modeling in deep learning for mobile edge*

Mobility modelling has become a significant difficulty in the MEC-based IoMT network. Users of wearable devices are often on the go, which causes connectivity with edge devices to be lost. Whenever a wearable user or device goes from one area to another, it enters a new territory each time, resulting in a performance drop. With the increase in mobile phone use and linked wearable devices, forecasting mobility has become a key component of comprehending MEC network needs and wearable devices. Once the mobility characteristics of users in a network are established, deep learning may be utilized to anticipate traffic patterns and develop more cost-effective IoMT network operating strategies [37, 38]. As a result, numerous academics successfully presented various techniques to address the mobility problem. Proposes a user-centric strategy for optimizing latency in an ultra-dense network by considering the energy economy during mobility management. In order to make an offloading choice, the suggested algorithm in anticipates a user's movement. Proposes frameworks that operate effectively with IoT devices that have restricted mobility. The GAMEC technique was utilized to optimize and shorten the response time of service invocation. In the MEC network, GAMEC is a mix of a genetic algorithm and a simulated annealing algorithm [39].

C. Intelligent caching in deep learning for mobile edge

MEC may leverage the user's proximity to cache locally relevant patient data nearby to minimize latency and respond to spikes of demand for individual patient data in an area. The answer was derived from many sources related to the data in IoMT. The extraction of data from a noise package is a difficult task. Deep learning has been demonstrated to increase network efficiency and reduce pressure on network resources by storing patient data near the user more than in regional data centres [40, 41]. Furthermore, intelligent gadgets' storage of local data necessitates a large capacity and building deep learning-based sophisticated algorithms necessitates massive data sets, imposing considerable computational complexity. Some research has leveraged user mobility and behavioural patterns to forecast application selections and construct deep learning caching algorithms to anticipate their needed patient data. However, future studies must address this issue by implementing an interoperable system. An interoperability interface based on machine learning may be employed inside the patient data advancement procedure using this technique [42].

D. Security and privacy in deep learning for mobile edge

The MEC network has strict data security and privacy challenges, which jeopardizes the IoMT network's resilience. The valid worries about data security and privacy with acquired data have stymied the adoption of large-scale deep learning systems at the MEC in 6G. Due to the need to share patient data across slices and the risk of data or use pattern breaches, security must be ensured while working with 6G mobile edge computing [43, 22]. In future, wearable sensors must authenticate the application when contacting MEC servers. IoMT-6G for MEC networks should also defend themselves from hostile actors and can employ deep learning to identify and prevent attacks. At the same time, novel slicing architecture and virtualized networks may also require deviations from industry-standard security solutions. Efforts to improve deep learning performance should also consider privacy. MEC has open research challenges. In the IoMT network, data may be stolen simply (through a deactivated edge node). As a result, protecting the network from various threats is a top priority. Future studies should restrict the data flow and provide minimal testing data to prove the absence of snoopers. In this manner, the problem of insecure initialization will be solved [44,22,23].

E. Microservice in deep learning for mobile edge Services

In 6G-IoMT, the mobile edge service has recently begun significantly changing from monolithic entities to graphs of hundreds of loosely linked microservices. Deep learning calculations may need several software dependencies, necessitating a method for isolating various deep learning services on common resources [45, 46]. Because of numerous significant obstacles, the microservice architecture deployed on edge to host deep learning services is still in its infancy [47]. 1) Handling deep learning deployment and management flexibly. 2) accomplishing live migration of microservices to decrease migration times and lack of availability of deep learning services because of user mobility, and 3) Orchestrating resources among cloud and distributed edge infrastructures to improve performance.

F. Energy utilization in deep learning for mobile edge

Wearable and implantable IoMT-6G devices have limited power stored in their batteries in MEC. As a result, this energy must be used wisely because training deep learning models necessitates a large amount of energy. However, minimizing deep learning's energy consumption is critical for battery-powered implantable and wearable edge devices like smartphones. The user energy consumption for data offloading fluctuates significantly during dynamic activity inside the mobile edge network [48, 49]. As a result, if there is no charging or replacement capability inside the network, users' batteries will begin to die. Replacing the battery was likewise not a good option and is almost impossible owing to the terrible network scenario. To address this problem, future research should concentrate on attempting to predict energy costs and developing algorithms which improve the energy efficiency of the systems they control since few attempts have merged these two crucial subjects [50, 51]. There are several unresolved problems concerning the capacity of large-scale deep learning models to be deployed with resource-constrained mobile edge computing platforms.

V. CONCLUSIONS

Mobile computing at the edge refers to its position at the outermost edge of a network, situated between user devices and cloud data centers. With the increasing demand for wireless networks, services based on the Internet of Medical Things (IoMT) have gained popularity. This study explores the concept of 6G IoMT and provides an overview of mobile edge computing and deep learning. The article highlights various advantages of mobile computing at the edge of 6G IoMT, including speed, reliability, and security. Additionally, it examines multiple applications of deep learning in mobile computing at the edge of 6G IoMT, such as computer vision, virtual reality, military surveillance, and natural language processing. The essay also identifies several challenges associated with deep learning for mobile computing at the edge in 6G IoMT, including offloading awareness, mobility modeling, intelligent caching, security and privacy, as well as microservice and energy utilization.

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