B5G AND EXPLAINABLE DEEP LEARNING ASSISTED HEALTHCARE VERTICAL AT THE EDGE: COVID-19 PERSPECTIVE

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ABSTRACT

B5G-based tactile edge learning shows promise as a solution to handle infectious diseases such as COVID-19 at a global level. By leveraging edge computing with the 5G RAN, management of epidemic diseases such as COVID-19 can be conducted efficiently. Deploying a hierarchical edge computing architecture offers several benefits such as scalability, low latency, and privacy for the data and the training model, which enables analysis of COVID-19 by a local trusted edge server.However, existing deep learning (DL) algorithms suffer from two crucial drawbacks: first, the training requires a large COVID-19 dataset on various dimensions, which is difficult for any local authority to manage. Second, the DL results require ethical approval and explanations from healthcare providers and other stakeholders in order to be accepted. In this article, we propose a B5G framework that supports COVID-19 diagnosis, leveraging the low-latency, high-bandwidth features of the 5G network at the edge. Our framework employs a distributed DL paradigm where each COVID-19 edge employs its own local DL framework and uses a three-phase reconciliation with the global DL framework. The local DL model runs on edge nodes while the global DL model runs on a cloud environment. The training of a local DL model is performed with the dataset available from the edge; it is applied to the global model after receiving approval from the subject matter experts at the edge. Our framework adds semantics to existing DL models so that human domain experts on COVID-19 can gain insight and semantic visualization of the key decision-making activities that take place within the deep learning ecosystem. We have implemented a subset of various COVID-19 scenarios using distributed DL at the edge and in the cloud. The test results are promising.

I. INTRODUCTION

The potential features of Beyond 5G (B5G) offer several key advancements such as energy efficiency, area traffic capacity, peak data rate, user expected data rate, spectrum efficiency, user mobility, low latency, and high connection density [1]. On top of these pillars, 5G can offer next-generation services for any particular vertical. The sudden appearance of the global pandemic COVID-19 has demonstrated the importance and essence of these 5G pillars,which we call B5G [2]. B5G provides key tools that can be leveraged in the pandemic situation, such as wireless cognition, sensing, imaging, communication, and positioning [3]. The three pillars of 5G — massive machine-type communications (mMTC), ultra-reliable, low-latency communications (uRLLC), and enhanced mobile broadband (eMBB) — can be configured for COVID-19-specific heterogeneous edge devices with an intelligent and flexible allocation of software-defined network resources in response to network dynamics. For instance, a CT-scan dataset for training a deep learning algorithm requires a highly reliable extreme bandwidth and a low-latency network to enable the rapid training of a deep learning model. Furthermore, B5G has the capacity to leverage deep learning models to support dynamic network slicing, in which each slice can be customized based on the underlying COVID-19 deep learning algorithm's need for GPU, edge/cloud resources, spectrum demand, and energy efficiency for use in applications

such as mobile broadband, tactile Internet, device-to-device communications, and massive dataset sharing.

Recent advancements in mobile edge computing have made B5G even more appealing [4]. The true power of ultra-low-latency communication is that it can leverage the first tier of data processing at the edge where the data is generated. In the case of COVID-19, this particular aspect is crucial from regulatory and data privacy perspectives. In addition, the speed, time and latency, cost, and volume of data transfers are optimized through edge-based processing. The need for data analysis at the edge arises in cases where decisions based on data processing must be made immediately for a patient. For example, there may be insufficient time for patient data to be transferred to cloud servers; there may be no connectivity at all. An intensive care unit (ICU) set up for COVID-19 patients is an area that could benefit from edgebased deep learning, where real-time data processing and decision making are important for closed-loop systems that must maintain critical physiological parameters, such as oxygen level, within a specific range of values.

II. LITERATURE SURVEY

1)**The Potential Short- and Long-Term Disruptions and Transformative Impacts of 5G and Beyond Wireless Networks: Lessons Learnt From the Development of a 5G Testbed Environment**

AUTHORS: M. N. Patwary et al.,

The capacity and coverage requirements for 5 th generation (5G) and beyond wireless connectivity will be significantly different from the predecessor networks. To meet these requirements, the anticipated deployment cost in the United Kingdom (UK) is predicted to be between £30bn and £50bn, whereas the current annual capital expenditure (CapEX) of the mobile network operators (MNOs) is £2.5bn. This prospect has vastly impacted and has become one of the major delaying factors for building the 5G physical infrastructure, whereas other areas of 5G are progressing at their speed. Due to the expensive and complicated nature of the network infrastructure and spectrum, the second-tier operators, widely known as mobile virtual network operators (MVNO), are entirely dependent on the MNOs. In this paper, an extensive study is conducted to explore the possibilities of reducing the 5G deployment cost and developing viable business models. In this regard, the potential of infrastructure, data, and spectrum sharing is thoroughly investigated. It is established that the use of existing public infrastructure (e.g., streetlights, telephone poles, etc.) has a potential to reduce the anticipated cost by about 40% to 60%. This paper also reviews the recent Ofcom initiatives to release location-based licenses of the 5G-compatible radio spectrum. Our study suggests that simplification of infrastructure and spectrum will encourage the exponential growth of scenario-specific cellular networks (e.g., private networks, community networks, micro-operators) and will potentially disrupt the current business models of telecommunication business stakeholders - specifically MNOs and TowerCos. Furthermore, the anticipated dense device connectivity in 5G will increase the resolution of traditional and non-traditional data availability significantly. This will encourage extensive data harvesting as a business opportunity and function within small and medium-sized enterprises (SMEs) as well as large social networks. Consequently, the rise of new infrastructures and spectrum stakeholders is anticipated. This will fuel the development of a 5G data exchange ecosystem where data transactions are deemed to be high-value business commodities. The privacy and security of such data, as well as definitions of the associated revenue models and ownership, are challenging areas - and these have yet to emerge and mature fully. In this direction, this paper proposes the development of a unified data hub with layered structured privacy and security along with blockchain and encrypted off-chain based ownership/royalty tracking. Also, a data economy-oriented business model is proposed. The study found that with the potential commodification of data and data transactions along with the low-cost physical infrastructure and spectrum, the 5G network will introduce significant disruption in the Telco business ecosystem.

2)**Radiological Findings From 81 Patients with COVID-19 Pneumonia in Wuhan, China: A Descriptive Study**

AUTHORS: H. Shi et al.

Background: A cluster of patients with coronavirus disease 2019 (COVID-19) pneumonia caused by infection with severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) were successively reported in Wuhan, China. We aimed to describe the CT findings across different timepoints throughout the disease course. Methods: Patients with COVID-19 pneumonia (confirmed by next-generation sequencing or RT-PCR) who were admitted to one of two hospitals in Wuhan and who underwent serial chest CT scans were retrospectively enrolled. Patients were grouped on the basis of the interval between symptom onset and the first CT scan: group 1 (subclinical patients; scans done before symptom onset), group 2 (scans done ≤1 week after symptom onset), group 3 (>1 week to 2 weeks), and group 4 (>2 weeks to 3 weeks). Imaging features and their distribution were analysed and compared across the four groups. Findings: 81 patients admitted to hospital between Dec 20, 2019, and Jan 23, 2020, were retrospectively enrolled. The cohort included 42 (52%) men and 39 (48%) women, and the mean age was 49·5 years (SD 11·0). The mean number of involved lung segments was 10·5 (SD 6·4) overall, 2·8 (3·3) in group 1, 11·1 (5·4) in group 2, 13·0 (5·7) in group 3, and 12·1 (5·9) in group 4. The predominant pattern of abnormality observed was bilateral (64 [79%] patients), peripheral (44 [54%]), ill-defined (66 [81%]), and ground-glass opacification (53 [65%]), mainly involving the right lower lobes (225 [27%] of 849 affected segments). In group 1 (n=15), the predominant pattern was unilateral (nine [60%]) and multifocal (eight [53%]) ground-glass opacities (14 [93%]). Lesions quickly evolved to bilateral (19 [90%]), diffuse (11 [52%]) ground-glass opacity predominance (17 [81%]) in group 2 (n=21). Thereafter, the prevalence of ground-glass opacities continued to decrease (17 [57%] of 30 patients in group 3, and five [33%] of 15 in group 4), and consolidation and mixed patterns became more frequent (12 [40%] in group 3, eight [53%] in group 4). Interpretation: COVID-19 pneumonia manifests with chest CT imaging abnormalities, even in asymptomatic patients, with rapid evolution from focal unilateral to diffuse bilateral ground-glass opacities that progressed to or co-existed with consolidations within 1-3 weeks. Combining assessment of imaging features with clinical and laboratory findings could facilitate early diagnosis of COVID-19 pneumonia.

III. SYSTEM ANALYSIS AND DESIGN

EXISTING SYSTEM:

While caring for thousands of COVID-19 patients, hospital staff, nurses, physicians, administrators, scientists, and engineers have also been pursuing ways to optimize care to face the onslaught of daily new cases. ML and AI is becoming more prevalent in healthcare and medicine, and the worldwide COVID-19 crisis presents a critical situation that demands implementation of ML approaches, whether applications are for medical treatment research, patient care, allocating resources, or managing hospital volume. Medical personnel in all clinical settings, including doctors and nurses, need a support system in a shared decision-making process that includes patients and their families

DISADAVANTAGES:

- Data Collection Problem
- With increasing health data, evidence-based prediction tools trained and validated properly and often can guide overwhelmed hospital frontlines and administrators to make informed decisions in a challenging time

PROPOSED SYSTEM:

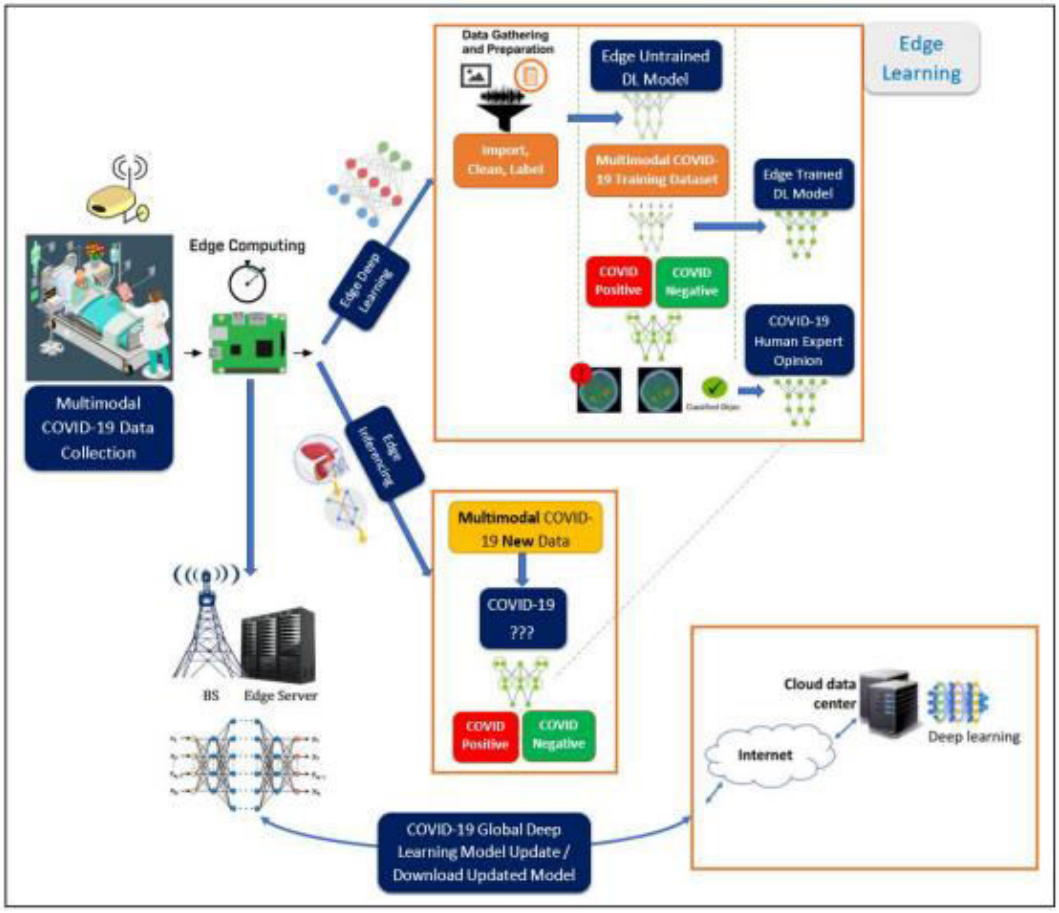
We developed each of the applications to test various aspects of COVID-19 treatment within a 5G application scenario. To comply with data security requirements, we utilized FIPS 140-2

validated cryptographic algorithms. We implemented each of the applications as part of proof-of-concept through different open-source libraries We also added the necessary environment to be able to train custom Caffe plus .The COVID-19 non-invasive body temperature module was implemented using an off-the-shelf body pose detector; the location of the face was identifi ed by the DL algorithm where the temperature value is augmented

ADAVANTAGES:

- We used several python libraries for testing 5G edge server protocols at UE and edge base stations
- We tested various deep learning scenarios, such as making handoff decisions in a sliced 5G network, efficient and reliable network slicing in 5G networks

SYSTEM ARCHITECTURE:



IV. IMPLEMENTATION

Implementation is the stage of the project when the theoretical design is turned out into a working system. Thus it can be considered to be the most critical stage in achieving a successful new system and in giving the user, confidence that the new system will work and be effective.

The implementation stage involves careful planning, investigation of the existing system and it's constraints on implementation, designing of methods to achieve changeover and evaluation of changeover methods.

MODULS:

1. **User**
2. **Image detection**
3. **Video detection**
4. **DeepLearning**

MODULE DESCRIPTION

1 User:-

The buying_price attribute is used to describe the buying price of the cars. It ranges from [1…4] where 1 represents the lowest price and 4 is representing highest price..

2 Image detection:-

We used images from a thermal camera with correct radiometric calibration and radiometric Exif data loaded onto the image. We developed the code in Python and tested it on both Windows 10 and Ubuntu 19.10 with the NVidia driver, Cuda 10.0, and Cudnn 7.6.5. In order to facilitate use in portable sites, we also tested an Adafruit AMG8833 thermal camera sensor mounted on our Jetson Nano-embedded environment so that it could be deployed to mobile sites as needed by health or law enforcement offi cials. We tested the UAV capability with the DJI Mavic 2 Enterprise Dual drone with FLIR MSX Thermal imaging, Dynamic zoom functionality, and Password protection for data security. The thermal images from the drone were used by Openpose and OpenCV libraries to detect the live body temperature of COVID-19 patients or subjects

3.**Video detection:-**

Each of the applications houses the necessary DL models. For example, the body temperature module can be trained to accurately and non-invasively monitor a COVID-19 patient's body temperature in real-time and issue alerts on abnormal temperatures. In order to augment the temperature data with a privacy-oriented dataset of human motion videos, an Openpose external library could be utilized. B5G can facilitate continuous remote monitoring and diagnosis by supporting mobile edge devices with DL models and 5G networks' fast data-load speeds.

4 . DeepLearning:-

Deep learning algorithms run data through several "layers" of neural network algorithms, each of which passes a simplified representation of the data to the next layer. The Deep Learning algorithms are concerned with building much larger and more complex neural networks and, as commented on above, many methods are concerned with very large datasets of labelled analog data, such as image, text and video. DL algorithms can run local or global datasets. The local edge node can also download the necessary DL models from the global space. For example, if a local hospital in a certain country wants to update the human-tohuman spreading pattern, it can publish the local dataset on national and global sites, allowing people with COVID-19 to mark their past locations to warn others who might have come into contact with them.

V. CONCLUSION

In this article, we have introduced a COVID-19 management framework based on a distributed deep learning neural network. The framework leverages mobile edge computing, in which deep learning takes place both at the edge and in the cloud deep learning environment. The local edge deep learning model benefits from the recent advancement of B5G verticals and thus offers a tactile Internet experience for COVID-19 solutions. As part of the distributed learning, each local DL platform updates the global DL model, which can be shared with edge servers around the world that are serving COVID-19 patients. To conduct proof-of-concept, we have developed a set of deep learning models that can run on edge or cloud nodes and perform edge or global model-training, testing, validation, and inference operations. We have also introduced the explainability layer for each algorithm so that the DL algorithms reveal semantics that will be needed by medical doctors for COVID-19 diagnosis

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