Preventing COVID-19 Using Edge Intelligence in Internet of Medical Things

R. Mahalakshmi and N. Lalithamani

Abstract Internet of Medical Things (IoMT) is a smart interwoven technology enabled by the advancements made in multi-disciplined fields of medical devices, networking technologies, healthcare applications and artificial intelligence. The current spread of the coronavirus disease (COVID-19) globally has thrown innumerable challenges against human survival. To overcome this pandemic situation, an innovative healthcare solution is vital for saving human lives and mitigating the viral spread. We propose an E-Health+ system that can provide remote patient assistance anytime, anywhere. E-Health+ makes use of artificial intelligence in edge nodes for data processing coupled with Federated learning for swift prognostic medical advice for connected patients during their critical times in IoMT. The medical advice or assistance provided is based on the requests arising in a real-time basis with minimal response times, thereby reducing latency and also the much-needed privacy preservation towards the sensitive patient data.

Keywords COVID-19 · Internet of Medical Things (IoMT) · Remote health care · Edge intelligence · Federated learning

1 Introduction

The novel coronavirus has become the biggest healthcare challenge mankind has faced in the current techno-evolving times. The viral transmission and fatality rate, due to COVID-19, are still rising despite the first case being reported more than two years ago. The viral spread among the world population was attributed to touching an infected surface, coming in contact with the nano-level droplets released in air when an infected person coughs or sneezes resulting in a communal spread. Added

R. Mahalakshmi · N. Lalithamani (✉)
Department of Computer Science and Engineering, Amrita School of Computing, Amrita Vishwa Vidyapeetham, Coimbatore, India
e-mail: n_lalitha@cb.amrita.edu

R. Mahalakshmi
e-mail: r_mahalakshmi@cb.students.amrita.edu

D. Gupta et al. (eds.), *International Conference on Innovative Computing and Communications*, Lecture Notes in Networks and Systems 473,
https://doi.org/10.1007/978-981-19-2821-5_18

to that, he or she might be an active carrier throughout the virus incubation period which may last for 5–15 days. So, the spread has been a growing chain around the world as a pandemic, and it is still far from being contained. Though vaccinations are fast paced in countries like India and USA, mutated strains of the virus are still affecting people in different parts of the world. So, precaution and preparedness are the most efficient ways to overcome the pandemic.

Although the prescribed sanitisation and personal distancing measures are helpful in containing the viral spread, the elderly and people with chronic conditions like lung diseases, asthma, diabetes, cancer, hypertension, immune deficiencies, pregnancy, obesity, pulmonary diseases, cardiovascular and neurological problems are comorbid to COVID-19. And such people are at high risk in contracting and spreading this deadly virus. So home quarantining such population can help in containing the viral spread and saving lives. But continuous and timely health assistance should also be provided to these patients based on their day-to-day health conditions.

Internet of Medical Things (IoMT) as a technology is powered by advanced medical devices, networking technologies, healthcare applications, artificial intelligence (AI) and machine learning (ML). The medical devices are built with Wi-Fi capabilities that enable them to make machine-to-machine connections and transfer the sensed data from patients to the medical applications. So, with these technologies at hand, health assistance and medical directives can be provided for the remotely home quarantined, critical-care and aged patients from anywhere, anytime through their hospitals. The vital parametric data from their wearable or mobile phone sensors and health monitors can be analysed continuously to provide unbiased and timely health assistance. This can help them in managing their risk factors along with their illness without hospital visits.

On a technical perspective, the data collected from patients' sensors and health monitors are sent to edge, fog or cloud for analysis which is returned with appropriate remedial action or advice for patients. Cardiac and blood pressure monitors, blood glucose monitors, implanted cardiac defibrillators, pacemakers, respiratory devices, hearing devices, vital sign monitors and oximeters are some of the few connected devices from which the patient data is sensed and processed for analytics.

2 Related Work

AI-empowered machine learning algorithms can detect the interrelationships between the clinical parameters sensed, diagnose the present state of health for the patient and suggest treatments, appropriate health directives. IoT as a technology can deliver e-Health services towards pandemic management [1] using sensors that monitor patients in real time. The study explored the evolution and management phases of IoT and sensor technologies, leading to the state where the current COVID-19 challenges like virus tracing, tracking and migration can be realised using them.

Blueprint for smart connected community scenarios was proposed in [2], which can proactively prevent, control and monitor the COVID-19 epidemic using IoT and data-supported connected environment. The global rise of cases and mortality due to COVID-19 has pushed the research community to seek answers from an interrelated perspective to understand the virus better to root it out.

With the availability of worldwide COVID-19 data from December 2019 to the present, one of the prominent research threads was the impact of comorbidity on people affected by this virus. The study on COVID-19 patients [3] who are comorbid are said to develop severe health complications, which may also lead to death due to the complicated nature of the viral reaction. In a report by Centre for Disease Control [4], three levels of evidences were presented for the different types of underlying chronic conditions and their role in the viral progression. These evidences were the research findings focussed on a single or combination of the chronic diseases on COVID-19.

Higher mortality rate was observed in older patients with Type2 diabetes, and the effect of their medication on COVID-19 was studied [5–7] in China. A study with the help of logistic regression model [8] based on clinical COVID-19 data from Chicago medical centre was used to analyse the risk factors associated with hospitalising the critically ill.

Analysis of risk association for patients with Type I, Type II and other diabetic types [9] was performed with the help of logistic regression for COVID-19 cases in UK hospitals over a 72-day period. The findings concluded that there was an increased risk associated with diabetes, and a third of the total deaths occurred in people with diabetes.

Mortality prediction with the help of machine learning models on patients with COVID-19 in Korea was investigated in [10]. This was based on their combined data from national health insurance Korea and the COVID-19 patient data.

Recent research findings highlight the role of edge computing in reducing the gap or time delay in providing patient care, occurring due to the technical challenges in a connected medical environment. Building an edge computing based on application needs, long-term maintenance routines was outlined in [11], along with the listing of different edge computing platforms.

Computational cost for machine learning at edge with a case study was proposed in [12]. The computational effort was claimed to be reduced by 80% with classification accuracy declining by 3%. Benefits from federated learning for digital health solutions were explored by [13] along with the challenges that still need to be addressed.

Above studies on COVID-19 and other viral diseases like Ebola, SARS and MERS have shown the world that they are capable of creating pandemic situations, as they are silent contagions and are transmitted even before any symptom can appear from an infected person. So, a contactless healthcare service for people has become an irrefutable need in current times.

Smart edge-based healthcare system [14] can efficiently address the healthcare needs on a global level. Computing Resource Allocation strategy for Internet of Medical Things was proposed in [15] that considered energy consumption and the time delay for effective data processing. Federated learning can be the enabling technology in mobile edge computing and this was suggested by [16] as part of their survey on Federated Learning.

Usage of federated learning in a microgrid energy management system was explored in [17] for energy load predictions. Latency minimisation for different offloaded platforms near edge was analysed by [18]. Collaborative data analysis with the help of federated learning in distributed environment was proposed by [19], where the performance achieved showed improvement.

Advanced and rapid growth of smart health technologies involving sensors, robotic process automations, telemedicine products, telehealth services and applications, cloud-based electronic health records, edge computing, medical health data analysis with AI and machine learning and telecommunication connectivity growth has paved the way for achieving contactless, remote health monitoring into a reality.

In this perspective, we propose an E-Health+ system that can provide remote healthcare assistance, which can be complemented along with the government envisioned telemedicine initiatives. Our E-Health+ system proposes a remote healthcare model with a novel architectural setup, data processing capabilities at edge devices and gaining edge intelligence with the help of federated learning. COVID-19 data analysis with machine learning model was performed to demonstrate the power of AI in deriving appropriate inferences from data to provide contactless healthcare.

3 E-Health+

E-Health+ is envisioned as a real-time remote, healthcare system, which can provide health assistance for patients based on their health conditions. Other vital services including the COVID-19 pandemic management, health assistance for aged and critically ill patients. Monitoring, planning and coordination of disease control, immunisation / vaccination for citizens, etc., are envisioned to be part of this system. E-Health+ (Fig. 1) system can be complemented to the existing healthcare network consisting of private and rural healthcare centres, diagnostic laboratories, multi-speciality hospitals and registered pharmacists.

Large amount of data gets generated by sensing the vital health parameters like blood pressure, blood glucose level, heart rate by health monitors, sensors and smart wearable devices worn by the patient. This data is gathered, processed and analysed by our edge intelligence subsystem to provide quick actionable intelligence to patients at the edge nodes, which are closer to them. Thus, gathering and generating intelligence at edge minimises the delays arising in the health network, thereby reducing the latency.

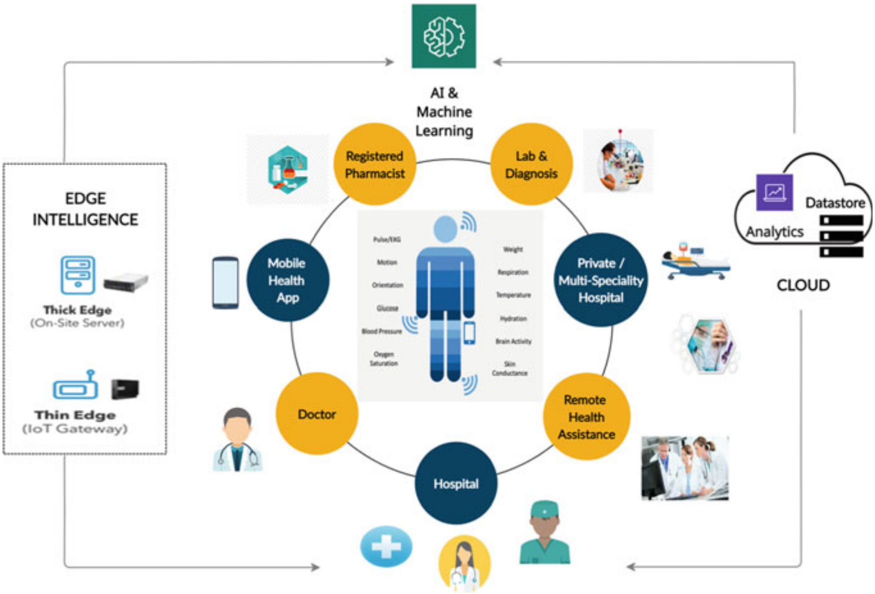

Fig. 1 E-Health+ component subsystems

3.1 Edge Intelligence

Edge intelligence subsystem is envisioned to be part of the existing hospital network consisting of doctors, remote healthcare assisting unit, diagnosis laboratory, pharmacy, hospital in IoMT. It is a decentralised computing architecture where the distributed edge nodes are positioned closer to the patients' sensors/mobile devices and stand connected 24×7 to perform data analysis with the help of edge services foreseen. This removes the delay arising due to latency involved in collecting and moving the data from patients' devices to cloud for analysis and bringing the analysis responses back to the patients.

The data processing services in the edge nodes aggregate the patient's data, decide and designate this aggregated data to a suitable node in the network with the help of our resource allocation (RA) framework. The decision for selecting an appropriate node is evaluated on the basis of battery power left and its processing capability, etc. With the appropriate medical intelligence extracted after the analysis, further course of actions in the form of therapy, medicine or other health assistance is suggested through the application or short message by the hospital. So, edge intelligence along with our proposed federated learning approach can provide swift responses to patients in any medical emergencies.

3.2 Federated Learning

Federated learning (FL) is a machine learning technique where a centrally trained machine learning model from cloud is loaded in the edge nodes. Edge nodes here can also be the patient's mobile phone which gets trained and tuned with the new aggregated patient data. Here only the model used for prediction is shared between the edge and cloud, while the sensitive patient data is held in his device, thereby ensuring complete privacy. Figure 2 summarises the FL process which ensures privacy in medical data, lower latency and results in smart predictions, thereby saving time and energy. With appropriate foresight gained in this learning process, the E-Health+ system can provide appropriate medical directive needed by the connected patients.

Machine learning models like neural networks, support vector machines, decision trees, logistic regressors and classifiers can be used in federated learning. The training data for federated algorithms reside at the distributed edges and the model is trained in multiple locations with multiple iterations. This removes the constraint of a large dataset needed to train a model normally. As the model gets trained at edge, data need not be shared, and the trained model gets updated, thereby preserving patient privacy.

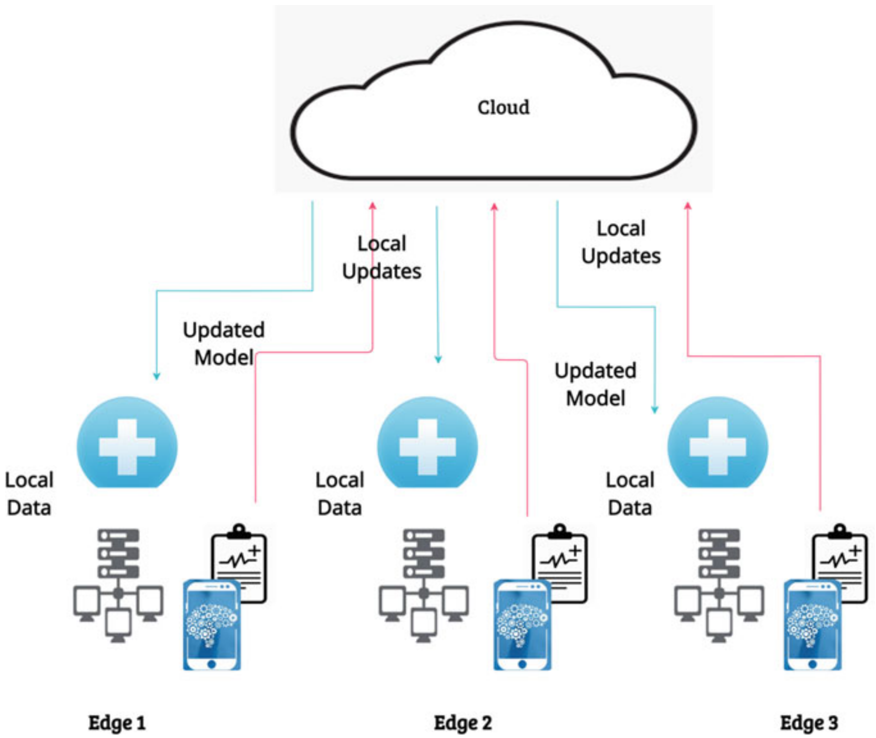

Fig. 2 Federated learning at edge nodes

Data for the device-hosted models are collated from the edge nodes of edge intelligence subsystem. And the data is not independently, identically distributed due to the heterogeneous nature of the devices. A central orchestration mechanism organises the training but will not be accessing individual edge device's data. The steps involved in FL with respect to a model can be summarised as:

1. Initially, the ML model from cloud is distributed to Edge 1, Edge 2, etc. and is updated using the locally sensed data.
2. These edges send the local updated model to the cloud.
3. The server at cloud aggregates the local model sent by edges into the global model.
4. The server sends the global model to all the edges concerned.
5. The edges integrate the global model, into their local model.

The communications between the edges and the server are encoded in binary format describing the updates along with any meta-data. This way the patient data privacy is ensured in addition to the no-sharing data policy. Several open challenges still exist in the areas of adaptation of an appropriate neural learning architecture for FL, data partitions that are to be made vertical or horizontal and others. Despite such challenges federated learning along with data processing at edge reduces the data travel time in the network, which will result in reduced latency and power requirements. Federated learning will be focussed more in our future work comprising of AWS cloud services (Green Grass for Edge services) and Raspberry Pi boards as edge nodes.

3.3 E-Health+ Process Flow

The process flow of the E-Health+ system is summarised in Fig. 3, where based on patients' requests arising due to health needs or the alarm raised due to the anomalistic sensor data, the data pre-processor swiftly decides on the nature of the situation as to emergency or not and appropriately routes the aggregated data to edge intelligence subsystem or to the cloud for deep analytics. The edge intelligence subsystem is the Open API services running in the edge server. It categorises the request based on the severity, nature and complexity to push it either to the federated learning or the resource allocation module. Here the selection between the two is facilitated by the core services running in the server.

The communications from the edge server to these modules belong to the publish/subscribe method where the server just pushes the requests down the queue, thereby preventing any time delay. Both the FL and RA modules pick the requests as it keeps checking for new messages from the server. Resource allocation framework is a mechanism envisioned to route and designate suitable edge nodes to process the data quickly to obtain insight. With FL, the data is held at the patients' device which is acted upon by the ML algorithm to get the appropriate course of action. And the result is pushed back to the server, which can route it to the user.

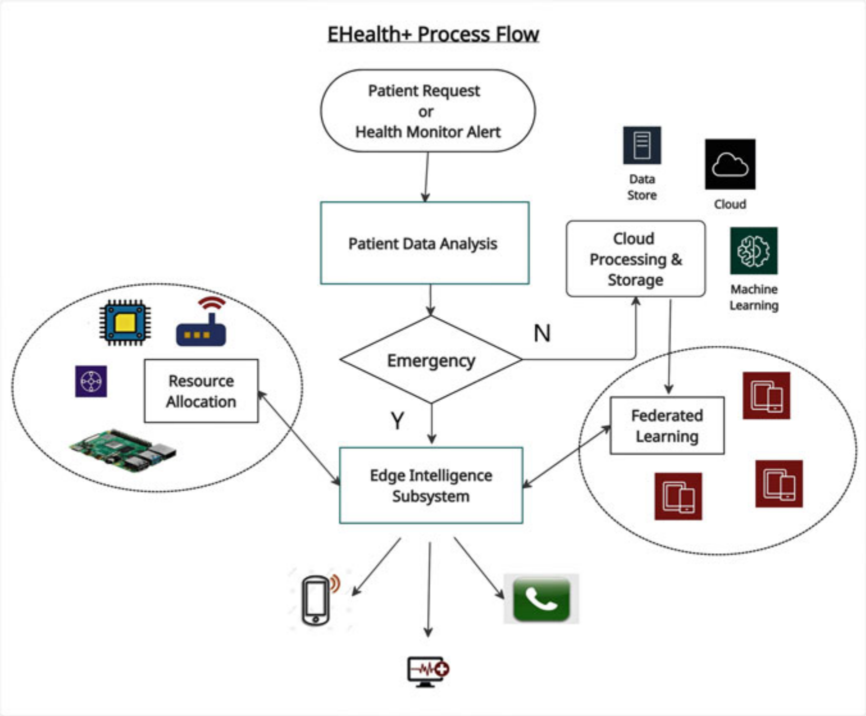

Fig. 3 Flow Diagram for EHealth System

3.4 COVID-19 Data Analysis

As part of our current work, we wanted to reaffirm the fact that by applying appropriate machine learning algorithm at edge devices, we can extract a wealth of hidden inferences from the sensed patient data. With this inference at hand, we can advise/ alert the connected patients accordingly. So, we started with the analysis of COVID-19 data from github [20], to gain appropriate insights about the nature of the pandemic, and come up with some predictions. We pre-processed and cleaned the data for inconsistencies using Python Scikit Library. Statistical summary, plots for COVID-19 cases, deaths worldwide, summary for cases in India have been generated which quickly summarise the COVID-19 scenario currently.

Starting with the worldwide COVID-19 summary (Fig. 4) clearly indicates the significant rise in the new confirmed, active and recovered cases, despite the marginal rise in death rates. This can be attributed to the improvement in the diagnosis, treatment and facilities like oxygen supplies ramped up by the governments.

COVID-19 cases summary worldwide since the year 2020 till date show an upward trend indicating the situation to be in the rise including second and third waves in different countries depending on the containment measures adapted. It can also be

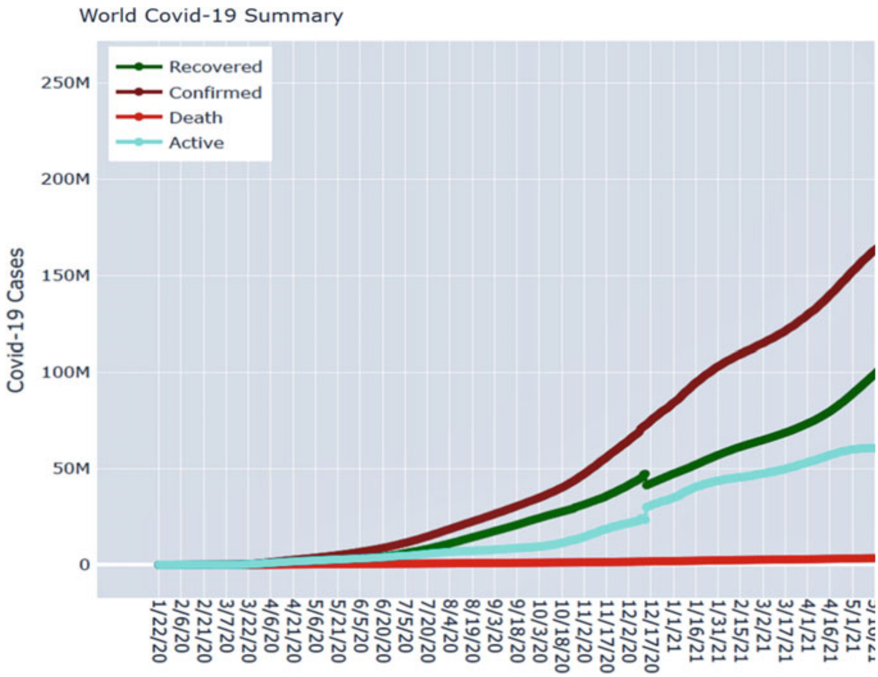

Fig. 4 COVID-19 summary as of Aug 2021

noted that, the death count is not rising in the same rate as that of COVID-19 case count indicating the recovery rate to be increasing, which is a promising trend in reduced mortality rate during second and third waves of this pandemic.

When comparing the current state of quick-paced vaccination progress (Fig. 5) in India and the rise in the new cases count, it clearly indicates the pandemic is not over. And the world still needs all the precautionary measures to be followed indicating the recovery rate to be increasing, which is a promising trend in reduced mortality rate during second and third waves of this pandemic.

It can also be noted that the vaccination drive in India has reached above 70 lakhs in September when compared with worldwide vaccination. And the dip in the vaccinations on certain dates corresponds to the non-availability of vaccines in different states.

The new COVID-19 cases count (Fig. 6) continues on a declining note with due credit for the aggressive vaccination drive adapted by the government.

Further, analysis based on the type of viral transmission presented in Tables 1 and 2 help us in quickly understanding the nature of the infection that was spreading due to the factors like population per square metre and the absence of face masks to block the viral entry into our system in different countries.

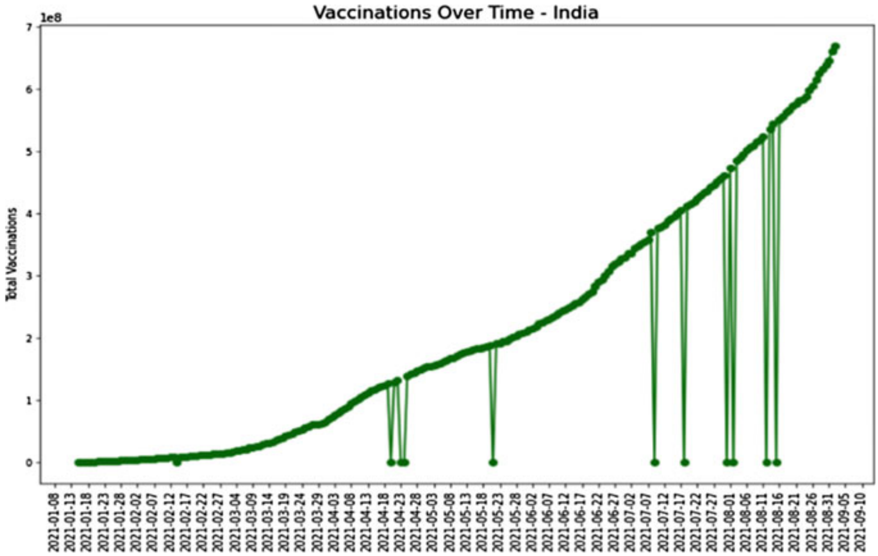

Fig. 5 Vaccination summary—India

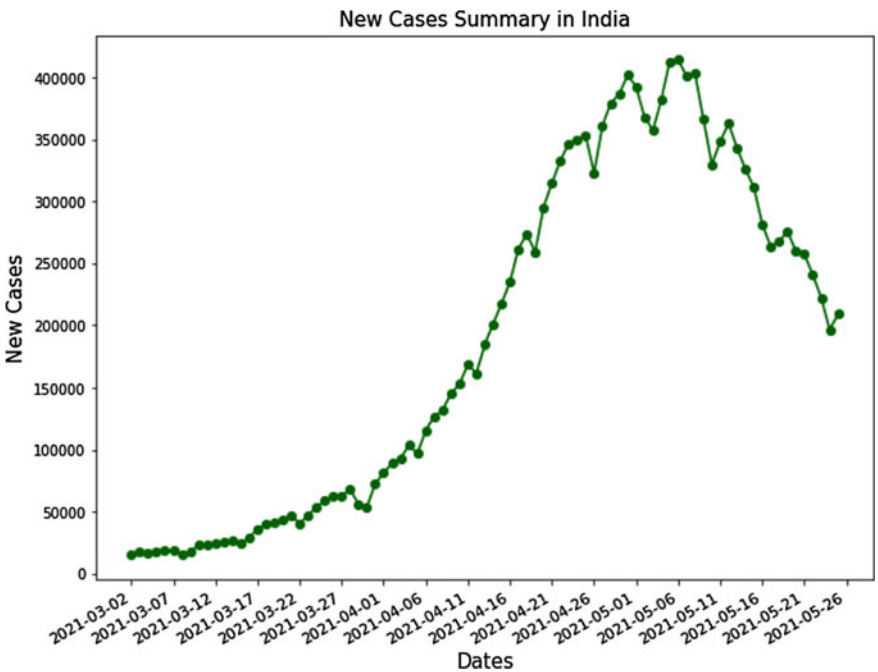

Fig. 6 New COVID-19 cases in India

Table 1 Countries with COVID-19 transmission type as “sporadic cases”

	Name	Cases—cumulative total	Deaths—cumulative total	Transmission classification
2	India	11,112,241	157,157	Clusters of cases
4	Russian Federation	4,257,650	86,455	Clusters of cases
8	Italy	2,925,265	97,699	Clusters of cases
24	Portugal	804,562	16,317	Clusters of cases
34	Morocco	483,654	8623	Clusters of cases
38	Japan	432,773	7887	Clusters of cases
44	Slovakia	308,083	7189	Clusters of cases
45	Malaysia	300,752	1130	Clusters of cases
48	Nepal	274,143	2774	Clusters of cases
50	Kazakhstan	262,725	3389	Clusters of cases
52	Bulgaria	247,038	10,191	Clusters of cases
55	Azerbaijan	234,537	3220	Clusters of cases
64	Slovenia	190,081	4111	Clusters of cases
66	Egypt	182,424	10,688	Clusters of cases
74	Myanmar	141,896	3199	Clusters of cases
79	Bahrain	122,395	449	Clusters of cases
81	Albania	107,167	1796	Clusters of cases

3.5 Results and Discussion

In the steady state of improvements seen with respect to COVID-19 cases, we have taken the active and recovered cases for comparison (Fig. 7) since the onset of the pandemic for different countries. And it can be clearly understood that the number of active cases is higher in India, despite the fact that the recovered cases are reported to

Table 2 Countries with COVID-19 transmission type as "Cluster of Cases"

	Name	Cases—cumulative total	Deaths—cumulative total	Transmission classification
41	Saudi Arabia	377,383	6494	Sporadic cases
97	Singapore	59,936	29	Sporadic cases
124	French Polynesia	18,387	139	Sporadic cases
153	Djibouti	6066	63	Sporadic cases
174	Liechtenstein	2642	52	Sporadic cases
183	Monaco	1953	24	Sporadic cases
190	Cambodia	820	0	Sporadic cases
193	Bermuda	705	12	Sporadic cases
194	Faroe Islands	658	1	Sporadic cases
196	Mauritius	610	10	Sporadic cases
199	Cayman Islands	438	2	Sporadic cases
201	Brunei Darussalam	186	3	Sporadic cases
203	Grenada	148	1	Sporadic cases
206	Timor-Leste	113	0	Sporadic cases
207	Fiji	59	2	Sporadic cases
208	New Caledonia	58	0	Sporadic cases

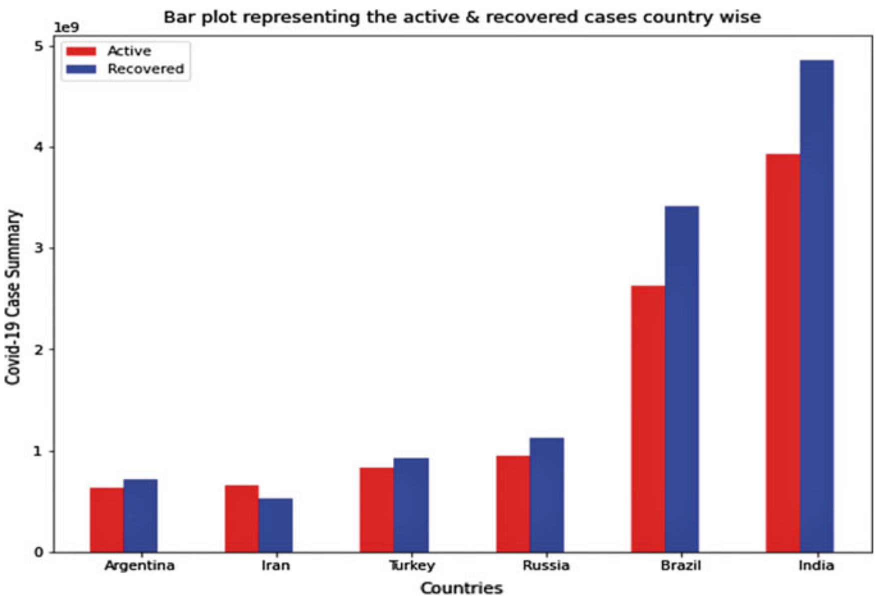

Fig. 7 Summary of active and recovered cases

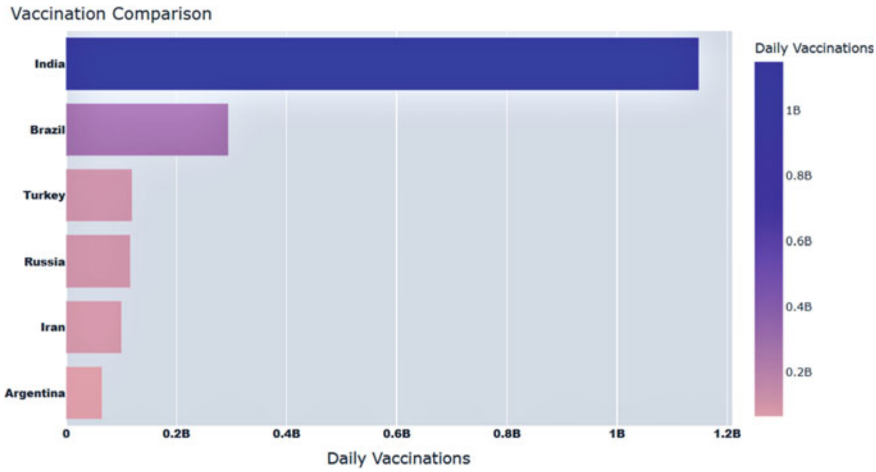

Fig. 8 Daily vaccinations summary for countries

be higher than the active cases. Also, it is to be noted that India ranks as the topmost level (Fig. 8) in terms of daily vaccinations when compared with the other countries considered.

Based on the exploratory data analysis carried out with the COVID-19 data, we could gain certain insights on the pandemic and try to look for unconventional ways to address the health issues faced by patients around the world. COVID-19 along with other emerging global epidemics, clearly indicate, healthcare solutions need to be innovative and time sensitive in order to save lives. In this aspect, our proposed system can provide a latent, remote health assistance anytime, anywhere.

The novelty of our proposition lies in the combinatorial deployment of using AI through federated learning and effective resource allocation framework that reduces latency. Although results in the above two significant research areas have shown to reduce latency in different domains, our objective is to prove that by integrating these two areas in the healthcare domain, a secure remote reliable and time bound health assistance can be provided for patients through our proposed work.

4 Conclusions and Future Enhancements

In this chapter, we proposed E-Health + system which is a contactless digital healthcare solution that can provide automated, personalised healthcare assistance based on the current health conditions of patients in pandemic situations or otherwise. The proposed system is to be evaluated with verifiable performance metrics with respect to latency and edge computing capabilities. We also performed a detailed exploratory data analysis on COVID-19, which helped in understanding the role artificial intelligence in understanding the vast amount of data generated by sensor devices to derive useful insights. Similar to these machine learning techniques used in analysis, appropriate learning models can be developed and deployed in the edge devices which is the next step in our work. This can help in achieving our objective to reduce latency and provide contactless health care.

References

1. Ndiaye M, Stephen S, Obi O, Adnan M, Abu-Mahfouz Hancke GP, Kurien AM, Djouani K (2020) IoT in the Wake of COVID: a survey on contributions, challenges and evolution. IEEE Access 8:186821–186839. https://ieeexplore.ieee.org/document/9220109
2. Gupta D, Bhatt S, Gupta M, Tosun AS (2021) Future smart connected communities to fight COVID-19 outbreak. Internet Things 13. https://doi.org/10.1016/j.iot.2020.100342
3. Sanyaolu A, Okorie C, Marinkovic A, Patidar R, Younis K, Desai P, Hosein Z, Padda I, Mangat J, Altaf M (2020) Comorbidity and its Impact on Patients with COVID-19. SN Compr Clin Med 1–8
4. Report by CDC, Centre for Disease Control and Prevention: Evidence used to update the list of underlying medica conditions that increase a person's risk of severe illness from COVID-19 May 2021 (Updated). https://www.cdc.gov/coronavirus/2019-ncov/hcp/clinical-care/underlyingconditions.html
5. Chen Y, Yang D, Cheng B, Chen J, Peng A, Yang C, Liu C, Xiong M, Deng A, Zhang Y, Zheng L, Huang K (2020) Clinical characteristics and outcomes of patients with diabetes and COVID-19 in association with glucose lowering medication. Diabetes Care 43. https://doi.org/10.2337/dc20-0660
6. Zhu L, She Z, Cheng X, Qin J, Zhang XJ, Cai J et al (2020) Association of blood glucose control and outcomes in patients with COVID-19 and pre-existing type 2 diabetes. Cell Metab 31:1068–1077. https://doi.org/10.1016/j.cmet.2020.04.021
7. Bode B, Garrett V, Messler J, McFarland R, Crowe J, Booth R, Klonoff DC (2020) Glycemic characteristics and clinical outcomes of COVID-19 patients hospitalized in the United States. J Diabetes Sci Technol 14(4):813–821. https://doi.org/10.1177/1932296820924469
8. Gottlieb M, Sansom S, Frankenberger C, Ward E, Hota MPH (2020) Clinical course and factors associated with hospitalization and critical illness among COVID-19 patients in Chicago, Illinois. Acad Emerg Med 27:963–973
9. Barron E, Bakhai C, Kar P, Weaver A, Bradley D, Ismail H (2020) Associations of type 1 and type 2 diabetes with COVID-19 related mortality in England: a whole-population study. Lancet Diabetes Endocrinol 8:813–822. https://doi.org/10.1016/S2213-8587(20)30272-2
10. An C, Lim H, Kim DW, Chang JH, Choi YJ, Kim SW (2020) Machine learning prediction for mortality of patients diagnosed with COVID-19: a nationwide. Sci Reports 10, Article number: 18716, Nature Report
11. Ning H, Li Y, Shi F, Yang LT (2020) Heterogeneous edge computing open platforms and tools for internet of things. Futur Gener Comput Syst 106:67–76
12. Gómez-Carmona O, Casado-Mansilla Kraemer FA, López-de-Ipiña D, García-Zubia J (2020) Exploring the computational cost of machine learning at the edge for human-centric Internet of Things. Futur Gener Comput Syst 112:670–683
13. Rieke N, Hancox J, Li W, Milletarì F, Roth HR, Albarqouni S, Bakas S, Galtier MN, Landman BA, Hein KM, Ourselin S, Sheller M, Summers RM, Trask A, Xu D, Baust M, Cardoso MJ (2020) The future of digital health with federated learning. Digital Med 3. https://doi.org/10.1038/s41746-020-00323-1
14. Pathinarupothi RK, Durga P, Rangan ES (2019) IoT-based smart edge for global health: remote monitoring with severity detection and alerts transmission. IEEE Internet Things J 6:2449-2462

15. Wang J, Wang L (2021) A computing resource allocation optimization strategy for massive internet of health things devices considering privacy protection in cloud edge computing environment. J Grid Comput 19:17
16. Lim WYB, Luong NC, Hoang DT, Jiao Y, Liang YC, Yang Q, Niyato D, Miao C (2020) Federated learning in mobile edge networks: a comprehensive survey. IEEE Commun Surv Tutorials 22(3), THIRD QUARTER
17. Firouzi R, Rahmani R, Kanter T (2021) Federated learning for distributed reasoning on edge computing. Networks and Technologies (ANT), Elsevier
18. Cooke RA, Fahmy SA (2020) Quantifying the latency benefits of near-edge and in-network FPGA acceleration. In: EdgeSys '20. ACM. https://doi.org/10.1145/3378679.3394534
19. Imakura A, Inaba H, Okada Y, Sakurai T (2021) Interpretable collaborative data analysis on distributed data. Expert Syst Appl 177
20. Github Dataset link. https://github.com/owid/covid19data/tree/master/public