A Survey on Deep Transfer Learning and Edge Computing for Mitigating the COVID-19 Pandemic

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Abstract

Global Health sometimes faces pandemics as are currently facing COVID-19 disease. The spreading and infection factors of this disease are very high. A huge number of people from most of the countries are infected within six months from its first report of appearance and it keeps spreading. The required systems are not ready up to some stages for any pandemic; therefore, mitigation with existing capacity becomes necessary. On the other hand, modern-era largely depends on Artificial Intelligence(AI) including Data Science; Deep Learning(DL) is one of the current flag-bearer of these techniques. It could use to mitigate COVID-19 like pandemics in terms of stop spread, diagnosis of the disease, drug & vaccine discovery, treatment, and many more. But this DL requires large datasets as well as powerful computing resources. A shortage of reliable datasets of a running pandemic is a common phenomenon. So, Deep Transfer Learning(DTL) would be effective as it learns from one task and could work on another task. In addition, Edge Devices(ED) such as IoT, Webcam, Drone, Intelligent Medical Equipment, Robot, etc. are very useful in a pandemic situation. These types of equipment make the infrastructures sophisticated and automated which helps to cope with an outbreak. But these are equipped with low computing resources, so, applying DL is also a bit challenging; therefore, DTL also would be effective there. This article scholarly studies the potentiality and challenges of these issues. It has described relevant technical backgrounds and reviews of the related recent state-of-the-art. This article also draws a pipeline of DTL over Edge Computing as a future scope to assist the mitigation of any pandemic.

Keywords: AI for Good, COVID-19, Deep Learning, Edge Computing, Pandemic, Review, Transfer Learning.

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1. Introduction

The COVID-19 is a disease caused by a novel coronavirus called 'SARS-CoV-2'. This virus is transferable from human to human and its spreading, and infection factors are very high [1, 2]. Over nine million people are infected and approx half million are died within just six months from it's fist report, and it is increasing steadily [1]. The World Health Organization (WHO) has declared it a pandemic [3, 4]. But this is not the only pandemic human civilization is facing, there are many outbreaks had come in the past or it may come in the future [5, 6]. The appropriate drugs, vaccines, infrastructure, etc. are not available up to some stages of any outbreaks. Therefore, mitigate these types of diseases with existing capacity becomes most important in those stages [7, 8]. Many researchers from all over the world trying hard to develop such kind of techniques to cope with such challenges [9, 10, 11].

Modern-era largely depends on Artificial Intelligence(AI) including Data Science; Deep Learning (DL) is one of the current flag-bearer of these techniques [12]. Therefore, these techniques could also assist to mitigate COVID-19 like pandemics in terms of stop spread, diagnosis of the disease, drug & vaccine discovery, treatment, and many more [13, 14]. But to trained this DL, large datasets as well as powerful computing resources are required. For a new pandemic, data insufficiency and it's variation over different geographic regions is a huge problem, so here Deep Transfer Learning (DTL) would be effective as it learns from one task and could apply in another task after required fine-tuning [15]. On the other hand edge devices such as IoT, Webcam, Drone, Intelligent Medical Equipment, Robot, etc. are very useful in any pandemic situation. These types of equipment make the infrastructures sophisticated and automated which helps to cope with an outbreaks [16]. Though, such devices are equipped with low computing resources which represent the main challenges of Edge Computing(EC) [17]. As a way to overcome this challenge, transfer learning could be a possible way to consolidate the needed computational power and facilitate more efficient EC. Therefore, DTL in edge devices as an EC could be smart techniques to mitigate a new pandemic [18]. This survey article has tried to report all these issues scholarly as potentialities and challenges with relevant technical backgrounds. Here, we also proposed a possible pipeline architecture for future scopes to brings DTL over EC to assists mitigation in any outbreaks.

[1] https://www.worldometers.info/coronavirus/

1.1. *Contributions of this Article*

Some highlights of the contributions of this article are as follows:

- Presented a systematic study of Deep Learning (DL), Deep Transfer Learning(DTL) and Edge Computing(EC) to mitigate COVID-19.
- Surveyed on existing DL, DTL, EC, and Dataset to mitigate pandemics with potentialities and challenges.
- Drawn a precedent pipeline model of DTL over EC for a future scope to mitigate any outbreaks.
- Given brief analyses and challenges wherever relevant in perspective of COVID-19.

1.2. *Organization of the Article*

Starting from the introduction in section 1, the remainder of the article organized follows. Section 2 for technical background whereas review of generic state-of-the-art of DTL in EC in section 3. Existing computing(DL, DTL, EC & Dataset) to mitigate pandemic in section 4. A proposed pipeline of DTL in EC to mitigate pandemics in section 5. Finally, conclusion in section 6.

2. Technical Backgrounds

The main focus of this article is how DL, DTL, EC, and it's associate could assist to mitigate any pandemics. The possible roles and challenges of these techniques in a pandemic, especially for COVID-19, are mentioned in section 4. This section has tried to bring an overview and general progress of DL, DTL, and EC in the following three subsections.

2.1. *Deep Learning(DL)*

Deep learning (DL) (also known as hierarchical learning or deep structured learning) is one of the effective inventions for modern-era of Artificial Intelligence (AI) [12]. Until the decade '90s, classical machine learning techniques were used for making inferences on data and prediction. Nevertheless it had several drawbacks such as depend on handcrafted features, bounded by human-level accuracy, etc [19]. But in DL, handcrafted feature engineering is not required rather features are extracted from data during training. In addition, DL can make more accurate classifications and predictions with the help of innovative algorithms, computing power of modern machines, and the availability of Big Datasets [20]. Nowadays, DL methods have been successfully applied for several AI-based medical applications such as Magnetic Resonance Imaging (MRI) images analysis for cancer and diabetes diagnoses, conjunction with biometric characteristics, etc [21].

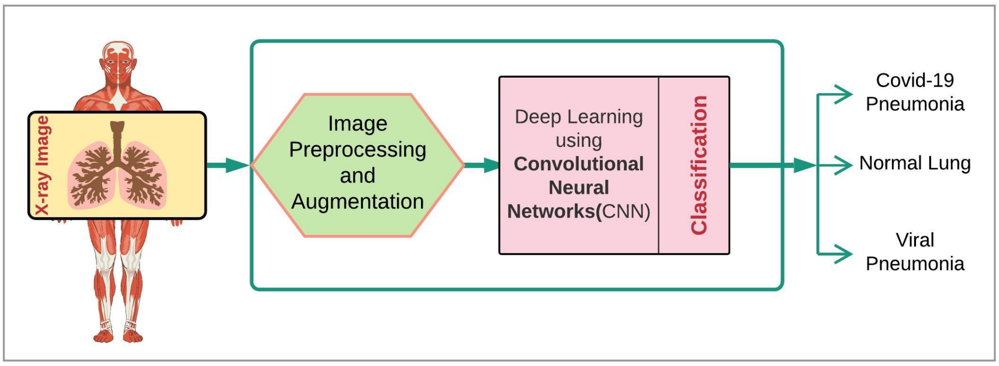

Figure 1: A overall block diagram of a Deep learning-based screening system.

DL is a kind of learning algorithm or model under the umbrella of AI which is based on Artificial Neural Networks(ANN) [22]. These models are trained using dataset through backpropagation algorithm [23] and a suitable optimizer method [24]. The inherent capacities of such DL model such massive parallelism, non-linearity, and capabilities of feature extraction have made them powerful and widely used [20]. There are several variety of DL algorithm such as Convolutional Neural Networks(CNN) [25, 26], Recurrent Neural Networks (RNN) [27], Long Short Term Memory(LSTM) [28], GAN [29], etc. After success of a CNN-based model, called AlexNet [30], many deep learning model has proposed such ZFNet [31], VGGNet [32], GooglNet [33], ResNet [34], DenseNet [35], etc specially for computer vision tasks [36]. In figure 1 we try to illustrate a typical methodology of a DL based screening system, where the system uses a DL algorithm (CNN) to predict whether the X-ray images of suspected patient's lung is normal or having viral pneumonia or COVID-19 pneumonia.

In the time of the COVID-19 crisis, when the numbers of infected patients are at a time very high and the disease is still spreading, many research groups are using the DL techniques for screening COVID-19 patients by detection fever temperature, viral and COVID-19 pneumonia, etc. In addition, DL is using or could be used for other purposes such as patient care, detection systematic social distancing violation, etc [37]. As for reference, S. Wang et.al used a CNN-based DL for screening COVID-19 patients with an accuracy, sensitivity, and specificity of 89.5%, 87%, and 88% respectively by using their computed tomography (CT) images [38]. Similarly, in another study [39] L.

Wang et.al used chest X-ray images for a screening of COVID-19 cases with 83.5% accuracy. The description of such works is in section 4.1.1.

2.2. Deep Transfer Learning(DTL)

Transfer Learning is a technique that effectively uses knowledge of an already learned model to solve another new task (possibly related or little related) with require of minimal re-training or fine-tuning [40, 41]. Since DL requires a massive training data compared to traditional machine learning methods. So, the requirement of a large amount of labeled data is a big problem in solving some critical domain-specific tasks, specifically the applications for the medical domain, where the making of large-scale, high-quality annotated medical datasets is very complex, and expensive [42]. In addition, the usual DL model requires large computing power such as GPU enabled sever, although researchers are trying hard to optimizing it [43, 44]. Therefore, Deep Transfer Learning (DTL), a DL based Transfer Learning try to overcome this problem [45]. DTL significantly reduces the demand for training data and training time for a target domain-specific task by choosing a pre-trained model (trained on another large dataset of same target domain) for a fixed feature extractor [46] or for further fine-tuning [47]. Figure 2 demon-

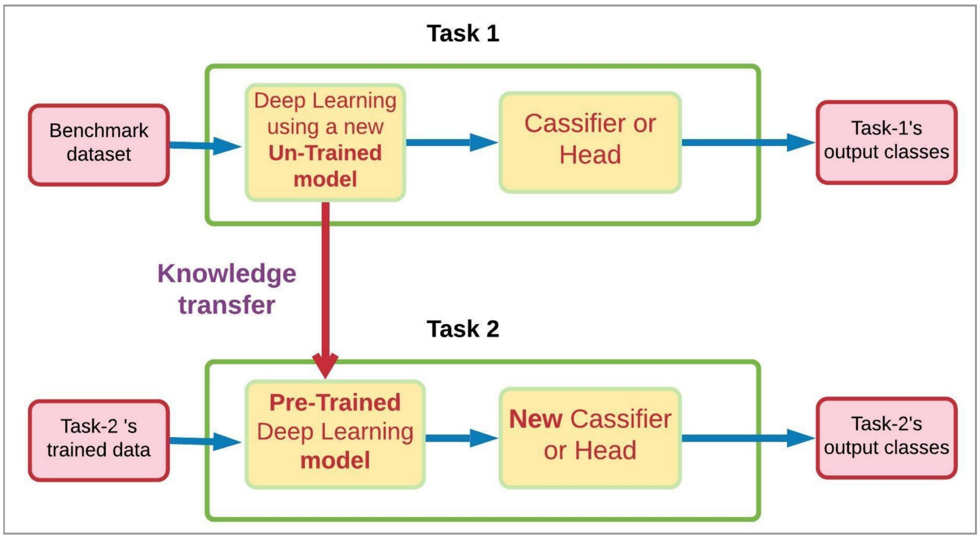

Figure 2: Block diagram of an example of Deep Transfer Learning.

strating the main steps methodology of a Deep Transfer Learning approach, where an untrained model is trained using benchmark dataset (task-1) for feature extraction. Then that pre-trained model is further used to tackle a new challenge such as the task (task-2) of COVID-19 by just replacing only few last layers in the head of the architecture and required fine-tuning.

So far, many DTL models have been proposed [15]. A few recent are reported and discussed in the article. In a research study [45], Mingsheng Long et.al proposed a joint adaptation network. It learns a transfer network by aligning the joint distributions of multiple domain-specific layers across domains based on a joint maximum mean discrepancy. In another study [48], Yuqing Gao and Khalid M. Mosalam proposed a state-of-the-art transfer learning model based on VGG model [32]. They have used ImagNet [49] dataset for features extractor and their hand label construction images for fine-tuning. Abnormality classification in MR images through DTL proposed in a study [50]. The authors of that study also have used pre-trained ResNet34 model with fine-tuning. In a research practice [51], a DTL for diagnosing faults in target applications without labeling was proposed. Their framework used condition distribution adaptation. Q-TRANSFER [52], another DTL framework proposed by Trung V. Phan et.al. To mitigate the dataset insufficiency problem in the context of communication networking, a DTL-based reinforcement learning approach is used.

As the COVID-19 disease spread is terrifying all over the world, screening, quarantine, and providing appropriate treatment to COVID-19 patients has become the first priority in the current scenario. But the global standard diagnostic pathogenic laboratory testing is massive time consuming and more costly with significant false-negative results [53]. At the same time, tests are are hardly to be taken place in the common healthcare centres or hospital due to limited resources and places compared with the high volume of cases at one time. To combat this kind of situation, the researcher from this domain are trying hard to develop some possible DTL models to mitigate this challenges [54, 55]. As for example M. Loey et.al in [54] use DTL along with the GAN model on their very limited, only 307 chest X-ray images to test COVID-19 disease based patient chest X-ray. Here, they have three pre-trained state-of-the-art model namely AlexNet [30], GoogleNet [33], and ResNet18 [34]. Among these three pre-trained GoogleNet give the highest accuracy in their experimental studies.

2.3. Edge Computing(EC)

In the era of cloud computing, maximum technology depend organization in the world rely on very few selected cloud providers for hosting and computation. The user's data from millions of devices around the world is being delivered to some centralized cloud providers for processing or computation. This data transformation always resulted in extra latency and extra bandwidth consumption [56]. The explosive proliferation of IoT devices along with the requirement of real-time computing power have forced to move the scenario of computing paradigm towards Edge computing. Therefore, instead of relying on doing all the work at a cloud, it focuses to start the computational process close to the IoT devices (near to the source of data) in order to reduce the utilized bandwidth and latency [57, 58]. Sometime in Edge computing, an additional nearby server called Fog is associated between the cloud and the Edge or IoT devices. It locally stores the copy of densely used data from the cloud and it provides additional functionality to IoT devices to analyze and process their data locally with real-time working capability. Hence only the relevant data from IoT devices is need to transferred to the cloud through the Fog server [59].

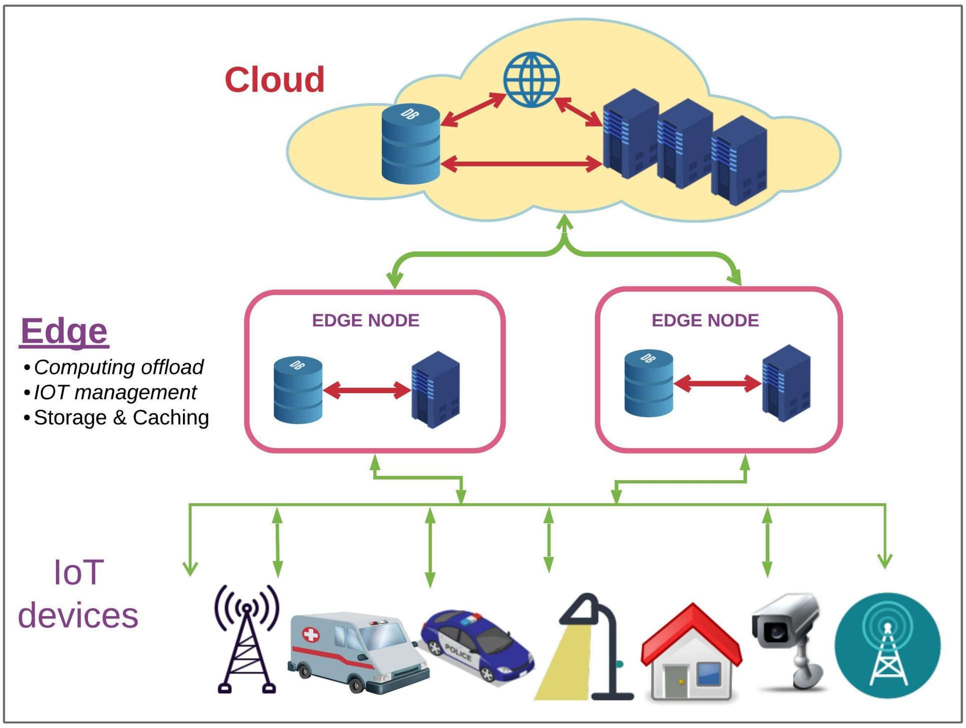

Figure 3: Hierarchy of Edge, Fog, and Cloud Computing.

In figure 3 the hierarchy of a possible framework for Edge Computing association with Fog and Cloud computing is illustrated. The data are collected from various IoT devices are being pre-processed before sending by Edge to Fog server for the analysis and computation with the real-time speed (because of the minimal distance between Edge layer and IoT devices and the local database of Fog). While the cloud holds the central control system and it manages the whole database of the system. The database on the cloud is continuously uploaded by the Fog only when it has important data or information.

Although EC is not a new concept but it becomes popular in the last five years in the era of IoT [60, 61]. Few recent different type of state-of-the-art of EC are mentioned in this section as a way to familiarize the reader with the recent development with the era of EC and its potential benefits in mitigating COVID-19 as pandemic. EdgeIoT [62], a study of mobile EC proposed by X. Sun et.al. It is a SDN-based EC work with Fog Computing(FC) [63] to provide computational load locally. In a study [64], F. Wang et.al have proposed a joint offloading strategy of mobile EC and wireless power transfer. This scheme tried to address energy consumption, latency, and access point issues in IoT. In another study [65], Wei Ding et.al propose a field-programmable gate array-based depth-wise separable CNN accelerator to improve the system throughput and performance. They have used double-buffering-based memory channels to handle the data-flow between adjacent layers for mobile EC. On the other hand, G. Premsankar et.al in their case study [66] have discussed how efficient mobile gaming can run through EC. In a study [67], S. Wang et.al have proposed a mobile edge computing with an edge server placement strategy. In their multi-objective constraint optimization-based EC have tried reduced delay between a mobile user and an edge server. In-Edge AI [67], an integrate the deep reinforcement learning techniques and Federated Learning framework with mobile edge systems are proposed by X. Wang et.al. This framework intelligently utilizes the collaboration among devices and edge nodes to exchange the learning parameters for betterment. In another recent study [68], an integrated two key technologies, ETSI and 3GPP are introduced to enhanced slicing capabilities to the edge of the 5G network. In the case of COVID-19 like pandemics, discussion of the possible role of EC is done in section 4.3.

3. Review of Related State-of-the-art

Although the whole article is referred and cited current relevant state-of-the-art wherever relevant, this section is dedicated to provide a review on some of the very generic recent state-of-the-art works related to transfer learning approaches over edge computing. As mentioned in section 2.1, the progress of DL is very fast but when it comes to application in Edge or IoT devices then a huge gap is noticeable [69]. However, researchers are working hard to cope with the challenges, as results in many computing ideas, optimized model, as well as some computing accelerator devices, comes in picture [70, 71]. Deep Transfer Learning as mentioned in section 2.2 is one such area that is useful where the size of datasets is not sufficient [45]. This transfer learning is also useful where computing resources are not sufficient such as Edge or IoT devices [72]. Since edge computing becomes popular in the last few years, so, we restricted this review to the last five years with chronological order.

Lorenzo Valerio et.al have studied the trade-off between accuracy and traffic load of computing in edge-based on transfer learning [73]. They have suggested that sometimes the partial model needs to move across edge devices and data will stay at those edge devices and vice-versa. In a study [74], Tingting Hou et.al proposed a transfer learning approach in edge computing for proactive content caching. In their learningbased cooperative caching technique they have used a greedy algorithm for solving the problem of cache content placement. On the other hand, Junjue Wang et.al proposed a model [75] for live video analytic through drone using edge computing. They have used a transfer learning approach to formulate a pre-trained model to apply a few aerial view image classification. In another study [76], Ragini Sharma et.al proposed a teacher(large networks) student(small network at edge) model using transfer learning. The applied different transfer learning techniques of teacher-student with considering accuracy and convergence speed.

Qiong Chen et.al used a multitask transfer learning in their work [77]. In their data-driven cooperative task allocation scheme, they have used the concepts of the Knapsack problem to prioritized the tasks before transferring them for use in another task. In a study [78], Wen Sun et.al suggested an edge-cloud framework. Here, pre-trained networks used in their framework that are trained in the cloud. In other work, Rih-Teng Wu et.al proposed an edge computing strategy for autonomous robots [79]. They have used CNN with pruning through the transfer learning technique. In their presented work, pr-trained VGG16 [32] and ResNet18 [34] are used for classification after fine-tuning. Cartel [80], a model of collaborative transfer learning approach for edge computing was proposed by Harshit Daga et.al. Here, they have created a model-sharing environment where a pre-trained model was adapted by each edge according to the needs. In a study [81], Yiqiang Chen et.al proposed a framework using Federated Transfer Learning for Wearable Healthcare (FedHealth). They have first performed data aggregation using federated learning and then created personalized models for each edge using transfer learning. OpenEI [82], an edge intelligence framework that was proposed by Xingzhou Zhang et.al. This framework with lightweight software equips with the edges as well as intelligent computing and data sharing capability.

In a research study [83], Changyang She et.al proposed a reliable low latency communication and edge computing system. They have adopted deep transfer learning in the architecture to fine-tune the pre-trained networks in non-stationary networks. This proposed work was designed for future 6G networks systems. On the other hand, Guangshun Li et.al proposed a task allocation load balancing strategy for edge computing [84]. They have used the concept of transfer learning from cloud to intermediate node to edge. In another study [85], Gary White and Siobhan Clarke have proposed a deep transfer learning-based edge computing for urban intelligent systems. They have also used VGG16 pretrained network at edge devices and experimented to classify Dog vs. Cat images. MobileDA [86], a domain adaption framework in edge computing was proposed by Jianfei Yang et.al. Here, a teacher network was trained in a server and transfer knowledge or feature to student networks was implemented at the edge side. Their model was evaluated and obtained promising results on an IoT-based WiFi gesture recognition scenario. Davy Preuveneers et.al proposed a resource and performance trade-off strategy for a smart environment [87]. They have used a transfer learning model for less training efforts in smart edge devices. In their study, multi-objective optimization also was utilized to optimize the trade-off between computing resources uses and performances.

4. Existing Computing (DL, DTL, EC & Dataset) to Mitigate Pandemic

As mentioned in section 1, the appropriate drugs, vaccines, infrastructure are not ready up to some stages of any pandemic. Therefore, to cope with challenges existing knowledge, infrastructures, AI-based models could be exploited to mitigate such pandemic. This section tried to bring four insights of the discussion topics and their roles in mitigating pandemics. Each of them is systematically discussed with potentiality with recent state-of-the-art and challenges.

4.1. Deep Learning Approaches to Mitigate Pandemic

4.1.1. Potentiality

As described in section 2.1, Deep Learning(DL) can extract features directly from labeled data. In COVID-19 like pandemic data are new, so, handcrafted feature engineering might be difficult. But for DL, no feature engineering required, so that problem could be solved. The DL can assist in many ways to mitigate COVID-19 like pandemics along with other healthcare issues [88]. Some of them are Testing Sample Classification, Medical Image Understanding, Forecasting, etc [89]. Some recent DL based models have already proposed to cope with pandemics are listed and their main features are highlighted in table 1. This table brings some proposed peer-reviewed as well as few promising pre-print works. Table 1 has placed some recent works in upper rows.

Table 1: Recent DL based works to mitigate pandemics

Reference of Proposed Works	**Dedicated task of a Pandemic**	**Main Contributions**
F.Ucar and D.Korkmaz [90]	Deep Bayes-SqueezeNet based diagnosis of COVID-19 from chest X-ray images.	• Develop an intelligent diagnosis system for COVID-19 using practical DL model for medical image processing. • A new decision-making system for detecting COVID-19 with the integration of conventional and state-of-the-art methods for chest X-ray.
D. Das et.al [91]	Screening chest X-ray images to classify COVID-19 positive or negative using a CNN model.	• Proposed a CNN based model called Truncated Inception Net for the task. • Their works pointed out a good accuracy on different datasets to classify COVID-19 pneumonia, Normal Pneumonia, Tuberculosis, and healthy cases.
C.Butt et.al [92]	Screen COVID-2019 pneumonia with multiple CNN-based model.	• A study that compared results of multiple CNN models to classify CT samples with COVID-19, influenza viral pneumonia, and no-infection. •Mentioned an accuracy of 0.996 (95%CI: 0.9891.00) for COVID-19 vs Non-COVID-19 cases in CT studies, and calculated a sensitivity: 98.2% and specificity: 92.2%.
H. Mukherjee et.al [93]	A shallow CNN-based automatic COVID-19 cases detected using chest X-rays.	•Proposed a light-weight shallow CNN-tailored model that can detect COVID-19 positive cases in chest X-rays. • They considered different dataset including MERS, SARS, and pointed out a good accuracy on automatic detection of these cases.
S.Hu et.al [94]	COVID-19 Infection Detection and Classification from CT Images.	• Weakly supervised DL for detecting and classifying COVID-19 infection from CT images. • Minimize the requirements of labeling of CT images.
T.Ozturka et.al [95]	An automated detection of COVID-19 cases using raw chest X-ray.	• A DL-based COVID-19 vs No-finding as well as COVID-19 vs No-finding vs. Pneumonia as binary and multi-classification model. • A combined of YOLO and DarkNet model [96] used as the backbone of the model to achieved a good accuracy.
E.Luz et.al [97]	COVID-19 Patterns Detection in X-ray Images.	• Identification of COVID-19 disease. • A resource efficient model with overall accuracy of 91.4%, COVID-19, sensitivity of 90% and positive prediction of 100% in the dataset from [98].
M. Zhou et.al [99]	Differentiating novel coronavirus and influenza pneumonia using CT images.	• An early diagnosis tool on chest CT images for differentiate COVID-19 pneumonia and normal Influenza with transferability.
O.Gozes et.al [100]	Automated Detection & Patient Monitoring using Deep Learning on CT Image Analysis.	• A model utilizing 2D-3D DL for clinical understanding. •Proposed a systematic continuous monitoring methodology for COVID-19 patients and their clinical data to make a statistical Corona score for monitoring their progress.
S.M. Ayyoubzadeh et.al [101]	Predict the incidence of COVID-19 in Iran.	• Data were mined that taken from Google Trends. • Linear regression and LSTM models were used to estimate COVID-19 positive cases
L. Li et.al [102]	Fully automatic DL framework to detect COVID-19 using CT images of chest.	• Developed a DL-based model, COVNet to detect COVID-19 by extracted features from chest CT images. • Collected dataset consisted of 4356 chest CT images from 3,322 patients from six different hospital.
L. Wang et.al [39]	An publicly available chest X-Ray image dataset and a CNN for detection of COVID-19.	• Proposed a publicly available COVID-Net, a deep CNN for the detection of COVID-19 cases from CXR images. • COVIDx, an open access chest X-ray(CSR) dataset consisting 13,800 CSR images of 13,725 patients.
S.J. Fong [103]	A forecasting model of COVID-19.	• A Composite Monte-Carlo simulation forecasting model. • A case study of using the above simulation through DL.
A. Lopez-Rincon et.al [104]	Identification of SARS-CoV-2 from Viral Genome Sequences.	• Interaction between viromics and DL model. • A DL-based model for assisted detection tests for SARS-CoV-2.
S. Chae [105]	Predicting infectious disease using DL and Big data.	• A study on DL and LSTM model over ARIMA model to predict future infectious diseases. • Proposed model tried to improve existing surveillance systems to detect future infectious diseases.

4.1.2. Analysis and Challenges

From table 1 it could be drawn one conclusion that the majority of the works are for assisting radiologists to diagnose diseases. Some of are mentioned forecasting, fake news alert, etc, but more critical parts of this pandemic maybe addressed by this DL approach. Successfully apply DL in COVID-19 or any running pandemic has three main challenges. The first one is a shortage of reliable datasets. As data collection and validation are a time-consuming process as well as privacy issues also there whereas a pandemic or epidemic comes suddenly. The second one is the variety of data of a pandemic virus. This COVID-19 virus 'SARS-CoV-2' has mutating itself over different geographic regions, environments, and time [106, 107]. Therefore, the pandemic dataset collected from one region may not be work to drawn inference on the pandemic of other regions. The third one high computational resources required for a DL model whereas to cope with an outbreak IoT or Edge Device (ED) are useful for many purposes [16]. Though these types of equipments have low computing resources.

In order to overcome such challenges, cleaver implementation of relevant AI strategies is required. For the first two challenges, DTL or few shot learning and GAN [29] could be a possible approach towards possible solutions. DTL has described in section 4.2 whereas details about GAN are out of the scope of this article. The third challenge could be mitigated using Cloud Computing, Fog Computing, and Edge Computing [108]. However, for Cloud or even Fog Computing latency and data security & privacy could be a problem. Therefore, Edge Computing could be effective for the third challenge, which has described in section 4.3.

4.2. Deep Transfer Learning to Mitigate Pandemic

4.2.1. Potentiality

Section 2.2 has described about Deep Transfer Learning (DTL) in general. In this sections, how DTL could help to mitigate COVID-19 like pandemics is described. As mentioned, sufficient datasets of COVID-19 or any running pandemic are difficult to develop in a short period of time. Therefore, to exploit the benefit of DL to cope with COVID-19 or other pandemics are a bit challenging. Therefore, DTL could be effective in this case. As through DTL a DL model could be trained using a large scale benchmark dataset and learned features could be used in the domain of COVID-19 [55]. Many researchers are trying hard to use this DTL in the domain COVID-19 for many purposes. We have tried to summarize in table 2 some of the recent state-of-the-art along with their main contribution towards mitigation of pandemics. As the number of peer-reviewed work is limited as this pandemic is new, so this table also has listed some pre-print works, which have tried to introduce some of the contributions in mitigating this current pandemic.

Table 2: Recent DTL based works to mitigate pandemics.

Reference of Proposed Works	**Dedicated tasks of a pandemic**	**Main contributions**
J. P. Cohen et.al [109]	A severity score prediction model for COVID-19 pneumonia for frontal chest X-ray images using beside tool.	• A DTL model that was pre-trained on large size non-COVID-19 chest X-ray datasets for predicting COVID-19 pneumonia. This study uses a pre-trained model predicts a geographic extent score of range 0-8 with 1.14 MAE and lung opacity score of range 0-6 with 0.78 MAE. • A COVID-19 chest image dataset from a public COVID-19 database were scored retrospectively by three experts.
S.Minaee et.al [110]	Predicting COVID-19 using transfer learning from Chest X-Ray Images.	• DTL on a subset of 2000 of 5000 radiograms was used to train four popular CNN, including ResNet18, ResNet50, SqueezeNet, and DenseNet-121, to identify COVID-19 disease. • Evaluated these trained models on the remaining 3000 radiograms and achieved a sensitivity rate of 97%(5%), while a specificity rate of 90% approx.
S.Basu et.al [111]	Screening COVID-19 using chest X-Ray images.	• A domain extension transfer learning with pre-trained deep CNN, that is tuned for classifying among four classes: normal, other diseases, pneumonia, and Covid19. • A 5-fold cross-validation has experimented and overall accuracy measured 95.3%0.02.
N.E.M Khalifa et.al [112]	An Experimental Case on a limited COVID-19 chest X-Ray dataset.	• A study on neutrosophic and DTL models on limited COVID-19 chest X-Ray dataset. • They first converted grayscale X-ray images into neutrosophic images then applied pre-trained AlexNet, GooglNet, and ResNet18 to classify four classes: COVID-19, Normal, bacterial, and virus pneumonia.
B.R. Beck et.al [113]	Predicting commercially available antiviral drugs that may act on SARS-CoV-2 through the DL model and a drug-target interaction.	• Drug-target interaction model called MT-DTI to recognize commercially available drugs that could use for SARS-CoV-2. • Proposed a list of antiviral drugs identified by this MT-DTI model.
A. Narin et.al [114]	Automatic Detection of COVID-19.	• Three different CNN (ResNet50, InceptionV3, and Inception-ResNetV2)-based models for the detection of COVID-19 infection using X-ray radiography. • Proposed pre-trained ResNet50 has given the best result among these three.
I.D. Apostolopoulos et.al [55]	Performance evaluation of state-of-the-art CNN architectures through TL over medical image classification.	• Suggested DL with X-ray imaging may extract significant bio-markers related to the COVID-19 disease. • A dataset of 1427 X-ray images consisting of 224 images of Covid-19 disease, 700 images of common bacterial pneumonia, and 504 images of normal conditions.
B. Subirana et.al [115]	New crowd-source AI approach to support health care dealing with COVID-19.	• A proposed transfer learning works on recognition of cough sound recording by phone as a diagnostic test for COVID-19.
N.E.M. Khalifa et.al [116]	Detection COVID-19 using GAN and TL method.	• A combination of GAN and DTL models for enhancing accuracy of testing. • Their ResNet18-based combined model achieved state-of-the-art accuracy in a chest x-ray dataset.

4.2.2. Analysis and Challenges

DTL does task adaption that is very necessary for analyzing, diagnosing as well as mitigating COVID-19 like pandemics. The number of studies is not large; in addition most of the existing studies and experiments on COVID-19 were applied for chest image analysis as cited in table 2. Only a few among them are proposed for target drug interaction, cough sound classification, etc. Lots of work could be done to mitigate this pandemic such as Intensive Care Unit(ICU) Monitoring, Patient Care, Hygienic Practice Monitoring, Wearing Personal Protective Equipment(PPE) Monitoring, Monitoring Systematic Social Distancing, Automatic fever detection, rumor detection, economical and social impact, etc. Most of these works could be easier when AI is cooperating and forming such a model along with IoT or ED [37]. Some issues could be solved by EC as described in section 4.3. Though a better system could be delivered when the most suitable algorithm applied on EC. One possibility of archiving this when DTL implemented alongside with EC which as conceptually describes in section 5.

4.3. Edge Computing to Mitigate Pandemic

4.3.1. Potentiality

Edge or IoT devices-based sophisticated equipments such as smart medical equipment, webcam, drone, wearable sensors, etc are very useful in a pandemic like situations [117]. As mentioned in section 2.3, edge computing brings the computation to near edge devices. It reduces latency, security & privacy issue, etc. Therefore, this computing paradigm will be very effective to mitigate a pandemic situation [118]. The researchers from all over the world are trying hard to bring this along with other AI techniques to mitigate current COVID-19 pandemic [16, 119]. So far only a limited number of studies have investigated the use of EC in obtain an efficient and effective mitigation system of COVID-19. This subsection tried to bring some potentiality and scopes which shall help to mitigate COVID-19 like pandemics. Table 3 has mentioned some EC based studies on COVID-19 and related healthcare.

4.3.2. Analysis and Challenges

EC works on site, so, many benefits could draw from EC with IoT or ED. Nevertheless as mentioned IoT or ED has limited computing resources. Therefore, to get the benefit of modern AI algorithm such as DL it is still challenging. To cope with these challenges researchers from all over the world are working hard to propose many ideas [70, 126, 18]. But so far only a few studies on EC in pandemic are proposed in limited areas of application as mentioned in table 3. Assisting many critical COVID-19 related tasks such

Table 3: Recent EC based works to mitigate pandemics.

Reference of Proposed Works	Dedicated task related to a pandemic or healthcare	Main contributions
A.Sufian et.al [37]	EC based model to stop spread COVID-19	• An EC based ICU, Critical Areas monitoring model. • Proposed DL and Computer Vision-based surveillance model.
C.Hegde et.al [120]	An open-source EC for clinical screening system.	• Fever and Cyanosis detection using visible and far-infrared cameras emergency department. • This image segmentation-based EC uses open source hardware.
A.A.Abdellatif et.al [121]	Data and application-specific energy-efficient smart health systems	• An optimizes medical data transmission from edge nodes to a healthcare provider with energy efficiency and quality-of-service. • Managing a heterogeneous wireless network through EC to provide fast emergency response.
A.H. Sudhro et.al [122]	QoS optimization in medical healthcare applications.	• A window-based Rate Control Algorithm to QoS in mobile EC. • A framework for Mobile EC based Medical Applications.
M.Chen et.al [123]	Smart Healthcare System.	• Edge cognitive computing-based smart healthcare mechanism to dynamic resource allocation in healthcare.
P.Pace et.al [124]	Efficient Applications for Healthcare Industry 4.0	• Proposed BodyEdge, an architecture suited for human-centric applications in context of the emerging healthcare industry. • A tiny mobile client module with EC for better health service.
H.Zhang et.al [125]	Smart Hospitals Using Narrowband-IoT.	•An architecture to connect intelligent things in smart hospitals based on Narrowband IoT. • Smart hospital by connecting intelligent with low latency.

as remote sensing-based COVID-19 patient monitoring, Hygienic practice monitoring, systematic social distancing monitoring in a crowded area, etc could be done through EC [37]. This article brings a conceptual model of EC with DTL in section 5 as a future scope to cope with such challenges.

4.4. Dataset to Mitigate Pandemic

4.4.1. Potentiality

Data is the fuel of a modern computing. Whether it is medical field or retailer market, in every field data are the most precious things. Recent AI techniques are mostly follow data driven approaches [127, 128]. DL or DTL based algorithms almost fully depend on the dataset. Therefore, to cope with a pandemic, data is one of the driving forces. For a pandemic as COVID-19, the dataset could be chest X-ray, CT images, pathological images, geographical region based spreading patterns, seasonal behavior, regional mortality rates, impact on the economy, etc. [129]. In table 4 some available datasets related to COVID-19 like pandemics are mentioned with brief description.

Table 4: Some Dataset for COVID-19 like pandemics.

Name of dataset and Reference	Brief description
COVID-CT-Dataset [130].	• A publicly CT scan dataset consisting of 275 positives for COVID-19 cases.
COVID-19 X-ray image dataset with two different combinations for applying with DTL models.[55]	• One dataset of 1427 X-ray images consisting of 224 images of Covid-19 disease, 700 images of common bacterial pneumonia, and 504 images of normal conditions. • Another dataset of 1442 X-ray images consisting of 224 images of Covid-19 disease, 714 images of common bacterial pneumonia, and 504 images of normal conditions
COVID-19 Image Data Collection [98].	• It was a crowd-sourcing hosting currently contains 123 frontal X-rays images.
Chest CT Images [102]	• A dataset consisted of 4356 chest CT exams from 3,322 patients. • Data are collected from six hospitals of average age is 49 years, among them 1838 male patients.
Coronavirus Twitter Dataset [131].	• A multilingual COVID-19 Twitter dataset that has been continuously collecting since Jan 22, 2020. • It consists of an online conversation about COVID-19 to track scientific misinformation, rumors, etc.
COVIDx CXR Dataset [39].	• This dataset consisting of 13,800 images of chest radiography across 13,725 patients.
Epidemiological COVID-19 data [132].	• Individual-level data from municipal, provincial, and national health reports, as well as additional information from online reports. • All data are geo-coded including where available, including symptoms, key dates, and travel history.
H1N1 Fever Dataset [133].	• Two datasets collected at Narita International Airport during the H1N1 pandemic 2009. • The first dataset only 16 candidates and the second one is 1049 collected using infrared thermal scanners.
Registry data from the 191820 pandemic. [134].	• A high-quality vital registration data with mortality for the 191820 pandemic from all countries.

4.4.2. Analysis and Challenges

As mentioned data is driving force to which bring the knowledge but it not easily available. Specially COVID-19 or a sudden pandemic, gathering data and arrange it in a knowledgeable form are not expected as an easy task. Although for COVID-19, many sectors are very active as a result many data sources are quickly oriented towards COVID-19 pandemic. Some data sources are listed in table 5 where COVID-19, as well as other pandemic data, are available, so, researchers may use them for many purposes. The main challenges are sufficient datasets especially machine-readable datasets in every affected sector are yet to be available. Therefore, that are the challenges for data-driven AL algorithms or models, hence existing studies on real data and analysis are few. Although some related datasets mentioned in table 4 are available but most of them are for clinical purposes. As said this novel coronavirus is behaving differently across geographic regions, different environments, etc. Therefore, data of one region may not be effective to enhance knowledge in other regions. Data privacy and security also are considered ones of the big issues. To this reason this article suggesting transfer learning

Table 5: Some Data Sources for COVID-19 like pandemics.

Sources and/or Reference	**Brief description**
World Health Organization(WHO) [3]	• WHO leading this battle by providing each and every possible data and information. • Most of the data are unstructured so it bit challenging to feed into an AI model.
Johns Hopkins University is in the forefront to provide COVID-19 dataset [135] through their portal: https://coronavirus.jhu.edu	• A machine-readable dataset that aggregates relevant data from country-level governmental, academic sources, journalistic, etc. • Some notable COVID-19 dataset are 'county-level time-series', 'healthcare system-related metrics', 'climate', 'transit scores', 'hospital', etc.
University of Oxford dataset regarding COVID-19 at their portal: https://www.bsg.ox.ac.uk/news/coronavirus-research-blavatnik-school.	• Oxford Covid-19 Government Response Tracker (OxCGRT), an index-based data indication which govt. taking what kind of policy. • Several policy data of different govt. taken during pandemic including education policy and their impact.
European Union provides an open data portal: https://www.europeandataportal.eu/en/highlights/covid-19.	• Open data and COVID-19: provide many dataset medical data, spreading data, etc. • An Interactive map are provided and by clicking region specific dataset can be downloaded.
European Center for Disease Prevention and Control(ECDC): https://qap.ecdc.europa.eu/public/extensions/COVID-19/COVID-19.html.	• Many datasets about infectious diseases including COVID-19. • Enhanced surveillance dataset including daily update dataset, medical dataset, public health in communicable diseases.
Google: https://google.com/ covid19-map/.	• Different statistical, numeral data including number active cases, number of death, number of recovered. • Provide COVID-19 interactive map in addition dedicated dataset search engine that is also available.
GitHub: https://github.com/open-covid-19/data.	• An open repository where many datasets is stored. • Many research projects stores their data and mentioned links to their article, but they provide a link to see and access the COVID-19 dataset.
Kaggle: https://www.kaggle.com/c/covid19-global-forecasting-week-#.	• An online community of data scientists and machine learning practitioners • Forecasting dataset and other COVID-19, or pandemic dataset available.

approaches to be used in developing models for mitigating COVID-19 like pandemics or epidemics.

5. A Precedent Pipeline of DTL over EC to Mitigate COVID-19.

As mentioned 4.1.2, DL has some limitations to cope with the challenges of a pandemic whereas section 2.2 has described the task adaptability through DTL where data shortages are there. Section 2.3 mentioned the potentialities of EC where computing power is low. Therefore, the merging of these three computing models could be more effective in assisting the mitigation of pandemic situations. This combined model, that is, Deep Transfer Learning over Edge Computing (DTLEC) will take the power of DL through DTL as well as would be applicable in critical sectors by EC to cope with a sudden pandemic. There are some studies that exist in DTLEC as in [70] and some related work mentioned in section 3. However, these works are still in general concept or their proposed methods were targeted to some other application areas. As per literature studies, this idea has not been studied or experimented to mitigate COVID-19 pandemic. This section tried to present a precedent working pipeline of DTLEC to assist mitigation of pandemic or epidemic.

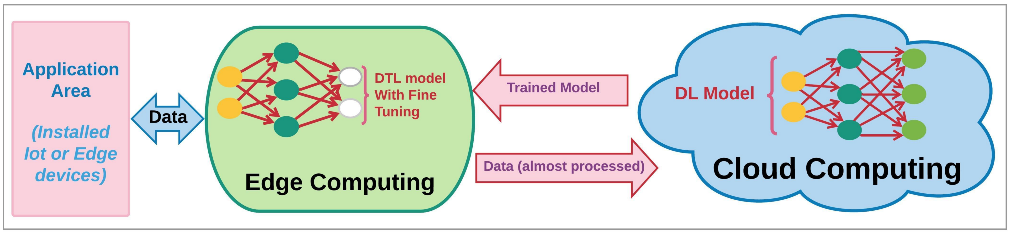

Figure 4: Proposed pipeline for DTL in EC.

5.1. Model Description

DTLEC model could be helpful in the healthcare sector, quarantine center, or other critical areas where an outbreak may arise. This methodology shall also use in remote health monitoring including elder people care at home. As in figure 4 edge or IoT devices that are set up in those areas may be embedded with EC, and then it could be connected with a cloud server. A state-of-the-art DL model shall train in GPU enabled cloud server by using a publicly available dataset for feature extraction. Then a pre-trained model (with extracted weight or features except for classification layer) shall push down to the edge devices. In edge devices required fine-tuning mechanism to be implemented into that model with some real data. In this way, the model may ready to work in some critical areas where outbreaks are affected such as hospitals, crowded places, and many more.

In figure 5 a typical current COVID-19 outbreaks situation and possible working model are shown. This figure illustrating the proposed framework to tackle the COVID-19 situation by using DTL in EC in both COVID-19 patient care and management systematic social distancing. In the first scenario, we may use several healthcare sensors like blood pressure sensors, body temperature sensors, webcam, etc to sense the data about the running health condition of each patient. Then all of the collected data would be sent to the EC layer where a pre-trained DL based model will be used to process the captured data and making an inference out of it. If the generated report is a critical health condition then an automatic system alert message will be sent with all the details to the hospital control room and also to

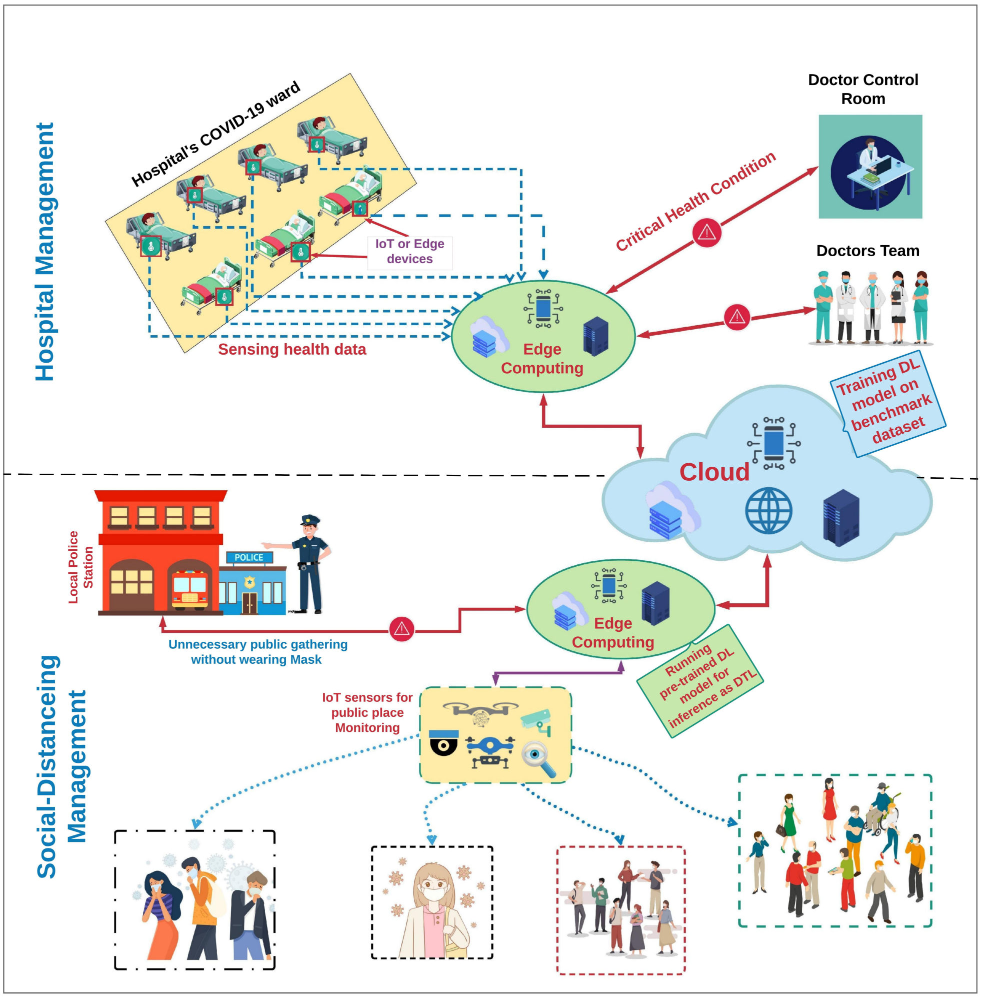

Figure 5: Framework for Edge Computing.

all the doctors of associated team. In the second scenario, several public place monitoring sensors (like a drone, CCTV, traffic cameras, etc) could be used to detect unnecessary illegal crowd with or without wearing personal protective equipment (PPE) with help from the DTLEC-based model. If the model finds any such activities then an automatic alert message will be sent with details to the nearby police station or any respective authority.

5.2. Future Challenges

This model may be successfully deployed in some critical sectors such as hospitals, airports, markets, emergency service areas, and those areas which are the primary hotshots for spreading infectious deceases. This methodology may also use for remote health monitoring with further study. The model has to be work on real data to draw the inference. In order to make it successfully deployed, lots of collaborative work need to be done, which may face many challenges. Some challenges need to be addressed such as (i.) At first, IoT or Edge devices need to be connected with each other and a cloud server, hence am optimized sensor type of networking protocol will be required. (ii.) EC through DTL need be implemented, for that appropriate pre-trained deep learning need be carefully selected after some studies. (iii.) For the transfer learning approach, using only EC is not sufficient, while the adoption of EC-Fog-Cloud combined model would be more useful. A deep learning model shall be trained at a cloud server using a publicly available dataset for feature extraction. After that pre-trained model will push down to the edge where limited re-training (or fine-tuning) shall be carried out to orient a few last layers for required inference. So, at least a small size pandemic dataset with ground truth label needs to be created. Here, the Fog server could work as a cluster. (iv.) Security and privacy issues of data need to be addressed. This inquires much more attention in analyzing numerous vulnerabilities associated with such an outbreak due to rumors and fake news. Besides, the privacy of captured data from multiple sources (things in IoT or individuals) will open a new research direction for the near coming future. (v.) A new simulation model is required for experimental studies. These are a few of the many challenges we can work for.

6. Conclusion

This article has tried to bring potentialities and challenges of Deep Transfer Learning, Edge Computing and their related issues to mitigate COVID-19 pandemic. It has also proposed a conceptual combined model with its scope and future challenges of working at critical sites and real data. As the running pandemic is new, so, there is a limited number of peer-reviewed studies and experimental results. Therefore, this systematic study article also considered some pre-print studies which are tried to make some contributions in mitigating running pandemic. The running pandemic definitely will be mitigated but there will be a leftover impact on global health, economics, education, etc. Therefore, mitigation of this pandemic as early as possible becomes necessary to restrict further worsen. In addition, every scientific community of the world needs to think wisely to get prepared to cope with such kind of crisis in a case similar outbreaks appear in the future. This article will definitely assist the research community; especially the practitioners of deep transfer learning and edge computing, to work further in developing many methodologies, tools, and applications, towards the mitigation of running pandemic or any future pandemic if that arises.

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