An IoMT based Big Data Framework for COVID-19 Prevention and Detection

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Abstract
Internet of Medical Things (IoMT) has gained significant attention in the healthcare industry as it is reshaping modern healthcare systems by incorporating technological, economic, and social possibilities. The novel severely contagious respiratory syndrome coronavirus called COVID-19 has emerged as the most critical global challenge for public health. COVID-19 is highly contiguous and spread from person-to-person interaction. Therefore, there is a need to avoid physical interactions between patients and medical health workers. In this regard, an effective and trustworthy daily healthcare service is needed that facilitates remote monitoring of patients on a daily basis. To accomplish this need, we briefly present the role of IoMT-based technologies in COVID-19 and proposed a framework named, cov-AID which remotely monitors and diagnose the disease. The proposed framework encompasses the benefits of IoMT sensors and big data analysis and prediction. Moreover, cov-AID also helps to identify COVID-19 outbreak regions and alert people not to visit those locations to prevent the spread of infection. The cov-AID is a promising framework for dynamic patient monitoring, patient tracking, quick disease diagnosis, remote treatment, and prevention from spreading the virus to others. The suggestion and challenges for applying big data to combat COVID-19 are also discussed.
Keywords:
IoMT, Big data Framework, Remote Diagnosis, Remote Patient Monitoring, COVID-19 outbreak Detection

1. Introduction

An IoMT could establish a network of interconnected healthcare devices having sensors for diagnosing and monitoring patients' health status [1]. These sensors build smart devices which help patients and healthcare workers to communicate smartly even from distinct locations. This massive connectivity permits devices and sensors to detect, analyze, and connect. Therefore, these devices alert patients, doctors, and other health workers by interacting with them inevitably, to provide services smartly [2]. These smart applications are growing exponentially as a result there is an incredible rise in the number of interconnected IoMT devices that increases the data traffic over the network [3]. The diverse sensors, devices, and applications become the source of big data [4]. Big data frameworks incorporate conventional devices and components to acquire, store and analyze various types of data by utilizing equal handling ability to accomplish complex changes and analysis [5]. However, structuring and developing a big data framework for a particular task is not an inconsequential or simple function [6]. Subsequently, the data acquired from several, heterogeneous and self-ruling sources with evolving and complex collections is continuously developing [7]. Besides, the ascent of big data applications where data acquisition has increased exponentially that is beyond the ability of commonly utilizing equipment and software platforms to store, analyze and maintain within an acceptable measure of time [8].

The extraction of values from big data sources must be analyzed for predictions to prevent and cure diseases [9]. The current situation of the COVID-19 pandemic which originated in late 2019 [10], has become the focal point of medical research [11]. COVID-19 is a virus that causes respiratory infections in humans. It travels in respiratory droplets when an infected person coughs, sneezes, talks, sings, or breathes near another person within six feet [12]. Because of the profoundly contiguous nature of COVID-19, it is difficult to examine COVID-19 patients physically [13]. Several researchers have proposed solutions for this problem. Aman [4] surveyed the IoMT technology, application, architecture, and security developments for COVID-19. Qiong Jia [14] provided a big data framework, comprising prevention mechanisms, prevention, response, and recovery. Nasajpour [7] presented a study to define the role of IoT in monitoring and diagnosing the COVID-19 symptoms. Swayamsiddha [15] proposed a framework - Cognitive IoT (CIoT) for remote patient monitoring of COVID-19 patients. Abdel-Basset [16] used disruptive and emerging technologies for COVID-19 analysis such as IoT, IoMT, AI, big data, autonomous robots, drone technology, virtual reality (VR), and blockchain.

All the aforementioned frameworks do not provide a layered architecture to elaborate the functional tasks explicitly in a detailed way. Therefore, this work proposes a layered big data framework ‘cov-AID’ that utilizes the IoMT remote assessment technology for the prevention and detection of COVID-19. The cov-AID framework consists of six layers. These layers, altogether builts a comprehensive framework that provides remote sensing, data integration, data analytics, and various applications

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specific to COVID-19. The proposed framework enables devices and software applications to be used for preventing the spread of COVID-19 by early diagnosis and patient monitoring.

The rest of the paper is organized as follows. Section II presents the proposed framework overview, and each layer description in a very detailed. The challenges of the proposed framework are described in Section III. Finally, the conclusion of the paper is given in section IV.

2. cov-AID - A Proposed Framework

The cov-AID framework aims to apply IoMT and other big data tools and technologies in the prevention, detection, and spreading of COVID-19. The framework encompasses all steps from the big data generation to analysis and applications needed to assist healthcare in preventing and treating COVID-19. The framework comprises six layers layer as shown in Fig.1: 1) Big data generation layer, 2) Big data acquisition layer 3) big data storage server layer 4) Big data query and processing layer 5) Big data analytical layer 6) Big data application. Each of the framework layers are discussed using bottom-up approach as follows.

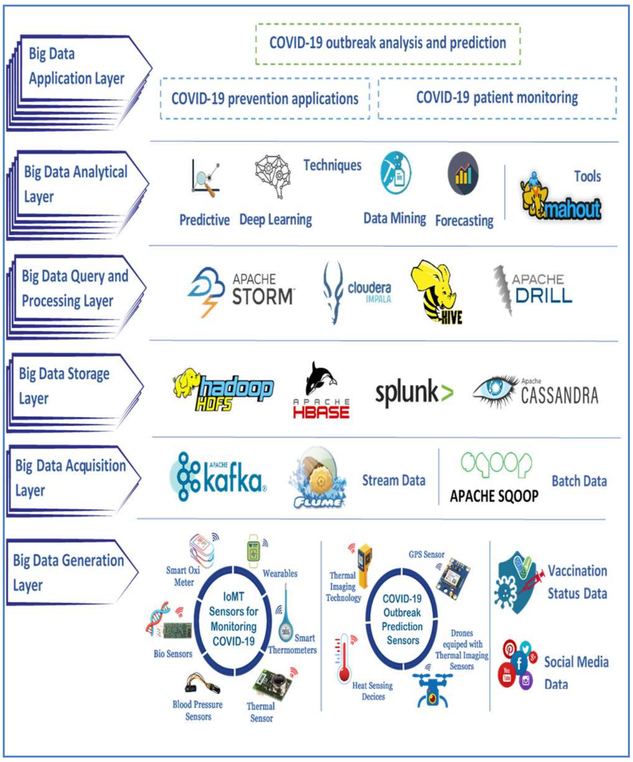

Fig. 1 cov-AID – An IoMT based framework, for preventing, monitoring, and predicting outbreak regions of COVID-19.

2.1 Big Data Generation Layer

From Every few seconds, millions of smart devices generate data streams using IoMT sensors [17]. The data for cov-AID has been collected from big data sources; IoT and IoMT sensors, centralized vaccination status records, and social media platforms. Various medical applications like drug discovery, disease detection, toxins of defense interest, prosthetic devices, etc enforce IoMT biosensors [18]. Temperature sensors are used to measure the environmental temperature and body heat [19]. Thermal heat sensors are used that measure the environment heat density for the calculation of the crowd in a particular area [20]. Infrared sensors support remote access to thermal imaging cameras [21], non-contact infrared thermometers [22]. Sensors for electrocardiogram (ECG) [23], photoplethysmography (PPG) [23], and ballistocardiogram (BCG) [24] are used with determining blood pressure using pulse transit time or pulse wave analysis [25]. Electroencephalogram (EEG) sensor [26], Pulse Oximeter [27], Electromyography (EMG) sensor [28], etc. help in the collecting real-time medical health parameters. The data of locations where COVID-19 symptoms are detected is generated by GPS sensors [29] with thermal imaging technology [30]. IoMT sensors are also used in cov-AID for tracking the origin of the outbreak and helps people to identify COVID-19 positive patients, ask them to maintain saved distance, and complete the quarantine period.

The data from other sources such as records of vaccination status is also collected by this layer of the cov-AID framework. Social media feed from different areas is monitored that leads to identifying the current COVID-19 situation in the locations. Furthermore, it helps in recognizing the false indications, evaluating mental health, detecting or predicting COVID-19 cases, analyzing government responses to the pandemic, and evaluating the quality of health information depicted in awareness videos. Additionally, the vaccination status of the public gives an estimate of the safety precaution taken from the virus. The information indicates the number of people who are unvaccinated and at risk from the novel COVID-19 virus., please refer to [1].

2.2 Big Data Acquisition and Storage Layers

The data acquisition stage does not perform by collecting data but also includes transmission, and pre-processing of data. The data which is gathered from the prior Data Generation stage is compiled proactively by distributed or centralized servers. This compiled data block is now transmitted to a master node(s) in the Hadoop cluster. Once the compilation of data is completed, it is transported towards the data storage layer which subsequently starts analyzing. In the account of this extensive source of data, may have various formats and structures accordingly, therefore data pre-processing is a necessity. To provide a unified view of combined data acquired from the different sources, data integration can be used. The inaccurate and incomplete data is amended or removed in the pre-processing stage of data, to improve the worth and the validity of data.

The further processing of data is handled by Hadoop's HDS [31]. HDFS cluster comprises the collection of DataNodes and a single NameNode. DataNode stores the acquired actual data while NameNode manages the metadata of the file system. One or more blocks are generated by the splitting of big data and then a set of DataNode stores these blocks.

2.3 Big Data Query and Processing Layer

Hadoop Yarn [32] provides core computations for big data examination. The YARN and HDFS execute on a similar arrangement of nodes, allowing tasks to be analyzed on the nodes in which data related to Covid-19 identification is present.

Impala and Hive are utilized for cov-AID to peruse the COVID-19 data from the HDFS to select, process, or create data of interest. After creating a Hadoop cluster data querying layer executes on top of it which permits getting immediate outcomes. It ought to be noticed that different data querying components, for example, Apache Pig [33], which makes MapReduce activities, can be utilized.

2.4 Big Data Analytical Layer

The acquired COVID-19 data is shared to improve the efficiency of patients' diagnosis and monitor them remotely providing a protected environment for doctors and medical health workers from the virus. The diagnosis is performed on the trained dataset for the similar symptoms' patterns found in the patients of COVID-19. To help the government take possible actions that avoid the spread of the virus, the locations of the COVID-19 outbreak are identified. The infected areas can then be sealed so no one can travel in and out of those areas. The analytics utilize the data for proposing new big data applications by applying the techniques of data visualizing, correlations, and mining.

Data security needs to be maintained when sharing such data. Various tools are used to analyze data such as SAMOA [36] and Mahout [35] for mining big data, and Tableau for big data visualization [34], . There are two main objectives for the data analytics stage; to learn and to respond. Remote health advice can be offered to the patient by sharing the health status with the doctors and paramedical staff. The sustainability of the system is maintained by the active participation of patients and their attendants by data visualization of the COVID-19 patient and outbreak status. dashboard in the response stage, the data is analyzed by doctors and health practitioners. They diagnose the disease and prescribe medicines and monitor the health status of the patients.

2.5 Big Data Application Layer

The huge amount of data generates from the patients' monitoring IoMT applications from their homes or hospitals are supported by the scalability of big data. The patients' biometric measurements, such as blood pressure and heartbeat, may be transmitted to the big data servers for analysis without exposing healthcare workers to the infection. IoMT big data applications are a very crucial tool for medical practitioners to deal with infectious diseases. COVID -19 symptoms detection via IoMT sensors and detection of COVID-19 outbreak origin are the two directions in which the cov-AID applications' analysis moves.

2.6 COVID-19 prevention applications

COVID-19 is a virus that sends from one individual to another subsequently its avoidance is a preferred solution over its cure [37]. WHO [38] announces precautions to forestall the disease that incorporates the directions to individuals to keep away from swarmed places and close contact with Covid symptoms patients, clean and disinfect hands and things that interact with different people, wear a careful mask openly places to keep from transmitting the virus starting with one individual then onto the next while breathing, sneezing, and cough. These precautions can be checked and kept up with by a few anticipation applications, for example, home isolate revelation and insights, emergency supplies and gear, rapid screening, and reconnaissance, close contact covid positive patients.

These applications guarantee that COVID-19 precautions must be taken by the residents in any case an alarm will be produced to the concerned specialists. The travelers and suspected patients are isolated regardless of whether they don't have any clear clinical symptoms of COVID-19, in this way the quick identification of such cases can be achieved. cov-AID empowers these people with venture-out history to associate themselves to medical benefits for rapid diagnosis with insignificant blunder through organization applications. The territorial joining of electronic wellbeing records of suspected COVID-19 people as they head out from one country to the next. Moreover, the spread of the virus can be constrained by the ideal mediation of the medical services and public specialists just as by singular readiness. The cov-AID empowers people to recognize the COVID-19 positive patients nearby and to maintain possible distance and precautions.

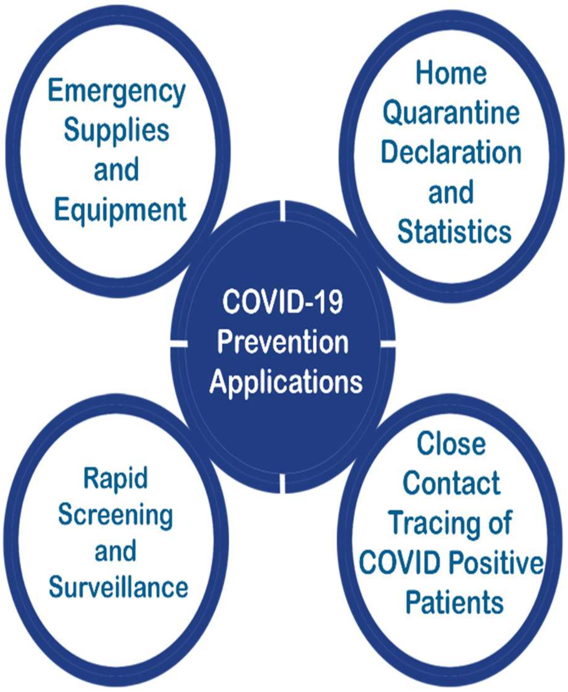

Fig. 2 cov-AID supports the applications for prevention of spreading COVID-19

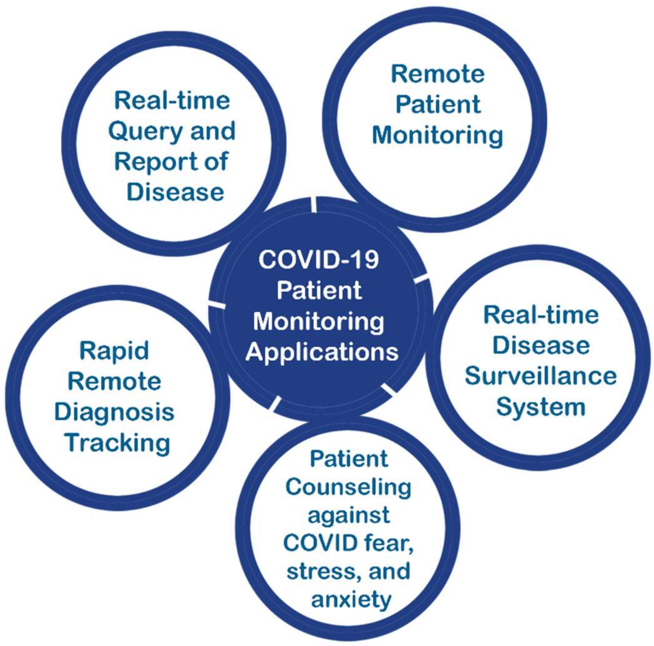

Fig. 3 cov-AID supports the applications for COVID-19 patients' remote monitoring

2.7 COVID-19 patient monitoring applications

COVID-19 virus is exceptionally infectious, the para-medical staff is in a highly vulnerable state to this infection during examining and COVID-19 patients. Therefore, cov-AID supports applications to remote monitoring and meetings between medical care professionals and COVID-19 patients utilizing shrewd video conferencing platforms and telemedicine. These applications incorporate; Remote patient monitoring, Real-time Disease Surveillance System, Real-time query and report of disease, Patient Counseling against COVID fear, stress, and anxiety, Rapid Remote diagnosis. Moreover, these application helps patients to self-isolate and self-screening at home and remotely send results to the medical services professionals. The Computed Tomography (CT) scans or X-rays can also be performed remotely from the control room through the real-time videos and pictures that can be additionally handled by AI-enabled visual sensors [39–41]. This likewise empowers contact-not so great early detection of the virus. Extra wellbeing administrations, for example, mental stress help applications can be effortlessly coordinated into IoMT platforms to give counseling administrations and treatment to the affected people and COVID-19 victims.

2.8 COVID-19 outbreak analysis and prediction applications

To identify the outbreak of COVID-19, real-time daily update data can be analyzed. This data includes cases of COVID-19 positive patients, the number of cured cases, and the number of deaths due to COVID-19 in various locations. The severity of the increased number of cases can be predicted by analyzing big data collected from the IoMT sensors using AI and machine learning. Based on this data analysis better decision-making solutions can be proposed to help medical authorities and policymakers to control the situation of COVID-19 in a particular region. Each one who is connected to the cov-AID network will have access to the big data applications which are connected to the centralized government programs, hospitals health care programs such as precautionary, diagnosis, and treatment programs. For screening and surveillance purposes several national and international arrival stations such as railway stations, bus stands, airports, hostels, hotels, etc., have been installed with thermal imaging-based facial recognition [41].

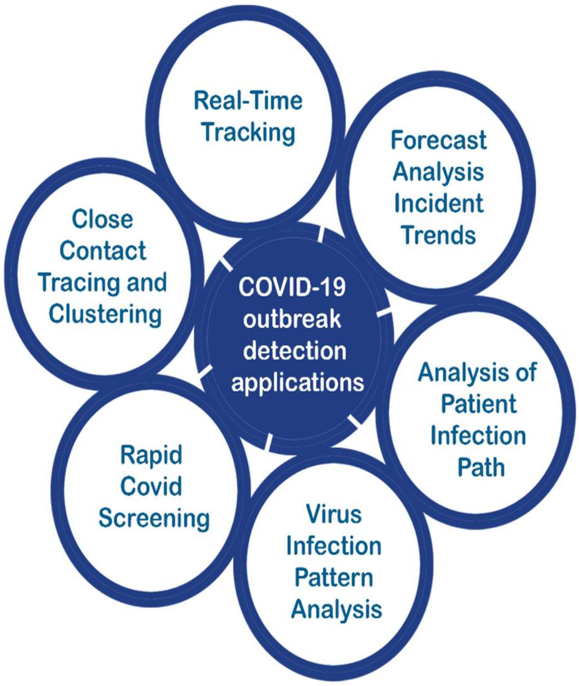

Fig. 4 cov-AID supports the applications for COVID-19 outbreak detection

cov-AID assists to control the further spread of the virus by automatic screening and surveillance of the suspected and positive cases. To simplify the tedious work of controlling the spread of the pandemic government and health care authorities can access the database servers having records of COVID-19 screening results with location history. This can also be helpful to alert other personals against contracting such suspected or confirmed cases. cov-AID applications enable the system to categorize area-wise distribution by clustering the location data of the COVID-19 confirmed cases. The infected areas can be marked as containment zones depending upon the number of confirmed cases. This can be possible by interconnecting medical healthcare systems with the big data systems having data with the location of the suspected or confirmed cases. Through the AI framework, the government can alert the hospitals about these areas to perform a health screening and provide AID to them rapidly. cov-AID also assists government authorities to establish laws and take rapid actions to spread the infection from the containment zones. [42]. Applications such as real-time tracking, forecast analysis incident trends, analysis of patient infection path, virus infection pattern analysis, rapid covid screening, and close contact tracing and clustering are provided in the cov-AID framework.

3. Proposed framework challenges for Adoption of IoMT

Although the cov-AID framework can help to lower the impact of a global pandemic to a greater extent, there are a few challenges that should be addressed. The security and privacy of the individuals' data is a major concern. The resilience to malicious attacks, and vulnerable communication protocols are also another problem in a massive interconnected heterogeneous big data network. Healthcare IT is also facing the three topmost challenges mobile and remote workforce, security of medically-connected gadgets, and cloud security.

This causes an increase in the use of remote IoMT devices that are connected with cloud platforms, cloud-based applications, and services to operating healthcare functions. This has lead to an increase in security risks like malware attacks, breaches, and phishing. The research on the performance of IoMT wearable sensors is still an open challenge to avoid unnecessary delays and inaccurate results. The mental health due to the stress and fear from COVID-19 patients during a pandemic can be monitored and personalized therapy solutions can be provided by integrating emotion-aware abilities into IoMT and mental state assessment. The cov-AID still has ethical issues as an open question.

It was reported by the IT leaders that urgent and primary care facilities, hospitals, and companies related to pharma had accelerated network resiliency demands and cloud security due to how pandemic had driven changes since March 2020. From the beginning of the COVID-19 pandemic, there has been a reported increase by 95% of respondents regarding network traffic.

Cybersecurity and data security, lack of basic cybersecurity awareness within busy clinical staff are some other challenges that had been raised by the adoption of IoMT systems. In many countries the regulations and lack of licensing for IoMT systems reside, preserving and fortifying the safety of patients which gets difficult to adjust connectivity when it is mattered the most. Different health organizations execute diversity in monitoring systems and IoMT diagnosis and the inter-operability of system devices by different manufacturers. IoMT based systems still have standardization issues. It is also needed to reduce human errors to improve the adoption scale of patients' remote monitoring and diagnosis systems. Advanced Analytics is required to get accurate results.

4. Conclusion

This paper presents an IoMT based big data framework, cov-AID, which facilitates in preventing the COVID-19. The framework not only assists in providing remote healthcare facilities to COVID-19 patients by monitoring and treating them but also helps by detecting the outbreak regions of COVID-19. cov-AID is a promising framework for remote diagnosis, dynamic monitoring, rapid treatment at the home comfort, and prevention from spreading the virus. Likewise, the rapid strategies can be carried out cost-effectively to handle the emergencies that happened to the patients. cov-AID also maintains systematic storage for big data analysis and prediction of the disease and remote online consultation. This framework has the potential to facilitate not only COVID 19 frontline workers but also help government in preventing the further outbreak. We would like to extend this framework by incorporating a security and privacy layer.

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