A CASE STUDY BASED ANALYSIS ON REMOTE MEDICAL MONITORING WITH AWS CLOUD AND INTERNET OF THINGS (IOTs)

Gokul H, Atharva deshmukh, Shraddha Jathar, Amit Kumar Tyagi
School of Computer Science and Engineering, Vellore Institute of Technology
Chennai, Tamil Nadu, India
Department of Computer Engineering, Terna Engineering College, Navi Mumbai, 400706, Maharashtra, India

gokul.h2020@vitstudent.ac.in, atharva1525@gmail.com, shraddha14.jathar@gmail.com, amitkrtyagi025@gmail.com

Abstract. *The Twenty-first Century has seen great advancements in computing, machine understanding and healthcare. With Covid19, it has become more evident that technology can impact healthcare and related disciplines deeply. Computer Vision combined with the latest advancements in digital image processing and deep learning has enabled researchers to see and understand microscopic objects in detail. It has also enabled doctors to make better decisions related to treatment. Computer Vision has helped to set up automated screening centres combined with thermal scanners. A lot of data is produced now which can be put together to train better algorithms and to get better results. In this research paper, we explore the role* Computer Vision *has played in modern healthcare and how it continues to influence the industry. Remote monitoring of IoT devices enables remote monitoring of data transfer or validity from IoT devices. Remote Monitoring of IoT Devices ingests real-time device data from IoT devices in order to analyse the condition of each IoT device and provide you notifications if there are data transmission difficulties or data that is out of range. Remote monitoring of IoT devices also provides a framework for gathering diagnostic data in order to derive outcome-oriented insights about the health of your assets. Computer vision allows computers and systems to extract useful information from digital photos, movies, and other visual inputs through the internet.*

Keywords: Computer Vision, Healthcare, Deep Learning, Cancer, COVID19

I. Introduction

Computer Vision (CV) is one area in which humans have made great advancements in the 21st century. In simple terms, it uses the camera to capture images and make meaningful interpretations from them. It has artificial intelligence and deep learning techniques of its own and many work uses deep learning techniques with Computer Vision to achieve greater results. In this research paper, we explore various areas in healthcare and analyse how specific problems are solved by their application. If we see the content covered section-wise, Section II covers topics related to new CV based diagnosis approaches and how CV improves existing diagnosis methods. Section III covers advancements in the field of surgery where CV ensures the safety of patients. Section IV analyses various work done in treating medical conditions.

Section V is dedicated to advancements related to Covid 19. Section VI covers a few miscellaneous works done in the field. Section VII concludes the paper.

Ⅱ. Diagnosis

A cure for disease can only be effective when it is applied for the right illness. Diagnosis forms the base of healthcare. A lot of technological advancements are happening in the field and Computer Vision contributes to improving the accuracy and process of diagnosis. In this section, we explore how facial morphology can show symptoms for illness followed by stress detection and diagnostic advancements in specific diseases like dementia and cancer.

As healthcare systems become more advanced, monitoring a patient outside the hospital has become a necessity. Computer Vision not only does automatic medical diagnosis but can also provide an objective secondary second assessment which can help medical personnel reach more solid conclusions and thus provide proper medical care. The latter one can be considered the best option now since it would be a chance for machine learning algorithms to get experience with more training data. A variety of symptoms are identified physically and research shows, that face alone can show symptoms of up to 30 medical conditions [1]. Along with normal imaging techniques, new techniques like thermal scanning and Stereo photogrammetry can help us see visual cues and symptoms which are otherwise not diagnosable.

Research shows that Parkinson's disease could cause abnormal eye movement [3], hepatitis could cause yellow face [4], autism and depression could cause disturbances in facial expression [5]. facial muscular contraction can represent pain which might be helpful for doctors to monitor a patient. These symptoms, if identified earlier, can produce significant results in cure and recovery. The advantage of computers over humans in detecting visual cues is their ability to see beyond the visible region of the spectrum. Thermal imaging can identify psychiatric, respiratory and ophthalmological conditions. The stereophotogrammetry method can detect facial paralysis and morphological abnormalities [1]. Bell's palsy can be detected using Microsoft Kinect [1].

Stress can lead to a decrease in quality of life and other medical conditions. Detecting stress levels in daily life and taking measures to balance it can be beneficial in the long run. A study finds that Computer Vision can be used to predict stress levels by tracking blink rate, head motion and eyebrow-raising and lowering [8]. Muscle hyperactivity can also be detected from videos which indicate an increase in stress levels.

Computer Vision and imaging techniques can be applied to medical selfies that can then be processed to identify various diseases like jaundice and prostate cancer. Jaundice is a health condition caused by a high level of bilirubin in the blood Infants are most affected by this. The yellow discolouration is one identifiable symptom. Phototherapy is proven to be an effective cure for this. In a study, infants were analysed by an HD camera [6] which initially does colour transformations in the region of interest. It then analyses and decides whether phototherapy is required or not. An SMS is sent and the machine is turned on or off accordingly.

Jaundice is a symptom of prostate cancer and detection of jaundice would help to detect and to cure prostate cancer at an earlier stage. Biliscreen is an app that detects bilirubin levels of a person by analysing their eye [7]. It uses two devices to calibrate and capture an image which is then processed to measure the bilirubin level. This app comes to the rescue as a disease like prostate cancer has jaundice as a preliminary system. This app tracks even minor changes not noticeable by the human eye thus enabling physicians to make better decisions and early diagnoses.

Misinterpretation accounts for 10-30% in diagnosis errors [38]. Radiologists can make mistakes by identifying malignant cancer as benignant or can approve false-negative results. Prognosis is as important as the diagnosis. Computer aided diagnosis (CAD) [9] system can improve the accuracy of diagnosis. It uses deep learning combined with Computer Vision to perform segmentation and feature extraction. Many conditions like dementia, pneumonia, cancer and covid can be more accurately diagnosed with a computer aided diagnosis. Condition-specific methods are discussed below.

Alzheimer's disease can be detected at an early stage through MRI scans. A study [39] proposes a transfer learning-based method for analysing structural MRI images. Research shows that machines do a better job predicting Alzheimer's disease than clinicians [40].

Breast cancer detection is mostly done by breast mammogram screening methods. Its accuracy is low with detecting cancer in the dense breast, especially with younger women [41]. Computer Aided Design (CAD) uses image segmentation to identify suspicious areas which are then confirmed by physicians. It classifies abnormalities as benign or malignant. Computer Vision techniques used include texture-based segmentation, low-level thresholding and mathematical morphology [41]. Techniques using convolutional neural networks (CNN) show significantly higher results than those using statistical methods.

Ultrasound is commonly used to diagnose prostate cancer and early detection may improve the survival rate. Noise in ultrasound makes it difficult to perform classical automatic segmentation. 3D segmentation along with CAD can detect prostate boundaries and guide the biopsy system [41].

In the case of lung cancer, lung nodules are detected through a computer tomography (CT) scan. Rib cage and air packets interfere with the detection of lung nodules. A proposed system [41] Uses stereoscopic visualisation and background blurring for nodule detection cards and supervised learning methods further decrease the identification of false positives.

In Skin cancer, colour quantization and region growing algorithms are proven to detect malignant melanoma [42]. Which accounts for the majority of mortality of skin cancer.

AI-driven digital histopathology is a new field that has emerged due to advancements in the field of Computer Vision. Humans are limited to a certain level of visual perception which can sometimes lead to inconsistencies in diagnosis. Computers can improve the efficiency of such routine tasks and can also analyse the morphological structure invisible to the human eye. One example is the localisation quantification of morphological features like cells, nuclei and mitosis [43].

Computer Vision and deep learning have been able to diagnose dozens of skin conditions by using techniques like lesion-specific differential diagnosis. In ophthalmology methods like optical coherence tomography (OCT) along with Computer Vision algorithms were able to diagnose conditions like glaucoma and childhood blindness [43].

A lot of work that is mentioned above is built on top of the existing systems. Such an approach helps the widespread adaptation of these technologies without much cost overhead. It can save professionals time and doctors can focus their time on people who require urgent attention.

Ⅲ. Surgery

Computer Vision can help ensure additional patient safety in operating rooms during surgery. Humans are prone to error and might lose focus when doing a job repeatedly or for a long time. This section explores how surgical video analysis can play an important role followed by its impact on minimally invasive surgery and open-heart surgery.

New technology makes operating rooms complex and surgical safety is currently implemented by trained human observers who collect data manually. Computer Vision tools can be trained and used to collect data that avoid human errors and ensure privacy. It can also analyse how healthcare professionals perform their job or check for any protocol breach [13]. Research shows the real-time tracking of the operating environment during a laparoscopic cholecystectomy [33]. It measures situational awareness and other factors in real-time. A multi-source acquisition system identifies intraoperative distractions [35]. Hawthorne effect clearly states that the behaviour changes can be situational and does not reflect typical behaviour [34], even considering this the system takes care of the safety concerns. In some cases, it can detect and notify any bleeding that is unattended. Another research study implements analysis of situational awareness [36]. CONDOR (Connected Optimised Network and Data in Operating Rooms) [13] and Black Box (Surgical Safety Technologies Inc, Toronto, ON) [33] are two real-world implementations of the above-mentioned technology.

Minimally invasive surgery [MIS] is often preferred over normal surgery as it reduces post-recovery time and causes less trauma. Computer Vision helps MIS achieve its true potential. Here we discuss laparoscopic MIS. Recent innovations in Computer Vision can help construct a 3D viewpoint of the scene. A lot of visual information is lost when a scene from a 3D world is represented in 2D. Computer Vision algorithms when trained on preoperative data were able to even detect malignant tumours which could be hidden from a surgeon's viewpoint [22].

Computer Vision is also used in live open-heart surgery to track surgical motion with minimum inconvenience to surgeons [37]. The camera is mounted above the operating table.

Ⅳ. Treatment

As the life expectancy grows higher more people would need access to healthcare facilities. Public hospitals receive a huge number of patients and may not be able to give attention to everyone. The traditional methods involve face to face assessment done periodically which requires a professional's presence. With the help of Computer Vision, a team in Malaysia has developed a low-cost patient monitoring system [14]. It has an emotional module that continuously analyses the facial expressions of the patient and predicts emotion levels. It also has a vital module that includes an array of sensors. When the values go beyond limits a notification is sent to medical personnel. This helps unattended patients get medical care in case of an emergency.

Mental health is as important as physical health and has to be treated when needed. Research shows that more than seventy percent of cases are not treated or brought to attention [11]. Cognitive impairment is one such situation. Cognitive impairment can be defined as one's inability to perform cognitive functions like thinking, memorising and reasoning [12]. Early diagnosis and constant follow-ups are needed in many cases for effective treatment. Digital biomarkers are one way to measure cognitive health. They are objective quantifiable data collected by devices that can analyse psychological and behavioural patterns. Meanwhile, the individuals must also feel comfortable using the devices. Digital games are one such activity where the user has to perform a cognitive function at the same time to feel comfortable. Researchers have been able to identify and incorporate 10 digital biomarkers into the Microsoft solitaire collection which can then be processed by an Open-source Computer Vision library [10]. This technology has great potential as millions of people suffer from these conditions and early detection through easy and cost-effective methods could make an impact.

Medication helps cure illness and plays an important role in healthcare. One of the challenges faced in this area is the use of correct medicine in prescribed doses and any change might result in a fatality or even death. A system is proposed to verify medicine dispensing using an attentive Computer Vision approach [15]. One can enter the patient id into the machine which can automatically retrieve the prescription details from the database and the pills in the dispensing cup can be cross-verified. If there is any mismatch the system alerts the user of the change. It uses a pill descriptor vector (PDV) which contains data, enough to identify pills uniquely. It contains planar geometry components, colour and infrared components and surface intensity descriptors. The new data set using rotation-invariant image descriptors further helps with the identification.

V. Covid19

The SARS-CoV-2 or Covid-19 pandemic has hit humanity very hard. Researchers around the globe contributed a lot of resources to fight Covid19. This time has been dubbed as ‘Science of the times’ [27] for the enormous and quick response of the science community. In this section, we discuss how Computer Vision helps tackle problems related to diagnosis, treatment and prevention of Covid-19.

A. Diagnosis
Diagnosis of Covid-19 traditionally uses techniques like Reverse transcriptase quantitative polymerase chain reaction (RT-qPCR). While tests like RT-qPCR are proven accurate it is expensive, time-consuming and is manual. With an ever-increasing number of patients, it is not feasible for everyone to undergo these tests. Computed Tomography (CT) scans are also used to confirm Covid-19 but it is limited to the ability of a medical professional to identify abnormalities in the result to confirm it. Computer Vision can help doctors make a better prognosis. Three classes of work have mainly been found and it includes using UNet++ semantic segmentation model [31], VNET based segmentation model [32] and binary classification model [30]. UNet++ semantic segmentation model identifies infected areas of a person's scan from a healthy one. This model has been trained and tested with a 46,096 CT image dataset and has shown significant positive results. It was deployed at the Renmin Hospital of Wuhan University (Wuhan, Hubei province, China) [29]. This was the only model which was applied in real life.
X-ray Radiography is a low cost widely available solution. COVID-Net proposed by Darwin AI enables detection of Covid-19 from chest X-rays [21]. It can classify a scan as normal infection, non-covid infection and covid infection. It has achieved 92.4%accuracy in tests. Other techniques were also developed using various neural networks and deep learning techniques [20].

B. Treatment
Although no treatment has been found for Covid-19 to date. Computer Vision and deep learning algorithms can help classify patients according to the severity of their illness. A respiratory simulation model (RSM) can classify several respiratory patterns with great accuracy and precision. It is then used to calculate a disease progression score called corona score. Patients can be classified based on this corona score.

C. Prevention
It is time tested that prevention is better than cure [28]. A lot of effort has been put into developing technologies that prevent the spread of Covid-19. Computer Vision algorithms are

used in China to verify if people are wearing the mask [20]. Infrared thermography is also used in public places to screen people with fever and can replace one on one manual scanning [23]. Drones were also equipped to scan mass crowds. Germ identification from microscopic datasets was proposed by Edouard A. Hay [24]. Other technologies like controlling elevators and doors use Computer Vision to prevent transmission of Covid-19 through surfaces by touching [25]. In Jakarta YOLO and MobileNet SSD was used to ensure social distance and object counting through CCTV cameras installed around the city [26].

Ⅵ Other works

Healthcare is about the prevention, treatment and diagnosis of diseases. Supporting people with disabilities is also a part of healthcare. Wearable devices are now capable of tracking various parameters of our health like pulse, rate etc. Research [19] takes wearable devices and does palm recognition thus enabling us to analyse gestures, fingertip movements etc. This can form the foundation for user interfaces for people with disabilities.

Another research [18] tracks upper body joints, performs spatiotemporal segmentation, hand gesture recognition and human pose estimation to understand sign language. It enables people who use sign language [American sign language] to communicate through video, which can be automatically interpreted. Although the research is now limited to static images, real-time programs are expected to be developed soon.

This research [17] takes a completely different approach by trying to mimic human vision using Computer Vision and deep learning. Initially, the brain activity of subjects is recorded using 28 channel EEG (Electroencephalography) while they look at various image classes. This helps analyse how visual classification is done by the human brain. Then a Computer Vision system is deployed to classify visual descriptors extracted from the understanding of human neural processes. Both systems combined try to transfer the visual capability of humans into machines.

Human activity recognition is a recently developed field in Computer Vision and a research paper [16] explores various methods for tracking and analysing human behaviour. It also discusses various challenges and limitations of these methods.

E-Sanjeevani is a real-world application that focuses on integrating medical selfies into electronic health records (EHR), which can be processed by Computer Vision algorithms to identify potentially masked diseases [2]. It uses local binary pattern LBP and multidimensional big data analysis with machine learning and Computer Vision algorithms to achieve it.

VII.AWS System for real-time remote patient health monitoring

Figure 1 gives our proposed AWS-based architecture for real-time patient health monitoring.

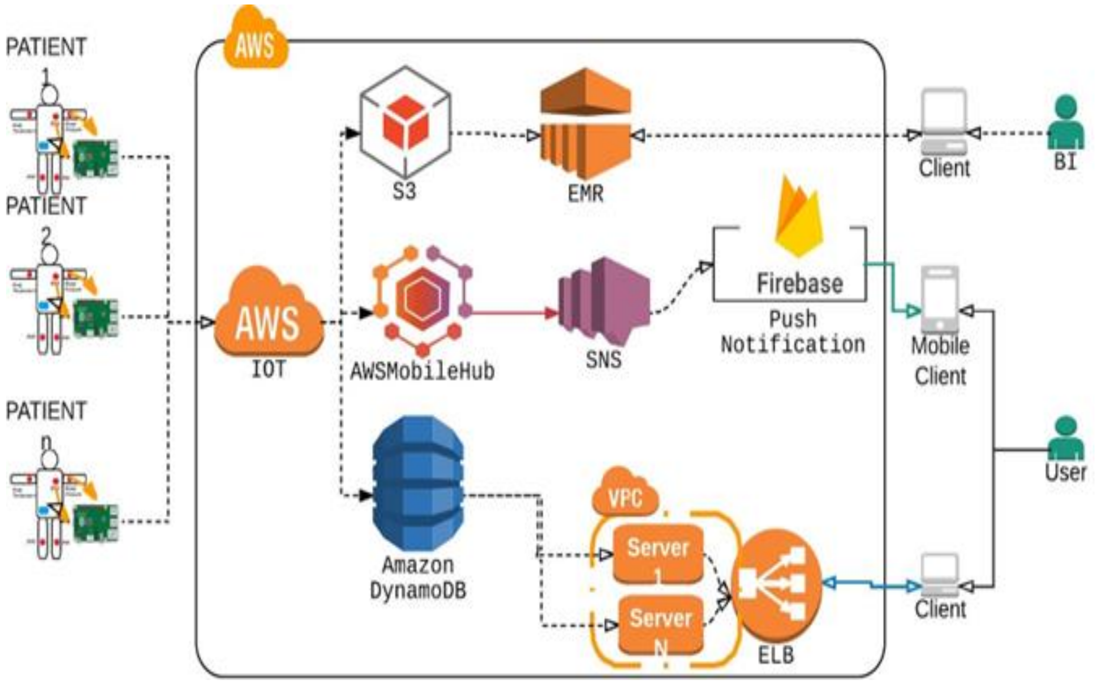


Figure 1 : Architecture of the health monitoring system.

DATA PRODUCER : This is the data source, which is represented by a Raspberry Pi card in this case. It captures sensor signals and sends them to the Internet using the NOD-RED programming tool. This tool is used to connect online services, APIs, and hardware devices; in our system, it connects the producer to the gateway in order to deliver MQ messages containing the collected data.

One issue here is the loss of connectivity with the central server, which results in data loss. As a result, the raspberry pi can be configured to preserve data in buffer memory until the connection is restored. Finally, the Raspberry Pi may be outfitted with a simple decision programme that will sound an alarm for the patient in emergency conditions.

AWS IoT : It is a framework that enables safe, bidirectional communication between Raspberry Pi devices and the Amazon Web Services cloud. Based on the content of the data, the IoT service determines the next step to take: if the monitored health parameters are normal, the data is saved in S3 and DynamoDB; otherwise, the IoT service sends a signal to alert the system's connected parts of the emergency situation.

EVENT : It indicates the warning that the system sends to the physician in the event of an emergency. This alert makes use of Amazon SNS (Simple Notification Service) to send messages to Android or iOS applications that are linked to a service called Mobile-Hub, which acts as an event handler between the AWS IoT gateway and the SNS service. From a single integrated console, mobile-Hub can monitor application usability as well as statistics and analytics on requests.

DESTINATION : The AWS IoT gateway sends data to DynamoDb and S3 (Simple Storage Services) databases. The goal of using S3 is to instantly store all incoming data and prepare it for analysis. The purpose of DynamoDb, like any other database, is to examine data through a web application. As shown in Figure 4, the application is linked via Elastic Load Balancer (ELB), which handles user access traffic and distributes it among active servers utilising the Auto Scaling concept. These servers operate within a virtual environment known as a VPC (Virtual Private Cloud), which use a Private IP address for speedier communication.

DATA EXPLORATION : We employ Elastic MapReduce (EMR), a Hadoop-based service, for processing large amounts of data in a distributed environment in a timely and cost-effective manner. It also enables for the treatment of unstructured data in parallel across numerous clusters.

This system allows health professionals to be alerted in real-time in the event of a medical emergency involving a patient being followed. It also allows for large medical databases to be analysed by artificial intelligence algorithms to extract useful information, allowing professionals to base clinical diagnoses in part on statistical inferences suggested by the machine. In addition, it allows hospitals and medical offices to eliminate challenges associated with the management and maintenance of large IT equipment.

VIII. Needs for the health monitoring system

1. Sensors and gateway communication

Continuous improvements in microelectronics over the last few decades have secured a high degree of component integration, resulting in the emergence of miniature electronic devices made of micro-sensors capable of autonomously collecting and transmitting data. As a result, the new Internet of Things (IoT) paradigm arose, associating items, connection, and the Internet, and representing the interchange of information and data between these devices and the Internet. Since then, the idea of carrying sensor devices by Man to remotely transmit information or simply for connections inside the human body has sprung up, giving rise to a large number of potential applications that cover, in no particular order, areas such as health, entertainment, sports, or human-machine interaction.

Sensors, a gateway device, and a server are the three main components of IoT communication. For medical applications, the sensors are either wearables or surgically placed on the patient and connect with the gateway through a short-range wireless protocol, typically ZigBee or Bluetooth. The gateway connects to the Cloud server via an access network, such as Ethernet, WiFi, or 3G / 4G LTE protocols.

2. Cloud Computing Solution

The amounts of information created by IoT activities for a given application might quickly exceed the hardware and storage capabilities supplied by isolated servers. This is why the utilisation of servers from off-site platforms has gained popularity. This new computer paradigm is known as Cloud computing, and it entails providing enterprises or individuals with on-demand computing resources via the Internet. These resources could include infrastructure services (IaaS) like servers for data storage or processing capabilities. Platform services (PaaS), such as the application development environment, can also be included. Finally, they can be software as a service (SaaS) applications. This method of computing allows you to save money on purchasing and maintaining pricey hardware. 4 The servers can be rented on demand, based on technical parameters (power, bandwidth, and so on), or at a set price. Cloud computing is also distinguished by its adaptability: depending on the user's skill level, one can administer one's own server or simply use remote apps in SaaS mode.

3. Definition of needs

The needs of any Cloud computing-based application appear first in the infrastructure domain (IaaS); one searches for a cloud provider that ensures total availability, dynamic scalability, and transparency to the solution's hardware needs.

Real-time remote medical monitoring of patients is distinguished by the transfer of small amounts of data from diverse sources in terms of connectivity. In this scenario, a machine-to-machine connection protocol is more convenient than the usual HTTP protocol. The new MQTT protocol has proven to be fairly useful in this field, owing to its lightness and capacity to manage a large number of deployed IoT devices, as well as its efficient communication and low-power operation.

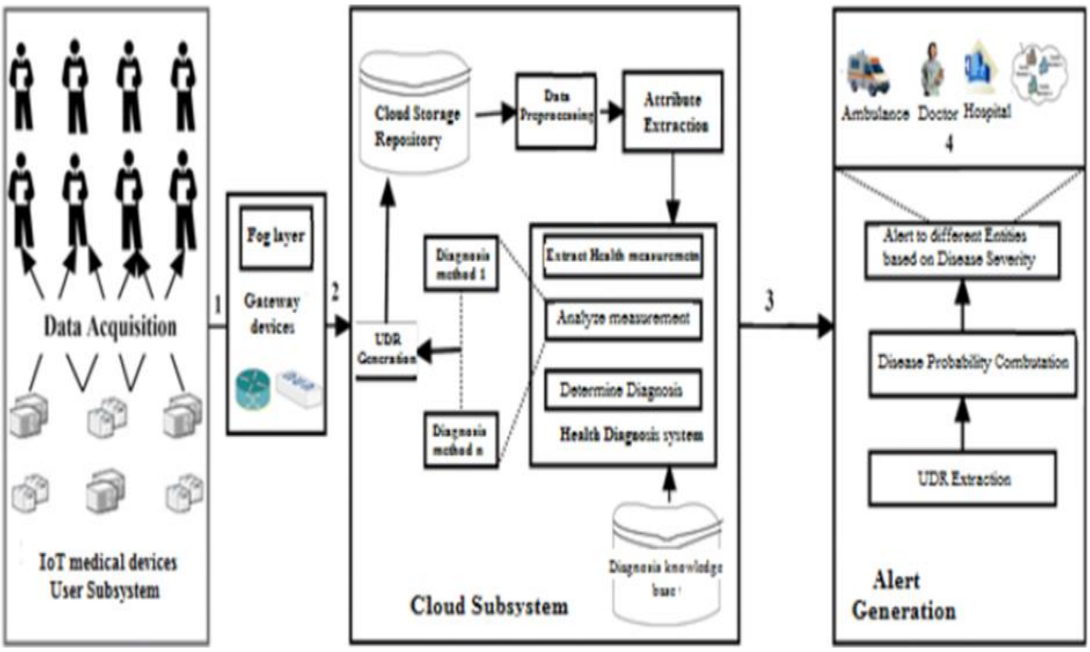
Another key feature is data treatment; fact, received data must first go through particular analysis to see whether there are any severe conditions that require immediate medical intervention; otherwise, the data is fed directly into a database for ultimate data analysis. All of these characteristics are programmable and fall under the purview of the PaaS domain.

Finally, SaaS services, such as APIs from the cloud provider, can be utilised to not only update and manage the services, but also to integrate the used applications in a familiar way for the end user.

IX. IoT healthcare applications

Cloud integration

Remote health monitoring via smartphone application IoT data is stored in the cloud platform, which provides flexibility, scalability, and greater resources for data processing. Because IoT data is collected from various sensors, it is effectively stored at a cloud-side server known as a cloud storage repository. Few researchers' medical operations are incorporated into the cloud and improved healthcare by employing cloud technology. Students' physiologically based qualities are measured and saved in a different type of format on the cloud. When the user subsystem has finished collecting data from IoT medical devices, it sends it to the cloud subsystem for diagnosis. According to the emergency message provided to the doctor, hospital, and caregivers.The study created a hierarchical computing architecture (HiCH) for a patient monitoring system that includes autonomous data management and processing at the layer's edge.



Cloud integration with Healthcare IoT system

To provide a solution for network delay in healthcare processing by remotely, a framework called as UbeHealth is developed to examine issues in network delay and QoS (Quality of Service) factors such that it delivers performance enhancement in healthcare at smart cities. The fuzzy rule-based neural classifier has been proposed for disease diagnosis and disease severity reduction. This approach examines data processing from the cloud using a secure storage mechanism, which includes phases such as data retrieval, aggregation, partitioning, and merging.

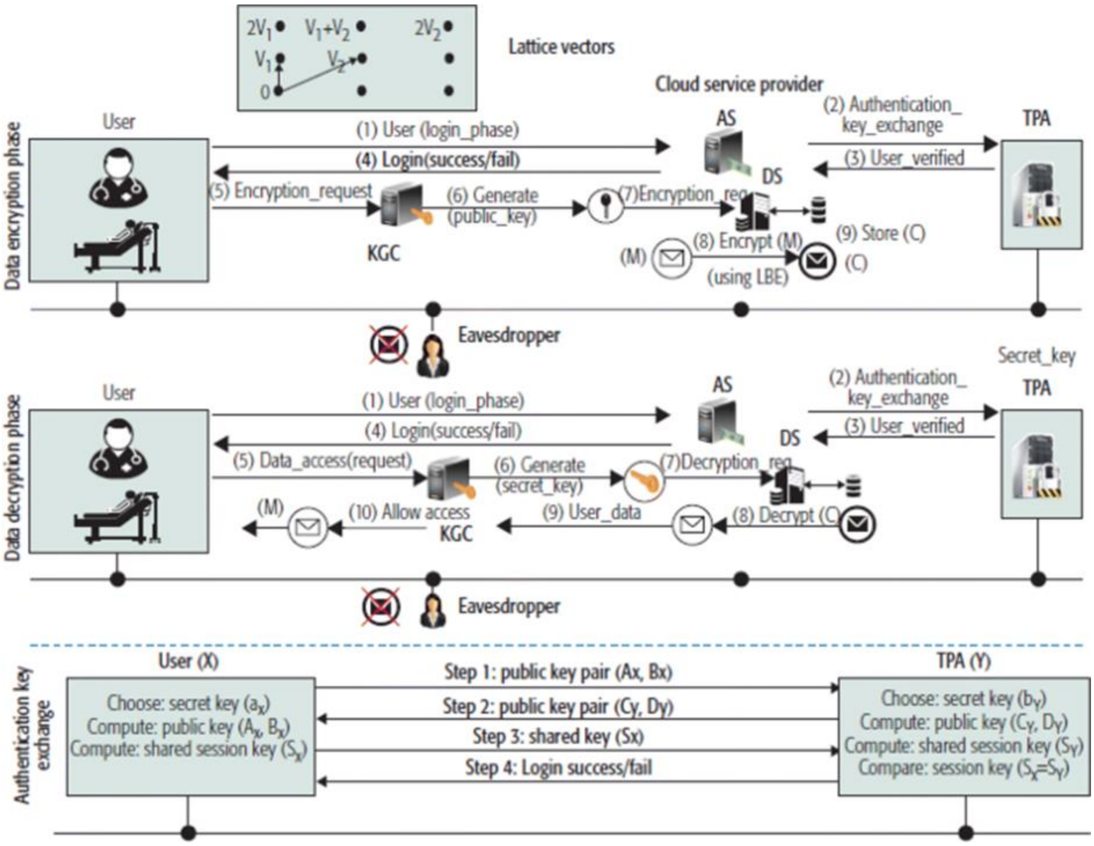
Big data in IoT healthcare

Big data storage technology has been critical in recent years for storing massive amounts of healthcare data. The cloud storage gets massive and is managed by a technology known as Big data. According to recent research, the mix of big data and cloud is affecting remote healthcare. Amazon Elastic MapReduce (EMR) offers a novel way to handle huge data and get it into a cluster. The Amazon EMR provides a separate mechanism for loading data into the Hbase cluster.Loading sensor data from Amazon S3 to Hbase with the tool acting as an Apace pig. Apace pig is utilised for data analysis in distributed databases, therefore healthcare applications can greatly increase their scalability. A lightweight methodology for semantic annotation of Big data in IoT heterogeneous data is devised. The unique method is offered for predicting air quality in metropolitan areas and providing a more healthy living for city dwellers. The suggested UHBigDataSys is built with Spring Framework and analyses the parameters of Air Quality Indicators (AQIs) for Urban Healthcare.

Security in IoT

Because hackers or attackers can readily access sensor data, security has been a big worry in the IoT, so it is critical to study the most recent security approaches in IoT.creates the IoT-oriented data insertion approach with privacy preservation known as IDP. The major goal of this suggested method is to improve data access time, increase resource utilisation, and reduce energy consumption while adhering to data privacy limitations. The Non-dominated Sorting Genetic Algorithm II algorithm is used to maintain privacy while saving energy (NSGA-II).The trustworthy computation is performed locally on the user's health profile using real health data, and the recommendation process is performed at the cloud healthcare recommender service. The radio-frequency identification encryption algorithm employed in secures medical data in IoT. Data flow in the network environment is crucial for health information. The purpose of this research is to create a data privacy framework based on a biometric-based security system and a resource-constrained wearable health monitoring system. Information from the Internet of Medical Things (IoMTs) is studied to improve security in medical applications.

The Authentication Server (AS), the Key Generation Center (KGC), and the Database Server make up the Cloud Service Provider (CSP) (DS). To secure data in smart healthcare, a Lattice-based Secure Cryptosystem is deployed. This process is divided into four stages: setup, key creation, data encryption, and data decryption. The lattice polynomial vectors are utilised as input in the first phase, and the KGC (private and public key) is generated and shared with the Database Server in the second phase (DS).The message is utilised as an input parameter in the last phase, which is combined with the random polynomial. If a user requests access to the medical data, the KGC sends the secret key pair to the DS over a secure channel. The plaintext message is processed by the DS using the input parameters and the secret key combination. The LSCSH architecture is depicted in Fig. 3, which also includes the key exchange process [30]. This proposed method was compared to other appropriate schemes in terms of communication and computation cost.



LSCSH architecture in healthcare IoT

X. Challenges in healthcare IoT

IoT has been used in a variety of applications to provide different sorts of support for the healthcare system, such as patient monitoring and a smart home system for diabetes patients. The following are the major issues that occur in the healthcare system.

• IoT enables tremendous flexibility; for example, if a patient requires constant care, he or she can live at home rather than in a hospital and be monitored on a frequent basis using IoT technology. Some wearable gadgets, such as sensors, are painful to the patient's body.

• The data transported from the sensor to the control device and then to the monitoring centre, affecting the data quality due to noise. A better architecture aids in the transmission of data while preserving its integrity. The noise removal technique can also be used to improve the data signal.

• The majority of existing ECG monitoring methods utilise guided signal analysis. This raises the cost and may result in detection inaccuracy. Machine learning can be used to analyse signals, which improves efficiency and lowers costs.

• As the number of sensors and devices grows, so does the amount of energy required to process them, increasing power leakage and energy consumption. • An optimization algorithm can be employed to reduce energy use. Monitoring a large number of users in the IoT necessitates additional storage and mainframe resources, which can be avoided by keeping the data in the Cloud. However, IoT integration with the cloud adds to the complexity.

• Another significant issue in the IoT is privacy, which is exacerbated by the fact that gadgets are more prone to assault. These devices have limited resources and it is difficult to apply encryption algorithms to them.

XI. Conclusion

Computer Vision plays a major role in the healthcare system. Starting from diagnosis to cure it influences almost all aspects of the system. It is clear that Computer Vision helps in the early detection of diseases can help save the patient. Computer Vision is used to detect symptoms from the face. Computer aided diagnosis improved many existing diagnosing methods for better accurate prediction. Cancer is detected in its early stages. Surgical video is a rich data source and can be analysed to improve the safety of the procedure. New surgical methods like minimally invasive surgery take great advantage of Computer Vision and deep learning methods. Patients can now be monitored without human intervention. Mental health can now be continuously tracked. Medication can now be verified before it is taken. In the case of Covid19, it helps us achieve more significant results in the shorter timeline and ensured safety by mass crowd temperature scanning. Beyond healthcare facilities also helps u track your daily health. It offers great relief to people with disabilities as now they can technically overcome it. Even the human visual system is tried to copy into the machine. Computer Vision has come a long way and now contributes significantly to our life. We expect even more contributions in the field of healthcare in future

XII. Acknowledgement

I would like to express sincere gratitude to my institution Vellore Institute of Technology in Chennai and my mentor Dr Amit Kumar Tyagi for introducing me to the idea of writing a research paper.

XIII. Conflict of interest

The author states that there is no conflict of interest.

References

[1] J. Thevenot, M. B. López and A. Hadid, "A Survey on Computer Vision for Assistive Medical Diagnosis From Faces," in IEEE Journal of Biomedical and Health Informatics, vol. 22, no. 5, pp. 1497-1511, Sept. 2018, doi: 10.1109/JBHI.2017.2754861.

[2] J. S. Vuppalapati, S. Kedari, S. Kedari, R. Vuppalapati, C. Vuppalapati and A. Ilapakurti, "The Role of Selfies in Creating the Next Generation Computer Vision Infused Outpatient Data Driven Electronic Health Records (EHR)," 2018 IEEE International Conference on Big Data (Big Data), 2018, pp. 2458-2466, doi: 10.1109/BigData.2018.8622458.

[3] P. H. Tseng, I. G. Cameron, G. Pari, J. N. Reynolds, D. P Munoz, and L. Itti, “High-throughput classification of clinical populations from natural viewing eye movements,” J. Neurol., vol. 260, no. 1, pp 275–284, 2013

[4] M. Liu and Z. H. Guo, “Hepatitis diagnosis using facial color image,”Medical Biometrics. ICMB 2008 (vol. 4901 of Lecture Notes ComputerScience). New York, NY, USA: Springer, 2007, pp. 160–167.

[5] "P. Wang, C. Kohler, and R. Verma, “Estimating cluster overlap on manifolds and its application to neuropsychiatric disorders,” in Proc. IEEEConf. Comput. Vis. Pattern Recognit., 2007, pp. 1–6".

[6] Hashim, Warqaa & Al-Naji, Ali Abdulelah & Al-Rayahi, Izzat & Oudah, Munir. (2021). Computer Vision for Jaundice Detection in Neonates Using Graphic User Interface. IOP Conference Series: Materials Science and Engineering. 1105. 012076. 10.1088/1757-899X/1105/1/012076.

[7] Alex Mariakakis, Megan A. Banks, Lauren Phillipi, Lei Yu, James Taylor, and Shwetak N. Patel. 2017. BiliScreen: Smartphone-Based Scleral Jaundice Monitoring for Liver and Pancreatic Disorders. Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. 1, 2, Article 20 (June 2017), 26 pages. DOI:https://doi.org/10.1145/3090085

[8] D. Manousos et al., "Contactless detection of facial signs related to stress: A preliminary study," 2014 4th International Conference on Wireless Mobile Communication and Healthcare - Transforming Healthcare Through Innovations in Mobile and Wireless Technologies (MOBIHEALTH), 2014, pp. 335-338, doi: 10.1109/MOBIHEALTH.2014.7015979.

[9] Charleen, C. Angelica, H. Purnama and F. Purnomo, "Impact of Computer Vision With Deep Learning Approach in Medical Imaging Diagnosis," 2021 1st International Conference on Computer Science and Artificial Intelligence (ICCSAI), 2021, pp. 37-41, doi: 10.1109/ICCSAI53272.2021.9609708.

[10] K. Gielis, J. Kennes, C. D. Dobbeleer, S. Puttemans and V. V. Abeele, "Collecting Digital Biomarkers on Cognitive Health Through Computer Vision and Gameplay: an Image Processing Toolkit for Card Games," 2019 IEEE International Conference on Healthcare Informatics (ICHI), 2019, pp. 1-12, doi: 10.1109/ICHI.2019.8904511.

[11] Henderson C, Evans-Lacko S, Thornicroft G. Mental illness stigma, help seeking, and public health programs. Am J Public Health. 2013;103(5):777-780. doi:10.2105/AJPH.2012.301056

[12] Roy E. (2013) Cognitive Impairment. In: Gellman M.D., Turner J.R. (eds) Encyclopedia of Behavioral Medicine. Springer, New York, NY. https://doi.org/10.1007/978-1-4419-1005-9_1118

[13] L. R. Kennedy-Metz et al., "Computer Vision in the Operating Room: Opportunities and Caveats," in IEEE Transactions on Medical Robotics and Bionics, vol. 3, no. 1, pp. 2-10, Feb. 2021, doi: 10.1109/TMRB.2020.3040002.

[14] A. A. Zainuddin et al., "Patient Monitoring System using Computer Vision for Emotional Recognition and Vital Signs Detection," 2020 IEEE Student Conference on Research and Development (SCOReD), 2020, pp. 22-27, doi: 10.1109/SCOReD50371.2020.9250950.

[15] R. Palenychka, A. Lakhssassi and M. Palenychka, "Verification of Medication Dispensing Using the Attentive Computer Vision Approach," 2018 IEEE International Symposium on Circuits and Systems (ISCAS), 2018, pp. 1-4, doi: 10.1109/ISCAS.2018.8351202.

[16] Wei, Zhiqiang & Nie, Jie & Huang, Lei & Wang, Shuang & Li, Zhen. (2017). A Review on Human Activity Recognition Using Vision-Based Method. Journal of Healthcare Engineering. 2017. 1-31. 10.1155/2017/3090343.

[17] C. Spampinato, S. Palazzo, I. Kavasidis, D. Giordano, N. Souly and M. Shah, "Deep Learning Human Mind for Automated Visual Classification," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017, pp. 4503-4511, doi: 10.1109/CVPR.2017.479.

[18] S. Gattupalli, "Human Motion Analysis and Vision-Based Articulated Pose Estimation," 2015 International Conference on Healthcare Informatics, 2015, pp. 470-470, doi: 10.1109/ICHI.2015.78.

[19] F. R. Hsu, Y. -H. Kuo, S. -Y. Wei, Y. -H. Hsieh and D. C. Nguyen, "A Study of User Interface with Wearable Devices Based on Computer Vision," in IEEE Consumer Electronics Magazine, vol. 9, no. 1, pp. 43-48, 1 Jan. 2020, doi: 10.1109/MCE.2019.2941463.

[20] A. Ulhaq, J. Born, A. Khan, D. P. S. Gomes, S. Chakraborty and M. Paul, "COVID-19 Control by Computer Vision Approaches: A Survey," in IEEE Access, vol. 8, pp. 179437-179456, 2020, doi: 10.1109/ACCESS.2020.3027685.

[21] Wang, L., Lin, Z.Q. & Wong, A. COVID-Net: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images. Sci Rep 10, 19549 (2020). https://doi.org/10.1038/s41598-020-76550-z

[22] Bartoli A, Collins T, Bourdel N, Canis M. Computer assisted minimally invasive surgery: is medical computer vision the answer to improving laparosurgery?. Med Hypotheses. 2012;79(6):858-863. doi:10.1016/j.mehy.2012.09.007

[23] "BB Lahiri, S Bagavathiappan, T Jayakumar, and John Philip. Medical applications of infrared thermography: a review. Infrared Physics & Technology, 55(4):221–235, 2012"

[24] "Edouard A Hay and Raghuveer Parthasarathy. Performance of convolutional neural networks for identification of bacteria in 3d microscopy datasets. PLoS computational biology, 14(12):e1006628, 2018"

[25] J. Katti, A. Kulkarni, A. Pachange, A. Jadhav and P. Nikam, "Contactless Elevator Based on Hand Gestures During Covid 19 Like Pandemics," 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS), 2021, pp. 672-676, doi: 10.1109/ICACCS51430.2021.9441827.

[26] M. Lanang Afkaar Ar et al., "A computer vision-based object detection and counting for COVID-19 protocol compliance: a case study of Jakarta," 2020 International Conference on ICT for Smart Society (ICISS), 2020, pp. 1-5, doi: 10.1109/ICISS50791.2020.9307594.

[27] "Coronavirus research is being published at a furious pace, (accessed February 24, 2022). URL: (https://www.economist.com/graphic-detail/2020/03/20/coronavirus-research-is-being-published-at-a-furiouspace)."

[28] Borysiewicz L. Prevention is better than cure. Clin Med (Lond). 2009;9(6):572-583. doi:10.7861/clinmedicine.9-6-572

[29] Jun Chen, Lianlian Wu, Jun Zhang, Liang Zhang, Dexin Gong, Yilin Zhao, Shan Hu, Yonggui Wang, Xiao Hu, Biqing Zheng, et al. Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution computed tomography: a prospective study. medRxiv, 2020.

[30] "Lin Li, Lixin Qin, Zeguo Xu, Youbing Yin, Xin Wang, Bin Kong, Junjie Bai, Yi Lu, Zhenghan Fang, Qi Song, et al. Artificial intelligence distinguishes covid-19 from community acquired pneumonia on chest ct. Radiology, page 200905, 2020."

[31] "Zongwei Zhou, Md Mahfuzur Rahman Siddiquee, Nima Tajbakhsh, and Jianming Liang. Unet++: A nested u-net architecture for medical image segmentation. In Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support, pages 3–11. Springer, 2018."

[32] E. Gibson et al., "Automatic Multi-Organ Segmentation on Abdominal CT With Dense V-Networks," in IEEE Transactions on Medical Imaging, vol. 37, no. 8, pp. 1822-1834, Aug. 2018, doi: 10.1109/TMI.2018.2806309.

[33] S. Guerlain et al., “Assessing team performance in the operating room: Development and use of a ‘black-box’ recorder and other tools for the intraoperative environment,” J. Am. Coll. Surg., vol. 200, no. 1, pp. 29–37, 2005

[34] McCambridge J, Witton J, Elbourne DR. Systematic review of the Hawthorne effect: new concepts are needed to study research participation effects. J Clin Epidemiol. 2014;67(3):267-277. doi:10.1016/j.jclinepi.2013.08.015

[35] " M. G. Goldenberg, J. Jung, and T. P. Grantcharov, “Using data to enhance performance and improve quality and safety in surgery,” vol. 152, no. 10, pp. 972–973, 2017"

[36] "J. E. Bardram and N. Nørskov, “A context-aware patient safety system for the operating room,” in Proc. 10th Int. Conf. Ubiquitous Comput. (UbiComp), 2008, pp. 272–281."

[37] Stenmark M, Omerbašić E, Magnusson M, Andersson V, Abrahamsson M, Tran PK. Vision-Based Tracking of Surgical Motion During Live Open-Heart Surgery. J Surg Res. 2022;271:106-116. doi:10.1016/j.jss.2021.10.025

[38] "Gao, J., Jiang, Q., Zhou, B., & Chen, D. (2019). Convolutional Neural Networks for Computer-Aided Detection or Diagnosis in Medical Image Analysis: An Overview. Mathematical Biosciences and Engineering, 16(6), 6536-6561. doi:10.3934/mbe.2019326"

[39] M. Hon and N. M. Khan, "Towards Alzheimer's disease classification through transfer learning," 2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 2017, pp. 1166-1169, doi: 10.1109/BIBM.2017.8217822.

[40] "S. Kloppel, C. M. Stonnington, J. Barnes, F. Chen, C. Chu, C. D. Good, ¨I. Mader, L. A. Mitchell, A. C. Patel, C. C. Roberts et al., “Accuracy of dementia diagnosisa direct comparison between radiologists and acomputerized method,” Brain, vol. 131, no. 11, pp. 2969–2974, 2008."

[41] Howard Lee and Yi-Ping Phoebe Chen. 2015. Image based computer aided diagnosis system for cancer detection. Expert Syst. Appl. 42, 12 (July 2015), 5356–5365.

[42] M. E. Celebi, Y. A. Aslandogan and P. R. Bergstresser, "Unsupervised border detection of skin lesion images," International Conference on Information Technology: Coding and Computing (ITCC'05) - Volume II, 2005, pp. 123-128 Vol. 2, doi: 10.1109/ITCC.2005.283.

[43] Esteva, A., Chou, K., Yeung, S. et al. Deep learning-enabled medical computer vision. npj Digit. Med. 4, 5 (2021). https://doi.org/10.1038/s41746-020-00376-2