IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 7.918 ⁜ Vol. 11, Issue 12, December 2022

DOI: 10.17148/IJARCCE.2022.111252

Cloud-Based AI Systems for Real-Time Medical Imaging Analysis and Diagnostics

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Abstract: Automatic disease diagnosis using medical imaging has been a hot research topic in the past few years. Over the past decade, significant research efforts have been made in X-ray and CT image analysis and diagnosis of different diseases, including but not limited to laparoscopic surgical actions, kidney stone types, Alzheimer's disease, and other general diseases like heart problems. Medical imaging is a very helpful and effective tool for the diagnosis of atypical and common symptoms. In recent years, novel and enhanced imaging methods have been developed for the effective extraction of medical images with advanced resolution and other enhanced features. However, although modern imaging modes are advanced and very effective for extraction, the interpretation of these images is still labor-intensive and requires high expertise in the relevant field. There is a growing void between the discovery of images and their interpretation due to the scarcity of expert doctors in this field. The solution is automation, and the best approach to deploy such automation at a grand scale in real life is to utilize AI. Artificial intelligence comprises various fields that assist in tackling tough problems in automation, such as computer vision, natural language processing, and robotics. Among these different fields, computer vision has achieved tremendous success in recent years and is very active in both academia and industry. Numerous intelligent computer vision systems are deployed in different domains, including but not limited to autonomous driving, agriculture, wildlife, security, social media, smart retail, and health care. The healthcare domain is one of the most active computer vision research areas due to automatic medical imaging diagnosis becoming an increasingly attractive research problem. Early automatic diagnosis is essential for providing timely interventions. It is difficult to discover effective workaround solutions for complex processes like human actions, building structure parsing, security event understanding, and so on. But it is comparatively easier to devise solutions. Thus, significant research efforts have been made in medical image analysis and disease diagnosis.

A worldwide pandemic has become a challenge, endangering the lives of a vast number of populations and putting tremendous pressure on the healthcare systems in all nations. A large number of healthcare units and hospitals in some regions tend to be overwhelmed, and the majority of patients are feared to be unattended. For some other remote areas, it is a challenge to access these kinds of healthcare facilities. The whole world is facing this unexpected catastrophe. Researchers, engineers, and organizations of all kinds are collaborating, and fighting the virus by developing preventive solutions in engineering, medication, and policy. Deep Learning has taken health care research topics by storm over the past decade, enabling substantial breakthroughs in building intelligent automated systems for medical image analysis, disease diagnosis, behavior understanding, drug development, and personalized device delivery. Various hardware and software infrastructures have been adopted for the training and testing of AI models. However, all these infrastructures are pollutant and energy-inefficient, contributing adversely to climate change. Thus, greener alternatives need to be utilized for AI in health care. Greener techniques for training, testing, and deployment of deep learning models have been actively researched recently, especially due to the rising scalability of AI models and their energy-intensive inference. Both hardware and software techniques have been devised to make smarter strategies to train, test, and deploy large AI models. This research identifies healthcare imaging architecture on a newly modified architecture composed of fog-cloud computing. Integration of AI with this architecture is expected to significantly reduce the execution cost of these systems, enabling wide adoption in this domain.

Keywords: Cloud-based medical imaging, AI diagnostic imaging, Real-time image analysis healthcare, Cloud AI radiology, Medical imaging AI software, Remote diagnostic tools AI, Deep learning medical imaging, AI-powered imaging diagnostics, Cloud computing in radiology, Real-time healthcare analytics, Medical image processing AI, Radiology automation cloud AI, Edge-cloud integration medical AI, Neural networks for diagnostics, Secure cloud medical data analysis.

I. INTRODUCTION

In the healthcare domain, pandemics have notably accelerated the need for effective needs in data analysis and health-care solutions. One of the crucial fields of healthcare is the analysis of medical images, such as chest X-rays and a CT scan. Manually checking the medical images captured by hospitals requires considerable effort, time, and cost. Moreover,

DOI: 10.17148/IJARCCE.2022.111252

during such pandemics, huge numbers of suspected infected patients should be checked immediately using these medical images to isolate the suspected patients from the healthy ones. Unfortunately, these images are usually uploaded to centralized cloud computing servers. With the huge number of uploaded images, it becomes impractical for the cloud to directly analyze and check all these images. Centralized cloud computing servers have logistical complexities in providing services for time-critical applications in circumstances where there is no internet access such as health monitoring in remote and developing regions.

Due to the complexity of the images and their volume, the image analysis is time-critical; hence, the efficiency and accuracy of the healthcare images management represent vital aspects. The need for cloud services to improve access to health data services in developing countries is seen as an important step toward further economic growth. However, their logistics complexity concerning scale. The bigger the cloud is, the sooner the bottleneck arises. This is further complicated by the risk of improper online behavior by patients and vendors and the lack of trust in the information technology and cloud services themselves. The proposed architecture uses on-device fog computing and presents a modified CNN for image analysis. However, the limitations of medical hardware devices are ignored, and they are assumed to be hosted in the cloud, which is impractical in fast and huge image analysis systems.

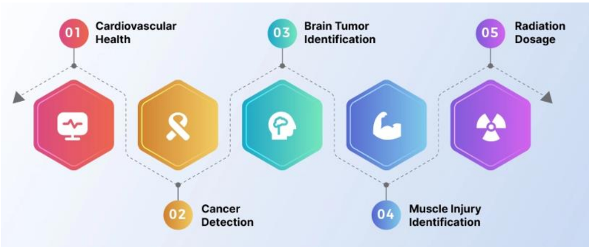

Fig 1: AI Systems for Medical Imaging Analysis and Diagnostics.

1.1. Background and Significance

In the past few years, the emergence of pandemics such as COVID-19 has emphasized the need to adopt precise and effective solutions for healthcare data. This data, which may involve every aspect of healthcare, will impact several domains. Particularly, huge signified healthcare data involves thorough recording and examining patient medical images such as X-ray, CT, or MRI datasets, which are generally in images format. As an example, healthcare images acquired by hospitals and placed in their health registry systems (HRS) must be examined thoroughly for diagnosing the patient's health status and providing the proper clinical treatment. This prognosis may require input of several experts wishing to view the images and provide their feedback regarding where the anomaly occurs. The complex corresponding systems ought to be configured for quick and precise analysis of the radiological images to take the proper treatment. Nonetheless, a significantly time-consuming process follows for local expert examination of the acquired images, as each image must be transferred over the Internet to the centralized cloud computing servers for analysis. In the healthcare sector, automated systems for diagnostics remain basic to fast and precise management of the medical image data. For COVID-19, the predicted lung opacity through chest X-ray images is basic for the detection of the disease for a patient. Design and deployment of the models must concern the multiple aspects of healthcare signified data, which should be highly precise and fast, besides being aware of huge data complexity. Of concern is the storage aspect, where some systems prefer only transfer and storage of the data in the cloud. Nonetheless, capturing such data using low-cost sensors results in huge bandwidth. Regarding the computational effort, analysis of the stored healthcare images by model implementation is risky since huge volume of data is involved. Furthermore, it is of utmost importance to assure analysis within a conventional time-frame, whereas quarantine is critical in the case of COVID-19 patients. Finally, adequate automation and model accuracy must be provided to avoid human error in false positives/negatives. Conversely, manual examination of the radiological images remains one of the most prominent tasks in the diagnosis of patient health status.

II. CLOUD COMPUTING IN HEALTHCARE

Over the past few years, the field of healthcare image analysis has been revolutionized due to the efforts and developments in deep learning models and cloud-based architectures. Due to the pandemic of COVID-19, the healthcare image analysis has become one of the most challenging issues to be addressed using the healthcare infrastructure and artificial intelligence (AI) methods. The inadequacy of manually examining the X-ray and CT-scan images for checking the presence of COVID-19 could precipitate the healthcare management issue. Notably, this is another gigantic task in the healthcare system, since there are large numbers of both chest X-ray and CT-scan images, which must be transmitted to the respective healthcare organizations for further investigation.

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Healthcare management becomes more complicated and challenging unless this architectural and infrastructural separation system is overcome from fog-to-cloud. The calculation speed, accuracy of the large-volume image classification, and identification of the presence of diseases played a significant role in healthcare accurate image management architecture. It results in a healthier environment as well as better quality of life. A cloud-based architecture is one of the most widely accepted systems in the healthcare field through which unlimited storage and supple resource computation can be provided to satiate the necessity and objectives of the organization.

Despite such several advantages, the cloud-based architecture is unable to handle the challenges in healthcare image analysis architecture, due to its incapacity for real-time analysis. This undoubtedly leads to major inconveniences, whether in the detection of the COVID-19 existence from CXR or the CT-scan imaging. Although the speed of deeper models is observed, this latency persists among several parts of the architecture, where the CEO of AWS has pointed out 'the cost of transmission is getting big, bandwidth is getting expensive…'. Due to the high cost of moderation, there would be a possibility of rejection to accept for higher r-models such as a R-FCN for detection and other fully convolutional models for segmentation. There is an emerging wide negligible interval of the latency, where the existence of cloud scanning stability, searching, and full pipeline processing systems gradually increases. Such predictions lead to overlook the prediction in the second parts of the pipeline either rolling the initial investment at all since there are no interesting returns remaining to exploit few time-consuming computers.

2.1. Benefits of Cloud Computing

Rapid advances in medical imaging Artificial Intelligence (AI) present unprecedented opportunities for automatic analysis and extraction of data from large collections of imaging data. The recent development of Cloud computing offers the promise of economical access to vast resources, and extreme scalability. Here an exploratory investigation into the suitability of cloud-provisioned compute resources for the purpose of performing AI-based curation of a very large public collection of imaging data - the National Lung Screening Trial (NLST) Computed Tomography (CT) images - is presented. The evaluation of two cloud resources provided by the National Cancer Institute Cancer Research Data Commons (CRDC) - Terra and Seven Bridges-Cancer Genomics Cloud (SB-CGC) platforms - upon which to run segmentation AI algorithms for a cohort containing >126,000 CT volumes from >26,000 patients is described. The efficacy of the cloud resources is established via the processing of a subset of 20,000 CT volumes, where it is shown that utilization of >21,000 Virtual Machines (VMs) completed the analysis in under 9 hours. In contrast, it is estimated that performing the same analysis on single workstation hardware with 192 cores would take ~522 days. This enormous advantage is predicted to increase further with expansion in cohort size and number of images analyzed, making cloud solutions essential to progress in medical imaging research and data science.

The emergence of pandemics such as COVID-19 has made significant advancements in healthcare surface patterns, emphasizing the vital need for effective healthcare data analysis solutions. One of the healthcare data types is medical images, which are commonly used across various healthcare sectors. However, the manual examination of medical images is a cumbersome dataset such as corona X-ray images, and CT-scans are necessary. Depending on the size and type of data, the healthcare images are stored in edge devices with limited resources. These healthcare images must be transferred from the edge obstacles to centralized cloud computing servers, which is not feasible all the time due to logistical complexities, amount of data, security concerns, and privacy issues. Additionally, in the medical field, speed and accuracy in the analysis of medical images are needed to ensure efficient healthcare image management and quick actions. Hence this research paper presents an intelligent healthcare architecture to analyze the data in smart edge devices to overcome healthcare image analysis issues.

2.2. Challenges and Limitations

Cloud computing system for medical diagnosis and treatment investigation has many technical, regulatory, and legal issues to be solved for smooth functioning. Primarily there are four issues that need to be considered carefully, as it involves the safety and well-being of clients, and risks falling under the exposure of legal prosecution. The technological environment is ever-changing around the globe and MedCloud is in continuous need of upgrading. New product(s), services, and security features with texture-based technologies are added regularly to the system and compliance to new policies and laws is also necessary. In the most user-centric approach, the MedCloud service should ensure that issues like breach of data security, buckle-free EMR implementation, the application of appropriate diagnostic equipment, and viable operations in a favourable environment do not feature in the service. Medical images of a client/client's family can only be shared by a healthcare provider after the patient's consent. Service to be provided to potential users should be reported to users such that they are aware of the possibility of unwanted viewing of images shared by them with healthcare providers.

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Technical issues need to be resolved before actually launching the system. With the earliest launch, the MedCloud design would be subjected to trial by competitive users. To be effective in combating unwanted viewing of medical images, competitive users would need to have extensive knowledge of architecture, interfaces, and closure of the design prior to launch. Competitive users are skilled in software bug identification and exploitation with a view to exposing the design in a public forum before exploiting those bugs as well. Thus, closing the design from competitive uses would call for designers' commitment to the highest quality goal. There isn't any formal methodology for bug-free design other than strong technical competency and broad base collaboration among teams and professionals. Hence MedCloud's operational safety would be largely reliant on designers and engineers being at the absolute top of their game. In the case of new technology support, availability of trained and competent personnel cannot be ascertained and before formal training personnel would be reliant on expertise for either developing or upgrading technology.

Equ 1: Convolution Operation (Image Feature Extraction).

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(i+m, j+n) \cdot K(m,n)$$

- I: Input image matrix
- K: Kernel (filter)
- $S(i,j)$: Output feature map value at position (i,j)

III. AI TECHNOLOGIES IN MEDICAL IMAGING

In this section, the presentation of AI technologies in medical imaging is divided into three main areas. Each area is further elaborated on with several representative studies along with a brief introduction to the technical features in consideration of the focus of this section. With the rapid development of technical fields such as deep learning and GPUs, the medical imaging field has been influenced a lot; various applications of image analysis and interpretation in real clinical scenarios have been proposed and studied. The technical features of the state-of-the-art AI technologies in consideration of the above-mentioned areas are summarized in the following subsections.

Compared with the traditional machine learning methods, DL models do not require feature engineering anymore and automatically learn features based on the given data. CNNs and RNNs are two types of neural networks that have been widely used in medical imaging tasks. To apply DL techniques in the medical imaging domain, CNNs as the representative architectures together with their variants and extensions have been studied in more detail. The notable studies applying CNNs in image tasks include segmentation tasks in cardiac imaging, retinal vessels, colon adenoma/Tumor automatic detection, lesion detection in breast ultrasound, classification tasks in CT colon cancer screening, fracture diagnosis, 3D CXR COVID-19 diagnosis, and biomarker extraction based on brain tissue segmentation. There are also RNN modeling-based works for sequential image processes with time- and space-gathered images, as well as attention mechanism-based studies; however, these studies happen mostly in clinical text/note.

To take advantage of models pre-trained on a large-scale public database to medical imaging tasks with small-data issues, transfer learning-based methods and pre-trained models have gained more popularity recently. Therefore, pre-trained models are also frequently used on a public CT COVID-19 database as feature extractors or input for fine-tuning. In addition, several coding-decoding architectures are specifically designed in 2D conditional generation tasks, and 3D coding-decoding architectures in data distortion correction and super-resolution tasks. With more than 37,000 articles searchable in public citation APIs, there is a very active publishing community in the medical imaging AI domain.

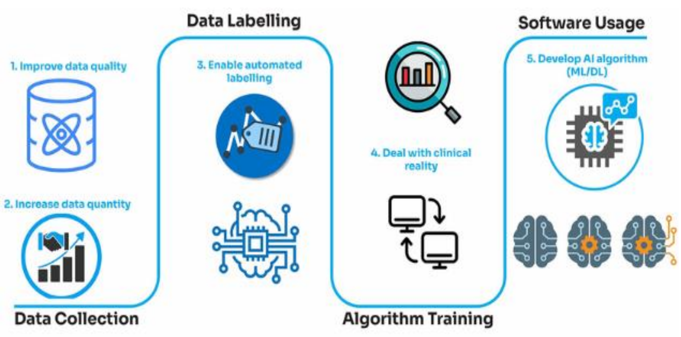

Fig 2: AI Technologies in Medical Imaging.

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3.1. Machine Learning Algorithms

Machine Learning (ML) algorithms are part of AI that helps radiologists in image analysis and interpretation. These algorithms perform image analysis and interpretation on their own and aid radiologists in making better decisions. Recent rapid advancements in data science and ML algorithms have paved the way for deep learning (DL) algorithms. The DL algorithms are continuously learning algorithms, making decisions on data rather than rules, allowing them to handle a variety of tasks other than imaging analysis. Research is focused on three-dimensional (3D) volumetric data, where images are spatiotemporally correlated. Frequency analysis is another research area, where the full set of data measurement is not available, and the data have a low sample rate. These algorithms assist radiologists in making decisions on various data types, including traditional X-ray, CT, MR, positron emission tomography (PET), new imaging modalities, and radiology records. ML has been used for many years in the field of natural language processing, and it would likely be used in reinforcement learning. Tests on a set of 230 radiology reports showed high precision, accuracy, and recall in text recovery.

MRI scanning is time-consuming and challenging due to the variety and high number of sequences often required to be performed. Improving efficiency in MRI performance could yield a significant reduction in cost. Recently, a fundamental study on the ML algorithm was ongoing, where neural networks were used to help decide the ideal time allotment per scan depending on different information boundaries, based on the intended objective and clinical requirement. Currently, researchers are focusing on the study's overall algorithm performance accuracy and perception time for specific decisions. There is room for improvement in MRI scanning time, where a deep image prior (DIP) framework was proposed. For this framework, CNNs have the intrinsic ability to regularize various problems without pre-training. This shows that the process of using CNNs for recovery may have a certain independence against the loss function and network architecture rippling down to the initialization method. In cancer research, DL algorithms efficiently analyze technical, lab, and bioinformatics data.

3.2. Deep Learning Techniques

Deep learning (DL) uses neural networks (NNs) with a large number of layers to learn patterns and representations of data in a hierarchical manner. The architecture of a deep NN typically consists of a large number of interconnected processing elements, or neurons, organized in layers. Each layer combines the output of the previous layer and maps it to an output vector using an activation function. Popular activation functions include the rectified linear unit, hyperbolic tangent, and sigmoid function. The output of the top layer is combined to measure the goodness of fit using a cost function. Gradient descent algorithms, such as stochastic gradient descent and Adam, are most commonly used to estimate the optimal parameters of the networks by minimizing the cost function. This process consists of taking small steps along the gradient in the direction of decreasing cost through back-propagation. Neural networks with many hidden layers can learn to recognize patterns over an increasing range of spatial scales. Compared with traditional hand-engineered features, DL is data-driven and automatically learns a high-dimensional hierarchy of representations from raw data.

Increasingly available and notably affordable computational power and storage resources, coupled with an ever-growing volume of data, have significantly spurred the rapid rise of DL in various fields of scientific and technical activity. This rising trend is also found in medical imaging, where its remarkable success on several high-profile problems has attracted an increased level of attention from the medical image analysis community. Since 2012, the release of more popular architectures, large annotated datasets, and the public availability of pretrained models have allowed even researchers without extensive experience in DL to train state-of-the-art models on their own datasets of various modalities. In addition, several medical device manufacturers have developed and marketed advanced commercial software packages that bundle a range of DL utilities onto a standard graphical user interface.

IV. REAL-TIME IMAGING ANALYSIS

Advancements in the use of Artificial Intelligence (AI) for medical image analysis have spurred the deployment of Machine Learning (ML) and Deep Learning (DL) AI systems in clinical settings around the world. This revolution in AI methods applied to medical image analysis provides modern tools to extract clinical intelligence from data generated in the course of care delivery. Such tools can thus assist clinicians in the detection and diagnosis of disease in medical images, and more generally improve patient outcomes. Built on the investment in large systems and technology, an open-source, cloud-based AI framework is presented to enable real-time medical image analysis. A collection of deployed clinical AI systems in production with care delivery partner sites is discussed along with a description of a closed-loop AI system that actively learns from human inspection of AI-generated predictions in production.

To facilitate the creation and collaborative use of AI systems at a larger scale with diverse partners, a cloud-based AI system is presented. Herein is described the design, architecture, and all of the major components of the system, along with the technical details for building a unified medical image analysis ecosystem for the adoption and collaboration on AI systems. The central elements of the cloud-based AI system, including the data processing pipelines, standard model architecture designs, and ML frameworks that span the whole lifecycle of AI systems, starting from data ingest, pre-processing, training, and inference deployment in the cloud. Technologies such as workflow engines, Feature Store, and pipelines built on it that help manage and optimize the whole AI system in the cloud are also detailed.

To enable a large-scale inspection of the AI system predictions and accelerate the real-world testing of AI methods, a collaborative data labeling platform built on a cloud-based serverless architecture with effective sampling strategies and practical usage policies was constructed. To ensure the confidentiality, usability, and performance of sensitive medical imaging data for AI development, an ML-optimized cloud-based data lakehouse architecture was proposed and extensively deployed at Stanford AI for Health. A research lab that bridges the broad domain of medical applications and AI technologies was also established to augment and broaden the training data and refined model parameters for higher classification performance.

4.1. Image Acquisition Techniques

There are various acquisition techniques to obtain the images seen in the previous section. Fundus photography is currently the gold standard, with some manufacturers providing good-quality color or near-infrared fundus cameras. Modern devices also provide image quality metrics, which are becoming increasingly useful as they are the object of post-acquisition real-time on-device analyses by AIs. Analog devices provide a clear and uniform image, but require an additional filter or LED source to present the acquired image in grayscale or for fluorescence angiography images. Optical coherence tomography (OCT) is also rapidly evolving, with the recent introduction of swept-source OCT systems pushing the anterior segment imaging capability to the mm scale. Other still immature systems of imaging include ultrasound, ultrahigh field imaging, or near-infrared spectroscopy.

Eye-tracking devices are of utmost importance for ensuring proper eye fixation during image acquisition. All devices currently on the market rely on slightly modified and existing general purpose eye-tracking systems. This seems to become the standard approach in the field, as neural networks are currently very good at finding pupils and gaze points in images. As such, proper fixation and eye movement consideration on fundus imaging during acquisition have been all but solved. For devices with short working distance, i.e. for those images presenting the angle, retina, or the optic nerve surface, eye tracking cannot rely solely on the pupil and gaze signature, due to occlusions and small structures.

Previous attempts at image enhancement from other domains have relied on a subgroup of the parameters affecting image quality. While blurry and noisy images are taken and enhanced with CNNs or generative adversarial networks, in ophthalmic imaging a plethora of different cameras at different tightness points may be examined. This intrinsic variability is usually not handled from an ownership or user standpoint. Well calibrated internal parameters provide better organized search royalties on lawful enhancement results, but corner cases will always exist. For sale prices of 10,000€ on fundus cameras, or the introduction of point-source fundus attachment adapters for 300€ smartphones, no technique should remain hidden behind a customer or business specific operating system.

4.2. Data Processing Methods

As large amounts of imaging data are acquired daily at institutions around the world, researchers interested in processing this data to derive information that can aid in improved diagnostics, triage, or patient care delivery are requesting these data for offsite analysis with Artificial Intelligence- (AI) driven approaches. However, to satisfy Health Insurance Portability and Accountability Act (HIPAA) and other privacy guidelines, imaging data need to undergo de-identification prior to being released from a Data Center. With the increase in AI-driven approaches, researchers are requesting unprecedented volumes of medical imaging data which far exceed the capacity of traditional on-premise client-server approaches for making the data research analysis-ready. Consequently, cloud-based solutions that can serve the kind of specialized scalable data preparation processing workloads that are in high demand by the imaging research community are needed.

The first step in this processing workflow is identifying imaging studies that meet scientific need and eligibility criteria. When imaging studies are identified for research use, the anonymization software retrieves and de-identifies the images from the clinical archive. As this software runs on an older server and on smaller data volumes, the rejection rate of candidate studies will soon surpass the processing capability of the existing infrastructure. This scenario presents the opportunity to develop a cloud-native scalable processing workload for off-site de-identification of studies selected for research via the Data Core.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

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The next section describes a flexible solution for on-demand de-identification that combines the use of mature software technologies with modern cloud-based distributed computing techniques to enable faster turnaround in medical imaging research.

AI in medicine is defined as any system that is able to perform a task that requires human intelligence. AI is being implemented in radiology departments globally to assist radiologists in the arduous task of analyzing and interpreting medical imaging. With the variety of models available and rapid advancements in AI, developing an AI application to handle medical imaging data is now possible; however, it requires a long process of proper fine-tuning and resolution of technical issues. AI algorithms are divided into image analysis, which focuses purely on generating a classification for a specific target to aid in diagnosis, and image generation, where models generate modeling data that restructure or enrich the input images.

V. INTEGRATION OF AI AND CLOUD TECHNOLOGIES

Technological advancements, the ubiquitous availability of Internet services, and the prevalence of wireless communication have changed the lives of billions of people on Earth. Nevertheless, health issues are still one of the largest concerns for almost all governmental organizations and officials in every country. To monitor health status, profiling physical activity, or more generally to better manage any chronic health issues, it is essential to employ innovative and intelligent solutions that can help upgrade the health device with recognition capabilities and provide early warning or alert situations. Intelligent health analysis platforms can analyze data and provide diagnostic results for European patients. Healthcare systems can be supported by cutting-edge intelligent cloud services.

Deep Learning (DL) is a subfield of AI that is being extensively researched and applied in a wide range of domains to analyze images and/or data. In healthcare, DL has drawn particular interest in recent years. It is a more sophisticated subset of AI, consisting of algorithms that endeavor to emulate brain functioning. By analyzing large amounts of training data, such as medical imaging or patient information, DL networks can be developed and trained to identify, classify, and diagnose diseases, propose therapies, and customize treatments and care. To develop these networks, comprehensive and complex mathematical modeling is involved to fully describe the problem domain as well as to create best-fitting architectures with a considerable amount of hyperparameters.

To automatically analyze the provided medical images, a modification of a deep CNN-based architecture that can support the fog computing paradigm is introduced. The proposed architecture can be configured into one of three types to enhance efficiency and reduce costs while maintaining high accuracy in COVID-19 detection. A curated dataset of X-ray images was also compiled. The proposed architecture was deployed and evaluated on various deployment types with different configurations including fog, edge, and cloud. It obtained high accuracy on the test set across all configurations, ensuring that further enhancements and additions to the architecture would not impede the rapid performance required for medical applications.

5.1. Architecture of Cloud-Based AI Systems

Cloud-based systems for AI in medical imaging rely on three main components: the cloud service provider, organizations subscribing to the cloud computing services, and the local AI system integrating AI techniques with other computing and networking technologies. Various cloud providers of AI services are available, offering a range of services such as AI platforms, infrastructure, and applications. In healthcare organizations, cloud-based AI services can promote AI development and deployment without hardware costs. Cloud-based AI systems for medical imaging typically involve the following tasks: (1) uploading data to the cloud and collating it, including necessary pre-processing; (2) exporting AI training process data to the cloud, training AI models using the enriched cloud data, and conducting hyper-parameter search; and (3) using its own data to evaluate the accuracy of the AI models adapted from the cloud and preparing post-report files for cloud diagnosis purposes.

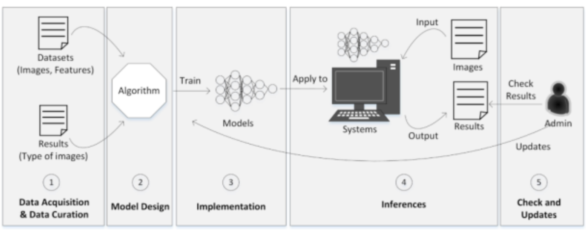

Fig 3: Architecture of Cloud-Based AI Systems.

DOI: 10.17148/IJARCCE.2022.111252

Cloud-based AI applications for medical imaging use widely distributed resources to support a massive number of medical imaging devices and healthcare organizations. They offer comprehensive services, such as collecting healthcare images, pre-processing the images for AI inference, exploring and developing AI systems for early diagnosis, maintaining AI systems for continuous monitoring, and promoting health image/factor-sharing data. Recently, many innovations have been explored to provide cloud-based AI applications for public health. Several systems for cloud-based detection, diagnosis, and segmentation of COVID-19 from lung images were proposed. Some were remotely used to deliver AI-enabled diagnostic services using a pre-trained COVID-19 image diagnostic model. Some initiatives focused on developing general AI diagnostic models for COVID-19 images using publicly available massive data. A recent effort was made to explore the applications of healthcare datasets by artificial intelligence researchers to diagnose viral infections from lung images of patients potentially infected with COVID-19.

5.2. Data Management in the Cloud

Despite the apparent ease of use and accessibility of cloud providers, they are not considered the best option for all medical imaging repositories, especially for small centers, or in whole countries when a national repository is the objective. This chapter aims to present a general architecture for a particular instance of a cloud-based medical imaging repository; it will try to describe the operative functions that have to be supported and the interactions between the entities involved. A messaging solution in Python is used to integrate with a secure cloud provider, preserving the patients' privacy in all stages of the full data management process. The evaluation results prove that the system can be implemented without any noticeable delays.

Overall, a cloud repository solution for a medical imaging information system using efficient connectivity to a secure cloud provider is described. The proposed architecture acknowledges the heterogeneous environment and the particular operative procedures of imaging centers and patients, has been tested under real operation conditions and fulfills all the requirements of a national medical imaging information system in a secure way. It does not rely on an exclusive or expensive technology and can be used with any conventional database without introducing modifications at the application level. Future work will focus on porting the system to a virtual machine in the secure cloud.

Historically, medical imaging repositories have been supported by indoor infrastructures. Usually, departments or imaging modalities have dedicated servers and storage, resulting in a high redundancy of medical diagnostic information, dispersed information and availability, serious safety issues, and inaccessible data pictures. Those processes have to be carried on, for example, when computer storage is fully allocated, when some physical failures affect the servers, or because of inopportune matters such as imaging center closure or changes in the network infrastructure. Data access and storage efficiency for affordable big data management is a current task under investigation, profoundly impacting health institutions and patients' health.

VI. CLINICAL APPLICATIONS

AI integration into health agencies can be facilitated through automated pipelines for medical imaging data acquisition, monitoring, retrieval and processing. Clinical AI systems can retrieve, monitor and process medical imaging data in real time by significantly reducing latency in their retrieval and processing in acquired form. Medical imaging data can be uncoupled from attribution of protected health information to allow integration with existing health-care systems and AI models for near-real-time processing. Once processed with an AI model, imaging findings can be conveyed to users through existing health-care infrastructure. Automated workflow pipelines that connect with hospital picture archiving and communications systems can be deployed to facilitate clinical AI and health-care delivery, benefitting both health-care institutions and end-users in the clinical setting.

The challenges and solutions for the classes of automated workflow pipelines to better facilitate end-user access to AI-enhanced imaging findings in the clinical setting have been delineated. While these solutions can add almost no burden to the sources of the medical imaging data, they can enable timely and thorough access to processed imaging findings by end-users who would otherwise have little or no access. The automation of secondary workflow functions should be prioritized to ensure timely and thorough access for end-users who need them most while minimizing the burden of novel system integration on health-care institutions. Custom-made solutions can bring end-users of AI models much of their benefit by enabling access while efficiently routing around their burden of system integration.

6.1. Radiology

Artificial intelligence (AI) technology is continuously evolving with the main purpose being to help view large amounts of data and provide rapid clinical decision support. There are two major categories of AI applications: those requiring prior system training via examples and those needing to be modified according to rules. In medical imaging practice, AI

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DOI: 10.17148/IJARCCE.2022.111252

improvement is being rapidly integrated into radiological workflows. AI-aided products that help detect, assess, and track are now commercially available on the market. The audience of this section will be both deep learning practitioners in radiology centers and imaging AI vendors developing products.

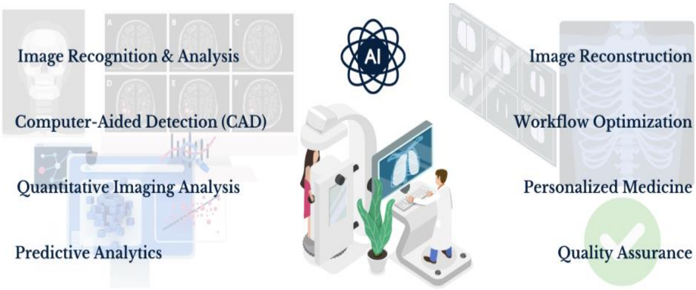

Fig 4:AI in Radiology.

In addition to the workflow components, a few research topics concerning integration for deep learning are discussed. The major parts of the deep learning literature are also briefly examined. AI is set to be routinely utilized to automatically detect anomalies in the medical images. The trained AI model would classify each detected ROI according to severity. In the case of positivity for a serious anomaly, a rapid communication path to specific radiologists with proper credentialing and a loud alerting method would be activated. By the introduction of AI-aided severity scoring in medical imaging centers, it would be possible to identify anomalies that would require very rapid intervention.

6.2. Pathology

In pathologic practice, after proper fixation, tissue specimens are micro sectioned into thin slices to prepare permanent histological sections, stained, and glued onto glass slides. Most pathology samples undergo morphological and microscopic examination with the aid of an optical microscope. In recent years, with improvements in optical microscopes and imaging systems, digitized whole-slide images (WSIs) of glass slides have become indispensable for clinical pathology. Pathologists can observe and analyze high-resolution glass slides and WSI images viewed under a microscope remotely. In addition, telepathology and information technology management systems are favored to establish a cloud-based digital pathology diagnosis system. One advantage of digital pathology is a highly accurate digital diagnosis with artificial intelligence (AI) algorithms. Some studies employed deep learning to detect and diagnose cancer from WSI pathology slide images automatically and applied AI methods to classify the WSI whole slide into several disease categories.

Most studies employed multi-center datasets to enhance feature generalization based on different acquisition equipment settings, and reported that a certain amount of target center data was needed to well-apply its algorithm to some untested data. However, they used a training set containing data from several centers to train their classification model. Recent studies reported a rapid system for detecting and classifying histopathological images into several disease categories. A few studies employed deep learning models to detect only invasive carcinoma (IC) from the WSIs. One reported a two-stage visual transformer method for breast cancer detection on WSI images and a one-stage Cascade Mask R-CNN model for breast cancer image detection in pathology images. Most studies on WSI histopathological images, however, focused on breast cancer detection in the cascade system. They constructed a one-stage deep learning model to detect the location of invasive carcinoma only with certain data from its target center effectively, irrespective of the acquired equipment and institute. The proposed model may help pathologists make a more accurate and faster diagnosis and postoperative treatment planning.

6.3. Cardiology

Cardiac imaging plays an important role in the diagnosis of cardiovascular disease (CVD). Heart disease remains the leading cause of death globally; thus, early diagnosis is crucial. Imaging techniques, including cardiac ultrasound, cardiac magnetic resonance (CMR), computed tomography (CT), and nuclear medicine, are used to diagnose heart disease, as they allow for the assessment of its structure, perfusion, and function. Machine learning (ML) has been widely used in cardiac imaging. However, its role has been limited to visual and quantitative assessment of cardiac structure and function. It consisted primarily of detection, classification, and quantitative measurement of anatomical structures and cardiac function, mainly relying on hand-crafted features. However, with the advent of big data and machine learning, new opportunities are emerging to build artificial intelligence tools that will directly assist the clinician in the diagnosis of CVDs. It is crucial to create a new paradigm that allows cardiologists to utilize computer-aided detection (CAD) systems to guide them to focus on informative areas on the image and eventually increase diagnostic accuracy while lowering interpretation time.

Keeping pace with other imaging modalities, recent advances in machine learning, especially deep learning, are opening new avenues in the analysis of CMR images of various applications. Cardiac MRI is an emerging standard for noninvasive assessment of cardiac diseases. CMR is a valuable diagnostic and prognostic tool, as it provides diagnostic and prognostic values in a broad spectrum of clinically relevant outcomes of CVD. The primary role of machine learning is to enhance clinical workflows by integrating procedural, analysis, and diagnostic components to improve overall care efficiency. Automation of each of these components increases the efficiency of clinical workflows. Optimizing image acquisition to reduce scan times and improve image quality is enabled through motion and contrast enhancement and process automation. To this end, deep learning methods trained on data collected during routine clinical actions may provide fast, low-cost, and effective solutions in an otherwise complicated environment. A promising trend is to exploit high-resolution data as prior information to guide raw data reconstruction from indirect observations. With a higher computational burden, these ML techniques have shown great promise in improving time-critical applications by substantially reducing computed times, like spectral estimates and imaging.

VII. CASE STUDIES

The rapid advances in medical imaging Artificial Intelligence (AI) offer unprecedented opportunities for automatic analysis and extraction of data from large imaging collections. Investing in cloud computing provides the most economical access and extreme scalability. The feasibility of performing large-scale imaging analysis using AI methods on cloud-provisioned compute resources was investigated. The AI-based curation of the National Lung Screening Trial (NLST) Computed Tomography (CT) images served as a motivating example. The cloud platform evaluated is the one available as part of the . The wide range of imaging analysis tasks targeted include: 1) automatic anatomic image segmentation; 2) automatic extraction of radiomics features characterizing the segmented structures. The large cohort of >126,000 CT volumes from >26,000 patients makes it impractical to run these analyses on a single workstation; however, the use of large numbers of compute resources can make such investigations feasible. Using a total of >21,000 Virtual Machines (VMs) we completed the analysis in under 9 hours, as compared to the estimated 522 days needed on a single workstation. A careful evaluation of numerous tradeoffs towards optimizing the use of cloud resources for large-scale image analysis is presented. Alongside architectural details of the analysis, open source implementation of the developed workflows, and practical recommendations for utilizing the cloud for large-scale medical image computing tasks are also shared. The output of this analysis, a total of 9,565,554 segmentations of the anatomic structures and the accompanying radiomics features is made publicly available.

Stress on the importance of timely and accurate diagnosis of Coronary Artery Disease (CAD). Shortcomings of conventional imaging methods and the quest for a viable alternative in Magnetic Resonance Imaging (MRI) or Cardiac Magnetic Resonance (CMR) are discussed. Current automated CAD detection methods and challenges posed by real-time implementation on low-power mobile devices are illustrated. The need for a multidisciplinary approach consisting of collaboration between domain experts, data scientists, and hardware engineers are highlighted to overcome the challenges. Since deep Convolutional Neural Network (CNN) models have yielded state of the art achievements in addressing computer vision challenges, a recent effort to design a lightweight CNN model for real-time implementation as a classifier is described. The proposed lightweight CNN provides a viable solution for real-time CAD detection in connected healthcare settings, despite the reduction in computational requirements. By optimizing the model's architecture and parameters, an optimal balance between computational efficiency and classification accuracy is targeted. The performance of the lightweight model is thoroughly analyzed, demonstrating its potential to improve the deployment of AI systems in resource constrained environments.

Equ 2: Dice Coefficient (Segmentation Accuracy).

$$\text{Dice} = \frac{2|A \cap B|}{|A| + |B|}$$

- A: Ground truth segmentation
- B: Predicted segmentation

7.1. Successful Implementations

The proposed cloud-based solution for COVID-19 detection is demonstrated in a public cloud environment that uses a dataset gathered from various worldwide databases. The demonstration comprises a multi-workflow streaming system that integrates smart devices and fog nodes that route the inputs to the proposed cloud service. It should be noted that the CNN model is trained and utilized as the core of the method. However, the running time associated with a different model is different. The selection of the architecture depends on the dataset and analysis needed.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 7.918 ⁜ Vol. 11, Issue 12, December 2022

DOI: 10.17148/IJARCCE.2022.111252

Success in imaging-based applications is often framed in terms of human image-based perception, as physicians are trained to conduct interpretation and diagnosis based on imaging datasets. As AI-based tools are being introduced to augment and assist image-based analysis and interpretation tasks, the role of imaging-based decision-making has evolved from being exclusive to the subjective/clinical domain to becoming a multi-participant and sophisticated analytics process. One aspect of this evolution is the introduction of a cloud-based solution for efficient on-demand data management and processing. A cloud-based solution for large-scale medical imaging data management and analysis is suggested, focusing on system design and development rather than specific tools and services. The proposed architecture and system benefits and limitations of this design in real-world situations are discussed.

New large-scale public and affordable data resources are introduced to augment conventional imaging studies that commonly focus on small cohorts collected in laboratory conditions. Monitoring systems, mobile devices, and other sources have been developed to collect continuous long-term imaging monitoring. Once data is collected, providing immediate usability and interpretability can greatly improve the predictive capability and credibility of the proposed AI systems. Recent advances in medical imaging AI have raised the prospect of automatic analysis of and data extraction from large imaging collections. In cloud-based AI systems, numerous image-based or multi-model AI tools have been developed to curate raw imaging datasets through standard image analysis pipelines for real-world usability.

7.2. Lessons Learned

In designing a deployable cloud-based pipeline for real-time medical imaging analysis and diagnostics, several important lessons learned include, but are not limited to the following. First, although 2D medical images were chosen intentionally due to their relatively small dimensionality and simplicity of architecture, ML systems still require an extensive parameter grid search for optimal performance. Each network architecture had over ten hyperparameters to optimise. Unfortunately, this can be extremely arduous, requiring long run times for hyperparameter tuning, especially on restricted hardware. Therefore, setting a proper baseline candidate model with default hyperparameters initially would be helpful. Then this baseline model can be used to incrementally tune the most significant hyperparameters for improved performance, perhaps beginning with architectural hyperparameters such as learning rate, kernel size, and strides. Finally, in addition to model architecture, categorical and context-based hyperparameters should also be explored carefully, such as whether to cut-off regions as background image tiles, and the sizing and shape of input images.

Model performance degradation post-deployment can often occur due to distribution shifts between training and validation/test frames. For such situations, it may be advantageous to engineer the training set to include a family of perturbations on the validation set. In this pipeline case, a follow-up study on pre-training models on a large dataset of orthogonal images was conducted to improve performance; however, it caused domain shift problems in some cases. Besides better anticipating performance degradation when generalising to unseen data, it may be helpful to discuss qualitatively with domain experts the important features the model is expected to focus on. This exercise could help in developing interpretable models and a clearer understanding of the inference process, detecting artefacts, and debugging them on erroneous inferences.

Another related lesson learned is that developing a robust, deployable machine learning system is tedious and involves navigating various technical and computational issues for every pipeline component. Not only does one need a reliable data source with high-quality labels, adequate harmonisation, and production-level preventative safeguards, but also adequate benchmarking and evaluation frameworks incorporating diverse quantitative metrics, ease of testing, and adaptable thresholds for actionable inferences. Therefore, it may be more efficient to suggest pre-defined codes and folders on a repository website containing such computational codes, components, and templates. Such a platform would also benefit major healthcare stakeholders, including clinicians and other proponents, by providing an avenue for code donation or collaboration.

VIII. FUTURE TRENDS

The rapid proliferation of extremely-low-latency cloud infrastructure has made it possible to scale web-based applications and hyperparameter tuning of machine/deep learning models. Increasingly real-time medical imaging analysis and diagnostics systems will be scalable across multiple cloud providers, empowering facilities to process thousands of imaging tests daily for decision support. Important optimizations will include improved test batching strategies or video streaming implementations for real-time scanning. Research systems will also become increasingly multi-modal, combining AI systems for processing text, images, videos or other signals. In particular, many open-source approaches exist for performing brain detect or object detection using single-photon light detection to cooperate cameras, cameras with laser scanning, or dual-structured illumination microscopy.

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified ⁜ Impact Factor 7.918 ⁜ Vol. 11, Issue 12, December 2022
DOI: 10.17148/IJARCCE.2022.111252

The natural evolution for research medical imaging is AI-assisted imaging, where the AI system models uncertainties to display informative imaging with adjustable trade-offs between artefacts and noise. Multi-modal always-on real-world audio-visual eye-tracking with a bearable form factor can already infer the populations of attention states. In addition to being computer vision-based diagnostics, various concepts to release biomarker information for pregnancy or other conditions using deep understanding of proximity to sensors are present or adopted in low-cost prover devices. Such devices would not be pre-trained with transfer learning but should instead be able to learn from end-users, e.g. to detect new states using little data through normalization of latent event embeddings or deep reinforcement learning to hypothesize reflected state space. Devices would not be mass-produced, instead, companies would purchase IP as license and assemble low-cost systems in distributed factories with regenerative environmentally friendly materials.

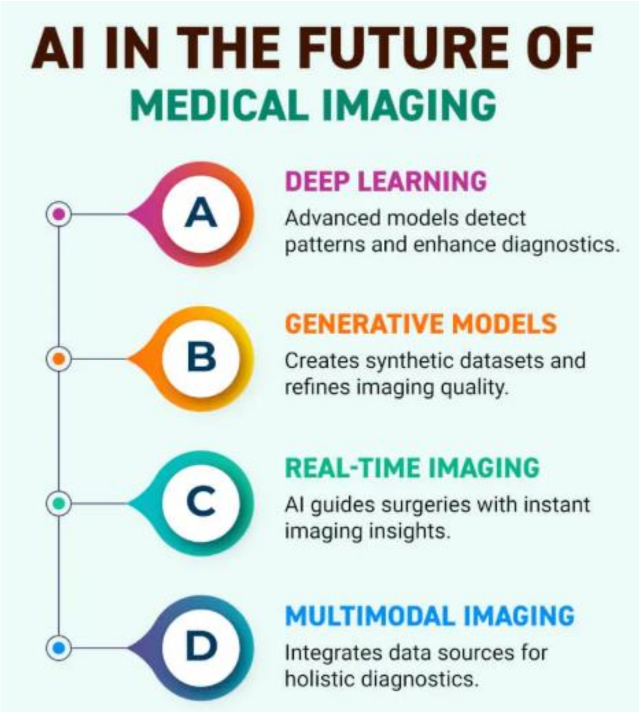

Fig 5: Future of AI in Medical Imaging.

Aggressive standardization of low-cost deep learning medical imaging power outlets or satisfaction levels with serial events of sequential remote medical instruments, user-experience optimizations with standard UI/UX libraries also empower too cheaper and safer task-agnostic low-latency optimal detection, attention aberrant states in human visual searches using eye-gaze heat-map modelling or cloud initiatives to enable designing tech that promotes affordable and safe algorithmic decision-making. Options to fall-back either to initial health data sources or aggregated data from other organizations using standardized representations of instrument limitations empower systemic health paradigms to not use any privacy and safety-law circumvented governance models for deep learning search engines or marketplaces, combining the strengths of extensive databases and task-agnostic models in R&D with better interpretations and much-reduced systemic biases.

8.1. Advancements in AI Technologies

The COVID-19 pandemic placed extraordinary stress on a healthcare system that was already being pushed past its breaking point, and it spurred the global adoption of telehealth platforms for remote visits. In ICU domains worldwide, an extensive drive towards AI tools has been initiated, and the levels of these tools' integration into current workflows varies widely, from basic visualization to fully integrated solutions. AI applications have been developed with focus on every aspect of the workflow, from proprietary devices that not only image the patient with a chest X-ray but also analyze it with integrated AI tools, to solutions which recommend playlists of existing, free-standing imaging and decision-support apps which the user has to search for and launch manually. Cloud-hailing solutions are on the rise, enabling hospitals without adequate hardware or infrastructure to join the AI revolution by deploying scalable applications on low-end devices. Therefore, unattended processing of data from PACS systems in near-real-time settings, on viewing-workstation-level solutions which make the same raw data available to all devices in a single-click-accessible format, are needed to complement these offerings.

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified ⁙ Impact Factor 7.918 ⁙ Vol. 11, Issue 12, December 2022
DOI: 10.17148/IJARCCE.2022.111252

Interpretation needs to be guided by the current tasks, and traversing a view to be dissected to get the pertinent imaging information frictionlessly is deemed vital for understanding. Just as digital phones brought myriad imaging possibilities, AI will usher in an era of targeted interpretation, and the future of diagnostics and research lies with the processing chain disentangling imaging and reporting. Additionally, cloud-hailing AI techniques can be used for archival which will alter the understanding of older imaging datasets.

Traditional PACS systems archive images along with identifiers connecting the digitized images with the institution's data, and vague natural language descriptions were made to manually archive ultrasound data. One cloud-hailing system was able to automatically interpret previously unseen ultrasound scans from unforeseen devices within a single clinic. It was noted that after a single cloud-based contact with the AI, all subsequent hospital-based inquiries of stored ultrasound images became interpretable via the cloud and historic cases were flocked to its interpretation horizon. Therefore, PACS archives could be easily cleaned up and every intelligent system would have access to commodity databases.

8.2. Evolving Cloud Infrastructure

Healthcare services tend to almost entirely depend on documentation enigmas. Therefore, data collection and representation methods should comply with the highest standards to remove bloatedness and enhance the quantity of knowledge exhibited. Because data enters exaggerated reality to satisfy business requirements, the domain of data should undergo cleansing and scrubbing prior to computable representation. Evolving patterns and technologies in data warehousing and mining endorse the incompleteness and inconsistency issues and offer services on holistic data access in a uniformity paradigm.

Cohesion describes how closely related and focused the tasks are within a component. Components with low cohesion perform a variety of tasks that are only loosely related. Tight cohesion within a component is desirable. Coupling describes the level of interdependence among the modules in a software system.

The term is used in two senses. Importantly, it can convey either the explicit result of coupling techniques used during implementation or the potential for interaction based on the architecture. Natural strategies for coupling components exist. As preferred rules of thumb, one-way coupling dependencies are preferred, and two-way couplings with shared global variables, data stores, or files are avoided. Weak/declarative couplings are preferred over strong/implementation couplings. The latter ruins component reusability and reconfiguration, as component internals must be revamped when reconfiguring or reusing off-the-shelf components. Techniques for analyzing coupling strengths and also for controlling them exist.

IX. CHALLENGES IN IMPLEMENTATION

This article reviews the rising possibilities of cloud-based systems for medical imaging and diagnostics, particularly those that employ artificial intelligence for real-time analysis of patient studies. Possible solutions for deployment of AI-based tools in the medical imaging domain, such as secure cloud architecture and federated learning, are identified and discussed. Prior to implementation, challenges associated with integration of such systems in healthcare environments, such as regulatory barriers, need for robust real-world validation and quality assurance to ensure safety and efficacy, are described.

Evaluating next generation medical technologies in clinical practice, such as cloud-based systems for medical imaging and diagnostics, is fraught with challenges. Established medical technologies must ensure safety, efficacy and accuracy, and regulatory bodies monitor this 'pre-market' validation. Other hurdles include stakeholder buy-in, integration with existing workflow and IT architecture, and careful consideration of cost-benefit analysis. However, healthcare's transmissible nature and consequent liability make it difficult for many technologies – even those deemed safe and efficacious – to enter clinical practice.

The clear advantages of AI-based tools in medical imaging, from mere augmentation to assistance to automation to replacement, make addressing these challenges necessary. This is why a new study to explore the legal and ethical challenges involved in the deployment of AI-based systems for automated medical imaging and diagnostics was created. New technology implementation is usually preceded by consideration of these challenges, but not sufficiently so for AI systems. Failure to adequately integrate AI systems into the environment, possible bias stemming from 'black box' algorithms are all areas warranting further investigation. Friends of the first author involved in the healthcare space were consulted to define the issue of 'implementation priorities', and description of AI systems followed.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁂ Impact Factor 7.918 ⁂ Vol. 11, Issue 12, December 2022

DOI: 10.17148/IJARCCE.2022.111252

Equ 3: Inference Latency in Cloud AI Systems.

$$T_{\text{total}} = T_{\text{upload}} + T_{\text{compute}} + T_{\text{download}}$$

- T_{upload}: Time to send image to cloud
- T_{compute}: Processing time (AI model inference)
- T_{download}: Time to receive results

9.1. Technical Barriers

Despite the significant promise it holds, the implementation of AI solutions in the field of breast imaging diagnosis is hindered by numerous technical barriers, with data accessibility and quality being the foremost concerns. In order to develop an AI model, a considerable amount of high-quality data is preferred to effectively train the algorithm for maximal performance. However, such data is not always readily available, for multiple reasons. The governance under which imaging datasets are made available differs across countries, and in many cases sharing sensitive data such as mammograms is not possible, due to legislation. Furthermore, many hospitals do not have robust picture archiving and communication systems, and thus even if data can be shared, it may not be in a suitable standardized form usable for research. Such technical limitations ultimately lead to a shortage of AI algorithm development towards these modalities.

Another technical barrier is the constraint for data quality. Even when sufficient data is collected for training the model, it is vital that the data is of sufficient quality. The grading of data quality can differ from one institution to another, leading to a biased model. For instance, the same image of an MG may be of diagnostic quality in one hospital but ultimately deemed insufficient in another institution which expects optimal high-quality image acquisition. Simply put, if training data is of low quality, the model may not be guaranteed to yield optimal results. The great need for data quality and quantity thus constitutes a technical disadvantage for the development of AI algorithms for the imaging modalities. AI algorithms for the detection of breast cancer will show clinical and safety benefits over existing technological solutions. Nonetheless, a lack of understanding between developers and consumers currently poses a barrier. Organizations are currently in the process of constructing a detailed blueprint based on existing examples to ensure that submitted algorithms are in a suitable format for understanding the proposed AI-based solution. However, how such documents can be generated while also specifying requirements for algorithm performance still needs to be clarified. Questions such as whether measures of explainability are sufficient at this stage remain unanswered. AI approaches have been shown to outperform previous computer-aided detection systems, which were often based on traditional image processing and machine learning techniques. AI-based systems, which are, in essence, statistical models born from data, have been shown to offer superior detection performance.

9.2. Organizational Resistance

There is widespread research in the field of medical imaging and AI for the detection and characterization of pathologies. Projects aiming to develop machine learning algorithms are prepared using a rather automated engineering approach. However, many of those efforts fail as, by design, they are not viable for bringing a clinical application to life. This raises the broader question of how to bring research efforts to a state where they can usefully contribute towards supporting or augmenting clinical workflows, and what kind of systems requirements are most likely to encourage use and engage users rather than triggering organizational resistance. Radiologists have far more rules, regulations, and steps required for applying AI/ML than in all other cases of AI Research use. In searching for a platform where radiologists can accelerate their research efforts and develop an AI engine suitable for clinical use, creating a dish with half-cooked and incomplete components results in frustration and disillusionment. The major challenges with using existing platforms or pursuing another developmental route are considering data guidelines, patient privacy issues, the impossibility of searching for non-DICOM or non-PHI data, and the most critical issue of trust regarding the applicability and usefulness of AI/ML systems.

The best-designed systems take a limited approach to meet user needs. The design of such systems should already eliminate as much manual intervention as possible, so that human errors and effort are reduced to an absolute minimum. Machine learning is data-hungry. Curation of high-quality, machine-learning-ready data is a key design principle. Despite the tremendous growth of the amount of available data, tenders addressing this issue will find that it is strictly limited. The data mining and transformation for continuous handling by computer systems must, nevertheless, occur while retaining familiar workflows for radiologists. The architecture must run on hardware and infrastructure that makes sense in terms of ownership, cost, and scale. Well-designed systems will not fail silently to provide for the better, at times, industry-scale, need of forensics.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⋇ Impact Factor 7.918 ⋇ Vol. 11, Issue 12, December 2022

DOI: 10.17148/IJARCCE.2022.111252

X. CONCLUSION

Concurrent with the rapid growth of science and technology, several technologies are being integrated into existing systems to enhance their reliability and advance not only the appropriate medical fields but also the quality of life in both clinical and preclinical conditions. One of these technologies is artificial intelligence, which, in several applications, can replace other tools that are either hard to construct or not representing enough features to be compact and precise. Coupled with solutions such as data clouding and the emergence and popularization of numerous imaging modalities, AI integration can be considered a prime candidate for non-invasive analytics. On the other hand, using AI in this arena is in need of a great deal of attention to the convergence of several disciplines, which renders the task extremely difficult even with the appropriate building blocks in hand. One of the options to simplify the need for converting medical facilities into susceptible 'demand-driven' supporters of AI-based processing is to automate the ontogeny of the necessary processes via 'whole-pipe' solutions, which can integrate the uncovered tools and edge solutions seamlessly into the complete pipeline. In this form, it becomes easy to connect the strategies and use purpose-specific sub-pipes. Other building-block elements need additional consideration, among which are the choice of data preparation, congestion and handling of proper health record protection, model shielding, and user interfacing solution based on clinical construct.

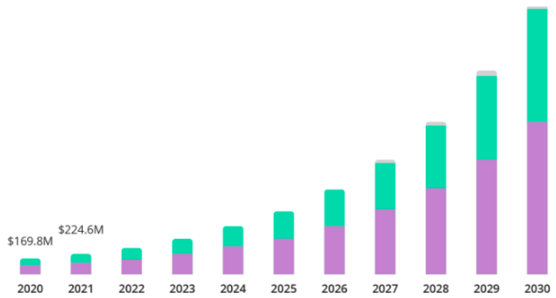

Fig 6: AI and Medical Imaging: Transforming Diagnosis & Care.

By solely focusing on the medical imaging width of this task, interference with the display knowledge of the existing cloud-based analysis solutions, which are mostly used for clinical diagnosis, some new tools have been developed. On the integration side, measures are being deployed not only to automate pre-and post-filtering tasks but also increase the convenience for busy hospital professionals by rendering wider accessibility owing to urgency and compatibility requirements. On the output side, a new automatic sharing tool coupled with sending contacts has been elaborated, enabling clinical users to easily send or share imaging insights with their peers. Inputting to health records is still on the ground floor, which must be addressed after the completion of the aforementioned toolboxes.

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IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 7.918 ⁜ Vol. 11, Issue 12, December 2022

DOI: 10.17148/IJARCCE.2022.111252

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