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Healthcare Utilizes AI in Developing Countries Rural Areas

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Abstract. Scientists and care providers are concentrating to artificial intelligence (AI) in the healthcare industry. It focuses on clinical decision-making, patient data and diagnostics, health services management, and predictive medicine. Deep learning, thinking, and other computing techniques that mimic human intelligence are commonly referred to as artificial intelligence (AI). Adaptation, participation, and sensory comprehension. This paper presents entire analysis of Artificial Intelligence with applications related with health care.

Keywords: ***Artificial Intelligence, Medicines, Healthcare, Computer vision***

1. Introduction.

Deep learning is mostly used in AI applications for image diagnostics. The simplest way for software engineers to obtain information about the latest deep learning technique is to survey the CV field [1]. The major conferences in the globe for computer vision (CV) education are the European Conference on Computer Vision (ECCV), the World Congress on Computer Vision (ICCV), and the Compute Vision and Pattern Recognition (CVPR) [2]. Artificial intelligence (AI) is a broad term for computing innovations that mimic human intelligence's supporting systems, including cognition, deep learning, engagement, adaptation, and sensory perception. The COVID-19 pandemic has generated a compelling a need quick, widespread, reliable, and reasonably priced testing because lung imaging is an essential adjunctive tool in the detection and treatment of the illness. According to the American College of Radiology and the Fleischner Society Consensus Statement, imaging for COVID-19 is advised in cases of worsening respiratory symptoms and, in settings with constrained resources, for the triage of patients with moderate-to-severe clinical features and a high probability of disease. There are two main duties here [3]. In clinical scenarios where a false negative RT-PCR result is suspected, the first step is diagnosis, including incidental diagnosis and presenting supporting evidence. expected prognosis

In the framework of COVID-195,6,7, the field of AI in MI is expanding, and expectations are strong that AI will assist radiologists and clinicians in their work.

2. Diagnostic imaging levels of AI automation.

If AI in diagnostic testing also uses equivalent criteria during the development and evaluation processes, it will be helpful as a comparison. The National Highway Traffic Safety Administration (NHTSA) categorized robotics into five levels shown in fig.1 to help people better understand the level of autonomy in automated driving. Levels 0 through 4 of AI automation in diagnostic radiology have been derived[4]. Level 0 is further divided into two categories: AI-assisted image processing (level 0+) and manual image processing (level 0). Recent advances in artificial intelligence (level 0+)-based image preprocessing utilizing GAN for synthetic imaging have been made quickly. Level 1 is the use of a computer to aid with only one type of picture recognition, such as the detection of lung nodules in a chest CT. Level 2 involves complex image recognition at several locations, including lesions on the liver, pneumonia, and lung nodules. Diagnostic imaging capabilities are Level 3.comparable to humans. The diagnostic imaging is at Level 4.abilities not found in humans. Table 1. Given the Frequency of AI techniques when several techniques were used

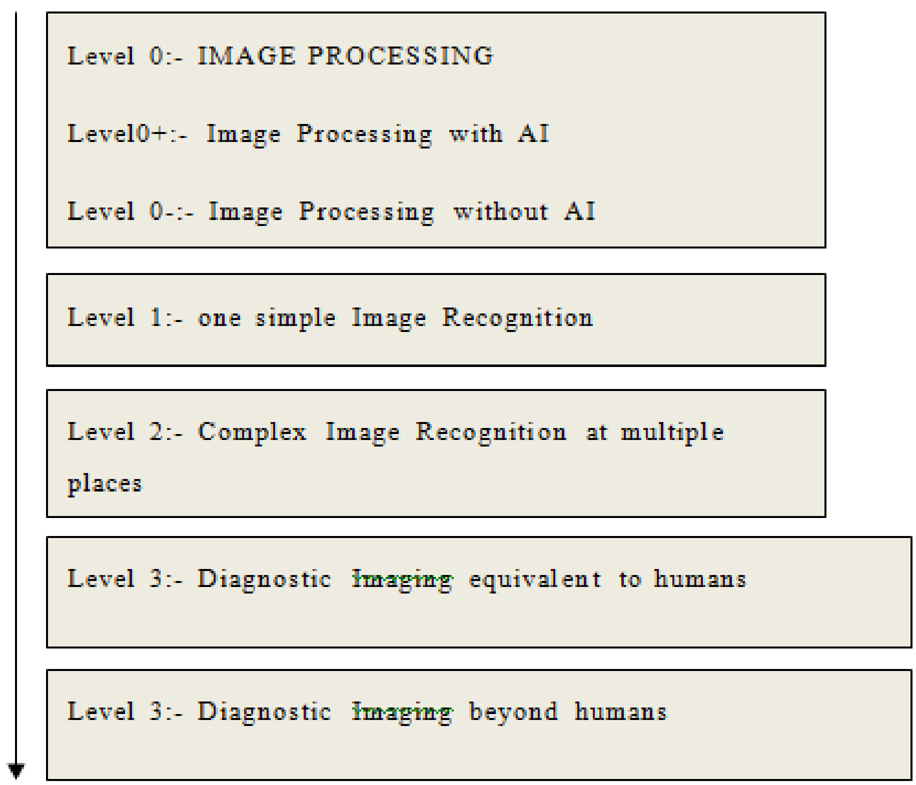

Fig.1. Diagnostic imaging levels of AI automation

Table 1. Frequency of AI techniques when several techniques were used

AI methods used in several Methods	Frequency (%)
Fuzzy Logic	2
Machine Learning	3
Knowledge base systems	5
Expert Systems	6
Total	16

3. A Perspective of Healthcare AI Technology for Developing Countries' Rural Areas

Given their specific circumstances, rural areas must have their own healthcare AI system. Here, we outline what the multilevel medical AI service network aspires to achieve [5-8].

3.1. Top level- Medical AI National Center Its aim is to coordinate country efforts to develop, promote, and upgrade healthcare AI systems while encouraging global cooperation. To make sure the success of this multilevel intelligent Healthcare network infrastructure, multi - party cooperation is necessary.

3.2. Middle level- County hospitals as well as state or provincial hospitals may develop regional medical AI support centers. The major responsibilities of these are to train primary health care providers, maintain, repair, and update, gather ,frontline medical AI systems and report epidemiological data from primary EHRs. To treat patients with serious and complex ailments, these institutions may also be furnished with specialized medical AI systems.

3.3 Basic Level - Frontline medical AI system: This system is intended for use in the most fundamental rural healthcare facilities, such as community or private clinics.

4. Collections of common image data for supervised methods.

Even as effective learning techniques have improved, transfer learning is a crucial tool for supervised learning of diagnostic medical imaging. Using medical images for radiological diagnostic AI training before oversight. Use of standard image data sets is important [9]**.**

4.1. Video annotation tool from Irvine, California (VATIC). VATIC is an active, free video summarizing tool that crowdsources financing through Amazon Mechanical Turk.

4.2.CoPhIR. To carry out comprehensive assessments of the scaling of the SAPIR organizational productivity utilized for pattern matching in audiovisual content, the Content-based Sem Image Retrieval (CoPhIR) test collection was developed. The data gathered so far is the nation's biggest collection of multimedia metadata that can be used to investigate scaled similarity search techniques. CoPhIR comprises.

4.3. Tiny Images Dataset. The Tiny Images collection, which consists of 79,302,017 images, each of which is a 32 32 color image, can be downloaded using the links on this page [10].

4.4. MNIST Database. The MNIST database of handwritten digits, which is accessed from this website, has 60,000 samples in the training set and 10,000 samples in the test set. 106 million completed images

4.5. MF2 and MegaFace. An image library of faces usually contains 5 million pictures. An median of seven photos are sent to each of the 700,000 participants. Additionally, information is given regarding the bounding box that surrounds the face.

5. Counter-measures

5.1. Financial Issue. The largest issue for developing nations has always been their sluggish economies, particularly in rural areas. Dalaba et al. looked into the costs associated with installing a computer-assisted clinical decision-support system in addition to just provide antenatal and birth care in Northern Ghana. They noticed a decline in the percentage of delivery difficulties and a drop in the number of actual deaths [12].

5.2. Technical Issue. A frontline rural clinic in many developing nations is likely to include a nurse with little experience working alongside a technician or paramedic with a 10th or 12th grade education. But almost all smart healthcare systems were created to help skilled healthcare practitioners. Therefore, it is imperative to have a user-friendly operating system that is tailored for the needs of the local rural health personnel. Voice recognition technology, for example, is an automatic and intelligent way to reduce workloads that is compatible with AI-related technologies.

5.3. Infrastructure Issue. Some rural communities lack access to electricity and/or the internet, have poor transit options, and have terrible environmental conditions. As a result, we must consider these concerns when developing the system.

5.4. Patient Provider Relationships. The use of medical AI-related technologies has been proposed in several reports, despite this. A variety of obstacles, mainly monetary ones, will stand in the way of the adoption of medical AI technology in developing nations' rural areas, although they are not intractable. (for instance, mCDSS using a tablet) could make client consultation less effective because the patient may overlook nonverbal cues while focusing. However, the majority of studies have revealed increases in patient and healthcare provider trust.

Conclusion. Artificial intelligence (AI), a fast evolving branch of computer science, is now being actively applied in the medical industry to enhance clinical work's professionalism and effectiveness while also reducing the risk of medical errors. The disparity between urban and rural health services is a critical issue in developing nations, and the lack of skilled healthcare professionals is a major contributor to the unavailability and poor quality of healthcare in rural areas.

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