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Revolutionizing Healthcare - Exploring the Transformative Power of Automation and AI

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Abstract: *In the pursuit of optimizing healthcare delivery and improving patient outcomes, the field of healthcare is undergoing a transformative shift from a reactive approach to a proactive one. This shift is facilitated by two upcoming technological developments: automation and artificial intelligence (AI). The abundance of data generated in the era of digital advancement presents both opportunities and challenges for healthcare. This paper explores the application of AI and machine learning in healthcare, focusing on the challenges posed by the exponential growth in data volume, the analysis of unstructured data, and the rapid pace of data refreshment. It examines the role of AI and machine learning in generating clinical decision support, uncovering disease subtypes and prognostic markers, and generating new hypotheses. In addition, this paper highlights the transformative potential of automation, AI, and robotics in healthcare, showcasing their ability to enhance efficiency, accuracy, and precision in patient care. By embracing these technological advancements, healthcare can achieve continuous progress in meeting the ever-growing demands and aspirations of the field while improving patient outcomes.*

Keywords: *automation, AI, healthcare, robotics*

1. Introduction

In the pursuit of continuous progress in enhancing our capacity to efficiently and effectively accomplish work tasks while minimizing redundant efforts and maximizing performance, which is a universal aspiration transcending generations and scientific disciplines, the field of healthcare is undergoing a transformative shift from a reactive approach to a proactive one [1]. This transformation is being facilitated by two upcoming technological developments: automation and artificial intelligence.

The era of digital advancement has brought forth a wealth of data, coupled with significant strides in computing power for data collection, storage, and connectivity. This abundance of data has unleashed immense potential for data exploitation, creating an unprecedented opportunity for innovation in the field of data science. As a result, the discourse surrounding artificial intelligence (AI), machine learning (ML), and automation has become highly intense.

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When we consider the application of these technologies in healthcare, three data aspects have sparked particular interest. Firstly, the exponential growth in data volume presents both opportunities and challenges. The vast amounts of data generated can create efficiencies, reduce costs, and generate ever larger and more complex datasets. Secondly, a substantial portion of the available healthcare data is unstructured, further complicating its analysis and utilization. This unstructured data includes medical notes, imaging reports, and other textual or visual data that require advanced algorithms to extract meaningful information. Lastly, the rapid pace at which data is refreshed poses significant hurdles to traditional statistical methodologies [2].

Artificial intelligence, as defined by Barr and Feigenbaum, encompasses the realm of computer science concerned with the design of systems that demonstrate characteristics associated with human intelligence and behavior. In the context of healthcare, artificial intelligence can leverage automation and machine learning to process and analyze vast amounts of data, generating clinical decision support, uncovering disease subtypes, associations, and prognostic markers, and generating new testable hypotheses [3]. Machine learning, on the other hand, empowers computers with the ability to learn without explicit programming, enabling them to adapt and improve their performance over time [4].

Automation, in the context of healthcare, refers to the delegation of tasks to machines or computer systems, alleviating procedural burdens [5]. By automating repetitive and time-consuming tasks, healthcare providers can focus more on patient care and complex decision-making processes, while ensuring efficiency and accuracy.

2. Work Processes, Technological Automation and Cutting-Edge Healthcare Delivery in the 21st Century

Healthcare in the 21st century encompasses intricate tasks and the management of vast amounts of data. The delivery of healthcare involves interconnected workflows encompassing clinical, administrative, and population-level processes [6]. These workflows involve various individuals such as patients, caregivers, clinicians, and staff, and are referred to as the sequence of tasks performed within and between work environments [7]. The digitization of paper-based workflows without proper adaptation has created an ecosystem that contributes to burnout and hinders the full utilization of technology for optimizing patient care through automation. Inefficient workflows pose a widespread challenge affecting everyone in healthcare, including clinicians burdened with caredelivery

tasks and patients and caregivers dealing with complex care management responsibilities.
The increasing adoption of health information technology (IT) and the availability of modern computational technology offer opportunities for more effective and efficient workflows through automation. Automation, which involves using technology to monitor and control the delivery of products and services, can enhance efficiency in healthcare delivery across different domains (Figure 1). However, healthcare has not fully embraced automation in the same way as other industries. Valuable insights can be gained from the application of automation in non-healthcare sectors, offering lessons that can be applied to healthcare [8].

Figure 1. Areas within healthcare that can be automated [9]

3. Use of DL and ML in Healthcare

The essential difference between deep learning (DL) and machine learning (ML) is the methodology they employ in their systems, the amount of data and the way it is structured. The mentioned differences are the exact reason for DL being more accurate than ML, whereby it is more commonly applied or used as a replacement for aged ML techniques in healthcare [10].
Addressing machine learning, the use of deep neural networks (DNN) has appeared to be of a desired interest, especially in radiology, for it is a branch of medicine primarily related to image diagnostics. Moreover, in computer-aided detection and diagnosis (CAD), machine learning methods are utilized to analyze data and make a certain assessment of the patient's condition.

Deep learning uses distinct neural networks for discrete operations, i.e., for image, text and speech processing, etc. A convolutional neural network (CNN) is used for finding patterns in images, recognizing objects, categories, classes and can also be useful for recognition of audio and similar signal-data. A recurrent neural network (RNN) is mainly employed in natural language processing and speech recognition. Deep learning comes often as a combination with computer vision and natural speak recognition which are subfields of AI per se [11]. Expert systems belong to AI as its subcategory and are as such used for performing diagnostics and further analysis based on the collected data provided by electronic healthcare systems [12]. They can be also used for giving an accurate prognosis about a patient's disease, similar to aforementioned deep learning techniques that analyze pictures and predict the outcome. Expert systems are also, as almost every segment of AI, powered by neural networks, i.e., entirely machine learning/deep learning.

3.1. Radiologic Applications of ML/DL

Deep learning methodology has been presented as a well-tempered yardstick for image processing analysis whilst showing promising results in segmentation and registration. Of a special interest was application of CNN in solving the problem of medical imaging segmentation which include the approaches to the segmentation of tumors, lungs, biological cells and membranes, bone tissue, cell mitosis and tibial cartilage. In addition to performing such operations, two-dimensional convolutional neural networks were utilized [11]. The problem however occurs in patch-based methods which requires focusing on a certain part of the image and then re-processing it in the latter stage. The 2D-CNN method is considered to be rather impracticable for the described reason, wherefore fully convolutional neural nets or fCNN were introduced by Kang and Wang [13]. Their main advantage of fCNN is taking the image as a whole without patching it, whereby redundancies are minimized. However, fCNNs produce segmentations of lower quality compared to the input images. Therefore, Bosch et al. proposed a three-layer convolutional encoder network for multiple sclerosis lesion segmentation that is a combination of convolutional and deconvolutional layers which is allowing segments and input images to be of the equal quality. The aforementioned network can also be employed in fields of semantic segmentation and lesion localization (Figure 2).

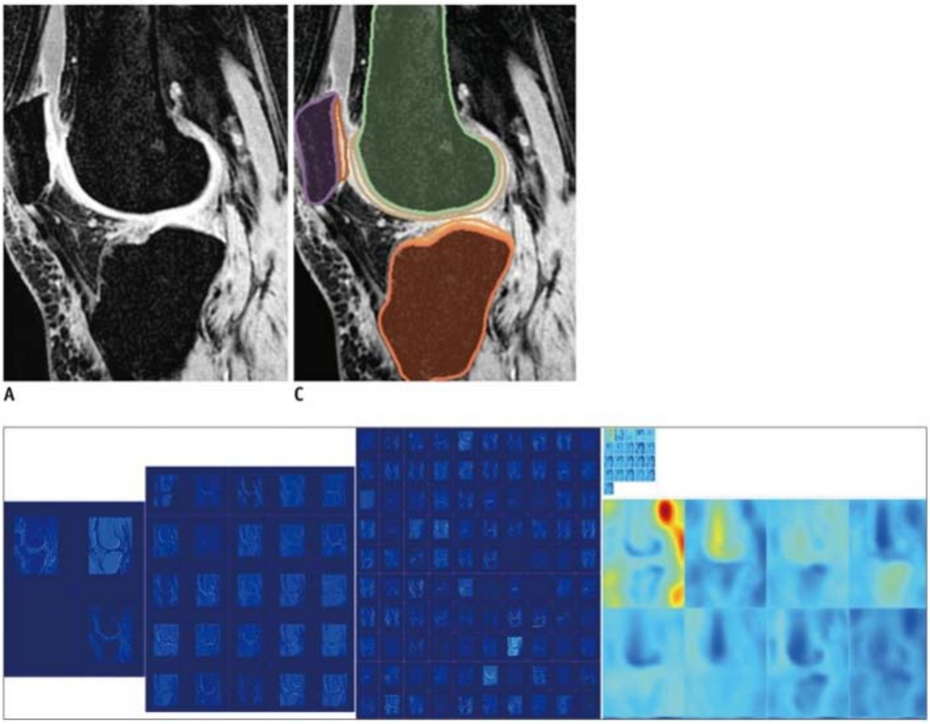

Figure 2.Semantic segmentation of a knee MRI (A – input image; B- response maps with different depths in fCNN; C – output result).

3.2. Computer-aided detection and diagnosis (CAD) in predictingillnesses

A computer-aided detection and diagnosis is a class of computer systems that aim to assist in the detection and/or diagnosis of diseases through a ‘’second opinion’’ [14]. Many different variations of CADs (Figure 3) have found its implementation as a part of picture archiving and communication systems (PACS).

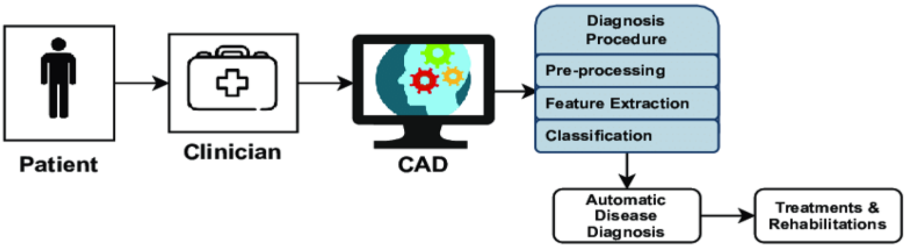

Figure 3. The diagram of functioning of CAD [15]

CAD consists primarily of two layers: detection and false positivity reduction. However, the current background of CAD attaches to it an epithet of the weak performance, since its sensitivity to imaging protocols and noise, reduces its presence in routine clinical practice to minimum. Applying deep learning techniques to CAD could be a definite solution on the path towards upgrading CADs. Recent studies of the deep learning-based CAD show a high accuracy in detecting breast and lung cancer as well as Alzheimer's disease. In addition, CAD systems are proposed for the early diagnosis of Alzheimer's disease based on fusion of anatomical (MRI) and functional (^{8}F-fluorodeoxyglucose positron emission tomography or FDG-PET) multimodal images [16].

3.3. Healthcare Virtual Assistants

AI virtual assistants, not only medical but also those for non-medical purposes, are powered by deep-learning algorithms that learn from the responses of people their communication is limited to. AI virtual healthcare assistants have myriad advantages, some of which are reduced waiting times, obtaining daily medical advices, practicability, anonymity and easing the pressure on doctors[17]. Recently, AI chatbots have shown therapeutic qualities which can be crucial for keeping the mental well-being of an individual.

One of the primary benefits of healthcare virtual assistants is their ability to provide personalized and on-demand support to patients. Patients can engage with virtual assistants through various channels such as voice commands or text-based interfaces, allowing them to access information, ask questions, and receive real-time assistance. Virtual assistants can offer guidance on symptoms, help with self-diagnosis, provide medication reminders, and offer general healthcare advice. By empowering patients with reliable and immediate information, virtual assistants contribute to patient education and enable individuals to make more informed decisions about their health.As healthcare virtual assistants continue to evolve, advancements in AI and NLP technologies are enabling them to become more sophisticated and capable of handling complex medical queries and interactions. They can integrate with electronic health records (EHRs) and other healthcare systems, ensuring seamless data exchange and enhancing clinical decision support. Additionally, virtual assistants can learn from patient interactions, continuously improving their performance and accuracy over time.

4. Robotics in Healthcare

Robotics in healthcare has emerged as a transformative field, revolutionizing the way medical procedures are performed, patient care is delivered, and healthcare professionals operate. By combining the power of robotics with advancements in artificial intelligence (AI) and precision engineering, robotic technologies have paved the way for significant improvements in diagnosis, surgery, rehabilitation, and patient assistance [18].

4.1. Robotics and AI in surgery

Robotics-assisted surgery is the name for the use of a mechanical device to assist surgery in place of a human-being or in a human-like way. There are three types of robotic systems used in surgery [19]:

• Active systems undertake pre-programmed tasks while remaining under the control of the operating surgeon;

• Semi-active systems allow a surgeon to complement the system's pre-programmed component;

• Master–slave systems lack any autonomous elements; they entirely depend on a surgeon's activity. In laparoscopic surgery or in teleoperation, the surgeon's hand movements are transmitted to surgical instruments, which reproduce them.

Surgeons can also be supported by navigation systems, which localize positions in space and help answer a surgeon's anatomical orientation questions. Real-time tracking of markers, realized in modern surgical navigation systems using a stereoscopic camera emitting infrared light, can determine the 3D position of prominent structures [20].

4.2. Rehabilitation and Robotics

Plethora of AI and robotic systems support rehabilitation tasks such as risk prevention, treatment and monitoring [21]. Fall detection systems use smart sensors which are supposed to alert the medical staff if the patient requires help. Built-in system powered by AI allows these systems to learn human behavioral patterns and characteristics over time. Robots can support patients in recovering motions after a stroke using exoskeletons [22], or recovering or supplementing lost function[23]. This means that a robot can be used to help the individual to train and recover motoric functionalities after a certain critical condition.

The use of proper rehabilitative procedures is essential for motor recovery in patients with conditions like brain injury, stroke, or chronic pain. Limb rehabilitation, especially upper and lower limb, is common but often requires trained healthcare professionals. Remote treatment using home-based medical devices has emerged as a suitable solution for accessibility challenges. Advanced technologies like robotics, machine learning, and IoT have been employed to provide rehabilitation. Examples include IoT-aided robotic devices,sensors for control, remote monitoring, and natural user interfaces. However, replicating the skills of physiotherapists and providing more complex therapies remain challenges. Integration of IoT technology allows observation, management of multiple patients, and personalized therapy suggestions. Future rehabilitation systems should focus on multi-modal approaches, such as the ROBIN rehabilitative robot [24]. Research explores augmented reality, video games, and play to enhance patient engagement and motor function. However, the high cost of rehabilitation robots and limited access to supervised environments hinder their widespread adoption. Efforts should be made to develop low-cost systems suitable for unsupervised settings, with adaptability to tailor therapy routines based on patient progress [18].

4.3. Robotics and AI for Telemedicine

Robotics and artificial intelligence (AI) are playing increasingly significant roles in advancing telemedicine [25], the practice of delivering healthcare remotely. These technologies are transforming the way healthcare is provided, enabling more efficient, accurate, and accessible care for patients worldwide.

Robotic systems are being integrated into telemedicine to facilitate remote examinations, diagnostics, and even surgeries. Tele-robotic systems allow healthcare professionals to remotely control robotic devices equipped with cameras, sensors, and specialized instruments to examine patients in real-time. This enables experts located at a different location to perform procedures and make informed medical decisions. For example, a surgeon in one location can remotely operate a surgical robot to perform minimally invasive surgeries on a patient located miles away. This technology extends specialized medical expertise to underserved areas, reduces travel requirements for patients, and enhances access to high-quality care [26].

AI-driven technologies are also revolutionizing telemedicine by augmenting medical decision-making, improving diagnostics, and enhancing patient monitoring. AI algorithms can analyze vast amounts of patient data, including medical records, imaging scans, and patient-reported symptoms, to assist healthcare providers in making accurate diagnoses and treatment recommendations [27]. AI-powered diagnostic systems can quickly and accurately interpret medical images, such as X-rays or CT scans, aiding radiologists and reducing the time needed for diagnosis. Additionally, AI-based chatbots and virtual assistants can interact with patients, gather information about their symptoms, and provide preliminary assessments or guidance on appropriate care options.

The combination of robotics and AI in telemedicine holds immense potential for remote patient monitoring. Connected devices, wearable sensors, and remote monitoring systems can collect real-time patient data, such as vital signs, activity levels, and medication adherence, and transmit it to healthcare providers. AI algorithms can analyze this data for early detection of health issues, flagging any abnormalities or changes that may require medical intervention. Remote patient monitoring powered by robotics and AI enables proactive care management, early intervention, and improved patient outcomes, particularly for individuals with chronic conditions who need continuous monitoring and timely medical attention.

Systems supporting telemedicine support, among others, the triage, diagnostic, non-surgical treatment, surgical treatment, consultation, monitoring, or provision of specialty care [28].

- Medical triage assesses current symptoms, signs, and test results to determine the severity of a patient's condition and the treatment priority. An increasing number of mobile health applications based on AI are used for diagnosis or treatment optimization [29]
- Utilization of IoT technologies and inserting smart and wearable devices into quasi smart homes; they are meant for collecting data from patients and helping in everyday life [30].
- Telemedicine for specialty care is designed for tracking the patient's mood and things related to mental health; such devices tend to attempt to socialize emotionally detached and socially isolated patients in order to reduce anxiety, depression and similar mood disorders [31].
- ASUS Zenbo Bot is a robot specially designed for children for treating ADHD, autism and similar attention disorders [32].
- Robot DE NIRO is similarly designed to interact safely and friendly with humans in order to promote socialization [33].

4.4. Robotics and AI for Prediction and Precision Medicine

Prediction and precision medicine aim to provide individualized healthcare solutions by considering various factors, including genomic variations, lifestyle factors, environmental influences, and demographic characteristics. By leveraging robotics and AI, healthcare professionals can harness the vast amount of available data and apply advanced algorithms to predict disease risks, identify early warning signs, and tailor interventions accordingly [34].

Furthermore, precision medicine relies on the integration of multiple data sources and the application of sophisticated algorithms to deliver targeted and personalized treatment plans. Robotics and AI play a crucial role in this process by providing comprehensive analysis and interpretation of patient data. AI algorithms can detect subtle patterns and trends in patient health records, genetic profiles, and treatment outcomes, helping healthcare professionals make more informed decisions about treatment strategies. By considering individual variations and optimizing treatment plans based on precise patient characteristics, precision medicine aims to improve treatment outcomes, minimize adverse effects, and enhance patient satisfaction.

4.5. Natural Language Processing in Healthcare

Natural Language Processing (NLP) is a field of Artificial Intelligence (AI) that enables machines to understand and communicate in natural language, like humans do. This subcategory of AI is also powered by machine learning/deep learning techniques, for the large datasets are to be dealt with (Figure 4). Healthcare natural language processing uses specialized engines capable of scrubbing large sets of unstructured data to discover previously missed or improperly coded patient conditions. This helps to uncover the disease which was not previously coded, i.e., it is being pointed to hidden patterns in order to maintain a high-quality AI-powered healthcare [35].

NLP negation is another process which helps doctors to identify the absence of certain symptoms. AI recognizes the keywords such as ‘’unlikely’’, ‘’not present’’, etc. For example, NLP may analyze the phrases and say whether the patient has breast cancer for instance. Therefore, the system must be familiar with the medical natural language and know all forms of negation in one’s language.

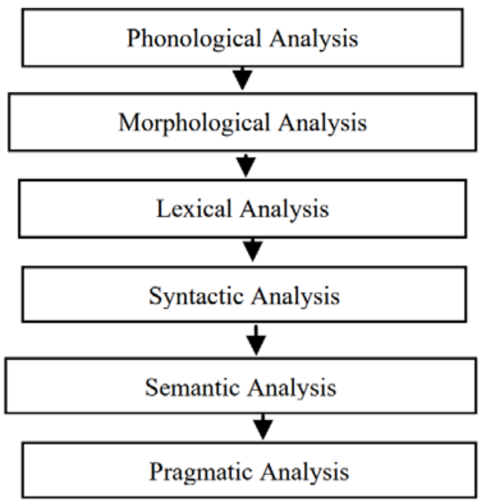

Figure 4.Levels of NLP in Healthcare

5. Conclusion

Based on a comprehensive overview of the progress in AI technology over the years and the extensive efforts invested in its development and enhancement, it can be inferred that this field is poised for continuous advancement and is expected to give rise to a multitude of new technologies, particularly in the realm of medicine. The evolution of medical technology, spanning from advancements in optics to electromagnetism, has now encompassed artificial intelligence, enabling the medical profession to significantly improve patient outcomes and save countless lives.

The application of AI in medicine extends across various domains, ranging from leveraging collected data for accurate diagnosis and prognosis to actively assisting in surgical procedures, aiding patient recovery, and more. This technology has transformed the medical landscape by making complex procedures more precise and efficient, enhancing medical decision-making, and streamlining patient care. For instance, laser technology and corrective lenses have restored normal vision to millions of individuals, while electrically powered medical devices have facilitated improved motor function and increased life expectancy. AI has further revolutionized cognitive functioning, providing invaluable assistance in medical research, data analysis, and decision support systems.

Although it is true that access to AI in healthcare may be limited in some developing countries, the undeniable benefits it brings to medical practice will inevitably propel its widespread adoption and accessibility. As the field progresses, it is foreseeable that virtual medical assistants and similar applications will become indispensable tools, transcending geographical barriers and empowering healthcare professionals worldwide. The ultimate goal is to ensure that the advantages and advancements brought forth by AI are universally available, promoting equitable healthcare outcomes on a global scale.

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