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Prospects of Artificial Intelligence in the Improvement of Healthcare Professions: A Review

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ABSTRACT

In 1956, the development of engineering science led to the birth of the first intelligent machines. This has led to the term Artificial Intelligence (AI) coined by a scientist named John McCarthy. The basic purpose of AI is to minimise human cognitive function. Advanced computer technology allows humans to do comparative critical thinking and simulate intelligent behaviour by producing intelligent modelling to solve boost and uplift cracking problems, imaging knowledge, and making a decision. Consequently, rapid analytical technique progress, powered by the increasing data availability in healthcare, has directed a paradigm shift in the healthcare system, especially in the analysis of medical imaging in the disease of oncology by detection of brain tumours. It helps the diagnosis of cancer stages based on the abnormal cell growth in the brain. AI is also important in diagnosis and treatment in other medical departments like dermatology, nephrology, ophthalmology, pathology, pulmonary medicine, endocrinology, gastroenterology, and neurology. In recent years, AI has played a key role in pharmacy, drug delivery, drug discovery, drug formulation development, hospital pharmacy, and poly-pharmacology. The term AI has a broad range of applications in medicine, medical statistics, medical diagnosis, human biology, pharmacy, clinical, and robotics. Automated selective medication uses the scientific task approach of pharmacists and is only possible by the use of AI. Algorithmic tasks reserved by using AI automation and such type of AI demonstration are better than pharmacists in comparison. In general terms of AI, the minimal intervention of humans implies intelligent behaviour through computer models. The invention of robots is deemed the starting point of the AI journey. It started with the introduction of robotic biosynthetic machines utilised to support medical personnel. In the meantime, an AI is capable of analysing complex clinical and medical data where a potentially significant data set relationship can be used for treatment and predicting outcomes in the case study and diagnosis.

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Introduction

Artificial Intelligence (AI) in the Healthcare Profession

The use of AI in medicine (Hamet & Tremblay, 2017) can be categorised into physical and virtual use. The physical use of AI is represented by the utilization of robotic machines to assist elderly patients and attending surgeons. Meanwhile, the virtual use of AI entails the informatics approach from a level of in-depth learning management information to control the health management system under the umbrella of physician treatment decision guidance and electronic health records. The mainstream area of AI covers different fields like cardiology, oncology, urology, and radiology. In the context of pharmacy, pharmacists should lead in designing, implementing, and evaluating ongoing AI-related technologies and applications directly affecting medication use and task processes. AI plays a unique role in new drug delivery and discovery by target nano-robots. AI also impacts ethical complexities and society of these wider applications of economic value, proof of medical utility, and interdisciplinary development strategies.

Ancient Calculation &Computation

The natural evolution process in the general computational methods is based on the natural selection mechanism and survival of the fittest in solving real-world problems. Genetic algorithms are used widely in ancient computational techniques. The scientist John Holland 1975 proposed a class of optimization algorithms and stochastic search based on the evolution of natural biological diversity (Holland et al., 1975). That work solves many problem solutions at hand, and the solution of the next generation will evolve. In this way, the population arrives at satisfactory solutions. The best-fit solutions added to the population and eliminated the inferior ones. In this way, by repeating the better element, repeated improvement will produce population survival and generate new problem solutions. The search for information in making medical decisions often requires big and complex searchers; for example, cell identification specialists decide whether the cell is malignant or not and provide a clear diagnosis of the malignancy. Genetic algorithms exploit the natural evolution mechanism to search efficiently in a given space. Through the application, they perform different tasks like diagnosis, medical imaging, prognosis, signal processing scheduling, and planning. The genetic algorithms principles are utilised to predict lung cancer (Jefferson et al., 1997), critically ill patients, melanoma, and the outcome of warfarin (Narayanan & Lucas, 1993), while the computerised analysis of mammography (Chan et al., 1998) and magnetic resonance imaging MRI segmentation calculation of brain tumours also count the efficacy of strategies treatment. It was also helpful for computerised analysis of 2-D images for cancer diagnosis (Handels et al., 1999).

Hybrid Intelligent Systems

Each AI technique has its strengths and weaknesses. Learning is mainly concerned with the neural network, fuzzy logic with imprecision, and ancient computation with optimization and search. The useful edge of these technologies is the combination in a complementary manner to evolve the hybrid intelligent system. These hybrid systems boost knowledge extraction from raw data and accommodate common sense use like a human reasoning mechanism. It impacts the adaption of rapidly changing and unknown circumstances. Examples of hybrid systems include fuzzy systems for designing Artificial neural networks (ANNs), genetic architecture neural networks, and genetic algorithms for automatic training. In this light, the hybrid system explores many diversified clinical scenarios such as tumour diagnosis, digital mammogram (Verma & Zakos, 2001) for microcalcification, coronary artery stenos as the diagnosis, calculation anaesthesia depth (Allen & Smith, 2001), and viability assessment of myocardial infection (Behloul *et al.*, 2001).

Processing Of Natural Language

The machine understands the genetic data and images of Electrophysiological Data, and machine learning (ML) algorithms can directly perform quality control processes. Sometimes, large amounts of information, like clinical laboratory reports, physical examinations, operative notes, and hospital discharge summaries, are incomprehensive and unstructured for a computer program. Under this context, natural language processing extracts useful information from the narrative text, and it helps make many clinical decisions (Kantor, 2001). Natural Language Processing has two main pathways, i.e. 1- Classification 2- text processing.

Using historical databases-based text processing (Afzal *et al.*, 2017), Natural Language processing identifies a series of keywords related to diseases in clinical notes. The keyword subsets are selected by monitoring their effects on the distribution of normal and abnormal cases. The approved standard keyword enriches the structured data-making to support the clinical decision. The pipeline Natural Language Processing has been developed for the assistance of clinical decisions, arrangement of treatment alerts, adverse effect monitoring, and so on. Natural Language Processing, introduced for reading chest reports of X-rays, would assist the system of antibiotics in indicating to the physician the need for therapy like anti-infective and also used in the auto-monitoring of laboratory-based adverse effects (Miller *et* *al.*, 2017).

Machine Learning &Deep Learning in A New Era

An advanced and modern technique like deep learning is an extension of a classical neural network (Devunooru *et al*., 2021). Some think that deep learning with many layers is a neural network, as shown in Figure 1, which is not feasible with a neural network. The data work of deep learning can explore more complex non-linear patterns. The other reason for deep learning's popularity is due to the complexity of data and the increase in volume. According to the literature survey, the application of deep learning has been done nearly two times in recent years. The main use of deep learning in the medical radiology department depicts that images are high-volume and naturally complex (Altman, 2017).

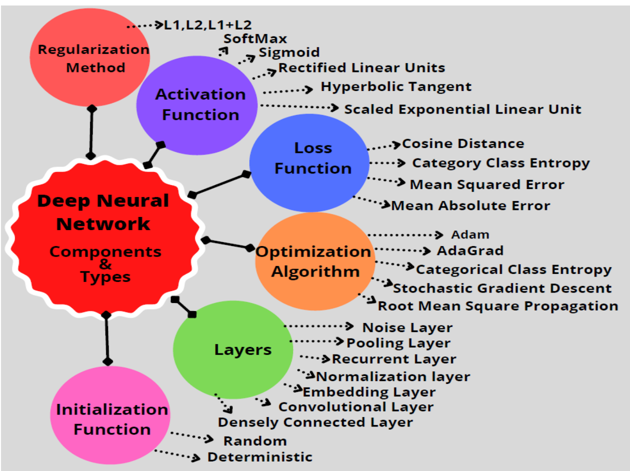

Figure 1: Medical AI (Development Stages) in Clinical Integration

Background of AI in Medicine

Promising applications of AI were identified in the middle of the twentieth century when scientists proposed and developed many clinical decisions to support the system (Miller., 1994). These approaches were very successful in 1970 (Shortliffe, 2012), for instance, in the field of ECG interpretation disease diagnoses (De Dombal *et al*., 1972), selection of appropriate treatment clinical reasoning interpretations (Barnett et al., 1987), and assisting the physician in the complex cases in generating diagnostic hypotheses as shown in Figure 2. However, the rule-based system is very expensive to build and can be fragile. Moreover, they require human authorization and decision rules, like a textbook (Roberts et al., 2017).

Higher-order interaction encoding is a difficult task in different segments of knowledge authorised by different experts, and the system performance is narrow due to the comprehensiveness of prior knowledge of medicine. The implementation of the system includes probabilistic and deterministic reasoning narrowed down to the clinical context, which prioritises the recommended therapy and diagnostic hypothesis (Deo, 2015).

Figure 2: AI Applications in different healthcare professions

The first-generation AI system emphasises expert medical knowledge and the rules of robotic decisions. The advancement in AI research in recent years has mainly focused on the method of machine learning accounting for data identification and complex interactions. It depends on the task intent to solve the primary algorithm of machine learning, which can be bifurcated into supervised and unsupervised categories. In the first category of the supervised method of machine learning work by gathering a large number of training cases (for example, fundus photographs) and desired label output (such as in the presence and absence of a doctor) and analysis of all patterns of labelled *Paris* of input and output, the advantage of the algorithm to calculate correct one output for a given input on new cases (Yu & Snyder, 2016).

Supervised machine learning algorithms are designed to identify the parameter of optimal and in models to reduce the deviation between their assumption of training cases. The observed associations in the case study are generalised to the case but not included in dataset training. The model test set can be evaluated by regression, classification, characterization of similar outcome labels, and most tasks supervised by the model of machine learning. The category of unsupervised learning links to the underlying pattern in unlabelled data for finding original data from sub-cluster, identifying data outliers, or for data production representation of low dimension. It is noted that the identification representation of low-dimension for labelled instances is achieved effectively in a supervised way. Moreover, machine learning-enabled AI application facilitates previously unorganised pattern discovery in data without a specific task for each task to account for complex interaction in the input features.

Building framework machine learning provides a proffered framework for AI utilities (Roberts et al., 2017). Deep learning applications have mostly been driven by AI In recent years, which helps in the training of artificial neural networks and is a large source of labelled data. From the year 2012, image task classification has been improved by deep learning. Deep feed-forward network of neural enhanced by the deep residual neural network by permission of skip connections, preventing the model performance saturation (Goodfellow *et al.*, 2016). The latest neural networks contain more than 100 layers where multiple layers in the neural network model produce complex relations in input and output. However, more data is needed, and the latest architectural design requires more computation time to achieve optimal performance (Gill, 2017).

In designing neuronal mathematical operation and method regularization by different layers, such convolution layers are very beneficial for temporal relations. In contrast, the circular connection of recurrent layers uses model temporal events. The model performance increases many functions of initialization and activations (Jha & Topol, 2016), where the combination of components handles the neural data and enables a neural network with or without depending on temporal or spatial. Figure 3 presents an automated diagnosis of medical imaging, one of the most successful medical AI applications. Image-based diagnosis is front and centre in many medical specialities like dermatology, pathology, cardiology, ophthalmology, and radiology (Jha & Topol, 2016).

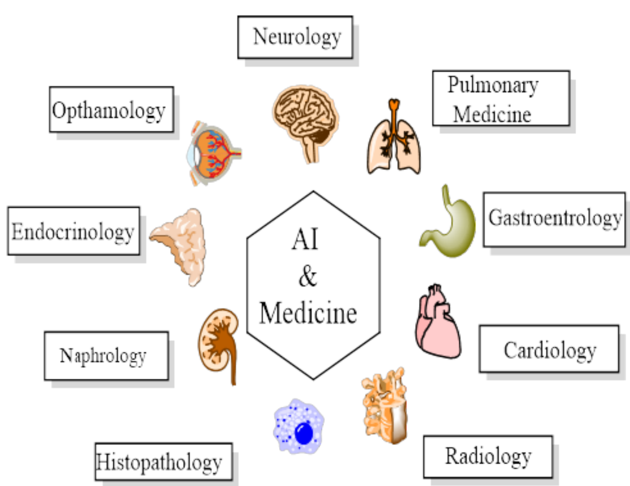

Figure 3: AI Importance in Medical Treatment

AI& Magnetic Resonance Imaging (MRI) Segmentation

MRT for tumour segmentation is an example of modern AI technology used in tumour analysis (Deshmukh & Jadhav, 2014). Different tumour segmentation method of brain MRI image has different advantages and disadvantages. The recent segmentation method is done through various efficient and suitable parameters for quantitative analysis (Liew, 2018). MRI allows human body image structure extraction for information about the patient (Gordillo *et al*., 2013). This advanced computerised technology helps specialists obtain physicians' information and measure tumour growth (Mukherjee, 2017). MRI imaging technology is also used to explore brain anatomy and injury at high-resolution quality with a large amount of data (Dogra *et al*., 2020).

A technician does not easily analyse a large amount of data and manually extracts the region which is affected (Dignum, 2018). Hence, different steps for segmentation are applied for a detailed description of anatomical regional segmentation in MRI. The development of modern techniques and technology allows images to be captured and analysed more precisely and accurately to resolve the degree of complexity (Myronenko, 2018). For the accurate and high-resolution imaging of brain disease diagnosis, the technique of MRI is delicate to the characteristics of the disease (Xuan & Liao, 2007). For the investigation of the processing of the medical image from the patient, the image set was collected. Enhancement techniques can increase the quality of the image. The method of image segmentation is important and accurate in the procedure of imaging processing (Pereira *et al*., 2016). The extraction of focal factures from segmented and enhanced images is the final step of image processing linked to post-imaging processing.MRI imaging is a non-invasive technique of imaging in medical science for intensive discussion.MRI of the brain and tumour segmentation, The fully convolutional neural network (FCNN) and conditional random field (CRF) are both combined; the only difference in groups and similarity index can be measured by global criterion and graph partition problem (Wadhwa *et al*., 2019). The segment image calculation is based on the method utilization. MRI images of the brain tumor are helpful in the diagnosis and stage of the tumor.

For the analysis of brain tumours, the MRI graph cut method is very common due to the processing and analysis of tumour images (Salem *et al*., n.d.). This is obtained from the results of experimentation. In the early step of Mathematical Morphological Reconstruction (MMR) by use of a computer for the diagnosis of a tumour (Fischl *et al*., 2002). The removal of artefacts and noise in the pre-processing stage of image segmentation helps verify the feature of texture and statistical findings to determine whether the brain tumour is benign or malignant (Figure: 4). Therefore, the MRI is a good technique for tumour diagnosis (Tustison *et al*., 2015).

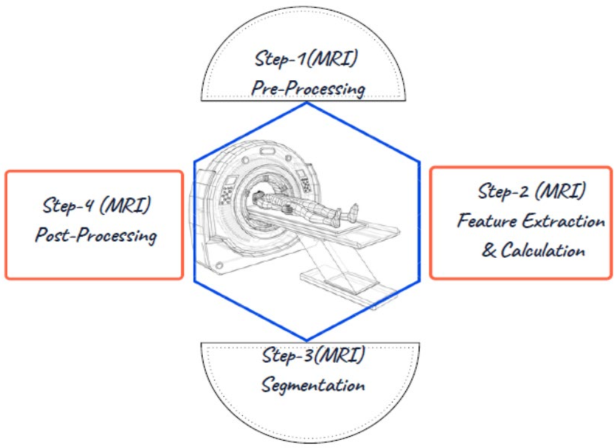

Figure 4: View of AI &Magnetic Resonance Imaging Segmentation

Drug Discovery and Artificial Intelligence

In pharmaceutical chemistry, Klopman (1984) introduced the structure-activity relationship (SAR) study in organic molecules (Klopman, 1984). It is based on the computer-automated structure evaluation, where the KNL code helps in reorganising the structure of the molecules. The coding routine of the molecules is based on a linear coding routine and is further recognised automatically by analysing biophores along with tabulation. The actual structure of the molecule is responsible for the molecule's statistical and biological activity. This method was applied to the tumour cell to identify aromatic hydrocarbon of polycyclic (Ketoxime carbamate-pesticides activity and tumour cell study of N-nitrosamine in rats. This was followed by Cherksaov, who generated the idea of small chains of peptide preparation with the broad-spectrum activity of antibiotics to gather information accumulated in chemical biology. Array technology uses peptides to form the unique composition of a peptide chain that is very active and is designed randomly by two libraries of a peptide containing 9-amino acid.

Agatonovic-Kustrin & Beresford (2000) conducted random sampling and prepared one million virtual peptides in the models, and their activity was observed successfully. It was found that these peptides are highly effective against top candidates and have the property of multidrug resistance along with better antibiotic activity than four commonly used antibiotics. Moreover, it is more effective as compared to antimicrobial peptides that are an advanced candidate in clinical and more powerful against bacterial strain *Staphylococcus aureus* infection when tested in in-vivo models of the animal.

Other studies, like Aliper *et al.* (2016), proposed novel approaches for utilising the deep neural network for the estimation of several drug pharmacological activities. 678 drug samples were used, and A549, MCF-7, and PC-3 were used in the cell line. Researchers obtained training on deep neural networks to study the therapeutic use of several drugs using gene expression data. The study reported that the deep neural networks offered high accuracy in classifying drugs into different therapeutic categories. It also reflected the advantages of data gained from human cell line experimentation.

AI Importance in Pharmacy

Previously, a pharmacist's responsibility is to ensure that prescriptions (Vyas *et al*., 2018) indicate the right amount of medicine, specifically when multiple medications are dispensed and ensure no drug-drug interactions between the different types of medicine (Vyas *et al*., 2018). These scenarios have changed dramatically in the last five years. Technology advances have increased doctors’ trust in robots and AI in handling big data. Subsequently, companies and institutes employ robots (Vyas *et al*., 2018) to perform tasks previously performed only by humans.

Pharmaceutical companies isolate a large number of molecules with the potential to combat specific kinds of diseases(Khanna *et al*., 2020). However, as such, they have no tools at their disposal for identification. The heavy cost and long period required for drug development and production by pharmaceutical companies. AI allows pharmaceutical companies to reduce the time and cost of drug development increase the return on investment, and it may affect the end-user cost (Khanna *et al*., 2020); (Liu *et al*., 2017). As shown in Figure 5, the main advantage of AI is that it is faster, more accurate and superior in analysing data as compared to humans, and AI can analyse big data that normally do not fit conventional computers. AI has been mostly used in areas of research such as gene mutation, where big data is used to obtain important information (Ulfa *et al*., 2019 and Vyas *et al*., 2018).

Figure 5 AI Advantages &Disadvantages in the healthcare profession

AI Tools & Pharmacy Profession

Different AI tools have been utilised in the pharmaceutical industry to meet the current needs. These AI tools have presented encouraging outcomes (Knebel & Greiner,

2003) and gained popularity in the industry.

Oncology by Supercomputer Waston

IBM, a renowned computer company, has designed a supercomputer named Waston (Rouse, 2017). It combines AI and advanced sophisticated software to answer complex questions. For instance, in cancer treatment, Waston (Bambauer, 2017) assists oncologists in making better decisions on cancer treatment plans. It works based on patient clinical information from expertise, big data networks, and treatment options (Ross & Swetlitz, 2017). It is capable of analysing both the context and the meaning of any data type presented in both properly structured and unstructured clinical notes and reports. Waston gathered data on critical patient information and executed it in the write-up in English format, which provided a true treatment plan for the patient (Khatib & Ahmed, 2020). It also collaborates critical attributes from the patient file for clinical research, external research, and big data after determining the most suitable treatment plan for the patients (Boyd & Chaffee, 2019), as shown in Figure 6. Waston supercomputer also has a big array of information from literature by MSK, 290 medical-related journals, nearly 200 textbooks, and twelve million text pages (Bambauer, 2017).

Figure 6: Computer Base Tools Used in AI & Drug Discovery

Robot Pharmacy

The main aim of robotic applications in the field of pharmacy is to enhance patients through identifying and prescribing medications. Recent reports by UCSF Medical Center documented the use of robotic technology to prepare approximately 3.5 million medication doses without error. This proves that modern robotic technology provides better and more accurate medication delivery compared to humans. Robotics help prepare medicine for cancer treatment and assist in the preparation of injections and oral preparations. Nurses and pharmacists in modern medical centres, such as UCSF, can optimise their expertise by mainly focusing on patient care and working with physicians (Khatib & Ahmed, 2020).

Conclusion

The progress in Al in the field of healthcare, made possible by the large-scale technology development has shown considerable progress. The application of AI, specifically in clinical, pharmaceutical, imaging technologies, clinical and drug discovery, is still in the primary stage of implementation and validation. AI has not yet been explored fully due to the diversity in healthcare professions, and very limited assessment cases have been identified. While medicine, pharmacy, drug discovery, and imaging technologies require more practical outcomes and more testing, studies have found that such an intervention helps medical practitioners identify connections and sources of the anticipated outcomes. AI is a critical technological area in the advancement of the healthcare system where healthcare professionals can integrate AI and human deliberation in all medical fields for better identification and decision-making. The advantages of AI in healthcare should be considered to steer its future growth.

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Authors' contribution

T.A.K: Guidance & supervision and contributed final draft preparations. M.U.M & S.N.A.B: Contributed reference management and writing of introduction. M.M.A: Contributed to figure development. M.A.N: Contributed to reviewing & editing. All authors have read and agreed.

Conflict of Interest

The authors declare no conflict of interest.

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