



Artificial Intelligent Medical Systems In Health Care Services

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ABSTRACT

This paper will discuss the relationship between healthcare stakeholders and intelligent medical systems. It examines how intelligent systems might affect healthcare. The study was prompted by the interest and investment shown in intelligent agents like Siemens since their initial trial deployments in healthcare organizations, prior to physician feedback. Here we discuss the pros and cons of using intelligent medical systems, as well as some ethical issues. The sociotechnical implications of intelligent systems in healthcare are explored. The article also compares Convolutional Neural Networks to state-of-the-art approaches and discusses potential decision makers' roles in assessing medical personnel's attitudes toward intelligent systems prior to final deployment. Clinical decision support systems promise to help clinicians make individualized, valued, and effective decisions that benefit patients. To make neural networks predictive, the company creates information architectures for hospitals. To help a clinician make a diagnosis the platform collects and organizes data Limited Memory AI systems have memory so they can use past experiences to inform future decisions. Machine learning analysis of genetic data from large populations will allow for personalized nutrition recommendations and drug treatment refinements, increasing the likelihood of successful therapy for a variety of diseases. AI-optimized therapy recommendations reduce the risk of unintended patient consequences. Preventing unexpected drug interactions can help improve patient outcomes.

Keywords: Health Care, Intelligent Systems, Socio-Technic, Agents, Decision Making.

1. INTRODUCTION:

Artificial intelligence (AI) is a broad branch of computer science. In general, the role of artificial intelligence is largely needed to create machines.[1-3]. It was Short life's MYCIN, developed at Stanford University in 1976, that was capable of performing tasks that require human intelligence. New expert systems capable of Artificial intelligence is simply the process of creating various computer programs, inputting them into the computer, and making a machine think and act through it, just like a human thinks and acts. Artificial intelligence enables a machine to do various tasks that a human can do with the five senses of hearing, seeing, tasting, consuming, feeling, without the help of a human have emerged as a result of recent AI advances. Preliminary considerations for intelligent medical agents are summarized in this paper [4, 5].

The Case studies with advertising characters, prior deployments of the Clinical Decision Support System (CDSS) [6-10]. As shown in Figure 1, the overall architecture of AI with Health Analytics is sponsored by intelligent agent software vendors and serves to inform pre-adoption considerations.

It is prudent to interpret the findings of these case studies in light of academic findings [11-14]. In the following sections, we describe the literature survey, intelligent systems in healthcare, the results and conclusions.

2. LITERATURE REVIEW:

Artificial intelligence includes cognitive abilities such as planning, problem solving, multidisciplinary thinking, learning ideas, and implementing what is learned [15]. Artificial intelligence typically enables a machine to learn from past experiences [16], adapt automatically to decisions it faces [17], think like a human and find ways to solve problems, and ultimately make the right decisions [18].

Although the definitions seem trivial, they have had a huge impact on computer science. With various subsets of machine learning and artificial intelligence provided instructions and diagrams for inputting programs into machines [19]. The IT department's main duties are to develop a various parameters of the platform to perform upgrades and maintenance. Time management, patient care, and treatment effectiveness must be balanced with job satisfaction and family responsibilities [21-24]. They may have created their own work routines and data repository without regard for administrative or IT policies.

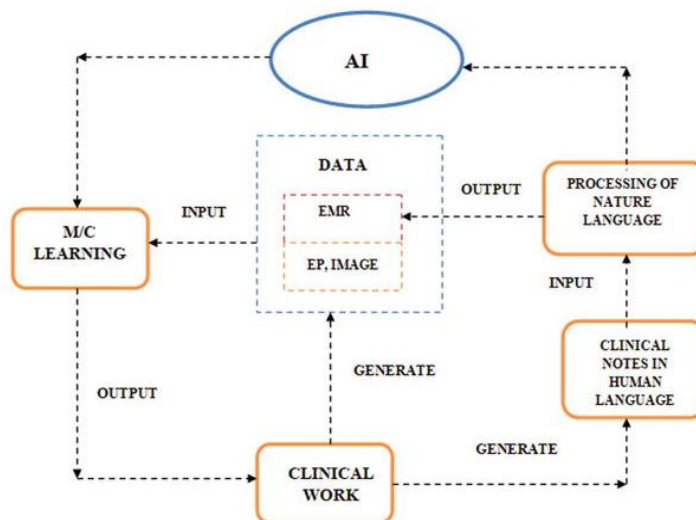


Figure 1: Overall Architecture of AI with Health care Analytics

The strain on human capabilities paved the way for what software companies market as more cost-effective, time-efficient, and accurate technical solutions. Benefits such as infinite memory space and unstructured data processing make intelligent agents like Watson candidates [25, 26]. While intelligent agents have advanced in technology, the role they should play in medical treatment and whether medical staff truly require their assistance has been overlooked. These include human doctor replacement [27], diagnostic accuracy guarantee [28], and human-dependent data repository.

3. INTELLIGENT SYSTEMS IN HEALTHCARE:

3.1 Precision Medicine with AI

Precision medicine combines bioinformatics, genetics, EMRs, and machine learning. Individuals differ greatly in physiology, biochemistry, and genetics. With modern medical technology, doctors can now accurately reflect these subtle differences. [29].

The FDA has approved over 25 drugs that target specific genetic sequences. Cure Match is a pioneering organization that tackles cancer. Genomic sequencing is a sophisticated technique that reveals specific DNA mutations that cause cancer. Contrast this with the hundreds of thousands of possible genetic mutations and millions of medication combinations that can cause cancer. Also, each person's cancer is distinct. The massive amount of data generated each time a cancer sample is sequenced is a monumental task. Cure Match analyses millions of genomic data points to provide oncologists with advanced treatment decision support. The platform analyses patient genomics, identifies critical individual genetic markers, and ranks viable treatment options based on their expected effect on the patient's tumor anomalies.

3.2 Drug Discovery using ML

Artificial intelligence systems do not have memories, they are all about tasks. Since they lack memory, they cannot inform future experiences by past experiences. An example of this is IBM-developed Deep Blue, which beat world chess champion Garry Kasparov in 1990. Although Deep Blue could recognize and predict the pieces on the chessboard, it lacked memory and was therefore unable to use past experiences. The technology allows neural networks to reason over each patient's knowledge corpus. An individualized "decision recommendation" that balances patient preferences with medical knowledge to maximize the likelihood of effective therapy.

3.3 Clinical Decision Support System with AI

Inefficient drug development costs pharmaceutical companies billions of dollars annually. The drug discovery process's scale, complexity, and high failure rate stifle innovation and drive up average drug prices. An infinite number of unique proteins, medicines, and compounds generated by artificial intelligence in pharmaceutical research can be sorted, prioritized, and analyzed by machine learning algorithms. Pfizer and Johnson & Johnson, for example, already have large data science teams analyzing molecular models and forecasting chemical interactions. Because genomics can now see how genetic variation affects how patients react to new medications, successful AI applications in drug discovery are now possible. Pharma companies will benefit greatly from mass producing these chemical combinations. Less waste means less cost, better treatment, and more impact on the average person.

3.4 Optimization of Clinical Workflow

A hospital's budgeting department constantly juggles patient inflows and outflows among numerous service divisions. Patient flow optimization is similar to how hospitals design processes and systems to maximize an individual's efficiency throughout their healthcare journey. Routing patients to the appropriate department, referring them to additional specialists if needed, obtaining lab results, and returning patients to the hospital if necessary. AI can automate and manage much of the paperwork required at each stage. AI in patient flow has the potential to revolutionize healthcare because algorithms can intelligently predict "sticky" points in a process. Programs can predict emergency resource demand, allowing employees to prepare. Artificial intelligence in healthcare and medicine can help C-level executives plan ahead and optimize internal processes. For example, non-emergency patients could receive automated advice and reminders to avoid unnecessary ER visits when a routine checkup would suffice. This procedure may be automated to avoid clogging the ER's arteries. KenSci provides an AI-powered platform for optimizing hospital workflows. In near-real time, the patient flow management tool shows administrators how many patients are coming in, how long they are staying, and how much room is available.

4. RESULTS AND DISCUSSION:

The models were evaluated using hold out and tenfold cross-validation. Artificial intelligence systems are built with social intelligence that understands emotions. These can infer human intentions and monitor behavior. These have the ability to be integrated members of human groups. Artificial intelligence systems are self-aware. Such machines understand the current state. This type of system has not yet been fully developed.

The tenfold cross validation technique divides the data set into ten parts. Artificial Intelligence is associated with the technology called Automation. Thus, the amount and types of tasks that can be performed through automated tools are expanding. As a result, each data point is tested nine times. The result is then computed by averaging the metrics' values. Repeats rule-based data tasks traditionally performed by humans. When machine learning technology is combined with this, robotic process automation tasks become highly automated.

In practice, a binary classifier will produce one of four outcomes:

The term "True Positive" indicates the number of patients in the danger zone.

False Negative (FN) is a term that refers to the proportion of patients the high risk to low risk range.

The term "False Positive" indicates the high risk zone.

False Negative (FN) is a term that refers to the proportion of patients classified as low risk who are actually high risk.

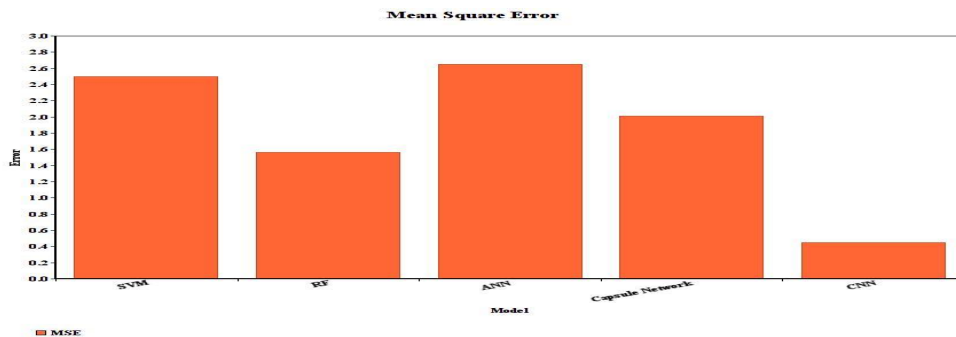


Figure 2: Mean Square results

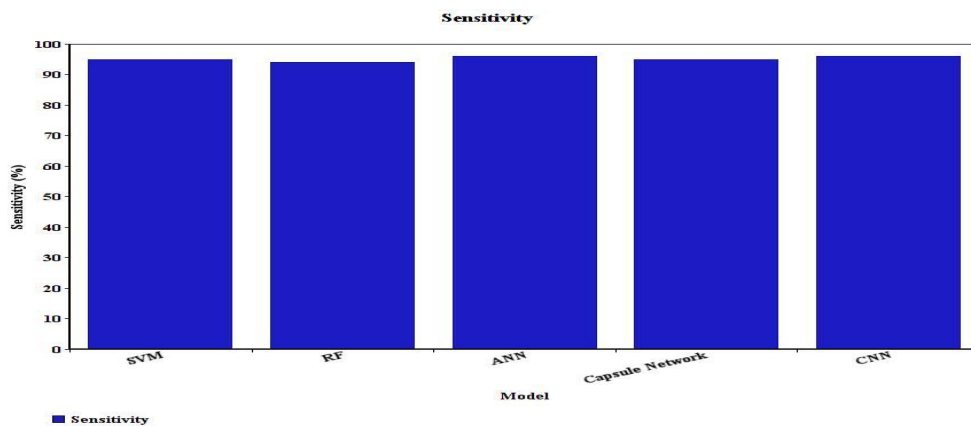


Figure 3: Sensitivity Results

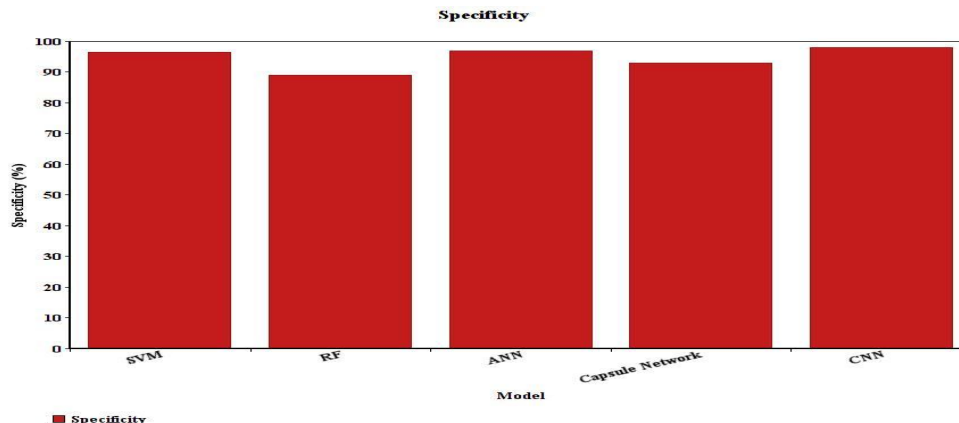


Figure 4: Specificity Results

From the Fig. 2,3,4 it is evident that CNN provides higher results compared to other state-of-the-art approaches with high sensitivity and specificity and low mean square error for heart disease prediction.

5. CONCLUSION AND FUTURE WORK:

Machine learning is a method of making a computer work without programs. Deep learning is a subset of machine learning. Machine learning can be simply referred to as the predictive automation of analytics. Machine learning can be classified into three categories namely supervised learning, unsupervised learning and reinforcement learning. Through supervised learning, data sets are labeled. Through this, patterns can be detected and used to label new data sets. In unsupervised learning, the data sets are sorted without similarity and dissimilarity since they are unlabeled. In reinforcement learning, artificial intelligence systems are given feedback after performing one or more actions, even if the data sets are not labeled. Machine vision technology gives a machine the ability to see. Through this, it captures and analyzes visual information. It is largely compared to human vision. It is used in a variety of applications from handwriting recognition to medical image analysis.

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