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Integration of AI Medical Systems in Healthcare Analytics

Dr. Anchugam[1] and Dr. Jayanthila Devi[2]
Post-Doctoral Research Fellow, Srinivas University, Mangaluru, Karnataka, India[1]
Professor, Srinivas University, Mangaluru, Karnataka, India[2]

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, before physician feedback. Here we discuss the pros and cons of using intelligent medical systems, as well as some ethical issues. The socio technical 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-maker roles in assessing medical personnel's attitudes toward intelligent systems before final deployment.*

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

I. INTRODUCTION

Expert medical systems have been around for a long time [1-3]. It was Short Life's MYCIN, developed at Stanford University in 1976, that was the first research effort to solve real-world problems and provide clinical assistance. New expert systems capable of machine learning, reasoning, and decision-making have emerged as a result of recent AI advances. Preliminary considerations for intelligent medical agents are summarized in this paper [4, 5].

Due to the lack of academic papers on intelligent agents and feedback from medical professionals who have used them in real-world practice, the paper now includes a balanced account of the consequences of implementing intelligent agents in healthcare organizations on the daily activities of medical staff. Case studies with advertising characters, and 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.

II. LITERATURE REVIEW

Humans [15], technology [16], and legacy practices [17] are all expected to work cooperatively for the benefit of the patient while also taking into account the concept of job satisfaction for medical personnel [18]. Using systemic thinking techniques, it is possible to distinguish between the system and its constituents.

A comprehensive intelligent agent may face numerous challenges when transferring data between departments and stakeholders. First, stakeholders have wildly varying priorities [19]. Budgets, feasibility studies, and resource allocation are the administrative and managerial duties. The IT department's main duties are to develop a viable IT strategy, manage security risks, and 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.

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.

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These include human doctor replacement [27], diagnostic accuracy guarantee [28], and human-dependent data repository.

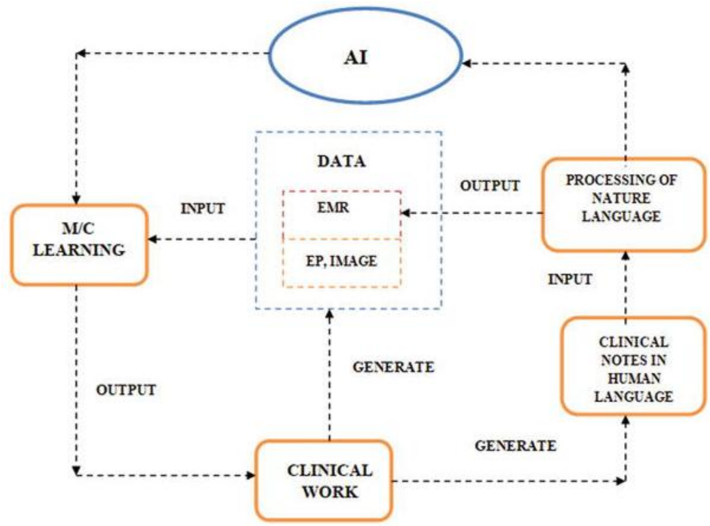

Figure 1: Overall Architecture of AI with Healthcare Analytics

III. INTELLIGENT SYSTEMS IN HEALTHCARE SYSTEMS

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. 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 [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 is also used in clinical decision support in healthcare and medicine. Healthcare professionals make recommendations based on their years of training and experience. Due to the enormous amount of experience-based inferential knowledge required for a seemingly simple diagnostic, machines are unable to successfully replicate it. Clinical decision support systems promise to help clinicians make individualized, valued, and effective decisions that benefit patients. Saperi Systems is one company poised to revolutionize Clinical Decision Support. 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 like medical history, care preferences, allergies, genetics, domain-specific knowledge, medical literature, and treatment procedures. 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.

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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 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.

IV. RESULTS AND DISCUSSION

The models were evaluated using hold-out and tenfold cross-validation. The holdout method divides data into training and test sets. The training set is used to train the classifier, while the testing set is used to evaluate its performance. The data were retrieved from UC Irvine's repository. The holdout method uses two data splits: 70% training and 30% testing. The dataset is split into two parts: training and testing.

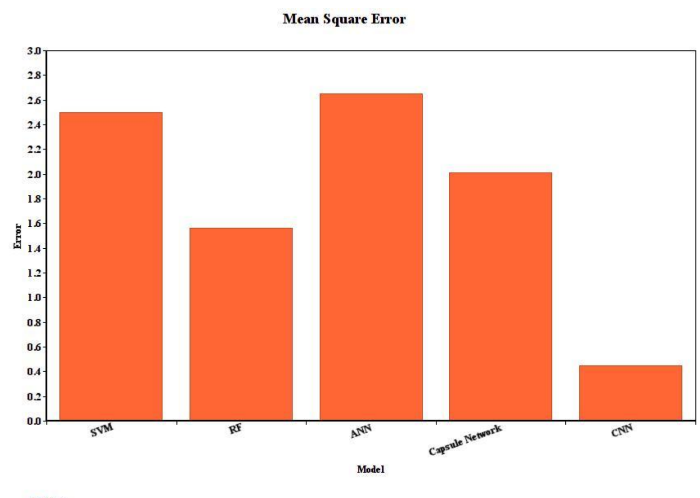

Figure 2: Mean Square results

The tenfold cross-validation technique divides the data set into ten parts. The model is tested on one of the ten partitions, and trained on the other nine. As a result, each data point is tested nine times. The result is then computed by averaging the metrics' values. The main advantage of tenfold cross-validation over a single hold-out set evaluator is lower variance. Thus, it becomes less sensitive to any partitioning bias in the training or testing data.

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

- The term "True Positive" refers to the number of patients classified as having a high risk of developing a disease.
- False Negative (FN) is a term that refers to the proportion of patients classified as high risk who are low.
- The term "False Positive" refers to the number of patients who are classified as high-risk despite their low risk.
- False Negative (FN) is a term that refers to the proportion of patients classified as low risk who are high risk.

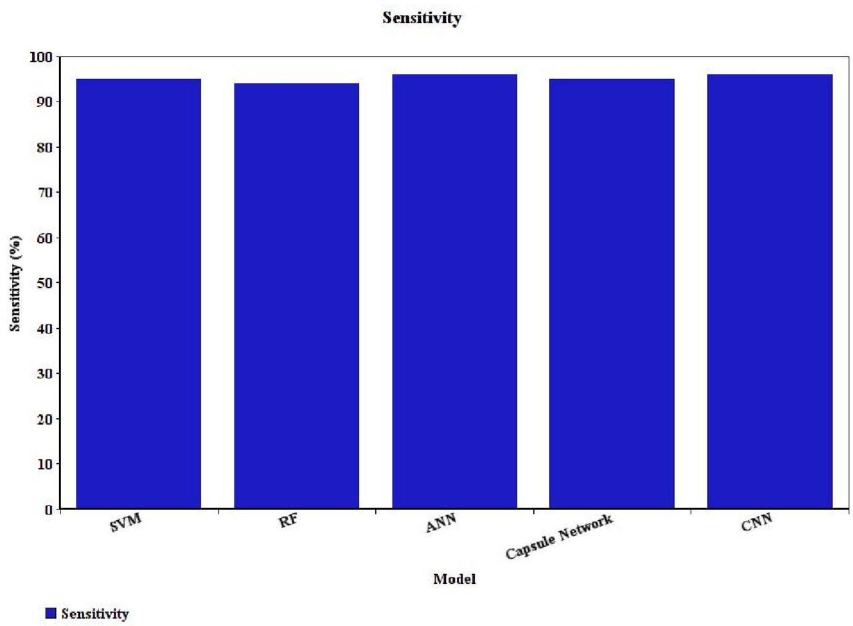

Figure 3: Sensitivity Results

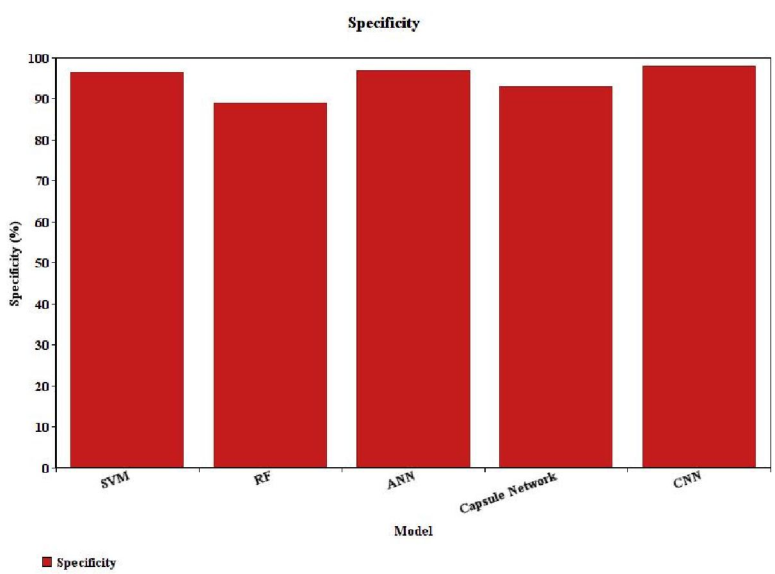

Figure 4: Specificity Results

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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.

V. CONCLUSION AND FUTURE WORK

Artificial intelligence (AI) in healthcare generates a plethora of healthcare information by examining and reviewing the most common diseases. Machine learning (ML) and natural language processing (NLP) are two major categories of artificial intelligence (AI) devices. The neural network and the support vector machine (SVM) are two popular traditional machine learning methods (ML). A typical artificial intelligence (AI) system includes machine learning (ML) to analyze structured data like ERP, images, and genetic data, and natural language processing (NLP) to deduce unstructured works. Because of the inherent risk, these AI applications in healthcare have historically been regulated. When healthcare professionals understand why machines make the decisions they do, these machines will gain prominence within the hospital ecosystem and eventually become indispensable.

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