Use of AI in Healthcare

Ms. Anamika Pandey¹, Mohd Shajeb Faruqui², Md Monirul Haque³, Hamza Asfaq⁴ ¹Guide, Computer Science and Engineering, IIMT College of Engineering, Greater Noida, Uttar Pradesh ^{2,3,4} Computer Science and Engineering, IIMT College of Engineering, Greater Noida, Uttar Pradesh

Abstract- Artificial intelligence (AI) has been developing rapidly in recent years in terms of software algorithms, hardware implementation, and applications in a vast number of areas. In this review, we summarize the latest developments of applications of AI in biomedicine, including disease diagnostics, living assistance, biomedical information processing, and biomedical research. The aim of this review is to keep track of new scientific accomplishments, to understand the availability of technologies, to appreciate the tremendous potential of AI in biomedicine, and to provide researchers in related fields with inspiration. It can be asserted that, just like AI itself, the application of AI in biomedicine is still in its early stage. New progress and breakthroughs will continue to push the frontier and widen the scope of AI application, and fast developments are envisioned in the near future. Two case studies are provided to illustrate the prediction of epileptic seizure occurrences and the filling of a dysfunctional urinary bladder.

1. INTRODUCTION

In computer science, artificial intelligence (AI), sometimes called machine intelligence, is intelligence demonstrated by machines, in contrast to the natural intelligence displayed by humans and animals. Leading AI textbooks define the field as the study of "intelligent agents": any device that perceives its environment and takes actions that maximize its chance of successfully achieving its goals. Colloquially, the term "artificial intelligence" is often used to describe machines (or computers) that mimic "cognitive" functions that humans associate with the human mind, such as "learning" and "problem solving".

As machines become increasingly capable, tasks considered to require "intelligence" are often removed from the definition of AI, a phenomenon known as the AI effect. A quip in Tesler's Theorem says "AI is whatever hasn't been done yet." For instance, optical character recognition is frequently excluded from things considered to be AI, having become a routine technology. Modern machine capabilities generally classified as AI include successfully understanding human speech, competing at the highest level in strategic game systems (such as chess and Go), autonomously operating cars, intelligent routing in content delivery networks, and military simulations.

2. HISTORY

Thought-capable artificial beings appeared as storytelling devices in antiquity, and have been common in fiction, as in Mary Shelley's Frankenstein or Karel Čapek's R.U.R. (Rossum's Universal Robots). These characters and their fates raised many of the same issues now discussed in the ethics of artificial intelligence.

The study of mechanical or "formal" reasoning began with philosophers and mathematicians in antiquity. The study of mathematical logic led directly to Alan Turing's theory of computation, which suggested that a machine, by shuffling symbols as simple as "0" and "1", could simulate any conceivable act of mathematical deduction. This insight, that digital computers can simulate any process of formal reasoning, is known as the Church-Turing thesis.[29] Along with concurrent discoveries in neurobiology, information theory and cybernetics, this led researchers to consider the possibility of building an electronic brain. Turing proposed changing the question from whether a machine was intelligent, to "whether or not it is possible for machinery to show intelligent behaviour". The first work that is now generally recognized as AI was McCullouch and Pitts' 1943 formal design for Turing-complete "artificial neurons".

3. CHALLENGES

The cognitive capabilities of current architectures are very limited, using only a simplified version of what intelligence is really capable of. For instance, the human mind has come up with ways to reason beyond measure and logical explanations to different occurrences in life. What would have been otherwise straightforward, an equivalently difficult problem may be challenging to solve computationally as opposed to using the human mind. This gives rise to two classes of models: structuralist and functionalist. The structural models aim to loosely mimic the basic intelligence operations of the mind such as reasoning and logic. The functional model refers to the correlating data to its computed counterpart.

The overall research goal of artificial intelligence is to create technology that allows computers and machines to function in an intelligent manner. The general problem of simulating (or creating) intelligence has been broken down into subproblems. These consist of particular traits or capabilities that researchers expect an intelligent system to display. The traits described below have received the most attention.

3.1 Reasoning, problem solving

Early researchers developed algorithms that imitated step-by-step reasoning that humans use when they solve puzzles or make logical deductions. By the late 1980s and 1990s, AI research had developed methods for dealing with uncertain or incomplete information, employing concepts from probability and economics. These algorithms proved to be insufficient for solving large reasoning problems because they experienced a "combinatorial explosion": they became exponentially slower as the problems grew larger. In fact, even humans rarely use the step-by-step deduction that early AI research was able to model. They solve most of their problems using fast, intuitive judgments.

3.2 Knowledge representation



An ontology represents knowledge as a set of concepts within a domain and the relationships between those concepts.

Main articles: Knowledge representation and commonsense knowledge

Knowledge representation and knowledge engineering are central to classical AI research. Some "expert systems" attempt to gather together explicit knowledge possessed by experts in some narrow domain. In addition, some projects attempt to gather the "commonsense knowledge" known to the average person into a database containing extensive knowledge about the world. Among the things a comprehensive commonsense knowledge base would contain are: objects, properties, categories and relations between objects; situations, events, states and time; causes and effects; knowledge about knowledge (what we know about what other people know); and many other, less well researched domains. A representation of "what exists" is an ontology: the set of objects, relations, concepts, and properties formally described so that software agents can interpret them. The semantics of these are captured as description logic concepts, roles, and individuals, and typically implemented as classes, properties, and individuals in the Web Ontology Language. The most general ontologies are called upper ontologies, which attempt to provide a foundation for all other knowledge by acting as mediators between domain ontologies that cover specific knowledge about a particular knowledge domain (field of interest or area of concern). Such formal knowledge representations can be used in indexing content-based and retrieval, scene interpretation, clinical decision support, knowledge

discovery (mining "interesting" and actionable inferences from large databases), and other areas.

4. PLANNING





A hierarchical control system is a form of control system in which a set of devices and governing software is arranged in a hierarchy.

Main article: Automated planning and scheduling Intelligent agents must be able to set goals and achieve them. They need a way to visualize the future—a representation of the state of the world and be able to make predictions about how their actions will change it-and be able to make choices that maximize the utility (or "value") of available choices. In classical planning problems, the agent can assume that it is the only system acting in the world, allowing the agent to be certain of the consequences of its actions. However, if the agent is not the only actor, then it requires that the agent can reason under uncertainty. This calls for an agent that can not only assess its environment and make predictions but also evaluate its predictions and adapt based on its assessment.

Multi-agent planning uses the cooperation and competition of many agents to achieve a given goal. Emergent behavior such as this is used by evolutionary algorithms and swarm intelligence.

5. LEARNING

Machine learning (ML), a fundamental concept of AI research since the field's inception, is the study of computer algorithms that improve automatically through experience.

Unsupervised learning is the ability to find patterns in a stream of input, without requiring a human to label the inputs first. Supervised learning includes both classification and numerical regression, which requires a human to label the input data first. Classification is used to determine what category something belongs in, and occurs after a program sees a number of examples of things from several categories. Regression is the attempt to produce a function that describes the relationship between inputs and outputs and predicts how the outputs should change as the inputs change. Both classifiers and regression learners can be viewed as "function approximators" trying to learn an unknown (possibly implicit) function; for example, a spam classifier can be viewed as learning a function that maps from the text of an email to one of two categories, "spam" or "not spam". Computational learning theory can assess learners by computational complexity, by sample complexity (how much data is required), or by other notions of optimization. In reinforcement learning the agent is rewarded for good responses and punished for bad ones. The agent uses this sequence of rewards and punishments to form a strategy for operating in its problem space.





A parse tree represents the syntactic structure of a sentence according to some formal grammar.

Natural language processing(NLP) gives machines the ability to read and understand human language. A sufficiently powerful natural language processing system would enable natural-language user interfaces and the acquisition of knowledge directly from human-written sources, such as newswire texts. Some straightforward applications of natural language processing include information retrieval, text mining, question answering and machine translation.

6. CYBERNETICS AND BRAIN SIMULATION

In the 1940s and 1950s, a number of researchers explored the connection between neurobiology, information theory, and cybernetics. Some of them built machines that used electronic networks to exhibit rudimentary intelligence, such as W. Grey Walter's turtles and the Johns Hopkins Beast. Many of these researchers gathered for meetings of the Teleological Society at Princeton University and the Ratio Club in England. By 1960, this approach was largely abandoned, although elements of it would be revived in the 1980s.

6.1 Symbolic

When access to digital computers became possible in the mid-1950s, AI research began to explore the possibility that human intelligence could be reduced to symbol manipulation. The research was centered in three institutions: Carnegie Mellon University, Stanford and MIT, and as described below, each one developed its own style of research. John Haugeland named these symbolic approaches to AI "good old fashioned AI" or "GOFAI". During the 1960s, symbolic approaches had achieved great success at high-level "thinking" simulating in small demonstration programs. Approaches based on cybernetics or artificial neural networks were abandoned or pushed into the background. Researchers in the 1960s and the 1970s were convinced that symbolic approaches would eventually succeed in creating a machine with artificial general intelligence and considered this the goal of their field.

6.1.1 Cognitive simulation

Economist Herbert Simon and Allen Newell studied human problem-solving skills and attempted to formalize them, and their work laid the foundations of the field of artificial intelligence, as well as cognitive science, operations research and management science. Their research team used the results of psychological experiments to develop programs that simulated the techniques that people used to solve problems. This tradition, centered at Carnegie Mellon University would eventually culminate in the development of the Soar architecture in the middle 1980s.

6.1.2 Logic-based

Unlike Simon and Newell, John McCarthy felt that machines did not need to simulate human thought, but should instead try to find the essence of abstract reasoning and problem-solving, regardless whether people used the same algorithms. His laboratory at Stanford (SAIL) focused on using formal logic to solve a wide variety of problems, including knowledge representation, planning and learning. Logic was also the focus of the work at the University of Edinburgh and elsewhere in Europe which led to the development of the programming language Prolog and the science of logic programming.

6.1.3 Anti-logic or scruffy

Researchers at MIT (such as Marvin Minsky and Seymour Papert) found that solving difficult problems in vision and natural language processing required ad-hoc solutions—they argued that there was no simple and general principle (like logic) that would capture all the aspects of intelligent behavior. Roger Schank described their "anti-logic" approaches as "scruffy" (as opposed to the "neat" paradigms at CMU and Stanford). Commonsense knowledge bases (such as Doug Lenat's Cyc) are an example of "scruffy" AI, since they must be built by hand, one complicated concept at a time.

6.1.4 Knowledge-based

When computers with large memories became available around 1970, researchers from all three traditions began to build knowledge into AI applications. This "knowledge revolution" led to the development and deployment of expert systems (introduced by Edward Feigenbaum), the first truly successful form of AI software. A key component of the system architecture for all expert systems is the knowledge base, which stores facts and rules that illustrate AI. The knowledge revolution was also driven by the realization that enormous amounts of knowledge would be required by many simple AI applications.

6.2 Sub-symbolic

By the 1980s, progress in symbolic AI seemed to stall and many believed that symbolic systems would never be able to imitate all the processes of human cognition, especially perception, robotics, learning and pattern recognition. A number of researchers began to look into "sub-symbolic" approaches to specific AI problems. Sub-symbolic methods manage to approach intelligence without specific representations of knowledge.

6.2.1 Embodied intelligence

This includes embodied, situated, behavior-based, and nouvelle AI. Researchers from the related field of robotics, such as Rodney Brooks, rejected symbolic AI and focused on the basic engineering problems that would allow robots to move and survive.[166] Their work revived the non-symbolic point of view of the early cybernetics researchers of the 1950s and reintroduced the use of control theory in AI. This coincided with the development of the embodied mind thesis in the related field of cognitive science: the idea that aspects of the body (such as movement, perception and visualization) are required for higher intelligence.

Within developmental robotics, developmental learning approaches are elaborated upon to allow robots to accumulate repertoires of novel skills through autonomous self-exploration, social interaction with human teachers, and the use of guidance mechanisms (active learning, maturation, motor synergies, etc.).

6.2.2 Computational intelligence and soft computing Interest in neural networks and "connectionism" was revived by David Rumelhart and others in the middle of the 1980s.[171] Artificial neural networks are an example of soft computing—they are solutions to problems which cannot be solved with complete logical certainty, and where an approximate solution is often sufficient. Other soft computing approaches to AI include fuzzy systems, Grey system theory, evolutionary computation and many statistical tools. The application of soft computing to AI is studied collectively by the emerging discipline of computational intelligence.

7. HEALTHCARE



A patient-side surgical arm of Da Vinci Surgical System

AI in healthcare is often used for classification, whether to automate initial evaluation of a CT scan or EKG or to identify high-risk patients for population health. The breadth of applications is rapidly increasing. As an example, AI is being applied to the high-cost problem of dosage issues—where findings suggested that AI could save \$16 billion. In 2016, a groundbreaking study in California found that a mathematical formula developed with the help of AI correctly determined the accurate dose of immunosuppressant drugs to give to organ patients.



X-ray of a hand, with automatic calculation of bone age by computer software

Artificial intelligence is assisting doctors. According to Bloomberg Technology, Microsoft has developed AI to help doctors find the right treatments for cancer. There is a great amount of research and drugs developed relating to cancer. In detail, there are more than 800 medicines and vaccines to treat cancer. This negatively affects the doctors, because there are too many options to choose from, making it more difficult to choose the right drugs for the patients. Microsoft is working on a project to develop a machine called "Hanover"]. Its goal is to memorize all the papers necessary to cancer and help predict which combinations of drugs will be most effective for each patient. One project that is being worked on at the moment is fighting myeloid leukemia, a fatal cancer where the treatment has not improved in decades. Another study was reported to have found that artificial intelligence was as good as trained doctors in identifying skin cancers. Another study is using artificial intelligence to try to monitor multiple high-risk patients, and this is done by asking each patient numerous questions based on data acquired from live doctor to patient interactions. One study was done with transfer learning, the machine performed a diagnosis similarly to a well-trained ophthalmologist, and could generate a decision within 30 seconds on whether or not the patient should be referred for treatment, with more than 95% accuracy.

According to CNN, a recent study by surgeons at the Children's National Medical Center in Washington successfully demonstrated surgery with an autonomous robot. The team supervised the robot while it performed soft-tissue surgery, stitching together a pig's bowel during open surgery, and doing so better than a human surgeon, the team claimed. IBM has created its own artificial intelligence computer, the IBM Watson, which has beaten human intelligence (at some levels). Watson has struggled to achieve success and adoption in healthcare.

8. CONCLUSION

In this paper, we reviewed the latest developments in the application of AI in biomedicine, including disease diagnostics and prediction, living assistance, biomedical information processing, and biomedical research. AI has interesting applications in many other biomedical areas as well. It can be seen that AI plays an increasingly important role in biomedicine, not only because of the continuous progress of AI itself, but also because of the innate complex nature of biomedical problems and the suitability of AI to solve such problems. New AI capabilities provide novel solutions for biomedicine, and the development of biomedicine demands new levels of capability from AI. This match of supply and demand and coupled developments will enable both fields to advance significantly in the foreseeable future, which will ultimately benefit the quality of life of people in need.

9. ACKNOWLEDGEMENT

First & foremost, praises & thanks to the God for his shower of blessings throughout my research work to complete the research successfully. I would like to express my deep & sincere gratitude to my parents for their love, prayers, care & sacrifices for educating & preparing me for my future. I would also like to express my gratefulness to all my academic colleagues & friends for their constant encouragement. Finally, my special thanks go to all the people who have supported & encouraged me to complete the research work directly or indirectly.

REFERENCES

- [1] Minsky M. Steps toward artificial intelligence. Proc IRE 1961;49(1):8–30.
- [2] Weng J, McClelland J, Pentland A, Sporns O, Stockman I, Sur M, et al. Autonomous mental development by robots and animals. Science 2001;291 (5504):599–600.
- [3] Wooldridge M, Jennings NR. Intelligent agents: theory and practice. Knowl Eng Rev 1995;10 (2):115–52.
- [4] Huang G, Huang GB, Song S, You K. Trends in extreme learning machines: a review. Neural Netw 2015;61:32–48.
- [5] Hopfield JJ. Neural networks and physical systems with emergent collective computational abilities. Proc Natl Acad Sci USA 1982;79(8):2554–8.
- [6] Watts DJ, Strogatz SH. Collective dynamics of 'small-world' networks. Nature 1998;393 (6684):440–2.

- [7] Zucker RS, Regehr WG. Short-term synaptic plasticity. Annu Rev Physiol 2002;64:355–405.
- [8] Schmidhuber J. Deep learning in neural networks: an overview. Neural Netw 2015;61:85–117.
- [9] LeCun Y, Bengio Y, Hinton G. Deep learning. Nature 2015;521(7553):436–44.
- [10] Arel I, Rose DC, Karnowski TP. Deep machine learning—a new frontier in artificial intelligence research. IEEE Comput Intell Mag 2010;5(4):13–8.