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THE APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN THE MOROCCAN HEALTH CARE SYSTEM- UROLOGY

THESIS

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بسم الله والحمد لله رب العالمين،

سبحانك لا إله إلا أنت السميع المجيب لا إله إلا أنت الحليم العظيم، لا إله إلا أنت
رب السماوات ورب الأرض ورب العرش الكريم. لا إله إلا أنت وحدك لا شريك
لك لك الملك ولك الحمد وأنت على كل شيء قدير. اللهم لك الحمد والشكر كما
ينبغي لجلال وجهك وعظيم سلطانك.

وَاللَّهُمَّ صَلِّ وَسَلِّمْ وَبَارِكْ عَلَى مَنْ بِالصَّلَاةِ عَلَيْهِ تَحَطُّ الْأَوْزَارُ، وَتُنَالُ مَنَازِلُ
الْأَبْرَارِ، وَرَحْمَةُ الْعَزِيزِ الْغَفَّارِ اللَّهُمَّ إِنَّا نَسْأَلُكَ مِنْ خَيْرِ مَا سَأَلَكَ مِنْهُ مُحَمَّدٌ نَبِيُّكَ
وَرَسُولُكَ، وَنَعُوذُ بِكَ مِنْ شَرِّ مَا اسْتَعَاذَ بِكَ مِنْهُ مُحَمَّدٌ نَبِيُّكَ وَرَسُولُكَ، اللَّهُمَّ إِنَّا
نَسْأَلُكَ حُبَّهُ.. وَحُبَّ مَنْ يُحِبُّهُ، وَحُبَّ كُلِّ عَمَلٍ يُقَرِّبُنَا إِلَى حُبِّهِ.

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Abbreviations and symbols:

AI: artificial intelligence

ML: machine learning

DL: deep learning

NN: neural network

ANN: Artificial neural networks

ESs: expert systems

CNN: convolutional neural network

KDD: Knowledge Discovery in Databases

MIT: Massachusetts Institute of Technology

HIPAA: Health Insurance Portability and Accountability

Unimate; Unimation, Danbury, Conn, USA: names of one of the first Robot arms

ESs: expert systems

DAI: Distributed Artificial Intelligence

RNFL: nerve fiber layer

VF: visual field

CDS: Clinical decision support

AUC: area under curve

GDPR: General Data Protection Regulation

CMU: Carnegie Mellon University

PCNL: percutaneous nephrolithotomy

SWL: shockwave lithotripsy

TUL: trans-ureteral lithotripsy

AMD: Age-related Macular Degeneration

SFR: stone-free rate

CT: Computed tomography

CROES: Clinical Research Office of the Endourological Society

FDA: food and drug administration

TEMS: TRANSANAL Endoscopic Micro-surgery

MIS: Minimally invasive surgery

MICCAI: The Medical Image Computing and Computer-Assisted Interventions

INTRODUCTION

Artificial Intelligence (AI) is a major technological advancement that has evolved significantly the last decades, It was initially conceived as a simple "if-then" rules. Today, AI encompasses a broad field of science and technology dedicated to creating intelligent machines and computer programs capable of performing tasks that typically require human intelligence¹, such as learning, reasoning, problem-solving, and decision-making.

It can be defined in two main ways: (i) as a science aimed at understanding the nature of intelligence and developing intelligent machines², or (ii) as a discipline focused on creating methods to solve complex problems that require intelligent approaches.

AI has advanced from its early stages to now include sophisticated algorithms that mimic human cognitive functions. These algorithms identify patterns and analyze data, allowing machines to learn from past experiences and apply that knowledge to future scenarios. This capability is especially valuable in fields like healthcare, where AI can dynamically support clinical decision-making and personalize patient care, moving beyond static. If we take landmarks as an example, surgeons find it challenging to detect them during surgery. That's where the potential of AI is required. However, AI brings new challenges, prompting organizational researchers to explore how it will reshape workforce structures, job design, decision-making processes, and knowledge management in the future, especially in health care, where precision is most needed.

¹ Pettersen, 'Why Artificial Intelligence Will Not Outsmart Complex Knowledge Work'.

² Dilek, Cakir, and Aydın, 'Applications of Artificial Intelligence Techniques to Combating Cyber Crimes'.

I. History of AI:

I.1) Evolution of AI:

Charles Babbage (1791–1871)

was an English mathematician, inventor, and mechanical engineer, often considered the "father of the computer." He is best known for conceptualizing and partially designing the Analytical Engine, a mechanical general-purpose computer, which laid the groundwork for modern computing.

Babbage was also a professor of mathematics at Cambridge University and contributed to various fields, including economics and statistics. His earlier invention, the Difference Engine, was designed to automate mathematical calculations, particularly polynomial functions, but was never fully completed during his lifetime.

Despite his ground-breaking ideas, Babbage's projects were plagued by funding issues, technical challenges, and his exacting perfectionism, leading to the Analytical Engine remaining unfinished. However, his designs and concepts were later recognized as visionary, influencing the development of early computers in the 20th century.

Babbage's work demonstrated the potential of machines to perform complex calculations and process data, making him a pivotal figure in the history of computing³.

³ Grzybowski, Pawlikowska-Łagód, and Lambert, 'A History of Artificial Intelligence'.

Augusta Ada King,

Countess of Lovelace, commonly known as Ada Lovelace, was an English mathematician and writer born on December 10, 1815, to the poet Lord Byron and Anne Isabella Milbanke. She is widely recognized as one of the first³ computer programmers due to her work on Charles Babbage's early mechanical general-purpose computer, the Analytical Engine.

Despite her limited formal education, Ada showed a strong aptitude for mathematics from a young age, encouraged by her mother. She became interested in Babbage's work in the 1830s and began a collaboration with him. In 1843, she translated an article on the Analytical Engine by the Italian engineer Luigi Menabrea and supplemented it with her own notes, which were longer than the original article. Her notes included a detailed method for calculating Bernoulli numbers using the machine, which is considered the first algorithm designed for a machine, earning her recognition as the world's first computer programmer.

Ada Lovelace envisioned the potential of computers beyond mere calculation, imagining them as capable of creating art and music, a vision that was far ahead of her time. She died of uterine cancer on November 27, 1852, at the age of 36. Despite her early death, her pioneering work laid the foundation for modern computing, and she is celebrated as a visionary in the field of computer science.

Alan Mathison Turing (1912–1954)

Was a pioneering British mathematician, computer scientist, logician, and cryptanalyst, widely considered one of the fathers of computer science and artificial intelligence.

Early Life and Education:

Born in London, Turing showed early talent in mathematics and science. He studied at King's College, Cambridge, where he was recognized for his work in probability theory. He later earned a PhD from Princeton University, where he developed the concept of a "universal machine," which laid the groundwork for modern computers.

World War II and Codebreaking:

During World War II, Turing worked at Bletchley Park, the British codebreaking center. He played a crucial role in breaking the German Enigma code, which significantly aided the Allied war effort. His creation of the Bombe, an electromechanical device, was instrumental in decrypting messages and is credited with shortening the war.

Post-War Contributions:

After the war, Turing worked at the National Physical Laboratory, where he developed one of the first designs for a stored-program computer, known as the ACE (Automatic Computing Engine). He later moved to the University of Manchester, where he continued his work on computing and developed concepts related to artificial intelligence, proposing the famous "Turing Test" to measure a machine's ability to exhibit intelligent behavior³.

The first working AI programs were written in 1951 to run on a particular computer, the Ferranti Mark I machine at the University of Manchester (United Kingdom); the chequers (i.e., checkers; draughts) – playing program was written by Christopher Strachey and a chess–playing program by Dietrich Prinz. In 1952–1962, Arthur Samuel of IBM (International Business Machines Corporation) wrote a more advanced checkers–playing program. In 1955, he created a version that learned (improving its playing) every time it was played, arguably the first practical application of AI. In 1956, the “Logic Theorist” program, written by Allen Newell, J.C. Shaw and Herbert A. Simon (at The Carnegie Institute of Technology, now Carnegie Mellon University (CMU), in Pittsburgh) was demonstrated for the first time. This is also known as the first usage of AI computer technology. This program was the first deliberately engineered to perform automated reasoning. Also in 1956, the term “Artificial Intelligence” was coined for the first time by John McCarthy in naming the Dartmouth College Summer Artificial Intelligence Conference, held at Dartmouth College (Hannover, New Hampshire, USA). The conference was organized by McCarthy, Morris Minsky, Nathan Rochester of IBM, and Claude Shannon. In 1958, McCarthy also wrote the computer language Lisp, which was central to the computer development of AI. Later, in 1959, McCarthy and Minsky founded the laboratory of AI at the Massachusetts Institute of Technology (MIT) in Cambridge.

In 1978, Herbert A. Simon won the Nobel Prize in Economics for his “theory of bounded rationality” one of the cornerstones of AI known in that field as “satisficing.” Also, in 1978, the MOLGEN program, written by Mark

Stefik and Peter Friedland at Stanford University, demonstrated that an object-oriented programming representation of knowledge could be used to plan gene cloning experiments. In the 1970s, David H Hubel and Torsten N Wiesel, a Holocaust survivor, studied vision in mature and immature cats, identifying the neuronal impulses generated in the process and laying the foundation for computer-generated visual images. In 1981, they received the Nobel Prize for Medicine and Physiology for this work. In 1980, Kunihiro Fukushima, known as “the maverick who gave machines the gift of sight,” following up on the work of Hubel and Wiesel, published his neurocognition, , which was the original deep convolutional neural network (CNN) architecture. Fukushima proposed several supervised and unsupervised learning algorithms to train the parameters of deep neurocognition such that it could learn internal representations of incoming data. In 1969, Fukushima introduced the ReLU (Rectifier Linear Unit) activation function in the context of visual feature extraction in hierarchical neural networks. It was later argued that it has strong biologic motivations and mathematical justifications. In 2011, it was found to enable better training of deeper networks, compared to the widely used activation functions prior to 2011(e.g., the logistic sigmoid (inspired by probability theory) and its more practical counterpart, the hyperbolic tangent). As of 2017, the rectifier was the most popular activation function for deep neural networks.

Also, in the 1980s, Yann André LeCun and his colleagues, notably Yoshua Bengio and Geoffrey Hinton, later called the “Godfathers of Artificial Intelligence,” introduced convolutional nets to accomplish optimal character

recognition, necessary, among other things, for reading and interpreting texts in languages that use characters instead of letters. In 2018, LeCun, Bengio, and Hinton received the Turing Award, known as the Nobel Prize for Computing, for this work.

In 1997, the Deep Blue chess machine (IBM) defeated the (then) world chess champion, Garry Kasparov. In 2015, Google DeepMind's AlphaGo (version: Fan) defeated three-time European Go champion professional Fan Hui by five games to 0.

In February 2020, Microsoft introduced its Turing Natural Language Generation (T-NLG), the “largest language model ever published at 17 billion parameters.” In November 2020, AlphaFold 2 by DeepMind, a model that performs protein structure predictions, won the CASP competition. Also in 2020, OpenAI introduced GPT-3, a state-of-the-art autoregressive language model that uses deep learning to produce a variety of computer codes, poetry, and other language tasks exceptionally similar and almost indistinguishable from those written by humans. Its capacity was ten times greater than that of the T-NLG.

ChatGPT, an AI chatbot developed by OpenAI, debuted in November 2022. It was initially built on the GPT-3.5 large language model. While it gained considerable praise for the breadth of its knowledge base, deductive abilities, and the human-like fluidity of its natural language responses, ChatGPT also garnered criticism for, among other things, its tendency to “hallucinate”, a phenomenon in which an AI responds with factually incorrect answers with high confidence.

The release triggered widespread public discussion on artificial intelligence and its potential impact on society. By January 2023, however, ChatGPT had more than 100 million users, making it the fastest-growing consumer application to date.

1.2) History of AI in Healthcare:

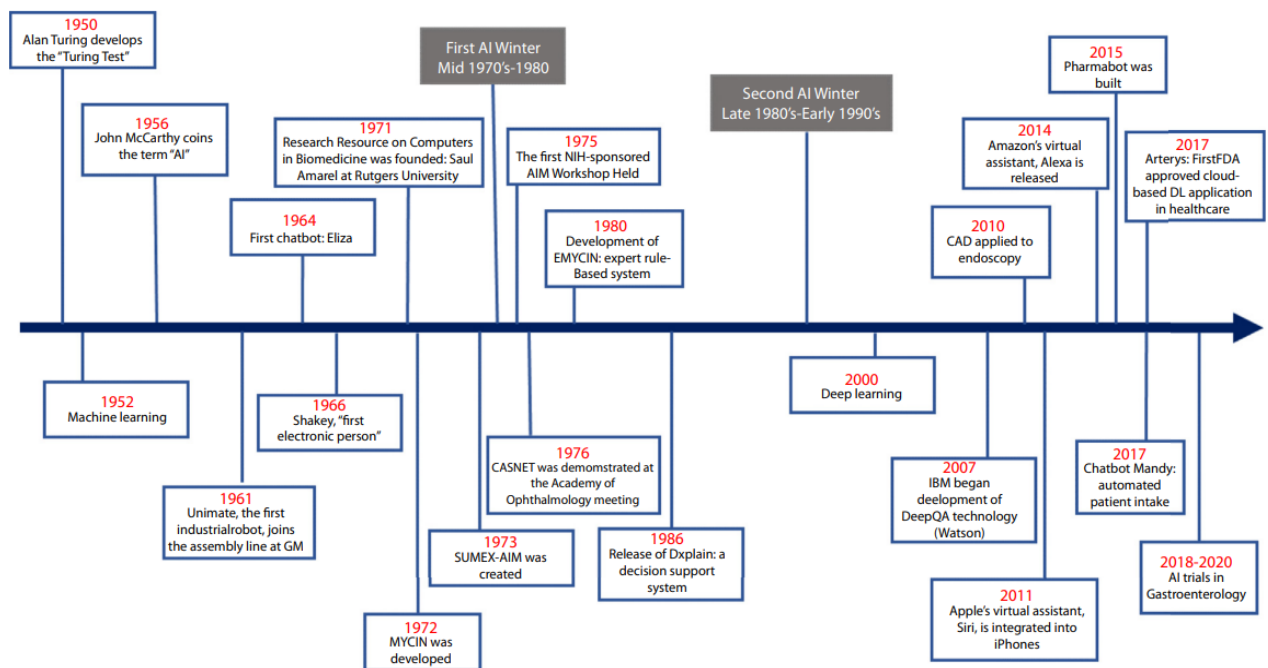


FIGURE 1 : TIMELINE OF THE DEVELOPMENT AND USE OF ARTIFICIAL INTELLIGENCE IN MEDICINE. AI, ARTIFICIAL INTELLIGENCE; DL, DEEP LEARNING; FDA, U.S. FOOD AND DRUG ADMINISTRATION; CAD, COMPUTER-AIDED DIAGNOSIS.⁴

The progressive growth and development of the AI platform in medicine are chronicled below and organized by specific periods of seminal transformation.

From the 1950s to the 1970s, early AI was focused on developing machines that could make inferences or decisions that previously only humans could make. The first industrial robot arm (Unimate; Unimation, Danbury,

⁴ Kaul, Enslin, and Gross, 'History of Artificial Intelligence in Medicine'.

Conn, USA) joined the assembly line at General Motors in 1961 and performed automated die casting. Unimate was able to follow step-by-step commands. A few years later (1964), Eliza was introduced by Joseph Weizenbaum. Using natural language processing, Eliza was able to communicate using pattern matching and substitution methodology to mimic human conversation (superficial communication), serving as the framework for future chatterbots. In 1966, Shakey, “the first electronic person,” was developed. Created at Stanford Research Institute, this was the first mobile robot to be able to interpret instructions. Rather than simply following 1-step commands, Shakey was able to process more complex instructions and carry out the appropriate actions. This was an important milestone in robotics and AI. Despite these innovations in engineering, medicine was slow to adopt AI. This early period, however, was an important time for digitizing data that later served as the foundation for future growth and utilization of AIM. The development of the Medical Literature Analysis and Retrieval System and the web-based search engine PubMed by the National Library of Medicine in the 1960s became an important digital resource for the later acceleration of biomedicine. Clinical informatics databases and medical record systems were also first developed during this time and helped establish the foundation for future developments of AIM. The 1970s to 2000s Most of this time period is referred to as the “AI winter,” signifying a period of reduced funding and interest and subsequently fewer significant developments. Many acknowledge major winters: the first in the late 1970s, driven by the perceived limitations of AI, and the second in the late 1980s, extending to the early 1990s, driven by the excessive cost of developing and maintaining expert digital information databases. Despite the

lack of general interest during this time period, collaboration among pioneers in the field of AI continued. This fostered the development of The Research Resource on Computers in Biomedicine by Saul Amarel in 1971 at Rutgers University. The Stanford University Medical Experimental–Artificial Intelligence in Medicine, a time–shared computer system, was created in 1973⁴ and enhanced networking capabilities among clinical and biomedical researchers from several institutions.

A “backward chaining” AI system, MYCIN, was developed in the early 1970s.¹⁴ Based on patient information input by physicians and a knowledge base of about 600 rules, MYCIN could provide a list of potential bacterial pathogens and then recommend antibiotic treatment options adjusted appropriately for a patient’s body weight. MYCIN became the framework for the later rule–based system, EMYCIN. INTERNIST–1 was later developed using the same framework as EMYCIN and a larger medical knowledge base to assist the primary care physician in diagnosis.

From 2000 to 2020: Seminal advancements: In AI In 2007, IBM created an open–domain question–answering system, named Watson, that competed with human participants and won first place on the television game show Jeopardy! in 2011. In contrast to traditional systems that used either forward reasoning (following rules from data to conclusions), backward reasoning (following rules from conclusions to data), or hand–crafted if–then rules, this technology, called DeepQA, used natural language processing and various searches to analyze data over unstructured content to generate probable answers. This system was more readily available for use, easier to maintain, and more cost–

effective. By drawing information from a patient's electronic medical record and other electronic resources, one could apply DeepQA technology to provide evidence-based medicine responses. As such, it opened new possibilities in evidence-based clinical decision-making. In 2017, Bakkar et al.. used IBM Watson to successfully identify new RNA-binding proteins that were altered in amyotrophic lateral sclerosis. Given this momentum, along with improved computer hardware and software programs, digitalized medicine became more readily available, and AIM started to grow rapidly. Natural language processing transformed chatbots from superficial communication (Eliza) to meaningful conversation-based interfaces. This technology was applied to Apple's virtual assistant, Siri, in 2011 and Amazon's virtual assistant, Alexa, in 2014. Pharmabot was a chatbot developed in 2015 to assist in medication education for pediatric patients and their parents, and Mandy was created in 2017 as an automated patient intake process for a primary care practice.

II. Artificial intelligence versus human intelligence:

We agree that AI is a technological simulation of the way humans possess situations, though it does not "think" in the way humans do. Instead, it processes information using algorithms and mathematical models to simulate certain aspects of human cognition, such as learning, pattern recognition, and decision-making. Here's how AI mimics thinking:

Data Processing and Pattern Recognition:

AI systems are trained on large amounts of data. They use statistical methods to recognize patterns within this data. For example, in image

recognition, an AI might learn to distinguish between cats and dogs by analyzing thousands of labeled images and identifying the unique features of each.

Algorithms and Machine Learning

AI relies on **machine learning (ML)** algorithms, which allow the system to improve over time by learning from data. There are different types of machine learning:

- **Supervised Learning:** The AI is trained on labeled datasets, and it learns to make predictions or decisions based on this data.
- **Unsupervised Learning:** The AI identifies patterns or relationships in unlabeled data without explicit instructions.
- **Reinforcement Learning:** The AI learns by interacting with an environment, receiving feedback in the form of rewards or penalties, and optimizing its actions to maximize reward.

Neural Networks and Deep Learning

In advanced AI, particularly in deep learning, systems use **artificial neural networks**

inspired by the structure of the human brain. These networks consist of layers of interconnected nodes (neurons) that process data in complex ways. By adjusting the "weights" of connections between these nodes through repeated training, AI can learn to make more accurate decisions or predictions.

Judging by the volume of publications in the last two decades, Artificial Neural Networks is **the most popular AI technique in medicine**.

ANNs are computational analytical tools that are inspired by the biological nervous system. They consist of networks of highly interconnected computer processors called ‘neurons’ that are capable of performing parallel computations for data processing and knowledge representation. Their ability to learn from historical examples, analyse non-linear data, handle imprecise information, and generalise, enabling application of the model to independent data, has made them a very attractive analytical tool in the field of medicine.

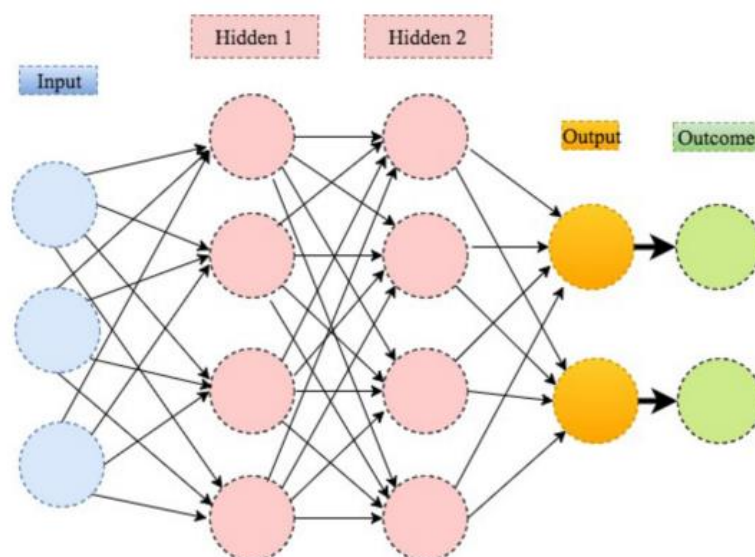


FIGURE 2: AN ILLUSTRATION OF NEURAL NETWORK⁵

Simulating Cognitive Tasks

AI doesn't "understand" the way humans do, but it can mimic specific cognitive tasks:

⁵ Jiang et al., 'Artificial Intelligence in Healthcare'.

- **Learning:** AI can learn from historical data to improve its accuracy over time.
- **Decision-Making:** By analyzing inputs, AI can make decisions based on pre-defined criteria or by optimizing for the best outcome.
- **Problem-solving:** AI can apply mathematical models to solve problems, such as finding the shortest route in navigation systems.

Probabilistic Reasoning

AI often uses probabilistic models to handle uncertainty, much like how humans make decisions based on likelihoods. For instance, AI may assign probabilities to different outcomes and choose the one with the highest probability of success.

Key Differences from Human Thinking:

No Consciousness: AI lacks self-awareness, emotions, intuition, or the subjective experience of thinking.

- **Task-Specific:** Most AI systems are designed to perform narrow tasks, like language translation or image recognition, whereas human thinking is far more general and adaptable.
- **No Intuition or Creativity (Yet):** AI relies on logic and data. While it can generate solutions that seem creative, it doesn't experience creative insights the way humans do.

Here's a little table to simplify the difference

Aspect	Human intelligence	Artificial intelligence
Adaptability	Highly adaptable to new, unfamiliar environments and tasks.	Limited adaptability; excels in predefined tasks.
Creativity	Can be highly creative, producing original ideas, art, and innovations.	Lacks true creativity; generates based on existing data.
Processing Speed	Limited by biological constraints (neurons, brain capacity).	Processes information at incredible speeds, depending on hardware.
Multi-tasking	Can handle multiple complex tasks but often with limited efficiency.	Capable of parallel processing at very high efficiency.
Problem-solving	Able to think abstractly, reason logically, and consider ethical/moral implications	Excels in problem-solving within its programmed domain, but lacks abstract reasoning and moral understanding.

TABLE 1:EXAMPLES OF THE DIFFERENCE BETWEEN AI AND HUMAN INTELLIGENCE.⁶

Although the AI community in the 21st century has shifted to more complex models of the brain (e.g. neural networks and machine learning), AI continues to rely heavily on models from cognitive science. Moreover, among AI scholars, human intelligence is typically viewed as being in line with traditional intelligence quotient (IQ) tests – that is, defined in terms of humans’

⁶ ‘ARTIFICIAL INTELLIGENCE VS HUMAN INTELLIGENCE’.

ability to reason and think, problem solve, think abstractly and use previous experiences in new situations. Furthermore, working memory is a key dimension when defining intelligence and is almost always synonymous with concentration because it directs the individual's attention when he or she is solving problems. Hence, working memory is key when sorting out relevant information needed to solve problems. The employment of games, such as chess and Go, is a recurring theme in the history of AI research and is typically used to illustrate AI's potential . Games such as chess are based on logic and mathematical combinations, and quizzes are based on one's ability to remember lexical facts. In 1997, IBM's Deep Blue computer beat the world champion Kasparov in chess, and in 2011, IBM's Watson computer won the television show Jeopardy! However, behind these games' façades is the stark reality that the current capabilities of AI systems, such as IBM's Watson or Google's AlphaGo, are quite narrow. Tasks must be defined discretely, and the analytics within these systems are only as good as the data upon which the analyses depend. These systems have been fed with data or solutions that provide correct answers or facts at a speed that enables them to logically outperform humans⁷

In summary, while AI can simulate aspects of human thinking through advanced algorithms and data processing, it doesn't "think" like humans. It works based on data-driven computation rather than conscious thought or understanding.

⁷ Pettersen, 'Why Artificial Intelligence Will Not Outsmart Complex Knowledge Work'.

III. The applications of Artificial intelligence:

Artificial Intelligence (AI) in the form of neural networks and expert systems has applications in nearly all human activities. The combination of high precision and low computation time makes AI a cutting-edge technology. Robots and expert systems (ESs) are already taking over workshop-level jobs in large industries, moving humans into more supervisory roles. Stock brokerage firms now use AI to analyze data, make predictions, and buy or sell stocks without human interference. Some key applications of AI are as follows:

III.1) The applications of AI In Agriculture:

The application of AI in the agricultural sector has become increasingly evident⁸. This sector faces numerous challenges, such as improper soil treatment, disease and pest infestations, big data requirements, low productivity, and a knowledge gap between farmers and technology. AI's flexibility, high performance, accuracy, and cost-effectiveness are transforming the field. It helps with soil management, crop management, weed control, and disease management, leading to higher yields and more efficient farming practices.

III.2) The applications of AI in Combating Cyber Crimes:

Classic AI approaches focus on individual human behavior, knowledge representation, and inference methods. Distributed Artificial Intelligence (DAI²), however, focuses on social behavior, such as cooperation, interaction, and knowledge-sharing among different units

⁸ Eli-Chukwu, 'Applications of Artificial Intelligence in Agriculture: A Review'.

(agents). The process of solving distributed resolution problems relies on sharing knowledge and cooperation among agents. From these concepts emerged the idea of intelligent multi-agent technology, which plays a vital role in combating cyber crimes.

III.3) The applications of AI In the Gaming Industry:

One of the most well-known applications of AI in gaming is its use in chess. Though these machines are not as intelligent as humans, they use brute-force algorithms to scan hundreds of positions every second to determine the next move⁹. Additionally, AI is being integrated into motion-sensing devices like Microsoft's Xbox 360 Kinect for body motion detection. However, this technology is still in its early stages and requires further advancement for broader, everyday applications.

III.4) The applications of AI in Heavy Industries:

AI-driven robots have become commonplace in heavy industries and are employed in tasks that are considered dangerous for humans¹⁰. These robots also enhance efficiency as they can work continuously without the need for breaks, thus overcoming the limitations of human fatigue.

III.5) The applications of AI In Weather Forecasting:

Neural networks are now being used to predict weather conditions. Historical data is fed into the neural network, which then analyzes patterns in the data to predict future weather events. Expert Systems: Expert systems are machines trained to have specialized knowledge in specific fields. They are

⁹ Das et al., 'Applications of Artificial Intelligence in Machine Learning'.

¹⁰ Li et al., 'Applications of Artificial Intelligence in Intelligent Manufacturing'.

designed to solve problems in niche areas by using statistical analysis and data mining, deriving solutions through a logical sequence of yes–no questions. An expert system comprises three main components. Knowledge base; Stores all the necessary information, rules, data, and relationships relevant to the system's domain of expertise.

Inference engine. Uses the knowledge base to analyze queries and provide solutions or recommendations in a manner similar to a human expert.

Rules: Conditional statements that link input conditions to the final solutions.

III.6) The applications of AI In Data Mining and Knowledge Extraction:

Data mining, a rapidly growing field, is part of a larger process called Knowledge Discovery in Databases (KDD). KDD involves several steps, including data selection, cleaning, pre–processing, and transformation, prior to data mining¹¹. Data mining uses algorithms to uncover hidden patterns and relationships within large datasets. AI, as a broader field than machine learning, involves knowledge representation, knowledge acquisition, and inference, which are fundamental techniques in the AI landscape.

III.7) The applications of AI in Healthcare all over the world:

Over the decades, new equipment has emerged in the medical field, and we have witnessed the importance of artificial intelligence (AI) in improving aspects of healthcare. AI will likely be incorporated into routine clinical care in the near future. This promise has led to growing focus and investment in AI

¹¹ Borana, 'Applications of Artificial Intelligence & Associated Technologies'.

medical applications both from governmental organizations and technological companies.

Artificial intelligence has the potential to transform medical practice by offering innovative solutions to improve quality of care, increase operational efficiency and reduce costs; a study conducted by IBM Watson Health found that AI algorithms can improve the accuracy of cancer diagnoses by up to 96%, compared with 70% for traditional methods (Esteva et al., 2017). Analysis of various AI applications in medical diagnostics and their ability to improve the accuracy and efficiency of care by evaluating AI-assisted diagnostic systems shows a significant reduction in diagnostic errors of 25%, 30% compared to traditional methods, with improvements in these percentages particularly in the diagnosis of complex and rare diseases. Before AI systems can be deployed in healthcare applications, they need to be ‘trained’ through data that are generated from clinical activities, such as screening, diagnosis, treatment assignment and so on, so that they can learn similar groups of subjects, associations between subject features and outcomes of interest. These clinical data often exist in but are not limited to the form of demographics, medical notes, electronic recordings from medical devices, physical examinations, and clinical laboratory and images. Specifically, in the diagnosis stage, a substantial proportion of the AI literature analyzes data from diagnosis imaging, genetic testing, and electrodiagnosis.

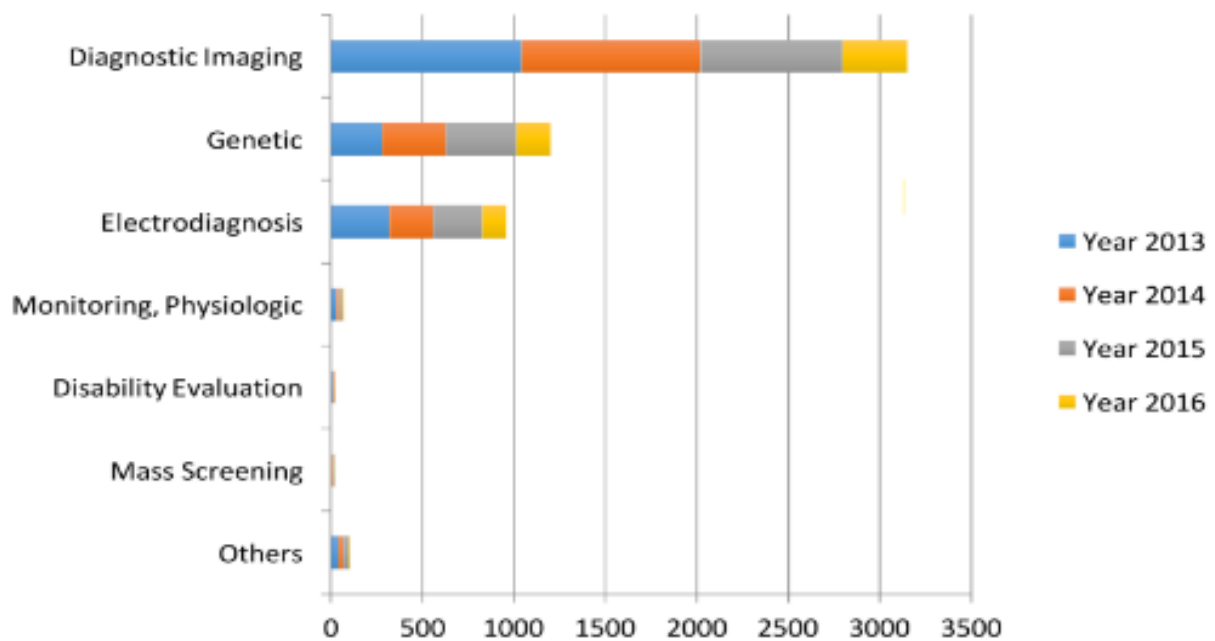


FIGURE 3:THE DATA TYPES CONSIDERED IN THE ARTIFICIAL INTELLIGENCE (AI) LITERATURE¹².

Applications of AI. In medical specialties:

III.7.a) The applications of AI in Radiology:

The specialty relies on machines, so the goal was the use of computer programs (techniques below) to give the machines the ability to interpret the results based on previous interpretations,

Ordering of Imaging Tests: There has been a long-standing interest in using AI techniques to assist clinicians with medical decisions, including for radiology order entry, with early works by Kahn and Swett dating over 3 decades ago. A CDS created with machine learning algorithms could automatically evaluate the clinical query considering a holistic clinical picture using extracted information from the electronic medical records, such as symptoms, physical examination findings, laboratory results, pathology

¹² Ramesh et al., 'Artificial Intelligence in Medicine'.

reports, and previous imaging data to determine which imaging examination is most appropriate based on local guidelines.³ The CDS would be seamlessly integrated into the computerized order entry system and would provide immediate guidance to clinicians without disrupting the normal workflow

Automatic Protocols: Protocols are a crucial step in the radiology workflow to ensure that the optimal test is performed to allow proper diagnosis. Alas, it is also a very time-consuming task, often performed by radiologists or radiology trainees. Radiologists' time and abilities could be put to better use by having machine protocol requisitions, with radiologists remaining available to verify that the adequate protocol was selected when technologists have doubts. Lee assessed a convolutional neural networks (CNNs) classifier, which utilized short-text classification to evaluate whether MSK MRI studies should be performed according to a routine or tumor protocol.¹⁷ The k agreement for protocol assignment by the CNN and radiologists was 0.88. The system demonstrated a sensitivity of 92.10%, a specificity of 95.76%, an area under curve (AUC) of 0.977, and an overall accuracy of 94.2%. An AI-based protocols system could screen the patient's records for contrast allergy, renal dysfunction, pregnancy, noncompatible implantable devices, and the presence of metallic foreign bodies, which could impact the type of imaging that the patient can safely undergo. Artificial intelligence could also help optimize MR protocols. Until now, the selection of imaging planes and pulse sequences for a protocol was based on an assessment by human reviewers. However, this task can be performed using machine learning. For example,

Richardson demonstrated the ability of a CNN to evaluate the value of MR sequences for the diagnosis of anterior cruciate ligament tears.

Scheduling: Given the long waiting times for MRI in Canada, AI tools to automatically prioritize more urgent exams would be helpful to avoid delays in the diagnosis and treatment of time-sensitive conditions, such as sarcoma. The radiology appointments could be automatically coordinated with clinical follow-up appointments or dialysis sessions, when applicable.

They should also be planned for the adequate scanner, such as dual-energy CT or a 1.5T strength magnet to reduce metal artifact, if there is metallic hardware at the area of interest, with the AI system screening for the presence of hardware in the clinical and past radiological data.⁴ Moreover, AI could help in maximizing patient throughput to optimize the use of the limited MRI resources in the Canadian setting. For example, Nelson et al.

presented complex, nonlinear, high-dimensional models using machine learning to predict missed MRI appointments.¹⁹ A “no-show” is a lost opportunity for another patient to be scanned or to undergo an image-guided procedure and contributes to waiting times; therefore, such predictive models could help adapt booking strategies. The work by Muelly et al. suggests that MR scanner utilization could be increased by improving the scheduling

Magnetic Resonance Imaging Image Acquisition: The use of limited MRI resources can also be optimized by reducing scan times, thereby increasing patient throughput. Artificial intelligence tools can help accelerate MRI examinations, such as with undersampling and super-resolution.²¹ Such

techniques have permitted the acquisition of excellent-quality images without compromising diagnostic accuracy, both adequately depicting (A, B) medial meniscal tears and (C) cartilage thinning with subchondral marrow signal alterations in 3 different patients. Reprinted Figure in Johnson et al. To foster developments in image reconstruction for accelerated MRI, in a collaborative effort, Facebook AI Research and NYU Langone Health released the fastMRI data set. It is the first publicly available large de-identified imaging data set, comprised of MRI k-space data as well as Digital Imaging and Communications in Medicine images from knee MRI examinations. Artificial intelligence systems may also provide automated quality control, thereby reducing the need to recall patients for repeat examinations.

Another exciting innovation in the production of MR images is the creation of synthetic MR images from CT images. Lee et al. studied the use of generative adversarial networks to transform spine CT images into axial T2-weighted MR images. When 2 experienced MSK radiologists evaluated the similarities between the synthetic and the real MR images based on the disc signal, degree of disc protrusion, muscle, fat tissue, facet joint signal, degree of stenosis, thecal sac, bone, and overall appearance, the average similarity was 80.2%. When 2 radiologists, 2 spine surgeons, and 2 residents blindly classified real and synthetic MR images, the failure rate ranged from 0% to 40%¹³. On quantitative analysis, the mean absolute error value of synthetic MR images was 13.75 to 34.24 pixels (average 21.19 pixels; Figure 4) and the peak signal to noise ratio of 61.96 to 68.16 dB (mean 64.92 dB). Generating

¹³ Gorelik and Gyftopoulos, 'Applications of Artificial Intelligence in Musculoskeletal Imaging'.

synthetic MR images from CT spine images may be particularly useful for patients who are unable to undergo MRI.

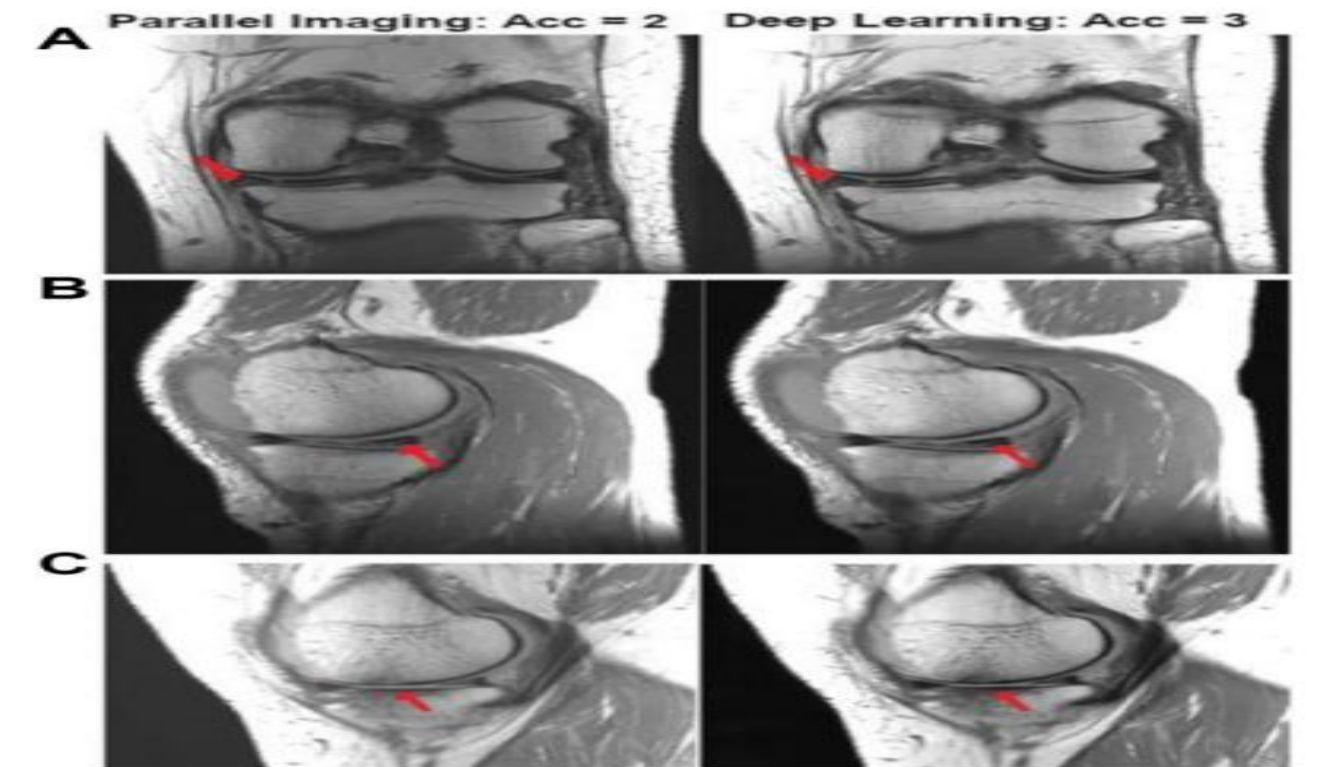


FIGURE 4:MAGNETIC RESONANCE IMAGES RECONSTRUCTED WITH PARALLEL IMAGING (LEFT) AND VARIATIONAL NETWORK DEEP LEARNING (RIGHT), ¹³

Computed Tomography Image Acquisition Developments in AI may also help improve image quality in computed tomography. For example, they may assist in decreasing artifacts related to orthopedic hardware. Zhang and Yu described the use of a CNN for metal artifact reduction, which merges original and corrected images data for artifact suppression. Artificial intelligence algorithms have also shown promise in reducing CT radiation dose while still ensuring a high quality of images. Image Interpretation Although AI can assist the imaging value chain in many of its components, it is AI's capacity to detect findings and suggest diagnoses that has received the most attention in recent years. The following section outlines some of AI's achievements in image

interpretation for MSK radiology. Bone Age Leaps in AI developments have been facilitated by competitions. Most notably, in the field of computer vision, the 2012 ImageNet Large Scale Visual Recognition Challenge played a major role in promoting the advancement of CNNs. The first prize of that competition was won by the Canadian team of Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton, who presented a CNN-based algorithm now known as AlexNet, which demonstrated an impressive top-5 test error rate of 15.3%, better than the second-best model by 10.9%.²⁷ Their work illustrated the advantages of CNNs and played a highly influential role in the field of computer vision. Similarly, in the field of Radiology, the Radiological Society of North America Pediatric Bone Age Machine Learning Challenge promoted collaborative efforts in furthering AI developments in medical imaging through competitions.²⁸ This challenge aimed at determining the best machine learning-based approaches for most accurately determining bone age.

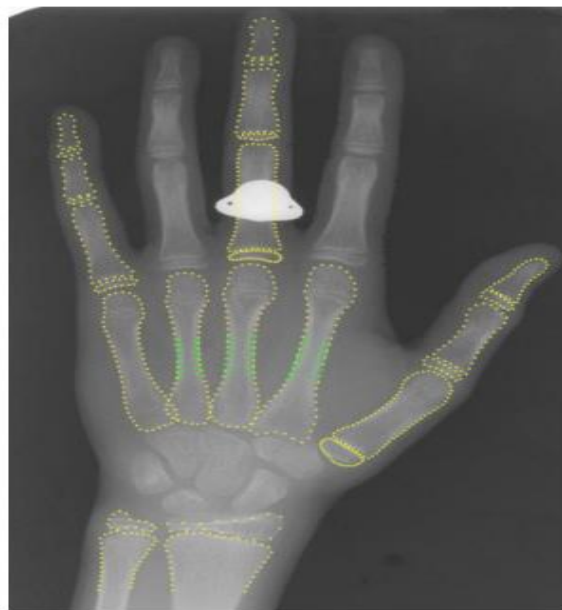


FIGURE 5: COMPUTE THE AGE OF INDIVIDUAL BONES USING SHAPE, INTENSITY,

AND TEXTURESCORES¹³.

Bone Fragility Another chance for opportunistic radiologic screening is the assessment for bone fragility. Early detection of decreased bone mineral density offers an opportunity for prompt treatment aimed at decreasing the risk of fracture and improving quality of life and survival. Several computer-aided diagnosis systems have been studied for the evaluation of bone quality on dental panoramic radiographs. Such a tool gives the chance to screen for osteoporosis incidentally on visits aimed at dental care. Kathirvelu et al. presented such a semiautomated measure of mandibular cortical thickness on a dental panoramic radiograph to identify patients at risk for low bone mineral density. Their approach consisted first of selecting a region of interest inferior to the mental foramen with median filtering and intensity normalization for image enhancement.

FRACTURES :

Fractures In many Canadian hospitals, there is no routine after-hours coverage by radiologists for the interpretation of radiographs. In the evening and overnight, emergency department physicians, therefore, make decisions based on their own assessment of radiographs, which subsequently get interpreted by the radiologist during the daytime. This may lead to discrepancies that may potentially impact patient's outcomes, such as in the case of hip fractures where a delayed diagnosis and surgery may portend a poorer prognosis.³⁸ Artificial intelligence could aid with automatic fracture detection. Multiple studies have assessed the use of AI for the detection (and classification) of fractures both in the axial and appendicular skeleton on

radiographs and computed tomography and have shown promise (Figure 6).^{2,33,39,40} In a systematic review which included 10 studies (8 for fracture detection at the ankle, hand, hip, spine, wrist, and ulna; 1 for classification of femoral diaphyseal fractures; and 1 for both detection and classification of proximal humeral fractures), the area under the receiving operating characteristic curve (AUC) achieved in 5 studies was 0.95 to 1.0, and the accuracy for 7 studies was 83% to 98% for fracture detection.⁴⁰ The AUC was 0.94 in 1 study, and the accuracy was 77% to 90% in 2 studies for fracture classification. The performance of AI was higher than that of human readers in 2 studies for the detection and classification of hip and humeral fractures and was similar to that of human readers in 1 study for the detection of wrist, hand, and ankle fractures. Authors noted that fractures in the studied areas are frequently displaced and, therefore, easier to identify. Artificial intelligence models could possibly be less accurate for less evident fractures, such as nondisplaced femoral neck or scaphoid fractures. A limitation of CNN-based models is that they must be trained for separate body parts, unlike humans, who translate their knowledge of fractures to any site.

Including a nondisplaced transcervical (A, B), angulated transcervical (C, D), displaced and minimally angulated intertrochanteric (E, F), and displaced and angulated subtrochanteric (G, H) fractures. Areas that most contributed to image classification were the fracture site, except for subtrochanteric fractures, where it was the trochanteric region.

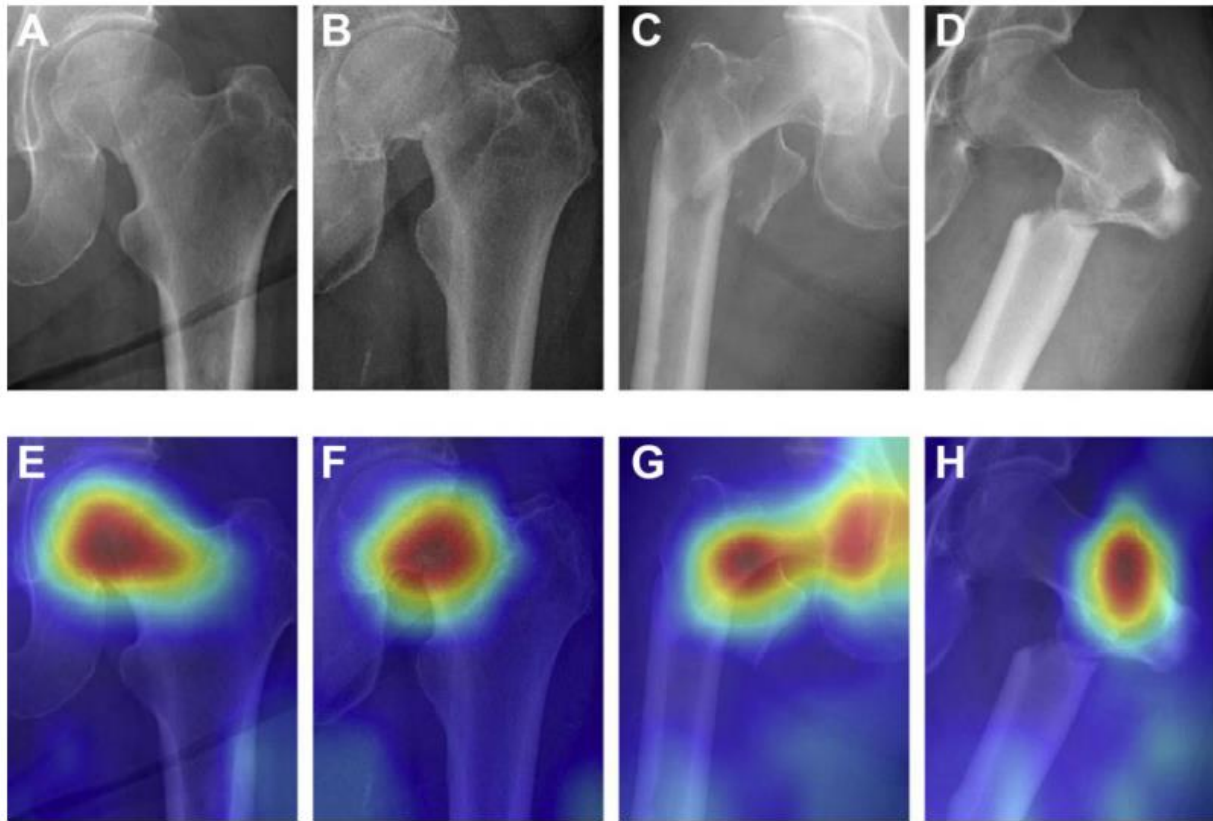


FIGURE 6: SALIENCY MAPS IN 4 REPRESENTATIVE EXAMPLES OF AUTOMATICALLY DETECTED HIP FRACTURES, USING CNN¹³.

Musculoskeletal Oncology

The detection of metastatic bone lesions ^{50,51} and the monitoring of their temporal evolution on serial scans can be facilitated by AI methods.⁵² Machine learning can also be useful in assessing treatment response for osseous metastases. In a study by Acar et al, sclerotic bone lesions in patients with prostate cancer could be classified as metastases (with ⁶⁸Ga-prostatespecific membrane antigen expression on positron emission tomography/computed tomography) versus sclerotic lesions with complete response (without ⁶⁸Ga-prostate-specific membrane antigen expression) using CT texture analysis and machine learning, with the best performance

obtained using a weighted k-nearest neighbor technique, which demonstrated an AUC of 0.76.⁵³ Artificial intelligence can also help diagnose the origin of metastases, such as in a study by Lang et al, in which radiomics and deep learning methods could differentiate spinal metastases from lung and other cancers on dynamic contrast-enhanced MRI with an accuracy of up to 0.81.⁵⁴ The diagnosis of primary bone tumors can also be assisted by AI, with works published on this topic by Lodwick et al as early as the 1960s.⁵⁵ Prediction of tumor recurrence can also be achieved with AI, as illustrated by the work of He et al who used an Inception V3 CNN to predict local recurrence of giant cell tumor of bone based on MR and clinical data.⁵⁶ Similarly, AI may help with the diagnosis of soft tissue tumors.^{57,58} For example, Malinauskaite et al. presented a machine-learning classifier that could distinguish between lipoma and liposarcoma on MRI using radiomic features with an AUC of 0.926, with a performance superior to that of 3 MSK radiologists.⁵⁸ Moreover, using radiomic features and machine learning classification techniques, the histopathological grade of soft tissue sarcomas can be predicted with an AUC of up to 0.92 (accuracy of 0.88).⁵⁹ Machine learning methods may also assist in monitoring posttreatment changes of soft tissue sarcoma on MRI

Osteoarthritis and Cartilage Imaging

The aging Canadian population entails an increased prevalence of osteoarthritis with an associated rise in demands on the health care system, including medical imaging.⁶¹ The radiographic grading of osteoarthritis may be automated by AI, which would expedite and standardize its interpretation. Thomas et al. presented an automated deep learning model to stage knee

osteoarthritis according to the Kellgren–Lawrence system using the Osteoarthritis Initiative radiographs, which reached an average F1 score of 0.64 and accuracy of 0.66 compared to the best individual radiologist's F1 score of 0.60 and accuracy of 0.60, with no manual image preprocessing required.⁶² The qualitative and quantitative assessment of cartilage on MRI can also be augmented with AI methods, which would make the assessment of osteoarthritis more precise and consistent. Several deep learning systems for the automated detection of cartilage lesions have already been developed.⁶³, “People should stop training radiologists now. It's just completely obvious that, within five years, deep learning is going to do better than radiologists... It might be 10 years, but we got plenty of radiologists already,” Hinton said at a machine learning conference in Toronto.

III.7.b) The applications of AI in Cardiology:

A research study in the UK showed that ML could improve cardiovascular risk prediction by correlating complex interactions between risk factors. The researchers provided data on 295,000 patients to four ML algorithms (random forest, logistic regression, gradient boosting machines, neural networks) for training purposes for correlating medical history with heart attack rates. Next, the algorithms were made to predict which of the additional 82,000 patients would have heart attacks based on their records¹⁴. The best-performing ML algorithm, neural networks, accurately predicted 7.6% more events than the American College of Cardiology/American Heart Association (ACC/AHA) method with 1.6% fewer false alarms. For the given test sample size of

¹⁴ Ahuja, ‘The Impact of Artificial Intelligence in Medicine on the Future Role of the Physician’.

approximately 83,000 records, this correlates to 355 more patients whose lives could have been saved. The authors concluded that “Machine learning significantly improves accuracy of cardiovascular risk prediction, increasing the number of patients identified who could benefit from preventive treatment, while avoiding unnecessary treatment of others”. Another study by Dawes et al. (2017) developed a ML algorithm that enabled them to predict outcomes in patients with pulmonary hypertension with high accuracy. Medical data from 250 patients were used for the study. According to the authors the ML algorithm “improved survival prediction independent of conventional risk factors in patients with newly diagnosed pulmonary hypertension”

III.7.c) The applications of AI in Gastroenterology:

The application of AI in gastroenterology has expanded greatly over the last decade. Computer-assisted diagnosis can be applied to colonoscopy to improve the detection of and differentiation between benign versus malignant colon polyps.⁷ By using the EUS platform, AI has been used to help differentiate chronic pancreatitis from pancreatic cancer, a common clinical challenge.^{29,30} DL can also be developed to perform prediction models for prognosis and response to treatment. Several ANNs have been created and tested for diagnosis and prediction models in gastroenterology. In a retrospective study of 150 patients, 45 clinical variables were used to make a diagnosis of GERD with 100% accuracy. presented a prospective, multicenter study of 2380 patients in which ANN used 68 clinical variables to predict the mortality in nonvariceal upper GI bleeding with 96.8% accuracy. AI has been used for prognostication of survival in esophageal adenocarcinoma, to predict

relapse and severity of inflammatory bowel disease,³⁴ and to inform probability of distant metastases in esophageal squamous cell carcinoma, among other similar applications.²⁸ These early studies suggest promise for future application to clinical practice. AI-ASSISTED ENDOSCOPY AI-assisted endoscopy is an evolving field with a promising future. Initial applications included computer-aided diagnosis (CAD) for the detection, differentiation, and characterization of neoplastic and non-neoplastic colon polyps. A recent randomized controlled trial of 1058 patients demonstrated a significant increase in adenoma detection rates with the use of CAD compared with standard colonoscopy (29% vs 20%, $P < .001$), with an increased detection of diminutive adenomas (185 vs 102, $P < .001$) and hyperplastic polyps (114 vs 52, $P < .001$). There was no statistical difference in the detection of larger adenomas.³⁶ Optical biopsy sampling of colorectal polyps has also been evaluated by several groups using CAD models on images and videos with narrow-band imaging, chromoendoscopy, and endocystoscopy. The diagnostic accuracy of these models has been reported between 84.5% and 98.5%.⁵ A CNN was developed to determine invasiveness of colorectal mass lesions suspected to be cancer where a diagnostic accuracy of 81.2% was achieved.³⁷ AI has also been applied to improve imaging in Barrett's esophagus. de Groof et al³⁸ recently developed a CAD system that was 90% sensitive and 88% specific (89% accurate) in classifying images as neoplastic or nondysplastic Barrett's esophagus. The CAD system had higher accuracy than 53 nonexpert endoscopists (88% vs 73%). Similarly, a real-time CAD system was developed and trained using 1480 malignant narrow-band images and 5191 precancerous narrow-band images and was able to differentiate early

esophageal squamous cell carcinoma from precancerous lesions with 98% sensitivity and 95% specificity (area under the curve, .989). CNN-based models have also been applied to detecting small-bowel capsule endoscopy anomalies and gastric cancer. Cazacu et al³⁰ reported using ANNs in conjunction with EUS to assist in differentiating chronic pancreatitis from pancreatic cancer, with a sensitivity of 95% and specificity of 94%. The role of AI in endoscopic practice continues to evolve at a rapid pace and has benefited from the overall technological revolution in the endoscopy and imaging space in recent years. Although much of the technology reported has been proof of concept, 2 systems are approved for use. ENDOANGEL (Wuhan EndoAngel Medical Technology Company, Wuhan, China), a CNN-based system developed in 2019, can provide an objective assessment of bowel preparation every 30 seconds during the withdrawal phase of a colonoscopy, achieving a 91.89% accuracy. A recent randomized controlled study used the device to monitor real-time withdrawal speed and colonoscopy withdrawal time and demonstrated significant improvement in adenoma detection rates using ENDOANGEL-assisted colonoscopy versus unassisted colonoscopy (17% vs 8%; odds ratio, 2.18; 95% confidence interval, 1.31–3.62; $P = .0026$). The second system, GI Genius (Medtronic, Minneapolis, Minn, USA), is an AI-enhanced endoscopy aid device developed to identify colorectal polyps by providing a visual marker on a live video. It is approved for use in Europe and undergoing clinical evaluation in the United States. In a validation study, GI Genius had an overall sensitivity per lesion of 99.7% and detected polyps faster than endoscopists in 82% of cases. In a recent randomized controlled trial, Repici et

al48 demonstrated a 14% increase in adenoma detection rates using this CAD system

III.7.d) The applications of AI in Oncology and pathology:

The field of pathology depends on the trained eye of the pathologist to render a diagnosis of a biospecimen¹⁴. Given the many different types and subtypes of disease and the avalanche of new data in the form of different biomarkers and genomics data, this is becoming an increasingly difficult task for the pathologist. In addition, fewer of the nation's senior medical students choose to pursue a career in pathology. In this scenario, DL-based approaches have a significant role to play. For example, researchers at Google trained a DL-based CNN to assist with the detection of metastatic breast cancer in lymph node tissue on specimen images with an accuracy comparable to that achieved by human pathologists. It is clearly a challenging task to look for very small deposits of cancer on a specimen slide, but an AI-based system suffers from no such problem and can scan any number of specimen slides with no loss of accuracy due to fatigue. Couple this with the expected amount of big data in the form of human genomic data, human pathologists will find it nearly impossible to stay current with the emergence of these new biomarkers without the help of ML. On a different note, ML has been shown to accurately predict how long a kidney will function adequately in patients with chronic kidney damage. Specifically, a research team at Boston University used renal biopsies to train DL based CNN to predict kidney function. The researchers found that CNN algorithms “were more precise and accurate than traditional pathologist-estimated scoring systems when calculating kidney decline”¹⁴.

Clearly, AI-based systems have the potential to augment clinical decision-making for nephrologists.

The importance of anatomic pathology to diagnose and classify disease cannot be underestimated. The pathologist's diagnosis on histological slides is at the centre of diagnosis, for clinical and pharmaceutical research and, most importantly, for decision-making on how to treat cancer patients in the daily practice. The need for accuracy in histopathologic diagnosis of cancer is increasing as personalized therapy requires accurate biomarker assessment, rapid development of digital microscopy has enabled digitalization of histological slides at high-resolution and high speed, which can now firmly support training, research and diagnostics in pathology. The appearance of digital image analysis (DIA) algorithms holds promise to improve the volume precision of histomorphological evolution.

Recently, FDA approved the first whole slide imaging system for digital pathology which marks a new era of digital image analysis in pathology. There is currently also a rising interest and competition concerning digital image analysis solutions for clinical applications. Pathology is an image-related discipline, primarily with the brightfield microscope as the major working platform for tissue representation. Several digital image analysis platforms have been developed to support the pathologist's assessment of digitized slides. Such applications aim to increase diagnostic accuracy, reliability, reproducibility, and efficiency by enabling quantitative image analysis. However, digital image analysis for histopathology has been available for decades. During this time, methods have been developed to decrease

variability in image quality, for example, colour standardization, spatial filtering, denoising, or enhancement.

Although image analysis of IHC has gone beyond human capability to quantify expression, such DIA systems have not changed daily pathology practice. A potential explanation is that different platforms have unique algorithms to detect and classify objects (cells and tissue compartments) and handle staining intensities. Furthermore, there is a very limited number of studies comparing different DIA platforms¹⁵. The Aperio Digital Pathology operator-supervised system has been compared with the fully automated Definiens Tissue Studio software for scoring ER and PgR expression in breast cancer, showing a good correlation between the two platforms. In a recent study, the between-platform concordance was tested in Ki67 scoring between two DIA systems using VDS. Consecutive sections were stained for cytokeratin (CK) 8/18 and Ki67. Then, the authors digitally aligned the corresponding slides to score Ki67 in the CK-positive tumor regions. The authors showed high agreement between the two DIA platforms using VDS. Cell detection performance was compared between two platforms in another detailed study. The authors built a DIA algorithm to segment cell nuclei in breast cancer stained with several IHC and FISH markers. The authors compared the sensitivity and positive predictive values (PPV) of the new algorithm and other DIA platforms in cell nuclei segmentation applying pathologists' nuclear marking as a ground truth. Although it was demonstrated that the PPV values

¹⁵ Acs, Rantalainen, and Hartman, 'Artificial Intelligence as the next Step towards Precision Pathology'.

ranged between 87% and 94% amongst the different DIA systems, the between-platform reproducibility in Ki67 scoring was not investigated¹⁵.

AI has begun to be applied not only to medical images but also to omics data, such as genome information. For example, using AI to analyze RNA expression, DNA methylation, point mutations, and omics data of the copy number variation published in The Cancer Genome Atlas (TCGA), Ramazzotti et al. succeeded in predicting the prognosis of cancers. Chaudhary et al. used DNA methylation, mRNA, and miRNA omics data of liver cancer with AI to perform dimensional compression and then used the Cox proportional hazards model to identify prognostic features. As mentioned above, AI has been applied to various cancers, including gynecologic malignancies. This review describes the use of AI for the three major gynecologic forms of cancers: cervical, endometrial, and ovarian cancers.

Case study: assisting oncologists in India using IBM Watson IBM's AI-based Watson for Oncology, a cognitive computing platform trained by Memorial Sloan-Kettering Cancer Center that analyzes data to identify evidence-based treatment options, has been adopted by Manipal Hospitals' corporate and teaching facilities in India (IBM, 2015). Watson has the ability to read and understand natural language. As of December 2015, Watson for Oncology had ingested nearly 15 million pages of medical content, including more than 200 medical textbooks and 300 medical journals (IBM, 2015). Each month, Watson ingests about 10,000 new scientific articles and data on 100 new clinical trials to keep up-to-date on new findings (Cavallo, 2017). A note of caution may be appropriate here. Watson for Oncology treatment recommendations are not

based on its own insights from this data. Instead, they are based on training by physicians of Memorial Sloan Kettering Hospital who feed Watson information about how patients with specific characteristics should be treated. Hence, its accuracy and overall value may be limited by differing medical practices and economic circumstances). It may be fair to say that Watson for Oncology, while developing rapidly, is still in its early stages of development. As of 2015, there were 1 million new cancer cases diagnosed every year in India, and this is expected to rise (IBM, 2015). In addition, India faces a shortage of oncologists, surgical oncologists, and radiation therapists. Given the increasing number of cancer patients in India, fewer oncologists to treat them, the broad geographic footprint, and the rapid increase in scientific and clinical knowledge about care, physicians in India face a challenging time in staying up-to-date about best practices in treatment and care management. In this scenario, it was hoped that IBM Watson could help physicians in Manipal hospitals deliver the most advanced, effective, and cost-effective treatment to their cancer patients. According to a study published by Manipal Hospitals in 2018, Watson for Oncology was concordant with the hospital's multidisciplinary tumor board in 93 percent of breast cancer treatment decisions. However, showing that Watson agrees with the doctors only shows that it is competent in applying existing methods of care, not that it can improve them.

Surgical specialties:

III.7.e) The applications of AI in Ophthalmology:

Practices are already using ML and DL to revolutionize vision care. The immediate impact has been observed in the field of retinal diseases. An AI-based device has already been FDA-approved to detect diabetic retinopathy. Schlegl et al. developed a deep learning-based system to “automatically detect and quantify intraretinal cystoid fluid (IRC) and subretinal fluid (SRF). This system accurately characterized the pattern of intraretinal fluid in patients with wet AMD or retinal vein occlusion (RVO) and distinguished between intraretinal cysts and subretinal fluid. The authors conclude that deep learning in retinal image analysis provides an accurate means “for the differential detection of retinal fluid types across the most prevalent exudative macular diseases and OCT devices”

Diabetic Retinopathy is an eye disease known for its visual complications. It is the leading cause of blindness in people during their first productive years. The health burden is accentuated by the enormous cost per capita. This has further increased since the introduction of anti-VEGF agents. Very often, the disease does not present manifest symptoms before reaching a stage advance. However, if detected early, visual impairment can be avoided through early intervention which is also the most cost-effective option. Given the alarming increase in the number of people affected by diabetes and the lack of retinal specialists, an analysis computerized fundus images using an approach automated system reduces the burden on the health system in the DR screening and offers a near-ideal system for its management. Therefore,

screening will be useful for all stages of the disease and will also be useful in avoiding blindness in 90% of patients.

The enthusiasm in the field of artificial intelligence has led to several studies using retinal images to test the performance of AI in detecting DR (Diabetic Retinopathy) ¹⁶. Historically, the Wisconsin Fundus Photograph Reading Center (FPRC) has been the benchmark for scientific trials assessing the severity of DR, including the Diabetes Control and Complications Trial (DCCT) and the Diabetic Retinopathy Clinical Research Network (DRCR.net). The use of AI to assess retinal images is appealing because it aligns with the current trend of teleophthalmology and telemedicine. Selected patients with sight-threatening DR should be referred to a specialist. The urgent referral of these patients is crucial because DR affects individuals in their early productive years of life.

IDx-DR is the first AI algorithm approved by the Food and Drug Administration (FDA) for DR detection. After initial training based on a French database (Messidor-2), the device is paired with a non-mydratic retinal camera, and the captured images are sent to a cloud server. The server then uses the IDx-DR software and a "deep learning" algorithm to detect signs of DR based on an autonomous comparison with a reference dataset, considering that the device's sensitivity and specificity are below 90%. Therefore, it is not reliable.

¹⁶ Farahat et al., 'Application of Deep Learning Methods in a Moroccan Ophthalmic Center'.

It is crucial for patients and doctors to know that current-generation devices are not 100% reliable. A false negative result can provide a false sense of security about the status of retinopathy. For now, a full eye fundus exam remains the gold standard for screening and cannot be replaced by this device until proven otherwise.

Meanwhile, Google, through its DeepMind division, has developed a DR detection algorithm with a sensitivity of 96.1% and a specificity of 93.9%. Finally, OphtAI, a division of the French company Evolucare, also has a very efficient automatic DR detection algorithm (sensitivity 99%, specificity 87% in 3 seconds). It has CE marking and is integrated into a promising platform for DR screening through telemedicine (Figure 7).

Moreover, there are some studies with multimodal data to more precisely confirm a disease, such as combining optical coherence tomography (OCT) of the macula with eye fundus images to identify diabetic macular edema. The wide variety of techniques in different studies indicates that we are on the brink of a massive development of AI in healthcare. As new AI systems begin to perform better than human ophthalmologists, a fear may arise that machines could take over our jobs, but experts assure us that AI will only enhance our clinical toolkit. Let's wait and see what wonderful technologies the future holds for us.



FIGURE 7: AN AI ALGORITHM CAPABLE OF DETECTING RD IN EARLY STAGES AUTONOMOUSLY¹⁷

AI systems are also being used beyond retinal diseases. “AI systems are being developed and evaluated to diagnose and grade cataract in pediatric patients based on an analysis of slit-lamp images, diagnose glaucoma based on measurement of the retinal nerve fiber layer (RNFL) thickness and visual field (VF) and diagnose keratoconus based on Scheimpflug tonometry”. It is becoming more important that an ophthalmologist learn about the use of AI.

AMD17: AMD (Age-related Macular Degeneration) is a chronic and irreversible macular disease and one of the leading causes of central vision loss in individuals over the age of 50. With the demand for regular screening in such a condition, an automatic diagnostic tool for AMD can reduce the workload of clinicians.

Many studies have reported their preliminary results. Most of them use fundus images as the original input material and extract features of early, intermediate, and late AMD to distinguish them from healthy images. These

¹⁷ Moutei et al., ‘L’intelligence artificielle en ophtalmologie’.

tools achieve sensitivity ranging from 87% to 100%, with relatively high accuracy. It is thought that taking a fundus photo as input is less expensive than optical coherence tomography (OCT) examination. However, there is also research combining OCT with deep learning for AMD.

As we all know, intravitreal injections of anti-VEGF drugs are the first-line treatment for exudative AMD, and follow-up is also very important. Bogunovic et al. use an algorithm to observe responders to treatment using OCT images. Some researchers combine machine learning with OCT images to observe and predict the possibility of retreatment.

The growing use of connected smartphones and tablets among seniors makes it possible to consider the personalized assessment of visual acuity (VA) and its monitoring at home. ForeseeHome represents a breakthrough in the home monitoring of wet AMD (Age-related Macular Degeneration). The device allows for a simple daily test to check for minimal changes in vision. It is based on the principle of early detection of distortions. Monthly reports are sent directly to the doctor, who is then alerted. According to Querques et al., ForeseeHome was more sensitive to changes in AMD than older home testing methods like the Amsler grid. The system is now FDA-approved and is being rolled out in the United States.

In the same vein, the Odysight application by Tilak was launched in 2019 for monitoring maculopathies: detecting pre-monitoring the progression of the disease by generating an alert for a decrease in visual acuity to anticipate the therapeutic response. which has CE Theapplication, marking, is likely the most advanced in this field to date.

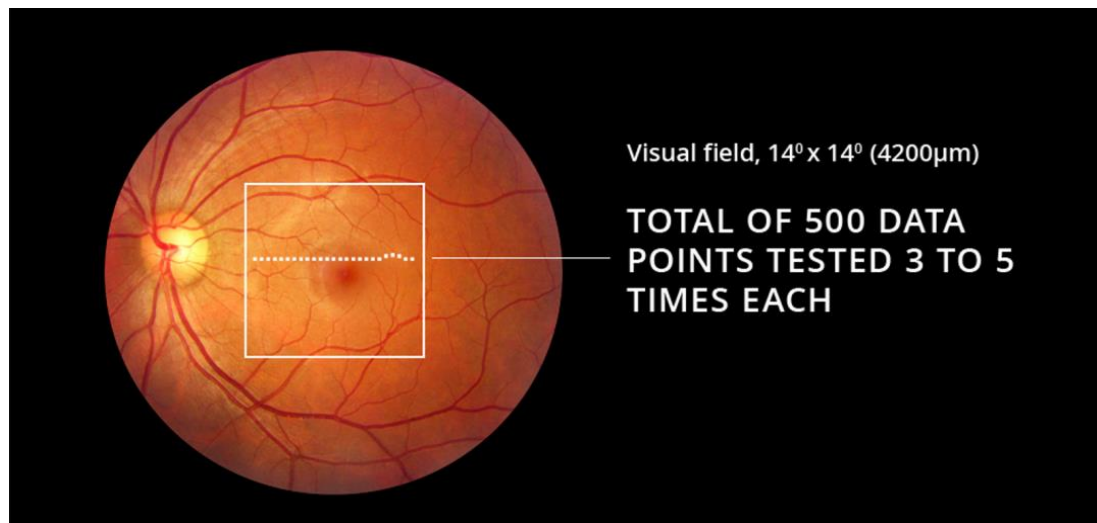


FIGURE 8: FORSEEHOME APPLICATION THAT DETECTS AGE-RELATED MACULAR DEGENERATION¹⁷

Glaucoma:

Glaucoma is a disease that primarily damages the optic nerve, which can lead to irreversible blindness. Therefore, early detection of glaucoma is highly necessary. It mainly depends on intraocular pressure, the thickness of the retinal nerve fiber layer of the optic nerve, and visual field examination.

Recent articles have shown high performance of AI algorithms in detecting and recognizing or classifying abnormalities in the visual field, optic disc, and OCT images of the optic disc and macula. These algorithms allow both the diagnosis of glaucoma and the determination of its stage.

A Korean team evaluated the performance of a deep learning algorithm for the overall analysis of images from non-mydratic retinal cameras.

III.7.f) The applications of AI in Gynecology:

Application of AI in Cervical Cancer and Cervical Intraepithelial Neoplasia

Many studies on cervical cancer and cervical intraepithelial neoplasia (CIN) have reported the utilization of AI, which can be mainly divided into the evaluation of colposcopy, MR imaging (MRI), CT, cytology, and human papillomavirus (HPV) data ¹⁸. Colposcopy Sato et al.¹⁴ analyzed 485 colposcopy images using deep learning to predict high-risk CIN. The diagnostic accuracy of the validation set was ~50%.¹⁴ Another report used colposcopy images of 19 435 patients from six centers to develop Colposcopic Artificial Intelligence Auxiliary Diagnostic System, a deep learning colposcopy diagnostic and biopsy guide system. The results of biopsy analyses assisted by this system were more accurate than those obtained by gynecologists alone (82.2% vs. 65.9%, 0.750 vs. 0.516, respectively; $p < 0.001$).¹⁵ Deep learning approaches also included HPV testing data. Miyagi et al.¹⁸ combined 253 colposcopy images containing CIN with HPV-typing information and developed a CIN lesion diagnosis algorithm using deep learning. The diagnostic accuracy of gynecologic oncologists was 0.843, whereas the accuracy of the deep learning algorithm was 0.941

Application of AI in Ovarian Cancer: AI research in ovarian cancer has been applied to basic research datasets, such as omics analyses. Effective immunotherapy requires the proximity of cytotoxic T lymphocytes and tumor cells. However, the factors that control the spatial distribution of T cells in the tumor microenvironment are not well understood. Desbois et al. combined

¹⁸ Sone et al., 'Application of Artificial Intelligence in Gynecologic Malignancies'.

transcriptome data with pathological images to analyze a large ovarian cancer cohort and developed a machine learning approach to molecularly classify and characterize tumor immunophenotypes¹⁸. Lu et al. extracted 657 quantitative mathematical descriptors from preoperative CT images of 364 patients with ovarian cancer.

Using machine learning, they developed a radiomic prognostic vector (RPV) for ovarian cancer that reliably identified 5% of patients with a median overall survival of less than 2 years. Furthermore, genetic, transcriptomic, and proteomic analyses from two independent datasets revealed that stromal phenotypes and DNA damage response pathways were activated in RPV-stratified patients with ovarian cancer. Some reports have also used the already mentioned TCGA database. Dong and Xu extracted miRNA expression levels from the ovarian cancer database of TCGA. Using these miRNA and clinical data, they developed a prognostic prediction model using an SVM approach. Their SVM-based model identified miRNAs that could predict tumor recurrence. Other publications classify carcinoma using machine learning. Using machine learning approaches with microarray data, Jansi and Devaraj aimed to extract important gene mutation groups suitable for cancer classification of patients with ovarian, lung, and colorectal cancer. The accuracy of ovarian cancer classification using 10 genes extracted by machine learning was over 95%. Another study applied AI to the early detection of ovarian cancer. Tanabe et al. converted data on glycopeptide expression in the sera of patients with ovarian cancer and non-cancer patients into 2D barcode information that was analyzed by a deep learning model. Based on the

evaluation of CA 125 and HE4 values, the diagnosis rate of early ovarian cancer reached 95%.

IV.6 g) The Applications of AI in ENT – ears–nose–throat:

Other dental diseases have known the utilization of AI applications, such as maxillary sinuses and oral cancer. The maxillary sinuses are structures that are commonly visualized using extraoral radiographs. Automated identification of the sinuses and detection of any pathology in them by AI can lead to a manifold decrease in misdiagnoses¹⁹. Kuwana et al. employed a deep learning object detection technique to detect maxillary sinuses and classify their lesions (inflamed or cyst) on panoramic radiographs. The performance of both identifications (sinusitis and sinus lesion) was higher than 90% and 80%, respectively. However, further studies are needed to collect more data for each type of sinus lesion. As oral cancer can grow and lead to the development of another one, advanced techniques are much-needed for its early detection. Praveena et al. proposed a fully automated system for detecting normal and cancerous images using a CNN. Furthermore, the cancerous regions are segmented for Mild or Severe classification. The proposed oral cancer system achieved an accuracy value of 99.7%

III.8.h) The Applications of AI in Dentistry:

Nowadays, many AI-based systems are used to modernize and automate the traditional techniques in dentistry. These systems aid in making the dentist's tasks easier by offering various services that improve the precision

¹⁹ Joudi et al., 'Review of the Role of Artificial Intelligence in Dentistry'.

of diagnostic, predict future dental diseases, and recommend treatments. The dental domain uses AI technology in many specialties, from detecting cavities to defining the human gender in forensic dentistry. Dental Cavities Dental caries is the most common dental disease that should be treated as soon as possible to not lead to other consequences¹⁹. A study done by Shankeeth et al. presented for the first time an automated caries detection and classification of third molars on panoramic radiographs. The authors used a pre-trained CNN-based deep learning model (MobileNet V2) on 400 panoramic radiographs and attained an accuracy of 87% on the test dataset. However, in this study, only cropped images were included. In contrast to this latter study, Seyyed et al. included images of jaws and teeth. Each tooth was determined and cropped using a Region-based Convolutional Neural Network (R-CNN), and these cropped images were then fed to the diagnosis network (GoogleNet) to identify whether the tooth is healthy, decayed, root-canaled, or restored. This proposed network had the highest accuracy compared to AlexNet and VGGNet16 with 92%, 88%, and 82%, respectively.

Orthodontics:

Since the treatment takes time to be realized, AI technology has clearly been used to identify the final form of teeth and show the result to the patient. In orthodontics, AI is mainly used to identify and analyze cephalometric landmarks, decision-making for tooth extraction, prediction of orthognathic surgery, and cervical maturation determination. J. Choi et al. proposed an original system for direct diagnosis of skeletal classification of malocclusion sagittally and vertically from the lateral cephalogram, eliminating the landmark

detection process. The multimodal CNN system was constructed based on 5,890 lateral cephalograms and demographic data and achieved an accuracy higher than 90% for both diagnoses¹⁹. However, the authors suppose that the trained data have been affected by selection bias. This skeletal classification of malocclusion plays a crucial role in the treatment planning process to determine whether an extraction pattern is needed. Peilin Li et al. used an ANN to predict if a patient needed an extraction or not. Additionally, they provided two artificial neural networks for the extraction and anchorage patterns. The accuracy of the three models was 94%, 83%, and 92%, respectively.

Recently, the cervical vertebrae are being used for age estimation by measuring bone age. Bone age allows assessment of skeletal maturation. In the determination of growth and development, skeletal maturation stages obtained from radiographic analyses are widely used in order to predict the time of pubertal development, to determine the growth rate, the peak period of growth, and the remaining growth and development potential. Few studies focused on this area of research. Kok et al. employed seven machine learning classifiers, namely logistic regression, k-nearest neighbors, decision tree, random forest, Naive Bayes, support vector machine, and artificial neural networks on 300 cephalometric radiographs to determine the different stages of cervical vertebrae (CVS). From all these cephalometric radiographs, the second (C2), third (C3), and fourth (C4) cervical vertebrae are evaluated and divided into six stages (CVS1–CVS6). The ANN had the best results in determining these stages, except for the fifth stage. Whereas Kim et al. proposed deep learning models for automatically estimating cervical vertebral

maturation on 600 cephalometric radiographs. Three modules were designed: a Classifier to classify the input image into one of the six stages implemented by the ResNet50, the second module is a Detector of Region Of Interest (ROI) to segment the original image around C2–C4 cervical vertebrae using the attention U–Net model, and the last module is a Segmentor to output only a binary image of the cervical spine. Therefore, the highest accuracy was achieved by assembling these three modules. However, orthodontic treatment alone cannot solve structural problems that need surgery. Therefore, and for the first time, Lee et al. performed a differential diagnosis of the indications of orthognathic surgery and orthodontic treatment based on cephalometric radiographs. The Modified–Alexnet model outperformed the MobileNet and Resnet50 models with an accuracy value of 96.4%.

Forensic dentistry:

In forensic dentistry, the gender prediction is an essential process to identify missing or dead person. Therefore, Isa ATAS proposed a deep transfer learning method of the pre-trained DenseNet121 model to classify male and female gender from 24,000 panoramic dental x-ray images. The proposed model was trained using different image resolutions. Thus, the 224×224 resolution obtained the highest accuracy of 97.25%. Isa also mentioned that the significant regions to consider in a gender classification are teeth and mandible circumference. In the same context, M.V. Rajee et al. proposed a new automated technique based on a ResNet50 model wherein they designed a novel filter to remove the noises in dental x-ray images in the preprocessing phase, in contrast to Isa's study that used the histogram equalization method.

As a result, the study of Rajee et al. achieved a higher accuracy with a 98.17% value.

Periodontics :

Artificial Intelligence is also being used in periodontics. Periodontal disease is one of the most prevalent oral diseases affecting humankind. It is the result of inflammation of the untreated gum that can destroy bone loss and, therefore, cause tooth loss. Where most of the studies only proposed the detection of radiographic bone loss (RBL) on dental panoramic radiographs, Chang et al. developed an automated method for detection and staging the periodontal bone loss according to the 2017 World Workshop criteria. Firstly, the developed CNN detects the boundary, the teeth, and the implants, then automatically classifies each tooth by analyzing a percentage rate of the radiographic bone loss. This method achieved an excellent result compared to a recent study that combined several models, namely automatic tooth detection and segmentation using a UNet network, then an object detection phase using the YOLO-v4 model, followed by the determination of the percentage of periodontal bone loss and staging of the periodontitis. However, future research is needed to improve the usage of these proposed methods.

IV. The applications of AI in Urology:

Urology is increasingly trending toward the incorporation of artificial intelligence (AI) into surgical practice, including some or even complete autonomy of imaging and pathology interpretation and surgical robots. Nevertheless, practical, ethical, monetary, and safety concerns exist raising a broader question regarding the future of AI in urology, and what are the potential advantages, implications, limitations, and how, specifically, should it be applied within the field?

Urothelial Cancer:

Artificial intelligence in urology Outcomes Prediction is Similar to prostate cancer. Imaging radiomic features and urine metabolite markers were used to detect urothelial cancer with the aid of AI algorithms²⁰. Xu et al. trained ML algorithms with mpMRI radiomic features to differentiate bladder tumor and bladder wall tissue. Garapati et al. used CT urography morphological features and textural features to predict bladder cancer stage. The authors showed that by using these radiomic features, the ML algorithms achieved an AUC of 0.7–0.9 in prediction. Using urine metabolite markers, researchers trained AI algorithms to detect malignancy. Shao et al. trained decision trees based on the urine metabolomic markers to detect bladder cancer. The decision tree obtained an accuracy of 76.6%, a sensitivity of 71.88%, and a specificity of 86.67%. Table(2)

²⁰ Chen et al., 'Current Status of Artificial Intelligence Applications in Urology and Their Potential to Influence Clinical Practice'.

Renal Cancer²⁰:

Early diagnosis of RCC is key to its successful management but can be clinically challenging. AI has allowed clinicians to use metabolomic data and Raman spectra to create models with which to accurately diagnose RCC prior to or during surgery. Zheng et al. sought to diagnose RCC using a nuclear magnetic resonance–based serum metabolite biomarker cluster. The authors first used ANNs to cluster and label serum metabolites as ‘healthy’ or ‘RCC’, then to predict the diagnosis of RCC in individual patients. Additionally, the study used the ANNs to evaluate patients with RCC who had undergone nephrectomy. Patients that were originally labelled as ‘RCC’ by the model were predicted as ‘healthy’ after undergoing nephrectomy. Haifler et al. used shortwave Raman spectroscopy to differentiate between benign and malignant renal tissue intra–operatively. By training an AI model using Raman spectra from RCC and normal tissue samples, the AI model could expedite the determination of cancerous over non–cancerous tissue during surgery compared with frozen–section pathology. **Table (2)²⁰**

Hydronephrosis/Urinary Reflux:

Imaging radiomic features and AI algorithms have also been applied to detect clinically significant hydronephrosis or urinary reflex. Blum et al. trained an ML model using renogram features to automatically detect hydronephrosis. The study showed that the ML model significantly improved the diagnostic accuracy of clinically significant hydronephrosis compared with looking only at half–time and 30–minute clearance. Cerrolaza et al. also trained ML models using ultrasound features to predict renal obstruction (half–time > 30 min).

Logvinenko et al. used ultrasonography findings to predict VUR on voiding cystourethrogram. They concluded that the AI model performed slightly better when compared to multivariate logistic regression. Patient outcome predictive modelling involves the development of mathematical models capable of analysing data to predict outcomes for individual patients. These models can be based on traditional statistical techniques or AI techniques. AI approaches have the capability to manage the imprecision and uncertainty which is common in clinical and biological data. Furthermore, these approaches are effective in processing big data that are too large or complex for conventional statistical techniques. **Table (3)** ²⁰

Prostate Cancer:

Patient clinicopathological features are the data commonly used to train AI algorithms to predict prostate cancer outcomes. Wong et al. developed patient-specific ML algorithms based on clinicopathological data to predict early biochemical recurrence after prostatectomy. The three ML algorithms trained using 338 patients achieved an accuracy of 95–98%, and an AUC of 0.9–0.94. When compared with traditional Cox regression analysis, the three ML algorithms had superior prediction performance. Tissue morphometric data, imaging radiomic features, and tissue genomic profiling were also used to predict patient outcomes. These studies showed that AI algorithms trained with clinicopathological data, imaging radiomic features, and genomic profiling outperformed the prediction accuracy of D'Amico risk stratification, single clinicopathological features, or multiple discriminant analysis, a type of conventional multivariate statistics. Other than patient factors, surgeons'

technical skills also impact patient surgical outcomes. Using objective surgical performance measurements derived directly from the surgical robot, Hung et al. developed and validated ML and deep-learning algorithms to predict patient length of hospital stay and urinary continence recovery after robotic radical prostatectomy. The ML algorithm achieved 87.2% accuracy in predicting length of hospital stay, and the deep learning model had a C-index of 0.6 in predicting urinary continence. Although these two studies were feasibility studies and were still in their infancy, they demonstrated new avenue of applying AI in surgical performance evaluation and patient outcome prediction

Table (3) ²⁰

Study	Application	Sample size	Training features	Algorithms/Models	Accuracy, %	Sensitivity, %	Specificity, %	AUC
Kim et al. [5]	Predict prostate cancer extra-capsular extension	944 patients (621 organ-confined disease; 323 non-organ-confined disease)	PSA, Gleason score, clinical T stage and positive prostate biopsy core count	NN	73.4	NA	NA	NA
				SVM	75.0	NA	NA	NA
				NB	74.8	NA	NA	NA
				BNs	74.4	NA	NA	NA
				CART	70.7	NA	NA	NA
Algohary et al. [6]	Detect prostate cancer on MRI	56 patients	MRI radiomic features selected by unsupervised hierarchical clustering	RF	68.8	NA	NA	NA
				QDA	72.0	75.0	60.0	NA
				SVM	52.0	60.0	40.0	NA
Ginsburg et al. [7]	Detect prostate cancer on MRI	80 patients	MRI radiomic features	LR	NA	NA	NA	0.61-0.71
Merisaari et al. [8]	Predict Gleason score on MRI	81 patients	MRI radiomic features	LR	NA	NA	NA	0.55-0.78
Fehr et al. [9]	Predict Gleason score on MRI	356 regions of interest from 147 patients	MRI radiomic features	t test SVM (Gleason 6 vs ≥ 7)	73-83	NA	NA	0.83-0.90
				AdaBoost (Gleason 6 vs ≥ 7)	64-73	NA	NA	0.60-0.74
				RFE-SVM (Gleason 6 vs ≥ 7)	83-93	NA	NA	0.91-0.99
				t test SVM (Gleason 3+4 vs 4+3)	66-81	NA	NA	0.94-0.99
				AdaBoost (Gleason 3+4 vs 4+3)	73-79	NA	NA	0.75-0.80
Kwak et al. [10]	Identify prostate cancer on pathology slide images	653 tissue samples (73 benign and 89 cancer samples in training set; 217 benign and 274 cancer samples in the testing set)	Digitized prostate specimen HE staining pathology image	Multiview boosting classifier (differentiate epithelium vs stroma)	NA	NA	NA	0.97-0.99
				Multiview boosting classifier (differentiate benign and malignant tissue)	NA	NA	NA	0.98
Kwak et al. [11]	Identify prostate cancer on pathology slide images	827 tissue samples (144 benign and 224 cancer samples in training set; 221 benign and 238 cancer samples in the testing set)	Digitized prostate specimen HE staining pathology image	CNN	NA	NA	NA	0.97
Nguyen et al. [12]	Automated Gleason scoring on prostate specimen slide	368 prostate tissue samples (1 per patient)	Digitized prostate specimen HE staining pathology image	RF (benign vs malignant)	NA	NA	NA	0.97
				LR (Gleason scoring 3 vs 4)	NA	NA	NA	0.82
Xu et al. [13]	Differentiate bladder tumour and bladder wall tissue on MRI	62 patients (62 cancerous region and 62 bladder wall region)	MRI radiomic features: 2D texture features, 3D texture features	SVM (2D)	70.16-78.23	NA	NA	0.72-0.83
				SVM (3D)	71.77-85.48	NA	NA	0.77-0.89
				RF (2D)	70.16-79.84	NA	NA	0.72-0.82
				RF (3D)	68.56-85.48	NA	NA	0.73-0.87
				SVM (RFE selected optimal features)	87.9	90.3	85.5	0.90
Garapati et al. [14]	Predict bladder cancer stage on CT urography	76 CT urography cases (84 bladder cancer lesions: 43 < T2; 41 \geq T2)	Pathological stage, CT urography morphological features, textural features	LDA (training set)	NA	NA	NA	0.91
				LDA (testing set)				0.88
				NN (training set)				0.89
				NN (testing set)				0.92
				SVM (training set)				0.91
				SVM (testing set)				0.89
				RF (training set)				0.89
				RF (testing set)				0.97
Shao et al. [15]	Predict presence of bladder cancer	87 bladder cancer patients and 65 patients without bladder cancer	Six urine metabolite markers (spectral ions)	DT: testing	76.6	71.9	86.7	NA
				DT: training (5-fold cross validation)	84.8	81.8	88.0	NA
Zheng et al. [16]	Early detection of RCC	126 patients (68 healthy participants, 48 RCC patients)	Serum metabolome biomarker cluster (choline, isoleucine, alanine, valine, leucine, creatine, lactate)	Clustering	Cluster analysis using Ward's method and Euclidean distance of serum metabolome identified 7 candidate metabolites			
				ANN: Healthy participants	91.3	NA	NA	NA
				ANN: RCC	94.7	NA	NA	NA
Haifler et al. [17]	Discriminate between normal and malignant renal tissue	6 clear-cell RCC specimens; 6 normal kidney tissue	Short wave infrared Raman spectroscopy	SMLR	92.5	95.8	88.8	0.94

TABLE 2: STUDIES USING ARTIFICIAL INTELLIGENCE TO DIAGNOSE UROLOGICAL DISEASE²⁰

Study	Application	Sample size	Training features	Algorithms/Models	Accuracy,%	Sensitivity,%	Specificity, %	C-index	AUC
Wong et al. [22]	Predict biochemical recurrence after radical prostatectomy	338 patients	Patient clinicopathological information	k-NN RF LR	97.6 95.3 97.6	78.0 76.0 75.0	69.0 64.0 69.0	NA NA NA	0.903 0.924 0.94
Harder et al. [23]	Predict biochemical recurrence after radical prostatectomy	90 patients (40 with PSA recurrence)	Prostate cancer tissue phenomics	Hierarchical clustering Naïve Bayes Classification and Regression Tree k-NN Linear Predictor SVM (linear kernel) SVM (radical bias function kernel)	86.6 83.3 83.3 85.5 87.8 86.7 82.0	82.5 80.0 70.0 80.0 94.0 77.5 75	90.0 86.0 94.0 90.0 80.0 94.0 88.0	NA NA NA NA NA NA NA	NA NA NA NA NA NA NA
Zhang et al. [24]	Predict biochemical recurrence after radical prostatectomy	205 patients (61 with biochemical recurrence)	MRI radiomic features	SVM	92.2	93.3	91.7	NA	0.96
Shiradkar et al. [25]	Predict prostate cancer biochemical recurrence on MRI	120 patients (70 training; 50 validation)	Patient clinicopathological data (PSA, Gleason score), and MRI radiomic features	LDA (radiomic alone, training) SVM (radiomic alone, training) RF (radiomic alone, training) SVM (radiomic alone, testing) SVM (radiomic + clinical, training) SVM (radiomic + clinical, testing)	NA NA NA NA NA NA	NA NA NA NA NA NA	NA NA NA NA NA NA	0.54 0.84 0.52 0.73 0.91 0.74	NA
Zhang et al. 2017 [26]	Predict biochemical recurrence after radical prostatectomy	424 patients (58 with recurrence)	Somatic gene mutation profiles	SVM (genetic signatures alone) SVM (genetic signatures + clinicopathological features)	66.2 71.3	NA NA	NA NA	NA NA	0.7 0.75
Lalonde et al. 2014 [27]	Predict prostate cancer biochemical recurrence after radiation or radical prostatectomy	397 patients (126 training; 154 and 117 testing)	Prostate cancer genes, general genomic instability, and tumour microenvironment	Hierarchical clustering RF (training set) RF (validation set 1, 100-loci DNA signature) RF (validation set 1, 100-loci DNA signature and clinical covariates) RF (validation set 2, 100-loci DNA signature) RF (validation set 2, 100-loci DNA signature and clinical covariates)	Identified four genomic subtypes with use of unsupervised hierarchical clustering. The four genomic subtypes of localized prostate cancer had significantly different prognoses A 100-loci (276 genes) DNA signature was generated NA NA NA NA NA	NA NA NA NA NA NA	NA NA NA NA NA NA	0.7 0.74 0.67 0.73	0.74 0.84 0.64 0.75
Hung et al. 2018 [28]	Predict length of hospital stay after radical prostatectomy	78 patients	25 surgical robotic APMs	RF (extended vs expected length of stay) RF (APMs and patient demographics) SVM (extended vs expected length of stay) LR (extended vs expected length of stay)	87.2 88.5 83.3 82.1	NA NA NA NA	NA NA NA NA	NA NA NA NA	NA NA NA NA
Hung et al. 2018 [29]	Predict urinary continence recovery after robotic radical prostatectomy	79 patients	16 clinicopathological features and 492 robotic APMs	Random survival forests Deep-learning model-based survival analysis	NA NA	NA NA	NA NA	0.58 0.6	NA NA
Lam et al. 2014 [30]	Predict 5-year mortality after radical cystectomy	117 patients (83 training, 17 validation and 117 testing)	Age, tumour stage, albumin level, surgical approach	ANN	77.8	NA	NA	NA	0.829
Wang et al. 2015 [31]	Predict 5-year mortality after radical cystectomy	117 patients	Gender, Age, Age range, albumin, surgical approach 1/2, preoperative albumin, tumour stage, follow up period, type of diversion	NN ELM RELM RBF SVM NB k-NN	72.2 76.7 80.0 76.7 75.6 73.3 72.2	77.6 73.5 85.6 79.0 75.4 73.8 75.1	68.1 81.5 72.4 75.3 77.0 73.4 70.1	NA NA NA NA NA NA NA	NA NA NA NA NA NA NA
Sapre et al. 2016 [32]	Predict urothelial carcinoma recurrence	Training set 81 patients (21 benign controls, 30 non-recurrence and 30 active cancer recurrence). Testing set: 50 patients	Urinary miRNAs (miR205, miR34a, miR21, miR221, miR16, miR200c)	SVM (recurrence) SVM (tumour presence): training SVM (tumour presence): testing SVM (T1) SVM (Ta) SVM (T2, 3, 4) SVM (high-volume) SVM (low-volume) SVM (low-grade) SVM (high grade) SVM (initial tumour)	NA NA NA NA NA NA NA NA NA NA NA	88.0 NA NA NA NA NA NA NA NA NA NA	48.0 NA NA NA NA NA NA NA NA NA NA	NA NA NA NA NA NA NA NA NA NA NA	NA 0.85 0.74 0.92 0.72 0.73 0.81 0.69 0.76 0.75 0.76
Bartsch et al. 2016 [33]	Predict recurrence risk of non-muscle invasive urothelial carcinoma within 5 years after transurethral resection of bladder	112 frozen non-muscle invasive urothelial carcinoma specimens	Genes from whole genome profiling (TMEM205, NFKBIA, KRT17, RPS6, GLTP)	GP (5 gene combined rule): training GP (5 gene combined rule): testing GP (3 gene rule): training GP (3 gene rule): testing	NA NA NA NA	77.1 68.6 80.4 70.6	84.6 61.5 90.0 66.7	NA NA NA NA	NA NA NA NA

TABLE 3: STUDIES USING AI TO PREDICT OUTCOMES OF UROLOGICAL DISEASES²⁰

Urolithiasis:

Percutaneous nephrolithotomy (PCNL) and shockwave lithotripsy (SWL) are widely accepted treatment options for urolithiasis; however, success rates can vary greatly and may require repeat or ancillary procedures when treatment fails. Aminsharifi et al. used ANN to predict stone-free rate after PCNL with 82.8% accuracy and the necessity of repeat PCNL with 97.7% accuracy. Mannil et al. used three-dimensional (3D) texture analysis from CT images in combination with body mass index, initial stone size, and skin-to-stone distance to predict the success of SWL using AI Models. Testing five AI algorithms with different permutations of 3D textural features with patient features, the authors reported AUC values ranging from 0.79 to 0.85, compared with an AUC of 0.58 when using only patient features. In another study, the same group used 3D texture analysis to predict the number of required shockwaves for successful SWL. Compared with linear regression and simple linear regression, AI had the highest predictive accuracy of the number of required shockwaves. Emonstrated this method where $k = 10$ in our study²¹. The constructed ANN had 25 neurons in the input layer, and each neuron was assigned to one preoperative variable. The output layer consisted of six nodes, each corresponding to one postoperative outcome(Figure 9):

²¹ Aminsharifi et al., 'Artificial Neural Network System to Predict the Postoperative Outcome of Percutaneous Nephrolithotomy'.

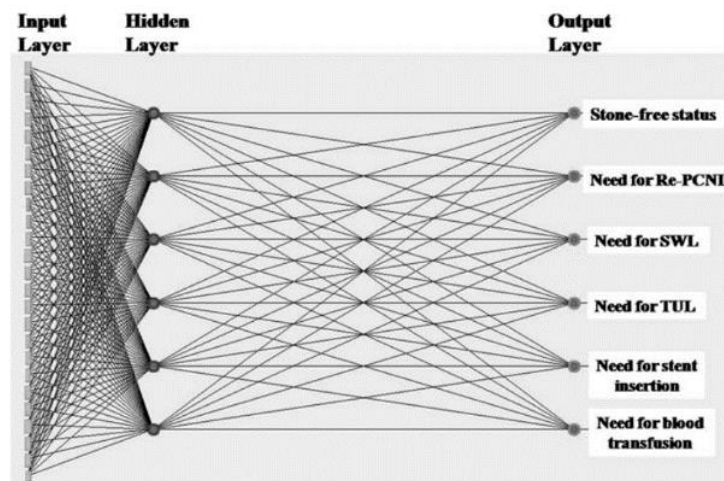


FIGURE 9: THE ANN MODEL DESIGNED TO PREDICT PERCUTANEOUS NEPHROLITHOTOMY OUTCOMES. SWL, SHOCKWAVE LITHOTRIPSY; TUL, TRANSURETERAL LITHOTRIPSY²¹.

Clinical application of the trained ANN (test set) The validated, adequately trained ANN was used to predict the postoperative outcome in the subsequent 254 adult patients (test set) whose preoperative values were serially fed into the system. To evaluate predictive accuracy of the system for each postoperative variable, the predicted values were compared with the actual outcomes (observed values), and true positive, false positive, accuracy, and precision rates of the system were calculated for each postoperative outcome variable (Table4), Because machine learning systems are based on AI, the more input is fed in, the better the training and more accurate the predictions:

<i>Preoperative variables</i>	<i>Intraoperative variables</i>	<i>Postoperative variables</i>
Age	Access point	Postoperative stone volume (mm ³) ^a
Gender	Radiation exposure during access (s)	Postoperative hemoglobin
Stone volume (mm ³) ^a	Total radiation (s)	Postoperative creatinine
Stone size (mm) ^b	Operative time (minutes)	Need for blood transfusion
Stone side (right to left)		Postoperative urine leakage (Double-J insertion)
Previous surgery in target kidney		Postoperative ancillary procedures (SWL, PCNL, TUL)
Hx of Diabetes		
Hx of Hypertension		
Preoperative hemoglobin (g/dL)		
Preoperative creatinine (mg/dL)		
Body mass index		
Renal anomaly		
Skeletal anomaly		
Stone location (upper, mid, lower calix, renal pelvis, staghorn, multiple)		
Stone lucency (opaque, semiopaque, lucent)		
Degree of hydronephrosis (mild, moderate, severe)		

^aStone volume = $a \times b \times c \times \pi \div 6$.

^bLargest diameter.

PCNL=percutaneous nephrolithotomy; SWL = shockwave lithotripsy; TUL=transureteral lithotripsy.

TABLE 4: VARIABLES CONSIDERED FOR ANALYSIS²¹

During the study period the authors used data from 454 patients. The first 200 patients were enrolled as the training set, and their data were used to construct and validate the ANN. The subsequent 254 patients (155 males, 61%) were considered the test set. Mean age in this group was 46.64 – 12.16 years, and mean stone burden was 6702.86 – 381.6 mm³.

ANN system, as an interconnected data mining tool, can prospectively analyze the relationships between variables. The accuracy and sensitivity of the system for predicting the stone-free rate, the need for blood transfusion, and post-PCNL ancillary procedures ranged from 81.0% to 98.2% (Table5). The stone burden and the stone morphometry were among the most significant preoperative characteristics that affected all postoperative outcome variables, and they received the highest relative weight by the ANN system.

	<i>True positive rate (sensitivity)</i>	<i>False positive rate</i>	<i>Accuracy (%)</i>	<i>Precision (positive predictive value)</i>
Stone-free status	0.83	0.19	82.8	0.83
Need for repeat PCNL	0.97	0.39	97.7	0.99
Need for SWL	0.98	0.12	98.2	0.88
Need for TUL	0.92	0.32	92.5	0.92
Need for stent insertion ^a	0.81	0.32	81.1	0.80
Need for blood transfusion	0.85	0.25	85.8	0.85

TABLE 5: PERFORMANCE OF AN ARTIFICIAL NEURAL NETWORK SYSTEM IN PREDICTING STONE-FREE STATUS²¹.

Although ANN, unlike statistical models, can be easily deployed using user-friendly software to simplify individual-based prediction and decision-making, the authors were aware that the results of this study and the application of ANN in the field of PCNL should be considered a preliminary step. All procedures in this study were done by fully competent surgeons; therefore, the effect of surgeon's experience and case volume on the outcome was not included. The same is true regarding the details of the PCNL operation (such as patient's position, rigid vs flexible nephoscopy, and type of lithotripter. Notwithstanding, one of the advantages of ANN is that the software can be easily updated with more preoperative and intraoperative variables in future versions, and the institutes can easily add other features to their software to customize it. Hence, the effect and the weight of any concerned variable can be easily calculated.

Cancer Drug Selection:

There is also a role for AI techniques in selecting effective drugs for cancer treatment. Using an ML algorithm, Saeed et al. quantified the phenotype of castration-resistant prostate cancer cells and tested the response of the cancer cells to > 300 emerging and clinical cancer drugs. They identified the

Bcl-2 family inhibitor navitoclax as the most potent cancer-specific drug for the cancer cells from a patient with castration-resistant prostate cancer.

Studies looking at applications of AI in Pediatric urology:

AI has been used in the field of pediatric urology for predicting the outcome of surgical procedures, severity of the condition based on imaging as well as detecting abnormalities in imaging (Table 6)²²:

Bagli et al. ^[16]	To predict sonographic outcome after pyeloplasty in children with ureteropelvic junction obstruction	<ul style="list-style-type: none"> • 84 children training set • 16 children test set 	ANN	100%	100%	100%
Logvinenko et al. ^[17]	To predict patients at high risk of VCUG abnormalities, based on RBUS findings	• 2259 patients	ANN Multivariate LR analysis	NA	For any grade VUR • ANN: 64% • MLR: 84%	For any grade VUR • ANN: 60% • MLR: 25%
Blum et al. ^[18]	To predict the need for surgery in UPJO cases based on dynamics of renogram	<ul style="list-style-type: none"> • 55 patients • 45 features 	• Linear support vector machine (SVM)	93%	91%	96%

TABLE 6: USE OF AI IN PEDIATRIC UROLOGY²².

Surgical Skill Assessment:

Surgical robots were introduced into surgical practice with the aim of improving precision, magnification, and surgical dexterity, allowing surgeons to perform delicate and complex procedures with more precision, flexibility, and control. For patients, robot-assisted surgery is a less invasive procedure with shorter recovery times, less pain, and blood loss without compromising surgical or functional outcomes compared with conventional open surgery. Robotic autonomy in surgical procedures would potentially allow distant and remote interventions, even from separate locations.

²² Department of Urology, Kasturba Medical College Manipal, Manipal Academy of Higher Education, Manipal, Karnataka, India et al., 'Artificial Intelligence (AI) in Urology-Current Use and Future Directions'.

Currently, complete autonomy has not yet been achieved, but its application in surgical procedures promises certain advantages over humans (insusceptibility to fatigue, resistance to tremors, scalable motion, greater range of axial motion, and others). Thus, combining the advantages of surgical robotics with AI could significantly reduce technical errors and operative times and allow for unprecedented non-invasive surgeries.

It is important, however, to create a distinction between robot-assisted surgery and AI Automation and autonomy exist on a spectrum, and total autonomy is the most refined form. Automatic machines are, to some extent, under the control of their operator. Their behaviors are totally predictable and follow established theories. Any variation in the behaviors of automatic systems is due solely to small adaptations that still follow predetermined parameters based on external conditions. If variations in its expected environment are too large, an automatic system would be incapable of adapting and would fail. Autonomy implies the ability to fulfill these large adaptations and changes to its environment without the input of an external user. This is done by “planning” its tasks, requiring wider sets of data and the use of cognitive tools not found in automatic systems. Degrees of surgical autonomy can be organized into six levels. Levels 4 and 5 are mostly theoretic and do not yet have examples of standardized application (Table 7)

Table 1 Levels of autonomy		
Level	Description	Example
0	No autonomy	Robots directly translate human movements ⁷
1	Robot assistance	da Vinci surgical system ⁸
2	Task autonomy	Autonomous prostate brachytherapy seed placement ⁹
3	Conditional autonomy	Aqua ablation of the prostate using the AquaBeam system ¹⁰
4	High autonomy	Human supervision: robot plans and performs operation ⁷
5	Full autonomy	No human involvement: robot plans and performs operation independently ^{7,11}

Table 7: assistance Robots and AI robots²³

Our center of interest is the third level of conditional autonomy since it is what science has reached so far.

Nowadays, surgical skill and performance evaluation are performed through manual peer assessment, requiring surgical experts to inspect surgical performance during surgery or review surgical videos. Such assessment is inefficient and introduces inter-observer variability. Minimally invasive surgery, especially robot-assisted laparoscopic surgery, provides high-quality surgical footage recorded in endoscopic view²⁴. With a custom data recorder, surgical instrument kinematic data and surgical robotic system events data can also be captured. These videos and surgical robot performance data can be applied to evaluate surgical performance automatically through AI techniques. Anatomical landmark recognition is a fundamental step towards automated surgical skill evaluation. Nosrati et al. and Baghdadi et al. described ML-based analysis of colour and textural visual features on robotic endoscopic

²³ Abid, Hussein, and Guru, 'Artificial Intelligence in Urology'.

²⁴ Baghdadi et al., 'Modeling Automated Assessment of Surgical Performance Utilizing Computer Vision'.

view to detect anatomical landmarks during a partial nephrectomy and radical prostatectomy. A logistic regression model was trained and validated using the four hand-crafted features with 30% holdout cross-validation. The model was tested on the remaining 6 procedures, and the accuracy of predicting the expert-based PLACE scores was 83.3%. This is the first automated surgical skill assessment tool, This method provides an objective evaluation of surgical performance with high accuracy compared to expert surgeons' assessment

Figure²⁴ (10)

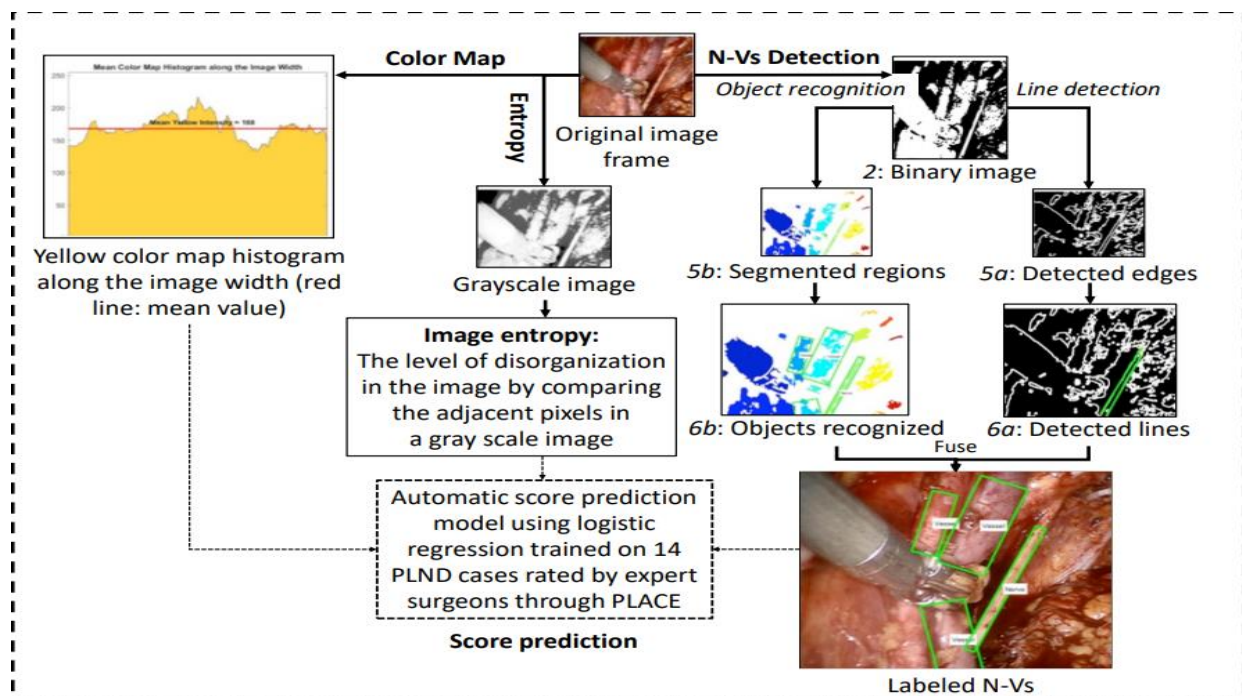


FIGURE 10: FEATURE EXTRACTION METHOD USING A FRAME-BY-FRAME COMPUTER VISION ALGORITHM FOR PROCESSING THE FEATURES OF NERVES AND VESSELS (N-Vs) DETECTION. (BAGHDADI ET AL)²⁴

Surgical instrument tracking is another component in automated performance evaluation. Ghani et al. and French et al. described instrument movement analysis to predict surgical skill and technique. The authors either manually annotated the laparoscopic instrument positions on the surgical videos or used instrument motion trackers to capture the instrument

movement data (velocity, trajectory, and relationship to contralateral instrument). They then trained ML algorithms with these data to predict the performing surgeon's expertise. The algorithms achieved accuracy in the range of 83.3–100%. Mentor–trainee trust, defined as mentor's assessment of trainee's performance quality and approving trainee's ability to continue performing the surgery, is another way of evaluating surgical performance. Shafiei et al. assessed mentor–trainee trust during robot–assisted surgery using electroencephalogram patterns of surgical mentor while observing procedures performed by surgical trainees. The authors used ML to identify key features of electroencephalography that distinguish trustworthiness from concerning performances.

V. Challenges and limitations of AI in healthcare:

AI offers promising advancements, particularly in healthcare, but addressing challenges related to data privacy and ethical concerns falls on the shoulders of its users and developers. Privacy policies and ethical standards must evolve in tandem with AI's progress, especially in medicine;

V.1) Common Challenges of AI in Healthcare in Morocco:

V.1.a) Lack of standard medical data:

One of the main challenges is the lack of adequate data infrastructure. Effective AI algorithms require large amounts of high–quality data. Unfortunately, the healthcare system in Morocco is fragmented, and there is a lack of standardization in data collection and management. This makes it difficult to access and analyze data for AI development²⁵. To overcome this

²⁵ 'AI for Healthcare in Morocco: Advances and Challenges'.

challenge, Morocco needs to invest in data infrastructure and create standardized systems for data collection and management.

V.1.b) Lack of Regulatory Frameworks for AI in Healthcare:

Another challenge is the lack of regulatory frameworks for AI in healthcare. Clear guidelines and regulations are needed for the development and use of AI algorithms in healthcare to ensure patient safety and privacy. To address this challenge, regulatory bodies in Morocco should collaborate with healthcare providers, researchers, and technology companies to develop comprehensive frameworks for the development and use of AI in healthcare.

V.1.c) Lack of Trained Personnel in AI in Healthcare:

A third challenge is the limited availability of trained personnel with expertise in AI and healthcare. Morocco needs to develop specialized training programs for healthcare professionals to enhance their knowledge and skills in AI and healthcare. Additionally, attracting and retaining talented individuals with expertise in AI to the healthcare industry in Morocco is essential.

V.2) Limitations of AI in Healthcare:

V.2.a) Data Privacy:

- **Patient Confidentiality:** AI systems rely on vast amounts of data, often involving sensitive patient information. Ensuring the protection of this data is paramount to comply with regulations like HIPAA (in the U.S.) or GDPR (in Europe). If AI systems mishandle this data or if it is exposed in a breach, patient confidentiality could be compromised.

- **Data Ownership:** Who owns patient data in AI systems? This question is still being debated. Patients, hospitals, and third-party companies may all have differing views on who should control the data.
- **Security Risks:** AI systems, if not secured properly, can be vulnerable to cyberattacks. Health data is particularly valuable and could be targeted by hackers for identity theft or fraud.

V.2.b) Ethical Concerns:

- **Bias in AI Models:** AI systems can inherit biases from the data they're trained on. If the training data lacks diversity (e.g., based primarily on one demographic group), the AI may make biased decisions that are less effective for certain populations. This can lead to unequal treatment outcomes.
- **Transparency and Accountability:** AI algorithms, particularly those based on machine learning, can be "black boxes" where it's difficult to understand how they arrive at certain conclusions. This can make it challenging to explain AI-driven medical decisions, raising concerns about transparency and accountability in patient care.
- **Autonomy and Human Oversight:** As AI becomes more capable, there's a risk that it might diminish the role of human healthcare providers. Ensuring that AI acts as a support tool rather than replacing human judgment is a critical ethical consideration.

V.3.c) Informed Consent:

- Patients may not always be fully aware of how their data is used or the role AI plays in their treatment decisions. Informed consent is vital to

maintain trust between patients and healthcare providers, but it can be complicated when involving complex AI systems.

Companies must implement robust technical safeguards in their AI healthcare solutions to prevent misuse, with clear accountability measures in place should they fail. Governments must also update existing legal frameworks, such as HIPAA (Health Insurance Portability and Accountability Act), or introduce new regulations as needed to ensure comprehensive protection.

VI) The applications of artificial intelligence in the Moroccan Healthcare system:

The use of artificial intelligence (AI) in healthcare in Morocco is gradually evolving, though the pace varies depending on specific initiatives and investments. Below are some concrete examples of AI applications in the Moroccan healthcare sector:

VI.1) during Covid-19:

In 2020, the outbreak and spread of COVID-19 triggered widespread economic and social changes. Governments around the world declared health emergencies to protect citizens and mitigate the pandemic's impact, while businesses were compelled to adopt digital technologies to counteract the disruptions caused by the virus. Morocco, like many other nations, was not immune to these challenges.

Even though we do not consider telemedicine a part of artificial intelligence, technological advancement is a step by step procedure and this must be mentioned.

As a developing country, Morocco has made significant progress in adopting information and communication technologies (ICT) and enhancing its network readiness. While certain sectors are more advanced than others, the overall trend toward digitalization is positive²⁶. However, Morocco still lags behind other emerging nations in terms of technological advancements. The COVID-19 crisis, nonetheless, shifted the perception of digital transformation,

²⁶ Nachit and Belhcen, 'Digital Transformation in Times of COVID-19 Pandemic'.

making it an urgent priority to ensure the continued delivery of essential services.

The lockdown imposed during the health emergency highlighted the critical role of digital transformation in both the public and private sectors. This period provided the Moroccan government with a unique opportunity to accelerate its digital strategy and improve the citizen experience through various technology-driven initiatives. Sectors like education and healthcare benefited from this rapid digital shift. Yet, despite this progress, the government still faces challenges in fully implementing digital transformation across these areas.

A survey conducted by Benkaraache et al. (2020) revealed dissatisfaction among teachers and students regarding distance learning, focusing on universities in urban areas. The situation is even more concerning in rural areas, where access to digital tools is limited. Additionally, there remains a general lack of trust in government online services, even when these services are approved, underscoring the need for greater efforts in raising digital awareness and fostering confidence in digital initiatives.

VI.2) Managing diabetes during Ramadan:

Presents a significant challenge for²⁷ healthcare professionals due to the increased risk of acute complications associated with fasting. To reduce this risk, clear guidelines for diabetes management during Ramadan have been developed. For diabetic patients who choose to fast, a pre-Ramadan consultation is recommended to assess the risks, educate patients on self-

²⁷ Motaib et al., 'Diabetes During the Fasting Month of Ramadan'.

management, and adjust their treatment plans accordingly. Moreover, even diabetic patients who do not fast during Ramadan are at risk of destabilizing their condition due to changes in dietary habits and meal times throughout the month. Poor glycemic control was defined as an increase of glycated hemoglobin level above 0.5% of its pre-Ramadan level with glycated hemoglobin above the glycemic target of patients according to ADA recommendations.

To predict poor glycemic control during Ramadan among non-fasting patients with diabetes, an interesting study by Motaib et al. was published 3 years ago, The authors used artificial intelligence-based machine learning models. First, they conducted three consultations, before, during, and after Ramadan, to assess demographics, diabetes history, caloric intake, anthropometric and metabolic parameters ²⁸ . Second, machine learning techniques were trained using the data to predict poor glycemic control among patients. Then, they conducted several simulations with the best-performing machine learning model using variables that were found to be the main predictors of poor glycemic control.

²⁸ Motaib et al., 'Predicting Poor Glycemic Control during Ramadan among Non-Fasting Patients with Diabetes Using Artificial Intelligence Based Machine Learning Models'.

The prevalence of poor glycemic control among patients was 52.6%. Extra tree Classifier was the best performing model for glycemic deterioration (accuracy = 0.87, AUC = 0,87). Caloric intake evolution, gender, baseline caloric intake, baseline weight, BMI variation, waist circumference evolution, and Total Cholesterol serum level after Ramadan were selected as the most significant factors in the prediction of poor glycemic control. The authors determined thresholds for each predicting factor among which this risk is present.

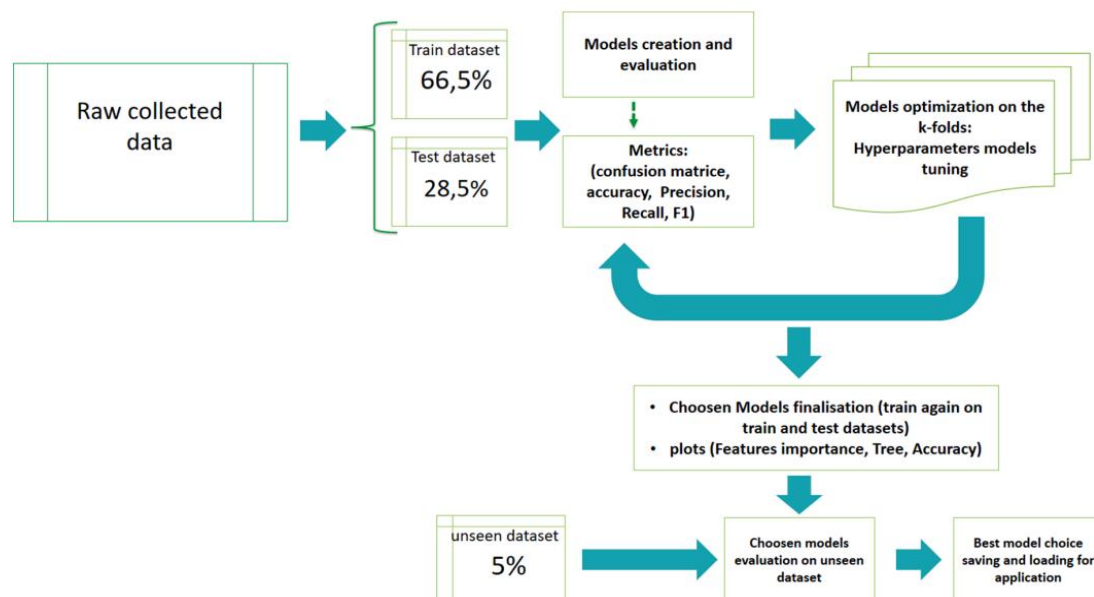


FIGURE 11: FLOWCHART EXPLAINING METHODOLOGY OF USING MACHINE LEARNING IN THE STUDY²⁸
[MOTAIB ET AL].

This finding's clinical use may help improve glycemic control during Ramadan among patients who do not fast by targeting poor glycemic control risk factors.

VI.3) AI-algorithms introduced into Moroccan Health care:

VI.3.a) Radiology:

The Medical Image Computing and Computer-Assisted Interventions (MICCAI):

After the analysis of all papers (n = 670) published in the whole 2021 calendar year, with the keywords “deep learning” and “medical imaging”, in three of the most important journals in the field, namely Medical Image Analysis, Radiology²⁹: Artificial Intelligence, and Journal of Digital Imaging. The results show that 94.1% of the imaging datasets used in these papers originated from 20 countries only and that 160 countries did not contribute any imaging datasets used to train and test new artificial intelligence solutions and applications.

There is a concern that if this trend continues, AI will increase the existing high inequalities in global radiology and, hence in global health.

The application of AI to medical imaging differs greatly from applications in other fields of AI. It requires a highly inter-disciplinary collaborative approach integrating elements and skills from mathematics, computer vision, image processing, data science, biomedical engineering, radiology, and clinical medicine. Challenges that are specific to AI in medical imaging include the difficulties in gathering, anonymising, curating, and annotating large and high-quality datasets of medical images to train and test new AI models.

The Medical Image Computing and Computer Assisted Interventions (MICCAI, Figure 11) is a major annual international conference that focuses on

²⁹ Lekadir et al., ‘FROM MICCAI TO AFRICAI: AFRICAN NETWORK FOR ARTIFICIAL INTELLIGENCE IN BIOMEDICAL IMAGING’.

the dissemination of new research in the fields of medical image computing and computer-assisted intervention. It is a major meeting for computer engineers and data scientists working in AI for medical imaging. Many of the methodological developments in the field are often first presented at MICCAI before they are disseminated as journal papers.

AFRICAI: AFRICAN NETWORK FOR AI IN IMAGING:

The African Network for Artificial Intelligence in Radiology and Imaging (AFRICAI) was created in January 2022. Its main objectives are to:

- Create, maintain and increase an inter-disciplinary community of active contributors to AI for radiology and imaging applications in Africa.
- Promote a culture of responsible and equitable sharing of African imaging datasets.
- Increase cooperation in the field within Africa and internationally.
- Promote the development of trustworthy, transferable AI solutions to address Africa-specific real-world healthcare challenges.

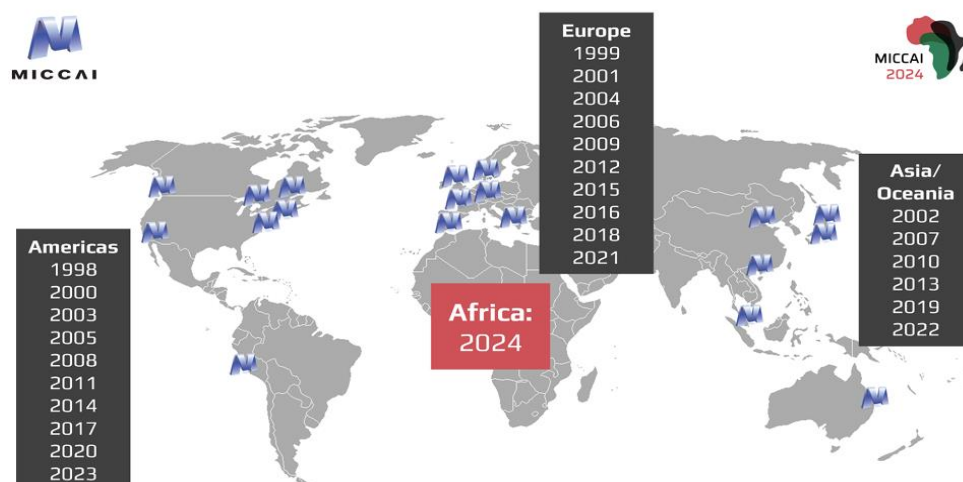


FIGURE 12: GEOGRAPHICAL DISTRIBUTION OF PAST MICCAI CONFERENCES. MICCAI 2024 IS THE FIRST EDITION TO TAKE PLACE IN AFRICA, SPECIFICALLY IN THE CITY OF MARRAKESH, MOROCCO²⁹ [LEKADIR ET AL].

The founding members of the AFRICAI network consist mostly of researchers based in Africa, or African researchers based outside Africa. Three weeks after its creation and without much advertising, the AFRICAI network attracted 275 new members from 23 African countries, including 36.2% self-identified female members. It is expected that over the next weeks and months, the network will grow significantly as dedicated campaigns will take charge and start organizing events. The plan is to target students with Master's degrees in computer science, biomedical engineering, data science, artificial intelligence, biomedical informatics, and related topics. Also, additional members from the clinical and radiology communities are needed.

Concrete applications of AI into Radiology in Morocco:

A study by Abdellaoui et al.³⁰ (2021) indicates that integrating AI into radiological diagnostics in Morocco has reduced diagnostic errors by 25% to – 30 % in pilot institutions.

Private Sector Adoption: Clinique Dar Salam in Casablanca has implemented AI-powered medical imaging platforms to enhance diagnostic capabilities. it has decreased the time needed to diagnose breast cancer from 20 minutes to just 3 minutes, improving patient outcomes.

In addition to medical imaging, AI is also being applied in other areas of healthcare in Morocco.

³⁰ 'AI for Healthcare in Morocco: Advances and Challenges'.

For example:

The Moroccan Ministry of Health has partnered with IBM to develop an AI-powered platform that can help detect and diagnose breast cancer, particularly in remote areas where there are no specialized healthcare providers. The platform uses AI algorithms to analyze mammogram images and identify areas that require further examination.

DEEPECHO, building an AI product developed by doctors and AI scientists aiming at reinforcing antenatal diagnosis.

The efficiency of healthcare services in Morocco, especially in the public sector, could be greatly increased by the implementation of AI technology. Morocco suffers from a shortage of medical professionals, especially in rural areas, which has led to protracted patient wait times. The use of AI technology can help solve this issue by making it possible for medical professionals to diagnose and treat patients more effectively and swiftly.

The way Moroccan radiologists perceive AI:

A Moroccan research was published in which the objective was to examine the perceptions and attitudes of medical practitioners toward artificial intelligence (AI) technologies, a Survey was distributed to radiologists; Within the survey³¹, 60% of respondents expressed confidence in their ability to grasp the fundamental concepts of medical AI However, this figure remains relatively lower compared to a study involving radiology residents in Saudi Arabia, where

³¹ Berrami et al., 'Understanding and Use of Artificial Intelligence Among Doctors in a University Hospital in Morocco'.

76% indicated the necessity of acquiring foundational knowledge of AI applications in medicine.

Among the concerns raised by physicians, 63% of residents indicated unease regarding reduced human interaction with patients following AI integration into medical practices. A comparable sentiment was noted in a Canadian study, where non-radiology residents expressed discouragement over diminished patient contact. Another noteworthy concern is the apprehension of being supplanted by AI applications, which was voiced by 44% of physicians. This apprehension significantly exceeded the levels found in a study involving radiologists and residents in Europe, where such fear did not exceed 13%.

VI.3.b) Moroccan artificial intelligence network in Oncology:

This multidisciplinary core group of researchers was established during the “First National Day on Artificial Intelligence in Oncology,” organized in a hybrid format by ENSAM Rabat, in collaboration with the Cancer Research Institute, the Euro-Mediterranean University of Fes, the Translational Oncology Research Team, and the Moroccan Association for Training and Research in Medical Oncology.

This network aims to address the needs of Moroccan patients and the healthcare system for better cancer patient care, explained Karim Ouldim, Director of the Cancer Research Institute, in a statement to MAP.

According to Mr. Ouldim, the goal is to unite the efforts of all stakeholders in the fields of research and innovation to develop a strategy and action plan

through a collaborative approach to development and public-private partnership.

"AI is involved in all aspects of cancer care," he noted, adding that it is also a "tool of today and the future" that allows for better patient management.

Evidence-based medicine scoring systems are vital in oncology, covering cancer risk assessment, prognostic staging, treatment selection, and surveillance monitoring. These systems often derive from advanced techniques like gene expression assays and next-generation sequencing (NGS)³² of somatic and germline genomes, leading to a growing list of predictive and prognostic factors deemed essential in the pathology field for decision-making, which now increasingly depends on digitalization. Digital pathology leverages imaging analysis powered by DL algorithms to provide accurate, reliable interpretations and predictions regarding the confounding factors linked to some histology presentations, including mutations, molecular features, prediction of therapy response, and survival. Besides, these advancements rely on electronically scanned and stored biopsy-based cancer genomic technology results. In the absence of such genomic technologies and a digital pathology database, the progress in digital pathology remains significantly hindered, leaving no room for AI integration. AI-based algorithms that form the digital oncology pillars, which rely on diverse oncologic imaging, are transforming how we diagnose and manage cancer, significantly enhancing diagnostic accuracy and streamlining workflows. These technologies are

³² Tafenzi, Essaadi, and Belbaraka, 'Digital Oncology in Morocco'; Joudi et al., 'Review of the Role of Artificial Intelligence in Dentistry'.

quickly moving from the laboratory to clinical settings. As these algorithms continue to evolve, we are anticipating even more innovative AI applications in cancer imaging. This progress opens up new possibilities for early detection and more effective management of cancer, opportunities that were once thought impossible.

Nevertheless, the lack of data regarding access to biomarker testing, NGS technologies, availability or easy magnetic resonance imaging access, and liquid biopsy testing needed to develop DL models or at least validate the previous established DL model with local patients is an uphill battle because not only are these data not electronically stored, but also these types of data are not routinely used at the department. The absence of a common digital patient registry, whether at the hospital, between departments, or at the national level, complicates matters even more. A larger, more homogeneous data set would make the work more representative and impactful, increasing the odds of acceptance in high-impact journals while presenting the population characteristics, which are often overlooked, ensuring opportunities and attractions for the aforementioned patients, and enhancing the robustness of statistical analyses and the quality of writing. New genomic technologies are revolutionizing cancer detection by allowing for the detection of cancer signals in blood. Multicancer early detection methods have emerged from this advancement. Ahlquist et al. emphasized that blood is a perfect medium for detecting cancer biomarkers, including circulating tumor cells and tumor cell-free DNA. The idea of a pan-cancer screening test is especially appealing since it provides an affordable means of early detection of several

less frequent malignancies. However, the full potential of these technologies is yet to be realized in our setting. Without the required detection methods and digital infrastructure, AI's transformational significance in this setting goes largely untapped. Radiography imaging is another specialty tackled by AI applied for the detection, diagnosis, and tracking of potential new metastatic or primary cancerous lesions, tumor characterizations, and prediction of some clinical endpoints such as mortality, disease recurrence, or progression. While these models are certainly not effective in healthcare management and decision-making, current breast imaging often incorporates AI-based models with at least five US Food and Drug Administration-approved algorithms. Despite challenges such as interobserver variability, AI-based detection is now being used for various tumor types, including prostate cancer, enabling segmentation, lesion detection, and workflow integration. In an attempt to overcome these problematics and catch up with the AI workflow, The authors initially developed and validated a comprehensive tool designed to predict overall survival and progression-free survival at various time points, based entirely on epidemiologic, pathologic³³, clinical, and therapeutic factors manually extracted from the medical records of Moroccan patients with lung cancer. They recognize the limitations of these ML models, such as their generalization and the biases associated with data extraction. While these issues do not render the work invalid, they do indicate a lack of specificity that was not apparent in univariate and multivariate analyses. In addition, the authors dedicated efforts to patients with early-stage breast cancer by

³³ Tafenzi, Essaadi, and Belbaraka, 'Digital Oncology in Morocco'.

evaluating the toxicity of chemotherapy agents, specifically anthracyclines and taxanes, through the deployment of an AI mobile health application for the purpose of managing treatment-related adverse events and reducing the need for frequent in-person visits. Another thought added to further advance and integrate AI into clinical practice is synchronizing previously developed models by incorporating additional variables from digital radiographic data, particularly from computed tomography (CT) scans with and without enhanced contrast. Unfortunately, these types of data are often missing from patients' medical records. This absence poses a significant barrier to the development of DL algorithms that rely on high-quality imaging data and a large sample size.

The robustness of such models depends on access to high-resolution images from anatomopathologic lenses or CT scans, or ideally both, which must be stored in a shared database. Regretfully, these kinds of details are frequently missing from patient medical records; occasionally, patients are only given the final report. It would be impossible to further discuss other AI necessities that include workflow education, training, patient implications, and ethical considerations, without sufficient persistence to advance AI from its current state to the next level. Collaborative efforts could be the key to this field's last push. To overcome these obstacles, the government, the private sector, and academia must unify their effort by pooling expertise and resources to create a robust infrastructure that will underpin AI integration. The combination of all these limitations constitutes a layer of complexity to Morocco's already challenging digital oncology landscape. In addition to

limiting individualized treatment options, regular genotyping also impedes thorough research efforts.

Without consistent access to a diverse set of biomarkers, the possibility of developing algorithms that can automatically scan slides and save time and resources in the future is considerably restricted. Essentially, the lack of sophisticated genotyping technology impedes advancements in research and medical care, underscoring a crucial field that requires funding and advancement.

VI.3.c) Ophthalmology:

Diabetic Retinopathy Segmentation: In computer vision and deep learning, image segmentation is partitioning an image into segments or highlighted groups of pixels considered as meaningful entities. To segment our color fundus images, the authors trained and tested a U-Net multi-class segmentation model on 200 labeled retinal images (Figure 13). U-Net has become a widely known medical image segmentation technique and has demonstrated excellent performance as a fully convolutional neural network. The U-Net architecture contains two “paths.” First, the contraction path, known as the encoder, is used to capture an image’s context. In fact, it is a combination of convolution and “max pooling” that not only reduces the image size, but it also generates a feature map, thereby decreasing the number of network parameters. The symmetric expansion path, also known as the decoder, is the second path. Due to the transposed convolution, it also provides precise localization. What characterizes the U-Net architecture is the shortened connections between the layers of equal resolution from the

analysis path to the expansion path. These connections provide important high-resolution features for the deconvolution layers.

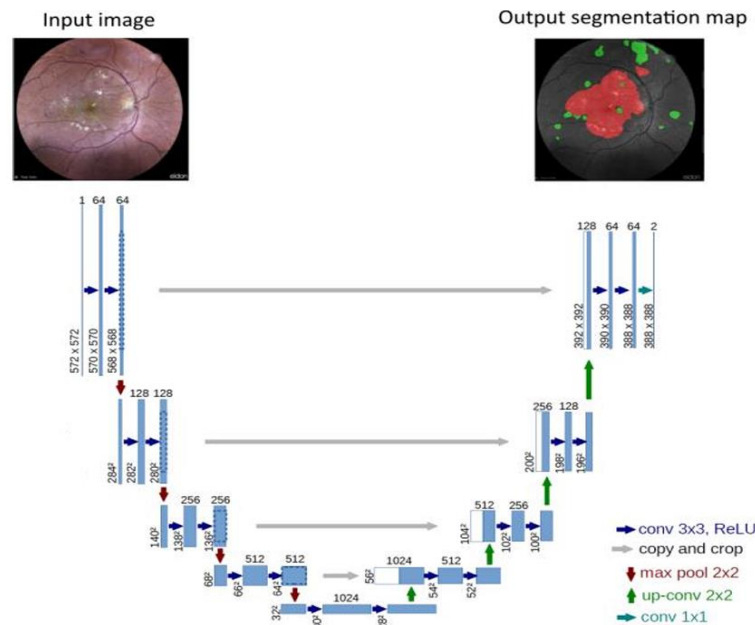


FIGURE 13:RETINAL FUNDUS IMAGES WITH DR SIGNS. [FARAHAT ET AL]

Diabetic Retinopathy Detection; care EIDONisanon-mydiaticretinal camera (Figure 14)³⁴. It is one of the first TrueColor confocal systems to set new quality standards in retinal imaging by combining the best features of scanning laser ophthalmoscopy (SLO) systems with those of basic fundus imaging. iCare EIDON is a retinal imaging system that provides high image quality as well as a confocal view in a non-dilating procedure, as well as a wide field and ultra high-resolution imaging. Furthermore, it distinguishes itself by offering users a variety of imaging modalities, including blue, TrueColor, and red-free and red confocal images, as well as infrared. In addition to this, it enables users to work in both fully manual and fully automated modes and to image through cataract and media opacities.

³⁴ Farahat et al., 'Application of Deep Learning Methods in a Moroccan Ophthalmic Center'.



FIGURE 14: CARE EIDON WIDEFIELD TRUECOLOR CONFOCAL FUNDUS IMAGING SYSTEM

The study is approved by the ethics committee of the Cheikh Zaid International University Hospital, and patient consent was obtained. In order to test both the segmentation and detection methods, 1000 color fundus images were collected from the Foundation Ophthalmic Center of Rabat. These images were taken by the EIDON retinograph, which can automatically produce composite images that allow an overview of the retina of the patient.

200 color images were taken from the Cheikh Zaïd International University in Rabat and then used for training and testing the U-Net algorithm. The image implementation procedure is still in progress. More masks are being manually created in order to improve the model dataset. Gimp software has been used to create masks. After being validated by expert ophthalmologists, all of them were saved as JPEG folders and divided into four folders (hard exudates, soft exudates, hemorrhages, and red small dots). These four folders

were then merged into two folders to keep only two classes, which are hemorrhages (small red dots and hemorrhages) and exudates (hard and soft exudates).

Abulcasis DR-AI Detection software:

In order to facilitate the use of the detection code, a graphical interface was created using QT Python and FPDF Python.

The first interface allows users to fill in fields with different information, such as 12 of 19 patients' names and dates, and they can also add comments, as shown in Figure15.



FIGURE 15: LOGIN INTERFACE³⁵. [FARAHAT ET AL]

Login interface.

A “Validate” button allows the user to validate the filled fields and then to choose the color fundus image path, as well as to switch to the second interface.

The second interface permits us to select a specific image to analyze (Figure 16). Once the “Detection” button is pressed, the third interface is displayed. A “Back” button allows one to go back to the first interface

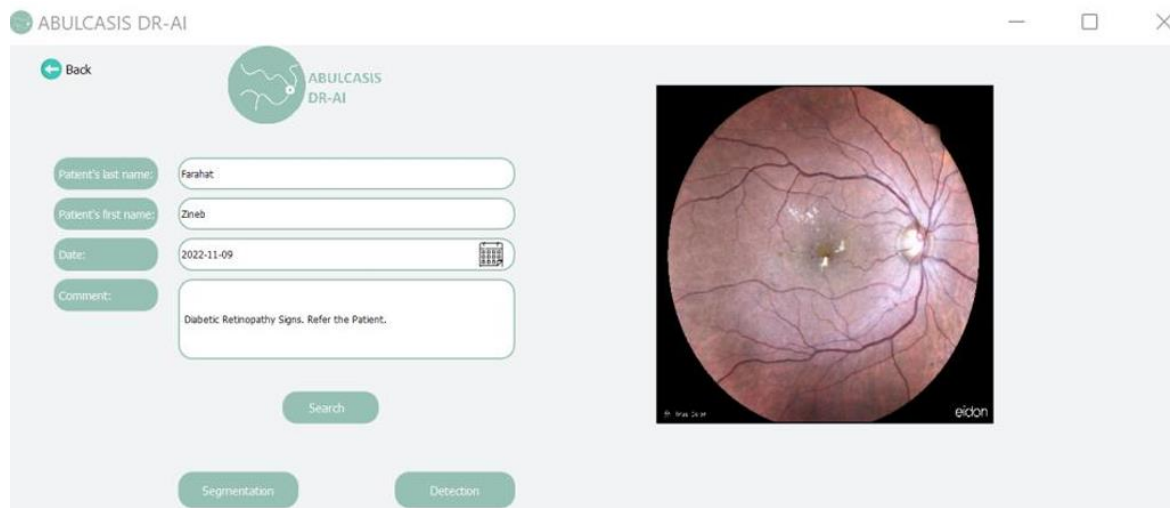


Figure 16: Image choice interface.

The detection result is shown after that, and the user can also enlarge the resulting image to see different details of the detected signs of DR. Furthermore, it is possible to add comments to describe the patient’s case.

With a growing diabetic population and an increasing gap between healthcare demand and the availability of trained professionals, early screening and management of diabetic retinopathy (DR) must be prioritized. Automating DR screening would be particularly beneficial in Morocco, where the number of doctors is insufficient to meet the needs of a rapidly expanding patient population. Artificial intelligence presents a promising solution for early screening, helping to address this health challenge and reduce blindness.

In this study, U-Net and YOLOv5 models were employed and compared for detecting hemorrhages and exudates in retinal images. The objective is to

implement the proposed method in medical caravans serving low-density areas, thereby enhancing tele-screening in ophthalmology, optimizing patient flow in healthcare facilities, and reducing unnecessary specialist visits and associated travel expenses.

Future work will focus on expanding the dataset with more labeled retinal images to further train the software, improve its performance metrics, and enhance its ability to recognize rare DR cases. However, the Abulcasis DR-AI software still has limitations that need to be addressed. Further research is required to develop a robust grading tool for DR severity.

VI.3.d) Study about the applications of AI in Moroccan Hospitals.

A study was recently released in the Faculty of Medicine of Tangier about the integration of artificial intelligence (AI) in the Moroccans' healthcare sector.

Case studies were gathered from databases at selected university hospitals and Moroccan medical centers, particularly the Mohammed VI University Hospital Center in Tangier, as well as hospitals in Casablanca, Rabat, and Fez. These institutions have seen significant improvements in operating room management and patient monitoring following the adoption of AI systems, including reduced waiting times and optimized use of human resources. The studies offered precise data on the tangible impact of AI technologies on healthcare facility performance.

The main objective was to show the advantages impacting of artificial intelligence in Morocco's health care³⁵:

Improved diagnosis and care: AI has significantly improved diagnostic accuracy in critical areas such as radiology and oncology. The integration of AI into radiological diagnostics in Morocco has reduced diagnostic errors by 25% to 30% in pilot institutions according to a study released by Abdellah et Al 2020, accurate diagnostics can mean the difference between life and death, particularly in rural areas where sources are limited.

Increased surgical precision: The use of surgical robots, such as the Da Vinci system, has demonstrated a 20% reduction in postoperative complications between 2020 and 2024, according to a recent study by Benjelloun et al. (2022). These advances underscore the direct impact of AI on surgical quality and patient outcomes. Indeed, Morocco has begun to integrate these technologies into its major hospital centers, with positive feedback in terms of improved operative results and reduced hospital stays.

Efficiency of hospital services: Around 35% of Moroccan hospitals have adopted AI systems for appointment management, reducing waiting times by an average of 30%, according to a study by Khoury et al. (2023). This reduction has not only improved the fluidity of hospital operations but also increased patient satisfaction, a key indicator of care quality.

Reduced operating costs: Due to the automation of diagnostics and administrative processes, Moroccan healthcare facilities achieved savings of

³⁵ Idaomar et al., 'Applications of Artificial Intelligence in Morocco's Healthcare Sector'.

15% to 20% between 2020 and 2024, according to research by Sefrioui et al. (2023). These savings strengthen the financial sustainability of the healthcare system, enabling resources to be reallocated to other critical areas such as medical equipment and staff training.

VII)The adoption of AI into urology in Morocco:

VII.1) Robotic surgery in Urology in Morocco:

Morocco took the first steps to robotic surgery in urology thanks to Dr. Younes Ahellals' initiative (urologist in Nice, France).

According to Dr. Younes Morocco has the potential to be a leader in robotic surgery in the African continent; what we lack the most is the political desire to integrate AI Into the Medical sector, of course, it is going to be difficult simply because a robot does not work by itself, we need experties.

Robotic surgery is teamwork. To make it a reality in Morocco, Dr. Younes Ahellal proposed that specialists (anesthetists and nurses) should take Training in Robotic Surgery in France and other developed countries.

Robotic surgery using the da Vinci surgical system has become widely accepted in urology, with newer robotic platforms expanding applications and improving affordability³⁶. This study evaluates the feasibility, safety, and short-term outcomes of the Toumai robotic system in three major urological procedures.

³⁶ Ahallal et al., 'PE108 Assessing the Initial Experience of Robotic Surgery in Morocco Using the Toumai® Robotic System'.

25 consecutive patients underwent bladder, renal, and prostatic surgeries using the Toumai system. Primary outcomes included technical feasibility (conversion rate) and safety (perioperative complications). Secondary endpoints covered key perioperative parameters: functional and oncological outcomes. The Toumai system operates under a master–slave protocol consisting of a Surgeon Console, Patient Platform, and Vision Platform.

13 patients underwent radical prostatectomy (RP), nine patients had nephrectomy procedures (five partial nephrectomies [PN] and four radical nephrectomies [RN]), and three patients had radical cystectomies (RC). No cases required conversion to an alternative surgical approach. Two patients experienced complications of Clavien–Dindo grade ≥ 3 , and there were no readmissions within 30 days. Median operating times were 190 (170–230) minutes for RP, 160 (110 – 180) minutes for PN, 90 (80–130) minutes for radical nephrectomy, and 300 minutes for RC. Off-clamp PN was performed in two cases, with a warm ischemia time of 15 (12–22) minutes in the remaining cases. No major robotic malfunctions occurred. At the 6–week follow–up, there was no evidence of tumor recurrence, preserved renal function, and satisfactory continence status.

This study reports the initial clinical experience with an innovative robotic platform in Morocco and North Africa. Complex urological surgeries were successfully completed without conversions and with minimal complications. Further investigations are necessary to validate these preliminary results. It is important, however, to create a distinction between robot–assisted surgery

and AI Automation and autonomy exist on a spectrum, total autonomy is the most refined form. (Table 5)

Here are some ideas about the future of artificial intelligence in the Moroccan health care system in urology:

AI-Enhanced Surgical Tools: AI helps with precise surgical planning using 3D imaging and preoperative data and it assists surgeons in distinguishing healthy tissues from diseased ones during procedures.

AI in Robotic Surgery: Integration with systems like the "Da Vinci Surgical System" enhances precision, stability, and flexibility during minimally invasive procedures, reduces human error and improves success rates in complex surgeries.

Simulation and Skill Development: AI-powered platforms provide advanced surgical simulations, allowing trainees to practice procedures in a risk-free virtual environment, It also Helps bridge the gap for rural and less experienced practitioners, ensuring uniform skill development across regions.

AI for Monitoring and Prediction: AI algorithms predict potential complications, such as infections or adverse reactions, based on patient data, and enhances post-surgical care, ensuring faster recovery and reduced hospital stays.

VII.2) Survey (Moroccan urologists and AI):

Objectives:

To study the applications of artificial intelligence (AI) in diagnosis, treatment, and outcome prediction in urologic diseases and evaluate its advantages over traditional models and methods.

To investigate the adoption of AI into the Moroccan healthcare sector, especially in urology.

Methods:

The following part represents the data collected from a questionnaire answered by urologists, The objective is to calculate the percentage of specialists using AI in daily activities, the understanding, and the way clinicians perceive AI in Morocco.

RESULTS:

We received 27 responses. Among the respondents, 15,4% are professors, 65,4% are specialists, and 19,2% are residents (Figure 17).

You are:
26 réponses

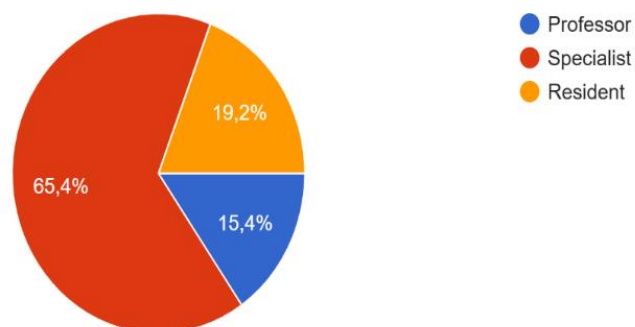


FIGURE 17: THE DOCTORS INCLUDED IN THE STUDY

Perceived potential applications of AI in urology:

The prevalence of physicians using AI in daily life is 63%;

22,2% are using diagnostic–AI (used to assist in identifying diseases, for example in radiology), and 29,6% to predict the outcome of diseases (eg: XGBoost and Logistic Regression models use biomarkers and clinical parameters to predict the progression and recurrence of bladder cancer), 11,1% in therapeutics (Robotic surgery, medical or surgical treatment). While 37% do not use AI, 44% are interested in trying it.

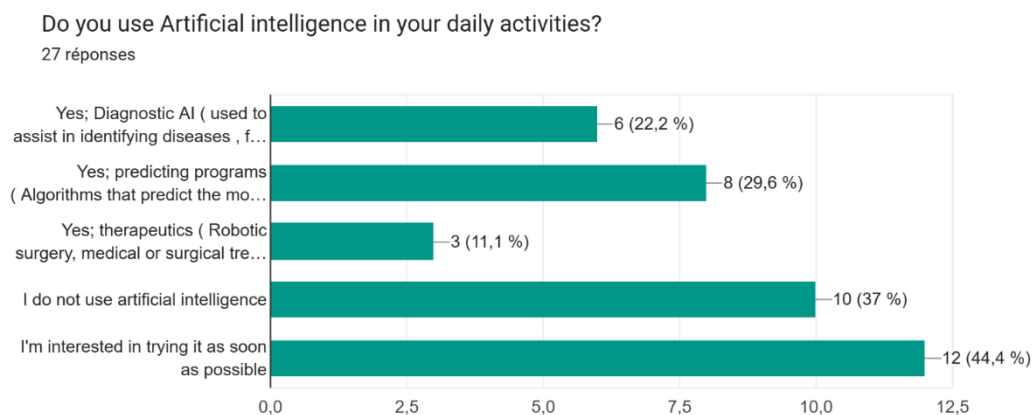


FIGURE 18: PERCEIVED POTENTIAL APPLICATIONS OF AI IN UROLOGY

AI Versus Human Intelligence:

Concerning the comparison between AI intelligence and human intelligence, 25,9% of physicians confirmed that AI is more efficient, 44,4 % think it's more precise, and 55% believe that it's more powerful. On the other hand, 18,5% think that AI is limited, and 3,7% assume it lacks creativity.

Artificial Intelligence compared to human intelligence is:

27 réponses

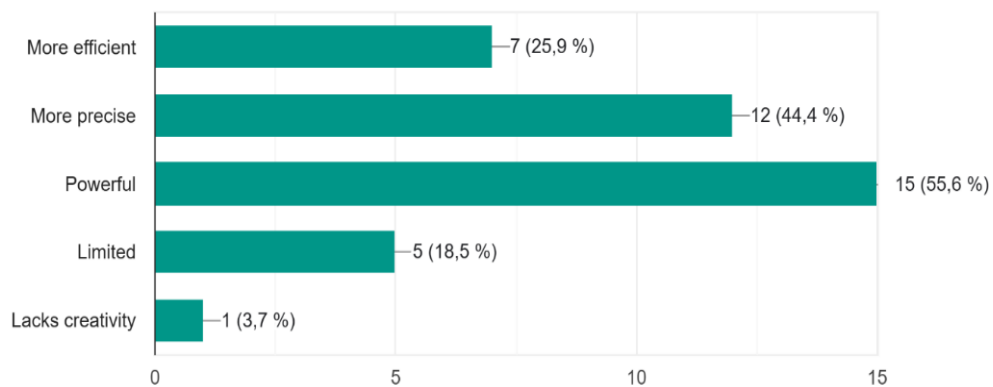


FIGURE 19: INTELLIGENCE; ARTIFICIAL OR HUMAN

Chatbot in urology:

92% of Moroccan urologists use chatbot (Figure21); 11% use it every day, 51% occasionally, and 92% confirmed that the informations provided by chatbot are useful (Figure20):

How often do you use ChatBot (or equivalent ChatGPT...)? ChatBot is a set of programs that can hold a conversation with a person using a series o...s that allow the construction of complex answers.
27 réponses

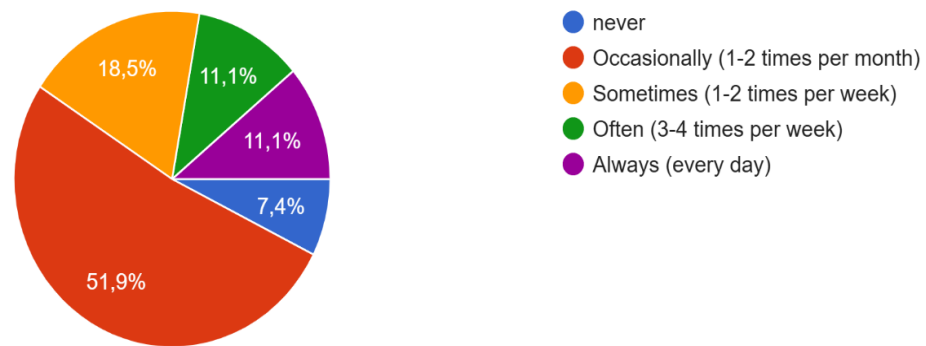


FIGURE 20: FREQUENCY OF USING CHATBOTS AMONG UROLOGISTS

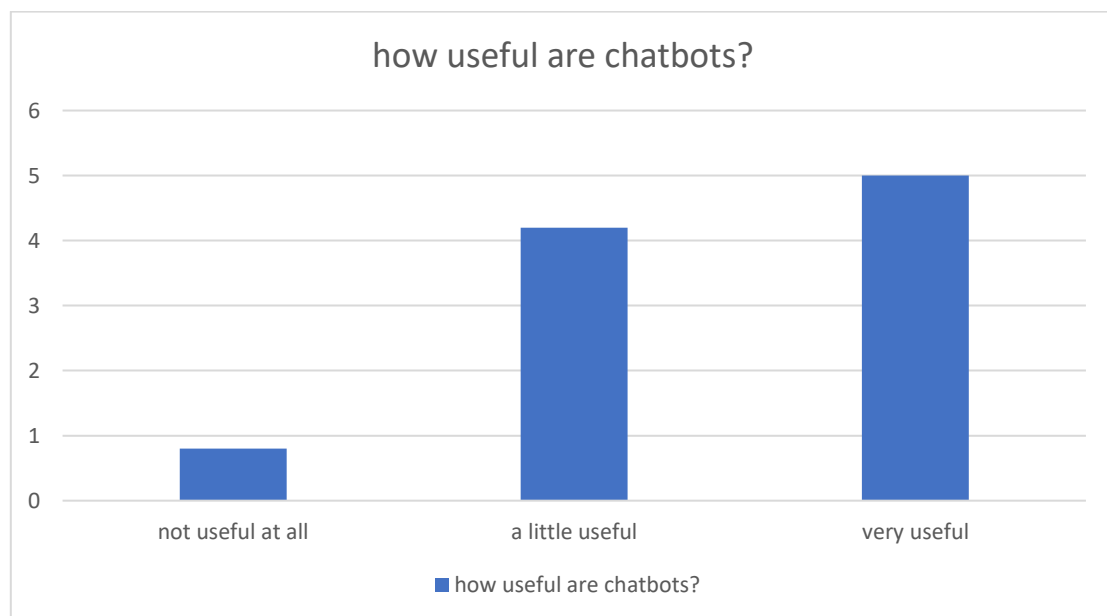


FIGURE 21: HOW USEFUL CHATBOTS ARE TO CLINICIANS

AI-Based algorithms in urology:

Among the perceived applications of artificial intelligence in urology, 44,4% of respondents reported that combining PSA levels with MRI data processed through AI enhance the prediction and detection of prostate cancer, 11% reported that AI is beneficial in detecting complications, while 5,6% assumed that predicting the urorisk is the most useful aspect.

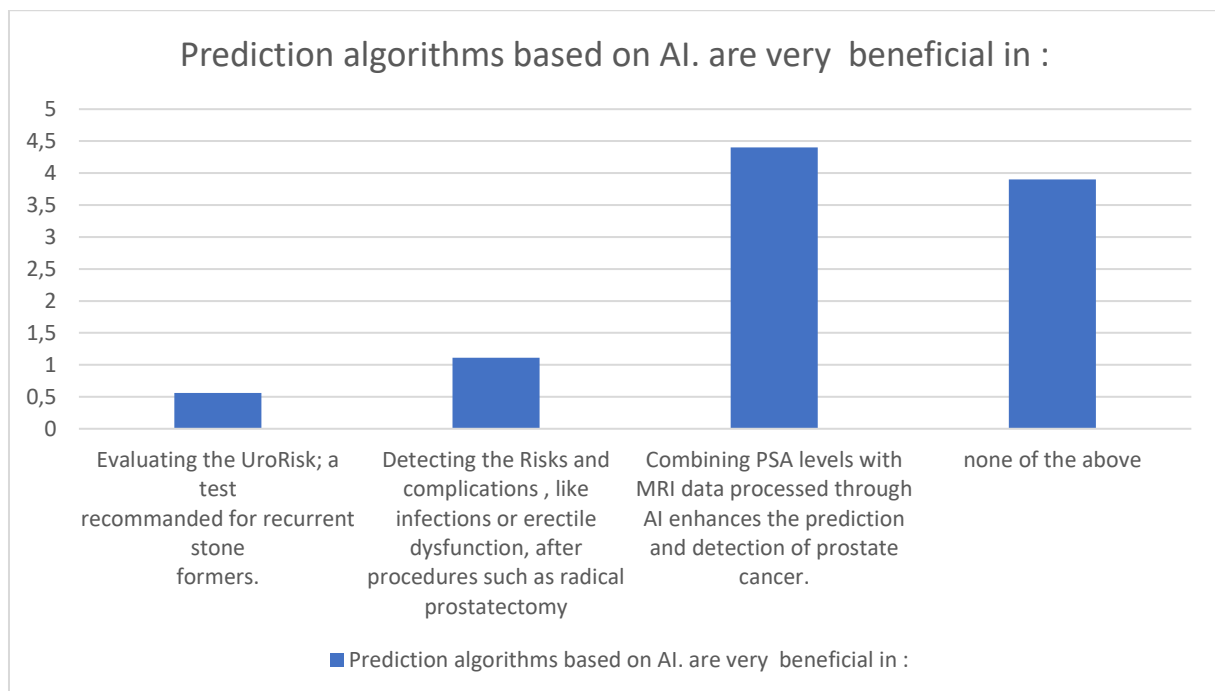


FIGURE 22: EXAMPLES OF AI-BASED ALGORITHMS IN UROLOGY

Robotic surgery in urology:

26% have no idea whether robotic surgery is beneficial or not, 7,3% considered that AI does not add any value during surgery, while 66,6% confirmed that AI is beneficial during surgery (Figure 23).

What is Your opinion about robotic surgery?
27 réponses

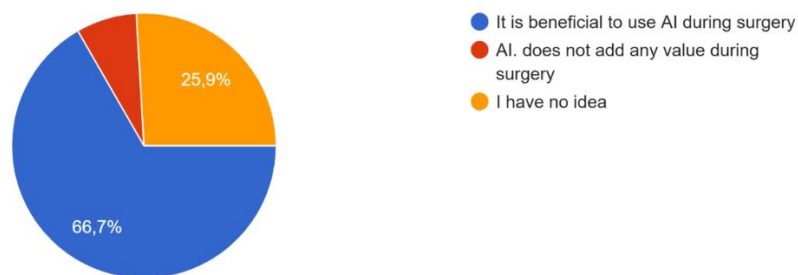


FIGURE 23: ROBOTIC SURGERY IN MOROCCO

Urologists' opinions about the adoption of AI into healthcare:

In this question, however, we got positive feedback: 80 % indicated that we must adopt AI because that's the way to gain expertise. 20% refuse the idea because of the experience we lack. (Figure24)

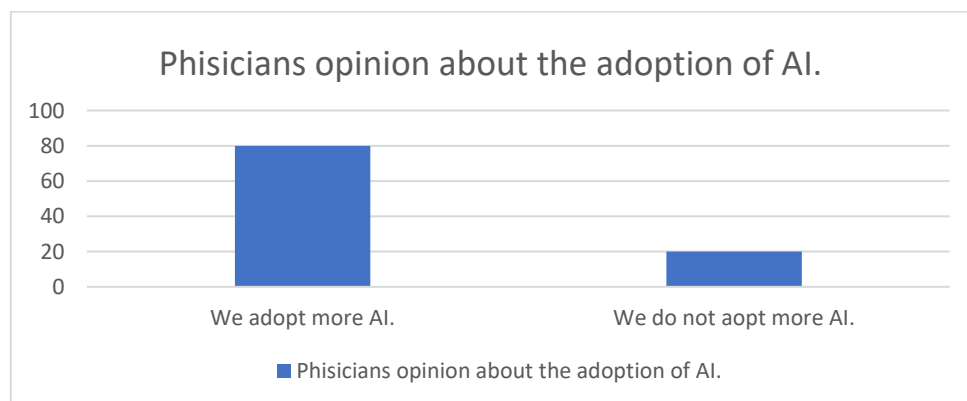


FIGURE 24: SHOULD MOROCCO ADOPT MORE AI INTO HEALTHCARE

Limitations of AI In health care:

The concerns perceived by the responding physicians regarding the use of artificial intelligence in the medical field are: the majority chose patient confidentiality, followed by security risks, then informed consent, and lastly, Job displacement.

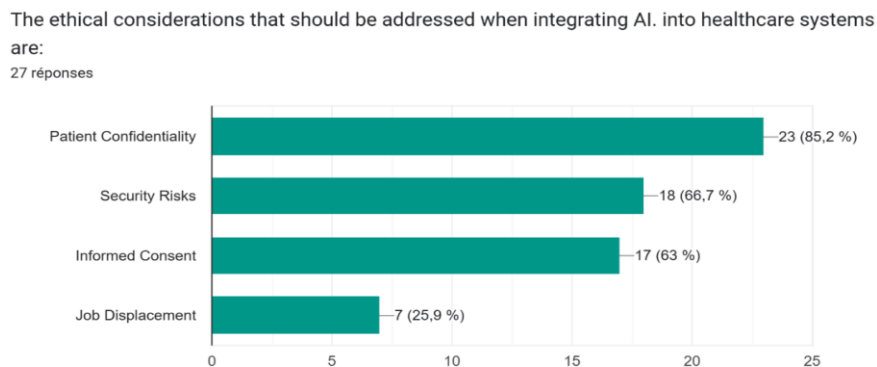


FIGURE 25: CONCERNS OVER ARTIFICIAL INTELLIGENCE

Here are some opinions that we received about artificial intelligence from participants

It new method for hep physician to do well

opportunity to take

AI used wisely helps improving our medical and surgical practices

The IA will be the cornerstone of surgery

AI is a vague domain that we don't know yet.

Artificial intelligence is the future

IA est tres souhaitable en pratique medical : –elle limite les erreurs medical et chirurgicale et –facile acces aux soins dans les zones reculées et les consultations à distance
– participe à la formation medical continue et l'encadrement du personnel de santé

IA is growing exponentially and upgrading once knowledge will be on a monthly basis or less

Discussion:

Since 2018, AI usage in Morocco has increased by 15% annually, closely mirroring India's growth rate of 18% per year over the same period (OMS, 2022). In Tunisia, AI adoption in healthcare has also expanded, though at a slightly lower rate of 12% per year (OMS, 2022).

These trends indicate that Morocco is competitively positioned among emerging countries in integrating AI into healthcare.

60% of Moroccan urologists incorporate AI into their practice, a promising adoption rate. In comparison, Moroccan studies report that 48% of physicists also utilize AI in their work³⁷.

Almost all participants believe that AI consists of much more creativity than human abilities. The consequence on the professional field is a matter of divergence. 75% of Moroccan urologists believe that AI is not as efficient as human intelligence. However, this perception is inaccurate, given the rapid and continuous advancements in AI development.

AI takes various forms, one of which is the chatbot. Chatbots are widely accessible and often available for free. By simulating human conversation, they provide an easy-to-use and intuitive platform for interaction.

Asking refined medical questions to Artificial Intelligence may constitute a source of knowledge. This issue was analyzed by various researchers who have explored the accuracy, reliability, and ethical implications of AI-generated medical information, particularly in the context of clinical decision-making, patient education, and diagnostic support³⁸.

In 2023, Researchers at Google introduced Med-PaLM, a specialized AI model designed to answer medical questions with higher accuracy and alignment with human expertise³⁹.

If Moroccan urologists do not recognize the role of AI in predicting and analysing medical data, this role is currently well approved.

The urinary stone was the more explored topic for AI added value. In fact, numerous studies have demonstrated the effectiveness of AI in detecting, classifying, and predicting the recurrence of urinary stones using advanced imaging techniques such as CT scans and ultrasound. Machine learning models have been particularly useful in automating stone detection, assessing stone composition, and predicting treatment outcomes, thereby enhancing clinical decision-making and reducing diagnostic errors.

Regarding the diagnosis step, a study introduced an AI algorithm that automatically detects urinary stones in CT images and calculates essential stone characteristics, such as volume and density. In a real-world emergency room scenario, the AI system achieved a detection accuracy of 95%, outperforming human specialists in speed and efficiency⁴⁰.

A study developed a machine learning model to preoperatively identify urinary infection stones in vivo. By analyzing clinical data from 1,168 patients, the model achieved strong discrimination with an area under the receiver operating characteristic curve (AUC) of 0.772. Urine culture positivity and urine pH were identified as significant predictors of infection stones⁴¹.

A study assessed machine-learning methods for recognizing urinary stones during endoscopy. Using images of 123 urinary calculi, both shallow classification methods and deep-learning-based methods were evaluated. The deep-learning approach achieved high sensitivity and specificity across various stone classes, indicating AI's potential to assist urologists in real-time stone identification during procedures⁴².

Nakamae et al have developed a machine learning model to predict the success of extracorporeal shock wave lithotripsy (SWL) in patients with ureteral stones. By analyzing various stone and patient characteristics, the model aimed to assist clinicians in treatment planning by forecasting SWL outcomes⁴³.

Detecting the risks and complications of prostatectomy using artificial intelligence models was analysed by several researchers who developed machine learning algorithms to predict postoperative outcomes, assess the likelihood of complications such as incontinence and erectile dysfunction, and optimize surgical planning to improve patient safety and functional recovery.

In 2024, researchers applied deep learning techniques to predict errors and assess surgical skill during robotic prostatectomy suturing. The AI model analyzed surgical video data to identify technical errors, offering insights that could enhance surgical training and patient safety⁴⁴.

In a population-based study, Wei. et al, combined AI with big data to predict lymph node involvement in prostate cancer patients. The model aimed to assist in preoperative planning by accurately identifying patients at higher

risk of lymph node metastasis, thereby informing decisions regarding the extent of lymph node dissection during prostatectomy⁴⁵

Several studies demonstrating the role of artificial intelligence in predicting and diagnosing prostate cancer before a prostate biopsy:

A deep learning model was trained on a large dataset of prostate MRI images to predict the presence of cancer. The model outperformed human radiologists in detecting cancerous lesions and showed promising potential in reducing unnecessary biopsies⁴⁶.

Another study published in *JAMA Oncology* used AI to predict prostate cancer in patients with elevated PSA levels before a biopsy. The AI model helped in identifying patients who were less likely to have prostate cancer, thus avoiding unnecessary biopsies⁴⁷.

A study published in *European Urology* focused on using AI to analyze multi-parametric MRI scans to predict prostate cancer in patients with abnormal PSA levels. The AI algorithm demonstrated high diagnostic accuracy, suggesting a potential reduction in the need for biopsies⁴⁸.

A model developed at a research institution integrated clinical, radiological, and genomic data to predict prostate cancer aggressiveness. The AI model demonstrated accuracy in determining whether prostate cancer was indolent or aggressive, assisting in treatment decision-making⁴⁹.

34% of Moroccan urologists are not convinced by the role of AI in robotic surgery, whilst it provides enhanced precision, efficiency, and outcomes for various surgical procedures.

In **robotic prostatectomy**, AI can assist in identifying critical structures like the nerve bundles and blood vessels to minimize the risk of injury. AI systems can also track the surgeon's movements and adjust in real-time to correct any deviations from the ideal path⁵⁰.

AI can also be used to train surgeons through virtual simulations. By leveraging AI-powered robotic systems, surgical trainees can practice various procedures in a controlled, risk-free environment before performing them on real patients.

AI-powered simulators, such as those used for **robotic laparoscopic surgery**, provide real-time feedback and analyze the trainee's technique, improving their skills over time⁵¹.

Moreover, AI can aid in real-time decision-making by providing instant analysis of the patient's data, such as imaging, vital signs, and historical medical records, which can help surgeons make informed choices during surgery⁵².

Additionally, AI can help in preoperative planning by analyzing patient data, 3D imaging, and anatomical models to assist in designing personalized surgical approaches. This can be particularly valuable in complex surgeries, where AI helps tailor the procedure to the patient's unique anatomy⁵³.

Some robotic systems integrate AI to provide automated assistance during surgery. For instance, robotic surgical systems like the **da Vinci Surgical System** use AI to assist with tasks like suturing and tissue manipulation. AI also has the potential to adapt in real time to changes in the patient's condition

or surgical environment. The **Intuitive Surgical da Vinci system** includes AI features that allow it to adjust the surgeon's movements automatically for improved precision during complex procedures like **robotic-assisted nephrectomy**⁵⁴.

More than 60% of Moroccan urologists are concerned about security risks and ethical issues with AI use, which matches with Toumi's thoughts⁵⁵.

This concern was highlighted by several authors who discussed the ethical complexities introduced by AI in healthcare, emphasizing the need for balancing technological benefits with patient safety, privacy, and the physician's role in patient care⁵⁶.

Conclusion:

In conclusion, this study highlights that Moroccan urologists remain uncertain or apprehensive about AI's impact in the urological field. However, the findings are limited by the small sample size. More extensive studies are needed to raise awareness within the Moroccan medical community about the importance of learning and integrating artificial intelligence into clinical practice.

Summary:

Artificial Intelligence (AI) is a branch of science and technology dedicated to creating intelligent machines and computer programs capable of performing tasks that typically require human intelligence.

In healthcare, AI has shown immense potential through its ability to streamline delivery systems, reduce diagnostic errors, and enhance patient outcomes. This research, supported by a thorough examination of current literature and case studies, illustrates how AI technologies can revolutionize healthcare practices, particularly in fields like urology, within the context of Moroccan healthcare.

The thesis also delves into the ethical considerations and future prospects of integrating AI into medical practices. It highlights the challenges and opportunities associated with AI adoption in Morocco, emphasizing the transformative impact it could have on advancing medical care. As new medical equipment continues to emerge, AI's role in healthcare is becoming increasingly vital, paving the way for its likely integration into routine clinical settings in the near future. This anticipated promise has sparked significant interest and investment in AI medical applications, both from governmental organizations and technological companies alike.

However, despite AI's potential to revolutionize healthcare systems globally, several deficiencies and challenges could hinder its effective implementation in Moroccan healthcare.

We take Urology as an example; AI-powered robotic surgery is widely used, offering precision, reduced recovery times, and improved patient outcomes. While in Morocco, the availability and use of AI-powered robotic surgery is limited in urology due to high costs and infrastructure challenges

Résumé:

L'intelligence artificielle (IA) est une branche des sciences et technologies consacrée à la création de machines intelligentes et de programmes informatiques capables d'accomplir des tâches nécessitant habituellement l'intelligence humaine.

Dans le domaine de la santé, l'IA a démontré un potentiel immense grâce à sa capacité à rationaliser les systèmes de prestation de soins, à réduire les erreurs diagnostiques et à améliorer les résultats pour les patients. Cette recherche, appuyée par une analyse approfondie de la littérature actuelle et des études de cas, illustre comment les technologies de l'IA peuvent révolutionner les pratiques médicales, en particulier dans des domaines comme l'urologie, dans le contexte du système de santé marocain.

La thèse explore également les considérations éthiques et les perspectives futures liées à l'intégration de l'IA dans les pratiques médicales. Elle met en lumière les défis et les opportunités associés à l'adoption de l'IA au Maroc, en insistant sur l'impact transformateur qu'elle pourrait avoir pour améliorer les soins médicaux. Avec l'émergence continue de nouveaux équipements médicaux, le rôle de l'IA dans la santé devient de plus en plus essentiel, ouvrant la voie à son intégration probable dans les environnements cliniques de routine dans un avenir proche. Cette promesse suscite un intérêt et des investissements considérables dans les applications médicales de l'IA, aussi bien de la part des organisations gouvernementales que des entreprises technologiques.

Cependant, malgré le potentiel de l'IA à révolutionner les systèmes de santé à l'échelle mondiale, plusieurs lacunes et défis pourraient entraver sa mise en œuvre efficace dans le secteur de la santé marocain.

Prenons l'urologie comme exemple : la chirurgie robotique assistée par IA est largement utilisée à l'international, offrant une précision accrue, des temps de récupération réduits et de meilleurs résultats pour les patients. Au Maroc, toutefois, la disponibilité et l'utilisation de la chirurgie robotique assistée par IA en urologie restent limitées en raison des coûts élevés et des défis liés aux infrastructures.

ملخص

(IA) الذكاء الاصطناعي

هو فرع من العلوم والتكنولوجيا مخصص لإنشاء آلات ذكية وبرامج حاسوبية قادرة على أداء مهام تتطلب عادةً الذكاء البشري.

في مجال الصحة، أظهر الذكاء الاصطناعي إمكانات هائلة بفضل قدرته على تحسين أنظمة تقديم الرعاية الصحية، تقليل الأخطاء التشخيصية، وتحسين نتائج المرضى. تعتمد هذه الدراسة على تحليل معمق للأدبيات الحالية ودراسات الحالة لتوضيح كيفية قدرة تقنيات الذكاء الاصطناعي على إحداث ثورة في الممارسات الطبية، خاصة في مجالات مثل جراحة المسالك البولية، ضمن سياق النظام الصحي المغربي.

تتناول الأطروحة أيضًا الاعتبارات الأخلاقية وآفاق المستقبل المرتبطة بدمج الذكاء الاصطناعي في الممارسات الطبية. تسلط الضوء على التحديات والفرص المرتبطة بتبني الذكاء الاصطناعي في المغرب، مع التركيز على التأثير التحويلي الذي يمكن أن يحدثه لتحسين الرعاية الطبية. ومع استمرار ظهور أجهزة طبية جديدة، يصبح دور الذكاء الاصطناعي في الصحة أكثر أهمية، مما يمهّد الطريق لدمجه المحتمل في البيئات السريرية الروتينية في المستقبل القريب. هذا الوعد يثير اهتمامًا واستثمارات كبيرة في تطبيقات الذكاء الاصطناعي الطبية، سواء من المنظمات الحكومية أو الشركات التكنولوجية. ومع ذلك، على الرغم من إمكانيات الذكاء الاصطناعي لإحداث ثورة في الأنظمة الصحية على مستوى العالم، فإن هناك العديد من الفجوات والتحديات التي قد تعيق تنفيذها الفعال في قطاع الصحة المغربي. على سبيل المثال، في مجال جراحة المسالك البولية، تُستخدم الجراحة الروبوتية المدعومة بالذكاء الاصطناعي على نطاق واسع دوليًا، حيث توفر دقة متزايدة، وأوقات تعافٍ أقصر، ونتائج أفضل للمرضى. ومع ذلك، في المغرب، تظل إتاحة واستخدام الجراحة الروبوتية المدعومة بالذكاء الاصطناعي في مجال جراحة المسالك البولية محدودًا.

Appendices: questionnaire

The applications of AI(artifiacial intelligence) in the Moroccan health-care system/urology.

In this research we tend to study the adoption of AI(artificial intelligence) in the Moroccan healthcare system, and how it can enhance patient care and clinical outcomes, particularly in the field of urology.

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Non partagé

You are:

- ☐ Professor
- ☐ Specialist
- ☐ Resident

Definition of artificial intelligence:

AI. is a technology that enable machines to perform tasks that require intelligent approaches (decision making, problem solving, learnig...) autonomously , in healthcare and beyond.

Do you use Artificial intelligence in your daily activities? *

- ☐ Yes; Diagnostic AI (used to assist in identifying diseases , for example in radiology)
- ☐ Yes; predicting programs (Algorithms that predict the mortality ,the evolution of a disease...)
- ☐ Yes; therapeutics (Robotic surgery, medical or surgical treatment)
- ☐ I do not use artificial intelligence
- ☐ I'm interested in trying it as soon as possible

Cette question est obligatoire.

Artificial Intelligence compared to human intelligence is: *

- ☐ Efficient
- ☐ More precise
- ☒ Powerful
- ☐ Limited
- ☐ Lacks creativity

How often do you use ChatBot (or equivalent ChatGPT...)? *

ChatBot is a set of programs that can hold a conversation with a person using a series of algorithms that allow the construction of complex answers.

- ☐ never
- ☐ Occasionally (1-2 times per month)
- ☐ Sometimes (1-2 times per week)
- ☐ Often (3-4 times per week)
- ☒ Always (every day)

To what extent do you find the information provided by ChatBot(or equivalent ChatGPT...) useful? *

- ☐ Not useful at all
- ☐ A little useful
- ☒ Very useful

AI-based programs

Programs or algorithms based on artificial intelligence that analyze complex data to simplify it for clinicians.

In which phase you use AI-based algorithms :

- ☐ interpretation; AI programs like PI-RADS Assist and PROMISE aid in mpMRI....
- ☐ diagnostic and planning; AI systems predict urolithiasis composition using CT scans or urinalysis data..
- ☐ traitement ;differentiating between benign and malignant kidney masses, guiding biopsy decisions...
- ☐ I do not use AI-based programs

Prediction algorithms based on AI. are very beneficial in :

- ☐ Evaluating the UroRisk; a test recommended for recurrent stone formers.
- ☐ Combining PSA levels with MRI data processed through AI enhances the prediction and detection of prostate cancer.
- ☐ Predicting the outcomes of surgical interventions like TURP (Transurethral Resection of the Prostate).

- ☐ Detecting the Risks and complications , like infections or erectile dysfunction, after procedures such as radical prostatectomy.
- ☐ none of the above

What is Your opinion about robotic surgery? *

- ☐ It is beneficial to use AI during surgery
- ☐ AI. does not add any value during surgery
- ☐ I have no idea

Morocco needs to adopt more AI. technologies in the medical sector. *

- ☐ yes ,the more we adopt the more experienced we get
- ☐ No, we lack experties

The ethical considerations that should be addressed when integrating AI. into healthcare systems are: *

- ☐ Patient Confidentiality
- ☐ Security Risks
- ☐ Informed Consent
- ☐ Job Displacement

Please write your opinion about artificial intelligence, and thank you for your participation.

Votre réponse

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SERMENT D'HIPPOCRATE

**Au moment d'être admis à devenir membre de la profession médicale,
je m'engage solennellement à consacrer ma vie au service de
l'humanité.**

**Je traiterai mes maîtres avec le respect et la reconnaissance qui leur
sont dus.**

**Je pratiquerai ma profession avec conscience et dignité. La santé de
mes malades sera mon premier but.**

Je ne trahirai pas les secrets qui me seront confiés.

**Je maintiendrai par tous les moyens en mon pouvoir l'honneur et les
nobles traditions de la profession médicale.**

Les médecins seront mes frères.

**Aucune considération de religion, de nationalité, de race, aucune
considération politique et sociale ne s'interposera entre mon devoir et
Mon patient.**

Je maintiendrai le respect de la vie humaine dès la conception.

**Même sous la menace, je n'userai pas de mes connaissances
médicales d'une façon contraire aux lois de l'humanité.**

Je m'y engage librement et sur mon honneur.

قَسَمُ أَبْفَرَاط

فِي هَذِهِ اللَّحْظَةِ الَّتِي يَتِمُّ فِيهَا قَبُولِي عُضْوًا فِي

الْمِهْنَةِ الطَّبِيبِيَّةِ أَتَعَهَّدُ عَلَانِيَةً:

بِأَنْ أُكْرِسَ حَيَاتِي لَخِدْمَةِ الْإِنْسَانِيَّةِ

أَنْ أَحْتَرِمَ أَسَاتِذَتِي وَأَعْتَرِفَ لَهُمْ بِالْجَمِيلِ الَّذِي

يَسْتَحِقُّونَهُ

أَنْ أُمَارِسَ مِهْنَتِي بِوَأْزَعٍ مِنْ ضَمِيرِي وَشَرَفِي

جَاعِلًا صِحَّةَ مَرِيضِي هَدَفِي الْأَوَّلَ

أَنْ لَا أَفْشِيَ الْأَسْرَارَ الْمَعْهُودَةَ إِلَيَّ

أَنْ أَحَافِظَ بِكُلِّ مَا لَدَيَّ مِنْ وَسَائِلٍ عَلَى الشَّرَفِ

والتَّعَالِيدِ النَّبِيلَةِ لِمِهْنَةِ الطَّبِّ

أَنْ أَعْتَبِرَ سَائِرَ الْأَطِبَّاءِ إِخْوَةً لِي

أَنْ أَقُومَ بِوَاجِبِي نَحْوَ مَرْضَائِي بِدُونِ أَيِّ اعْتِبَارٍ

دِينِي أَوْ وَطَنِي أَوْ عِرْقِي أَوْ سِيَاسِي أَوْ اجْتِمَاعِي

أَنْ أَحَافِظَ بِكُلِّ حَزْمٍ عَلَى احْتِرَامِ الْحَيَاةِ الْإِنْسَانِيَّةِ مِنْذُ

نَشَأَتِهَا

أَنْ لَا أَسْتَعْمِلَ مَعْلُومَاتِي الطَّبِيبِيَّةِ بِطَرِيقَةٍ تَضُرُّ ؟

بِحُقُوقِ الْإِنْسَانِ مَهْمَا لَاقِيتُ مِنْ تَهْدِيدٍ

بِكُلِّ هَذَا أَتَعَهَّدُ عَنْ كَامِلِ اخْتِيَارِي وَمُقْسِمًا بِاللَّهِ

وَاللَّهِ عَلَى مَا أَقُولُ شَهِيدٌ



أطروحة رقم 25/110

سنة 2025

تطبيقات الذكاء الاصطناعي في قطاع الرعاية الصحية المغربي

الأطروحة

قدمت و نوقشت علانية يوم 2025/04/07

من طرف

السيد أيوب غنوا

المزاد في 18 فبراير 1999 بالراشيدية

لنيل شهادة الدكتوراه في الطب

الكلمات المفتاحية

الذكاء الاصطناعي، الطب، الطب، الرعاية الصحية، جراحة المسالك البولية، الجراحة الروبوتية
الخوارزميات القائمة على الذكاء الاصطناعي، المغرب

اللجنة

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