An Over View On Using of Artificial Intelligence in Allopathic Medicine

Shankar Murthy. K[1], Salma siddiqa[2], Shifa hani[3]

[1]*Lecturer, Department of P.G Studies and Research in Biotechnology, Kuvempu University, Shankaraghatta-577451, Shivamogga district, Karnataka. INDIA*

[2,3]*Department of P.G Studies and Research in Biotechnology, Kuvempu University, Shankaraghatta-577451, Shivamogga district, Karnataka*

***Abstract*—Artificial Intelligence (AI) is emerging as a game-changing innovation in allopathic medicine, offering new possibilities for diagnosis, treatment, and patient care. By employing advanced computational approaches such as machine learning, deep learning, and natural language processing, AI systems can rapidly analyze vast amounts of clinical and biomedical data with higher accuracy than traditional methods. This capability enables early disease detection, personalized treatment planning, and predictive modeling of patient outcomes. AI is already making an impact through applications like automated medical imaging analysis, robotic-assisted surgeries, AI-powered chatbots for patient support, and clinical decision-support systems that guide physicians in complex cases. Furthermore, AI-enabled wearables and biosensors provide real-time monitoring of vital signs, facilitating preventive medicine and remote healthcare. The integration of AI also accelerates research in vaccine design, cancer detection, and digital pathology. Despite challenges related to data privacy, algorithmic bias, and ethical regulation, AI represents a powerful tool that is reshaping evidence-based allopathic medicine and advancing global healthcare delivery.**

***Index Terms*—Artificial Intelligence, Allopathic medicine, Drug discovery.**

I. INTRODUCTION

Artificial Intelligence (AI) has emerged as a transformative force in modern healthcare, revolutionizing the way diseases are diagnosed, treated, and managed. In allopathic medicine-the branch of medicine that uses scientifically tested drugs, surgery, and other interventions to treat or prevent diseases-Al plays a vital role in enhancing clinical decision-making, improving patient outcomes, and optimizing healthcare operations. Through advanced algorithms, machine learning, and data analytics, Al systems can process vast amounts of medical data, identify hidden patterns, and provide evidence-based insights that assist physicians in delivering precise and personalized treatments [1].

The integration of Al in allopathic medicine extends from diagnostic imaging and drug discovery to patient monitoring and predictive analytics. It enables early disease detection, supports rapid analysis of complex medical images, and aids in the design of novel therapeutic drugs with higher efficacy and fewer side effects. Moreover, Al-powered systems are increasingly being used to manage electronic health records, predict disease outbreaks, and even develop innovative medical devices. As technology continues to evolve, Al is becoming not just a tool but a partner in the clinical decision-making process marking a new era in evidence-based allonathic medicine.

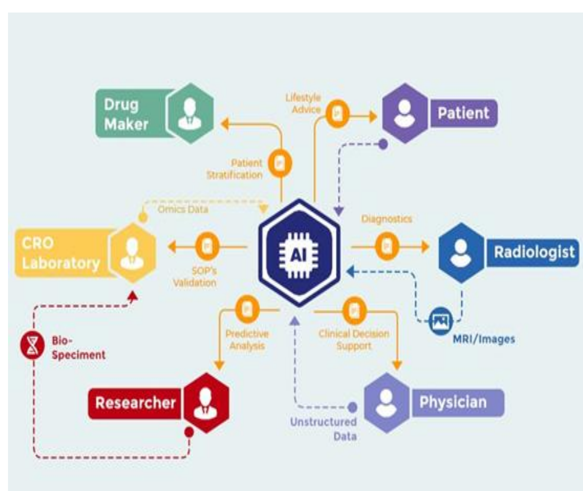

Fig.1 Artificial Intelligence in Allopathic Medicine

Artificial Intelligence (AI) in Allopathic medicine has evolved from early rule-based expert systems to modern machine learning (ML) algorithms. As early as the 1970s, systems such as MYCIN (a rule-based expert system for diagnosing bacterial infections) demonstrated the potential of computer-aided diagnosis by using encoded medical knowledge to assist clinical decision-making. These early efforts laid the foundation for AI's role in healthcare; however, it is the recent convergence of big data and advanced computing that has truly catalyzed AI's impact. In the last decade, the advent of deep learning, particularly convolutional neural networks for image analysis, and the widespread availability of electronic health records have driven the renaissance of AI applications across medical domains. High-profile commentaries have envisioned AI as a transformative force in medicine, capable of enhancing diagnostic accuracy, personalizing therapy, and improving workflow efficiency. Indeed, AI has already demonstrated performance comparable to that of experienced clinicians in tasks such as medical image interpretation and risk prediction, heralding a new era of 'augmented' intelligence that complements rather than replaces clinical expertise [2].

Despite this enthusiasm, the integration of AI into day-to-day clinical practice is still in its early stages in many fields. Key questions remain regarding the real-world effectiveness of AI tools, the best methods for implementing them alongside healthcare professionals, and how to address concerns regarding algorithmic transparency, bias, and ethics. To clarify the current state-of-the-art, a comprehensive review of AI applications was conducted across five major areas of medicine: diagnostic imaging, clinical decision support, surgery, pathology, and drug discovery.

AI's strength is in its ability to learn and recognise patterns and relationships from large multidimensional and multimodal datasets; for example, AI systems could translate a patient's entire medical record into a single number that represents a likely diagnosis. Moreover, AI systems are dynamic and autonomous, learning and adapting as more data become available.13 AI is not one ubiquitous, universal technology, rather, it represents several subfields (such as machine learning and deep learning) that, individually or in combination, add intelligence to applications. Machine learning (ML) refers to the study of algorithms that allow computer programs to automatically improve through experience.

ML itself may be categorised as 'supervised', 'unsupervised' and 'reinforcement learning' (RL), and there is ongoing research in various sub-fields including 'semi-supervised', 'self-supervised' and 'multi-instance' ML. Supervised learning leverages labelled data (annotated information); for example, using labelled X-ray images of known tumours to detect tumours in new images.'Unsupervised learning' attempts to extract information from data without labels; for example, categorising groups of patients with similar symptoms to identify a common cause.In RL, computational agents learn by trial and error, or by expert demonstration.

The algorithm learns by developing a strategy to maximise rewards. Of note, major breakthroughs in AI in recent years have been based on RL .Deep learning (DL) is a class of algorithms that learns by using a large, many-layered collection of connected processes and exposing these processors to a vast set ofexamples. DL has emerged as the predominant method in AI today driving improvements in areas such as image and speech recognition [3].

II. MAIN TOOLS OF ARTIFICIAL INTELLIGENCE

1. Machine Learning (ML): It is a subset of AI that enables computers to learn from data and improve performance without being explicitly programmed.Ex., TensorFlow (by Google) Scikit-learn (Python library), PyTorch (by Meta). It is used in Disease prediction, drug discovery and image recognition.

2. Deep Learning: An advanced branch of machine learning using neural networks to mimic the human brain's structure and learning process. Ex., Kera's Caffe Theano. It is used in Speech recognition and medical imaging (like MRI scan analysis).

3.Natural Language Processing (NLP): Enables machines to understand, interpret, and respond to human language.Ex., NLTK (Natural Language Toolkit), spaCy and GPT models (like ChatGPT) It is used in Chatbots, medical transcription and patient data analysis.

4. Computer Vision: Allows computers to interpret and understand visual data from the world (images, videos). Ex., OpenCV, YOLO (You Only Look Once) and ImageAI. It is used in Detecting tumors in X-rays or MRI scans and monitoring patient health.

5.Robotics and Automation Tools: Integrates AI into physical systems to perform tasks automatically.Ex., ROS (Robot Operating System), UiPath, Blue Prism (for robotic process automation). It is used in Surgery-assisting robots and automated drug dispensing.

6.Expert Systems: AI programs designed to mimic human decision-making in specific domains.Ex., CLIPS (C Language Integrated Production System), Drools (Rule engine). It is used in Clinical decision support systems and medical diagnosis.

7.Reinforcement Learning Tools: Systems that learn by trial and error to make decisions that maximize reward.Ex., OpenAI Gym, Ray RLlib. It is used in Personalized treatment planning and adaptive healthcare systems.

8.Data Science and Analytics Platforms: Used to collect, process, and analyze large datasets that feed AI systems.Ex., Apache Spark, RapidMiner, KNIME. It is used in Disease trend analysis and hospital data management

III. APPLICATIONS OF ARTIFIAL INTELLIGENCE IN ALLOPATHIC MEDICINES

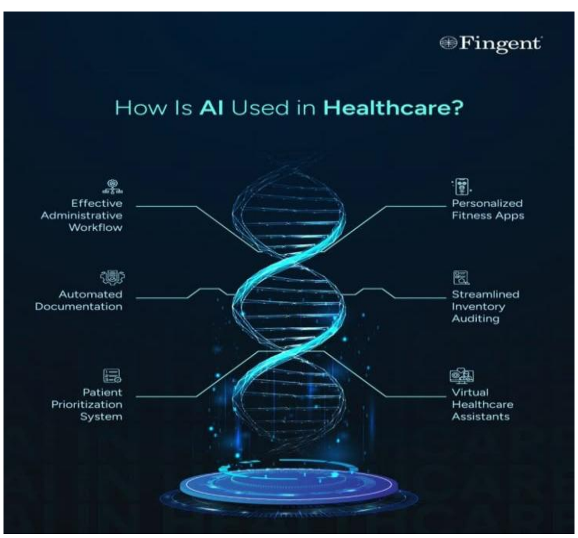

Fig.2 Applications of Artificial Intelligence

AI for Drug Discovery

Al technology in healthcare has helped pharmaceutical companies speed up their drug discovery process. It, on the other hand, automates the identification of targets. In addition, by analyzing off-target compounds. Al in healthcare 2021 aids in drug repurposing. As a result, in the Al and healthcare industries. Al drug discovery streamlines the process and reduces repeated work.

If proponents of these strategies are correct, Al and machine learning will bring in a new era of drug development that is faster, cheaper, and more effective. Some are skeptical, but most experts believe these tools will become more crucial in the future. Scientists face both obstacles and opportunities as a result of this transformation, particularly when the approaches are coupled with automation.

AI for clinical trials

A clinical trial is a procedure in which freshly manufactured treatments are given to people to test how well they work. This has taken a significant amount of time and money. The success rate, however, is quite low.

As a result, clinical trial automation has proven to be a benefit for Al and the healthcare business. Furthermore, Artificial Intelligence and healthcare assist in the elimination of time-

100–150 per year in 2007–2008 to 1000–1100 per year in 2017–2018. Researchers have applied AI to automatically recognizing complex patterns in imaging data and providing quantitative assessments of radiographic characteristics. In radiation oncology, AI has been applied on different image modalities that are used at different stages of the treatment. i.e. tumor delineation and treatment assessment. AI is the essential boosting power of processing massive number of medical images and therefore uncovers disease characteristics that fail to be appreciated by the naked eyes. AI in medical imaging research, the current role, the challenges need to be resolved before AI can be adopted widely in the clinic, and the potential future.

IV. CURRENT ROLE OF AI IN RADIOLOGY

Machine learning, as a subset of AI, also called the traditional AI, was applied on diagnostic imaging started 1980's.12 Users first predefine explicit parameters and features of the imaging based on expert knowledge. For instance, the shapes, areas, histogram of image pixels of the regions-of-interest (i.e. tumor regions) can be extracted. Usually, for a given number of available data entries, part of them are used as training and the rest would be for testing. Certain machine learning algorithm is selected for the training to understand the features. Some examples of the algorithms are principal component analysis (PCA), support vector machines (SVM), convolutional neural networks (CNN), etc. Then, for a given testing image, the trained algorithm is supposed to recognize the features and classify the image.

One of the problems of machine learning is that users need to select the features which define the class of the image it belongs to. However, this might miss some contributing factors. For instance, lung tumor diagnosis requires user to segment the tumor region as structure features. Due to the patient and user variation, the consistency of the manual feature selection has always been a challenge. Deep learning, however, does not require explicit user input of the features. As its name suggests, deep learning learns from significantly more amount of data. It uses models of deep artificial neural networks. Deep learning uses multiple layers to progressively extract higher level eatures from raw image input. It helps to disentangle the abstractions and picks out the features that can improve performance. The concept of deep learning was proposed decades ago. Only till recent decade, the application of deep learning became feasible due to enormous number of medical images being produced and advancements in the development of hardware, like graphics processing units (GPU). However, with machine learning gaining its relevance and importance every day, even GPU became somewhat lacking. To combat this situation, Google developed an AI accelerator integrated circuit which would be used by its TensorFlow AI framework tensor processing unit (TPU). TPU is designed specifically for neural network machine learning and would have potential to be applied on medical imaging research as well.

The main research area in diagnostic imaging is detection. Researchers started developing computer-aided detection (CAD) systems in the 1980s. Traditional machine learning algorithms were applied on image modalities like CT, MRI, and mammography. Despite a lot of effort made in the research area, the real clinical applications were not promising. Several large trials came to the conclusion that CAD has at best delivered no benefit and at worst has actually reduced radiology accuracy, resulting in higher recall and biopsy rates.

The new era of AI the deep learning has so far demonstrated promising improvements in the research area over the traditional machine learning. As an example, Ardila et al proposed a deep learning algorithm that uses a patient's current and prior CT volumes to predict the risk of lung cancer. The model achieved a state-of-the-art performance (94.4% area under the curve) on 6716 national lung cancer screening trial cases and performed similarly on an independent clinical validation set of 1139 cases. As a comparison of conventional screening by low-dose CT, per cancer.gov there are several associated harms: false-positive exams, overdiagnosis, complications of diagnostic evaluation, increase in lung cancer mortality, and radiation exposure. One false-positive exam example provided on the web site was 60%. Overdiagnosis was estimated at 67%. There is also radiation induced risk to develop lung cancer or other types of cancer later in life. AI-based diagnosis reduced these risks[4].

V. CURRENT ROLE OF AI IN RADIATION ONCOLOGY

In radiation oncology imaging research, AI has been applied in organ and lesion segmentation, image registration, fiducial/marker detection, radiomics etc. Similar to radiology, it started with traditional AI and now with deep learning.

For organ and lesion segmentation, the main goal is to segment the organs at risk automatically for treatment planning. Deep learning algorithms have been applied to segment head and neck organs, brain, lung, prostate, kidney, pelvis etc. Lesion segmentation applications include bladder, breast, bone, brain, head and neck, liver, lung, lymph nodes, rectum etc. The network can therefore analyze the entire image during training and allow for obtaining segmentation likelihood maps directly.

The automatic fiducial/marker detection is needed for real time tracking of the treatment area during the delivery. Most common methods require prior knowledge of the marker properties to construct a template. Recent proposed deep learning CNN framework requires no prior knowledge of marker properties or additional learning periods to segment cylindrical and arbitrarily shaped fiducial markers. The algorithm achieved high classification performance.

Radiomics, one of the most advanced AI applications in medical imaging research, is a novel approach towards the precision medicine. Radiomics consists two steps. First step is feature extraction. Images from multiple modalities might be included. Image segmentation algorithms are applied to segment the volumes of interest. After the segmentation, features will be extracted. Common features include texture, geometric information, tumor volume, shape, density, pixel intensity etc. The second step is to incorporate the extracted features into mathematical models to decoding the phenotype of the tumor for treatment outcome prediction. A successful outcome prediction can provide valuable information for precise treatment design. For instance, different lung cancer patients might share many similarities like histology and age. However, the images of the tumor might appear different, and the survival time might be very different If radiomics can take the image information, decode the phenotype, and therefore predict the survival time or prognosis prior to the treatment, different treatment regimens might be chosen. This is called personalized or precision medicine. Traditionally, precision medicine depended on biomarkers to estimate patient different prognosis or subtype, which usually required invasive biopsy. Radiomics, on the other hand, does not require invasive procedures. It was shown that features extracted from CT images of lung cancer patients alone correlate well with gene mutations and have prognostic powers.The success of radiomics can potentially avoid undesirable complications caused by biopsy and achieve the same or better prediction outcome [5].

Personalised medicines

The use of Artificial Intelligence techniques in setting up or building personalized medicine is important in terms of precision and accuracy of disease discovery, treatment, and drug administration. The control of adverse drug reactions. and enzymes metabolism which results in some people having issues eliminating drugs from their bodies, hence leading to overdose; while others eliminate the drug from the body before it gets the chance to work. The use of computers in hospitals and clinics to record medical activities or use of electronic health record (EHR) systems nowadays provides medical knowledge and data that can be used as a benchmark to enhance medical service delivery.

Artificial Neural Network as AI Algorithm in Personalized Medicine

The application of ANNs in medicine includes, but not limited to the diagnosis, imaging, back pain, dementia, pathology and prognosis evaluation of appendicitis, myocardial infarction, acute pulmonary embolism arrhythmias, or psychiatric disorders diseases,as stated by.

Some of the advantages of ANN as stated by are: Neural networks can learn linear and nonlinearmodels. Also the accuracy of models created by neural network can be measured statistically. Incomplete data and noise are tolerable by neural network. Neural networks models are flexible because they can be updated, hence making it suitable for dynamic environment such as health sector.

Virtual Health Assistance in Allopathic Medicine:

A credible application of NLP techniques is real-time Information exploration and restoration, ie, our healthcare assistant is capable of interpreting the medical language and take down important medical knowledge in real time from the most esteemed origin of data, not signifying that Al is making new treatments but rather empowering effortless access to authentic, precise data at the time of need.

Help in Diagnosis: Secondly, another useful NLP utilization Help in Diagnosis in healthcare. Ex: Database of American College of Radiology can be useful to fetch instructions of diagnosis for a radiologist reading a medical report using Al. This Al assistant will regularly ask the medical physician simplifying interrogations to make legitimate, useful diagnostic recommendations [6].

Analysis and Predictive Early Disease Prevention

Diseases are a global issue; thus, medical specialists and researchers are exerting their utmost efforts to reduce disease-related mortality. In recent years, predictive analytic models has played a pivotal role in the medical profession because of the increasing volume of healthcare data from a wide range of disparate and incompatible data sources. Nonetheless, processing, storing, and analyzing the massive amount of historical data and the constant inflow of streaming data created by healthcare services has become an unprecedented challenge utilizing traditional database storage. A medical diagnosis is a form of problem-solving and a crucial and significant issue in the real world. Illness diagnosis is the process of translating observational evidence into disease names. The evidence comprises data received from evaluating a patient and substances generated from the patient; illnesses are conceptual medical entities that detect anomalies in the observed evidence.

With the introduction of systems based on computers, the digitalization of all medical records and the evaluation of clinical data in healthcare systems have become widespread routine practices. The phrase "electronic health records" was chosen by the Institute of Medicine, a division of the National Academies of Sciences, Engineering, and Medicine, in 2003 to define the records that continued to enhance the healthcare sector for the benefit of both patients and physicians. Electronic Health Records (EHR) are "computerized medical records for patients that include all information in an individual's past, present, or future that occurs in an electronic system used to capture, store, retrieve, and link data primarily to offer healthcare and health-related services," according to Murphy, Hanken, and Waters.

Daily, healthcare services produce an enormous amount of data, making it increasingly complicated to analyze and handle it in "conventional ways." Using machine learning and deep learning, this data may be properly analyzed to generate actionable insights. In addition, genomics, medical data, social media data, environmental data, and other data sources can be used to supplement healthcare data.

Predictive analytics for health care are critical industry requirements. It can have a significant impact on the accuracy of disease prediction, which can save patients' lives in the case of an accurate and timely prediction but can also endanger patients' lives in the case of an incorrect prediction. Diseases must therefore be accurately predicted and estimated. As a result, dependable and efficient methods for healthcare predictive analysis are required[7].

VI. ROBOTIC SURGERY

Robotic surgery (RS) is an evolution of minimally invasive surgery that combines medical science, robotics, and engineering. Also known as robot-assisted surgery, it is a sophisticated technique that involves the use of specialized robotic platforms during surgical procedures to improve the precision of surgeons" movements in complex procedures and small anatomical spaces. RS allows for the filtering of hand tremors, thereby improving flexibility and minimizing involuntary inaccuracies. As a result, it leads to fewer surgical complications such as surgical site infection, less pain, less blood loss, shorter hospital stay, quicker recovery, and smaller, less noticeable scars.

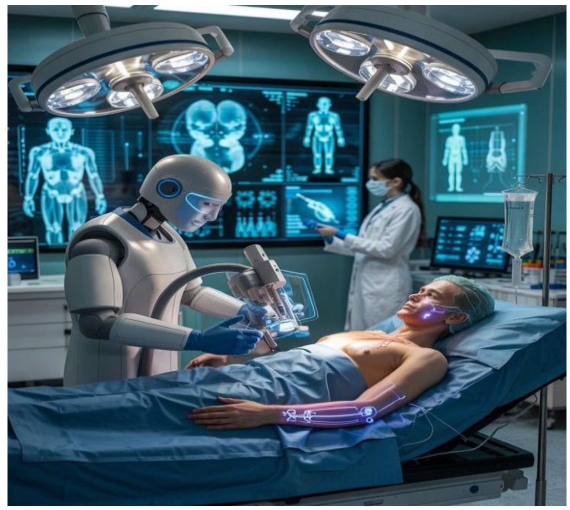

Fig.3 This Image represents Robotic Surgery

The first da Vinci robot in 2000 had three arms with an endoscope attached to one and two instruments. Two years later, a four-arm robotic version was approved, providing improved exposure of anatomical structures and reducing reliance on a surgical assistant. The console had two handles controlled by the surgeon, eliminating hand tremors and scaling down movements for greater precision. The 2006 da Vinci S platform had a 3D HD camera and a touchscreen display. In 2009, the da Vinci Si model was released, allowing dual console surgery and improved training for non-expert surgeons. The Si robot had an upgraded image system and real-time fluorescence imaging. In 2011, platform adjustments allowed for single-port access. The most advanced system from Intuitive Surgical to date is the da Vinci Xi platform, which was released in 2014[8].

VII. MENTAL HEALTH APPS

In a survey of 15,000 mental health apps conducted by the World Health Organisation in 2015, it was found that about 29% of them have their focus on mental health diagnosis, treatment, or support. Mental health apps also include functions such as symp tom tracking, diary entries, and appointment of medica-tion reminders as well as motivational quotes. These apps are aimed at being a form of self-help towards mental health outpatients, extending to those who have not been diagnosed. They can be used in conjunction with other comparative methods of intervention such as internet-based intervention which offers direct contact with a mental health practitioner. Arguably, mental health apps also extend the ability for the patient to track their symptoms through ecological momentary assess ment (EMA). There is engagement with the aspect of mental health lit-eracy in which the apps implement psychoeducation and self-assessment (EMA) on top of information on referral allowing the patient to assess what they have and request assistance from the nearest treatment centre[9].

Artifial Intelligence in Breast Cancer Detection

In breast cancer, Nottingham histological grade (NHG) is a well-established prognostic factor that provides information for clinical decision-making. Patients with oestrogen receptor (ER)-positive/human epidermal growth factor receptor 2 (HER2)-negative tumours with high-risk clinical factors such as high histological grade (i.e. NHG3) are often considered for adjuvant chemotherapy whereas patients whose tumors are associated with low-risk clinical factors (i.e. NHG1) can be spared chemotherapy. However, more than 50% of patients belong to the intermediate risk category, NHG2, of limited clinical value. Consequently, many patients may be overtreated with considerable side effects or undertreated with risk of recurrence.

Several multigene expression-based methods have been developed to predict the risk of recurrence for ER + early-stage breast cancer patients, in particular within the intermediate risk category. The most commonly used products include MammaPrint (Agendia Inc., Amsterdam, The Netherlands), Oncotype DX (Exact Sciences Corp., Madison, WI, USA), EndoPredict/EPclin (Myriad Genetics Inc., Salt Lake City, UT, USA) and Prosigna (Veracyte Inc., South San Francisco, CA, USA). Oncotype DX recurrence score (RS) was one of the first multigene assay-based tests to predict the distant recurrence in ER + node-negative tamoxifen-treated breast cancer patients by stratifying patients into low-, intermediate- and high-risk groups. Prosigna ROR score has been validated to predict the distant and late-distant (5–10 years) recurrence in postmenopausal hormone receptor-positive early breast cancer patients. Furthermore, models based on molecular signatures, like the Genomic grade index (GGI), have been proposed to improve the stratification of intermediate-grade patients. However, in clinical practice, the use of molecular multigene assays implies long lead times and remains expensive.

Enabled by the emergence of digital and computational pathology, deep learning-based whole slide image (WSI) classification models have recently been demonstrated to enable improved prognostic stratification of patients compared to routine pathology, and to enable faster and more precise information for clinical decision-making in several cancer types. Stratipath Breast (Stratipath AB, Stockholm, Sweden) is the first CE-IVD marked artificial intelligence (AI)-based image analysis tool for primary breast cancer risk stratification that is available for routine clinical use. Stratipath Breast provides risk stratification of breast cancer patients into low- and high-risk groups based on the assessment of routine haematoxylin and eosin (H&E)-stained tumour tissue slides from surgical resection specimens. In clinical practice, risk stratification of intermediate-risk ER+/HER2- patients is of particular interest, as improved prognostic information can provide guidance relating to treatment decisions for adjuvant chemotherapy, and thus reduce over- and undertreatment of patients. Stratipath Breast only requires an H&E-stained WSI from the resected tumour as input and uses a deep learning-based model to risk-stratify patients into low- and high-risk groups[10].

Cancer Detecting Sanitary Pads

mavirus (hrHPV) is associated with various HPV-related precancers and cancers.1 In recent years, HPV testing has gradually become the primary method for cervical cancer screening. Although cervical cancer screening has been found to be helpful in decreasing the incidence and mortality rate of cervical cancer, various factors (including medical infrastructure, culture and mentality, and society) may influence women's acceptance of clinician sampling. Among women with overdue screening, 29% were afraid of the stigma and 14% were had fear of pain in 2 studies .Self-sampling HPV testing is a proposed alternative cervical cancer screening for avoiding stigma and improving participation.However, to our knowledge, most existing self-sampling HPV studies were based on various sampling brushes inserted into the vagina, and patients may experience discomfort during sampling.7-11 Compared with these methods, menstrual blood (MB) collection is associated with less stigma and pain.

MB offers a snapshot of cervical HPV infection status. Given that it is a biological fluid with periodic expulsion, MB is easy to collect. This suggests that HPV testing based on sanitary pads may be a convenient and noninvasive approach. More importantly, next-generation sequencing (NGS) for HPV detection, emerging as a highly sensitive method for HPV genotyping, has not yet been applied to MB HPV testing, to our knowledge. This study was designed to investigate whether MB hrHPV capture sequencing may be a feasible and accurate approach to detecting hrHPV infection among women who are premenopausal [11].

Blue Dot Covid Prediction

The technological progress in the health sector is well demonstrated in the detection (here referred to as the process of identification of the disease) speed involving the recent case of novel coronavirus (COVID-19) where its identification was made relatively earlier. Such occurred in just seven days for human identification. compared to past outbreaks, like the severe acute respiratory syndrome (SARS), which took four months to be identified. However, interestingly, it is noted that an Artificial Intelligence (AI) driven algorithm provided an early detection and warning on the 31 December 2019; seven days before the World Health Organisation (WHO) released an official notice of the outbreak. In a similar scenario, an epidemic monitoring company called Metabiota, through the use of a predictive tool was able to determine and warn that countries like Thailand, South Korea, Taiwan and Japan were immediately susceptible to the coronavirus outbreak a week before it was officially confirmed in these countries.

The use of AI-driven algorithms for early detection of pandemics is in its maturation and may be a potent route in the near future to aid better preparedness. It is expected that as the precision of these technologies continue to advance, they will have a more pronounced role in promoting the formulation of novel health policies. This paper surveys how data and AI processes aided in the early stages of the detection of the COVID-19 pandemic and provides preliminary supporting evidence to showcase that enhanced data sharing protocols will contribute to future urban health policy internationally [12].

VIII. ETHICAL AND LEGAL CHALLENGES

As the prior section suggests, the use of AI in the clinical practice of healthcare has huge potential to transform it for the better, but it also raises ethical challenges we now address.

Safety and transparency

Safety is one of the biggest challenges for AI in healthcare. To use one well-publicized example, IBM Watson for Oncology. uses AI algorithms to assess information from patients’ medical records and help physicians explore cancer treatment options for their patients. However, it has recently come under criticism by reportedly giving “unsafe and incorrect” recommendations for cancer treatments. The problem seems to be in the training of Watson for Oncology: instead of using real patient data, the software was only trained with a few “synthetic” cancer cases, meaning they were devised by doctors at the Memorial Sloan Kettering (MSK) Cancer Center. MSK has stated that errors only occurred as part of the system testing and thus no incorrect treatment recommendation has been given to a real patient.

Algorithmic fairness and biases

AI has the capability to improve healthcare not only in high-income settings, but to democratize expertise, “globalize” healthcare, and bring it to even remote areas. However, any ML system or human-trained algorithm will only be as trustworthy, effective, and fair as the data that it is trained with. AI also bears a risk for biases and thus discrimination. It is therefore vital that AI makers are aware of this risk and minimize potential biases at every stage in the process of product development. In particular, they should consider the risk for biases when deciding (1) which ML technologies/procedures they want to use to train the algorithms and (2) what datasets (including considering their quality and diversity) they want to use for the programming.

Several real-world examples have demonstrated that algorithms can exhibit biases that can result in injustice with regard to ethnic origins and skin color or gender. Biases can also occur regarding other features such as age or disabilities. The explanations for such biases differ and may be multifaceted. They can, for example, result from the datasets themselves (which are not representative), from how data scientists and ML systems choose and analyze the data, from the context in which the AI is used, etc. In the health sector, where phenotype- and sometimes genotype-related information are involved, biased AI could, for instance, lead to false diagnoses and render treatments ineffective for some subpopulations and thus jeopardize their safety. For example, imagine an AI-based clinical decision support (CDS) software that helps clinicians to find the best treatment for patients with skin cancer. However, the algorithm was predominantly trained on Caucasian patients. Thus the AI software will likely give less accurate or even inaccurate recommendations for subpopulations for which the training data was underinclusive such as African American.

The term "personal data" is defined as "any information relating to an identified or identifiable natural person ('data subject')". The GDPR defines "processing" as "any operation or set of operations which is performed on personal data or on sets of personal data, whether or not by automated means," including collection, structuring, storage, or use. Whereas a "controller" is "the natural or legal person, public authority, agency or other body which, alone or jointly with others, determines the purposes and means of the processing of personal data," a "processor" means "a natural or legal person, public authority, agency or other body which processes personal data on behalf of the controller".

In the healthcare context, the definition of "data concerning health" under Article 4(15) of the GDPR is, in particular, relevant: "personal data related to the physical or mental health of a natural person, including the provision of healthcare services, which reveal information about his or her health status." The EU's GDPR is thus a lot broader in its scope compared to US' HIPAA, which only covers specific health information generated by "covered entities" or their "business associates".

IX. CYBERSECURITY

Cybersecurity is another important issue we need to consider when addressing legal challenges to the use of AI in healthcare. In the future, much of the healthcare-related services, processes, and products will operate within the IoT. Unfortunately, much of the underlying infrastructure is vulnerable to both cyber and physical threats and hazards. For example, sophisticated cyber actors, criminals, and nation-states can exploit vulnerabilities to steal or influence the flow of money or essential (healthcare) information. Such actors are increasingly developing skills to threaten, harm, or disrupt the delivery of vital (medical) services. Targets in the health sector may include hospital servers, diagnostic tools, wearables, wireless smart pills, and medical devices . All can be infected with software viruses, Trojan horses, or worms that risk patients' privacy and health . Moreover, corrupted data or infected algorithms can lead to incorrect and unsafe treatment recommendations. Hostile actors could get access to sensitive data such as health information on patients or could threaten patients' safety by misrepresenting their health. AIs are, in particular, vulnerable to manipulation.

Intellectual property law

Translating AI and big data into safe and effective "real-world" products, services, and processes is an expensive and risky venture. As a result, the commercial protection of AI and data-driven healthcare/life science technologies have become an exceedingly important topic. At the same time, there are continuing discussions about open science and innovation and the primary objective of more data sharing as well as increasing debates over access to such technologies and the pertinent data [13].

X. CONCLUSION

Artificial intelligence has emerged as a transformative force in allopathic medicine, revolutionizing the way diseases are diagnosed, treated, and managed. Through advanced algorithms and data-driven insights, AI enhances clinical decision-making, improves diagnostic accuracy, personalizes treatment plans, and optimizes healthcare delivery. From radiology and pathology to drug discovery and patient monitoring, AI applications are helping clinicians provide faster, safer, and more effective care.

However, while AI offers immense potential, its integration must be guided by ethical considerations, data privacy, transparency, and proper clinical validation. It is not a replacement for human expertise but a powerful tool to augment physicians' capabilities. In the future, a collaborative model where human judgment and artificial intelligence work hand in hand will define the next era of precision, efficiency, and innovation in allopathic medicine.

REFERENCES

[1] Artificial Intelligence in Health care,past,present,and futureFei jiang Ma,Yilong Wang, Qiang Dong,HaipengShen,Yongjun Wang,

[2] Artificial Intelligence in Clinical Medicine: Challenges Across Diagnostic Imaging, Clinical Decision Support, Surgery, Pathology, and Drug Discovery,[1]Department ofAnatomy, Faculty of Medicine, Istanbul Medeniyet University, Istanbul 34700, Türkiye; erenogut@yahoo.com.tr or eren.ogut@medeniyet.edu PMCID: PMC12468291 PMID: 41002784

[3] Artificial Intelligence in Clinical Medicine: Challenges Across Diagnostic Imaging, Clinical Decision Support, Surgery, Pathology, and Drug Discovery,[1]Department ofAnatomy, Faculty of Medicine, Istanbul Medeniyet University, Istanbul 34700, Türkiye; erenogut@yahoo.com.tr or eren.ogut@medeniyet.edu PMCID: PMC12468291 PMID: 41002784

[4] Artificial Intelligence (AI) Applications in Drug Discovery and Drug Delivery: Revolutionizing Personalized MedicineDolores R Serrano 1,2,, Francis C Luciano 1, Brayan J Anaya 1, Baris Ongoren 1, Aytug Kara 1, Gracia Molina 1, Bianca I Ramirez 1, Sergio A Sánchez-Guirales 1, Jesus A Simon 1, Greta Tomietto 1, Chrysi Rapti 1, Helga K Ruiz 1, Satyavati Rawat Dinesh Kumar 3, Aikaterini Lalatsa 4,5,Editor: Thierry VandammeAuthor information ,Copyright and License information PMCID: PMC11510778 PMID: 39458657

[5] Shaheen, M. Y. (2021, September). Applications of Artificial Intelligence (Al) in healthcare: A review. ScienceOpen. https://doi.org/10.14293/S2199-1006.1.SOR-.PPVRY8k

[6] Awwalu, J., Garba Garba, A., Ghazvini, A., &Atuah, R. (2015). Artificial intelligence in personalized medicine: Application of AI algorithms in solving personalized medicine problems. International Journal of Computer Theory and Engineering, 7(6), 439–444. https://doi.org/10.7763/IJCTE.2015.V7.999

[7] Healthcare predictive analytics using machine learning and deep learning techniques: a surveyAuthors: Mohammed Badawy, Nagy Ramadan, and Hesham Ahmed HefnyJournal: Journal of Electrical Systems and Information TechnologyPublication Date: 29 August 2023

[8] Robotic Surgery: A Comprehensive Review of the Literature and Current TrendsYeisson Rivero-Moreno 1,✉, Sophia Echevarria Editors: Alexander Muacevic, JohnR Adler PMCID: PMC10445506 PMID: 37621804

[9] A Systematic Review of the Efficacy of Mental Health Apps for Low- and Middle-Income CommunitiesOpen access,Published: 11 November 2023, Volume 9, pages 428–439, (2024)

[10] Validation of an AI-based solution for breast cancer risk stratification using routine digital histopathology images,Authors: Abhinav Sharma, Sandy Kang Lövgren, Mattias,Rantalainen, et al.Journal: Breast Cancer Research, Volume 26, Article Number: 123, Publication Year: 2024, Published Date: 14 August 2024, Publisher: BioMed Central (omedcentral.com)

[11] Jingjing Zhang, Xun Tian, Ye Chen, et al.Article Title: Feasibility and Accuracy of Menstrual Blood Testing for High-risk Human Papillomavirus Detection With Capture SequencingJournal: JAMA Network OpenPublished Online: December 23, 2021Volume and Issue: 2021;4(12) Article Number: e2140644

[12] Artificial Intelligence (AI) Provided Early Detection of the Coronavirus (COVID-19) in

China and Will Influence Future Urban Health Policy Internationally
[13] Authors: Zaheer Allam, Gourav Dey, and David S. JonesJournal: AI (Volume 1, Issue
[14] Publisher: MDPI, DOI: 10.3390/ai1020009
[15] Artificial Intelligence in Clinical Medicine: Challenges Across Diagnostic Imaging, Clinical Decision Support, Surgery, Pathology, and Drug Discovery,[1]Department ofAnatomy, Faculty of Medicine, Istanbul Medeniyet University, Istanbul 34700, Türkiye; erenogut@yahoo.com.tr or eren.ogut@medeniyet.edu PMCID: PMC12468291 PMID: 41002784