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Forum Paper

Challenges and Opportunities in Medical Artificial Intelligence

Chieh-Mei Tsai[1], Chieh-Ju Chao[2], Yung-Chun Chang[3], Chung-Chieh Jay Kuo[4], Albert Hsiao[5] and Alexander Shieh[6]

[1] *National Taiwan University, College of Medicine, Taiwan; jcc00112426@gmail.com*
[2] *Department of Cardiovascular Medicine, Mayo Clinic Rochester, USA; Chao.ChiehJu@mayo.edu*
[3] *Graduate Institute of Data Science, Taipei Medical University, Taiwan; changyc@tmu.edu.tw*
[4] *Viterbi School of Engineering, University of Southern California, USA; jckuo@usc.edu*
[5] *Department of Radiology, University of California, San Diego, USA; a3hsiao@health.ucsd.edu*
[6] *Keck School of Medicine, University of Southern California, USA; Alexander.Shieh@med.usc.edu*

ABSTRACT

Artificial intelligence (AI) applications in medicine and healthcare have been growing rapidly in recent years. More clinician-scientists have been interested in engaging in the medical AI field. A road map that guides medical professionals and information technologies to enter the field is in demand. An online panel discussion on AI in Healthcare was organized and conducted on May 22nd, 2023. Four panelists with mixed backgrounds were invited to provide their opinions on this topic. They included clinicians in radiology and cardiology and information technologists specialized in image processing, computer vision, and natural language processing. This forum paper recorded the main discussion points. The write-up was also edited and expanded to make their messages more complete in their current form. The content was

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centered around challenges, opportunities, and future directions in the integration of AI and Healthcare. Besides providing a comprehensive account of different viewpoints, panelists offered practical advice to young clinician-scientists who desire to enter the emerging medical AI field.

Keywords: Medical Artificial Intelligence, Deep Learning, Computer Vision, Natural Language Processing, Healthcare.

1 Introduction

In recent years, the application of artificial intelligence (AI) to medicine and healthcare has gained significant attention due to its potential in transforming the medical field. Due to the interdisciplinary nature of the medical AI field, it is difficult for medical professionals and information technologists to find a clear path to proceed. A road map that guides medical professionals and information technologies to enter this exciting field is in demand. To address this need, an online panel discussion on AI in Healthcare was organized by Chieh-Mei Tsai and Alexander Shieh. It was conducted on May 22nd, 2023. Four panelists were invited to provide their opinions on this topic. They had diversified backgrounds: a professor in radiology (Albert Hsiao), a clinician in cardiology (Chieh-Ju Chao), an information technology professor in a medical school (Yung-Chun Chang) specialized in natural language processing, and an engineering professor (C.-C. Jay Kuo) specialized in medical imaging, computer vision, and AI.

The panel discussion comprised three sections: 1) the panelists' position statements, 2) answering questions from moderators, and 3) answering questions from the audience. In the first section, panelists shared their individual views on the challenges and opportunities of medical AI and its potential impact. In the second and third sections, they answered questions from two moderators and participating audience, respectively. The raised questions covered a wide range of topics, e.g., potential changes in the medical field in the next decade due to AI, advice to medical students and doctors interested in AI research, assessment of different AI tools such as deep learning and radiomics, etc.

This forum paper goes beyond a summary of points given in the panel discussion. The material has been edited and expanded to make the messages more complete. It aims to provide a comprehensive overview of the current status with emphasis on challenges, opportunities, and future directions in the medical AI field. Furthermore, valuable advice is offered to young clinician-scientists who desire to enter the emerging medical AI field. While the field is advancing exceptionally, the core principles, challenges, and strategic approaches discussed by the panelists are expected to remain relevant and foundational within 5-10 years, aiding those who seek to navigate the dynamic landscape of medical AI.

2 Panelists' Position Statements

2.1 Professor Jay Kuo

Introduction and Background

I graduated from the Department of Electrical Engineering at the National Taiwan University in 1980 and, then, pursued my Ph.D. degree at Massachusetts Institute of Technology from 1982-1987. I have been with the University of California since 1989. My research lies in signal and image processing, machine learning, and artificial intelligence. I have collaborated with physicians and medical professors and students and conducted research in medical imaging for more than 20 years.

Past and Present of AI in Medical Imaging

There is a long history of applying computational methods to medical image analysis. Many techniques have been developed for medical imaging such as image segmentation, classification [37], and lesion detection. For example, radiomics have been used by radiologists to analyze medical images. We have seen a rapid advancement in this field due to deep learning [37, 49, 55] and the abundance of labeled data, which are needed for supervised learning, in the last decade. This new development has made people realize that this is not just an image processing problem but an AI problem. I would like to emphasize the main difference between the traditional approach and the modern AI approach lies in the amount of training data. Traditional methods have little training data. This is called unsupervised or weakly supervised approach. Modern AI methods rely on a large amount of training data, called a heavily supervised approach. The performance gain comes from supervised learning. Besides, deep learning networks demand much more computational resources. Thus, there is a higher cost to reach better performance.

Current Landscape of Medical AI Education

AI and data science are very popular nowadays, attracting attention not only from engineering schools but also medical schools and business schools. A visible and strong AI program in a medical school will play an important role in its ranking. Medical students and clinicians get more serious about the future impact of AI on their specialties and the medical field in general.

Barriers for Information Technologies

There exist two psychological barriers for information technologies to enter the medical AI field. First, they are not familiar with medical terms in the literature. Second, the most influential AI papers appear in journals and conferences on computer vision, machine learning, and computational linguistics. These papers tend to shape the value of engineering students. They may have the perception that medical AI is application-oriented, which is not as fundamental. Persistence can overcome the first barrier. It only takes a couple of weeks to get familiar with the medical terms. As to the second barrier, I would like to emphasize that novel AI techniques will arise from the medical field since the amount of training data is significantly less than images of dogs and cats in the ImageNet dataset. Medical AI is actually a challenging field that demands the best AI and machine learning (ML) researchers.

Barriers for Medical Professionals

Medical professionals may feel overwhelmed by mathematics and technical terms in engineering publications. We will need a group of people who serve as the bridge between IT and medicine. We will need new textbooks that introduce basic programming and mathematical tools to medical students. It is not difficult to get equipped with basic programming knowledge and tools, e.g., Python [26], PyTorch [74], TensorFlow [73], etc. Most people could learn the programming tools in 3-6 months.

Challenges and Opportunities

One challenge is explainable AI (XAI) [4, 81, 87, 93]. Doctors need to explain the AI outcomes to patients logically. AI provides predictions. Yet, doctors need to interpret and justify the results. Medical schools should spearhead interdisciplinary medical AI education and research. Medical students need to understand what AI can and cannot do. People may have an unrealistic expectation of AI, thinking it can do everything. On the other hand, people may have unjustified fear of AI, worrying that it would replace humans. In my own opinion, AI is far from replacing humans [30]. At least, it will not happen in the next several decades. Instead, AI will serve as a powerful tool for medical professionals and enhance their productivity. For example, doctors spend a lot of time writing medical reports [28, 79] nowadays. They only need to input several points, and a medical report can be generated automatically. To give another example, early diagnosis is crucial in medical treatment, say, breast cancer treatment [82]. If the cost of medical imaging and radiologic analysis can be significantly reduced, it will allow female adults to have annual screenings so that early diagnosis can be a common practice. Generally speaking, AI can aid doctors, allowing traditional tasks to be done more efficiently. This, in turn, would enable doctors to concentrate on more difficult problems. AI should be seen as a valuable assistant, not a rival.

2.2 Dr. Albert Hsiao: AI in Radiology

Introduction and Background

I'm a radiologist, and I also do a fair amount of research. I completed my undergraduate at Caltech in both computer science and biology, hoping to one day combine both fields and apply computers to medicine. Along the way, I founded a company called Arterys, which was acquired a few months ago. It was a pioneer in applying machine learning to medical imaging.

The Power of Deep Learning in Medical Imaging

What got my interest around seven years ago, was this new technology called deep learning. It was made possible by very powerful computers equipped with high-performance graphical cards. I had been using deep learning for a different technology, 4D flow MRI, which was the basis for founding the company Arterys. At that time, there was no real AI incorporated into this technology. 4D Flow was just a technology that could be applied to various aspects of heart disease [18, 19, 31, 66, 97], particularly in our congenital heart population at Stanford [9, 19, 38, 39, 43, 78, 92]. Later, when I became a faculty member in San Diego, I applied it to other things like neurovascular disease [60] and pelvic congestion [64, 97], which we are still working on today.

Collaboration and the Importance of People

Along the way, Arterys got interested in AI, which got me interested in AI as well. I realized it could be applied in many areas of medical imaging, from CT and MRI acquisition to data analysis in the cloud, and even assisting physicians at the workstation to make decisions in managing patients. However, the most important thing in making all of this possible is really the people we engage. It's the people you identify as mentors, whether they're clinical mentors or scientific mentors. It is the people you work with, including the students, the residents, and the fellows who want to learn about the new technology and how to apply it, that really shape the field and shape the future of our practice.

Collaboration with Industry: Funding and Mutual Beneficial Projects

In many ways, collaboration extends to industry because, in reality, technologies that impact patient care are delivered through industry. Industry takes the technologies that we invent and turns them into products. It is important to know that when I talk about industry collaborations, they provide funding to accomplish the work that we mutually work on. I always make sure to identify projects that are mutually beneficial to companies, and so we can collaborate. I have done a lot of integration, which includes not only building the 4D flow technologies into the scanners but also developing AI technologies that run the scanners, creating the intelligent MRI. Part of this intelligent MRI technology includes automated scanning of the heart using AI technologies and deep learning [2, 5].

Licensing and Technology Transfer

Another approach I have taken is licensing. After we develop an idea and prove that it works, we can license the technology to companies and different universities. At Stanford, the money goes back to the university, and a portion goes back to the inventors. At UCSD, we developed a technology that allows us to measure myocardial strain on MRI [65], and the company I started, Arterys, licensed it from the university. Some of the money from that arrangement comes back to inventors or to the lab to seed future inventions.

Impact on Clinical Care: Example of Hypertrophy Cardiomyopathy

One example of how these technologies have impacted clinical care is in patients with Hypertrophy Cardiomyopathy. We use the 4D flow technology to measure the pressure gradient across the left ventricular outflow tract and the strain algorithm to analyze heart function. The Arterys software deploys all these technologies, and the hospital licenses the clinical software from the company. This all occurs through the natural interfaces between industry, the university, and the hospital.

Advancements in MRI Technologies: Deep Learning and AI Algorithms

We have also developed other things to improve different MRI technologies. For example, we have developed a deep-learning algorithm to correct 4D flow data for abdominal and pelvic applications. Additionally, we have developed AI algorithms for measuring COPD severity [35], prognosticating patients, and even detecting pneumonia on chest radiographs [41, 42, 90]. These algorithms have been particularly useful during the COVID-19 pandemic, and we have optimized them to improve performance.

2.3 Dr. Chieh-Ju Chao: AI in Cardiology

Approach to AI and Current Role

From unsupervised machine learning and deep learning [3, 13, 14] to the latest visual transformers [47], I approach AI more as a problem-solving tool rather than delving into a specific AI field. When a clinical problem arises, we look for suitable tools to solve it. As Professor Kuo mentioned, all clinical hospitals and universities are promoting the development of AI algorithms. Mayo and Stanford also share this perspective, leading to a collaborative program between Mayo Clinic and Stanford Human-centered AI (HAI) Institute, which sends clinicians to closely work with AI researchers to fill the gap between the two fields. I was fortunately selected as the first clinician in this program, and currently working as a visiting scholar at Stanford HAI, working primarily with Professor Fei-Fei Li.

Clinical Doctors in the Multidisciplinary AI Field

A key question to clinicians is how a clinical doctor can enter this multidisciplinary field which seems to have a relatively high technical prerequisite. Essentially, it is a cost-benefit issue; it depends on your available time, desired outcomes, and preferred role within a multidisciplinary team. Considerations may vary depending on your career stage. As a medical student, you have the most flexibility and time. If you want to enter this field or advance technically, it is relatively easy. Even if you don't want to learn programming, you can still assist by labeling datasets. As a resident or fellow, time becomes more limited, so finding a good medical AI mentor is crucial. They can guide you to a suitable role and help you learn while practicing. If you're already an established faculty member, the quickest method might be to seek collaborators in the field of AI.

Learning Pathways in AI

As for learning, there are many online courses available that can help you understand AI models. Once you grasp the basics, you can dive into the field. The rest comes with experience.

Roles of Clinical Doctors in AI Teams

In a multidisciplinary team, a clinical doctor can play the role of a project designer, bringing up clinical problems and deciding which tools to use for their resolution. Data scientists can assist with model development and selection. These models are not set-and-forget; instead, the feedback of clinical user experiences is critical after the implementation of each model. Clinical doctors can also play a crucial role in understanding how the model may result in false positives and negatives, and how to address these issues.

Model Verification through Clinical Trials

Regarding the utility of these models, they need to be clinically tested, much like drugs are tested in clinical trials. For instance, Mayo Clinic's AI ECG model for atrial fibrillation screening has been quite successful [70], and Stanford EchoNet Team's model being able to precisely measure LVEF [36, 71], saving time for clinicians and sonographers while ensuring accurate and consistent results.

AI Applications and Challenges in Cardiovascular Imaging

I would like to elaborate more about AI applications in cardiovascular imaging since I specialized in this field. Techniques such as segmentation are applicable to Echo, CT, and MRI. We hope to automate function assessment, which is time-consuming for clinical doctors and sonographers. Deep learning models can assist in the diagnosis of cardiovascular diseases and guide the direction of workup. In diseases with suboptimal diagnosis classifications, we can also use techniques such as clustering or phenotyping to solve classification problems [15–17]. My award-winning research at ACC last year utilized unsupervised clustering to solve diastolic function classification [12], moving from consensus-driven to data-driven approaches for better classification.

Utilizing Generative Models for Healthcare Data Privacy

The latest development in this field is generative models (many of them are foundation models [6]. These models can generate images [33, 34, 104] and text [7], Compared to conventional models which have more straightforward functionality, generative models are capable to achieve more complex tasks and intellectually challenge our creativity to use them in solving various clinical problems. For example, data sharing among different hospitals can be challenging due to IRB issues [72]. With a generative model (either language or image generative model) in hand, you can generate the data you need without violating HIPPA rules, as the data isn't from real patients.

2.4 Professor Yung-Chun Chang

Natural Language Processing in Clinical Treatment: Report Generation and Information Extraction

Natural Language Processing (NLP) is revolutionizing clinical treatment by generating reports and extracting vital information from charts to accelerate clinical examination [10, 11]. In the diagnostic process, doctors spend a significant amount of time reviewing patients' medical histories to understand their current condition. Utilizing NLP and AI technologies to extract key features from clinical reports to accelerate this process. Finally, using NLP we will assist doctors in selecting medications and matching clinical trials.

Transforming Medical Imaging: Computer Vision and NLP

In recent years, NLP has transformed clinical treatment by automating the generation of reports from Medical Imaging data, thereby expediting the clinical examination process. For instance, data from computed tomography scans of patients can be used in computer vision models for lesion segmentation [11]. The resulting segmented image outlines significant lung nodules, which are then input into an NLP model. The NLP model performs semantic labeling and generates a report that describes the size, location, and severity of the nodules. Clinical recommendations, such as Lung-RADS score predictions, are also provided. It can even give appropriate clinical advice based on the severity of the patient (for example, further biopsy is recommended for late-stage lung cancer patients) It is worth noting that the preliminary results generated can be utilized as prompts for ChatGPT to generate more comprehensive and refined report content.

Accelerating Diagnosis: Extracting Information from Pathological Reports

Another aspect is the extraction of information from pathological reports, which aids in diagnosis and speeds up the process. For many studies, researchers often want to observe specific data, however, but these details are often embedded in reports that lack a standardized structure. Therefore, the NLP technique is adopted to extract this information from the textual content to enable further analysis and investigation. This extraction process enables pharmaceutical companies to effectively identify hospitals with a higher number of patients exhibiting specific characteristics, thereby optimizing their targeting strategies. Our prototype system is able to extract key features from pathology reports and allow medical professionals to seamlessly interact with the system. Within a matter of minutes, they can visualize results pertaining to specific patient groups or obtain statistical insights encompassing the entire hospital.

Medication Insights: Searching Similar Cases and Clinical Trials

In the domain of medication, the application of NLP techniques allows us to conduct searches for analogous cases by considering approximately 50 pathological features associated with each patient. By leveraging these identified similarities, we can deduce suitable medication options and evaluate survival rates. Furthermore, this approach enables us to explore global clinical trials that align with the specific requirements of patients [20]. Particularly for individuals with late-stage lung cancer, who often confront drug resistance, active participation in clinical trials can serve as a lifeline, offering new prospects for treatment and improved outcomes.

Expanding Applications: ChatGPT in Clinical Settings

In recent years, the adoption of ChatGPT has transcended traditional boundaries, permeating clinical applications. One notable application of ChatGPT is it can play a pivotal role in clinical decision-support systems. By integrating the vast medical knowledge base with the advanced language processing capabilities of ChatGPT, healthcare professionals can access real-time, evidence-based recommendations and guidelines, aiding in accurate diagnosis, treatment planning, and management of complex medical cases. The ability of ChatGPT to generate comprehensive and contextually relevant responses can facilitate efficient information retrieval and synthesis, ultimately supporting clinicians in making well-informed decisions. The integration of ChatGPT into the healthcare landscape exemplifies the remarkable versatility of generation models and their transformative potential in revolutionizing healthcare practices [69]. As a consequence, ChatGPT has emerged as a valuable tool with the potential to enhance communication, facilitate informed decision-making, and optimize patient care across a wide array of clinical applications.

Embarking on AI Research in Healthcare: Skills, Data, and Continuous Learning

Skills in computer science and data science are essential for healthcare professionals embarking on AI research in healthcare. The maxim "No data, no AI" underscores the reliance of research in this field on a data-driven approach. However, the distinctive data landscape in healthcare requires meticulous planning and consideration right from the outset of a project. Continuous learning and interdisciplinary collaboration are crucial factors that contribute to the success of this transformative journey. In addition, healthcare professionals engaging in AI research in healthcare must possess a strong foundation in computer science and data science. Understanding the unique characteristics of healthcare data and adhering to ethical considerations are crucial. By leveraging their clinical expertise and embracing computational approaches, healthcare professionals can contribute to the advancement of AI in healthcare and ultimately improve patient outcomes.

3 Moderators' Questions

3.1 AI's Impact on Medicine in the Next Decade

The first question posted to the panel is "How will AI change the medical field in the next 10 years?"

[Chieh-Ju]

Embracing AI in the Medical Field: Challenges and Considerations There is a lot going on, and hospital systems are trying to embrace AI and adapt to AI. But one thing to consider is that, while newer medical technologies are rapidly evolving, to some extent, the medical field is a relatively conservative field. For example, we are still using stethoscopes to check patients, which were invented more than 200 years ago (Rene Theophile Hyacinthe Laënnec, in 1816). If you see a high-tech engineer still using an iPhone 3, you may think that is anachronistic. This guy is really not catching up with the technologies, so you can see the different fashions between different industries. In medicine, you can still see the conventional approaches in daily practice, which are considered essential and may not be bad. In that way, clinicians still have physical interactions with patients, and that's a very important part of medical care. So the first question I want to address is, would AI replace human physicians [28]? Probably not. As a patient, you probably would not want to just have a diagnosis generated by an AI program shown in front of you, saying, "This is the cancer you have," and then going for chemotherapy. You would probably want a doctor who really holds your hand, saying, "I know what's going on, and you must be suffering a lot. We'll try our best to take care of you." This example shows a fundamental difference between human and AI/robotic doctors. So I would say humans would still be the core of the medical field, even in the era of AI.

The Role of AI in Specialties and the Importance of Human Interaction But we can see that AI has made rapid progress in radiology and pathology. These specialties deal less with living patients. There are differences between different specialties, and in clinical specialties where patient care is more involved, there are things that AI cannot be fully involved in. It really depends on how physicians and patients think and how AI can be integrated.

Factors Influencing AI Implementation in Hospitals It also depends on the effort, not just at the physician level. You have to consider the hospital level. Is the hospital really pushing for AI implementation and building AI infrastructure and data centers? This is an important consideration for AI implementation.

National Factors and Insurance Considerations for AI Adoption Also, at the national level, you need to consider insurance and reimbursement, as economic systems are the main drive behind this. Currently, in the United States, most applications would be reimbursed by insurance, but in Taiwan, it may be different.

Overcoming Obstacles: Data Sharing and Regulations Data-sharing policies in the future should be more open between hospitals. Currently, we're still regulated by HIPAA rules, but with generative models, these obstacles can possibly be overcome [61, 72, 88]. The other potential solution to clinical data limitations is leveraging data-efficient frameworks. For example, with foundation models, which are models pre-trained on large datasets, we can see that less data would be needed to build future well-functioning models through the fine-tuning process [6]. Additionally, federated learning that allows model training without substantial data exchange could be a solution as well.

Enhancing Human Work with AI in Medical Documentation and Imaging In the end, I believe AI is here to enhance human work instead of replacing humans. For example, large language models can be helpful in facilitating documentation [57, 91], which currently takes up a lot of clinicians' time. By utilizing these models, physicians can focus more on patients who need their attention. Additionally, automated image measurement and report generation can be helpful in radiology or cardiac imaging fields.

[Albert]

The Impact of Technology on Reading and Digitizing Images Back in the day, around 30 to 40 years ago, when MRI and CT scans were first introduced, some people questioned the necessity of radiologists. They marveled at the incredible capabilities of this technology, surpassing the limitations of traditional X-rays. They wondered, 'Why would we need radiologists anymore?'. Now, it is hard to find a radiologist who wants to spend their time reading X-rays. With thousands of entries flooding in, it is quite amusing that we are still called 'Radiologists.' This is just one example of how our field constantly evolves alongside new technology.

AI's Role in Enhancing Radiology Efficiency These days, we hardly read X-rays at all. Instead, we rely on PACS, a digital version of a lightbox, which allows us to digitize and store hundreds and thousands of images on a computer. It is amazing how this innovation enables us to read and interpret a massive volume of images, even from the comfort of our homes. We no longer need to delve into the intricacies of protocols and TCP. The images simply appear on our computer screens, ready for us to read. We dictate our observations, which are then stored in the computer, and shared with the patient's doctor, and ultimately, the patient. The field of radiology evolves rapidly, and as technology advances, we become more efficient, enabling us to attend to a greater number of patients within a shorter time frame.

Future Possibilities and Scaling with Technology I may not read as many films as a radiologist in Taiwan, but my workload is still quite busy. On some days, I may read four to five hundred films, including CT scans. It's quite remarkable when you consider that 20 years ago, this would have been unimaginable. The advent of AI has significantly enhanced our efficiency. It helps us screen and identify normal exams more confidently, allowing us to prioritize and focus on the more complex cases [56, 80]. Patients who are undergoing chemotherapy or experiencing perplexing symptoms demand our attention and analysis. With the aid of AI technologies, we can allocate our time more effectively and ensure that those who truly need it receive the care they require.

Advancements in MRI Technology and Radiologist Expertise In the realm of MRI, things have also progressed. Previously, I had to personally oversee every cardiac MRI, but now we have AI technologies integrated into the scanners themselves. These intelligent features have reduced the need for constant physical presence. Over time, the expertise of radiologists has shifted from operating scanners to analyzing and interpreting the valuable data they provide. It's becoming increasingly rare to find individuals with deep knowledge of physics who can handle MRI operations independently.

[Jay]

Inevitable Trend of AI Adoption in Hospitals The use of AI technologies in hospitals is an inevitable trend. It is just a matter of time. The value brought by AI includes lowering healthcare costs and increasing doctors' productivity. It is crucial and unavoidable for hospitals and healthcare systems to adopt AI gradually. I believe hospitals will eventually embrace AI on a larger scale. The speed of adoption depends on the culture and practices of each hospital. It may take a decade or less. As AI technology matures, we will see more and more applications in hospitals.

Challenges and Excitement in AI In the AI field, particularly deep learning, the technology is not yet fully mature. Its lack of explainability [4, 81, 87, 93] poses challenges but also sparks our imagination. The human relationship with AI is complex, with a mix of fascination and fear. To mitigate that, we need to explain AI's results in a way that everyone understands. I have spent a lot of time studying AI and would like to say that AI is not as frightening as most people think. It simply aids in automation. Eventually, many tasks will be performed collaboratively by AI and humans, but always under human supervision and guidance. It is important to note that the current AI capabilities are still not at their peak. It has limitations and can be further improved in many areas such as lower computational complexity, lower power consumption, and smaller model sizes, etc.

3.2 Guidance for Aspiring Medical Professionals

The second question posted to the panel is “Practical advice to young medical school students and doctors.”

[Yung-Chun]

Starting with Data Science Skills For doctors and medical students who want to engage in the field of AI, the first step is to start with data science skills. Building a strong foundation in data science equips them with the necessary tools and knowledge to effectively analyze and interpret medical data, enabling them to leverage AI technologies in healthcare applications.

Interdisciplinary Collaboration in AI Healthcare AI in healthcare is a multidisciplinary field that requires collaborative efforts across various domains. Effective implementation of AI technology in healthcare demands the ability to collaborate seamlessly across disciplines such as medicine, computer science, data science, and ethics. Developing and nurturing interdisciplinary collaboration skills right from the start enables professionals to leverage diverse expertise, drive innovation, and address complex healthcare challenges holistically.

Learning Opportunities Next, it is crucial to emphasize the aspect of continuous learning. In the rapidly evolving field of AI, there is a wealth of online resources readily accessible, offering the latest knowledge and insights that may surpass what the traditional school curriculum covers. Proactive engagement with these resources empowers doctors and medical students to stay updated with cutting-edge AI advancements, novel techniques, and emerging applications in healthcare. Embracing a lifelong learning mindset ensures professionals can leverage the full potential of AI to enhance patient care and drive transformative healthcare outcomes.

Data Analysis Challenges and Security In clinical practice, data management is a critical concern, necessitating a comprehensive understanding of proper and secure data utilization. Clinical researchers often find themselves in situations where they possess substantial patient data and seek to leverage AI tools like ChatGPT for analysis. However, the utilization of sensitive data with AI tools entails uploading them to the cloud. Consequently, in the current era of widespread AI adoption, particularly in the healthcare domain, prioritizing data security becomes paramount and necessitates heightened attention.

[Chieh-Ju]

Finding Your Role in a Multidisciplinary Team In a multidisciplinary team, there is a spectrum of roles you can take on. As a clinician, you can provide clinical insights and formulate relevant research questions for data scientists. Alternatively, you can be on the data scientist side, dealing with coding and simpler problems. An optimal goal would be having a substantial understanding of both fields, acting as a bridge between the two disciplines, and speaking the languages of both.

Investing in Coding and AI Knowledge For young clinicians interested in clinical AI, it's beneficial to have coding and AI knowledge. Investing in these areas earlier in your career gives you more flexibility in shaping your expertise. Even during medical school or internship, you can start developing these skills, which will make a significant difference in your ability to contribute to a multidisciplinary team.

Maintaining Your Identity as a Clinician Assuming you want to remain a clinician, your role in collaboration with data scientists is crucial. Your perspective as a clinician and user experience will provide valuable feedback and ensure the projects are useful in clinical practice. For example, if a model generates false positives, it's important to highlight the potential challenges it may pose in clinical scenarios.

Finding a Collaborative Team In the era of the internet, it's easier than ever to find people interested in multidisciplinary collaboration. Younger physicians can also seek mentors who are already involved in this field. The process of finding a collaborative team may be easier than you initially anticipate.

[Albert]

Identifying Your Driving Passion and Mission One principle I operate with is guiding students to discover what drives them and their passion. It could be a personal life experience or having a family member with a specific disease. This same passion will motivate them to delve deeper into their chosen field. My advice is to figure out your career goals, your mission. Once you have clarity, you'll know which tools you need to develop. For example, if you aspire to be a data scientist, you may pursue an education in computer science. However, this path may not apply to everyone. Another approach is identifying a problem, such as improving COPD diagnosis, driven by personal experiences. Then, you can collaborate with experts to find innovative solutions. There is no one-size-fits-all recipe; it's about being mission-driven and assembling a team to tackle the problem.

Mission-Driven Approach in Healthcare In healthcare, it's crucial to have a clear mission that inspires you. This could involve being a team leader and working towards solving a specific problem, driven by personal experiences or a desire to make a difference. For example, witnessing a family member's struggle with COPD may ignite a passion to improve its diagnosis and management. By developing the necessary skills and collaborating with experts, you can work towards creating innovative solutions. The key is to identify a mission and leverage the expertise of others. This allows you to make a meaningful impact in healthcare.

Tailoring Your Path based on Mission In pursuing a healthcare career, there is no fixed recipe or mandatory course. It's about being mission-driven and aligning your path with your goals. Whether it's acquiring specific skills or collaborating with professionals, your mission serves as your guiding force. By identifying a mission that resonates with you, you can focus on making a positive impact. This personalized approach empowers you to chase your passion and make a difference.

3.3 Critique on Current AI Research Methods in Healthcare

The third question posted to the panel is "Comments on existing methodologies in AI Research."

[Albert]

Convolutional Neural Networks and Image Generating Neural Networks A lot of what we've been focusing on in the past seven to eight years is working with convolutional neural networks, which are essentially neural networks that operate on images. There are two major classes of these networks. The first class consists of classification algorithms [29, 49, 86], which determine the class of an image, like identifying a picture of a cat or a dog or the heart. This is a common tool, although not extensively utilized in my lab. The second class, which we use more frequently, are image generating neural networks [33, 34]. These networks generate images based on other images. We employ them for tasks such as class segmentation [37, 63, 68, 83], where we identify specific regions like the heart or abnormalities such as pulmonary nodules. These algorithms fall under the category of image-based algorithms, as they operate on images to produce outputs. This has been our primary focus in the past eight years.

Expanding to Large Language Models In the future, I believe we will move towards utilizing large language models, such as GPT (Generative Pretrained Transformers) [8, 76, 77, 89] and similar models. These language models are incredibly powerful when it comes to generating text. The beauty of this approach is that once we have the ability to detect findings on an image, we can use these models to generate reports [54, 69, 89, 101]. Instead of manually communicating with colleagues, such as cardiologists or surgeons, I can generate a report that incorporates all the necessary information. This report generation process takes effort, as it requires analyzing the image, identifying findings, and interpreting them. By incorporating GPT algorithms into the workflow, we can reliably find all the necessary findings and generate accurate reports. This will lead to significant efficiency gains in the field.

Amplifying Practice Efficiency The future holds the potential for significant efficiency gains in radiology practice. With the integration of GPT algorithms for report generation and the ability to quickly review images and verify report accuracy, the overall efficiency of the practice can be amplified by at least tenfold. This means that with the same amount of effort, I can perform ten times as much work. It's an exciting prospect that could revolutionize the field and shape the next ten years of radiology practice.

[Chieh-Ju]

Tailoring Models and Balancing Resources I think the bottom line is there is actually no single superior algorithm. It's more about how you tailor your models or the tools in hand to re- ally solve your problem and also balance what kind of data you have and what kind of computational resources you have.

Challenges and Resistance in Cardiology In cardiology, we are following the path that pathology and radiology have gone through when it comes to applying and implementing AI into our clinical practice. We do experience some obstacles or resistance from clinicians in our preliminary attempts. They would question how to explain the AI findings and the trust is still not as high as the trust pathologists or radiologists currently have towards AI systems.

Breakthroughs in AI with Transformers I think one of the very important breakthroughs in the AI field is actually the Transformers, which led to the birth foundation models [89]. These are breakthrough technologies that can solve one of the major limitations in the medical AI field, which is the relatively limited data amount. Leveraging the generalization capability of foundation models can provide a solution to this problem by fine-tuning on smaller samples and avoiding overfitting.

Possibilities with Generative Models With generative models, we are very lucky to have these technologies. We're currently trying to generate reports from echocardiography images using new AI models. Some works in Radiology have demonstrated that we can use large language models to summarize radiology findings, and I think it is possible to have the same application on echocardiography [54, 69, 89, 101]. We didn't see these opportunities before the invention of Transformers, but now everything seems to be possible.

[Yung-Chun]

The Impact of Open-Sourcing and the Accessibility of Large Language Models The introduction of ChatGPT in the world of large language models generated significant interest among major companies from late November to early December last year until March. These models rely on a substantial amount of training data, making their involvement crucial. However, significant breakthroughs have emerged with the introduction of LLaMa released by Meta and the novel model Alpaca proposed by MIT. They have provided an opportunity for academic researchers to engage with large language models, enabling more individuals to participate in similar endeavors. This transition has paved the way for the emergence of smaller models in various fields. Exciting possibilities for impactful developments lie ahead in the future.

Advancements and Challenges in Medical AI The medical field presents unique challenges, including data scarcity and data imbalance, which pose significant obstacles. In the years ahead, advancements in healthcare models and technologies will prioritize addressing these issues more effectively. Generation models can play a crucial role in mitigating data imbalance problems, and GPT can be utilized to generate data and compensate for the lack of medical data [69]. Moreover, ensuring the interpretability of models holds immense value, particularly in the medical domain. Future advancements will focus on enhancing model interpretability to ensure trust and understanding. Lastly, the anticipated security concerns and model bias stemming from data imbalance will be addressed through future model enhancements. The field of healthcare is poised for remarkable progress and innovation.

[Jay]

Advancements in Data Science: Annotated Datasets and Deep Learning In the past decade, data science has advanced significantly due to the availability of large annotated datasets and the emergence of deep learning with multi-layered neural networks. A major challenge in neural networks is the non-linear activation function, making their interpretation difficult. I explained the purpose of nonlinear activation in [50, 51, 53] and proposed ways to remove it in [23, 25, 100].

Green Learning as Emerging AI Technology The newly developed AI technology, called green learning [52], offers excellent results, while allowing interpretability. The resulting AI solutions have significantly smaller model sizes compared to deep neural networks. They enable lower computational complexity and thus faster computation. They attract interests from smartphone companies like Apple and MediaTek. The technologies can be deployed on mobile devices easily. I believe the core tools of AI will continue to evolve, benefiting medical professionals as they view AI as a tool. Considering the environmental impact, very larger AI models such as ChatGPT consume excessive electricity and contribute to a huge amount of carbon footprint. In contrast, green learning solutions only need a fraction of these resources, leading to significant cost savings and lower carbon footprint. Green learning solutions have been developed in many application domains, e.g., image classification [24, 25, 96], texture and image generation [1, 58, 59], low-resolution face recognition [85], face gender classification [84], deepfake detection [21, 22], blind image quality assessment [67], anomaly detection [98], image forensics [102, 103], disease classification [62], point cloud classification, segmentation and registration [44–46, 99, 100]. Green learning offers an alternative to deep learning in data science and engineering.

The Future of AI and Data Science Deep learning and neural networks are fundamental tools in solving regression problems. They do not have the ability to learn complicated things with few examples like human intelligence, which is called weakly supervised learning. While AI and data science enable automation in simple tasks, human involvement remains crucial for complex tasks. Future doctors will be more efficient and productive with AI. Medical professionals can leverage AI tools with a high-level understanding. There are also opportunities in federated learning, which allows the sharing of trained models without data exchange [61, 88]. Federated learning [61, 88] allows model exchange without data exchange, and ensemble learning, which enables optimal performance through multiple models. The focus should be on developing smaller, energy-efficient, and reliable AI models.

[Chieh-Ju]

Cultural Difference in Perception of AI I can echo the viewpoint of Professor Kuo. Because now, many people view AI as something like a science fiction novel, imagining that it may threaten humans or replace our work. The way people look at AI now is similar to how people treat newer technologies back in time, and requesting for interpretability/explainability is likely a reflection of this worry. I personally think these concerns may not be entirely necessary. Just imagine our routine clinical practice when we perform ultrasound scans or use computers. In reality, most of us don't know the underlying principles and mechanisms behind it, and we are not worried about interpretability. Similarly, not everyone knows the physics behind MRI. They don't demand interpretability in those cases. However, when it comes to AI, there is a substantial demand for interpretability [81]. I feel that we are at a time of new technology evolution, and society just needs more time to digest all these changes.

Belief and Acceptance of AI For clinical physicians, the most important thing is whether you believe in it or not. Clinical medicine is more of an application science, so the true question is whether an algorithm is clinically useful (or helpful). Not everyone knows all the detailed biochemical mechanisms of beta blockers, or how the electric circuit work in a pacemaker while prescribing them. In the above cases, clinicians accepted these technologies (with an intellectual understanding to an extent) which are proven to be clinically useful through clinical trials. So if you are willing to accept such a useful tool, with a certain level of understanding, it is not a complete black box. You can anticipate what goes in and what comes out, similar to typing on a computer. The concept will be further elaborated in the suprahuman AI section.

4 Audience Questions

4.1 Measuring Gradients for Precise Intervention

[Audience] Can you measure the gradient in the renal arteries and smaller arteries before placing a stent using current MRI or CT resolution?

[Albert] Currently, there are technologies, such as coronary CT, and a company called HeartFlow, that allow for the estimation of gradients and pressure across stenosis. These technologies are FDA-cleared and can be used to measure the gradient before stent placement. While this is slightly tangential to the AI question, it demonstrates how AI technology enables us to do things we couldn't do before. AI has the potential to diagnose certain diseases that may be difficult for humans to identify, much like how MRI and CT revolutionized medical imaging when they were first introduced. So, AI opens up exciting possibilities for improved diagnostics.

4.2 Superhuman AI

[Chieh-Ju] In the field of evidence-based medicine (EBM), humans are not considered the gold standard. Expert opinions in the EBM pyramid are actually the lowest level of evidence. What matters most is whether clinical trials show efficacy. Again, not everyone fully understands the underlying biochemical mechanisms. After clinical trials support the use of certain medications, we accept their use and believe they are beneficial to patients until another trial disproves it. I think AI can follow a similar path. In clinical systems, we have already established a robust evidence-based pyramid. If AI can align with this approach, I would welcome its integration into the healthcare system. It would be reassuring to know that AI models can genuinely improve patients' clinical outcomes, making clinical practice more efficient and precise.

4.3 FDA Approval Challenges and Responsibility

[Audience] Dr. Chao, I have a question about your use of AI to predict normal sinus rhythm using EKG. I found an FDA-approved software that automatically selects parameters, but the data it generates differs from human-produced data. This has led to a hospital suing the company for substandard results. Are there limitations to AI development in clinical settings? How can we address situations where FDA-approved results differ from human-produced data?

[Chieh-Ju] Once a product receives FDA approval, it can be legally used in clinical settings. However, the challenge lies in determining the accuracy and usability of the product after it is on the market. Differences between AI selections and human selections can be attributed to training the model on a small database that may not generalize well to different patient populations or machine settings. While FDA approval provides legal grounds, the acceptance and preference of the product in the market become important factors in clinical practice.

[Jay] Responsibility is an issue as AI companies often shift their liabilities to users through terms and conditions in user's agreements. It is likely that doctors will bear the final responsibility by signing off on the use of AI products.

[Chieh-Ju] Humans can be blamed (in contrast to AI algorithms), and it is the doctor who ultimately bears the responsibility. User experience is crucial in clinical settings, and incorrect predictions from AI models greatly trouble clinicians, raising doubts about trusting the model and adding to their burden.

4.4 Calibration Challenges and Generalization

[Alexander] I would like to know how you calibrate the parameters of your product on MRI or CT when shipping it to different customers, especially when testing it on different manufacturers' machines.

[Albert] It is important to have good representation and variation of the image space when developing algorithms. For example, let's consider Pneumothorax detection on X-ray images. If an algorithm is trained solely on high-end academic center images from the United States, it may not perform well when applied in other regions like Africa. Technologists in different parts of the world may take X-rays in different ways, resulting in images with varying levels of extra space. Since the algorithm was not exposed to such diverse images during training, it could have a high false positive rate in regions where X-rays are taken differently. This exemplifies failed generalization due to a mismatch between the training and application data [27, 32, 40, 48, 75, 95]. To address this, when developing our algorithms, we ensure that our training images encompass the entire image space and include diverse variations encountered in the real world. This means including images from different machine strengths, variations in artifacts, and capturing the full range of circumstances. By spanning the image space during training, we ensure the algorithm is robust across different scenarios. However, each region may have slight differences, and we can use transfer learning [94] to fine-tune the algorithm for specific locations, hospitals, or equipment [42]. These challenges are solvable through technical solutions and do not require high-level changes.

4.5 From Medicine to AI

[Audience] What led you to transition from the medical field to AI in medicine?

[Chieh-Ju] Purely out of interest. I had an interest in physics and learned programming along the way. Eventually, I chose to return to clinical practice, but I still wanted to have a connection with the technical field. Recently, I happened to be drawn into the wave of AI.

[Albert] I don't consider AI as anything particularly special. It's just another software tool, similar to programming languages like C or Python or web development. It's just another instrument that I have access to. The difference now is that deep learning has made programming algorithms based on images a lot easier. In the past, it was challenging and time-consuming to program features and achieve reliable results. The beauty of deep learning is that you don't have to design all the features manually. You specify the desired outcome, and the neural network figures out the necessary features to produce that output. Personally, I'm excited about technology in general. I enjoy building things, and medical AI provides another avenue to pursue that interest and passion. It's just another way for me to create and innovate.

5 Conclusions

[Chieh-Mei]
Based on the insights shared by academic and industry leaders in the field of AI and Healthcare, it is clear that AI has a promising future in healthcare. The overall vibe is one of excitement and optimism for the potential benefits that AI can bring to medicine.

In particular, AI has already made significant impacts in Radiology and Cardiology, with more applications being developed every day. The use of deep learning methodologies such as CNNs for segmentation and classification, Natural Language Processing techniques like generation models, foundation models, Transformers, Computer Vision, and Machine Learning (both unsupervised and supervised) is being explored to improve patient outcomes.

For those interested in pursuing a career in this field, it is important to find your passion and goal while developing necessary data science skills through learning materials. The advantages of AI in healthcare are numerous, including increased efficiency and productivity while saving time and workload. However, there are limitations to consider such as problems with generalization.

Ethical issues surrounding data-sharing, privacy, safety, bias, transparency, and accountability must also be addressed. It is important to ensure that the development of AI in healthcare is done responsibly with a focus on improving patient outcomes while minimizing harm.

Overall, the outlook for AI in healthcare is positive with exciting opportunities for innovation and improvement. As long as we continue to address ethical concerns while developing new applications for AI in medicine, we can expect to see continued progress toward better patient care.

Finally, integrating artificial intelligence into healthcare presents a promising frontier with significant potential for future development. We can leverage AI's power to revolutionize healthcare and ultimately improve people's lives worldwide through our acceptance of AI technology while adhering to high standards in safety, ethics, and evidence-based medical care.

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Biographies

Yung-Chun Chang is an associate professor at the Institute of Data Science and Management at Taipei Medical University. After obtaining his doctoral degree in Information Management from National Taiwan University, he conducted postdoctoral research at the Institute of Information Science, Academia Sinica. He specializes in AI topics related to natural language processing and explores their applications in the biomedical field.

Chieh-Ju Chao is currently a cardiologist and assistant professor at the Mayo Clinic in the United States. In 2011, Dr. Chao graduated from the School of Medicine at Yang-Ming University and subsequently pursued specialized training in cardiovascular medicine and echocardiography at Mayo Clinic. His primary research focus lies in the application of artificial intelligence in clinical cardiac ultrasound. He was selected for the American College of Cardiology Young Investigator Award in 2022. Currently, Dr. Chao is visiting Stanford University Institute for Human-Centered AI to conduct collaborative research projects between Mayo Clinic and Stanford.

Albert Hsiao is an associate professor in the Department of Radiology at UC San Diego, specializing in cardiovascular and interventional radiology. He is the director of the AiDA Lab and has recently conducted extensive research related to deep learning. Additionally, he is one of the founders of Arterys, Inc., a medical imaging analysis company focusing on 4D cardiovascular magnetic resonance analysis.

Chung-Chieh Jay Kuo holds the William M. Hogue Professorship in Electrical and Computer Engineering at the University of Southern California (USC). He is a USC Distinguished Professor of Electrical and Computer Engineering and Computer Science, and the Director of the USC Multimedia Communication Laboratory (MCL). He received the B.S. degree from the National Taiwan University, Taipei, in 1980 and the M.S. and Ph.D. degrees from the Massachusetts Institute of Technology, Cambridge, in 1985 and 1987, respectively. Dr. Kuo is a Fellow of AAAS, ACM, IEEE, NAI, and SPIE. He is also an Academician of Academia Sinica in Taiwan.

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