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11 Conclusions

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Authors' contribution:

- Main chapter: AK, ND.

Abstract

This chapter reviews the preceding chapters and attempts to highlight common themes and important take-home messages for the future of artificial intelligence (AI) in cardiology. We attempt to look into the future to see what AI can do in cardiology, and how it might interact with other fields to maximise patient benefit. We hope to strike an optimistic note, but with the proviso that the undoubted potential benefits of AI in cardiology will not arrive unless we actively pursue them and set the right conditions for their realization.

Keywords:

artificial intelligence, AI, cardiology

AI methods, and in particular those based on the latest deep learning techniques (as described in Chapter 3) have made rapid progress across a range of applications in cardiology. Whilst some applications, such as diagnosis (Chapter 5) and prognosis (Chapter 6), are still mainly in the fundamental research stage, others, such as automated segmentation and biomarker quantification (Chapter 4) are now moving towards clinical translation. This means that now is a critical time for ensuring that these technical advances are matched by corresponding advances in terms of equitable patient benefit. This book has tried to showcase the state-of-the-art and raise important issues that should be considered with the aim of patient benefit in mind.

We have discussed the importance of answering the right question (Chapter 9). For example, although undoubtedly interesting, there is little patient benefit in producing an automated AI-based diagnosis tool for a task that can be easily and quickly performed by cardiologists. Linked to this point, we have highlighted the importance of assessing the impact of AI on clinical workflows and patient outcomes, i.e. what role will AI play and what would be the impact on patients (positive and negative) in this context?

We have also highlighted the importance of considering how clinicians will interact with AI, for example by reviewing and/or correcting outputs, or interpreting recommendations in a decision support setting (Chapter 8). Furthermore, how should these considerations affect the design of AI tools and the research challenges we should focus on?

A common theme running through several chapters of the book has been that of effective and clinically appropriate validation of AI. It is important to start simple, both in terms of the models used and the validation data employed - there is little point in using an unnecessarily complex model when a simple one will work just as well (c.f. the principle of Occam's razor). Likewise, when developing models it is often more efficient to control some of the variation in the data to begin with. Once the model is working well on the controlled data then complexity can be increased. However, with clinical translation in mind, it is imperative that validation eventually employs external validation sets consisting of large and diverse real-world clinical data. Furthermore, the validation should (eventually) be focused on the impact of the AI tools on patient outcomes, rather than surrogate measures such as classification accuracy. Finally, the benefits should be equitable, so when reporting validation results it is important to include complete and open re-

porting of performance across subgroups such as gender and race (Chapters 6 and 9).

Now is also the time to consider what comes next. We may soon be at a stage where much of the “low hanging fruit” for AI in cardiology have been picked (e.g. Chapter 4, Measurement and Quantification). However, as noted above, more challenging tasks remain, such as the role of AI in diagnosis (Chapter 5) and prognosis (Chapter 6), and these may have more specific requirements for AI tools such as interpretability/explainability.

It is important to bring patients and the general public with us on this journey into an AI-enabled future in healthcare. This raises the need for effective public engagement to address the public’s (often valid) concerns about the use of AI. Interpretability/explainability may also have a role to play here in engaging patients in decisions that will affect their futures.

As well as AI, another key concept dealt with in this book has been the role of “big data”. We live in an age where data are everywhere, and the combination of big data and AI has great potential if used sensibly and effectively. A key challenge is to find the right balance between the ready availability of large amounts of rich data and actually exploiting this richness in a proper manner. Big data may be a necessary but not sufficient condition for effective AI. However, there are valid privacy concerns associated with medical data and it seems unlikely that these will ever go away completely. New approaches such as federated learning (Chapter 5) offer great potential for the exploitation of big data for real patient benefit. Federated learning is a fast-moving field that we expect to significantly impact the field of AI in cardiology in coming years.

We should also be aware of the potential of combining AI with other, related research fields. For example, combining AI techniques with state-of-the-art biophysical modelling is highly promising in several respects. It allows access to physiological parameters not available from the imaging data (for example myocardial contractility, while images only allow estimating myocardial deformation). It also provides meaningful physiological guidance to data-based approaches, and therefore represents a promising way of overcoming AI’s lack of interpretability and could help to promote clinicians’ trust in AI. On a broader perspective, it enables the vision of a *digital twin* (Chapters 9 and 10) which can complement the existing data by simulating future scenarios of patient evolution or therapy, which will be of high value for moving from

generic healthcare to personalized medicine.

In summary, these are exciting times to be involved in AI research for cardiology (and other areas). But this is not a time to “take our eye off the ball” and sit back and expect patient benefit to arrive. On the contrary, this is the most critical time to make sure that we do the right things to ensure that everybody benefits from the coming changes in the way we analyze and exploit big data with AI.

It is arguably the case that most people working in AI and cardiology at the moment are very much from the technical side and lack the perspective/knowledge to address the key issues mentioned above. Therefore, interdisciplinary working has never been more important. It is crucial that technologists engage with the clinical aspects of their work, and that clinicians engage with the technological side. We hope that this book can motivate more people to begin this journey and help to bring tangible benefits to us all.

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