Applications of artificial intelligence in emergency medicine

Kiran Grant[1]; Aidan McParland (MSc)[1]

[1]Department of Medicine, University of Toronto, Medical Sciences Building, 1 King's College Circle, Toronto, ON, Canada, M5S 1A8.

Abstract

Artificial intelligence (AI) has long been thought to be the next major technological breakthrough in healthcare. While proposed applications of AI touch on nearly all aspects of medicine and healthcare, applications within emergency medicine (EM) appear particularly promising. With increasing emergency department (ED) wait times, a reliance on high acuity diagnostic decisions, and an environment that constantly pushes the cognitive bandwidth of its providers, AI interventions in EM pose substantial benefits to both EM physicians and the EDs and health systems they work within. AI has shown promise in numerous applications within EM, including in the interpretation of diagnostic imaging, predicting patient outcomes, and monitoring of patient vitals. However, barriers to widespread adoption and integration of AI remain. Ultimately, the extent to which AI is able to positively impact patient care will revolve around overcoming these barriers, likely through an evolution of both the technology itself, and the attitudes and regulations towards it.

Introduction

Artificial intelligence (AI) aims to enable computers to emulate human cognitive functioning. While the potential applications of AI are therefore seemingly endless, there is considerable excitement about what AI could mean to healthcare.[1] Emergency medicine (EM) has been at the forefront of discussions surrounding applications of AI in healthcare due to the uniqueness of EM practice. With increasing departmental flow challenges and wait times, a reliance on high acuity diagnostic decisions, and an environment that constantly pushes the cognitive bandwidth of its providers, the benefit of an AI intervention that could increase the speed and accuracy of clinical decisions poises EM to substantially benefit from this technology.[2] The most established applications of AI in EM are rooted within the emergency department (ED) itself. For example, AI has shown promise in the interpretation of diagnostic imaging, predicting patient outcomes, and monitoring patient vitals.[3] That being said, newer interventions have targeted the use of AI outside the hospital or ED, such as home monitoring programs and predicting infectious outbreaks.[4]

Here, a review of the current literature on AI application in EDs will be described in the context of current practices, limitations, and the direction that this new innovation is heading in the future.

Corresponding Author:
Kiran Grant
kiran.grant@mail.utoronto.ca

Applications of AI within the Emergency Department

One of the primary applications of AI within the ED is in triage. The triaging of patients within the ED fundamentally impacts patient flow, wait times, resource utilization and allocation, and risk-stratification.[4,5] While most EDs currently rely on clinical decision making in triage, there is evidence that AI systems could improve this process.[4,5] The Emergency Severity Index (ESI) is the most commonly used triage scale in the United States.[6] However, a challenge associated with this scale is that a large proportion of all ED patients are labeled as an ESI-3, or a mid-level of acuity, creating a challenge for accurate triage of this population. Several AI models have shown to be effective in delineating patients at this mid-acuity level.[7,8] One system, e-triage, was able to differentiate 65% of ESI-3 labeled patients and either increase or decrease their required triage severity more effectively.[7] AI systems were also effective in predicting the risk of severe complications such as sepsis, the likelihood of cardiac arrest within 72 hours, and earlier assessment of trauma patients who were likely to have a positive computed tomography (CT) head result.[9-11] Each AI application outperformed the comparative clinical decision making tool (mortality in ED sepsis score, thrombolysis in myocardial infarction Global Registry of Acute Coronary Events, and Canadian CT head algorithm, respectively).[5] While these prediction tools are less focused on the initial acuity of the patient, they still impact triage by informing the amount of investigations needed, how quickly said investigations need to be completed, and how closely the patient needs to be followed in the ED.

Similar AI interventions have been applied in the context of clinical monitoring. While the aforementioned tools can predict the likelihood of cardiac complications or sepsis based on a patient's initial presentation and basic work-up, other tools have been developed to monitor heart rate and rhythm and blood pressure dynamics over time to predict clinical complications. These AI interventions have been primarily focused on predicting sepsis and cardiac instability, and have been shown to perform equally or better than current clinical tools.[12,13] Other AI tools have used natural language processing (NLP), which involves computers interpreting text, to predict the likelihood of patients having appendicitis or influenza based on information in the clinical notes from the ED.[14,15]

Another core application of AI within EDs is in the interpretation of diagnostic imaging. AI interventions have been shown to have up to 94% sensitivity and 99% negative predictive value in detecting life-threatening pathology on head CT, such as subarachnoid hemorrhage, epidural hematoma, midline shift, hydrocephalus, and acute ischemic stroke.[16-19] Quick and accurate identification of these diagnoses is extremely valuable both in high volume tertiary centers with potentially lengthy waiting periods for radiology consultations and in smaller centers with limited access to radiology specialists. AI has also shown to be very effective in fracture diagnosis, both in common orthopedic injuries to the extremities, such as wrist and ankle fractures, and in more serious vertebral pathologies.[20,21] AI also shows promise in assisting in diagnosis from ultrasound investigations, such as detecting fluid on focused assessment with sonography for trauma (FAST), and providing an automated calculation of ejection fraction on echocardiogram.[22,23] Again, AI proves useful in determining if there is an obvious pathology present, thereby providing an additional safety net for EM providers, particularly in lieu of a specialist consult. Moreover, it helps in informing the allocation of ED resources and patient disposition planning.

Applications of AI outside the Emergency Department

While applications of AI to EM outside the ED are relatively new and validated to a lesser degree than those within the ED, several promising applications have been reported. Home monitoring, which is a natural progression from inpatient AI monitoring discussed above, has been shown to be effective in detecting acute exacerbations of chronic obstructive pulmonary disease, identifying 75.8% of exacerbations an average of 5 days before the patient sought treatment.[24] Similarly, AI interventions have been able to predict asthma exacerbations in children 1 week before symptom onset by using patterns in asthma symptoms, patient attributes, and environmental factors collected in a self-reported asthma symptom tracker database.[25] Wrist-worn accelerometers have been able to detect seizures with a high degree of accuracy, and specialized smart phone audio applications have been used to detect falls in the elderly.[26,27]

Through the analysis of tweets on Twitter, AI interventions were able to effectively predict influenza outbreaks by searching users within a given radius of a local hospital and monitoring tweets for key words such as "flu." The program then compared the identified key words with official statistics from sentinel hospitals and physicians, with high correlation.[28] Similarly, NLP has been applied to predict suicidal ideation and attempts on Twitter.[29]

An application of AI in emergency medical services (EMS) has been explored through the Corti AI system. Corti assists emergency dispatchers by analyzing the caller's speech and description and providing advice on what questions to ask next, indicating when a patient may have a particular presentation, such as a myocardial infarction or stroke. It also helps in data extraction, where the system can pull information on the caller's address and/or location to reduce time needed to complete the call and dispatch EMS.[30]

While each of these AI applications occurs in a pre-hospital environment, they may substantially reduce the burden on EDs and serve as early detection and warning systems for acute care events outside healthcare environments. By predicting which chronic diseases patients are in need of emergency care and when and where an infectious disease outbreak may occur, EDs would be better able to prepare for the patient type and volumes they may encounter. Further, by assisting emergency dispatchers, emergency medical and paramedic services could be dispatched more quickly and with more detailed clinical information.

Barriers and Limitations

Despite the vast potential for improved clinical care associated with the implementation of AI and machine learning in emergency care delivery, numerous technical, ethical, and acceptance issues surrounding this technology prevail.

Many of the studies that are presented here and others that have paved the way for implementation of AI in healthcare settings are retrospective analyses of datasets. Very few randomized controlled trials have been conducted on the benefits of AI in clinical contexts, and will surely be required for the widespread adoption of this technology. The accurate collection of healthcare data depends on consistency of data reporting and usage of electronic data records, so as to avoid "noisy data".[31] In both Canada and the United States, there is a lag with the acceptance of purely electronic medical records in EDs and there is minimal standardization between electronic medical record systems used between healthcare organizations. This presents challenges in broadly applying any one AI program across many EDs.

Another limitation involves the nature of the internally evolving algorithm by which neural networks and machine learning develop prognostic algorithms. We are faced with a turning point in technology where trust is placed in the hands of not just the human developer of the algorithm, but the computer to generate appropriate codes internally. This makes the replication and interpretation of AI algorithms somewhat opaque for both clinicians and patients, presenting numerous ethical and potentially medico-legal challenges. Furthermore, the healthcare data being collected is often confidential in nature, a common rate-determining step in large data mining projects that require constant updating and real time feedback for optimal performance. It will be important to classify available data with patient consent moving forward to avoid large breaches in confidential information, as has been seen in many non-healthcare large-scale AI projects to date.

Arguably one of the greatest sources of mistrust associated with widespread adoption of AI revolves around the idea that, as with the application of any AI technology, the program will always lack of a sense of the clinical "gestalt." Although the vast majority of proposed AI interventions will be able to assist physicians as opposed to operating independently, it remains important to be aware of when and where these algorithms are at play, and how they may inadvertently influence clinical decision making.

Conclusion

The practice of EM is unique in healthcare due to the acuity and variability of the environment in which it is practiced. With unpredictable patient populations requiring acute care decisions and interventions, and external stressors that further test providers' cognitive bandwidth, the delivery of acute care medicine lends to increased risk of human error. AI possesses significant promise in the emergency setting and has already begun to improve the efficacy and quality of care delivered in select interventions. As with the adoption of any new technology, barriers to implementation persist, but ultimately may be overcome as both the technology and the attitudes and regulations surrounding it evolve. The unique environment of EM is poised to see substantial improvements in departmental flow, prevention of emergency events, and human performance as a result of a growing partnership with AI.

References

1. Hamet P, Tremblay J. Artificial intelligence in medicine. Metabolism. 2017;69:S36–40. doi: 10.1016/j.metabol.2017.01.011.
2. Krittanawong C. The rise of artificial intelligence and the uncertain future for physicians. Eur J Intern Med. 2018;48:e13–4. doi: 10.1016/j.ejim.2017.06.017.
3. Ramesh AN, Kambhampati C, Monson JR et al. Artificial intelligence in medicine. Ann R Coll Surg Engl. 2004;86(5):334–8. doi: 10.1308/147870804290.
4. Berlyand Y, Raja AS, Dorner SC, et al. How artificial intelligence could transform emergency department operations. Am J Emerg Med. 2018;36(8):1515–7. doi: 10.1016/j.ajem.2018.01.017.
5. Stewart J, Sprivulis P, Dwivedi G. Artificial intelligence and machine learning in emergency medicine. Emerg Med Australas [Internet]. 0(0). Available from: https://onlinelibrary-wiley-com.myaccess.library.utoronto.ca/doi/abs/10.1111/1742-6723.13145
6. McHugh M, Tanabe P, McClelland M, et al. More patients are triaged using the emergency severity index than any other triage acuity system in the United States. Acad Emerg Med. 2012;19(1):106–9. doi: 10.1111/j.1553-2712.2011.01240.x.
7. Levin S, Toerper M, Hamrock E, et al. Machine-learning-based electronic triage more accurately differentiates patients with respect to clinical outcomes compared with the emergency severity index. Ann Emerg Med. 2018;71(5):565–574.e2. doi: 10.1016/j.annemergmed.2017.08.005.
8. Mondragon N, Istrate D, Wegrzyn-Wolska K, et al. Patient classification algorithm at urgency care area of a hospital based on the triage system. J Med Inform Technol [Internet]. 2013 [cited 2018 Oct 14];Vol. 22. Available from: http://yadda.icm.edu.pl/baztech/element/bwmeta1.element.baztech-6c468b18-3d7d-452a-93d2-7f15a5e3d44f
9. Scott H, Colborn K. Machine learning for predicting sepsis in-hospital mortality: An important start. Acad Emerg Med. 2016;23(11):1307–1307.
10. Taylor RA, Pare JR, Venkatesh AK, et al. Prediction of in-hospital mortality in emergency department patients with sepsis: A local big data–driven, machine learning approach. Acad Emerg Med. 2016;23(3):269–78. doi: 10.1111/acem.13009.
11. Molaei S, Korley FK, Soroushmehr SM, et al. A machine learning based approach for identifying traumatic brain injury patients for whom a head CT scan can be avoided. In: 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). 2016. p. 2258–61. doi: 10.1109/EMBC.2016.7591179.
12. Muniz GW, Wampler DA, Manifold CA, et al. Promoting early diagnosis of hemodynamic instability during simulated hemorrhage with the use of a real-time decision-assist algorithm. J Trauma Acute Care Surg. 2013;75(2 Suppl 2):S184–189. doi: 10.1097/TA.0b013e31829b01db.
13. Shashikumar SP, Stanley MD, Sadiq I, et al. Early sepsis detection in critical care patients using multiscale blood pressure and heart rate dynamics. J Electrocardiol. 2017;50(6):739–43. doi: 10.1016/j.jelectrocard.2017.08.013.
14. López Pineda A, Ye Y, Visweswaran S, et al. Comparison of machine learning classifiers for influenza detection from emergency department free-text reports. J Biomed Inform. 2015;58:60–9. doi: 10.1016/j.jbi.2015.08.019.
15. Deleger L, Brodzinski H, Zhai H, et al. Developing and evaluating an automated appendicitis risk stratification algorithm for pediatric patients in the emergency department. J Am Med Inform Assoc. 2013;20(e2):e212–220. doi: 10.1136/amiajnl-2013-001962.
16. Herweh C, Ringleb PA, Rauch G, et al. Performance of e-ASPECTS software in comparison to that of stroke physicians on assessing CT scans of acute ischemic stroke patients. Int J Stroke Off J Int Stroke Soc. 2016;11(4):438–45. doi: 10.1177/1747493016632244.
17. Yuh EL, Gean AD, Manley GT, et al. Computer-aided assessment of head computed tomography (CT) studies in patients with suspected traumatic brain injury. J Neurotrauma. 2008;25(10):1163–72.
18. Farzaneh N, Reza Soroushmehr SM, Williamson CA, et al. Automated subdural hematoma segmentation for traumatic brain injured (TBI) patients. Conf Proc Annu Int Conf IEEE Eng Med Biol Soc IEEE Eng Med Biol Soc Annu Conf. 2017;2017:3069–72. doi: 10.1109/EMBC.2017.8037505.
19. Liu J, Chen Y, Lan L, et al. Prediction of rupture risk in anterior communicating artery aneurysms with a feed-forward artificial neural network. Eur Radiol. 2018;28(8):3268–75. doi: 10.1007/s00330-017-5300-3.
20. Jamaludin A, Lootus M, Kadir T, et al. ISSLS Prize in Bioengineering Science 2017: Automation of reading of radiological features from magnetic resonance images (MRIs) of the lumbar spine without human intervention is comparable with an expert radiologist. Eur Spine J. 2017;26(5):1374–83. doi: 10.1007/s00586-017-4956-3.
21. Olczak J, Fahlberg N, Maki A, et al. Artificial intelligence for analyzing orthopedic trauma radiographs. Acta Orthop. 2017;88(6):581–6. doi: 10.1080/17453674.2017.1344459.
22. Sjogren AR, Leo MM, Feldman J, et al. Image segmentation and machine learning for detection of abdominal free fluid in focused assessment with sonography for trauma examinations: A pilot study. J Ultrasound Med Off J Am Inst Ultrasound Med. 2016;35(11):2501–9. doi: 10.7863/ultra.15.11017
23. Knackstedt C, Bekkers SC, Schummers G, et al. Fully automated versus standard tracking of left ventricular ejection fraction and longitudinal strain: The FAST-EFs multicenter study. J Am Coll Cardiol. 2015;66(13):1456–66. doi: 10.1016/j.jacc.2015.07.052.
24. Fernandez-Granero MA, Sanchez-Morillo D, Leon-Jimenez A. Computerised analysis of telemonitored respiratory sounds for predicting acute exacerbations of COPD. Sensors. 2015;15(10):26978–96. doi: 10.3390/s151026978.
25. Luo G, Stone BL, Fassl B, et al. Predicting asthma control deterioration in children. BMC Med Inform Decis Mak. 2015;15(1):84. doi: 10.1186/s12911-015-0208-9.
26. Kusmakar S, Karmakar CK, Yan B, et al. Detection of generalized tonic-clonic seizures using short length accelerometry signal. Conf Proc Annu Int Conf IEEE Eng Med Biol Soc IEEE Eng Med Biol Soc Annu Conf. 2017;2017:4566–9. doi: 10.1109/EMBC.2017.8037872.
27. Cheffena M. Fall detection using smartphone audio features. IEEE J Biomed Health Inform. 2016;20(4):1073–80. doi: 10.1109/JBHI.2015.2425932.
28. Aslam AA, Tsou M-H, Spitzberg BH, et al. The reliability of tweets as a supplementary method of seasonal influenza surveillance. J Med Internet Res. 2014;16(11):e250. doi: 10.2196/jmir.3532.
29. Burnap P, Colombo G, Amery R, et al. Multi-class machine classification of suicide-related communication on Twitter. Online Soc Netw Media. 2017;2:32–44. doi: 10.1016/j.osnem.2017.08.001.
30. Corti – AI that saves lives [Internet]. Corti. [cited 2018 Oct 15]. Available from: https://corti.ai/
31. Liu T, Lin Z, Ong ME, et al. Manifold ranking based scoring system with its application to cardiac arrest prediction: A retrospective study in emergency department patients. Comput. Biol. Med. 2015;67:74–82. doi: 10.1016/j.compbiomed.2015.10.001.