Leveraging AI and wearable technologies to triage emergency cases: A literature review

Introduction

The use of efficient and reliable technology can be vital in emergency situations where every second matters. Consumer-grade wearable devices and artificial intelligence (AI) have the potential to revolutionise emergency services by increasing efficiency and accuracy, saving time, and providing personalised, effective, and timely services (Aung et al., 2021; Jiang et al., 2017).

This literature review focuses on artificial intelligence (AI) based automated triage solutions that rely on vital sign data collected by consumer wearables and aims to answer two research questions:

RQ1. What role can consumer-grade wearable devices and AI play in emergency triage?

RQ2. What are the potential applications of automated emergency triage based on vital sign data collected by consumer-grade wearable devices and AI algorithms?

As the technology behind wearable devices and AI-based applications is changing rapidly, articles published before 2013 or in languages other than English were not included in the review.

Use cases for AI in automated emergency triage

AI currently has the potential to play an important role in the entire lifecycle of an emergency case, from early diagnosis based on detected symptoms to the discharge of the patient from the hospital (Berlyand et al., 2018; Stewart et al., 2018). Among these use cases, emergency triage stands out as the most important, as it would help save valuable time and treat emergency cases more efficiently. AI can contribute to emergency triage in two ways (Chenais et al., 2023):

a. AI-assisted self-triage: Self-triage is an essential step in the hospitalisation process to identify the urgency of an emergency case and avoid wasting the limited resources of emergency departments. The effectiveness of the tool patients will use to triage themselves is paramount. Although a structured pen-and-paper questionnaire (Eijk et al., 2014), a simple mobile application (Katayama et al., 2021) or a symptom checker app (Cotte et al., 2022) are proving useful for patients to automatically triage themselves based on symptoms, in the age of AI, AI-based applications can help patients determine the urgency of their medical situation and what type of emergency services they should seek, leading to a more proactive emergency lifecycle.

b. AI-assisted triage in emergency departments:

On many occasions, it has been demonstrated that wearables and AI-based technologies are also capable of assisting the triage of walk-in patients in emergency departments (Polley et al., 2021), leading to more accurate triage and efficient use of emergency resources (Chiew et al., 2019; Rendell et al., 2019). Such solutions are particularly beneficial when emergency departments are overcrowded (Inoue et al., 2020).

Of all the medical disciplines, radiology, which plays a crucial role in diagnosing cases, is at the forefront of AI-based healthcare technologies, thanks to the superior image processing capabilities of machine learning (ML) and deep learning (DL) models (Soun et al., 2021; Weisberg et al., 2020). The role that AI can play in the field of radiology includes handling of repetitive tasks and providing automated assessment, including AI-based diagnostic decision-making to advise the radiologists to prioritise the images that are flagged by AI (Jalal et al., 2021), which in turn improves the response time in the emergency departments.

However, the areas where AI can be useful are not limited to emergency radiology. Natural language processing (NLP) is proving effective in processing health records, clinical documents and reports to extract clues to a health problem (Elkin et al., 2021; Kulshrestha et al., 2021). ML models can also be useful for early diagnosis of abnormalities (Wijnberge et al., 2020). To support physicians with the best possible information and analysis, decision support systems are proving to be crucial (G. Segal et al., 2019; M. M. Segal et al., 2016; Sutton et al., 2020), although they are sometimes not well accepted by many due to poor design (Romero-Brufau et al., 2020).

With current developments in ML and an ever-expanding range of applications, it seems that AI-based applications will play a crucial role in emergency departments and the wider healthcare sector in the coming years.

The role of wearable technology

Wearable sensors offer the potential to continuously monitor patients' vital signs, reducing the burden on caregivers and providing early detection of deteriorating patients. Medical-grade remote devices have been tested in clinical settings to monitor patients' vital signs to detect deterioration (Breteler et al., 2020; Posthuma et al., 2020). However, medical-grade sensors are generally used in hospital settings or by patients with diagnoses that require monitoring. But the real value of wearable technologies in health seems to be in monitoring the vital signs of the wider population in order to gather as much information as possible from patients before they visit hospital or emergency departments, so that they can be accurately triaged.

The adoption rate of consumer-grade wearable technology has increased exponentially with 1.8 million units shipped in the last four years (2019-2022), representing a 381% increase over the previous four-year period (Statista, N.D.). In addition to the basic functionality of these devices, such as tracking time and communicating with the smartphone to which the device is connected, users are also using these devices to track their overall fitness levels (e.g., steps, distance, calories burned). In addition, many manufacturers of consumer wearable devices also offer the ability to monitor advanced health parameters, such as heart rate (El-Amrawy & Nounou, 2015), sleep quality (Roomkham et al., 2018), or oxygen saturation (Takahashi et al., 2022) which help the users to assess their overall condition. However, the accuracy of the data collected by consumer-grade wearable devices is usually considered questionable when compared to medical-grade devices (Zhang & Khatami, 2022) and some models have been tested to be inaccurate against medical-grade sensors (Hahnen et al., 2020).

However, recent studies suggest that consumer-grade wearable devices are capable of generating significantly accurate vital sign data (Auepanwiriyakul et al., 2020; Chow & Yang, 2020; Pipek et al., 2021), especially when it comes to heart rate monitoring (Gruwez et al., 2021). Because they are much more accessible than medical-grade sensors and wearable devices, and they cater to people with different budgets, consumer-grade wearables are more likely to facilitate vital signs monitoring for a wider population. Moreover, many wearable device manufacturers have received FDA clearance for their ECG functionality, including the biggest smartwatch producers Apple (FDA, 2020a), Samsung (FDA, 2020b) and Fitbit (FDA, 2022). Although, as the FDA explicitly states, these applications are not intended to replace traditional clinical practice, these clearances are a strong indication of the accuracy of the data provided by these devices.

Bringing AI and wearables together: Automated triage based on data collected from consumer-grade wearable devices

Because consumer wearable devices provide valuable and reasonably accurate health-related data, this data can be interpreted by AI to triage emergency cases more efficiently than manually. However, as consumer-grade wearables are still in their infancy, there are currently no comprehensive systems that combine the capabilities of these devices and AI to provide a comprehensive automated triage system.

In this respect, the Apple Heart study (Garcia et al., 2022) was ground-breaking. In the study (Turakhia et al., 2019), vital sign data was collected from a large sample of over 400,000 participants using Apple Watch, and notifications of irregular pulse were sent to the users when they were identified. Users were then asked to contact a telemedicine service provider via an app developed specifically for the study to initiate a virtual study visit, where a physician confirmed the self-reported data and assessed the participant's situation. Later, eligible participants were sent an ambulatory ECG monitoring device to validate the data collected by the Apple Watch and check the participant's condition. Finally, a final study visit was conducted. During each of these steps, the participant was asked to go to a hospital emergency department if they experienced critical symptoms. This study provides an example of a semi-automated triage system using wearable technology and assessment by healthcare professionals, with the potential to become a fully automated triage system.

Two ongoing studies may shed light on patient triage based on self-monitoring with consumer-grade smartwatches in the coming years. An ongoing study by Bin et al. (2022) aims to demonstrate that it is possible to remotely monitor an entire population using a consumer-grade smartwatch and a digital platform that collects vital signs data. However, technical challenges such as synchronisation interval and hardware issues, including low battery life, need to be overcome to make this a reality. On the other hand, the researchers at Karolinska Institutet focus on long-covid patients and how they can be monitored, and, if necessary, triaged based on smartwatch data (Karolinska Institutet, 2021).

COVID-19: An unfortunate opportunity to appreciate the power of AI in healthcare

COVID-19, arguably the deadliest pandemic in modern times, was a unique opportunity to demonstrate the power of artificial intelligence in healthcare and explore its potential applications (Lidströmer & Eldar, 2022). During the pandemic, hospital emergency departments were often overcrowded and healthcare professionals had to find new ways to triage the patients more effectively due to the nature of the disease: Positive cases could deteriorate very quickly, so time pressure was inevitable; positive cases could transmit the disease to other patients; and asymptomatic cases added to the challenges.

This challenging situation led many researchers to conduct retrospective studies based on the patient data collected during the pandemic, as well as prospective studies based on the current cases. As the early, pre-symptomatic diagnosis of COVID-19 largely relied on the vital signs, the continuous vital sign data provided by wearable devices was crucial in detecting abnormalities in one's health (Ates et al., 2021), as opposed to traditional tests in hospitals. In this regard, consumer smartwatches, which are readily available on the market, appear to be a viable option for collecting vital signs data on a large scale in order to detect COVID-19 cases before the onset of symptoms (Mishra et al., 2020). Using efficient ML models, detection rates are even higher and more accurate (Cho et al., 2022).

The use of commercial smartwatches and fitness bands goes beyond the early detection of COVID-19 cases. For example, it is also possible to determine how people react to the COVID-19 vaccine (Quer et al., 2022) and to track the condition of COVID-19 patients coming out of intensive care using consumer-grade wearables (Hunter et al., 2022).

All in all, it can be argued that COVID-19, as a large-scale pandemic, proved to be a real-world case demonstrating that data from consumer-grade smartwatches, combined with ML algorithms, can help identify COVID-19 cases early enough to triage patients appropriately.

Challenges

Although the future of automated triage using smartwatches looks promising, it is not without its challenges.

First and foremost, as such systems rely on smartwatch data collected from many different models, data integrity stands out as an important technical challenge that needs to be addressed (Garcia et al., 2022). Furthermore, the privacy of users must be given the utmost respect as this data may contain sensitive information (Singh et al., 2022).

As these techniques are still new to healthcare, clinicians react differently to each patient and each reading, often leading to unnecessary testing. Standardised guidelines published by health authorities could address this challenge. It is also highly likely that there will be a difference in the quality of service received between patients who have access to wearables and those who do not (Demkowicz et al., 2023).

Image processing is an area where ML can assist radiologists and could eventually help with automated triage. Yet, access to validated, high-quality datasets for training ML and DL models remains the biggest challenge before efficient and accurate models can be trained and deployed (Matheny et al., 2020).

Last but not least, the impact of AI-based solutions on the healthcare workforce needs to be explored in order to accelerate the adoption of these technologies (Aung et al., 2021; Hazarika, 2020; O'Neill, 2017).

Conclusion

Given the current state of research, it is premature to assume that AI-based technologies will replace physicians in emergency triage for many reasons. First and foremost, as suggested by Romero-Brufau et al. (2020), social factors, personal habits and many other human factors must be taken into account in order to accurately triage an emergency case. Therefore, AI is likely to play a supporting role in the foreseeable future, as best illustrated by the radiology example above.

With regard to RQ1, consumer-grade wearables that are readily available on the market, are capable of collecting accurate and continuous vital sign data from ordinary users who are not yet hospitalised. Coupled with robust AI algorithms, this data can play a critical role in emergency triage.

There appears to be no real-world example of a fully automated triage system based on consumer-grade wearable data and AI (RQ2). However, extensive studies such as Apple Heart (Garcia et al., 2022) or those based on the COVID-19 pandemic (Bartenschlager et al., 2023; Lidströmer & Eldar, 2022; Mishra et al., 2020) demonstrate that patients can be triaged pre-symptomatically and with significant accuracy. Given that the above challenges are being addressed, the future of automated triage looks promising.

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