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REVIEW

Applications of Artificial Intelligence in Cardiovascular Emergencies – Status Quo and Outlook

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ABSTRACT

Cardiovascular diseases are the leading cause of death, with many lives being affected by critical emergencies like heart attacks, strokes, and other acute conditions. Recognizing the early warning signs is crucial for highlighting the need for immediate medical attention, especially since a quick intervention may significantly improve short and long-term patient outcome. Artificial intelligence (AI) has become a key technology in healthcare, and especially in the cardiovascular field. AI, and in particular deep learning is well suited for automatically analyzing medical images, signals, and data. Its success rests on the availability of large amounts of curated data, and the access to high performance computing infrastructures for training the deep-learning algorithms. Thus, in cardiovascular care, AI plays a dynamic role in disease detection, predicting disease outcome, and guiding treatment decisions. This review paper details and discusses the current role of AI for the most common cardiovascular emergencies. It provides insight into the specific issues, risk factors, different subtypes of the diseases, and algorithms developed to date, followed by an outlook.

Keywords: cardiovascular diseases, artificial intelligence, deep learning, emergency

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INTRODUCTION

Cardiovascular diseases stand out as the foremost cause of mortality,[1] and a considerable number of deaths are linked to cardiovascular emergencies. These critical medical scenarios stem from abrupt events that demand prompt and immediate medical attention and intervention. The most prevalent cardiovascular emergencies encompass a range of critical conditions:[2,3]

- myocardial infarction: occurs when there is a blockage in the blood flow to a part of the heart muscle, resulting in damage or death of the heart tissue;
- cardiac arrest: represents a sudden and unexpected loss of heart function, leading to the cessation of blood flow. This life-threatening emergency demands immediate intervention through cardiopulmonary resuscitation (CPR) and defibrillation.
- stroke: a cerebrovascular event arising from the interruption of blood flow to the brain, either due to a blood clot (ischemic stroke) or bleeding (hemorrhagic stroke);
- pulmonary embolism: develops when a blood clot, typically originating from the legs, travels to the lungs and obstructs blood flow;
- aortic dissection: involves a tear in the inner layer of the aorta, the large blood vessel branching off the heart;
- arrhythmias: represent abnormal heart rhythms that can lead to serious complications, including cardiac arrest. Ventricular fibrillation, characterized by a chaotic and rapid heartbeat, is particularly perilous and necessitates immediate defibrillation.
- hypertensive crisis: denotes extremely high blood pressure requiring urgent medical attention to prevent organ damage.

Recognizing the signs and symptoms of these cardiovascular emergencies is paramount, and seeking emergency medical assistance promptly can make a crucial difference. Early intervention plays a pivotal role in significantly improving outcomes during these critical situations.

Artificial intelligence (AI) has become pervasive, finding applications across various sectors.[4] Notably, research in the integration of AI into healthcare stands as one of the most dynamic areas, with impressive accomplishments. Particularly, AI has made significant strides in medical image analysis and signal processing, benefiting from the transformative impact of deep learning-based techniques over the last decade on the field of AI. The success of incorporating deep learning into healthcare AI can be attributed to several factors, as outlined previously:[5]

- deep learning demonstrates high efficiency in extracting spatial and temporal associations from extensive databases. This is achieved through the automatic extraction of representative features from images or signals. Unlike manual procedures that require preselection of features, deep learning autonomously identifies the most important ones.
- the availability of substantial amounts of curated data is a key facilitator. Deep learning algorithms benefit significantly from large, well-organized datasets, enabling them to learn and generalize patterns effectively.
- access to high-performance computing infrastructure: the presence of a robust high-performance computing infrastructure is crucial for the training and testing phases of machine learning (ML) algorithms. Such an infrastructure ensures that complex deep learning models can be processed efficiently.

Cardiovascular applications stand out as particularly dynamic within the realm of clinical applications of AI.[6] The capabilities of AI in this context extend to aiding diagnoses by acquiring knowledge of various imaging features linked to specific pathologies.[7] Leveraging follow-up data, AI tools can be developed to forecast the progression of a pathology and predict patient prognosis.[8] Furthermore, AI finds utility in the selection, planning, guidance, and follow-up of therapeutic interventions in the cardiovascular domain.[9]

In this review, we discuss the existing applications of AI in the most prevalent cardiovascular emergencies. For each of them we briefly explain the pathology, with associated risk factors and disease subtypes. We then present the types of data typically used for diagnosis and treatment planning, and then discuss the AI algorithms already developed in the field. Finally, we include a discussion and conclusions section.

MYOCARDIAL INFARCTION

A heart attack, or myocardial infarction (MI), is an acute event for the heart. MI is caused by decreased or complete stop of blood flow to a portion of the myocardium.[10] MI can either occur silently and go undetected, or manifest as a catastrophic event, resulting in hemodynamic deterioration and sudden death. Most MIs are due to underlying coronary artery disease, the leading cause of death in developed countries.[11]

Key risk factors for MI include: advanced age, particularly in men above a certain age, a family history of cardiovascular diseases, tobacco use (both active and passive), hypertension, high cholesterol levels (especially LDL), diabetes, and factors related to obesity and a sedentary lifestyle.[12–14] MI exhibits diverse subtypes with unique characteristics, including ST-segment elevation myocardial infarction (STEMI), non-ST-segment elevation myocardial infarction (NSTEMI), and unstable angina:

- STEMI is identified by a distinct electrocardiogram (ECG) pattern and involves complete coronary artery blockage, necessitating immediate intervention.
- NSTEMI is characterized by a partial coronary artery blockage, leading to a different ECG pattern. NSTEMI demands prompt medical attention but may not require immediate intervention.
- unstable angina: while not a full-fledged myocardial infarction, it involves chest pain or discomfort due to reduced blood flow to the heart, serving as a warning sign for potential impending heart issues.

The diagnosis and treatment-planning of MI involve the analysis of various types of data, including:[15–17]

- clinical observations: MI history, symptoms and findings on physical examination are crucial in establishing the context of MI and possible causes;
- medical imaging: this involves the use of echocardiography, cardiac magnetic resonance (CMR), and coronary angiography to inspect the heart's anatomy and identify anomalies that might include blocked or clogged vessels;
- ECG continues to be a fundamental tool in diagnosing myocardial infarction and should be obtained and analyzed within 10 min of the patient's arrival.[18]
- laboratory tests: these include blood tests for troponin and creatine kinase – myocardial band (CK-MB), which identifies the presence of an MI and the extent of the damage.

Deep learning (DL), with its intricate neural network structures, has emerged as a powerful tool for enhancing the accuracy and efficiency of MI diagnosis. Acharya *et al.*[19] used an 11-layer deep convolutional neural network (DCNN) to diagnose MI, analyzing 10,546 normal signals and 40,182 MI signals, including cases with and without noise. The DCNN achieved accuracy rates of 93.53% for MI diagnosis in the presence of noise and 95.22% without noise. It is noteworthy that this method focused on lead II ECG. In comparison, the k-nearest neighbors (KNN) classifier proposed previously,[20] based on 12-lead ECG signals, achieved a diagnostic accuracy of 98.80%.

Reasat and Shahnaz[21] developed a DCNN architecture designed to process raw ECG signals from leads II and III, as well as augmented vector foot (AVF), aiming to distinguish between signals associated with inferior MI and normal conditions. The proposed DCNN network was implemented following a person-centered approach, wherein it was tested on one patient and trained on others. The diagnostic accuracy of this approach demonstrated improvement compared to the stationary wavelet transform (SWT) with KNN and SWT with support vector machine (SVM)[22] methods. Notably, the DCNN achieved the highest accuracy rate of 84.54% among the mentioned methods.

Liu *et al.*[23] combined a DCNN with a recurrent neural network (RNN) to diagnose MI, resulting in improved sensitivity (92.4%), specificity (97.7%), positive predictive value (97.2%), and F1 score (94.6%). This amalgamation of DL structures demonstrated superior performance compared to standalone DCNN and multilayer perceptron (MLP) methods.

Gupta *et al.*[24] proposed a modified ConvNetQuake neural network, uniquely designed to extract raw ECG records without the need for handcrafted feature extraction. The model achieved an impressive accuracy of 99.43%, showcasing the potential of DL in simplifying and optimizing diagnostic processes for MI.

Baloglu *et al.*[25] opted for an end-to-end DCNN model, which exhibited exceptional accuracy of 99.78% specifically on lead V4 for MI diagnosis. This indicates the adaptability of DL models to diverse lead configurations, enhancing their practical utility.

Tripathy *et al.*[26] introduced a DL-LSSVM model that combined with Fourier–Bessel series expansion-based empirical wavelet transform (FBSE-EWT) achieved a remarkable accuracy of 99.74%. The study emphasized the significance of integrating DL techniques with innovative signal processing methods for MI diagnosis.

Zhang *et al.*[27] explored the potential of GADF + PCANet + Linear SVM, reaching an accuracy of 99.49% based on lead II from the PTB database. Their approach showcases the importance of feature extraction techniques in optimizing DL performance for MI diagnosis.

Feng *et al.*[28] proposed a multi-channel classification algorithm to diagnose the the ECG signals of MID, combining a 16-layer DCNN with a Long Short-Term Memory (LSTM) net. The algorithm demonstrated a high accuracy rate of 95.4%, emphasizing the efficacy of multi-channel models in capturing nuanced information from raw signals.

These studies collectively underscore the transformative impact of DL in MI diagnosis, with each approach contributing unique insights and methodologies to enhance accuracy and efficiency in clinical settings.[29] All the above-described algorithms focus on ECG data. No studies have been reported to date addressing the use of AI on medical images acquired during the acute phase, e.g., during coronary angiography. Various such algorithms have been introduced in the past for the chronic or for the post-acute phase.[5]

SUDDEN CARDIAC ARREST

Sudden cardiac arrest (SCA) is a major international public health challenge, causing about 15–20% of deaths and affecting approximately 50–100 in every 100,000 persons.[30,31] It is important to highlight that success in ventricular fibrillation (VF) and cardiac arrest resuscitation greatly depends on timely interventions such as CPR and defibrillation.[32]

Although there are advanced first responder systems meant for cardiac arrest resuscitation, a recent study in North America revealed that the overall survival rate was only 4.6%. Regrettably, many given shocks do not result in spontaneous circulation restored.[33,34] This highlights the importance of the improvement of resuscitation techniques, as well as a deeper analysis of the challenges of SCA management.

Several risk factors contribute to SCA, including coronary artery disease, previous heart attacks, certain inherited disorders affecting the heart's electrical system, and structural heart abnormalities.[35,36] Disease subtypes may involve ventricular fibrillation (a rapid, chaotic heartbeat) or ventricular tachycardia (a fast, regular beating of the heart's lower chambers).

Anticipating and preventing SCA presents substantial challenges, impeding the efficacy and cost-effectiveness of current methods.[37] Clinical electrophysiology is vital in the interpretation of SCA, which is usually associated with underlying electrical abnormalities, and clinical electrophysiology focuses on studying the heart's electrical activity.

The adoption of AI-based tools is increasing to address complex issues, and these tools are well suited to meet the substantial needs in the field of clinical electrophysiology. As a result, AI tools have become essential in distinguishing the subgroup of SCA that is responsive to electrical shocks. Specifically, there is a need to identify new predictors of SCA in individuals.[38]

Different types of data play a key role in optimal treatment planning for SCA:[39]

- clinical observations: patient history, symptoms, and physical examination;
- ECG recordings give insight into the heart's electrical activity, helping identify irregular rhythms;
- medical imaging: echocardiography, cardiac MRI, and coronary angiography provide a glimpse into structural abnormalities;
- laboratory tests: blood tests can be useful in identifying underlying conditions contributing to SCA.

In the crucial acute phase, where quick decisions are necessary, AI algorithms have a great potential for analyzing in real time data from monitoring devices and diagnostic tests. AI algorithms are used for a variety of applications including:

- ECG interpretation: AI algorithms continuously analyze ECG data, rapidly detecting abnormal patterns indicative of arrhythmias.[40–43] This immediate analysis contributes to early and precise diagnosis during critical moments.
- clinical decision support systems: AI systems serve as efficient decision-making tools, rapidly providing accurate insights derived from a comprehensive range of clinical data. However, although AI has demonstrated potential in various healthcare domains, such as medical imaging[44] and diagnosis,[45] its application in CPR and cardiac arrest management faces distinct challenges.[46] One notable challenge lies in its limited ability to rapidly adapt to changes in the patients' condition, impeding real-time feedback provision to medical staff for timely adjustments and enhancements in CPR efforts.[47,48]
- continuous monitoring: AI, taking on the role of a vigilant guardian, may continuously monitor physiological parameters. An ongoing surveillance enables early detection of subtle changes preceding SCA, facilitating proactive interventions and potentially averting crises. AI algorithms demonstrate promising results in automatically identifying cardiac arrest events within audio and video recordings. This capability accelerates the recognition of cardiac arrest incidents, facilitating the prompt initiation of CPR and automated external defibrillators (AED) utilization.[44] Additionally, AI excels in identifying areas with an elevated likelihood of cardiac arrest occurrences. This valuable information enhances emergency response planning, allowing for more effective resource allocation. By leveraging historical cardiac arrest data, population density, and other pertinent

factors, AI contributes to optimizing the strategic placement and distribution of AEDs in public spaces.[49,50] The integration of AI systems with current AEDs and emergency response infrastructure poses a significant challenge, demanding meticulous consideration of data formats, communication protocols, and adherence to regulatory compliance.[51]

In August 2018, a ML model was incorporated into the clinical workflow of Copenhagen's emergency medical services to augment out-of-hospital cardiac arrest (OHCA) recognition. This model analyzed real-time dispatcher–caller conversations, aiding in prompt OHCA identification. From September 2018 to December 2019, the ML model provided alerts to dispatchers in instances in which emergency calls suggested a heightened probability of ongoing OHCA.[52,53]

In conclusion, the advent of AI-based algorithms has introduced promising prospects for addressing the acute phase of SCA. However, these algorithms are not without challenges, with a notable limitation being their restricted capability to promptly adapt to dynamic changes in the patients' condition. Overcoming these challenges is crucial for enhancing the efficacy of AI-driven interventions in critical scenarios like SCA, emphasizing the need for ongoing research and development in the field.

STROKE

According to the World Health Organization,[54,55] annually, 15 million people suffer a stroke, which represents the leading cause of disability and the second leading cause of death. Typically, a rapid intervention is required which can reduce the long-term effects that comprise of paralysis – partial or complete, vision and speech problems, and memory loss.

Stroke is a cerebral vascular disease in which part of the brain is no longer supplied with blood due to a blockage or rupture. This leads to brain cells not receiving the oxygen and nutrients carried within the blood, and, without appropriate treatment, they die. There are two main types of stroke based on the cause for the blood supply obstruction:[56] either a clot – ischemic stroke, or a bursting vessel – hemorrhagic stroke. A third type is the transient ischemic attack (TIA), also named 'warning stroke', referring to the case when a clot temporarily blocks a vessel. In cases in which the source of the stroke is unknown, the stroke is labeled as cryptogenic. The last type, brain stem stroke happens, as the name suggests, when the blood supply to the base of the brain is stopped.

Modifiable risk factors, either through lifestyle changes or treatment, account for 82–90% of all strokes and include:[57,58] high blood pressure, heart disease, diabetes, smoking, physical inactivity, and obesity. Risk factors that cannot be changed include older age, history of prior stroke, genetics, and sex – women being more likely to suffer a stroke.[59]

ISCHEMIC STROKE

Ischemic stroke is the most common type, accounting for 87% of all strokes.[59] The main objective of treatment is to remove the blood clot. This can be done through medication that aims to dissolve the clot and improve blood flow – thrombolysis, or through a mechanical procedure – thrombectomy. During the latter, a catheter is inserted through a blood vessel and then guided to the location of the blood clot, using continuous image scans. Finally, the blot clot is removed.[60,61]

If a person is suspected of suffering a stroke an urgent response is required as "time is brain". The more time passes, the more brain tissue is damaged and the consequences worsen. For this reason, the onset time of the symptoms is used to decide which type of imaging is required. Different variations of computed tomography (CT) and magnetic resonance imaging (MRI) are employed.[62] Non-contrast CT (NCCT) and/or CT angiography (CTA) are performed early on, when the onset is less than 4.5–6 hours. In an extended time window, perfusion images either from CT or MRI are taken to assess the potentially salvageable tissue, which drives the selection of patients that can benefit from reperfusion strategies such as intravenous thrombolysis (IVT) and endovascular treatment (EVT). CT perfusion (CTP) or DWI-FLAIR/DWI-PWI mismatch can distinguish between the ischemic core that is irreversibly damaged and the penumbra tissue that can be saved. On diffusion images (DWI, ADC) the infarct core is visible, while on perfusion images the ischemic tissue can be assessed. Perfusion MRI is a type of scanning in which the temporal change of a contrast agent through the tissue is captured by taking multiple 3D scans 1–2 seconds apart. From these raw images, perfusion maps are derived and used for clinical interpretation. They most common include cerebral blood volume (CBV), cerebral blood flow (CBF), and time to peak of the residue function (TMAX). FLAIR sequences in conjunction with DWI sequences are interpreted to estimate the onset time of acute ischemic stroke.[63]

Over the past years, several DL methods have been proposed to aid physicians in the diagnosis and treatment of patients with ischemic stroke by making use of the medical images that are routinely performed. To drive the research in this direction, in 2015 the first edition of the Ischemic Stroke Lesion Segmentation (ISLES) challenge was held at the International Conference of Medical Image Computing and Computer Assisted Intervention (MICCAI).[64] The aim of the challenge was to open source a dataset of diverse ischemic stroke cases for a fair and direct comparison of algorithms. The dataset includes MRI diffusion maps (DWI, ADC), perfusion maps derived from raw perfusion MRI, and, in recent years, FLAIR sequences.

Most of the solutions proposed at the challenge include a variation of the U-Net architecture.[65] In a previous study,[66] the solutions proposed to the ISLES 2016 and 2017 are described in brief and benchmarked. Other researchers implemented a 2.5D UNet with attention-gates in order to predict the final infarct lesion volume.[67] The network input consists of five consecutive slices from DWI, ADC, with an ADC threshold of less than 620×10^{-6} mm²/s, TMAX and its threshold mask with values greater than 6 s, mean transit time (MTT), CBF and CBV maps. Because of the limited dataset of 182 patients, 5-fold cross-validation was employed. They evaluated the predictions against the results obtained with the clinically available RAPID software and found that it yielded comparable performance: median Dice Index (DSC) 0.58 compared to median DSC of 0.55.

Benzakoun *et al*. compared three ML models for the task of predicting the final infarct lesion of patients with acute ischemic stroke.[68] They implemented Gradient Boosting, Random Forests and U-Net and evaluated them utilizing a 10-fold cross-validation strategy. The dataset consisted of 394 patients that had DWI images (before reperfusion therapy and a follow-up, 24 h later) and PWI images that were aggregated into TMAX, MTT, CBF and CBV. Similarly, the authors compared the results with the segmentations obtained by thresholding ADC and TMAX sequences as it usually happens in a clinical scenario. They found that Gradient Boosting performed best with a median Dice score of 0.53. Only TMAX sequences were finally used, given that additional sequences did not improve performance. Even though Gradient Boosting, trained with features extracted patch-wise, had the highest DSC, they acknowledge its limitations. A DL model is likely to outperform this ML solution if more data would be available.

Öman *et al*.[69] trained a 3D CNN with CTA images and analyzed whether the inclusion of flipped left and right sides of CTA source images (CTA-SI) – hemispheric comparison volume, and NCCT images enhance the CNN performance. Thus, three networks were evaluated. The dataset consisted of 60 patients, half of which had acute ischemic stroke of the middle cerebral artery. The authors used a free, open source implementation of DeepMedic. They measured the DSC, infarct volumes and voxel-wise area under the curve (AUC) to assess the performance. In addition, they inspected clinically relevant anatomical regions as defined by the Alberta Stroke Program Early CT Scoring system (ASPECTS) and marked them as stroke-positive or stroke-negative in both the ground truth and the predicted masks. The overall DSC for all three CNNs was in the 0.4–0.55 range. However, when considering the ASPECTS assessment, thus restricting the regions analyzed, the DSC increased for all three CNN models to 0.48 (CTA only), 0.69 (CTA + hemispheric comparison volume) and 0.72 (CTA + hemispheric comparison volume + NCCT). A notable change in the specificity was observed after the inclusion of the hemispheric comparison volume. The approach described in this paper has the benefit of decreasing the diagnostic time of acute ischemic stroke mainly by using primary imaging methods such as CTA and NCCT, as they are rapid and more commonly used in an emergency scenario than MRI.

The authors of [70,71] trained DL models on raw CTP images, thus avoiding the aArterial Input Function (AIF) selection that is needed for creating the perfusion maps. In [71] a temporal convolutional network (TCN) was implemented, using a dataset of 178 CTP scans of patients with acute ischemic stroke that was divided into three subsets with a 75/15/10 split. Ground truth masks were manually created by using follow-up scans (non-contrast CT or MR) that were acquired between 30 h and 7 days after stroke symptom onset. From the 4D CTP sequence a time window of 32 s was selected for training, thus a sequence consisted of 32 3D volumes. From these, each 2D slice was processed by a CNN to extract 32 corresponding feature maps that were then combined with the TCN. Finally, a decoder took the TCN output and generated a map of probabilities for each voxel. The evaluation yielded a DSC of 0.33 and an absolute volume error of 52.04 mL.

The authors of [70] describe a similar strategy, but instead of a TCN they apply a transformer encoder that merges the temporal features extracted with a standard CNN. To preserve the temporal order, an embedding layer is added for positional encoding. A decoder that mirrors the encoder sequentially upsamples the features to predict the lesion mask. Similar to U-Net, skip connections connect the decoder and encoder for recovering localized spatial information. For a fair comparison with [71] the same preprocessing pipeline was utilized, thus extracting 32-s image sequences from a 4D CTP scan. Each 2D slice was further cropped to only include the brain hemisphere where the stroke lesion was present. This approach, compared to [71] on the same test set, obtained a mean DSC of 0.45 and an absolute volume error of 58 mL, as opposed to a DSC of 0.40 and an error of 76 mL. Moreover, the proposed method yielded better performance with fewer parameters (2.5 M vs. 204.9 M) and a faster average runtime (2.27 s vs. 12.62 s). Both papers[70,71] acknowledge the limitations that processing raw 4D CTP imposes on the computational complexity, memory consumption, and the restrictive spatial context given to the network by feeding it only 2D images.

In [72] the authors devised three experiments in which they explored the performance of the Gated Attention MEchanism Ranking of multi-contrast MRI (GAMER-MRI) architecture in brain pathology. The first two experiments involved patients with acute and subacute ischemic stroke for which Trace-weighted (Trace), ADC, FLAIR and T1-weighted (T1w) images were acquired. The goal of GAMER-MRI was to rank the importance of each MR sequence in the final prediction. In one scenario, an in-house 3D pretrained network acted as feature extractor for the input MR contrasts (Trace, ADC, and FLAIR), followed by GAMER-MRI and a classifier that made the final prediction in order to distinguish patients with ischemic stroke from those with other pathologies or healthy individuals. The dataset was divided into training (5,002 patients), validation (1,061 patients), and testing (1,071 patients). The network obtained an AUC on the test set of 0.88. For the second experiment, 2D patch-based network was implemented for feature extraction. The goal was to classify patches of acute stroke lesion vs. healthy tissue. Since acute stroke tissue is more important than healthy tissue, the F1 score was used as evaluation metric and reported a mean test F1 score of 0.917.

Nael *et al.*[73] developed a multimodal DL system for detecting brain pathologies such as acute infarction, acute hemorrhage, and mass effect from multiple MRI images. The system consists of four 3D networks: one for detecting any abnormality and three image-to-image (3D UNet-like architecture) networks to detect the three abnormalities mentioned. Each network was trained on a specific set of contrast that could be extended if a particular sequence was available. For example, the infarct model required Axial ADC and Axial Trace contrasts, but if available it could process Axial T2*weighted, Axial T1-weighted, and Axial T2-weighted images. This was possible due to the orientation-specific feature combination layers that combine resulting features by excluding those from missing contrasts. A classifier head is added for each abnormality-specific network that outputs a probability for the presence or absence of a critical finding. In this research, a total of 12,143 MRI studies were included, out of which 1,219 (10%) had acute infarction, divided into 74% training, 9% validation, and 8% testing. The system was also evaluated on an external test set consisting of 1,072 studies. On the internal test set, for acute infarction the AUC was 0.95, sensitivity 92%, and specificity 88%, while on the external test data, AUC was 0.97, sensitivity 90%, and specificity 97%.

HEMORRHAGIC STROKE

Hemorrhagic or intracerebral stroke is a condition represented by a disruption in the brain's blood vessels leading to bleeding within the brain tissue itself, known as intracerebral hemorrhage (ICH). ICH constitutes approximately 10–20% of all acute strokes on a global scale and stands as the most perilous stroke variant. Its 30-day mortality rate can ascend to 40%, while the mortality rate over the span of 1 year may reach 60%.[74]

ICH comprises several subtypes: subarachnoid hemorrhage (SAH), subdural hemorrhage (SDH), epidural hematoma (EDH), intraparenchymal hemorrhage (IPH), and intraventricular hemorrhage (IVH). Each subtype of intracranial hemorrhage presents distinct clinical features, origins, and implications for patient management.[75]

In the context of diagnosis and planning the treatment, NCCT is the preferred imaging modality and the gold standard for identifying ICH,[76] due to its exceptional ability to accurately detect acute bleeding within the brain. Once diagnosed, treatment planning involves a comprehensive approach. Specialists use data from imaging studies, clinical assessments, and laboratory findings to formulate an individualized treatment strategy. This strategy may involve neurosurgical interventions to alleviate pressure or the removal of blood clots, management of blood pressure, and neurological support to optimize patient recovery.[77]

DL models have been used to aid in monitoring and analyzing neuroimages of acute stroke cases, providing methods to segment and measure lesions, detect strokes early, and identify suitable candidates for specific treatments. DL has been used in the management of acute hemorrhagic stroke, focusing on areas such as detailed labeling at pixel level, segmenting lesions in three dimensions, and detecting strokes.

Grewal *et al.*[78] devised the Recurrent Attention DenseNet (RADnet) specifically to discern ICH from 2D NCCT slices. They achieved an accuracy of 81.82% in predicting hemorrhages, akin to expert radiologists. Kuo *et al.*[79] introduced PatchFCN, a CNN trained on patches of

NCCT images, achieving a remarkable accuracy, marked by a receiver operating characteristic (ROC) AUC of 0.991, surpassing the performance of most radiologists. Ojeda *et al.*[80] evaluated a proprietary CNN architecture developed by AIdoc (Tel Aviv, Israel), which obtained US Food and Drug Administration (FDA) clearance for triaging patients post scan. Both models performed comparably to experts, even detecting abnormalities missed by specialists. AIdoc's CNN showed an overall accuracy of 98%, benefiting from extensive training data, while PatchFCN attained similar results using strong supervision on a smaller dataset.

A valuable aspect of ICH detection involves distinguishing between its different types—such as bleeding within brain tissue, ventricles, beneath the dura, or in the spaces around the brain—which demand distinct treatment approaches and sometimes urgent surgical procedures. The winners of the Radiological Society of North America Intracranial Hemorrhage Detection Challenge (RSNA), using a dataset with over 25,000 CT scans, leveraged a DL approach mimicking radiologists' interpretation processes to accurately classify acute ICH and its subtypes with AUCs comparable to expert radiologists (0.988 for ICH, 0.984 for EDH, 0.992 for IPH, 0.996 for IVH, 0.985 for SAH, and 0.983 for SDH).[81] Ye *et al.*[75] and Lee *et al.*[82] used modified CNNs to detect ICH and its subtypes using NCCT slices, with Ye *et al.* using a joint CNN–RNN architecture for enhanced robustness across different imaging parameters and locations.

In 2022, Gibson *et al.*[83] devised a single high-level DenseUNet architecture for automatic detection, subtyping, and segmentation of acute or subacute ICH on NCCT head scans. Their model achieved notable AUCs for various hemorrhage subtypes (0.93 for EDH, 0.92 for IPH, 0.96 for IVH, 0.90 for SAH, and 0.92 for SDH), suggesting potential for significant improvement and comparable performance to expert raters, based on robust training datasets.

In conclusion, stroke is not only a complex pathology, but also one in which time is critical. Major advancements have been made, especially in terms of imaging modalities, thus creating opportunities for research and innovations. However, the 3D and in some instances 4D images represent challenging input data because of the large amount of information that they encode, the need for powerful hardware, and more importantly their scarce availability. Studies with volumes in the order of thousands, such as [83] and [84], are usually run with internal datasets, in which external evaluation is difficult to perform. Nevertheless, they make the case that more data improves performance, and that more effort should be allocated to alleviate this issue.

PULMONARY EMBOLISM

Pulmonary embolism (PE), characterized by the presence of a blood clot (thrombus) in the pulmonary arteries, poses a significant health risk with a notable incidence and mortality rate. Central PE ranks as the third most common cardiovascular syndrome, following only myocardial infarction and stroke.[85] PE affects between 39 and 115 individuals per 100,000, and the closely associated deep vein thrombosis affects 53 to 166 individuals per 100,000.[86,87] This results in up to 300,000 deaths annually in the US alone.[87] Strong risk factors for PE include immobilization, trauma, surgery, cancer, and hospitalization.[87] Recent findings indicate COVID-19 as a factor as well.[88]

The clinical indications of acute PE are non-specific. Typically, suspicion arises when a patient exhibits dyspnea, chest pain, pre-syncope or syncope, hemoptysis, or hemodynamic instability.[89–91]

In the context of AI-based methods applied in an emergency setting, two features of PE are of high interest. First, distinguishing between acute and chronic PE, and second, the proximity of the PE to the pulmonary artery. Although chronic PEs are important to be monitored, the detection and treatment of acute PEs is time-critical, given that 34% of patients die within the first few hours of the acute event.[92] The location of the PE, classified into central, segmental, and subsegmental, is an important factor in determining the gravity of the PE and the further treatment, according to the guidelines of the European Society of Cardiology.[93]

The established benchmark for diagnosing Pes is CT pulmonary angiography (CTPA).[94] This medical imaging method enables the proper visualization of the pulmonary arteries, including subsegmental ones. PE computer-assisted detection (PECAD) has gained significant visibility in the past couple of years with the RSNA release of the public RSPECT dataset.[95] Subsequently, a ML Kaggle challenge was organized,[96] popularizing the dataset and setting a strong benchmark for the task. The dataset consists of 7,279 CTPA 3D volume studies with a slice-level binary annotation indicating the presence or absence of PE. Alongside the RSPECT dataset, other data collections suitable for PE detection have been made public.[97,98]

In the case of PECAD, the usual target application for the models is to generate patient-level predictions to be further used in triage settings. By prioritizing critical patients, more patients in urgent need of care will receive it faster, and at the same time lighten the ever-increasing workload of hospitals.[99,100]

TABLE 1. Comparison of results of state-of-the-art solutions. Although AI results are very good, they still obtain slightly worse results than those of a radiologist.

Model	F1 score
Buls[113] AI model	73.0 %
Weiker[110] AI Model	86.0 %
Cheikh[101] AI Model	86.1 %
Condrea[112] AI Model	91.0%
Cheikh[101] radiologist	92.4 %

The accessibility to PECAD-relevant data, together with the increase in computing power, have sparked a rapid development of PE detection solutions.[101–112] Methods for identifying PE rely on conventional image-processing approaches, using segmentation and thresholding techniques,[106–109] or on DL approaches,[101–105,110,112–114] which mostly rely on CNN architectures. Recently, vision transformers-based architectures[115] have been adopted for PECAD.[116]

Self-supervised learning methods have gained traction lately in the PECAD domain as well,[116–118] which potentially allows for a more data efficient approach for model training. This could translate into fewer costs related to accurately annotating data to obtain powerful PECAD models.

Most of the aforementioned models are applied only on medical imaging (CTPA), not taking into account other medical information such as case reports, mostly due to them not being available in public datasets. Although there are recent efforts towards the standardization of PECAD benchmarking through large public datasets,[95,96] many state-of-the-art approaches report their performance on large private in-house datasets, using different metrics. Herein, we focus on the F1 score for model evaluation in a PE triage setting, which is an established proxy for a balanced triage metric, maximizing both recall and positive predictive value.

We selected state-of-the-art approaches, presented in Table 1, all reporting their F1 score on large datasets. Alongside the ML models, the performance of radiologists has been also benchmarked by one of the papers, providing a useful point of reference.

Some PECAD applications have already been adopted in clinical practice, such as the solutions of AIDoc, Avicenna.AI[119] or Viz.AI, aiming to detect the presence of acute PEs.

AORTIC DISSECTION

The aorta is the largest and most important artery in the human body. It transports oxygenated blood from the heart to all the organs, and it has a vital role in the physiology of the human body. Therefore, it is one of the most studied and investigated vessels in the cardiovascular field. One of the major and most fatal pathologies that may occur is aortic dissection (AD). This is represented by a tear in the inner layer of the aorta and the progressive separation of the layers that comprise the vessel. It has a very high mortality rate, 40% at initial presentation, which increases by 1% every hour. AD has two main classifications: the DeBakey classification,[120] with three categories (type I, which involves the ascending aorta and progresses towards the aortic arch and the descending aorta; type II, which affects only the ascending aorta; and type III, which affects the descending aorta), and the Stanford classification,[121] which classifies the pathology into type A (TAAD), affecting the ascending aorta, and type B (TBAD), affecting the descending aorta.

To detect AD, clinicians use a variety of techniques, from classical clinical examinations to advanced imaging. As there are multiple imaging technologies, the study performed by Sayed *et al*.[122] presents a comprehensive understanding regarding the efficiency of each of them, with CT and MRA being the best performing ones. Ultrasound is another suitable option, and more flexible, even if the view is limited. Typically, an ECG is also acquired for additional information and context. It should be noted that there are also biomarkers, such as C-reactive protein,[123] matrix metalloproteinases,[124] etc., that can provide relevant information and a possible prediction of cardiovascular events such as AD. As far as treatment is concerned, type A is most of the times acute and therefore requires surgical intervention, whereas type B is treatable medically, usually being chronic and requiring routine checkups.[125]

As a popular solution for various pathologies, image-based algorithms have been proposed for the detection of AD.[126,127] Since the two types of AD differ in terms of medical procedures, urgency, and limitations, we will discuss them separately. Regarding the imaging data used for the following models, all of them use contrast-enhanced CTs.

TYPE A – ACUTE

The first solution presented by Wu *et al*. addresses the emergency surgical triage for incoming patients, by predicting in-hospital rupture of type A AD using random forest.[128] The algorithm has been trained on 1,133 CT scans of patients with TAAD in a 6-year time frame. The relevance of this study is high, as most of TAAD-focused research is usually centered on post-operatory use-cases, and no on-the-spot solution has been yet proposed to support the medical personnel in maximizing the survival rate. The random forest algorithm proposed 16 relevant features that represent the risk factors, which have been used to develop a prediction model.

The second study is centered on predicting the potential mortality in a 30-day window after the surgical operation for type A aortic dissection, by Macrina *et al.*[129] The data is acquired from a total of 121 patients operated over a time period of 7 years in a single health center. The study compares two AI approaches, a neural network (NN) and a logistic regression (LR) method. Both methods gave satisfactory results, with better statistics for the NN model. An important observation is that when tested on data from a second health center, some features were relevant for both centers, such as the presence of pre-operative shock, neurological symptoms, quantity of post-operative bleeding etc. By taking into account the results and metrics of the experiments, such as AUC and Gini coefficients, there is proof towards a possible applicability of the NN model in practice.

The third solution introduces an even longer-term mortality prediction after the operation for TAAD.[130] The data was collected from 235 patients between 2002 and 2008, with 32 potential predictors. Therein, a NN model was evaluated against a SVM. The study concluded that safely ruling out patients from surgery is not possible, but the prediction for long-term post-operatory mortality had satisfactory results.

TYPE B – CHRONIC

The first TBAD AI solution is a DL-based 3D segmentation of true lumen, false lumen, and false lumen thrombosis.[131] It used 147 CTA scans from 40 patients, with data being collected between 2003 and 2017. This was a supervised learning approach, where the ground truth annotations were labeled by a trained radiologist, and had four categories: true lumen (TL), false lumen (FL) without thrombosis, lumen with thrombosis (FLT), and background. Three models were tested, out of which the best one relied on two sequential residual U-nets: the first one provides the general aorta segmentation while the second splits it into subcategories. Regarding the performance for the different labels, TL and FL were satisfactory segmented, whereas for FLT further research was deemed required to obtain acceptable results.

A similar study was performed by Hahn *et al.*[132], in which they studied a more general, CT-based true- and false-lumen segmentation.[132] For the data, 153 thoracoabdominal CTAs from 45 patients were considered. A highly accurate aorta segmentation was obtained using the ALO algorithm with a dice score of 0.95, providing satisfactory results on both the true and false lumen segmentations.

Finally, a DL algorithm that uses contrast-enhanced CT images for segmentation and rapid automatic detection of AD has also been introduced.[133] This study also focused on the segmentation of the aorta, but with the aim of having a reasonably fast and real-time computation.

In conclusion, both type A and type B Ads are critical conditions that require further attention from the research community. The assessment of TAAD is time-critical, while on the chronic side, as TBAD is not always an acute condition, most of the research focused on segmentation methods and ways of identifying the dissection itself, with prospects for further treatment assistance solutions. Moreover, it would be beneficial to investigate different approaches to this topic, which rely not only on the medical images, but also on other input data, such as biomarkers or ECG.

ARRHYTHMIAS

Arrhythmias represent deviations from the expected sequences of cardiac electrical impulses, resulting from irregularities in the origin, rate, regularity, or conduction of these impulses.[134] The consequences of such abnormalities can manifest as a fast, slow, or irregular heart rate.

Cardiac arrhythmias frequently manifest as serious emergencies.[135] Fortunately, these conditions typically show rapid responsiveness to therapeutic interventions. Consequently, a comprehensive understanding of cardiac arrhythmias is crucial, especially for healthcare professionals working in emergency departments.[136] Diagnosis of arrhythmias involves examining the electrical activity of the heart through ECG.

Wit and Rosen[137] classified arrhythmias based on their causes, distinguishing between those caused by abnormal impulse generation, abnormal impulse conduction, or a combination of both. Hand[136] identified several common cardiac arrhythmias, categorized as follows.

A) Disorders of impulse formation

a) sinus bradycardia: characterized by a heart rate below 60 beats per minute (bpm) due to a slow discharge from the sinoatrial (SA) node;
b) sinus tachycardia: results from excessive SA node discharge, causing a heart rate exceeding 100 bpm;
c) sinus arrhythmia: involves variable impulse occurring rates in the SA node;
d) atrial fibrillation: marked by the replacement of re-

gular SA node rhythmic activity with rapid, chaotic depolarization of impulses throughout the atrial myocardium;

e) atrial flutter: occurs when a single abnormal focus in the atria regularly discharges impulses at a rate of 250–350 bpm;
f) ventricular tachycardia: arises when three or more ventricular extrasystoles occur sequentially;
g) ventricular fibrillation: manifests as chaotic, independent depolarization of parts of the ventricular myocardium.

B) Disorders of impulse conduction

a) first-degree atrioventricular (AV) block: characterized by delayed impulse passage through the AV node to the ventricles;
b) second-degree heart block: subdivided into Mobitz type 1 and Mobitz type 2. Type 1 involves a progressively increasing conduction time over several beats, while occasional dropped beats characterize type 2.
c) third-degree AV block: marked by complete cessation of AV conduction.

Recent research[138] has identified increasing age, male gender, double outlet right ventricle, atrioventricular septal defect, heart failure, obstructive sleep apnea, transposition of the great arteries, and congenitally corrected transposition as independent risk factors for specific arrhythmias. Notably, atrial fibrillation is the most common arrhythmia in individuals with congenital heart disease, followed by atrial flutter.

In current medical procedures, a thorough analysis of ECGs conducted by a skilled cardiologist is essential for diagnosing life-threatening cardiac arrhythmias. However, integrating computer-aided diagnosis systems in cardiac arrhythmia detection can significantly alleviate the workload of cardiologists, allowing them to allocate more time to treatment.[139]

A comprehensive review of DL methods developed for ECG arrhythmia classification[140] analyzed 75 studies reported between 2017 and 2018. In over half of the studies, CNNs emerged as the most suitable technique for feature extraction from ECG. Other extensively researched approaches included deep belief networks (DBN), recurrent neural networks (RNN), long short-term memory (LSTM), and gated recurrent units (GRU). DL methods demonstrated high accuracy in classifying conditions such as atrial fibrillation and supraventricular and ventricular ectopic beats.

In [141], ECG waveforms were transformed into binary images and used to fine-tune a CNN pretrained on a generic image dataset. The CNN, developed through transfer learning, served as a feature extractor, with its output fed into a simple neural network for final classification. The model showed an accuracy of around 92% on the testing subset, distinguishing between three different cardiac conditions (normal beats, artificial beats generated by a pacemaker, and right bundle branch block). RNNs were combined with CNNs in [142] and trained directly on the raw signals to distinguish between normal and abnormal ECGs. The model achieved a five-fold cross-validation accuracy of 0.834. Attia *et al.*[143] focused on identifying patients with atrial fibrillation, achieving an AUC of 0.90 using a model composed of residual blocks and convolutional layers. Hannun *et al.*[144] employed a deep CNN to detect and classify 12 rhythm classes in ambulatory ECGs. The model achieved an AUC of 0.97 and an F1 score of 0.837, surpassing the performance of an average cardiologist (F1 score 0.780).

A recent study[145] proposed a more complex DL approach to detect five arrhythmia groups (normal, supraventricular ectopic, ventricular ectopic, fusion, and unknown). A deep neural network analyzes the ECG signal and extracts a set of features for each patient. These features are then optimized through a genetic algorithm, and various classifiers (KNN, SVM, MLP) are used for the final detection. The best performance was obtained using the KNN classifier that achieved an F1 score of 0.897 and an accuracy of 0.98. In another recent research,[146] concerns arose regarding the interpretability of various DL models developed for arrhythmia detection. To address this issue, the authors proposed an explainable DL model capable of identifying normal sinus rhythm, pacemaker rhythm, and different states of arrhythmia, including complete AV block, second-degree AV block, and atrial fibrillation. The approach used separate modules employing convolutional layers to identify features such as heart rate, P-wave presence, and regular PR interval. Subsequently, these modules were ensembled and followed by fully connected layers trained for arrhythmia classification. The model was validated on internal and external test datasets, achieving an AUC of 0.976 and 0.966, respectively.

All these studies were conducted on datasets annotated either by a consensus committee of board-certified practicing cardiologists or by trained personnel under the supervision of cardiologists.

Despite their technical achievements, most studies did not include practical application scenarios or discussions on the feasibility of integrating DL-based solutions into wearable devices for real-time detection of acute arrhythmias. Isin and Ozdalili[141] suggested the potential integration of their model into a computer-aided diagnostic system designed to assist clinicians in their routine clinical practices. Based on their review, Ebrahimi *et al*.[140] noticed that DL-based arrhythmia classifiers are predominantly implemented as software on CPUs or GPUs, lacking a real-time solution. Parvaneh *et al*.[139] considered the feasibility of including such solutions in resource-limited devices an open research question. However, a recent survey[147] analyzed the performance of several intelligent wearable devices available on the market for acute atrial fibrillation detection, reporting overall high accuracies. Yet, in some of the cases, atrial fibrillation tended to be under-detected. Similar findings were reported in [148], in which, although no false positives were recorded, the sensitivity was only 41%. Consequently, the authors advise clinicians to be cautious before making decisions based on diagnoses provided by a wearable monitor.

HYPERTENSIVE CRISIS

Hypertension, or raised blood pressure (BP), is a significant public health issue and substantially increases the risk of cardiovascular diseases.[149,150] It is one of the most common non-communicable diseases worldwide, with various associated risk factors that can lead to complications such as coronary heart disease, heart failure, peripheral vascular disease, stroke, or chronic kidney disease, as well as to premature mortality and disability.[151] Hypertension (systolic blood pressure (SBP) > 140 mmHg or diastolic blood pressure (DBP) > 90 mmHg) is a critical indicator requiring immediate treatment and substantial lifestyle changes. Without proper actions and medication, uncontrolled hypertension can lead to a sudden and severe increase in BP, known as a hypertensive crisis (HC), defined as a SBP > 180 mmHg or a DBP > 120 mmHg.[152]

HCs are classified as hypertensive emergencies or urgencies, depending on the presence or absence of target organ damage.[153] Hypertensive emergencies represent severe elevations in BP that are associated with signs of end-organ damage. These can include cardiac issues (e.g., aortic dissection, cardiac ischemia, heart failure, pulmonary edema, or even stroke), renal dysfunctions (e.g., acute renal failure), or neurologic deficits (e.g., hypertensive encephalopathy). Other organ systems may also be affected by uncontrolled hypertension, which may lead to retinopathy, papilledema, or eclampsia.[153–155] In a hypertensive emergency, immediate and monitored BP reduction is crucial to avoid or minimize end-organ damage.[153] Hypertensive urgencies, on the other hand, refer to acute elevations in BP without evidence of target-organ damage. Patients with hypertensive urgencies frequently exhibit non-specific symptoms such as headache, epistaxis, dizziness, faintness, vomits, palpitations, or psychomotor agitation.[153–155] Managing hypertensive urgencies also requires lowering the BP, but more gradually than in hypertensive emergencies, typically over a period of days, without intensive monitoring.[153]

Several potential risk factors are significantly associated with HC: underlying health conditions like diabetes or kidney disease, a personal or family history of hypertension or cardiovascular diseases, obesity, a sedentary lifestyle, diets high in sodium, poor adherence and compliance to antihypertensive medication, smoking, intoxication with drugs like cocaine or methamphetamine, advanced age, infrequent medical checkups, taking medications that interact with each other in a way that increases BP, pregnancy, and being of male sex.[156–158]

The evaluation of a HC depends on the specific symptoms and signs exhibited by the patient. The initial assessment includes a detailed medical history and a physical examination to determine the nature and severity of the hypertensive event, and it guides the subsequent steps in effectively managing the condition. The medical history should focus on any past episodes of high BP, noting their frequency, duration, and severity; previous antihypertensive therapy, its results, and adverse effects; administration of medication or substances that might increase BP; history of sleep apnea; and on the evaluation of cardiovascular risk factors and other co-morbidities.[155,157,159]

The physical assessment should encompass a thorough examination of the abdominal area and palpation of the kidneys; heart, neck arteries, and abdomen auscultation to detect any murmurs, which might suggest arterial damage or aneurysms; and fundoscopy to check for retinopathy. The assessment should further evaluate abnormal cardiac rhythms; signs of hypertensive encephalopathy, such as headache, nausea, vomiting, or altered state of consciousness; and the presence of motor or sensory neurological deficits. Additionally, it is crucial to assess the lower extremities for the absence, reduction, or asymmetry in pulses. Monitoring other vital signs, including heart rate, BP, and oxygen saturation, is also essential in effectively managing a HC.[155,157,159]

Following the initial evaluation of the patient, if there are suspicions that there is a risk of target organs damage due to the HC, immediate laboratory testing should be performed, including urinalysis (hematuria and proteinuria), chemistry panels (creatinine, blood urea nitrogen levels), B-natriuretic peptide, and cardiac enzymes. Other complementary tests will also be carried out to identify acute damage in target organs and should be individualized according to the patient. An ECG is recommended in any patient suspected of having cardiac ischemia or left ventricular hypertrophy; head CT or MRI are advised in case of neurologic deficits; a chest X-ray can be particularly useful when the patient presents with dyspnea (shortness of breath); and thoracic CT angiography and Doppler echocardiography are recommended to confirm or rule out a dissecting aneurysm of the aorta.[155,157,159]

The prediction and early detection of hypertension are essential to prevent its onset and the associated health complications. Incorporating AI into the diagnosis and management of hypertension has the potential to improve patient care at all stages, from prevention to diagnosis and treatment.[160] Clinical implementations of AI-based solutions in hypertension diagnosis and management include hypertension detection, BP monitoring, as well as treatment pathway prediction.[161] In the past, hypertension detection was addressed as a classification task. For example, in [162] the authors proposed a logistic regression model to determine whether a person suffers from hypertension or not based on several factors such as sex, race, body mass index (BMI), age, smoking, kidney disease, and diabetes. The authors in paper [163] introduced a model to predict type 2 diabetes and hypertension. This model uses an individual's risk factors and an ensemble approach, combining multiple algorithms for improved predictive accuracy: MLP, SVM, decision trees (DT), and logistic regression (LR). LaFreniere *et al*.[164] described the use of a feed-forward neural network to classify the presence or absence of hypertension, based on the patients' electronic health records (EHRs). In [165], the authors proposed a method to classify BP into three levels: normotension, prehypertension, and hypertension. The approach uses a bidirectional long short-term memory (B-LSTM) network with time-frequency analysis based on photoplethysmography (PPG) signals. They further addressed the task in [165] by using a KNN algorithm based on raw PPG signals.

A different set of AI-based algorithms aimed to address the challenge of accurate and continuous monitoring of BP. The systolic and diastolic BP values are usually estimated from ECG and PPG due to their relative straightforward integration on wearable devices, such as smartwatches, thus allowing for continuous and non-invasive BP monitoring through adequate processing. This capability is essential for detecting and managing hypertension, since it overcomes the limitations of discrete BP readings, which might miss high-BP events over extended periods of time.[166] A first example of an AI-based algorithm for continuous estimation of BP is the one presented in [167], where the features obtained by denoising the ECG and PPG signals are fed to an AdaBoost regression model to predict the BP value. The model developed in [168] for BP prediction is based on demographic, physiological partitioning, and PPG features, and applies a lasso regression learning technique. Wang *et al*.[169] proposed a beat-to-beat BP estimation method utilizing solely PPG signals and employing an artificial neural network (ANN) for this purpose. The proposed method involves the use of a multitaper technique to extract the spectral components of the PPG signals. These components are then combined with two morphological features of the PPG signals to form the input features for the ANN. The approach presented in [170] tackles the issue of overlooking the temporal dependencies between input signals and output BP values by formulating the BP prediction as a sequence learning problem, where both the input and the target are temporal sequences. To effectively model the temporal dependencies in BP dynamics, a B-LSTM architecture was used.

Several studies focused on estimating BP values solely based on the ECG signals. For instance the authors of paper [171] introduced a method to estimate the SBP, DBP, and mean arterial pressure (MAP) by using a stack of ML models. Specifically, following a complexity analysis performed on the input ECG signals, the extracted features are first used to categorize the ECG signals into one of the three BP categories (normal, prehypertension, and hypertension) by using a stacking module, which consists of seven different algorithms that can model different structures in the data, such as KNN, SVM, random forest etc. The output of the seven models is aggregated and fed into a single meta-classifier, which is a random forest method. The output of the meta-classifier, along with the initial features, is then fed to the input of a regression module, which outputs the BP estimation.

In a groundbreaking approach, AI has been used to predict SBP from retinal fundus images, as reported in [172]. Although the mean absolute error of the predicted SBP (11.23 mmHg) suggests that the algorithm is not yet accurate enough to be used for diagnostic purposes, this development paves the way for future advancements in the field.

Moreover, in [173] the authors demonstrated the potential of AI-based systems to predict optimal treatment pathways for individual hypertensive patients, as well as to select the most appropriate medication, based on empirical data available in EHRs, by using LSTM models. The proposed LSTM models provide the best prediction for achieving the optimal BP control with various treatment combinations. Therefore, LSTM models hold the potential to serve as effective decision-supporting tools in developing personalized strategies for hypertension treatment.

DISCUSSION AND CONCLUSIONS

Cardiovascular diseases represent a substantial global health challenge, anticipated to persist as the predominant cause of mortality for the next two decades.[174] The application of AI has exhibited considerable promise in the diagnostic, managerial, and therapeutic aspects of cardiovascular diseases. Consequently, AI-based solutions have the potential to influence clinical care in diverse dimensions:

- emphasizing patient well-being by concentrating on outcomes relevant to the patient, particularly prioritizing intricate or acute cases (e.g., identifying and giving precedence to acute coronary syndromes) while avoiding unnecessary interventions;
- facilitating the transformation of care delivery by augmenting efficiency and productivity within healthcare systems;
- elevating the quality of care through precision medicine applications, including patient and risk stratification. This involves making informed clinical decisions related to diagnosis and treatment, ultimately optimizing patient outcomes.

Recent advancements in both theoretical frameworks and hardware capabilities have elevated the potential of AI solutions, enabling the comprehensive addressing of the aforementioned considerations. Moreover, AI holds the promise of facilitating the emergence of novel imaging modalities. Photon-counting CT in particular stands out as a prospective revolution in medical imaging. Initial applications in cardiac contexts have demonstrated remarkable outcomes in terms of resolution and the ability to characterize tissues effectively.[175]

Nonetheless, the predominant focus of existing AI-based approaches has been on stable and chronic patient scenarios rather than the acute phase. In this context, we have provided an overview of current AI-based approaches specifically tailored for the most prevalent cardiovascular emergencies. A noticeable gap persists between the computational tools developed in research settings and those readily available in clinical practice. This discrepancy is, in part, a consequence of the rigorous regulatory framework governing the design and dissemination of novel clinical solutions. Additionally, challenges in medical image analysis and inherent limitations in AI approaches contribute to the need for overcoming barriers to broaden the applicability of AI in clinical practice. The main challenges for the integration of AI in healthcare, particularly in addressing cardiovascular emergencies, include:

- data privacy and security: safeguarding sensitive patient data is paramount, and the secure handling of information in compliance with regulations, such as GDPR and HIPAA, poses a significant challenge as AI systems often require access to large datasets.
- data quality and bias: the efficacy of AI models hinges on the quality of training data. Ensuring representative and unbiased datasets is crucial to prevent biases in predictions that could disproportionately affect certain demographic groups.
- interoperability and integration: integrating new AI tools with existing healthcare technologies, such as EHR systems and medical devices, presents a challenge due to the diversity of technologies in healthcare systems.
- regulatory compliance: meeting rigorous regulatory standards while maintaining innovation and adaptability is a delicate balance, as healthcare is subject to stringent regulatory frameworks.
- clinical validation and evidence: demonstrating the clinical validity and reliability of AI algorithms is imperative for gaining trust and acceptance among healthcare professionals before widespread integration into practice.
- explainability and interpretability: the interpretability of AI models, especially DL models, is crucial in healthcare to explain the decision-making processes, ensuring transparency and trust among healthcare professionals.
- ethical considerations: addressing ethical concerns, such as transparency, accountability, and responsibility for decisions made by AI systems, is essential for the responsible development and deployment of AI in clinical practice.
- user acceptance and training: healthcare professionals may resist adopting AI technologies without proper training or if they perceive these technologies as threats to their roles. Adequate education is essential for the effective integration of AI tools by healthcare providers.
- cost and resource allocation: implementing AI systems can demand substantial financial and human resources. Healthcare organizations must carefully

consider the associated costs, including development, implementation, and maintenance, in relation to potential long-term savings and efficiency gains.

Addressing these challenges requires collaboration between technologists, healthcare professionals, policymakers, and other stakeholders to ensure that AI is deployed in a way that benefits patients, enhances clinical outcomes, and respects the principles and standards of the healthcare profession.

Finally, we note that ML, DL, and AI in general are changing the way medicine is practiced. While remaining challenges are being addressed, physicians need to embrace and be prepared for the AI era, paving the way toward better diagnosis and precision medicine in cardiology and cardiovascular imaging.

CONFLICT OF INTEREST

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