Role of artificial intelligence in defibrillators: a narrative review

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ABSTRACT
Automated external defibrillators (AEDs) and implantable cardioverter defibrillators (ICDs) are used to treat life-threatening arrhythmias. AEDs and ICDs use shock advice algorithms to classify ECG tracings as shockable or non-shockable rhythms in clinical practice. Machine learning algorithms have recently been assessed for shock decision classification with increasing accuracy. Outside of rhythm classification alone, they have been evaluated in diagnosis of causes of cardiac arrest, prediction of success of defibrillation and rhythm classification without the need to interrupt cardiopulmonary resuscitation. This review explores the many applications of machine learning in AEDs and ICDs. While these technologies are exciting areas of research, there remain limitations to their widespread use including high processing power, cost and the ‘black-box’ phenomenon.

INTRODUCTION
Artificial intelligence (AI) is a broad term that encompasses the many uses of machine-based data processing to achieve outcomes that would typically require human cognitive function.1 In recent years, AI has expanded its role within medicine. In particular machine learning, a type of AI where a model is trained by a learning algorithm from a data set and then applies this model to new data sets, has been widely used in a variety of medical fields. The availability of large data sets, combined with advances in machine learning technology, has led to an increasing number of medical applications in the last few years.1 In this review, we examine the use of machine learning in rhythm classification in automated external defibrillators (AEDs) particularly without interruption of cardiopulmonary resuscitation (CPR) and predicting successful shocks and electrical storm in implantable cardioverter defibrillators (ICDs). The European Society for Cardiology (ESC) and European Resuscitation Council encourage the use of AEDs by emergency services and non-medical members of the public to reduce time to defibrillation.2 The ESC also recommends the use of ICDs in patients with documented ventricular fibrillation (VF) or haemodynamically unstable ventricular tachycardia (VT) without reversible causes or 48 hours after myocardial infarction (MI) on chronic optimal medical therapy.3 While this is an exciting new area, there are some limitations to the widespread use of these technologies, which we evaluate in the Discussion section.

Machine learning
First, we will explain some of the key AI concepts that are discussed in this paper and are currently being used in ECG detection. Table 1 summarises some of these key concepts. There are multiple machine learning techniques, which can be broadly categorised as supervised and unsupervised learning, figure 1.

Unsupervised machine learning recognises patterns in unlabelled data sets. This can be useful in identifying subgroups from complex data and where labelled data sets are not available.1 The clusters or patterns found may not be related to the outcome of interest and complex data can require large amounts of preprocessing prior to use in order to yield useful outcomes. However, unsupervised methods have still been used in clinical applications, for example, to find patterns in electronic health record data where noise, heterogeneity and incompleteness limit the use of supervised methods.1

Supervised machine learning, on the other hand, involves training models to correctly classify input data with labelled outputs. This requires large numbers of labelled data sets for training. Once trained, these models can then be used to predict outcomes on new data sets in a process known as testing. This can be used for classifying distinct groups, that is, types of arrhythmias or for regression models in data with continuous outcomes. Common types of supervised machine learning algorithms include deep learning, support vector
machines (SVMs), random forest and K-nearest neighbour (k-NN).

Deep learning is a type of machine learning that mimics neural networks in the brain to perform high levels of data processing. Artificial neural networks (ANN) contain layers of nodes which manipulate and transform input data; the layers between the input and output layers are termed ‘hidden layers’. Weighted connections between these hidden layers adjust the signal based on importance. During training, these weights are typically ascribed a random value close but not equal to zero. Using these initial weights, an initial output classification is produced by a process called forward propagation. This prediction is then compared with the true outcome and an error signal is fed back to the model, so that weights can be adjusted in a process called back propagation. In this way, the model is optimised.

Convolutional neural networks (CNNs) are a type of ANN, which extract high-level features directly from raw data. They have been used extensively in medical imaging but can be used to analyse multiple types of one-, two- and three-dimensional data sets. As in ANNs, the inputs, for example, two-dimensional pixels or three-dimensional voxels, are passed through multiple layers of neurons before reaching the output. Each layer has a convolutional filter or kernel, which extracts the high-level features such as locality and subsimilarity. This removes the need for manual feature selection and introduction of human bias. For example, a CNN model was used by Cohen-Shelley et al for screening of moderate to severe aortic stenosis (AS). The CNN model has 62 convolutional layers and one classification output layer—moderate to severe AS or mild to no AS, figure 2. Each ECG represented a 12×5000 matrix, which was the input for the CNN. In the CNN, the weights and bias are constantly modified to reduce the difference between the given output and the labelled outcome in the data set.

| Term                                      | Definition                                                                                                                                                                                                 |
|-------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Artificial neural network (ANN)           | A deep learning algorithm based on biological neural networks with connected layers of nodes used for high levels of data processing.                                                                        |
| Convolutional neural networks (CNN)       | A type of artificial neural network which extract high level features directly from one-, two- and three-dimensional data for classification.                                                               |
| Support vector machines (SVM)             | Supervised machine learning models used for classification and regression analysis. Data are categorised using an optimal line or hyperplane which maximises distance of the hyperplane from its closest points or support vectors. |
| Random forest                             | Supervised machine learning model using a large number of decision trees called estimators, which are combined to give accurate predictions of outcomes.                                                     |
| K nearest neighbours (k-NN)               | Supervised machine learning model used for classification and regression based on the proximity of a new datapoint to (k) number of neighbouring labelled datapoints.                                |

Figure 1 Top-down approach to AI. Machine learning is a type of AI, which can be broadly split into supervised and unsupervised machine learning. We will mainly focus on the use of supervised machine learning techniques in defibrillators. Adapted from Refs. AI, artificial intelligence; ANN, artificial neural network; CNN, convolutional neural networks;

Figure 2 Schematic diagram of a convolutional neural network. Adapted from Ref. AS, aortic stenosis.
SVMs, random forest and k-NN are also supervised machine learning models. SVMs are used for binary classification. SVMs determine the optimum hyperplane to separate data into two classes. They do this by maximising the distance between the hyperplane and the points to which it lies closest, also known as support vectors. Random forest uses a large number of decision trees called estimators. Each of these estimators is trained using a random subset of samples and features from the training set, which increases the generalisability of the outcomes. The final classification is the mode (classification) or median (regression) outcome among the estimators. K-NN classification does not learn patterns from the training data to apply to new data sets but instead directly compares new data with training data. New data are compared with the k most similar points in the training set and assigned as the most common value (classification) or the mean/median (regression). K is a positive, non-zero integer that must be selected based on the specific dataset, number of features and individual problem.\(^{9}\)

**Medical applications of AI**

The clinical applications of AI have been rapidly expanding. One of the most commonly used settings for machine learning is medical imaging and diagnostics. In cardiac imaging, several AI techniques have been used for identification of structures of the heart, lesion detection and segmentation of heart tissue and histological tissue classification.\(^ {10}\)

ECG interpretation and classification of cardiac arrhythmias is another obvious application of AI. Manual ECG interpretation is subjective, error-prone and varies widely depending on the knowledge and experience of the clinician. Computer-generated ECG interpretation has been widely available since it was developed in 1960s; however, their manual feature recognition algorithms have faced criticism for missing the complexities and nuances of ECGs.\(^ {11}\) Deep learning models, in particular, CNNs, have been used for ECG interpretation with human-like accuracy, with one model even out-performing cardiologists.\(^ {12}\)

Whether the use of complex deep learning algorithms such as CNNs will be used routinely for automated ECG interpretation remains to be seen.

In the current age of wearable technology and smartwatches with single-lead ECG capabilities, automatic ECG interpretation is becoming particularly important. The Kardia Band (KB) records a single-lead ECG in Apple Watches. This is then paired with an app which uses CNNs to detect atrial fibrillation (AF). Bumgarner et al found that KB interpreted AF with 93% sensitivity and 84% specificity, compared with physician interpretations of KB recordings with 99% sensitivity and 83% specificity. Of the 113 ECG and KB recordings available, 57 of them were uninterpretable by the KB algorithm but were reviewed by clinicians with 100% sensitivity and 80% specificity. Therefore, this technology still requires clinician input and oversight for the best results and is not yet able to function autonomously.\(^ {13}\)

Not only can AI be used for standard ECG interpretation but also studies have been assessing its use as a screening tool for asymptomatic moderate to severe AS, asymptomatic left ventricular dysfunction and early pulmonary hypertension—helping in early diagnosis and intervention.\(^ {3}\)\(^ {14}\)\(^ {15}\) Attia et al used paired 12-lead ECG and echocardiogram data from nearly 45,000 patients at the Mayo Clinic to train a CNN for the identification of asymptomatic left ventricular dysfunction using the 12-lead ECG data alone. Their model had a sensitivity and specificity of 86.3% and 85.7%, respectively, and they found that those with a positive AI screen had a four times greater risk of developing ventricular dysfunction in the future than those without.\(^ {14}\) ECGs are low cost, non-invasive and widely available—making them an ideal candidate for a screening tool.

Another use of this ECG recognition technology is in defibrillators. AEDs were developed for use by untrained bystanders on those who have a sudden cardiac arrest in a public place.\(^ {2}\) ICDs are implanted in those with a high risk of sudden cardiac death.\(^ {3}\) The key to an appropriate and potentially life-saving shock from the ICD or AED is the recognition of a shockable rhythm such as VF and VT. These rhythms can result in a patient’s death unless a shock is delivered quickly. This is where AI may have a major role to play in reducing time to shock and increasing efficiency of recognition of shockable rhythms.

**METHODS**

A search was carried out on Medline and Embase on 3 April 2021 using the terms ‘AED’ ‘ICD’ ‘defibrillator’ together with ‘AI’ and ‘deep learning’. This resulted in 221 abstracts which were screened for relevance to our topic of ‘Applications of machine learning in AEDs and ICDs’.

**ECG interpretation for AEDs**

Both traditional machine learning and deep learning techniques have been used to classify shockable and non-shockable rhythms. Table 2 shows examples of the techniques, which have been evaluated for use in shock advice algorithms (SAAs) as well as additional applications of this ECG interpretation technology, for example, diagnosis of prearrest MI.

SVMs have been used in rhythm classification of ECG readings, see table 2. Rhythm analysis in AEDs needs to have both high specificity and sensitivity and low processing power, so the machines are cheap and easily available. Therefore, optimising the parameters for the algorithm can increase efficiency. Alonso-Atienza et al initially used an SVM with 13 ECG parameters, which have been used previously to characterise VF and shockable rhythms.\(^ {16}\) They then examined the utility of each ECG parameter individually using three different feature selection filters. They found threshold sample count, sample entropy (measure of similarity with an ECG signal segment) and VF filter (measure of residue after a
narrowband elimination filter is applied) to be the most effective in diagnosis of VF. Therefore, a system using just these three features could decrease processing power while maintaining accuracy.\textsuperscript{16} Li \textit{et al} similarly optimised their SVM algorithm with the use of only two parameters selected using a genetic algorithm, which mimics natural selection and eliminates weaker combinations to find the optimum combinations.\textsuperscript{17} They achieved higher sensitivities and specificities with two parameters compared with Alonso \textit{et al}. However, they both used different window sizes, parameters and databases making them difficult to directly compare. Difficulties also arise as many of these databases use ECG traces from Holter monitors, which differ from out of hospital cardiac arrest (OHCA) traces, which often have more noise. In future, a single public OHCA ECG database with training and test data sets which often have more noise. In future, a single public OHCA ECG database with training and test data sets would be useful to allow for comparison of algorithms and more similar training sets to actual OHCA traces.

| Study | Study design | Algorithm used | Sensitivity | Specificity | Accuracy | Main findings | Potential limitations |
|-------|--------------|----------------|-------------|-------------|----------|---------------|----------------------|
| Thanhhauser \textit{et al}\textsuperscript{13} | Prospective registry of ICD recipients | SVM | – | – | – | Automated detection of prior MI from VF waveform | Small sample size; Used induced, short duration VF which is more organised than in-field |
| Krasteva \textit{et al}\textsuperscript{33} | Retrospective Holter recordings of ventricular arrhythmias and AED recordings of OHCA | ANN | 99.6% | 98.7% | 99.3% to 99.5% | Accurate, automated detection of a shockable rhythm | Cases distributed unevenly with majority used for validation |
| Picon \textit{et al}\textsuperscript{37} | Retrospective public database analysis | CNN | 100% | 99.0% | 99.3% | CNNs can accurately detect shockable rhythms from short ECG segments | CNN models require large amounts of data and processing power to train |
| Coult \textit{et al}\textsuperscript{39} | Retrospective cohort study | SVM | – | – | – | Prediction of OHCA outcomes | Generalisability; Data collection limited to a maximum of four shocks |
| Elola \textit{et al}\textsuperscript{31} | Retrospective database analysis | CNN | 92.0% | 93.0% | 92.1% | A recurrent CNN is the superior model for circulation characterisation with a BAC of 90% for 3 s segments | Low specificity |
| Nguyen \textit{et al}\textsuperscript{40} | Retrospective public database analysis | CNN | 97.0% | 99.0% | 99.3% | Novel SAA to increase the probability of an appropriate AED defibrillation following cardiac arrest | – |
| Figuera \textit{et al}\textsuperscript{47} | Retrospective public database analysis | SVM | 97.0% | 99.0% | – | Automated detection of shockable rhythms. Interpretability is more challenging using OHCA data compared with Holter recordings | Long response time of over 7 min |
| He \textit{et al}\textsuperscript{48} | Retrospective cohort study | CNN | 91.0% | 91.0% | 85.6% | Improved automated prediction of defibrillation outcomes | No phenotypic data or data on long term survival; Low sensitivity and specificity |
| Tripathy \textit{et al}\textsuperscript{49} | Retrospective database analysis | Variational mode decomposition and random forest classifier | 96.5% | 98.0% | 97.2% | Variational mode decomposition and random forest classifier can be used for classification of VF/VT and non-shockable rhythms | Limited by the size and ECGs in databases used |
| Sannromán-Junquera \textit{et al}\textsuperscript{50} | Retrospective database analysis | SVM | – | – | – | Proposed SVM system uses information from the ICD to support the identification of anatomical region of the left ventricular tachycardia entry site | Single centre study; Additional covariates required for increasing accuracy |
| Li \textit{et al}\textsuperscript{51} | Retrospective ventricular tachyarrhythmia database analysis | SVM | 96.2% | 96.0% | 96.0% | Validation of a ML-based VF/VT classification system, argued to be superior to conventional classification | Selection of high-quality data |
| Alonso-Atienza \textit{et al}\textsuperscript{56} | Retrospective database analysis | SVM | 75.0% | 92.0% | 96.0% | Use of SVM algorithms combining ECG features significantly improves the efficiency for the detection of life-threatening arrhythmias | Generalisability |

ANN, artificial neural network; NSR, sinus rhythm; OHCA, out of hospital cardiac arrest; SAA, shock advice algorithm; SVM, support-vector machines; VF, ventricular fibrillation; VT, ventricular tachycardia.
SVMs have also been used for diagnosis of the cause of arrest based on ECG parameters. Thammhauser et al used an SVM to identify previous MI from VF waveforms. The diagnosis of previous MI based on VF morphology had previously been performed in animal studies, but this was the first human study that demonstrated ‘proof-of-concept’. This could be used to inform decision-making postcardiac arrest. Elucidating the cause of cardiac arrest is important postresuscitation for prevention of further episodes. However, this is in the early stages and would need to be used with the whole clinical picture for decision-making purposes.

Building on previous SVM models, Krasteva et al assessed a CNN for characterisation of rhythms. They used large samples of ECG traces, over 3000 and 6000 for training and validation, respectively. However, there were more than four times more non-shockable rhythm samples available compared with shockable rhythms. Their model used ECG traces as short as 2 s with maximal performance at 5 s, meaning their system would cause a minimal impact outcomes; an increase in preshock pause of just 5 s decreases survival by 18%.

The ability to continue chest compressions while analysing the rhythm would help to minimise interruptions. Table 3 summarises the use of machine learning technologies to analyse rhythms during CPR.

Adaptive filters have been used to remove CPR artefacts. These adaptive filters, such as least mean squares or recursive least squares, use signals recorded by defibrillators, including compression depth and thoracic impedance to model the artefact and remove it prior to rhythm classification. Isahi et al used a recursive least square filter to remove CPR artefacts and a CNN for rhythm classification. They found sensitivities and specificities of 95.8% and 96.1%, respectively. The use of such adaptive filters is limited practically as they rely on additional reference channels for information, which are not readily available in all standard AEDs. Similarly, Yu et al used noise-assisted multivariate empirical mode decomposition and least mean squares. Even following adaptive filters, ECG segments during CPR can still have more noise than standard ECGs, therefore using specific machine learning algorithms can confer increasing accuracy. Yu et al constructed a neural network to assess the rhythms and identify VF. They found sensitivities >95% and specificities >80%. However, the CPR artefacts were taken from porcine ECGs of pigs in asystole receiving chest compressions not real-life OHCA ECGs.

Didon et al developed a new protocol termed ‘Analyse While Compressing’ (AWC). AWC is a two-step process where the rhythm is initially analysed during chest compressions and if a shock is advised, the rhythm is confirmed in the absence of chest compressions prior to shock delivery. Reconfirmation of rhythm was still required in 34.4% of non-shockable rhythm cases where the rhythm was not able to be accurately classified, therefore CPR interruptions still took place.

To avoid the need for adaptive filters or external feedback devices, end-to-end analysis of the rhythm has been evaluated. Jekova et al aimed to optimise an end-to-end CNN model for shock advisory decision during CPR using real-life AED recordings in OHCA. Their CNN was able to extract features from raw ECGs during CPR with sensitivities and specificities of 89.0% and 91.7%, respectively. They tested their model on 5591 real-life cardiac arrest rhythms during CPR. Nevertheless, their sensitivities and specificities remain below the American Heart Association (AHA) recommendations for SAA by 1% for VF and 3.9% for asystole. Their database unfortunately lacked enough shockable VT rhythms, less than 0.2% of the total number of rhythms, therefore they were unable to report statistically significant sensitivities for VT. There is scope for further optimisation of the model possibly with further training datasets or additional layers and channels in the CNN to make the model useful clinically.
Implantable Cardioverter Defibrillators

ICDs rely on recognition of life-threatening VT and VF rhythms before delivering a shock. The SAA must differentiate between shockable rhythms and non-shockable rhythms including normal sinus rhythm, supraVTs, sinus bradycardia, AF and idioventricular rhythms. The SAA must have high sensitivity for shockable rhythms and high specificity for non-shockable rhythms, where the delivery of shock will confer no benefit and can even result in deterioration of the rhythm. Given the catastrophic consequences of missing potentially fatal rhythms, ICDs are programmed with a high sensitivity threshold in order to avoid missed shocks. However, this can lead to high numbers of inappropriate shocks. As a result of these shocks, there are device complications such as reduced battery life and requirement of earlier reimplantation. Moreover, for the patient, there is pain associated with the shocks, worse quality of life and increased risk of dangerous arrhythmias.28

Table 4 summarises our search on the use of AI in ICDs. Outside of the SAA, machine learning can be used to predict appropriate candidates for ICD insertion and identify adverse events secondary to ICD including risk of electrical storm. The use of machine learning to predict the success of defibrillation will be discussed below.

Electrical storm is a life-threatening condition defined as three or more sustained episodes of VT, VF or inappropriate ICD shocks in a 24-hour period. This can be life threatening despite an ICD and, therefore, identifying those at high risk is important. Models for prediction of electrical storm have been assessed; they found percentage of ventricular pacing, cycle length parameters...
and number of previously untreated tachycardias to be risk factors. 29, 30

Predicting success of defibrillator shocks
There are multiple potential benefits to the prediction of successful defibrillation. Currently, in OHCA, shocks are delivered, depending on rhythm assessment, following 2 min of CPR. 31 This resuscitation protocol does not consider the likelihood of shock delivery being successful at any point during the arrest. AI algorithms can be used to predict likelihood of shock success in the hopes that shocks could be delivered at the optimum time—a summary of these papers is in table 5.

SVMs have been used to predict successful defibrillation in VF arrest. 32–34 Multiple VF waveform characteristics were used in these studies; the best predictors of termination of VF including amplitude spectrum area—a frequency domain characteristic—and slope and root mean square amplitude—time domain characteristics. Howe et al. found an accuracy of 81.9% using their model with the aforementioned VF waveform characteristics. 35 However, this was only based on a small retrospective study of 41 patients with 115 defibrillation ECGs. Larger sample sizes would be required to validate this system. The accuracy of defibrillation success was improved with waveform capnography. Capnography is being used more frequently in cardiac arrest scenarios as it can also be used for early indication of return of spontaneous circulation. However, use would be limited in community AEDs where capnography is not commonplace and could have issues being implemented without training and ICDs where it is not available.

Shandilya et al. constructed a similar SVM algorithm assessing VF waveform characteristics with accuracy of 83.3%. 35 The patients in their study had received low voltage (120 J) shocks. While this is considered equivalent to higher energy shocks, it may affect how the results can be compared with similar studies. VF is the initial rhythm in only 20%–30% of cardiac arrests. 35 We have not seen studies yet assessing prediction of shocks in other rhythms such as VT.

| Study | Number of participants | Study design | Algorithm used | Most accurate predictive factors | Potential limitations | Benefits |
|-------|------------------------|--------------|----------------|---------------------------------|-----------------------|----------|
| Wu et al. 36 | 382 | Prospective registry analysis | Random Forest | HF hospitalisation, CMR-derived LA and LV volumes, Larger total scar and grey zone extent, Lower LA emptying fractions, Serum IL-6 | Observational study, Long enrolment for cohort, ICD programming parameters not prescriptive | Identification of predictive factors for appropriate ICD interventions in a cohort of patients suitable for primary prevention ICD insertion. |
| Van Hille et al. 26 | 62 | Retrospective database analysis | Drools and ontology reasoning modules | With finer level of granularity, DroolsL S would be preferred | Small sample sizes, Does not use specific instructions | Drools and ontology reasoning approaches are efficacious methods for the triage of AF alerts from ICD devices. |
| Shakibfar et al. 29 | 16,022 | Retrospective database analysis | Logistic regression—model 1, Random forest—model 2 | Total number of sustained episodes, Shocks delivered, Cycle length parameters | -- | Prediction of electrical storm using machine learning models based on ICD remote monitoring summaries during episodes. Random forest superior to logistic regression (p<0.01). |
| Shakibfar et al. 29 | 19,935 | Retrospective cohort study | Random forest and logistic regression | Percentage of ventricular pacing during the day, Activity of ICD during day, Average ventricular HR during day, Number of previously untreated tachycardias | Difficult to differentiate nsVT and VT, US only (generalisability) | Use of large-scale random forest showed that daily summaries of ICD measurements in the absence of clinical information can predict short term risk of electrical storm. |
| Ross et al. 57 | 71,948 | Retrospective registry analysis | Random forest and logistic regression | Family history of sudden death, NYHA 4, Previous ICD, Thoracic cardiac surgery and biventricular pacemaker insertion | Dual chamber ICDs only, No information on leads, Single rather than multiple imputation | Random forest can improve identification of mortality and adverse events by dual-chamber ICDs. |

AF, atrial fibrillation; HF, heart failure; IL-6, interleukin-6; LA, left atrium; LV, left ventricle; nsVT, non-sustained ventricular tachycardia; NYHA-4, New York Heart Association Classification 4; VT, ventricular tachycardia.
In a more recent paper, Shandilya et al performed a retrospective analysis of 153 patients with OHCA cardiac arrest who received at least one shock for VF. Using a multiple domain integrative model, a type of AI model, to classify ECG rhythms and predict defibrillation success, they found 78.8% accuracy with ECG rhythms alone. As above, addition of end-tidal CO₂ increased accuracy to 83.3%, unfortunately this information was only available for 48 patients.³⁶ They did not control for preshock pauses and ‘no-flow’ time before defibrillation, which has been previously shown to impact success.³⁶ This was a relatively small study, and larger sample sizes will be required to get more meaningful data. Current sensitivities and specificities are unlikely to be sufficient to justify changing the current protocols.

AI could also be used to aid decision-making for implantation of an ICD. Patients with previous MI are separated into high arrhythmia risk groups—who could benefit from an ICD—and low arrhythmia risk groups based on clinical guidelines. Clearly, it would be beneficial to risk stratify patients individually to appropriately provide ICDs to those who might benefit. Markers such as left ventricular ejection fraction and myocardial scar size have been used in AI systems to evaluate arrhythmia risk. Kotu et al used cardiac MRI features including size, location and texture of scarred myocardium to characterise labelled high and low risk groups.³² Using an SVM classifier, they were able to obtain an average accuracy of 92.6% with a combination of scar size and heterogeneity. This technology could be used clinically to aid decision-making, nevertheless the final decision would still need to be clinician led and on a case-by-case basis.

As well as predicting the success of ICD shocks, predicting need for a shock prior to the delivery would be useful clinically to warn patients and avoid side effects of ‘surprise shocks’. Au-Yeung et al used data from the Sudden Cardiac Death Heart Failure Trial where they collected preventricular tachyarrhythmia and regular rhythms from patients with congestive heart failure.³⁷ They analysed heart rate variability data 5 min and 10 s before tachyarrhythmia in attempt to identify a ‘signature’ ofVF/VT onset. They used both random forest and SVM to assess the data. They found a specificity of 75% for 5 min prediction and 80% for 10 s prediction. With these results, however, there would likely be many false positives. The study was limited as it only assessed patient with heart failure. It is possible that using additional features or more sensitive AI programmes could yield higher sensitivities that could be used in clinical practice.

### DISCUSSION

We have outlined above the enormous potential of AI in cardiology and specifically in AEDs and ICDs. Machine learning offers exciting prospects to reduce peri-shock pauses both with increased efficiency of SAAs and the ability of SAAs to classify rhythms without interrupting CPR. In ICDs, machine learning has a number of applications, which could improve the quality of life of patients, including prediction of shock and electrical storm. Despite the enormous potential of AI in the field of defibrillators, there are some limitations to be aware of. Commercially available AEDs already exhibit high specificity. Compared with ICDs, AEDs favour specificity over sensitivity to reduce inappropriate shocks. International standards advise AED sensitivity >90% and specificity of >95% for detecting coarse VF.²⁷ Nishiyami et al found on assessment of four commercially available AEDs that VF was diagnosed and treated correctly in almost all cases.²⁸ Given the technology already has such high rates, it could be argued that newer AI algorithms increase the cost and complexity of machines with minimal gain. However, none of the AEDs investigated could obtain both a >75% sensitivity for VT and >95% specificity for SVT.²⁹ In the future, looking to improve VT and SVT discrimination could be a key area for AI.
Overfitting represents a challenge to AI algorithms, whereby the model has learnt in such a way that the rules are only applicable to the training sample and are no longer generalisable. As well as drop-out regularisation, the large data sets now available help to mitigate overfitting in training of algorithms. In medical imaging, data augmentation has been used to artificially increase the data sets available by creating variants of original images in the data sets. Whether this could also be used with ECG traces is unclear. Multiple studies that were used in this review also discussed the issue of not having a single large database to use, so that algorithms could be compared. Therefore, the benefits of a single large database would be twofold.

A common issue within the field of AI is the ‘black-box problem’. This is the fact that some AI models, in particular, neural networks, lack interpretability in their decision-making process. Many of the studies we reported above have detailed in their methods, which parameters have been used in their algorithms. Nonetheless, it can be difficult to fully explain the outcomes reached based on these parameters. As neural networks become more complex with increasing numbers of layers, they become more difficult to interpret. Explainable AI has been a key area of research, particularly with potential medicolegal issues of incorrect shock decisions.

In the USA, bystander AED use occurs in only 2% of OHCA cardiac arrests. Another application of AI which we have not yet discussed is in drone delivery of AEDs in order to increase availability of AEDs and reduce to time to initial defibrillation. A recent simulation study in rural Canada found that drone-delivered AEDs decreased time to defibrillation by between 1.8 min and 8.0 min—which would have a great impact on mortality. AI could be used to calculate optimum geographical location and possible patrols to allow greatest access to AEDs. There remain some limitations with drone delivery currently including flight path restrictions and an inability to fly in rainy and windy conditions, which would need to be overcome before widespread use.

One of the most exciting future advances in machine learning use in AEDs is in rhythm recognition during CPR. This technology has developed from adaptive filters to remove CPR artefacts to the development of end-to-end SAAs. AHA recommended sensitivities and specificities have not yet been reached but with further optimisation of algorithms, this could become a reality soon. One key step will be the development of a large database of real-life AED traces during CPR. Jekova et al were able to use a large database but the proportions of VF for example did not meet criteria, and for further optimisation, more studies will be required. Current models have not been able to reduce ‘hands-off’ time completely as they often still require reconfirmation of the rhythm in the absence of chest compressions. Further optimisation of these algorithms remains an exciting area of research.
9 Cohen-Shelly M, Attia ZI, Friedman PA, et al. Electrocardiogram screening for aortic valve stenosis using artificial intelligence. Eur Heart J 2021;42:2885–96.
10 Carneiro G, Nascimento JC. Combining multiple dynamic models and deep learning architectures for tracking the left ventricle endocardium in ultrasound data. IEEE Trans Pattern Anal Mach Intell 2013;35:2592–607.
11 Nygård ME, Hulting J. An automated system for ECG monitoring. Comput Biomed Res 1979;12:181–202.
12 Hannun AY, Rajpurkar P, Haghpanahi M, et al. Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. Nat Med 2019;25:65–9.
13 Bumgarner JM, Lambert CT, Hussein AA, et al. Smartwatch algorithm for automated detection of atrial fibrillation. J Am Coll Cardiol 2018;71:1669–81.
14 Attia ZI, Kapa S, Lopez-Jimenez F, et al. Screening for cardiac contractile dysfunction using an artificial intelligence-enabled electrocardiogram. Nat Med 2019;25:570–4.
15 Kwon J-M, Kim K-H, Medina-Inojosa J, et al. Artificial intelligence for arrhythmia recognition and neural networks with optimized Hyperparameters for detection of Shockable and Non-Shockable rhythms. Sensors 2020;20:2875.
16 Alonso-Alenius F, Morgado E, Fernandez-Martinez L, et al. Detection of life-threatening arrhythmias using feature selection and support vector machines. IEEE Trans Biomed Eng 2014;61:832–40.
17 Li Q, Rajagopalan C, Clifford GD. Ventricular fibrillation and tachycardia classification using a machine learning approach. IEEE Trans Biomed Eng 2014;61:1607.
18 Thannhauser NJ, Rebergen DJ, et al. Computerized analysis of the ventricular fibrillation waveform allows identification of myocardial infarction: a proof-of-concept study for smart defibrillator applications in cardiac arrest. J Am Heart Assoc 2020;9:16727.
19 Krasteva V, Nastêtê S, Didon J-P, et al. Fully Convolutional deep neural networks with optimized Hyperparameters for detection of Shockable and Non-Shockable rhythms. Sensors 2020;20:2875.
20 Cheskes S, Schmicker RH, Christenson J, et al. Perishock pause: an independent predictor of survival from out-of-hospital shockable cardiac arrest. Circulation 2011;124:59.
21 Jekova I, Krasteva V, Mênêtre S, et al. Bench study of the accuracy of a commercial AED arrhythmia analysis algorithm in the presence of electromagnetic interferences. Physiol Meas 2009;30:695–705.
22 Snyder D, Morgan C. Wide variation in cardiopulmonary resuscitation intervention timings among commercially available automated external defibrillators may affect survival despite high defibrillation efficacy. Crit Care Med 2004;32:S421–4.
23 Issai I, Irusta U, Aramendi E, et al. Rhythm analysis during cardiopulmonary resuscitation using Convolutional neural networks. Entropy 2020;22: doi:10.3390/e22060695. [Epub ahead of print: 27 May 2020].
24 Yu M, Zhang G, Wu T, et al. A new method without reference channels used for ventricular fibrillation detection during cardiopulmonary resuscitation. Australas Phys Eng Sci Med 2016;39:391–401.
25 Didon J-P, Mênêtre S, Jekova I, et al. Analyze whilst compressing algorithm for detection of ventricular fibrillation during CPR: a comparative performance evaluation for automated external defibrillators. Resuscitation 2021;160:94–102.
26 Jekova I, Krasteva V. Optimization of end-to-end Convolutional neural networks for analysis of out-of-hospital cardiac arrest rhythms during cardiopulmonary resuscitation. Sensors 2021;21:4105.
27 Kerber RE, Becker LB, Bourland JD, et al. Automatic external defibrillators for public access defibrillation: recommendations for specifying and reporting arrhythmia analysis algorithm performance, incorporating new waveforms, and enhancing safety. A statement for health professionals from the American heart association Task force on automatic external defibrillation, Subcommittee on AED safety and efficacy. Circulation 1997;95:1677–82.
28 Sears SF, Conti JB. Quality of life and psychological functioning of ICD patients. Heart 2002:87:488–93.
29 Shafikbâr S, Yazdchi M, Aliaikhabesinebadi S. Predicting electrical storm using episodes’ parameters from ICD recorded data. Annu Int Conf IEEE Eng Med Biol Soc 2019;2019:4885–8.
30 Shafikbâr S, Shafikbâr S, Lund-Andersson C, et al. Predicting electrical storms by remote monitoring of implantable cardioverter-defibrillator patients using machine learning. Europe 2019;21:268–74.
31 Adult basic life support guidelines | resuscitation Council UK. Available: https://www.resus.org.uk/library/2021-resuscitation-guidelines/adult-basic-life-support-guidelines [Accessed 30 Sep 2021].
32 Kutu LP, Engan K, Borhani R, et al. Cardiac magnetic resonance image-based classification of the risk of arrhythmias in post-myocardial infarction patients. Artif Intell Med 2015;64:205–15.
33 Howe A, Escalona OJ, Di Maio R, et al. A support vector machine for predicting defibrillation outcomes from waveform metrics. Resuscitation 2014;85:343–8.
34 Shandilya S, Ward K, Kurz M, et al. Non-linear dynamical signal characterization for prediction of defibrillation success through machine learning. BMC Med Inform Decis Mak 2012;12:116.
35 Nadkarni VM, Larkin GL, Peberdy MA, et al. First documented rhythm and clinical outcome differences in hospital cardiac arrest among children and adults. JAMA 2006;295:50–7.
36 Shandilya S, Kurz MC, Ward KR, et al. Integration of attributes from non-linear characterization of cardiorespiratory time-series for prediction of defibrillation outcomes. PLoS One 2016;11:e0141313.
37 Au-Yeung W-T, Remus E, Bardy GH, et al. Development and validation of warning system of ventricular tachyarrhythmia in patients with heart failure with heart rate variability data. PLoS One 2018;13:e0207215.
38 Nishiyama T, Nishiyama A, Negishi M, et al. Diagnostic accuracy of automatically available automated external defibrillators. J Am Heart Assoc 2015;4: doi:10.1161/JAHA.115.002465. [Epub ahead of print: 01 Dec 2015].
39 M S, S S, H R. Understanding artificial intelligence based radiology studies: what is overtight? Clin Imaging 2020;68:6.
40 Wadden JJ. Defining the undefinable: the black box problem in healthcare artificial intelligence. J Med Ethics 2021. doi:10.1136/medethics-2021-107529. [Epub ahead of print: 21 Jul 2021].
41 Weisfeldt ML, Everson-Stewart S, Stitats C, et al. Ventricular tachyarrhythmias and cardiac arrest in public versus at home. N Engl J Med 2011;364:313–21.
42 Cheskes S, McLeod SL, Nolan M, et al. Improving access to automated external defibrillators in rural and remote settings: a Drone delivery feasibility study. J Am Heart Assoc 2020;9:16687.
43 Picon A, Irusta U, Alvarez-Gila A, et al. Mixed convolutional and long short-term memory network for the detection of lethal ventricular arrhythmia. PLOS One 2019;14:e0216756.
44 Coult J, Blackwood J, Sherman L, et al. Ventricular fibrillation waveform analysis during chest compressions to predict survival from cardiac arrest. Eur Heart J 2016;37:2692–700.
45 Elola A, Aramendi E, Irusta U, et al. Convolutional recurrent neural networks to characterize the circulation component in the thoracic impedance during out-of-hospital cardiac arrest. Annu Int Conf IEEE Eng Med Biol Soc 2019;2019:1921–5.
46 Nguyen MT, Nguyen BV, Kim K. Deep feature learning for sudden cardiac arrest detection in automated external defibrillators. Sci Rep 2018;8:1–12.
47 Figuera C, Irusta U, Morgado E, et al. Machine learning techniques for the detection of Shockable rhythms in automated external defibrillators. PLoS One 2016;11:e0159554.
48 He M, Lu Y, Zhang L, et al. Combining amplitude spectrum area with previous shock information using neural networks improves prediction performance of defibrillation outcome for subsequent shocks in out-of-hospital cardiac arrest patients. PLoS One 2016;11:e019115.
49 Tripathy RK, Sharma LN, Dandapat S. Detection of Shockable ventricular arrhythmia using variational mode decomposition. J Med Syst 2016;40:1–13.
50 Sanroman-Junquera M, Mora-Jimenez I, Almandral J, et al. Automatic support system for regionalization of ventricular tachycardia exit site in implantable defibrillators. PLoS One 2015;10:e0124514.
51 HajebMohammadaliou P, Cascella A, Valentine M, et al. Automated Condition-Based suppression of the CPR artifact in ECG data to make a reliable shock decision for AEDs during CPR. Sensors 2021;21: doi:10.3390/s211248210. [Epub ahead of print: 08 Dec 2021].
52 Hajeb-M S, Cascella A, Valentine M, et al. Deep neural network approach for continuous eeg-based automated external defibrillator shock Advisory system during cardiopulmonary resuscitation. J Am Heart Assoc 2021;10:19065.
53 Hu Y, Tang H, Liu C, et al. The performance of a new shock advisory algorithm to reduce interruptions during CPR. Resuscitation 2019;143:1–7.
54 Issai I, Irusta U, Elola A, et al. A robust machine learning architecture for a reliable ECG rhythm analysis during CPR. Annu Int Conf IEEE Eng Med Biol Soc 2019;2019:1903–7.
55 Fumagalli F, Silver AE, Tan Q, et al. Cardiac rhythm analysis during ongoing cardiopulmonary resuscitation using the analysis with the compression with fast reconfirmation technology. Heart Rhythm 2018;15:248–55.
56 Wu KC, Wongvibulsin S, Tao S, et al. Baseline and dynamic risk predictors of appropriate implantable cardioverter defibrillator therapy. *J Am Heart Assoc* 2020;9:e017002.

57 Van Hille P, Jacques J, Taillard J, et al. Comparing Drools and ontology reasoning approaches for telecardiology decision support. *Stud Health Technol Inform* 2012;180:300–4.

58 Ross JS, Bates J, Parzynski CS, et al. Can machine learning complement traditional medical device surveillance? A case study of dual-chamber implantable cardioverter-defibrillators. *Med Devices* 2017;10:165–88.

59 Okada DR, Miller J, Chrispin J, et al. Substrate spatial complexity analysis for the prediction of ventricular arrhythmias in patients with ischemic cardiomyopathy. *Circ Arrhythm Electrophysiol* 2020;13:281–90.

60 Ebrahimzadeh E, Pooyan M, Bijar A. A novel approach to predict sudden cardiac death (SCD) using nonlinear and time-frequency analyses from HRV signals. *PLoS One* 2014;9:e81896.

61 Marzec L, Raghavan S, Banaei-Kashani F, et al. Device-measured physical activity data for classification of patients with ventricular arrhythmia events: a pilot investigation. *PLoS One* 2018;13:e0206153.