# Artificial intelligence and cardiovascular magnetic resonance imaging in myocardial infarction patients

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## Abstract

Cardiovascular magnetic resonance (CMR) is an important cardiac imaging tool for assessing the prognostic extent of myocardial injury after myocardial infarction (MI). Within the context of clinical trials, CMR is also useful for assessing the efficacy of potential cardioprotective therapies in reducing MI size and preventing adverse left ventricular (LV) remodelling in reperfused MI. However, manual contouring and analysis can be time-consuming with interobserver and intraobserver variability, which can in turn lead to reduction in accuracy and precision of analysis. There is thus a need to automate CMR scan analysis in MI patients to save time, increase accuracy, increase reproducibility and increase precision. In this regard, automated imaging analysis techniques based on artificial intelligence (AI) that are developed with machine learning (ML), and more specifically deep learning (DL) strategies, can enable efficient, robust, accurate and clinician-friendly tools to be built so as to try and improve both clinician productivity and quality of patient care. In this review, we discuss basic concepts of ML in CMR, important prognostic CMR imaging biomarkers in MI and the utility of current ML applications in their analysis as assessed in research studies. We highlight potential barriers to the mainstream implementation of these automated strategies and discuss related governance and quality control issues. Lastly, we discuss the future role of ML applications in clinical trials and the need for global collaboration in growing this field.

## *Utility of cardiovascular magnetic resonance imaging in myocardial infarction and the need for automated analysis strategies*

Cardiovascular magnetic resonance (CMR) is an important cardiac imaging tool for assessing the prognostic extent of myocardial injury after myocardial infarction (MI) as endorsed by the European Society of Cardiology 2017 guidelines(1) and the Society for Cardiovascular Magnetic Resonance 2020 position paper.(2) Within the context of clinical trials, CMR is

useful for assessing the efficacy of potential cardioprotective therapies in reducing MI size and preventing adverse left ventricular (LV) remodelling in reperfused MI. It is currently the gold standard imaging modality to quantify MI size,(3) and it can delineate subendocardial MI as little as 1 gram in size(4) with a high degree of accuracy.(5) Native T1, T2, T2* and post-contrast T1-mapping (to derive extracellular volume [ECV] mapping)(6) can also enable deeper insights to be garnered into the pathophysiological processes post MI and their associated prognostic significance.

However, manual contouring and analysis can be time-consuming with interobserver and intraobserver variability, which can in turn lead to reduction in accuracy and precision of analysis. There is thus a need to automate CMR scan analysis in MI patients to save time, increase accuracy, increase reproducibility and increase precision. In this regard, automated imaging analysis techniques based on artificial intelligence (AI) that are developed with machine learning (ML), and more specifically deep learning (DL) strategies, can enable efficient, robust, accurate and clinician-friendly tools to be built so as to try and improve both clinician productivity and quality of patient care.

AI refers to computer algorithm-based techniques that enable machines to perform tasks that resemble human intelligence. ML methods encompass supervised, unsupervised, semi-supervised and reinforcement learning methods, amongst others, to achieve AI. DL is a set of advanced ML techniques that are based on artificial neural networks with hidden layers and can be used to detect and differentiate patterns in data. DL is currently the most popular ML method for medical image analysis.

In this review, we discuss important prognostic CMR imaging biomarkers in MI and the utility of current ML applications in their analysis as assessed in research studies (summarised in Table 1 and schematically depicted in Figure 1). We highlight potential barriers to the mainstream implementation of these automated strategies and discuss related governance and quality control issues. Lastly, we discuss the future role of ML applications in clinical trials and the need for global collaboration in growing this field.

### *Prognostic implications of myocardial infarction cardiovascular magnetic resonance imaging biomarkers*

The parameters of prognostic importance with clinical implications that may be amenable to automated analysis are volumetric analysis, infarct size, area at risk, presence of microvascular obstruction (MVO) and size of MVO.

Historically, left ventricular (LV) ejection fraction (EF) and LV volumes have been the established predictors of mortality in patients with coronary artery disease (CAD) and severe LV dysfunction.(7) Previous studies have shown that LV function and LV end-systolic volume (ESV) were the strongest predictors of cardiac death after MI.(8)

MI size refers to the size of the infarcted myocardium and is conventionally demarcated on late gadolinium enhancement (LGE) imaging. Morbidity and mortality post-ST elevation myocardial infarction (STEMI) is closely associated with acute MI size.(9) A meta-analysis of 2,632 patients showed that MI size assessed by CMR or SPECT within 1 month post-primary percutaneous coronary intervention from 10 randomised controlled trials was

strongly associated with heart failure hospitalisation and all-cause mortality at 1 year, with a 20% increase in relative hazard ratio for both these clinical outcomes for every 5% increase in MI size.(10) This further adds to the growing body of evidence that acute MI size is prognostic.

MVO results from the inability to reperfuse the coronary microcirculation in a previously ischaemic region despite revascularisation of the culprit epicardial vessel. MVO can be identified as a dark hypointense core within areas of hyperenhancement on early gadolinium enhancement imaging.(9) Intramyocardial haemorrhage (IMH) can occur if coronary microvasculature injury is very severe after MI, with resultant damaged vessel integrity and extravasation of red blood cells.(11) Both MVO and IMH are associated with larger MI size, adverse LV remodelling and overall worse clinical outcomes.(12) In general, prognosis worsens with larger MI size, with patients also more likely to have MVO and IMH with larger MI size. Prognosis for STEMI patients with MVO is worse than those without MVO.(13) Prognosis is worst for patients with MVO and IMH.(11)

The area-at-risk (AAR) refers to the myocardial territory supplied by the infarct-related culprit artery that was at risk of infarction and would have infarcted if revascularisation and reperfusion had not taken place to salvage the viable myocardium. The myocardial salvage index (MSI) normalises MI size reduction to AAR and as such is a more sensitive marker compared with MI size alone to assess cardioprotective therapy efficacy.(14) Post-contrast T1-mapping has recently demonstrated promise as an alternative technique to gadolinium enhancement imaging in quantifying MI size.(15) T1-mapping has the potential to complement clinical and imaging parameters and biomarkers to optimise risk stratification in MI patients.(9) Oedema, assessed by CMR using T2-mapping, occurs both in the viable and non-viable myocardium during the first week of a reperfused STEMI in the clinical setting.(16–19) Oedema-based area-at-risk measured by CMR can be used to assess myocardial salvage in clinical cardioprotection studies but the appropriateness of this has been called into question.(9)

### *Basic concepts of machine learning in cardiovascular magnetic resonance imaging*

Important image characteristics or features such as image contrast, noise characteristics, texture and motion are highlighted as part of a designed feature set to create a ML model that is trained using data. The model training, e.g. for image segmentation problems, involves using a ML method that allows the model to learn and optimise the parameters of the mathematical model from a set of CMR studies with ground truth segmentations performed by the human expert. The trained model is then used to predict segmentations. The training algorithm extracts the parts of the data that are important for the prediction task and collates the information together to produce the prediction result. ML models can perform either classification or regression tasks. Classification tasks involve discrete labels such as determination of the presence or absence of disease. Regression tasks involve continuous variables such as quantifying the percentage of infarcted myocardium of patients with an acute MI. The training dataset should be sufficiently large with representative variability to optimise performance. A validation dataset is used to evaluate a model’s performance and prevent model overfitting.

It has been challenging to identify optimal discriminative features to create ML systems for a given task. In order to circumvent the need to design these discriminative features, DL methods can be applied that can learn directly (end-to-end learning) from the training dataset. In myocardial contouring for example, DL methods will learn the image features that are most useful for predicting myocardial contour locations. A specific type of DL network known as convolutional neural network (CNN) is often used in image analysis-associated tasks. A typical CNN is made up of multiple layers including convolution layers, pooling layers, fully connected layer, skip layers and softmax layer.(20) Deep CNNs are complex and can contain millions of weights, and although the features resulting from the intermediate layers contain information relevant to the task, it is often difficult to interpret how the predictions are actually made or why the network might have failed to make the accurate prediction.

Depending on the availability of reference labels in the training dataset, ML algorithms can be grouped into supervised versus unsupervised learning. In supervised learning, training data of varying pathological status are labelled by human domain experts. In unsupervised learning, hidden structures within the training data are discovered during training. There are different ML methods suited to the varying complexities of the image analysis task. Some of ML methods often encountered in AI literature include linear regression,(21) support vector machines (SVM),(22) decision trees,(23) boosting methods,(24) linear discriminant analysis(25) and ensemble method.(26) In linear discriminant analysis for instance, ML model parameters are estimated by assuming a simple functional relationship between the data and the labels to separate data into normal and abnormal categories. The training data is learned and fit to a hyperplane by optimising linear coefficients. However, in complex and multi-dimensional problems involving large amounts of data, more advanced techniques such as support vector machines, random forests (applied to T2 map quantification(27)) and DL CNNs are required.(20)

### *Applications of machine learning in myocardial infarction cardiovascular magnetic resonance imaging analysis*

#### Image segmentation

Manually contouring the borders of the cardiac chambers and myocardium, known as segmentation, is a time-consuming process. In addition, differences in analysis output may still exist between expert readers. In this regard, ML algorithms can help to automate image segmentation and increase productivity, accuracy and reproducibility. This can be achieved through pixel-wise classification or regression-based techniques. Schuster et al showed that fully automated volumetric analysis of MI CMR is feasible and can be equally predictive of major adverse cardiac events when compared with conventional volumetric analysis.(28)

#### Myocardial tissue characterisation

Scar volume from LGE CMR imaging is a prognostic quantitative imaging biomarker.(20) Manual delineation methods of scar volume currently used in routine clinical practice are subjective, time-consuming and labour-intensive. In addition, despite using current thresholding techniques for LGE quantification, accuracy and reproducibility is still affected by intercentre variations, gadolinium kinetics variations and scattered patterns of LGE

distribution.(20) A novel, ML-based approach to LGE has been proposed by Fahmy et al(29) using deep CNNs to automatically quantify LV mass and scar volume on LGE images in patients with hypertrophic cardiomyopathy. This could be further extrapolated to quantify infarct size in patients with MI. ML can also be applied to streamline data processing and analysis of cardiac relaxometry.

Infarct size/ late gadolinium enhancement

Chen et al proposed an automatic MI segmentation approach based on CNNs to analyse CMR LGE sequences.(30) Their proposal demonstrated promising segmentation results when compared to the intraobserver and interobserver variations in manual segmentation, and to automatic segmentation with Gaussian Mixture Model. Engan et al designed an experimental framework for data exploration which involved computing a very large number of features to describe the characteristics of the regions of interest in the images and found that the addition of texture analysis can improve the discriminative power of scarred and non-scarred myocardium to distinguish between patients with high and low risk of serious ventricular arrhythmias post MI.(31) Kotu et al used pixel intensity-based and underlying texture information-based features to define different cardiac segments such as core and border areas in scarred regions of MI.(32) In another study by Kotu et al, the segmentation of scarred and non-scarred myocardium in MI patients is obtained using different features and feature combinations in a Bayes classifier, with segmentation of scarred myocardium being comparable to manual segmentation in all crossvalidation cases.(33) Larroza et al aimed to differentiate acute from chronic MI using ML techniques and texture features extracted from CMR imaging scans and they were able to conclude that texture analysis can be used for differentiation of acute from chronic MI on LGE sequences, and standard cine sequences in which the infarction is visually imperceptible in most cases.(34) Baessler et al performed a proof-of-concept study whereby stepwise dimension reduction and texture feature selection were performed, enabling the diagnosis of MI on nonenhanced cine images by using LGE imaging as the standard of reference.(35) They showed that texture analysis is feasible and allows for the diagnosis of small and large subacute and chronic ischaemic scars on nonenhanced cine CMR images with high accuracy.(35) In another study by Larroza et al, texture analysis was used to differentiate between infarcted nonviable, viable, and remote segments in MI.(36) Zhang et al demonstrated the use of a DL framework on non-contrast cine CMR that can confirm, detect and delineate transmurality and size of chronic MI.(37) This has positive implications particularly for patients with renal impairment who may be precluded from receiving gadolinium contrast but may require myocardial viability assessment on CMR.

Microvascular obstruction/intramyocardial haemorrhage

In another study by Chen et al, they proposed ML-based models to automatically evaluate the severity of MI from physiological, clinical, and paraclinical features.(38) Two types of ML models were investigated for MI assessment: the classification models classify the presence of MI and persistent microvascular obstruction, and the regression models quantify the percentage of infarcted myocardium of patients suspected of having an acute MI in the emergency department.(38) The prediction accuracy for the classification of myocardial state and regression quantification of infarcted myocardium were encouraging. Rosa et al proposed a new automatic method for MI quantification from LGE sequences.(39) Their novel

segmentation approach was devised for accurately detecting hyperenhanced lesions and also MVO areas. It also included a myocardial disease detection step which extended the algorithm for working under healthy scans. Goldfarb et al sought to determine the feasibility and performance of CMR water–fat separation and parametric mapping via DL techniques and demonstrated that myocardial fat deposition in chronic MI and IMH in acute MI could be well visualised with DL strategies.(40)

T1 mapping

Farrag et al implemented a DL-based method for automated LV segmentation of T1 maps performed using a shortened modified Look-Locker imaging (shMOLLI) sequence by superimposing prior information from cine CMR images in patients with myocardial fibrosis secondary to MI.(41) This helps to circumvent the issue with delineating endocardial-blood pool borders that conventional algorithms face in myocardial segmentation of T1-mapping images due to low signal gradients at the endocardial-blood pool boundary. The accurate delineation of myocardial borders will enable quantification of myocardial fibrosis from native (non-contrast) T1 maps.

Myocardial perfusion

Perfusion mapping uses AI to provide rapid quantification of myocardial blood perfusion by CMR imaging. In turn, quantitative myocardial blood flow (MBF) provides important prognostic information in patients with suspected CAD in addition to traditional cardiovascular risk factors.(42) Knott et al(42) have shown that in patients with known or suspected CAD, reduced MBF and myocardial perfusion reserve measured automatically inline using AI quantification of CMR perfusion mapping provided robust and independent prediction of major adverse cardiovascular events.

Radiomics

The ability of ML techniques to handle high-dimensional data has led to the development of radiomics, a novel field in which digital medical images are converted into mineable high-dimensional data by extracting a large number of quantitative imaging features based on mathematical and statistical methods. Within the field of radiomics, texture analysis allow for segmentation, analysis and classification of medical images based on underlying tissue textures as opposed to pure visual image interpretation. The application of radiomics to myocardial tissue characterisation may deliver deeper insights into complex tissue changes in association with pathophysiology of cardiovascular disease.(20)

In the area of MI, radiomics and texture analysis have been applied to the segmentation of myocardial scar and the differentiation between acute and chronic MI. Besides MI, texture analysis and radiomics have also been applied to differentiate between causes of myocardial hypertrophy,(43) prognostication in hypertrophic cardiomyopathy patients with systolic dysfunction,(44) T1 mapping-guided discrimination between hypertensive heart disease and hypertrophic cardiomyopathy,(45) and in the assessment of myocardial inflammation.(46)

Rauseo et al(47) analysed CMR images from the UK Biobank including for patients with history of ischaemic heart disease (IHD) and MI for CMR radiomic signatures and found that shape radiomics such as maximum 2D diameter of the LV and myocardium, myocardial cavity volume and surface area to volume ratio were most relevant in IHD and MI, indicating

the tendency for IHD to result in LV geometry alterations. Avard et al used radiomics analysis and feature identification on non-contrast cine CMR images to accurately detect MI, thus presenting a potential alternative diagnostic method to LGE CMR for MI.(48) Ma et al have shown that combining radiomic signatures of non-contrast-enhanced T1 mapping and T1 values can provide higher diagnostic accuracy for MVO and radiomic signatures can also provide incremental value in predicting LV longitudinal systolic myocardial contractility at six months.(49)

Prognostication

ML is well-suited to handle large amounts of clinical information and to find intrinsic structure within this body of information to predict clinical outcomes.(20) Random survival forests technique has been used to identify the top predictors of each outcome measure in the Multi-Ethnic Study of Atherosclerosis (MESA), and CMR-derived LV structure and function were identified as one of the top predictors of incident heart failure.(50) Information maximising component analysis, a supervised feature extraction method, has been used to determine more efficient and sensitive indices of overall remodelling between patients with MI and asymptomatic volunteers from the MESA study.(51) Supervised ML of CMR imaging scans has been used to predict occurrence of cardiac arrhythmia in patients with MI from image-derived scar texture features, size and location of scar.(52)

### *Barriers to implementation*

One limitation of ML techniques is the black-box nature of DL algorithms, where it is often unclear what information is used or what interactions between nodes and layers have occurred to derive a certain successful or unsuccessful classification or result.(20) The lack of transparency and explainability could affect user trust which can restrict the use of AI in healthcare. ML models for CMR imaging analysis also need to be robust and portable between scanners, sequences, imaging parameters and centres.(20) Radiomic analysis in particular, is highly dependent on image acquisition parameters that can affect texture and histogram-based intensity values.(47) Heterogenous datasets from different centres should be evaluated to check the validity of proposed ML algorithms on a large scale.(47) Large, publicly available CMR datasets also need to be developed so that different algorithms can be objectively compared for their performance.(20)

### *Governance and quality control*

Open source publication of computational processes, codes and datasets can help to mitigate the unpredictable failures of ML algorithms that may occur.(20) Current ML and DL methods can be vulnerable to adversarial attacks that can influence results and render models unsafe for clinical use. To ensure top quality of labelled training data, ground truth must be rigorously reviewed, particularly in clinical reporting where clinicians from different centres may disagree in reporting style and findings.(20)

### *Future applications and directions*

Controlled trials are required to evaluate the application of ML methods across multiple centres and varied patient groups. Validation should be performed using data from the same cohort as well as from other cohorts at different centres and using different acquisition devices. For continued advancement of the field, algorithms should be published in open source repositories to enable cross-checking, benchmarking, replication and improvement by international groups. In addition, although large cohort data sets have been used for ML training, these applications must be extended with care to specific patient groups with various pathologies and with fair representation so that variations between age, sex and ethnicities can also be accounted for.(20)

### *Conclusion*

AI, ML and more specifically DL can improve efficiency, reproducibility, precision and accuracy in the assessment of important prognostic imaging biomarkers in MI CMR scans through the development of automated CMR analysis strategies. Global collaboration through open-source publication of codes and datasets will help to further advance the field and improve governance, safety and quality control through knowledge sharing. Future directions include the incorporation of automated analysis within clinical trials that assess clinical outcomes, and the extension of existing ML applications to heterogenous patient cohorts.

Declarations of interest

Steffen E Petersen (SEP) provides consultancy to Circle Cardiovascular Imaging Inc., Calgary, Alberta, Canada. All other authors declare no conflicts of interest.

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Table 1. Summary of studies utilising artificial intelligence-enabled analysis methods on cardiovascular magnetic resonance imaging scans of myocardial infarction.

| Research group | Year of publication | Imaging biomarker | Results | Machine learning method(s) |
|---|---|---|---|---|
| Schuster et al(28) | 2020 | Volumetric analysis and infarct size analysis | Fully automated volumetric analysis of MI CMR is feasible and can be equally predictive of major adverse cardiac events when compared | Use of AI-based software (Manufacturer's undisclosed DL-based model) |

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| | | | with conventional volumetric analysis | |
| Chen et al(30) | 2022 | MI segmentation | Demonstrated promising segmentation results when compared to the intraobserver and interobserver variations in manual segmentation, and to automatic segmentation with Gaussian Mixture Model. | CNNs (versus Gaussian Mixture Model) |
| Engan et al(31) | 2010 | Scarred and non-scarred myocardium | Addition of texture analysis can improve discriminative power of scarred and non-scarred myocardium to distinguish between patients with high and low risk of serious ventricular arrhythmias post-MI | Maximum likelihood estimation with Bayes classifiers |
| Kotu et al(32) | 2013 | Core and border areas in scarred regions of MI | Pixel intensity-based and underlying texture information-based features were used to define different cardiac segments such as core and border areas in scarred regions of MI. | Probability function based on Bayes rule |
| Kotu et al(33) | 2013 | Segmentation of scarred and non-scarred myocardium in MI | Segmentation of scarred and non-scarred myocardium in MI patients obtained using different features and feature combinations in a Bayes classifier, with segmentation of scarred myocardium being comparable to manual segmentation in all cross-validation cases | Maximum likelihood estimation with Bayes classifiers |
| Larroza et al(34) | 2017 | Texture features extracted from | Demonstrated that texture analysis can be used for differentiation of acute | Three ML methods: Random forest, support |

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| | | infarcted area on LGE CMR images, and the entire myocardium on cine CMR. | from chronic MI on LGE sequences and standard cine sequences | vector machine (SVM) with Gaussian Kernel, and SVM with polynomial kernel. |
| Baessler et al(35) | 2018 | Subacute and chronic ischaemic scar | Enabled the diagnosis of MI on nonenhanced cine images by using LGE imaging as the standard of reference. Method involved stepwise dimension reduction and texture feature selection | Multiple logistic regression models |
| Larroza et al(36) | 2018 | Infarcted nonviable, viable and remote segments | Texture analysis was used to differentiate between infarcted nonviable, viable, and remote segments in MI | SVM |
| Zhang et al(37) | 2019 | Transmurality and size of chronic MI | DL framework was used on non-contrast cine CMR to confirm, detect and delineate transmurality and size of chronic MI. Also uses computer vision dense (optical) flow method. | Three DL methods: CNN, long short-term memory (LSTM), and stacked auto-encoder |
| Chen et al(38) | 2022 | Presence of MI and MVO and quantification of infarcted myocardium | Prediction accuracy for the classification of myocardial state and regression quantification of infarcted myocardium were encouraging | Methods used for regression: linear regression, support vector regression, decision tree regression, random forest, multilayer perceptron, gradient boosting, XGBoost, light gradient boosting, and ensemble method.<br><br>Methods used for classification: |

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| | | | | random forests and SVM with linear kernel function. |
| Rosa et al(39) | 2021 | Hyperenhanced lesions and also MVO areas. | Novel segmentation approach was devised for accurately detecting hyperenhanced lesions and also MVO areas. Also uses computer vision Otsu's method for image processing. | CNN, principal component analysis, and SVM |
| Goldfarb et al(40) | 2019 | CMR water–fat separation and parametric mapping | Myocardial fat deposition in chronic MI and IMH in acute MI could be well visualised with DL strategies | CNN |
| Farrag et al(41) | 2019 | Automated LV segmentation of T1 maps | DL-based method implemented for automated LV segmentation of T1 maps performed using a shortened modified Look-Locker imaging (shMOLLI) sequence by superimposing prior information from cine CMR images in patients with myocardial fibrosis secondary to MI | Modality independent neighbourhood descriptor (MIND) |
| Knott et al(42) | 2020 | MBF and myocardial perfusion reserve | In patients with known or suspected CAD, reduced MBF and myocardial perfusion reserve measured automatically inline using AI quantification of CMR perfusion mapping provided robust and independent prediction of major adverse cardiovascular events | CNN |

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| Rauseo et al(47) | 2021 | Maximum 2D diameter of the LV and myocardium, myocardial cavity volume and surface area to volume ratio | Shape radiomics such as maximum 2D diameter of the LV and myocardium, myocardial cavity volume and surface area to volume ratio were most relevant in IHD and MI, indicating the tendency for IHD to result in LV geometry alterations | SVM and random forest (RF) |
| Avard et al(48) | 2022 | Radiomics analysis and feature identification on non-contrast cine CMR images to accurately detect MI | Radiomics analysis and feature identification was used to accurately detect MI in non-contrast cine CMR images, presenting a potential alternative diagnostic method to LGE CMR for MI | SVM, RF, Extra Tree, Logistic Regression, Linear Discriminant Analysis, Quadratic Discriminant Analysis, AdaBoost, k-nearest neighbor (k-NN), Naïve Bayes, Multilayer Perceptron |
| Ma et al(49) | 2021 | Radiomic signatures of non-contrast-enhanced T1 mapping and T1 values | Combining radiomic signatures of non-contrast-enhanced T1 mapping and T1 values can provide higher diagnostic accuracy for MVO and radiomic signatures can also provide incremental value in predicting LV longitudinal systolic myocardial contractility at six months | LASSO regression analysis |
| Zhang et al(51) | 2015 | LV remodelling index post-MI | IMCA enables better characterisation of global remodelling than linear discriminant analysis, and can be used to quantify progression of disease and the effect of treatment | Linear discriminant analysis, principal component analysis, and information maximising component analysis (i.e. Information preserving |

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| | | | | component analysis)(53) |
| Kotu et al(52) | 2015 | Size, location, and textural information concerning the scarred myocardium | Texture features based on scar gradient and local binary patterns along with localisation features demonstrated good discriminative power when distinguishing low-risk versus high-risk patients for developing arrhythmias post-MI | k-NN and SVM |

Table legend: MI – myocardial infarction; CMR – cardiovascular magnetic resonance; AI – artificial intelligence; CNN – convolutional neural network; LGE – late gadolinium enhancement; DL – deep learning; MVO – microvascular obstruction; ML – machine learning; IMH – intramyocardial haemorrhage; LV – left ventricle; MBF – myocardial blood flow; CAD – coronary artery disease; IHD – ischaemic heart disease; IMCA - information maximising component analysis.

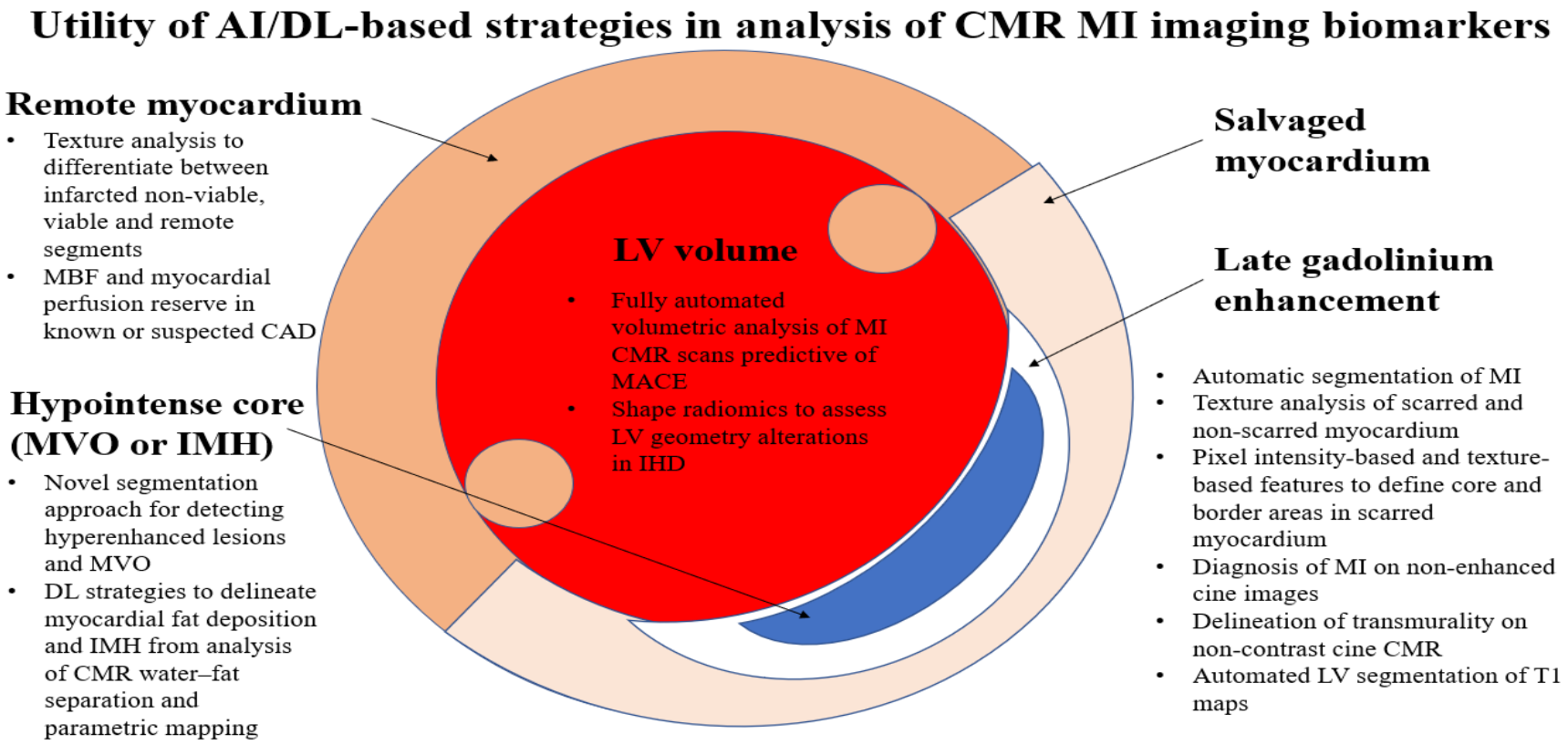


Figure 1. Utility of artificial intelligence/deep learning-based strategies in analysis of cardiovascular magnetic resonance myocardial infarction imaging biomarkers

Figure legend: MI – myocardial infarction; CMR – cardiovascular magnetic resonance; AI – artificial intelligence; DL – deep learning; MVO – microvascular obstruction; ML – machine learning; IMH – intramyocardial haemorrhage; LV – left ventricle; MBF – myocardial blood flow; CAD – coronary artery disease; IHD – ischaemic heart disease; MACE – major adverse cardiovascular events; IHD – ischaemic heart disease.