DeepMI: Deep Multi-lead ECG Fusion for Identifying Myocardial Infarction and its Occurrence-time

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Abstract—Myocardial Infarction (MI) has the highest mortality of all cardiovascular diseases (CVDs). Detection of MI and information regarding its occurrence-time in particular, would enable timely interventions that may improve patient outcomes, thereby reducing the global rise in CVD deaths. Electrocardiogram (ECG) recordings are currently used to screen MI patients. However, manual inspection of ECGs is time-consuming and prone to subjective bias. Machine learning methods have been adopted for automated ECG diagnosis, but most approaches require extraction of ECG beats or consider leads independently of one another. We propose an end-to-end deep learning approach, DeepMI, to classify MI from normal cases as well as identifying the time-occurrence of MI (defined as acute, recent and old), using a collection of fusion strategies on 12 ECG leads at data-, feature-, and decision-level. In order to minimise computational overhead, we employ transfer learning using existing computer vision networks. Moreover, we use recurrent neural networks to encode the longitudinal information inherent in ECGs. We validated DeepMI on a dataset collected from 17,381 patients, in which over 323,000 samples were extracted per ECG lead. We were able to classify normal cases as well as acute, recent and old onset cases of MI, with AUROCs of 96.7%, 82.9%, 68.6% and 73.8%, respectively. We have demonstrated a multi-lead fusion approach to detect the presence and occurrence-time of MI. Our end-to-end framework provides flexibility for different levels of multi-lead ECG fusion and performs feature extraction via transfer learning.

Index Terms—Transfer Learning, Cardiovascular Disease, Deep Learning, Health Informatics

I. INTRODUCTION

Cause of death globally, and four out of five CVD deaths are due to heart attacks (i.e., myocardial Infarction) and strokes [1]. Traditional diagnosis of heart attack mainly employ interpretation of ECG recordings, which requires precise acquisition devices and highly trained clinicians (i.e., cardiologists), both of which are in limited supply in resource-constrained areas. Cardiologists visually inspect the conventional 12-lead ECG waveforms as images when making diagnosis. However, such a process is tedious and can be highly subjective [2]. ECG readings are also sensitive to mounting position and prone to movement artefacts [3], resulting in noisy readings that add to the difficultly of making reliable diagnoses from them. This problem becomes more visible in low-resource

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settings where there is no/limited cardiologists. Numerous studies have also shown that it is not always possible to detect cardiovascular abnormalities from a visual inspection of the ECG trace alone, given the small amplitude and short PQRST durations involved [4]. In this context, computer aided diagnosis methods present a promising solution to the problem of analysing and identifying CVDs from ECG readings.

Automatic approaches using computer algorithms have been proposed to extract domain-specific handcrafted ECG features both in time- and frequency-domains for heart disease diagnosis [5]-[8]. (Compared to automatically learned features), Though handcrafted features, such as identifying complexes in the ECG trace, are simple and tractable, they might be susceptible to noise/motion artefacts and do not generalise across variations in patient characteristics, mounting positions and device specifications. Moreover, these approaches often require extensive pre-processing steps that are prone to error. Feature engineering also requires careful consideration and is associated with a time-consuming and labour-intensive model development process. By contrast, end-to-end deep learning methods can eliminate the need for explicit feature engineering, by learning optimal representations directly from the raw data for the task at hand. Additionally, there are currently no studies that have investigated the prediction of occurrencetime in MI (i.e., the age of a MI), information that is crucial for preoperative risk assessment [9]: patients with acute (i.e., within seven days) and recent (i.e., less than 30 days but longer than seven days) MIs are considered to be at higher risk of a perioperative cardiac event, while those with old MIs (i.e., more than 30 days) are at higher risk of perioperative cardiac morbidity. Such systems become handy, again, in low-resource settings, where there is no patient data archival practice; or in emergencies when a patient history might not be available on the spot.

In this paper, we present an end-to-end deep learning system for predicting the occurrence time of MI using 12-lead ECG waveforms (see Fig. 1). The contributions of the proposed approach are as follows: 1) spectral-based preprocessing that transforms time-series waveforms to spectrogram representations, which offer a more general representation that overcome issues of variability in sampling rates and device specifications across ECG manufactures; 2) application of cross-domain transfer learning between natural images classification and ECG waveform detection, to extract spectral features to reduce the dimension of the spectrograms and minimise redundant

information; 3) ultilising joint spectral-temporal modelling to encode the spatial and temporal information from multichannel ECG waveforms; 4) proposing the use of a variety of fusion approaches to combine information at different levels of data representation (i.e., data, feature and decision level fusions) aiming to utilise distinctive characteristics offered by each ECG lead; and 5) predicting the occurrence time of MI, utilising a large scale dataset containing > 15,000 patients and > 323,000 data samples, to provide timely intervention that can potentially improve patient outcomes.

The paper is organised as follows: Section II surveys the research literature on the topic of automated ECG analysis for CVD diagnosis, with a focus on MI detection. Section III presents the proposed framework, including different multilead fusion strategies and diagnosis modelling techniques. Section IV details the experimental setup including descriptions of the dataset used for validation, the set up of network architectures and parameters in the proposed approach, in addition to methods considered for comparison. Section V presents results and discusses important findings, whilst concluding remarks are provided in Section VI.

II. RELATED WORK

The potential diagnostic value provided by ECG signals, particularly for the diagnosis of CVDs such as MI, has long been recognised by researchers [4]. To date, the majority of automated methods proposed for detecting MI from ECG traces, have focused on identifying abnormalities in the morphology of the signals. These approaches often entail error-prone preprocessing steps, such as identifying ECG complexes and handcrafting features to learn from (e.g. [10]). The latter requires careful consideration and is associated with a time-consuming and laborious model development process. Deep learning methods by contrast, remove the need for feature engineering through their ability to automatically learn optimal representations directly from the raw data.

Given the success of deep learning in a wide range of application domains, a growing number of studies have investigated the use of end-to-end deep networks for ECG based CVD detection [11]–[20]. The most widely employed and often best performing architectures have been CNNs, e.g. [12], [15], [19], [20]. A smaller number of these studies considered RNNs [18], [21], whilst [17], [21] demonstrated that a cascaded CNN-LSTM model architecture achieved superior performance to either individual model architectures on their own. This provides supporting evidence to the broad fact that capturing local and more long-term temporal characteristics of ECG signals through joint modelling, as we consider in this study, is well motivated

Whilst deep learning methods have the potential to achieve state-of-the-art performance, this often entails a lengthy training and laborious model development process, requiring copious amounts of training data. This is particularly true when proposing sophisticated architectures from scratch, which contain many parameters that must be learnt. To overcome these challenges in data and labour requirements, transfer learning can be exploited. Transfer learning aims to leverage models

that are pre-trained, namely models that have been carefully developed for a different task and/or on a different dataset. For the task of CVD detection using ECGs, the works of [14], [22] showed the effectiveness of cross-domain transfer learning through their use of Google's Inception image recognition model [23]. In these works, raw ECG signal traces were treated as images to be analysed by the network, thereby directly emulating the analysis cardiologists perform. Our work differs from these, and other similar studies, in that we first map 1D ECG signals to 2D spectrogram representations, before treating the latter as an image to be analysed by a pretrained computer vision network through transfer learning. We consider the spectrogram representation as input, rather than the image of the ECG signal itself, as the former allows spectral time-varying information present in the signal to be better visualised. Thereby potentially enabling more clinically relevant information for diagnosis to be captured and learnt by an ML model. In previous work by the authors, we have shown the effectiveness of spectrogram image representations of physiological signals, such as PPG, for ML based disease diagnosis [24], [25].

More recently, the following are examples of studies that have employed end-to-end deep learning approaches for ECG based MI detection specifically [12], [13], [15], [19]-[21]. For the majority of these works, MI detection was framed solely as a binary classification problem (non-MI or MI), whilst in others MI localisation was the focus through a multiclass problem formulation. The latter concerned identifying different MI types characterised by the location of the blocked artery (e.g. posterior lateral MI), as an example, 10-classes of MI location are predicted in the work of [19]. The utility of discriminating between such MI types is clear, however prediction of MI by time-onset, as we propose in this work, has not yet been researched. Characterising MI diagnosis by estimated occurrence time has clear practical implications, as early detection of MI would enable proactive care management and intervention strategies to be enacted.

Published research in CVD detection from ECG signals, has primarily restricted itself to using a single lead [11], [12]. In the studies where multiple ECG leads were considered, individual models were developed and evaluated for each lead separately [19], that is without any data or result fusion, strategies we investigate extensively in this work. Whilst the use of 12 leads ECG may usually be limited outside clinical settings, and single lead analysis is advantageous in certain contexts (for example remote monitoring of patients), the work of [26] highlights the prevalence and seriousness of inhospital MI. In these contexts, patients can be consistently and conveniently monitored using the standard and inexpensive 12 lead ECG setup, which clinicians use in their entirety to make diagnoses. Importantly, research has shown that different ECG traces contain different predictive importance for MI diagnosis [15], highlighting the value of considering multiple lead fusion for CVD prediction in general [15], [17], [27], [28].

Research methods proposed to date for automatic CVD detection, have primarily developed and evaluated their methods on the open-source PhysioBank Physikalisch-Technische Bundesanstalt (PTB) ECG dataset [29], or on proprietary datasets

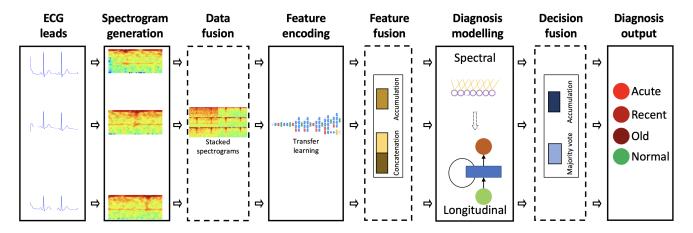


Fig. 1. Overview of the proposed framework: multi-lead ECG waveforms are provided as input, and spectrogram generation is used to encode the frequency-time characteristics. Transfer learning is applied to encode deep features using existing computer vision networks. Spectral and temporal models were employed for diagnosis modelling.

(e.g. [17]). High performance achieved on the detection of MI or MI types in the PTB dataset, may indicate that to assess the generalisability of developed methods, validation on new datasets is vital. To date, studies that have employed alternative datasets have often been small. For example in [17] models were trained on ECG records 10 seconds long from 362 patients with cardiovascular abnormalities. By contrast, we have developed our models using a dataset with over 17,000 patients and 323,000 ECG sample measurements, which is an order of magnitude higher than those used in the literature. Moreover, the dataset used in this work contain additional labels regarding the eventual time occurrence of MI, allowing us to investigate the possibility of predicting time-onset of heart attack from ECG readings alone.

III. PROPOSED FRAMEWORK: DEEPMI

In this section, we outline the system aspects of the proposed framework for identifying MI and its occurrence time.

A. Overview

Figure 1 shows the overview of our proposed approach. Given a dataset, \mathcal{D} , which contains η patients diagnosed for MI, i.e., $\mathcal{D} = \{S_i\}_{i=1}^{\eta}$, where S_i represents the i^{th} patient represented by 12 ECG leads, $\mathcal{S}_i = \{\mathbf{l}_i^j\}, j \in$ $[I, II, III, aVR, aVL, aVF, V_1, V_2, V_3, V_4, V_5, V_6]$. Each patient is diagnosed and the onset time of MI cases is determined clinically. Thus, the ground truth of S_i is $g_i \in$ {acute, recent, old, normal}. Thus, our approach focuses on predicting the diagnose label using an end-to-end trainable framework designed to operate with limited training data and in low computational resource settings. To this end, we, first, extract the frequency-time characteristics, i.e., spectrogram, of the ECG waveforms. Then feature encoding is done on these spectrograms via transfer learning using pre-trained computer vision networks. Diagnosis modelling is performed with spectral and longitudinal models, which encodes spatial and temporal information, respectively. To integrate information from different ECG leads, we employ different fusion

techniques. Next we describe the details of each step in the proposed framework.

Given the raw ECG waveforms, a preprocesing is applied to clean up the data, which includes filtering of patients with erratic ECG readings in one or more of the ECG leads. Particularly, missing readings which could occur due to loose mounting of the electrodes during ECG acquisition. To discard some of the noise/motion artefacts, often characterized by low and high frequency characteristics, we employed a band-pass filter (a high pass filter followed by a Gaussian filter) on all ECG recordings. Other pre-processing steps include the subsequent sampling of ECG windows per lead, i.e., $\mathbf{l}_i^j = [\mathbf{w}_{in}^j]_{n=1}^{\gamma}$, where \mathbf{w}_{in}^j represents the n^{th} window segmented from the j^{th} lead of the i^{th} patient and γ is the total number of windows from a patient lead, \mathbf{l}_i^j .

B. Spectrogram generation

Rather than using the raw ECG time-series to encode features for the MI diagnosis, the proposed framework employs a frequency-time (spectrogram) representation that captures the time-varying characteristics of the waveforms, and it is also robust across variations in device specifications such as sampling rate [30]. The spectrogram generation is computed from each \mathbf{w}_{in}^j by applying a Fourier transform, that results in a 2D frequency-time representation F_{in}^j . The subscript i is dropped henceforth to improve readability. We also normalise spectrograms by their maximum value, followed by a logarithmic scale to smooth the representation as

$$\hat{F}_n^j = \log\left(\frac{F_n^j}{max(F_n^j)} * 255\right). \tag{1}$$

The smoothed \hat{F}_n^j is then saved as image using the JPEG image format so that it resembles natural images for the transfer learning step. While other colormaps could also be used, we employed the 'viridis' colormap to convert the spectrogram array to an image after normalization in Eq. (1). The JPEG format is selected due to its efficiency but other formats could also be used.

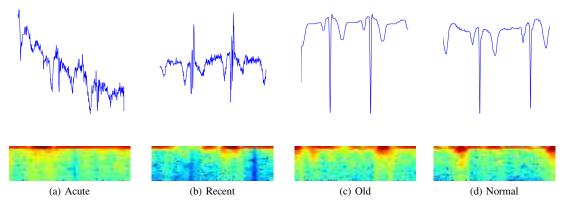


Fig. 2. Examples of ECG waveforms (top row) and their corresponding spectrograms (bottom row) from an aVR lead for a patient randomly selected from each class. Note: only 2-seconds duration of each waveform is shown to allow detailed visualisation of the patterns.

C. Feature encoding

The spectrogram generation provides an image-like representation that suits convolution-based deep learning encoding. However, designing a dedicated deep network and encoding features by training it from scratch poses an enormous training data requirement, computational resources to train and a prolonged hyper-parameter tuning process. As a result, we opt to utilise existing computer vision networks, such as GoogLeNet [23] and MnasNet [31], to encode features via a transfer learning approach. Thus, a hidden layer of these existing CNNs could be extracted from each normalised spectrogram input, \hat{F}_n , resulting a high-dimensional feature vector, $\mathbf{d}_n \in \mathbb{R}^{\tau}$. The use of such cross-domain learning exploits powerful existing architectures and relaxes the training data requirement.

D. Multi-lead fusion

The proposed framework offers a variety of fusion techniques to utilise the discriminant characteristics offered by the conventional 12 ECG leads [15]. To this end, *data*, *feature* and *decision* fusions are experimented with, details of which are provided below.

1) Data fusion: The spectrograms from different ECG leads are fused together at data level in spectrograms. the stacked Given of normalised spectrograms of the leads, $\{F_n^j\}$ $[I, II, III, aVR, aVL, aVF, V_1, V_2, V_3, V_4, V_5, V_6],$ the data fusion is applied as in Equation (2), which mimics the visualisation of the ECG leads by cardiologists in clinical practice [24]. This results in a stacked spectrogram, Φ_n , as the output of the data fusion.

$$\Phi_n = \begin{bmatrix} \hat{F}_n^I, & \hat{F}_n^{aVR}, & \hat{F}_n^{V1}, & \hat{F}_n^{V4} \\ \hat{F}_n^{II}, & \hat{F}_n^{aVL}, & \hat{F}_n^{V2}, & \hat{F}_n^{V5} \\ \hat{F}_n^{III}, & \hat{F}_n^{aVF}, & \hat{F}_n^{V3}, & \hat{F}_n^{V6} \end{bmatrix}.$$
(2)

In case of data fusion, transfer learning is applied to encode a single deep feature vector, \mathbf{d}_n , from the stacked spectrogram, Φ_n .

2) Feature Fusion: Another information fusion strategy from the multiple ECG leads could be implemented at the feature level. Namely, after deep features are extracted from the spectrogram of each lead, i.e., \mathbf{d}_n^j for $j \in [I, II, III, aVR, aVL, aVF, V_1, V_2, V_3, V_4, V_5, V_6],$ where each \mathbf{d}_n^j is extracted from the corresponding F_n^j . We have experimented with two feature fusion approaches: concatenation and accumulation. Concatenation refers to the stacking of the feature vectors to a single vector, i.e. the input to the modelling step becomes $\bar{\mathbf{d}}_n = \mathcal{C}(\mathbf{d}_n^j)$, where $\mathcal{C}(\cdot)$ represents the concatenation operation and, as a result, $\bar{\mathbf{d}}_n \in \mathcal{R}^{N_l \times \tau}$, where N_l represents the number of leads (i.e., $N_l = 12$) and τ represents the dimension of each \mathbf{d}_n^j . On the other hand, accumulation-based feature fusion, $A(\cdot)$, results in $\mathbf{d}_n \in \mathcal{R}^{\tau}$, with equal dimension as the individual feature vectors due to the accumulation operation being defined as:

$$\hat{\mathbf{d}}_n = \mathcal{A}(\mathbf{d}_n^j) = \frac{\sum_{l=1}^{N_l} \mathbf{d}_n^j}{N_l}.$$
 (3)

3) Decision Fusion: Decision fusion aims to exploit the distinctiveness in each lead by training a specific diagnosis model for each lead, after which the final output is obtained from the fusion of predictions from these lead-specific models. Given 12-lead ECGs, the diagnosis prediction specific to each lead results in $\mathbf{p}_n^j \in \mathbb{R}^{N_d}$, where N_d is the number of diagnosis classes. To obtain the final prediction output from these different lead models, we propose two different decision fusion techniques: accumulation and majority vote. Decision accumulation is applied similarly to feature fusion as in Equation (3) and the average of lead-specific prediction \mathbf{p}_n^j is computed. Majority vote, on the other hand, selects the most frequently predicted diagnosis class, across the different model leads, as the final predicted diagnosis.

E. Diagnosis modelling

After deep features are obtained in the transfer learning module, three diagnosis modelling techniques are developed in the proposed framework: *spectral* and *longitudinal* and joint *spectral-longitudinal*. These techniques are described more detail below.

1) Spectral modelling: This modelling approach only uses the spectral information, encoded as deep features, for diagnosis modelling. To do so, a dense layer is applied that takes the deep feature vector as input; which means \mathbf{d}_n during data fusion, $\bar{\mathbf{d}}_n$ during concatenated feature fusion, $\hat{\mathbf{d}}_n$ during accumulated feature fusion and \mathbf{d}_n^j during decision fusion. The output of the dense layer is $\mathbf{r}_n \in \mathbb{R}^{\kappa}$, where κ is the dimension of the dense layer. The dense layer helps to refine the spectral features and reduce the feature dimension (since $\kappa < \tau$) as

$$\mathbf{r}_n = \sigma(W_{rd}\mathbf{d}_n + \mathbf{b}_r),\tag{4}$$

where σ is a non-linear activation function, $W_{rd} \in \mathbb{R}^{\kappa \times \tau}$ is the weight matrix linking the deep feature vector and the dense layer, and \mathbf{b} is the bias vector. Note that during feature concatenation, τ becomes $N_l = 12$ longer. The prediction vector for the MI diagnosis, \mathbf{p}_n , is obtained by applying a softmax function on the dense layer output, \mathbf{r}_n , as

$$\mathbf{p}_n = \frac{e^{W_{sr}\mathbf{r}_n}}{e^{W_{sr}\mathbf{r}_n} + 1},\tag{5}$$

where $W_{sr} \in \mathbb{R}^{N_c \times \kappa}$ is the weight matrix linking the dense layer and diagnosis classes and N_c is the number of class labels. The diagnosis class corresponding to the index of the highest element in the prediction vector, \mathbf{p}_n , becomes the final prediction output by the proposed framework.

2) Longitudinal modelling: The spectral modelling above only encodes the spectral information in each sample window, \mathbf{w}_n , segmented from a long ECG waveform. However, subsequent samples possess temporal dependency as γ samples were segmented from each ECG lead. We propose a recurrent neural network to exploit these long-term temporal dynamics. Long short-term memory (LSTM) networks are designed to encode temporal dependency, and they handle the vanishing and exploding gradient problems better than the vanilla recurrent neural networks (RNNs) via their input, output and forget gates that act as switches to control memory information about the past.

Given the previous cell information, \mathbf{c}_{n-1} , the output gate, \mathbf{o}_n , the forget gate, \mathbf{f}_n , the candidate cell information, $\bar{\mathbf{c}}_n$, and input gate, \mathbf{i}_n ; the current LSTM hidden state, \mathbf{h}_n , can be computed as

$$\mathbf{h}_n = \mathbf{o}_n \odot \phi(\mathbf{f}_n \odot \mathbf{c}_{n-1} + \mathbf{i}_n \odot \bar{\mathbf{c}}_n) , \qquad (6)$$

where \odot is an element-wise multiplication and ϕ is a tanh activation function. The dimension of \mathbf{i}_n , \mathbf{h}_n , \mathbf{c}_{n-1} , \mathbf{c}_n , \mathbf{o}_n and $\bar{\mathbf{c}}_n$ is \mathbb{R}^{ν} , which is the number of neurons in the LSTM layer. Note that when only the longitudinal model is used, its input is the high dimensional deep features. Finally, a softmax function similarly to Equation (5) is applied on \mathbf{h}_n to obtain the MI diagnosis prediction, \mathbf{p}_n , using the longitudinal model.

3) Spectral-longitudinal modelling: Separate use of the spectral and longitudinal modelling approaches have the following limitations. The spectral model fails to encode the long-term temporal dependency existing between subsequent samples segmented from long duration ECG waveforms. On the other hand, the longitudinal model takes as input the high dimensional deep features (τ during data, feature accumulation and decision fusion, 12τ during feature concatenation)

obtained from the transfer learning step, which might result in overfitting due to the curse of dimensionality, especially when feature concatenation is used. We therefore propose a joint spectral-longitudinal model to address these limitations and utilise the advantages offered by both models, i.e. refinement of deep features and dimensionality reduction by the dense layer of the spectral model and the temporal encoding using LSTM in the longitudinal model. Thus, the output of the dense layer in the spectral model, \mathbf{r}_n , is used as input to the longitudinal model. As a result, the hidden state, \mathbf{h}_n , in the longitudinal model encodes the temporal dependency among subsequent \mathbf{r}_n . Finally, the softmax layer is used to predict the MI diagnosis, \mathbf{p}_n , similarly to Equation (5).

IV. EXPERIMENTAL SETUP

In this section, we describe details of the dataset used for development and validation of onset time prediction, the set up associated with the different stages of the proposed framework. Namely, spectrogram generation, transfer learning, spectral and longitudinal model architectures and their corresponding hyper-parameters. We also describe the variety of methods used for comparative purposes.

A. Dataset

The ECGs from 17,381 patients (11,853 MI and 5,528 Normal cases) were collected in the Provincial Key Laboratory of Coronary Heart Disease, Guangdong Cardiovascular Institute (GCI), which is located in Guangdong province, China. The study has obtained ethics committee approval and informed patient consent. Each 12-lead ECG waveforms was anonymised, sampled at 500 Hz and was 10 s long. The ECG signals for each patient contain the standard 12 leads, which are I, II, III, V1, V2, V3, V4, V5, V6, aVF, aVL, and aVR. Cardiologists annotated the MI cases furthermore into three sub-groups: Acute, Recent and Old based on hospital records like patient history, in combination with ECGs. The final GCI dataset resulted 1,489 Acute (MI occurred within 7 days), 5,377 Recent (MI occurred in less than 30 days but longer than 7 days) and 4,613 Old (MI occurred beyond 30 days) MI cases.

B. Parameter Setup

We set the duration of a sample, \mathbf{w}_n , to 1 s in order to achieve a balance between longer duration (which might have some degree of redundancy and also reduce the number of training samples) and shorter duration (which might lack enough information to do inference). We applied an overlapping percentage of 50%, between subsequent samples, which results a total of 323, 133 samples from each lead, of which: 28, 291 are Acute, 102, 163 are Recent, 87,647 are Old, and the remaining 105,032 are Normal samples. In the spectrogram generation step, we applied a Fourier transform, with a chunk of 0.1 s and an overlapping percentage of 90%, which results in a spectrogram representation with 91×26 resolution when stored as an image in JPEG format.

TABLE I

THE DESCRIPTIONS OF METHODS EMPLOYED AND COMPARED AGAINST EACH OTHER IN THIS STUDY. DIFFERENT FUSION TECHNIQUES, SUCH AS *Data*, *Feature* AND *Decision* WERE EXPERIMENTED. DATA FUSION INVOLVES STACKING OF THE SPECTROGRAMS FROM DIFFERENT LEADS; FEATURE FUSION REFERS TO THE AGGREGATION OF FEATURES EXTRACTED FROM MULTIPLE LEADS. DECISION FUSION REFERS TO THE AGGREGATION OF DECISIONS FROM DIFFERENT ECG LEADS. TWO TYPES OF MODELLING WERE ALSO EMPLOYED: *Spectral* AND *Longitudinal* THAT ENCODE SPATIAL AND TEMPORAL INFORMATION, RESPECTIVELY.

Method	Description
Data-Dense	Data fusion and spectral modelling using dense layers
Data-LSTM	Data fusion and longitudinal modelling using LSTM
Data-Dense-LSTM	Data fusion and spectral modelling using dense layers and longitudinal modelling using LSTM
Accumulation-Feature-Dense	Accumulation-based feature fusion and spectral modelling using dense layers
Accumulation-Feature-LSTM	Accumulation-based feature fusion and longitudinal modelling using LSTM
Accumulation-Feature-Dense-LSTM	Accumulation-based feature fusion and spectral modelling using dense layers and longitudinal modelling using LSTM
Concatenation-Feature-Dense	Concatenation-based feature fusion and spectral modelling using dense layers
Concatenation-Feature-LSTM	Concatenation-based feature fusion and longitudinal modelling using LSTM
Concatenation-Feature-Dense-LSTM	Concatenation-based feature fusion and spectral modelling using dense layers and longitudinal modelling using LSTM
Vote-Decision-Dense	Spectral modelling using dense layers and majority vote-based decision fusion
Vote-Decision-LSTM	Longitudinal modelling using LSTM and majority vote-based decision fusion
Vote-Decision-Dense-LSTM	Spectral modelling using dense layers, longitudinal modelling using LSTM, and majority vote-based decision fusion
Accumulation-Decision-Dense	Spectral modelling using dense layers and accumulation-based decision fusion
Accumulation-Decision-LSTM	Longitudinal modelling using LSTM and accumulation-based decision fusion
Accumulation-Decision-Dense-LSTM	Spectral modelling using dense layers, longitudinal modelling using LSTM, and accumulation-based decision fusion

Among existing computer vision networks, we experimented with GoogLeNet's Inception-v3 [23] and Mnas-Net [31] networks that are trained on natural images from ImageNet [32]. GoogLeNet is known to be quite robust due to its novel inception module and the fact that it has been validated across multiple domains. MnasNet, on the other hand, is considered a mobile computing friendly architecture, designed with limited resource settings in mind. Thus, we extract deep features from the penultimate layers of these networks using the spectrograms as input, resulting $\tau = 2,048$ and $\tau = 1,056$ dimensional deep feature vectors from the Inception-V3 and MnasNet networks, respectively. After deep feature encoding using transfer learning, the spectral model employs a fully-connected dense layer with a dimension of $\kappa = 16$ neurons with a ReLu activation. We have aimed for an LSTM network which is simple and consists of a single layer of size $\nu = 16$. The number of time steps in the LSTM is set to $\gamma = 19$ samples. Finally, the softmax layer consists a fully connected layer of size $N_c = 4$, which is equal to the number of diagnosis classes. During training a sparse-softmaxcross-entropy loss function is used with Adam optimiser and a learning rate of 0.01.

Both the GGH and PTB datasets used for the validation of the proposed framework exhibit imbalance of samples among classes. Though the number of MI cases is significantly higher than normal cases in GGH, the imbalance becomes smaller in the 4-class classification task OF MI onset detection since the MI cases further decomposed into Acute, Recent and Old classes. Considering the imbalance issue, we adopt the following strategies in our validation: a) we employ stratified cross-validation in our training; b) every batch is designed to contain proportional number of samples from each class; c) sparse-softmax-cross-entropy is applied as our loss function that weighs the loss accordingly; d) Area under receiver operating characteristic (AUROC) is applied as the main metric to compute the classification performance, as this metric better handles the potential class imbalances. AUROC for each class is obtained using a one-vs-all strategy, and overall AUROC

is computed from the average of AUROCs of all the four classes. We also employed accuracy, precision, sensitivity, specificity and F-score to evaluate MI detection performance. The confusion matrices are also provided to obtain more insights on the potential misclassification errors among the classes.

The proposed framework consists of a variety of fusion techniques (data, feature and decision) and modelling approaches (spectral, longitudinal and spectral-longitudinal). These were experimented with for every possible combination of fusion and modelling approaches. A summary of these methods is provided in Table I.

V. RESULTS AND DISCUSSION

In this section, we present the results obtained for the classification of MI cases from normal cases as well as the prediction of the onset time of MI (i.e. acute, recent and old), which was generally treated as a four-class classification problem. We also performed the comparison of the proposed framework with existing features and classifiers.

A. MI Detection

We first evaluated the performance of our proposed approach to detect MI cases from Normal cases using MnasNet features on the GGH dataset. To this end, Spectral, Longitudinal and Joint Spectral-Longitudinal models were evaluated on the stacked spectrogram (data-fusion) of multiple ECG leads. The results are shown in Table II, where an AUROC value of 85.2% is achieved using the Joint Spectral-Longitudinal model, higher than the independent performance of the Spectral and Longitudinal models.

B. Onset Time Detection of MI

Table III shows the AUROC (%) values per each diagnosis class across different fusion approaches: data, feature and decision. Overall, feature fusion was shown to outperform the other fusion approaches as the majority of the classes achieved

TABLE II

Performance of the proposed framework validated to detect MI cases from Normal Patients in the GGH dataset. Acc.: Accuracy, Pre.: Precision, Sen: Sensitivity, Spe.: Specificity, F: F_1 -score

Performance metrics (%)						
Methods	Acc.	Pre.	Sen.	Spe.	F	AUROC
Spectral	70.3	86.7	66.8	77.8	75.5	80.6
Longitudinal	73.2	83.9	75.3	68.6	79.4	79.8
Spectral-longitudinal	72.5	89.8	67.6	83.3	77.1	85.2

their highest performance through feature fusion approaches. Using GoogLeNet features (top half of Table III the following highest AUROC values are reported for the classes: Acute (82.9% using Concatenation-Feature-Dense-LSTM), Normal (96.9% using Concatenation-Feature-LSTM) and Old (87.4%) using Concatenation-Feature-Dense-LSTM). Using MnasNet features (bottom half of Table III), all the four diagnosis classes achieved their highest AUROC values using feature fusion approaches, i.e., Acute (81.5\% using Concatenation-Feature-LSTM), Recent (73.1% using Concatenation-Feature-LSTM)), Normal (98.2% using Concatenation-Feature-Dense-LSTM) and Old (75.1% using Concatenation-Feature-Dense-LSTM). Results suggest that Normal cases are, as expected, easier to detect compared to MI cases. On the other hand, MI cases are shown to be challenging to classify, particularly Recent cases as they are prone to being misclassified between the two extremes: Recent and Old. The results reported with MnasNet features in the bottom part of Table III are particularly encouraging, as competitive performance is achieved with GoogLeNet features. The MnasNet framework is relatively simple compared to GoogLeNet, with the lower dimensionality of MnasNet features ($\tau = 1,056$) proving to be an effective representation, particularly as input for the longitudinal models which otherwise were prone to overfitting using the $\tau = 2,048$ -dimensional GoogleNet features. This is shown by the fact that the two MI cases achieved the best performance with the Concatenation-Feature-LSTM method using MnasNet features.

Generally, the superior performance obtained using feature fusion approaches reflects the unique discriminative characteristics of each ECG lead, which need to be exploited during modelling rather than merging early before modelling using data fusion or lately using decision fusion after modelling. Comparison between two feature fusion techniques: accumulation and concatenation, reveals both are effective but concatenation is superior as the information corresponding to the distinctiveness of each lead is fed into the model while accumulation might lose this information. Although it is the simplest and least resource demanding, data fusion is shown to be the worst performing fusion technique, undoubtedly as the discriminative characteristics of the leads is lost too early before feature encoding.

The overall results shown in Table III provide further insights into the effectiveness of the proposed joint spectral-longitudinal modelling approach across the majority of the fusion techniques. The average AUROC performance show that joint spectral-longitudinal modelling achieved the high-

TABLE III

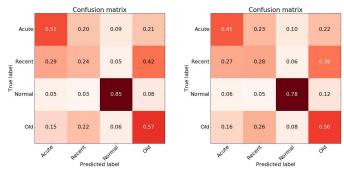
PERFORMANCE OF DATA, FEATURE AND DECISION FUSION APPROACHES
IN THE PROPOSED FRAMEWORK FOR THE DETECTION AND
CLASSIFICATION OF MI CASES USING SPECTRAL (DENSE),
LONGITUDINAL (LSTM) AND SPECTRAL-LONGITUDINAL (DENSE-LSTM)
MODELS, USING: GOOGLENET (TOP TABLE) AND MNASNET FEATURES
(BOTTOM TABLE). A: ACUTE, R: RECENT, N: NORMAL AND O: OLD

GoogLeNet features						
	AUROC per class (%)			Global (%)		
Method	A	R	N	o	AUROC	Accuracy
Data-Dense	70.0	62.2	83.8	63.5	69.9	69.9
Data-LSTM	75.7	66.1	92.7	69.2	75.9	73.4
Data-Dense-LSTM	78.1	53.9	85.9	67.9	71.4	70.3
Accumulation-Feature-Dense	76.4	64.4	86.4	64.1	72.8	71.3
Accumulation-Feature-LSTM	73.1	69.5	92.1	69.2	76.0	73.4
Accumulation-Feature-Dense-LSTM	77.8	65.7	93.9	72.2	77.4	75.6
Concatenation-Feature-Dense	80.8	66.6	95.0	87.4	77.8	75.0
Concatenation-Feature-LSTM	62.0	64.1	96.9	68.8	73.0	68.7
Concatenation-Feature-Dense-LSTM	82.9	68.6	96.7	73.8	80.5	77.1
Accumulation-Decision-Dense	74.0	65.2	85.3	64.0	72.1	71.0
Accumulation-Decision-LSTM	68.8	70.6	89.9	65.9	73.8	71.9
Accumulation-Decision-Dense-LSTM	74. 8	67. 2	93. 2	71. 9	76.8	75.8

MnasNet features						
	AUROC per class (%)			Global (%)		
Method	A	R	N	o	AUROC	Accuracy
Data-Dense	68.1	59.8	78.9	61.6	67.1	68.9
Data-LSTM	71.3	67.9	90.8	68.4	74.6	73.3
Data-Dense-LSTM	73.7	54.8	77.6	59.8	66.4	67.2
Accumulation-Feature-Dense	73.8	62.6	85.5	64.3	71.5	70.9
Accumulation-Feature-LSTM	72.1	68.0	91.0	68.5	74.9	73.8
Accumulation-Feature-Dense-LSTM	75.5	66.3	92.9	71.8	76.6	73.7
Concatenation-Feature-Dense	78.9	65.0	94.3	69.3	76.9	74.6
Concatenation-Feature-LSTM	81.5	73.1	97.7	74.7	81.8	78.3
Concatenation-Feature-Dense-LSTM	77.7	68.1	98.2	75.1	79.8	77.8
Accumulation-Decision-Dense	71.4	63.8	81.4	63.3	70.0	69.4
Accumulation-Decision-LSTM	70.3	68.6	90.8	67.1	74.2	74.7
Accumulation-Decision-Dense-LSTM	73.1	66.9	91.9	70.2	75.5	72.9

est in Feature Accumulation (77.4%), Feature Concatenation (80.5%), Decision Accumulation (76.8%) using GoogLeNet features. Similarly, superior performance by the spectrallongitudinal model is achieved using Feature Accumulation and Decision Accumulation using MnasNet features. Separately, longitudinal models achieved the highest in data fusion technique (75.9% using GoogLeNet and 74.6% using Mnas-Net features), where the feature dimension is not too long to lead to the curse of dimensionality and model overfitting. We also provided the accuracy metric in the last column, and the results showed similar behaviour as the AUROC, i.e., concatenation-based feature fusion superior performance, compared to the other fusion techniques. During the validation using MnasNet features, the LSTM-based longitudinal models tend to perform competitively with Dense-LSTM models, due to the smaller dimensionality of MnasNet features (1056) compared to GoogLeNet (2048), and hence less overfitting.

Among the decision fusion approaches, both majority vote and decision accumulation showed competitive performance. However, the former showed slight superiority over decision accumulation as shown in Fig. 3 (more in the Appendix), for the proposed joint spectral-longitudinal model. This is partly due to the loss of fine details resulting from the averaging performed in accumulation fusion techniques. Furthermore, the confusion matrices reveal misclassification errors observed in the classification of MI cases. It is clearly visible that the Normal class has been distinctively classified without significant misclassification with other MI cases. On the other hand, more misclassification errors occur among MI types, i.e. acute, recent and old. In summary, though data-fusion seems ineffective in leveraging the distinctiveness of the leads, care





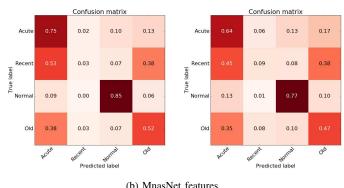


Fig. 3. Comparison of decision fusion approaches on (a) GoogLeNet and (b) MnasNet features. The first column contains *Majority vote* results and the second column *Decision accumulation*

must still be taken when considering feature concatenation or decision fusion strategies. Namely, constraints imposed by training resource considerations due to the curse of dimensionality that might arise for feature concatenation, or the need of independent modelling for each lead in decision fusion.

Our DeepMI framework not only demonstrates its feasibility in identifying an infarction from ECG readings alone, that is free from any clinical input, but it also indicates the predicted onset time of an infarction. Previous studies have shown that the occurrence time of an MI affects both the reinfarction rate, as well as mortality in surgery [33], [34]. In particular, the risk of developing an adverse cardiac event has been reported to decrease from 32.8% to 18.7% when surgery occurs within 30 days of MI, compared to surgeries occurring 31-60 days post-MI [34]. Utilising DeepMI could therefore provide the age of an MI from patient ECG readings only, without requiring previous patient histories or more involved laboratory test results. Our proposed framework could therefore be utilised to assist clinicians in remote settings, by providing additional information to assess patient risk.

C. Comparison with existing works and validation using a public database

Among existing works, we selected hand-crafted features from ECG waveforms validated with common classifiers and dedicated deep neural networks [35]. The handcrafted features were obtained from autoregressive parameter estimation using Burg's method, which was developed for spectral

estimation [36], and it estimates the autoregressive coefficients optimised for the input signal, by minimizing loss in forward and backward prediction errors. Such representation was shown to outperform the fast-Fourier transform method in encoding dynamics of time-series signals, including ECG waveforms [37]. Common classifiers were used to validate on the autoregressive representation, which include Random Forest, Logistic Regression, K-nearest Neighbors, Gradient Boosted Trees and Multi-layer Perceptron. In addition to the handcrafted feature representation, simple deep networks, such as convolutional neural networks (CNNs) and Recurrent Neural Networks (RNNs) were implemented on the raw ECG waveforms. The CNN architecture adopted a four-layer architecture, and subsequent 1-D convolution was applied. The RNN architecture was made of a single-layer LSTM component, with a 1024 hidden units (using LSTM cells). Similar train-test validation was employed as of [35], i.e., 10fold cross validation, and the AUROC performance of both the existing works and the proposed (Dense, LSTM and Dense-LSTM) framework with the data-fusion approach were shown in Table IV.

To further validate our proposed spectral-longitudinal model on a publicly available dataset, we used PhysioBank Physikalisch-Technische Bundesanstalt (PTB) [29]: The PTB ECG dataset comprises 15-lead ECG records of patients diagnosed with multiple heart diseases, sampled at 1000 Hz [38], [39]. In our evaluation, we only used 12-lead ECG data related to 148 (MI) and 52 (Healthy) subjects, with a total of 200 subjects. As the duration of ECG data may vary across subjects, we used only the first 10-second segment of each patient.

The results showed that handcrafted features performed inferior to our approach while Gradient Boosted Tree achieved higher performance compared to other non-deep learning based classifiers. The deep networks, i.e., CNNs and RNNs, that were trained from scratch with the raw ECG waveforms shown to underperform in their MI detection power, partly due to the limited amount of data available for training. This validates our approach which aims to utilize existing networks via transfer learning rather than designing a new network for each problem and train it extensively with a given dataset.

VI. CONCLUSION

Myocardial infarction (MI) is globally the leading of cause of death among cardiovascular diseases. Due to the delay and resource expenditure associated with diagnosis from laboratory based blood sample tests, it is common clinical practice to inspect the electrocardiogram (ECG) records of patients instead. However, such an approach is still time consuming and subject to interpretation bias. In most developing countries, the number of cardiologists to interpret the ECG records is far lower than demand requires. In this context, data-driven approaches can assist the diagnosis process by providing decision support to the domain experts on site. Particularly, understanding the onset time of MI is crucially important in providing effective and early intervention, thereby improving patient outcomes. To this end, we have proposed an end-to-end trainable deep

TABLE IV

AUROC (%), results from the publicly available PTB database [29], using existing works that employed hand-crafted feature, common deep learning classifiers, dedicated deep networks (CNN and RNN [35]). A comparison is conducted with data-fusion strategy of our proposed framework to detect MI cases from Normal cases.

PTB Dataset

	Method	Classifier	AUROC
Existing		Random Forest	68%
		Gradient Boosted Tree	70%
	Handcrafted	Multi-layer Perceptron	61%
		Logistic Regression	66%
		K-nearest Neighbor	64%
	Dani Lannina	CNN	49%
	Deep Learning	LSTM	49%
Proposed	Spectral	Dense	88%
	Longitudinal	LSTM	90%
	Spectral-Longitudinal	Dense-LSTM	94%

learning framework that takes raw ECG records and detects MI cases from normal (or non-MI cases), whilst also inferring the occurrence time of the heart attack as being either acute (within 7 days), recent (less than 30 days but longer than 7 days) and old (beyond 30 days). To do so, we employ a transfer learning technique that aims to exploit existing convolutional neural networks by representing the raw ECG time series with an image-like spectrogram representation. Importantly, we have experimented with a variety of fusion techniques to utilise the unique characteristics present among different ECG leads. We have proposed a joint spectral-longitudinal model, where the spectral component refines the high-dimensional deep features and applies dimension reduction to avoid the curse of dimensionality, and the longitudinal model encodes the temporal dependency among subsequent ECG samples. Encouraging performance, as high as 81.8% AUROC, is obtained when we validated the proposed framework on a cohort of > 17,000 Chinese patients. Though the onset-time detection performance could sometimes be less optimal, e.g., for Recent MI cases, the proposed platform could still provide useful insights, such as perioperative risks, particularly in lowresource settings where there is very minimal cardiologists-topatients and/or rich patient history is not common/available. Future work aims to expand the validation of the proposed framework to multiple recent networks, such as ResNeSt [40] and to utilize attention-based mechanisms in the longitudinal modelling stage.

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