Using Transfer Learning from a Self-Supervised model for ECG Classification

Introduction

In this investigation we will be classifying data from a collection of heartbeat signals from the ECG Heartbeat Categorization Dataset [1]. The ECG Heartbeat Categorization Dataset is a collection of two famous datasets, the MIT-BIH Arrhythmia Database [2] and the PTB Diagnostic ECG Database [3]. The aim of this project is to train a self-supervised model on the classification of the MIT-BIH data, and then use transfer learning to classify the PTB data into normal or abnormal classes. The datasets we are using contain data from Electrocardiography (ECG) tests. ECG signals are electrical signals detected on the skin as the heart contracts.

The MIT-BIH Arrhythmia Database consists of arrhythmia data collected at Boston's Beth Israel Hospital Arrhythmia Laboratory and MIT between 1975 and 1979. The database contains 48 half-hour excerpts of two-channel ambulatory ECG readings, 24 randomly selected and 25 selected ECG readings from a set of 4000 24-hour ambulatory ECG. The 25 were selected to give rarer, but clinically significant, arrhythmias better representation, as they would not be well-represented in the small 24 randomly selected samples. This dataset consists of 109,446 labelled samples, each cropped and padded, and has five labels: 0 - Normal beat (N), 1 - Supraventricular ectopic beat (S), 2 - Ventricular ectopic beat (V), 3 - Fusion beat (F), 4 -Unknown beat (Q) [4].

The PTB Diagnostic ECG Database is a collection of 549 records from 290 subjects taken at Physikalisch-Technische Bundesanstalt (PTB) in Germany. From the 290 subjects: 148 were diagnosed with myocardial infarction (MI), 52 were healthy and the remaining 90 had been diagnosed with seven different diseases. The ECG Heartbeat Categorization Dataset only uses the healthy and MI subject's data, meaning there are only two categories for this dataset: normal (healthy) and abnormal (MI).

Literature Review

There are mainly four steps for classifying arrhythmia using ECG: ECG signal pre-processing, heartbeat segmentation, feature extraction and classification [6]. The first two steps have already been done for the datasets we are using. Instead of doing any specific feature extraction we decided to experiment with using the entire signal so that the model could be used more generally. For the classification step we decided to research and experiment with different methods, we will now review these.

The first method is the Multi-Layer Perceptron (MLP), which is considered to be the most basic implementation of the artificial neural network. Constructed as a series of fully connected layers with non-linear activations and intermixed with dropout layers for data regularization. [8] The MLP has been demonstrated to be a simple but effective approach for arrhythmia classification [9].

The Convolutional Neural Network (CNN) is a highly popular model often employed in tasks such as Object Classification. However, studies have pointed towards an effective use of CNNs in the areas of arrhythmia and MI classification [1][7]. The CNN itself is a type of deep neural network architecture that makes use of a series of convolution, pooling, and activation layers. The purpose of the convolutional layer is to extract a feature from an area within some target data. The pooling layer on the other hand is designed to perform sub-sampling where the dimensions of the input data is reduced by a given factor. By stacking convolutional, activation function and pooling layers, a classical CNN architecture can be created.

Recurrent Neural Networks (RNNs) differ from their more typical feed-forward counterparts in that RNNs contain connections that form cycles. This property allows these networks to form internal memory and retain contained information over extended periods of time. With this RNNs can be used to model temporal behaviour making them effective when used against sequences of data across a temporal dimension [10]. However, they can suffer from a vanishing gradient. A more sophisticated version that addresses this is the Long Short-Term Memory architecture [11]. Another notable approach involves the model ensemble. Which takes multiple different models and combines the output of each in order to form an overall output. This method has been used to enhance the accuracy of classification tasks. This investigation will also consider the applications of transfer learning.

This is the process by which a given subset (or complete set) of weights are taken from a pre-trained model and used to form the base model for a similar task. Using transfer learning has often been demonstrated to result in far more effective models than ones that were initialized with completely random weights. In some cases, the weights will be set across the whole model, or a section of a model. These weights can also be locked during training in order to create a fixed feature extractor. When considering the problem of arrhythmia and MI classification, there is evidence to suggest that transfer learning, whereby a pretrained model for classifying arrhythmia is applied to MI classification, can yield improved accuracy [1].

Finally, we will be utilizing the method of representation learning. This is the process of using a self-supervised model against a dataset that has been labelled automatically. The process by which automatic labelling has been achieved in the past is via the applications of transformations. By applying transformations such as: rotations, stretches, translations and others. The subsequently generated data can then be labelled automatically by its transformation. By training a model on this transformed dataset, high level features can be learnt resulting in notable improvements to accuracy [5]. In addition to this, a multi-task version of representation learning can be used which divides the self-supervised task into several binary sub-problems which can then be optimized in parallel with each other. Multi-task learning has shown to be successful for ECG classification [5], as the different transformation classification tasks can help to learn the different aspects of ECG scans.

We performed some initial experimentation using 3 different classifiers: the MLP, CNN and LSTM. These models were trained on the raw datasets in a supervised manner. This was done in order to gain an understanding of the general effectiveness of these models against both datasets. Both datasets were split up with a train to test ratio of 9:1. Upon preliminary experimentation, it was noted that these methods performed slightly better on the PTB Diagnostic ECG Database then on the MIT-BIH Arrhythmia Database. There is however an exception for the LSTM which is shown in Table 1, the LSTM performed very well against the MIT dataset with a test accuracy of approximately 87.25%, but only achieving 83.85% for PTB. For PTB, the MLP also achieved an accuracy of 91.68%, whilst the CNN managed to achieve the best result with 97.46% accuracy.

However, to try and improve these results without altering the structure of the models, we would have to either acquire more data or perform transfer learning. In this investigation we chose the latter option. Specifically, we intend to train a model using the MIT dataset and then transfer the weights to a secondary model to classify the PTB & MIT-BIH datasets. However, this may not be enough to extract meaningful and truly generalized features that could be transferred to the new models. So, we decided to use a representational learning approach, so that we can improve the classifiers' ability to learn high-level features. Whereby a selfsupervised model would be used to train on an artificially modified version of the MIT-BIH dataset. These weights would then be transferred to the secondary model to be used to enhance the model's effectiveness against both datasets. Whilst some models perform better than others, some may extract different kinds of features from the data. To address this, we decided to combine the resulting final classifiers into an ensemble to further enhance their collective performance.



Problem Analysis

Model Type	Test Accuracy (MIT)	Test Accuracy (PTB)
MLP	90.38%	91.68%
CNN	92.28%	97.46%
LSTM	87.25%	83.85%

Table 1: Results from preliminary experiments on the MIT and PTB datasets

As an implementation, we begin by addressing the representational model. The first part of this is to construct an artificial self-labelling dataset based on the MIT-BIH Arrhythmia dataset. We applied 7 different transformations to each instance within the preexisting dataset (with the existing labels removed) These transformations are then applied after the padding has been removed, and the padding is then reapplied after the transformation. These transformations will be listed as follows. Negation, this maps out each signal by flipping it about the x axis e.g., y' = -f(x). Inversion, this reverses the direction of the signal in the x-axis. Noise, this transformations adds a certain amount of Gaussian noise to the signal. Shuffling, this splits the signal into n different segments and randomly shuffles them to form a mixed-up signal. Stretching, this stretches the signal by a factor of 2 in the x-axis. Squeezing, this stretches the signal by a factor of ¹/₂ in the x-axis. Scaling, this reduces the amplitude of the signal globally by a factor of 10. By applying these transformations, 8 different versions of the dataset will be created. And each of these are automatically labelled from 0-7. Examples of the transformations can be seen in Figure 1. The created dataset was split into a train to test ratio of 4:1.

With the representational dataset created, we then build the self-supervised model architecture for each model type, an example of this with the CNN can be seen in Figure 2. This architecture is repeated for each of the individual model types as seen Table 1. The individual models are built as follows.

The MLP consists of 7 fully connected layers. A dropout layer is included in the network to introduce regularization The network primarily uses the ReLU activation function with a Sigmoid activation for the output layer. The CNN is constructed via pairs of one-dimensional convolution and pooling pairs with a Leaky ReLU activation for the intermediate detector layer [12]. These pairs are repeated 3 times. The type of pooling used is max pooling. Upon completion of these layers, the output is flattened and is fed through 3 fully connected layers. These layers also utilize the Leaky ReLU activation function, except for the output layer which uses the Sigmoid activation. Finally, the LSTM is configured according to the Keras implementation of the LSTM. The LSTM itself takes in 64 units as a parameter and the output from this is fed through 2 fully connected layers. The hidden layer uses a ReLU activation function, whilst the final layer uses the sigmoid activation function.

A multi-task framework is also added to the representational models. In this design, there are 8 tasks. Each task is used to represent a binary classification problem for its respective transformation. Meaning that each task will attempt to classify if the incoming signal is or is not the respective transformation (including one for no transformation). This is represented in the network by 8 different fully connected layers, which all receive the output from the previous. These models are then trained on the representational dataset for 5 epochs. The model weights are then transferred to supervised architecture variants (see figure 3) and are trained on the PTB dataset for 20 epochs. Each model is trained with Binary Cross-Entropy Loss for PTB and Categorial Cross-Entropy for MIT-BIH. All of them are trained using Adam, and a mini-batch size of 64.

Finally, to improve the accuracies of the individual models, an ensemble is constructed out of the 3 trained models. This ensemble uses an averaging operation to fuse the outputs from each individual classifier to form an overall output. This final model is again trained for 20 epochs. This overall forms 3 different layers of models requiring 3 different weight transferences. This full process is depicted in Figure 3.

Implementation



Figure 2: Architecture of the self-supervised CNN

Trained on Representative data for 5 epochs

Trained on PTB data for 20 epochs

Trained on PTB data for 20 epochs

Figure 3: Depiction of all the weight transferences and training regimes needed to create the final model.

Evaluation

Upon experimentation with the additional transferred representation learning, we are met with positive results. For MIT, shown in Table 2, the CNN and the LSTM perform very well. With the LSTM making the largest gain in terms of accuracy with a percentage accuracy gain of 4.91%. Whilst this is small as an absolute value, it should be noted that all these models are operating at high degrees of accuracy, meaning that small gains can be quite significant. However, in the case of the MLP, the pre-training has had a detrimental effect causing to lose an accuracy of 3.2% when compared to its performance in Table 1. This implies that the MLP may not have responded well to the representational learning, causing it diverge away from learning meaningful features. The final ensemble scores the highest accuracy of 93.01%, verifying the small, but effective use of combining classifiers.

For PTB, both the CNN and the LSTM make positive gains, with the CNN reaching an accuracy of 98.01%. The MLP also fails to improve, but not by the same margin as for MIT. The final ensemble for PTB scores an impressive highest test accuracy of 98.49%.

Model Type	Test Accuracy (MIT)	Test Accuracy (PTB)							
MLP with Rep	87.18%	89.14%							
CNN with Rep	92.69%	98.01%							
LSTM with Rep	92.16%	97.04%							
Ensemble with Rep	93.01%	98.49%							
Table 2. Describe frame analysis and the strangformed encomple for the DTD 8 MIT									

Table 2: Results from preliminary experiments and the Transferred ensemble for the PTB & MIT BIH datasets

Conclusion

In summary, this investigation has highlighted the potential effective use of both representational learning and transfer learning to build superior models for ECG arrhythmia classification. Whilst this does not work in all cases, it does point towards an overall positive trend of improvement. In future, this investigation could be expanded to include a larger amount of both transformations for representational learning, and individual classifiers to push the limits of this concept's ability to improve classification performance. Therefore, this investigation can be considered a success.

Key References

pp.1-1.



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Appendix A – Raw Results

Training results of the Ensemble model with transferred representation learning









Training results of CNN, LSTM and MLP models with transferred representation learning



Initial Experiments of CNN, LSTM and MLP models











14

41

1.9e+03

12

6

10

42

1.8e+03







- 1750

- 1500

- 1250

- 1000

- 250









Actual















Appendix B – Screenshots

Screenshots

Supervised Only Experiments

MIT-BIH Dataset

-- MLP

Epoch 18/20
1563/1563 [========================] - 3s 2ms/step - loss: 0.1369 - accuracy: 0.9497 - val_loss: 0.3551 - val_accuracy:
0.8880
Epoch 19/20
1563/1563 [========================] - 2s 1ms/step - loss: 0.1396 - accuracy: 0.9481 - val_loss: 0.3967 - val_accuracy:
0.8784
Epoch 20/20
1563/1563 [===========================] - 2s 1ms/step - loss: 0.1317 - accuracy: 0.9520 - val_loss: 0.3356 - val_accuracy:
0. <mark>9038</mark>

- CNN

Epoch 15/20	
1563/1563 [====================================	0.4436 - val_accuracy:
0.9171	
Epoch 16/20	
1563/1563 [====================================	0.4661 - val_accuracy:
0.9228	
Epoch 17/20	
1563/1563 [========================] - 11s 7ms/step - loss: 0.0600 - accuracy: 0.9808 - val_loss: 0	0.4815 - val_accuracy:
0.9085	

- LSTM

-

Epoch 16/20	
1563/1563 [==================] - 120s 77ms/step - loss: 0.3633 - accuracy: 0.8742 - val_loss: 0.4148 - val_accura	IC
y: 0.8654	
Epoch 17/20	
1563/1563 [==================] - 120s 77ms/step - loss: 0.3417 - accuracy: 0.8817 - val_loss: 0.3727 - val_accura	IC
y: 0. <mark>8725</mark>	
Epoch 18/20	
1563/1563 [========================] - 126s 81ms/step - loss: 0.3455 - accuracy: 0.8806 - val_loss: 0.4215 - val_accura	IC
y: 0.8547	

PTB Dataset

- MLP

Epoch 18/20 205/205 [=====] 0.9162 Epoch 19/20	- 11s	51ms/step	- loss:	0.2148 -	accuracy:	0.9140 -	val_loss:	0.2293	- val_accuracy:
205/205 [=====] 0.9168 Epoch 20/20	- 10s	51ms/step	- loss:	0.2342 -	accuracy:	0.9101 -	val_loss:	0.2163	- val_accuracy:
205/205 [=====] 0.8907	- 10s	51ms/step	- loss:	0.2202 -	accuracy:	0.9136 -	val_loss:	0.2507	- val_accuracy:
- CNN									
/32 5									

Epoch 18/20	
205/205 [=====================] - 1s 7ms/step - loss: 0.0589 - accuracy: 0.9792 - val_los	ss: 0.0942 - val_accuracy: 0.9
698	
Epoch 19/20	
205/205 [======================] - 1s 7ms/step - loss: 0.0715 - accuracy: 0.9736 - val_los	ss: 0.0804 - val_accuracy: 0. <mark>9</mark>
746	_
Epoch 20/20	
205/205 [=====================] - 1s 7ms/step - loss: 0.0542 - accuracy: 0.9810 - val_los	ss: 0.0851 - val_accuracy: 0.9
739	

- LSTM

5	20									
Epoch 18/	20									
205/205 []	- 26s	129ms/step -	loss:	0.4368	 accuracy: 	0.7890 -	<pre>val_loss:</pre>	0.4812 -	val_accuracy:
0.7546										
Epoch 19/	20									
205/205 []	- 27s	129ms/step -	loss:	0.4404	 accuracy: 	0.7894 -	<pre>val_loss:</pre>	0.4922 -	val_accuracy:
0.7540										
Epoch 20/	20									
205/205 []	- 29s	140ms/step -	loss:	0.3863	- accuracy:	0.8220 -	<pre>val_loss:</pre>	0.3682 -	val_accuracy:
0. <mark>8385</mark>										

Added Representational Learning Experiments

MIT-BIH Dataset – Representational Models

- MLP

och 5/20 3/1563 [=======================] - 78s 50ms/step - loss: 0.2475 - accuracy: 0.9128 - val_loss: 0.4240 - val_a	ccuracy:
714 sch 6/20	
3/1563 [==========================] - 78s 50ms/step - loss: 0.2232 - accuracy: 0.9217 - val_loss: 0.4539 - val_a	ccuracy:
719 och 7/20	
3/1563 [=====================] - 83s 53ms/step - loss: 0.2112 - accuracy: 0.9269 - val_loss: 0.4769 - val_a 706	curacy:
- CNN	
ch 8/20	
3/1563 [========================] - 11s 7ms/step - loss: 0.0740 - accuracy: 0.9766 - val loss: 0.3582 - val acc	urac

1563/1563 [:	 =] -	11s	7ms/step	- loss:	0.0740	- accur	racy:	0.9766	- val	loss:	0.3582	- val	accurac
y: 0.9189													
Epoch 9/20													
1563/1563 [:	 =] -	12s	8ms/step	- loss:	0.0726	- accur	racy:	0.9760	- val	loss:	0.3485	- val	accurac
y: 0.9269													
Epoch 10/20													
1563/1563 [:	 =] -	13s	8ms/step	- loss:	0.0658	- accur	racy:	0.9788	- val	loss:	0.3815	- val	accurac
y: 0.9183													

- LSTM

och 16/20
63/1563 [========================] - 107s 68ms/step - loss: 0.1401 - accuracy: 0.9520 - val_loss: 0.3124 - val_accurac
0.9179
och 17/20
6 <u>3/1563</u> [=======================] - 107s 68ms/step - loss: 0.1300 - accuracy: 0.9557 - val_loss: 0.3052 - val_accurac
0.9216
och 18/20
63/1563 [=========================] - 107s 69ms/step - loss: 0.1330 - accuracy: 0.9536 - val_loss: 0.3611 - val_accurac
0.9099

Final Ensembles

MIT-BIH Dataset – Final Ensemble

och 10/20)										
3/1563 []	- 1	L72s	110ms/step -	loss:	0.0594	- accuracy:	0.9865	- val_loss:	0.4513 -	val_accurac
0.9192											
och 11/20)										
3/1563 []	- 1	L74s	111ms/step -	loss:	0.0518	 accuracy: 	0.9887	<pre>- val_loss:</pre>	0.4193 -	val_accurac
0.9301											
och 12/20)										
3/1563 []	- 1	L88s	120ms/step -	loss:	0.0563	 accuracy: 	0.9880	- val_loss:	0.4574 -	val_accurac
0.9185											

- MLP

Epoch 205/20 0.8893 Epoch 205/20	18/20 95 [====== 3 19/20 95 [========
0.8866 Epoch 205/20 0. <mark>8914</mark>	20/20 55 [===================================
- CN	IN
Epoch 205/20 787 Epoch	16/20 95 [
205/20 801 Epoch 205/20 753	18/20 35 [
	10/00

- LSTM

Epoch 18/20
0.0704
Enoch 19/20
205/205 [=================
0.9320
Epoch 20/20
205/205 [====================================
0.9677

-
Epoch 8/20
205/205 [====================================
y: 0.9766
Epoch 9/20
205/205 [====================================
y: 0.9849
Epoch 10/20
205/205 [====================================
y: 0.9340
-

PTB Dataset – Representational Models

========] - 17s 84ms/step - loss: 0.2571 - accuracy: 0.8960 - val_loss: 0.2585 - val_accuracy: ========] - 17s 82ms/step - loss: 0.2514 - accuracy: 0.8928 - val_loss: 0.2637 - val_accuracy: =======] - 16s 79ms/step - loss: 0.2390 - accuracy: 0.8994 - val_loss: 0.2633 - val_accuracy: =========] - 1s 7ms/step - loss: 0.0565 - accuracy: 0.9791 - val_loss: 0.0673 - val_accuracy: 0.9 ==========] - 1s 7ms/step - loss: 0.0514 - accuracy: 0.9834 - val_loss: 0.0614 - val_accuracy: 0.9 ============] - 1s 7ms/step - loss: 0.0499 - accuracy: 0.9808 - val_loss: 0.0745 - val_accuracy: 0.9

========] - 14s 70ms/step - loss: 0.0896 - accuracy: 0.9684 - val_loss: 0.0881 - val_accuracy: =========] - 14s 70ms/step - loss: 0.0950 - accuracy: 0.9696 - val_loss: 0.1784 - val_accuracy:

PTB Dataset – Final Ensemble

========] - 21s 105ms/step - loss: 0.0701 - accuracy: 0.9805 - val_loss: 0.0820 - val_accurac ========] - 22s 109ms/step - loss: 0.0701 - accuracy: 0.9816 - val_loss: 0.0866 - val_accurac ========] - 24s 117ms/step - loss: 0.0630 - accuracy: 0.9847 - val_loss: 0.1560 - val_accurac