Predicting Heart Disease: Investigating the Potential of the 1D CNN for Binary ECG Classification

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Introduction

- In April 2023, 25% of all deaths in the UK were attributed to various cardiovascular diseases (CVD) [1].
- The electrocardiogram (ECG) represents the electrical signals produced by the heart and is the key tool used by clinicians in determining heart condition.
- Visual inspection of ECGs can be a time-consuming process and prone to error, partly due to signal noise.
- Methods that automate ECG cardiac health classification whilst enhancing accuracy and efficiency have the potential to alleviate these issues.
- This study investigated the application of data analytic techniques including: support vector machine (SVM) allied to a 1D variant of the convolutional neural network (CNN) on ECG signals, to perform binary classification of healthy vs unhealthy heart status.
- The results demonstrated the 1D CNN had a greater potential so is focussed on in this poster.

Ideal ECGs

- An ECG provides a graphical representation of the electrical signals produce by the heart
- Key features include P and T waves as well as the QRS complex, as illustrated in Fig. 1.
- Clinicians typically use the shape, magnitude and duration of these features to infer diagnoses.

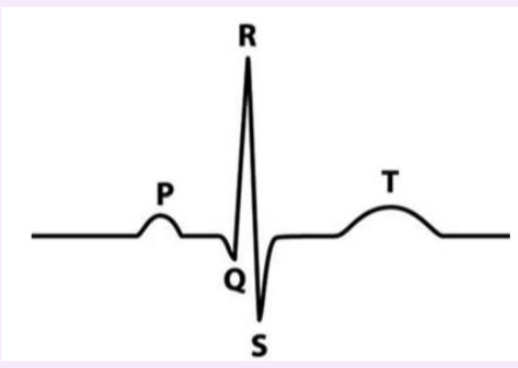

Figure 1: An ideal ECG with key features labelled [2]

Database

- Analysis was performed on ECG signals collated in the **PTB diagnostic ECG database** [3].
- This database contains 290 subject files of which 52 were labelled as healthy with the remaining attributed with a form of CVD.
- The data were filtered based on the length and quality of a patient's signals together with meta information such as their health state.
- A quality check was performed using Neurokit2's qualitative ECG quality algorithm which labelled each signal 'Excellent', 'Barely Acceptable' or 'Acceptable' as shown in Fig 2.
- Filtering resulted in 221 patients (46 healthy) each having from 1-6 signals of quality 'barely acceptable' or better.

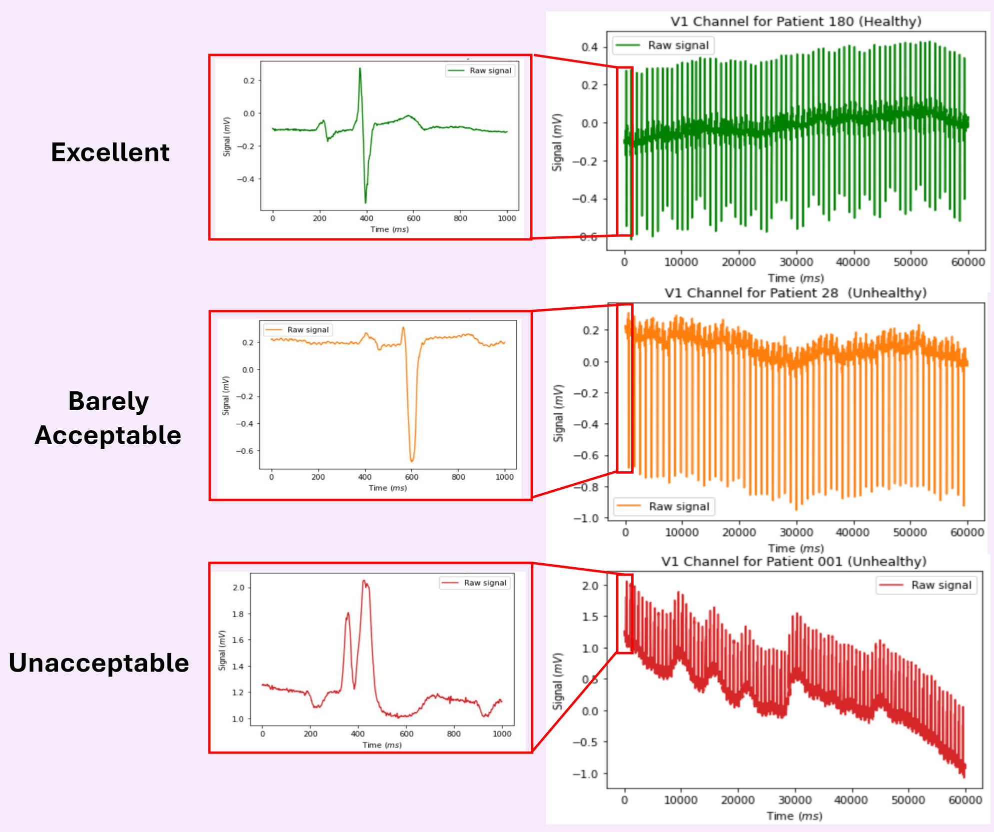

Figure 2: Example ECGs of each quality as determined by the Neurokit2 quality check [4].

Signal Preprocessing - DWT

- Patient movement, breathing and electrical interference can contribute to noise in ECG signals [5].
- This noise can be reduced through the **Discrete Wavelet Transform** (DWT) as seen in Fig. 4.
- The DWT sequentially splits a signal into low, *A*, and high, *D*, frequency components, as shown in Fig. 3.
- The coefficients considered to contain noise can then be discarded allowing a denoised signal to be reconstructed from the remaining components.

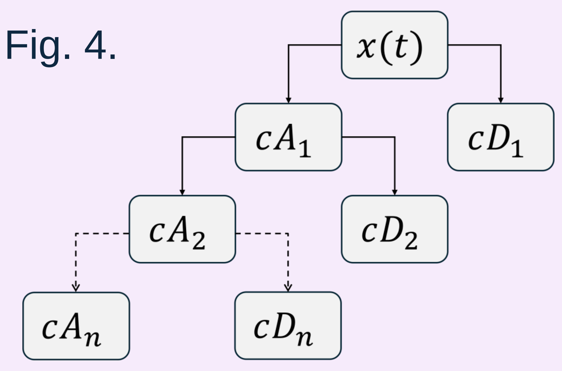

Figure 3: Schematic showing the process undertaken by DWT to split a signal, x(t) to the n^{th} order.

- The **Daubechies4** wavelet was used to reconstruct signals due to its central frequency factor of 0.7, representing its similarity with the ECG signal [6].

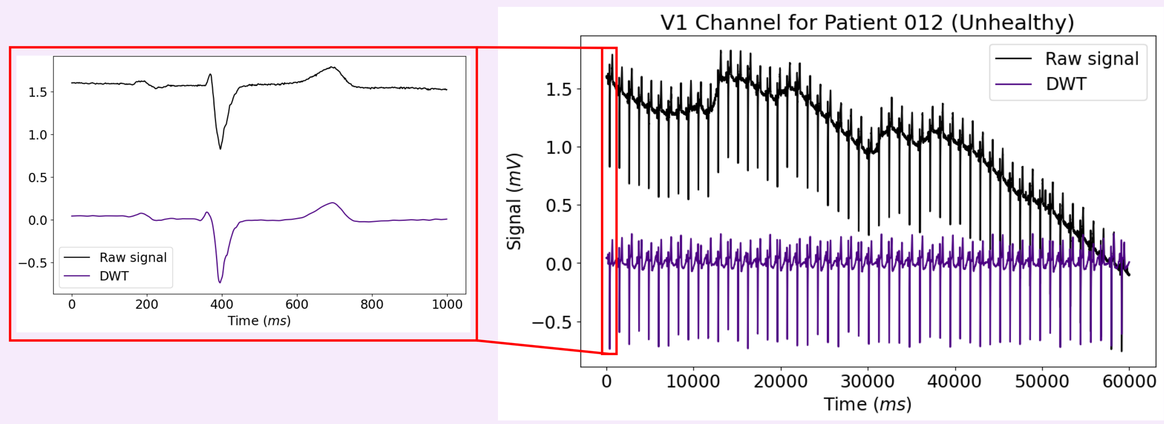

Figure 4: Noise reduction through DWT on a raw channel V1 ECG from an unhealthy patient.

1D Convolutional Neural Network

- The 1D CNN is a recently modified variant of the traditional 2D CNN, designed specifically for 1D data.
- It excels with time series data due to its proficiency in local feature detection, leveraging **temporal and spatial invariance** for superior pattern recognition [7].
- A 1D CNN takes the denoised time series as inputs and automatically extracts features to classify the data.
- The small size of the database considered here means a shallow network containing a single block is sufficient, illustrated in Fig. 5.

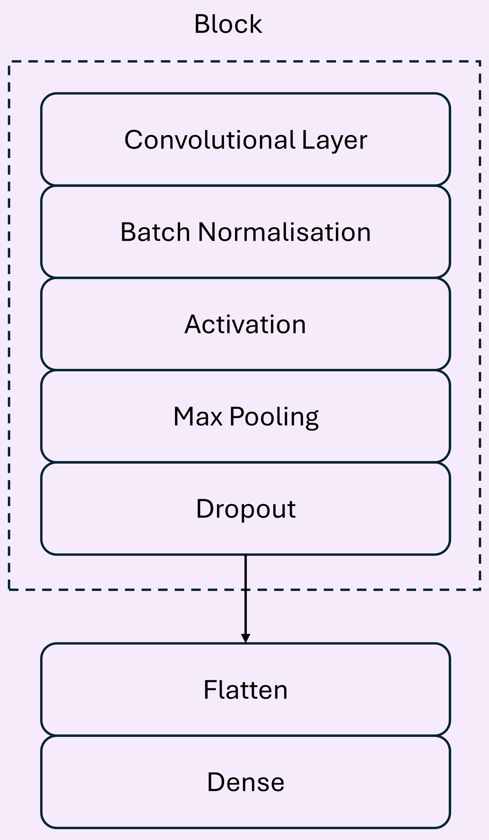

Figure 5: Schematic of 1D CNN structure. Code is available through the GitHub link below.

- The convolutional layer contains 16 filters each of kernel size 3 that slide over the inputted signals extracting features of high and low detail.
- The **ReLU activation function** introduces non-linearity, enabling the network to learn complex relationships beyond linear ones.
- Max pooling (pool size 2) selects the maximum value from every 2 datapoints. This halves the number of data points, increasing computational efficiency whilst retaining the most prominent features for classification.
- **Dropout** is used to regularise the model; a randomly selected half of the nodes is set to zero during training so that the network does not heavily rely on single features.
- The data are then flattened to a 1D array appropriate for the dense layer to make predictions through a **sigmoid activation function**.
- The model is trained through the minimisation of the **binary cross-entropy loss function**.

Model Training Evaluation

- Evolution of the model during training is shown in Fig. 6.
- The training accuracy peaks at values in the range of 0.98 before decreasing due to overfitting.
- **Early stopping** is implemented, returning the model to the optimal weights to improve model generalisation and combat overfitting.

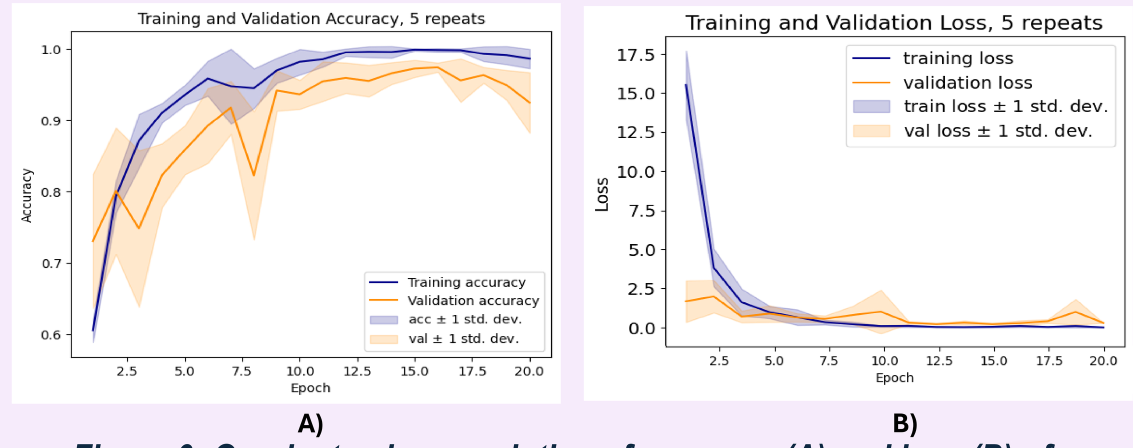

Figure 6: Graphs to show evolution of accuracy (A) and loss (B) of training and validation data with each epoch, over 5 repeats.

Model Performance Evaluation

- The average receiver operating characteristic (ROC) curve and confusion matrix over 5 iterations for the model are shown in Fig. 7.
- An area-under-the-curve (AUC) of 0.95 ± 0.01 in tandem with only an average of 11 signals misclassified, as shown in the confusion matrix, suggest the model has been very successful in its task.

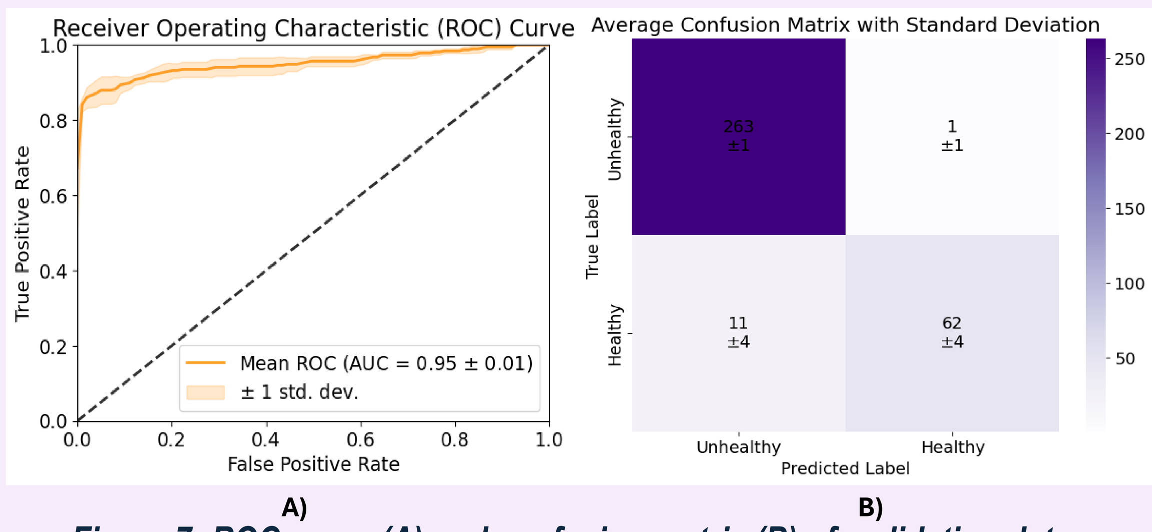

Figure 7: ROC curve (A) and confusion matrix (B) of validation data, over 5 repeats.

Accuracy	Balanced Accuracy	Precision	F1 Score	Recall
0.96 ± 0.01	0.92 ± 0.03	0.98 ± 0.02	0.91 ± 0.03	0.85 ± 0.06

Table 1: Summary of accuracy metrics portraying performance of model.

- Table 1 shows the different accuracy metrics used to further evaluate the performance of the model.

Conclusions and Future Work

- A **1D CNN** has the potential to provide an alternative AI based method of ECG diagnosis consistently achieving accuracies in the range of 0.96%.
- The model achieved **high precision** whilst the worst metric is *recall*, this suggests the model is **too conservative** with its positive (healthy) predictions and this is likely caused by the skewed nature of the database, despite making class weight allowances.
- The speed at which a diagnosis can be obtained using a pre-trained model compared to manual analysis by a clinician provides further incentive for continued investigation.
- Future work can investigate the generalisability of these models through application to different ECG datasets.
- Through applications on larger datasets, the potential of the CNN in the multiclassification problem of diagnosing specific disease types can also be investigated.

References

[1] BHF., *CVD Statistics – UK Factsheet*, 2024. [2] Savalia, S. & Emamia, *Cardiac arrhythmia classification by multi-layer perceptron and convolution neural networks*., *Bioengineering*., vol 5 no. 2, pp. 35, 2018. [3] Goldberger, A.L et al., *PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals*., *circulation*, *101(23)*, pp.e215-e220., 2000. [4] Makowski, D et al., *NeuroKit2: A Python toolbox for neurophysiological signal processing*. *Behavior research methods*, pp.1-8., 2021. [5] Gupta, V et al., *A simplistic and novel technique for ECG signal pre-processing*. *IETE Journal of Research*, *70(1)*, pp.815-826., 2024. [6] Martis, R.J et al., *ECG beat classification using PCA, LDA, ICA and discrete wavelet transform*. *Biomedical Signal Processing and Control*, *8(5)*, pp.437-448., 2013. [7] Liu, X et al., *Deep learning in ECG diagnosis: A review*. *Knowledge-Based Systems*, *227*, p.107187., 2021.

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View code on GitHub!