Non-Invasive Fetal Cardiac Arrhythmia Detection

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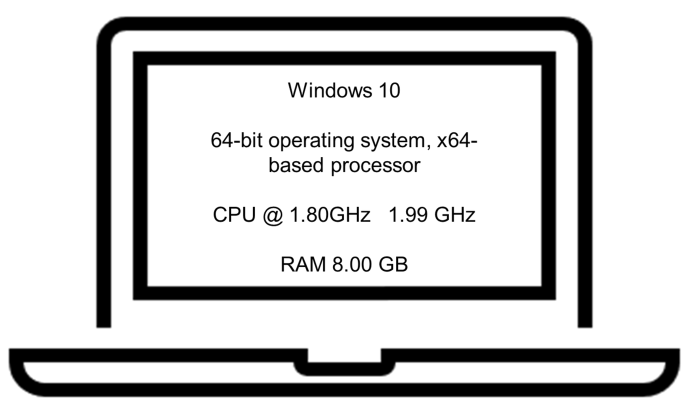
Abstract

Fetal cardiac arrhythmias defined as any irregular fetal cardiac rhythm or regular rhythm at a rate outside the reference range of 100 to 200 beat per minute (bpm). Arrhythmias discovered in about 1% of fetuses with about 10% of these considered as potential sources of morbidity. Although most fetal arrhythmias are benign, some can cause fetal hydrops and lead to fetal death. This means that up to 1 fetus in 100 need their arrhythmias to be closely monitored and if indicated, treated in-utero using antiarrhythmic therapy. The invasive direct fetal electrocardiogram monitors the fetal heart rate variability. This involved inserting electrode into the woman's cervix and attached it to the baby's head. Conversely, non-invasive fetal electrocardiography (NI-FECG) has the possibility to offer some added clinical information to assist in detecting fetal distress, and thus it offers novel diagnostic possibilities for prenatal treatment to arrhythmic fetus. This project proposed to develop a computer aided diagnosis system to classify arrhythmic fetus and normal rhythm fetus from non-invasive fetal electrocardiography (NI-FECG) using Multi-Layer Perceptron (MLP) and 1-Dimensional Convolutional Neural Network (1D CNN). The FECG signals are pre-processed and segmented into length of four ECG beats each. The segmented FECG are used to trained and test the baseline MLP and 1D CNN models of various layers. Further, the models experimented on model improvement methods together with K-fold cross validation and confusion matrix. Overall, 1D CNN model of five layers (with callbacks of patience=30) yielded the best validation accuracy of 94.99%.

Materials



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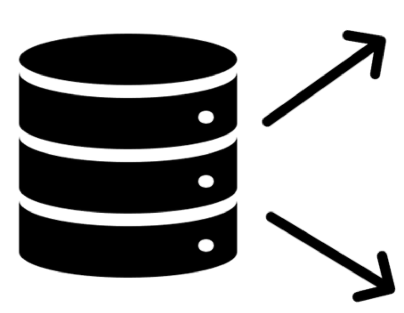
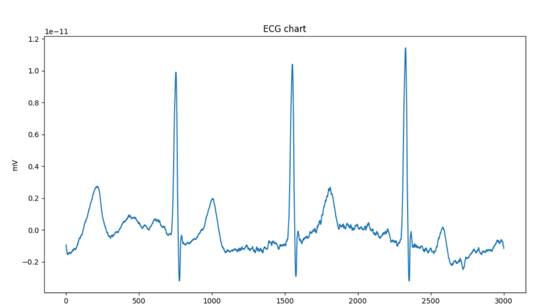
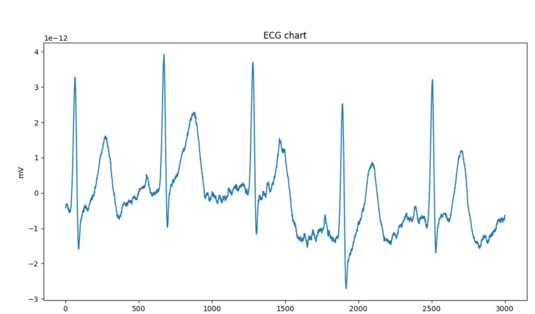


12 Arrhythmia Datasets

14 Normal Rhythm Datasets

Non-Invasive Fetal ECG Arrhythmia Database





Methods

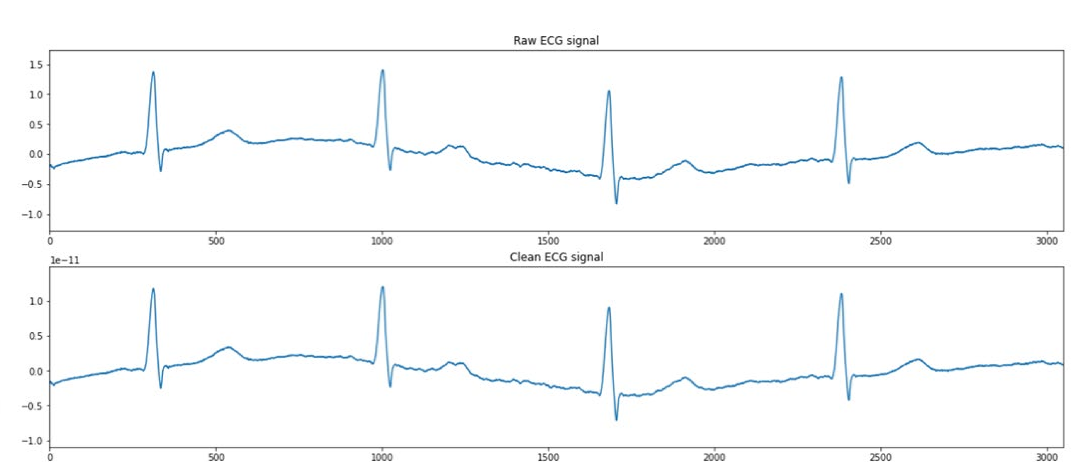
1. Data Pre-processing:

Baseline Wander Removal

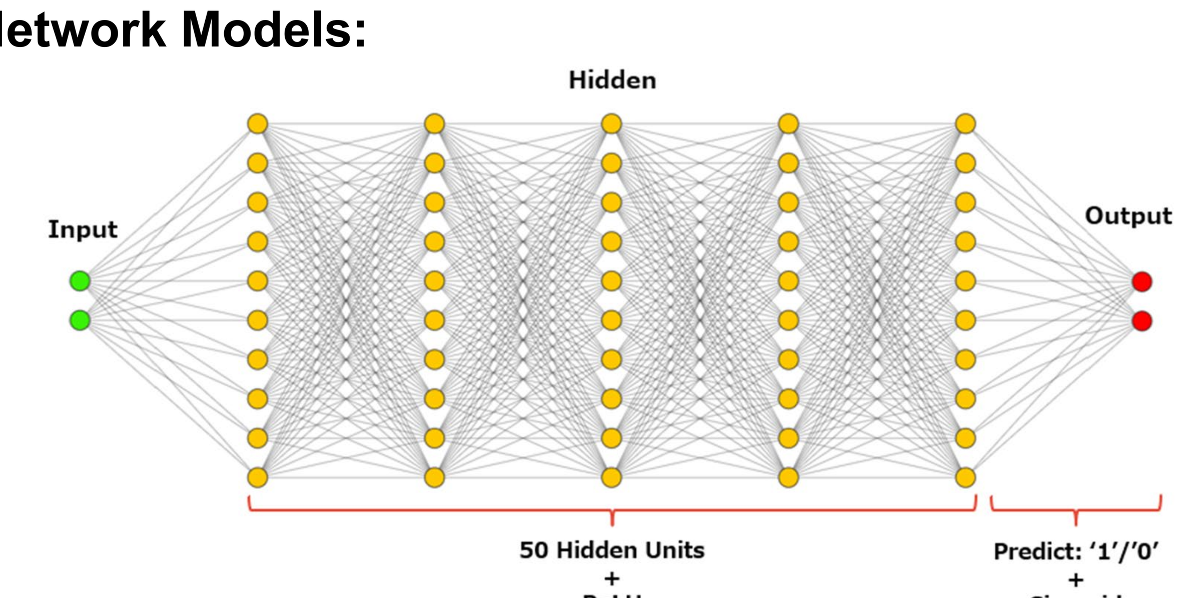
- Notch Filter
- Butterworth Bandpass Filter

Data Segmentation

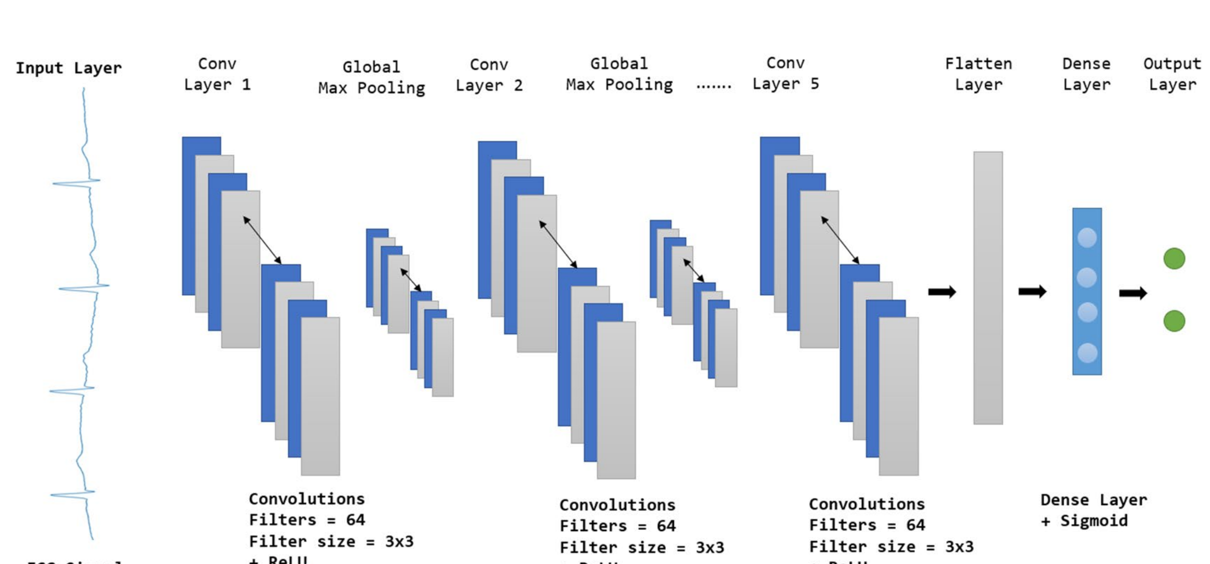
- 4 ECG Beats (3000 Datapoints)
- 2376 Segmentations per class



2. Neural Network Models:



Multi Layer Perceptron (MLP) Architecture



1D Convolutional Neural Network (CNN) Architecture

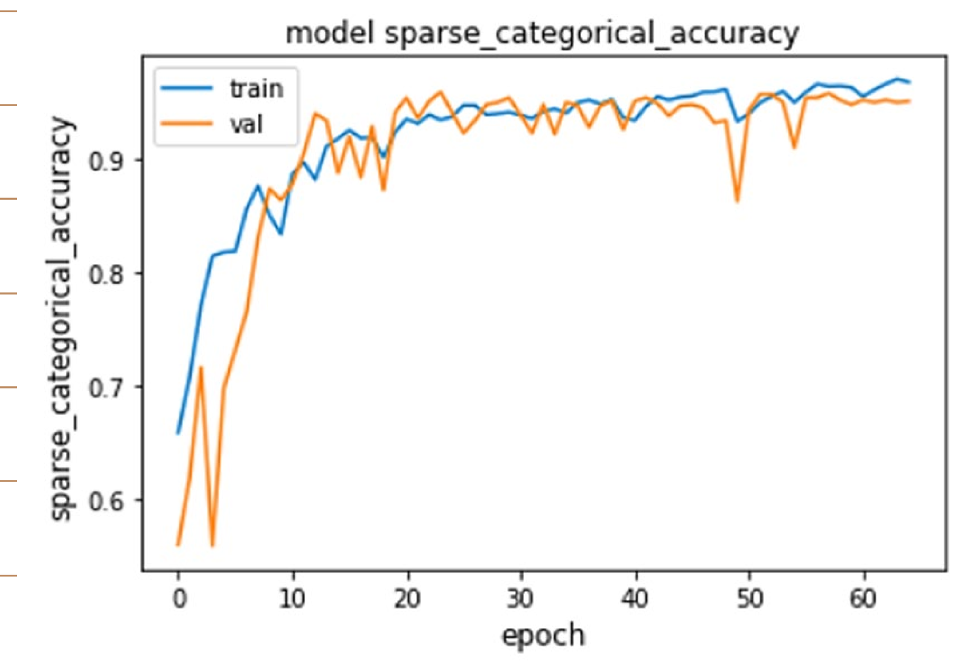
3. Model Improvement Methods

1. Callbacks
2. Dropouts (0.2, 0.4, 0.5)
3. Weight Regularization (0.0001)

Results & Data Analysis

Best Model Performances

5 Layers CNN
Global Max Pooling
Callbacks: Patience 30
94.99% Validation Accuracy
94.03% Training Accuracy
1 Epoch: ~38 secs
All Epochs: ~5776 sec



Confusion Matrix

		Predicted Results	
		No Arrythmia	Arrythmia
Actual Results	No Arrythmia	TN=670	FP=41
	Arrythmia	FN=45	TP=670

SCAN HERE FOR MODEL RESULTS

5 Convolutional Layers

(670+670/1426)*100 = ~94.2% (accuracy)

Discussion/Evaluation

Our results have made some observations relating to the type of model used and findings after applying model improvement methods.

We realized that different dropout values could either positively or negatively impact the model's performance. As shown in tables 1, 2, and 3, we can see the variations in accuracy results for each dropout value applied for the respective models. Some models performed better on some dropout values, while others showed signs of overfitting. Overfitting is identified when the training accuracy is higher than the validation accuracy.

Secondly, applying multiple model improvement methods simultaneously does not necessarily improve the model performance. Even though model improvement methods are designed to enhance the model's performance, using too many methods may do the opposite and decrease the model's performance instead. From tables 1, 2, and 3, we can see that with the combination of Callbacks, Weight Regularization, and Dropouts for both MLP and CNN, the model performance results are not as good as implementing one or two methods alone.

Next, from the results of the confusion matrix, not only were we able to obtain a close accuracy estimate of our model performance, but we can also view the types of classes the model is predicting, and the rate of True and False events predicted. Taking the confusion matrix results of our CNN model, we can see that our model's accuracy rate surpasses the misclassification rate, which tells us that the model has been successful in predicting more "True" events correctly. More correctly predicted "True" events boosted the model's precision rate to about 94%, which means that the model has a high capability of correctly classifying new input data into specific classes according to what it has been trained.

In conclusion, our 5 Layered CNN models with callbacks (patience 30) are chosen as our best machine learning algorithm for our project by having the highest validation accuracy, less tendency of overfitting and highest number of correct predictions compared to the MLP models. With CNN's algorithms and capability of learning and recognizing specific types of patterns in a dataset, it is an exceptionally useful tool to help us in detection of abnormalities within the FECG waveform complex.

Conclusions

- Developed a computer-aided diagnosis (CAD) system to classify arrhythmic fetus and normal rhythm fetus using NI-FECG.
- Overall, 1D CNN model of five layers with callbacks of patience 30 yielded the best validation accuracy of 94.99% at epoch 35.

References

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