







Collaborate · Innovate · Impact





Interpreting Deep Neural Networks for Single-Lead ECG Arrhythmia Classification

Sricharan Vijayarangan, Balamurali Murugesan, Vignesh R, Preejith SP

Jayaraj Joseph and Mohansankar Sivaprakasam

Motivation

* Deep Learning methods for arrhythmia detection

- Scales automated systems
- Removes requirement for expert rules
- Augments doctor's ability

* Limitations

- Black box
- Unreliable

* Requirement

- Correlation b/w model outputs and ECG input samples
- Comparing visualizations with medical literature



Contribution

* Novel adaptation of CNN saliency visualization to 1D ECG signals

* Extension of the LSTM visualization procedure for ECG signals

Rigorous analysis of the saliency maps

Draw comparisons to traditional diagnosis as highlighted in medical literature



Problem formulation

$$\text{Dataset} \rightarrow \ \{(x^{(1)},y^{(1)}),(x^{(2)},y^{(2)}),....,(x^{(m)},y^{(m)})\}$$

Input ECG Signal
$$ightarrow x^{(i)}$$

Labels
$$\to y^{(i)} \in \{0, 1, ... 7\}$$

$$FC \rightarrow z_3^{(i)} = F_3(z_1^{(i)}||z_2^{(i)};\theta_3)$$

Softmax
$$\rightarrow p(z_3^{(i)})$$



Rationale behind Architecture Choice

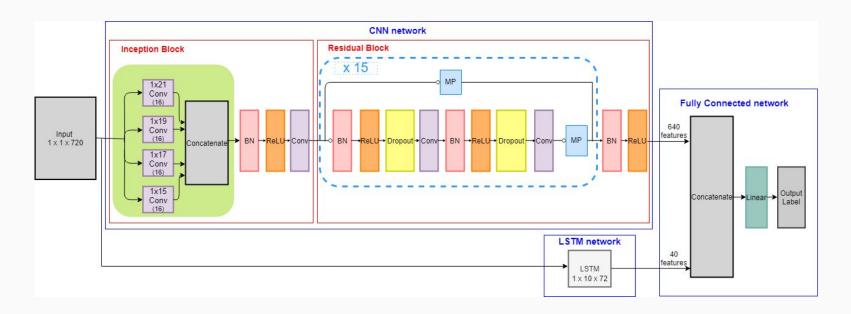
Three popular DL architectures in literature were compared for this specific 8 class classification problem.

| Model | Precision | Recall | F1-Score | Accuracy |
|----------------------|-----------|--------|----------|----------|
| Hannun et al. [2] | 0.93 | 0.93 | 0.93 | 0.93 |
| Zihlmann et al. [3] | 0.94 | 0.94 | 0.94 | 0.94 |
| Murugesan et al. [4] | 0.98 | 0.97 | 0.97 | 0.97 |

Murugesan *et al.*'s model is clearly the best for this classification task. Thus, it was chosen for the interpretability task.



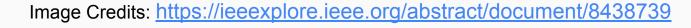
CONT.



Architecture Design







Dataset Description

| Rhythm Types | MITDB | LTAFDB | LTDB | Total |
|--------------|-------|--------|-----------------|--------|
| N | 75013 | 10756 | 517402 | 603171 |
| PVC | 7121 | 1318 | 5137 | 13576 |
| PAC | 2542 | 14914 | - | 17456 |
| AFIB | 102 | 7241 | () | 7343 |
| SVTA | 22 | 3265 | - | 3287 |
| SBR | - | 11323 | | 11323 |
| LBBB | 6580 | - | - | 6580 |
| RBBB | 5400 | | - | 5400 |



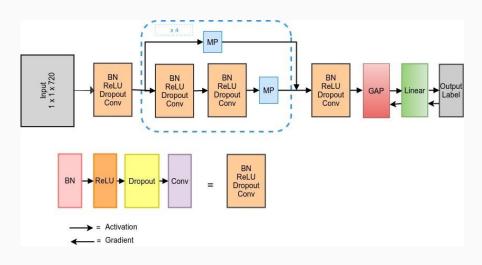


Visualization of CNN

Activation of unit $k \to f_k(x)$

Weight for class C corresponding to Unit 'k' $ightarrow w_k^c$

$$\text{I/p to Softmax} \rightarrow \sum\nolimits_k w_k^c \sum\nolimits_x f_k \! \left(x \right) \quad \text{CAM} \rightarrow M_c(x) = \sum\nolimits_k w_k^c f_k(x)$$



- CAM of vector length 48 is obtained.
- Upsampled to 720





LSTM Visualization

LSTM visualization (ψ) network Input ECG signal $(\mathbf{x}_{1:T})$ Mask $(\mathbf{m}_{1:T})$ Weights of the saliency term λ_1 Weights of the smoothing term λ_2

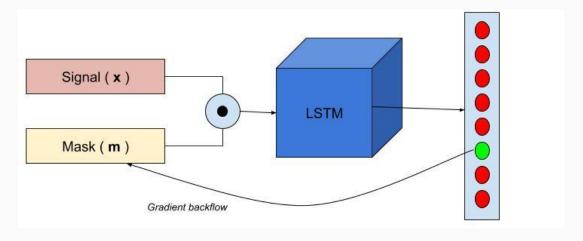
$$J = \underset{m_{1:T}}{argmin} \ \lambda_1 || \mathbf{1} - \mathbf{m}_{1:T} ||_1 + \lambda_2 \sum_{t=1}^{T-1} |\mathbf{m}_{t+1} - \mathbf{m}_t| + s_c(\psi(\phi(\mathbf{x}_{1:T}; \mathbf{m}_{1:T})))$$

$$\phi(\mathbf{x}_{1:T}; \mathbf{m}_{1:T}) = \mathbf{m}_{1:T} \odot \mathbf{x}_{1:T} + k(\mathbf{1} - \mathbf{m}_{1:T})$$



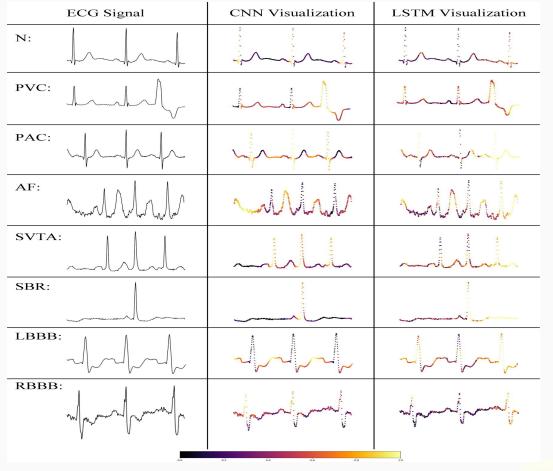
CONT

- Initially, $m_{1:T} = 0$
- λ_1 , λ_2 and learning rate are set to 1, 0.001 and 0.001 respectively.
- Gradient update is done for 500 iterations.



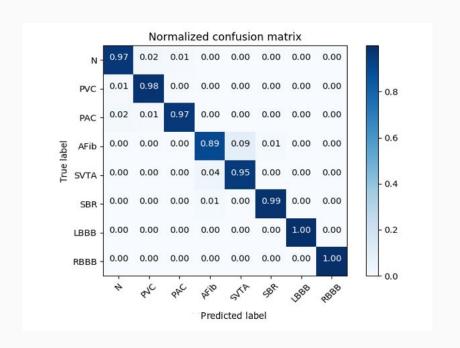


ECG Visualization





CONT.



Iterations = 500Iterations = 1000 Iterations = 1500 0.2 0.4 0.6 0.8

Confusion Matrix of Predictions

Interpretability w.r.t epochs no





Conclusion and Future scope

- A novel adaptation of visualization techniques of CNN and LSTM for ECG signals was proposed.
- Visualizations were observed to line up with the clinical literature in ECG interpretation
- Extension to other arrhythmia classes
- Extension to entire arrhythmia records
- Exploring Explainability











Collaborate · Innovate · Impact





Thank you

Contact _sricharanv@htic.iitm.ac.in