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Tendencies of Unsupervised Learning on ECG Signals

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Introduction

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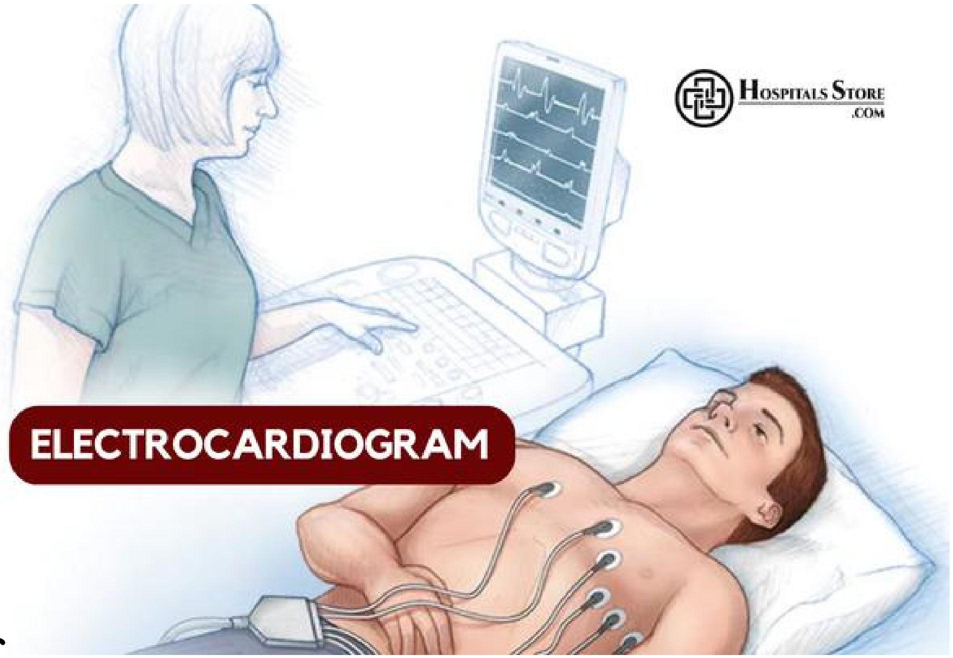
- Cardiovascular diseases are one of the major causes of mortality worldwide, so the development of effective methods for diagnosing and monitoring cardiac activity is important.

- Electrocardiography (ECG) is one of the most informative non-invasive procedures to help understand the state of the human cardiovascular system.



- Today, convolutional neural network is a working solution for most tasks related to the analysis of medical data, in particular ECG signals.

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Challenge for deep neural networks - high dimensionality of ECG data.

Solution: use convolutional autoencoder (unsupervised learning) to reduce the dimensionality of the signal by extracting informative features from the signals, eliminating noise in them, but still preserving their semantics.

The main questions:

- What does the network actually learn during unsupervised learning?
- To what extent can the obtained data representations be interpreted by humans?

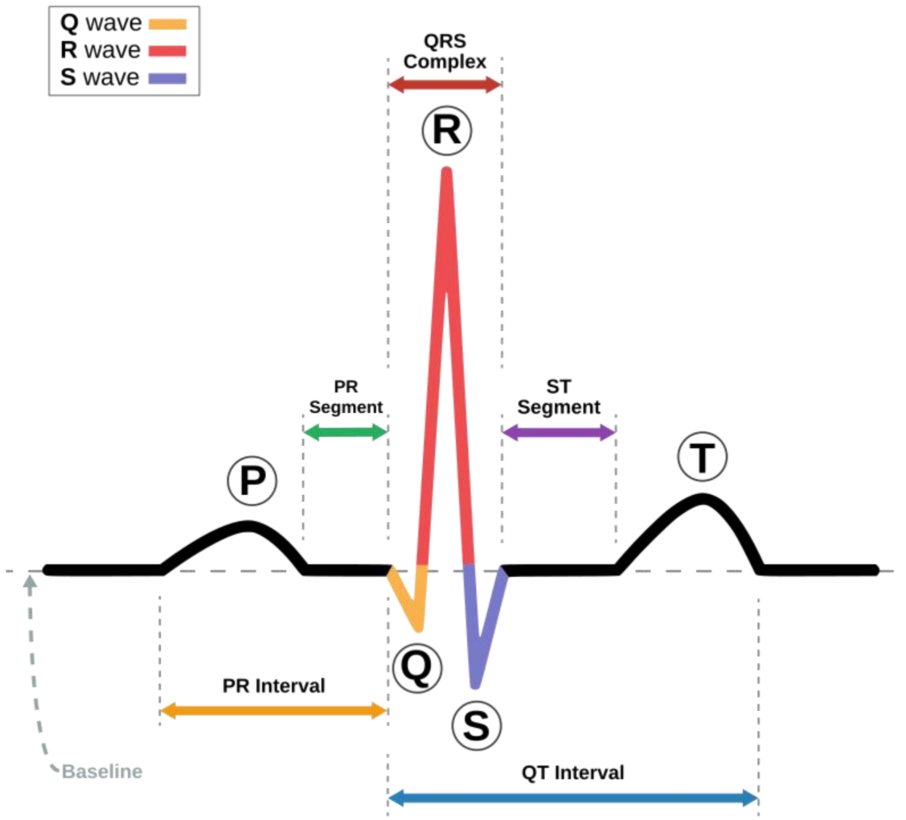
The aim of this study: to investigate what happens inside an already well-trained convolutional autoencoder by searching for specialized neurons for different wave types in ECG signals.

Relevance of this study: currently there is no well-performing system capable of classifying into a large number of classes.

Task formulation: to investigate the presence or absence of specialization in trained neurons of a convolutional autoencoder applied to ECG signals using statistical hypothesis testing.

To do this:

- Measure the activations of the of the hidden layer neurons for each of the considered wave types (QRS complex, P-wave and T-wave);
- Compare the activation results with each other to answer the question whether there are distinct differences between them.



Problem statement

Assuming that a given neuron is specialized in some type of wave, such as P-wave, its activation on P-wave should systematically differ from its activation on other types of wave.

Mann-Whitney criterion is used to test the null hypothesis that the samples are not statistically different.

- The result is **p-value** – represents a probability that measures the evidence against the null hypothesis
- if p-value ≤ chosen significance level ➡ reject the null hypothesis and suggests that there is a statistically significant difference between two samples.

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Scheme for detecting neuron specialization

Obtain neuron activation samples for P-wave, QRS complex and T-wave

Compare samples pairwise using the Mann-Whitney test

Analyze the obtained p-values

For the considered signal type: if in **two pairs containing** the given **wave type**, the **p-value** is **less than the chosen significance level**, and in the **third pair not containing the given wave type**, the **p-value** is **greater than the chosen significance level,** then it means that the analyzed neuron is specialized only in considered signal type

Data description and preparation

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Dataset: LUDB is a database of ECG signals with labeled boundaries and peaks of P, T and QRS complexes.

Description:

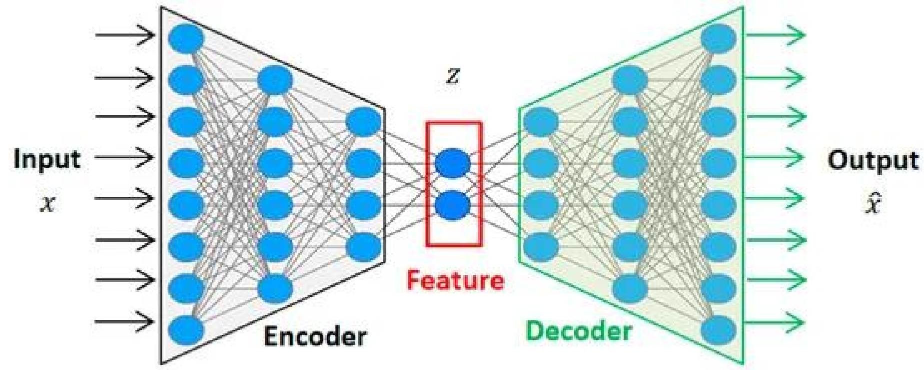
- Consists of 200 ECG signal recordings of 10 seconds each in 12 leads representing different ECG signal morphologies.
- The boundaries of P, T waves, and QRS complexes were manually annotated by cardiologists for all 200 records.
- Each record contains the corresponding diagnosis.

Data preparation: All the data was divided into training set, test set and experiment set in the proportion of 80%, 11% and 9% respectively. Then, in the training and test set, chunks of a length equal to 656 were extracted using each of the ECG leads.

Description of network architecture and training process

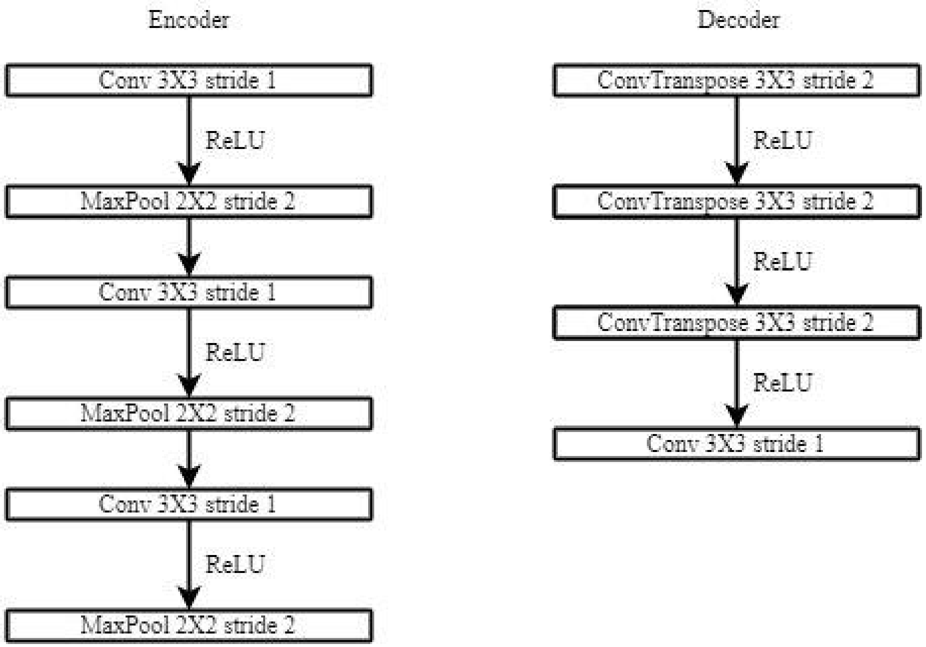
General structure of autoencoder:

- The encoder compresses the input data into a representation in a latent space;
- The decoder reconstructs the original input data from this representation



Architecture of the developed convolutional autoencoder:

- 3 convolutional encoder layers and 3 convolutional decoder layers



Training process:

- 50 epochs;
- Train set consists of 6566 records;
- Validation after each epoch on 730 records;
- MSE Loss and Adam optimizer.

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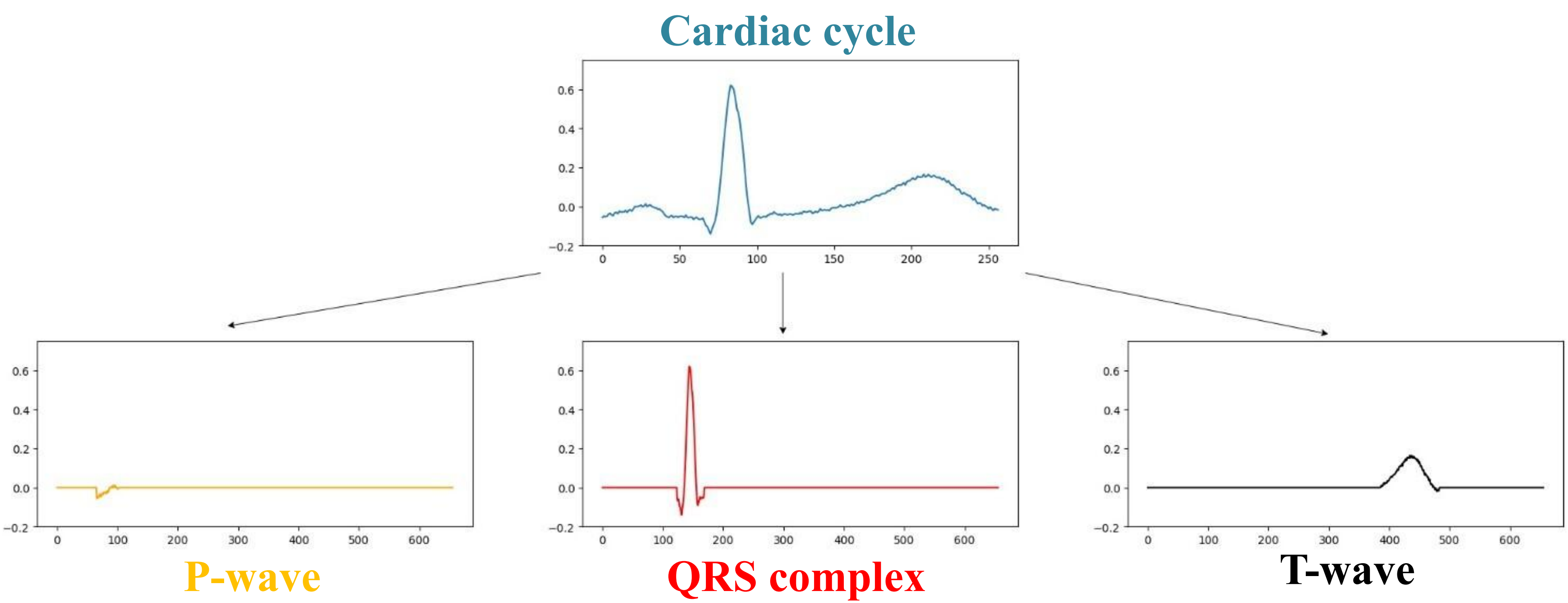
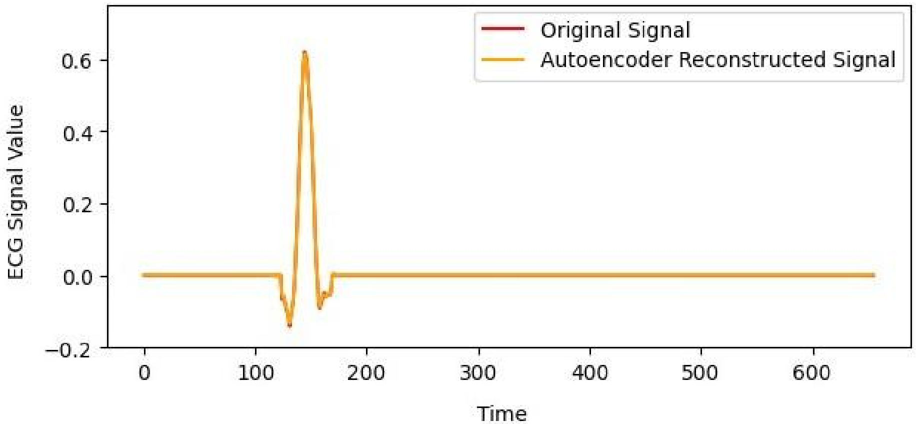
Scheme of experimental data generation:

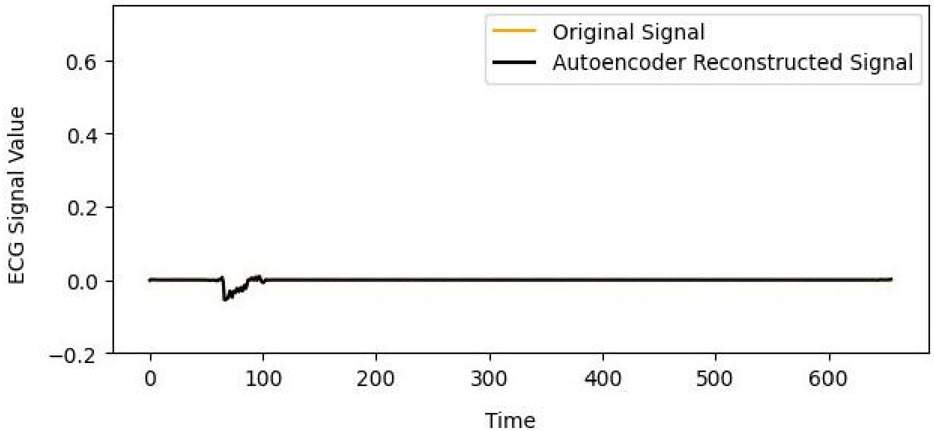


OY: ECG signal values
OX: time

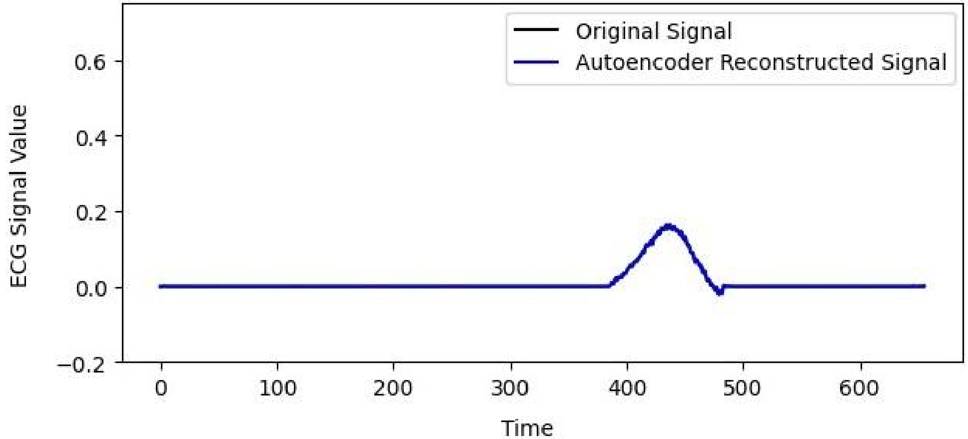
The result of interpolation:



QRS complex



P-wave



T-wave

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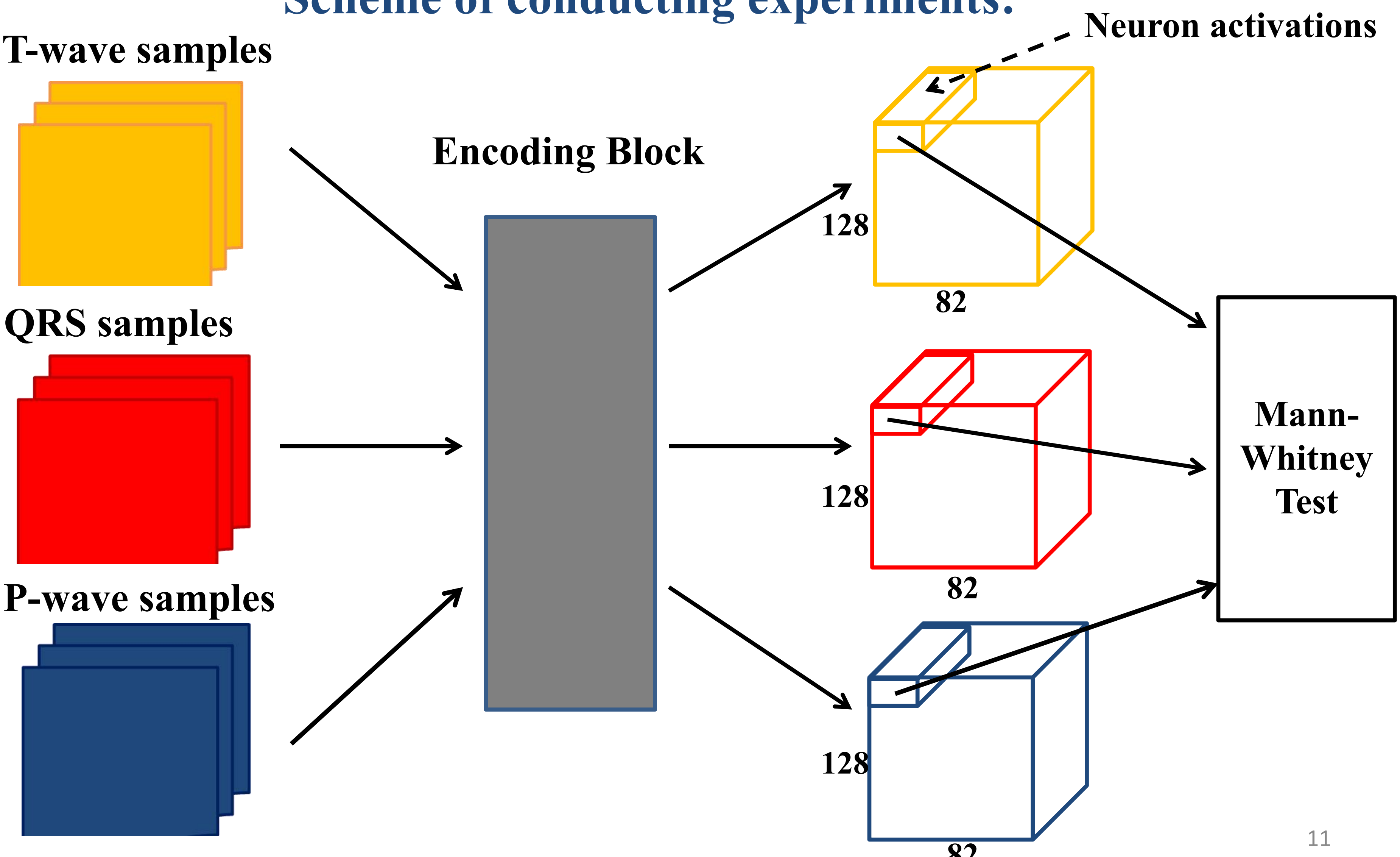
Scheme of conducting experiments:



Results

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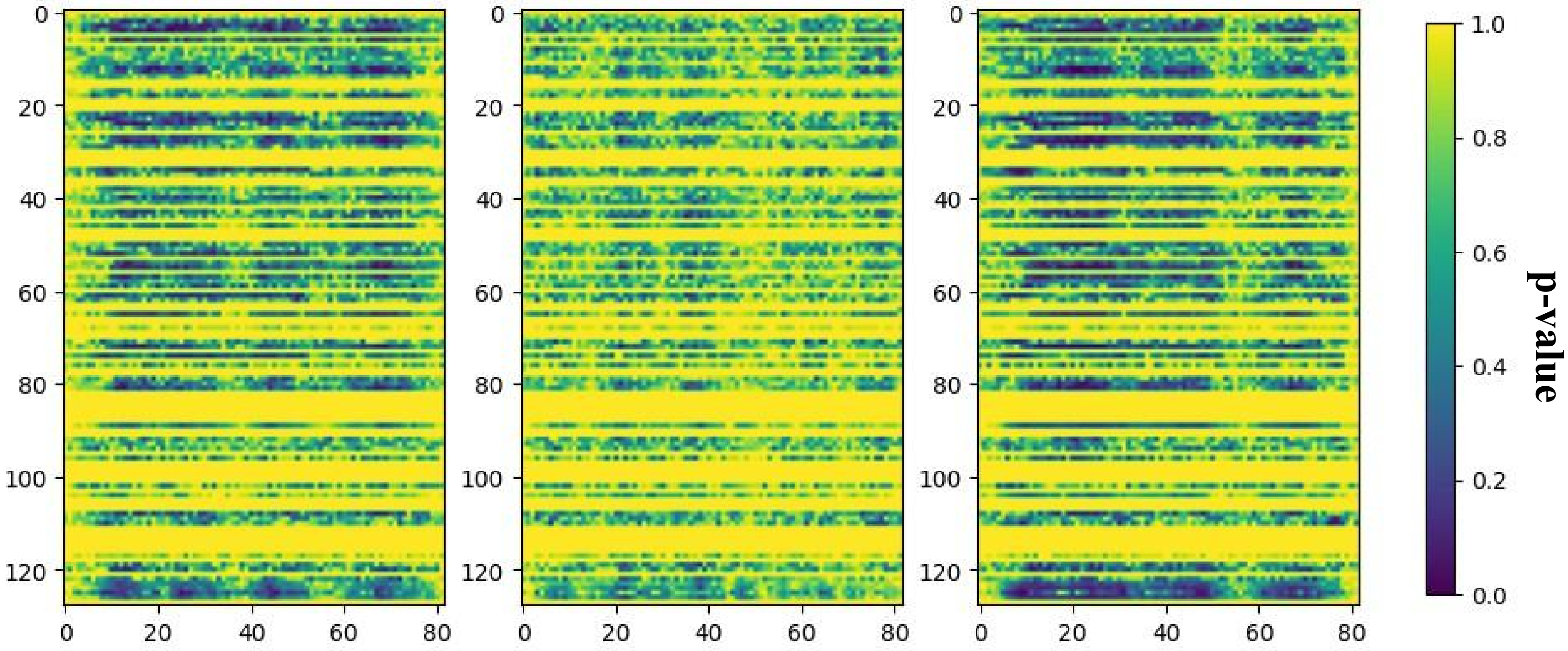
Specialized neurons are defined as those neurons for which p-value in two of three cases is less than 0.05 (chosen significance level).

Heatmaps of obtained p-values from the Mann-Whitney Test:



a) p-values from the Mann-Whitney test for activation samples of QRS and T

b) p-values from the Mann-Whitney test for activation samples of QRS and P

c) p-values from the Mann-Whitney test for activation samples of P and T

Results

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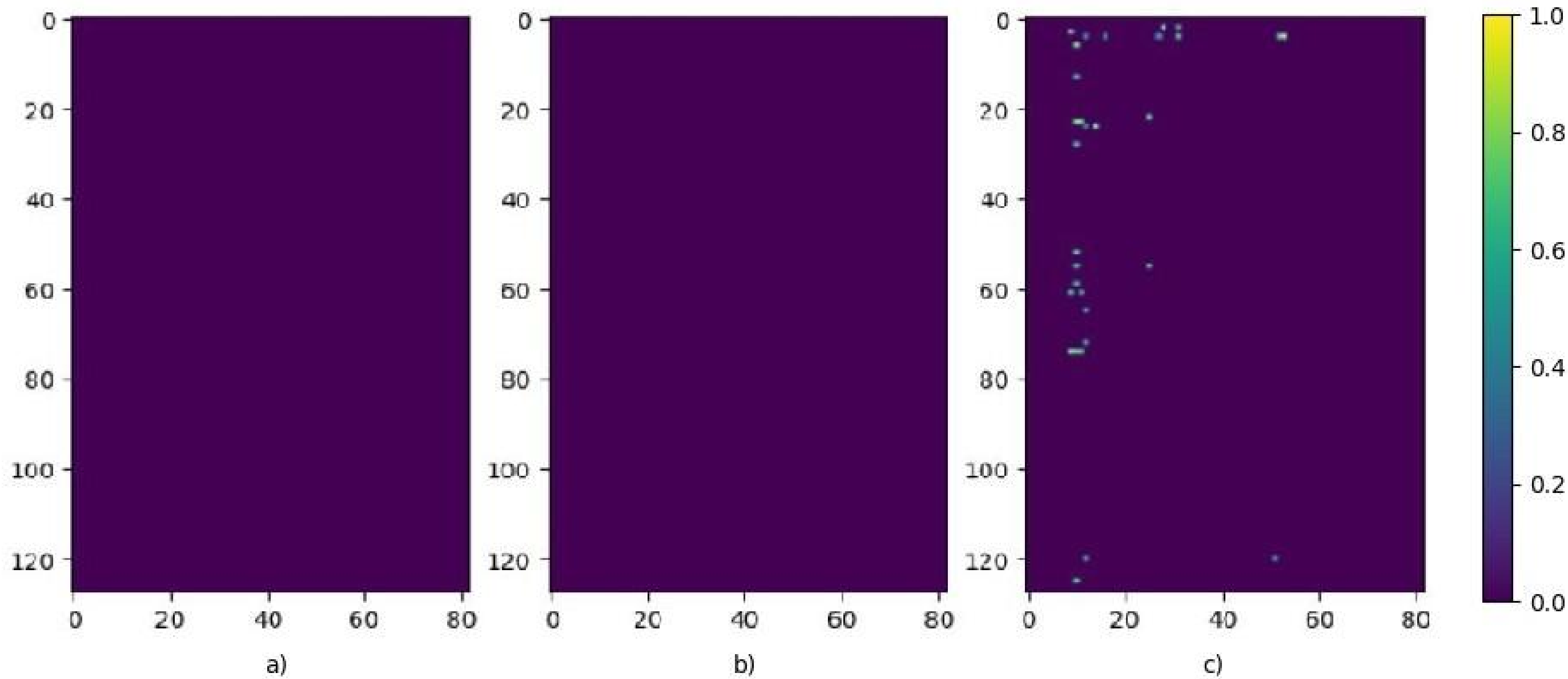
Heatmaps of specialized neurons:



Neurons specialized in the QRS complex

Neurons specialized in the P-wave

Neurons specialized in the T-wave

The more specialized the neuron is, the closer its value is to 1 in the heatmap.

Results

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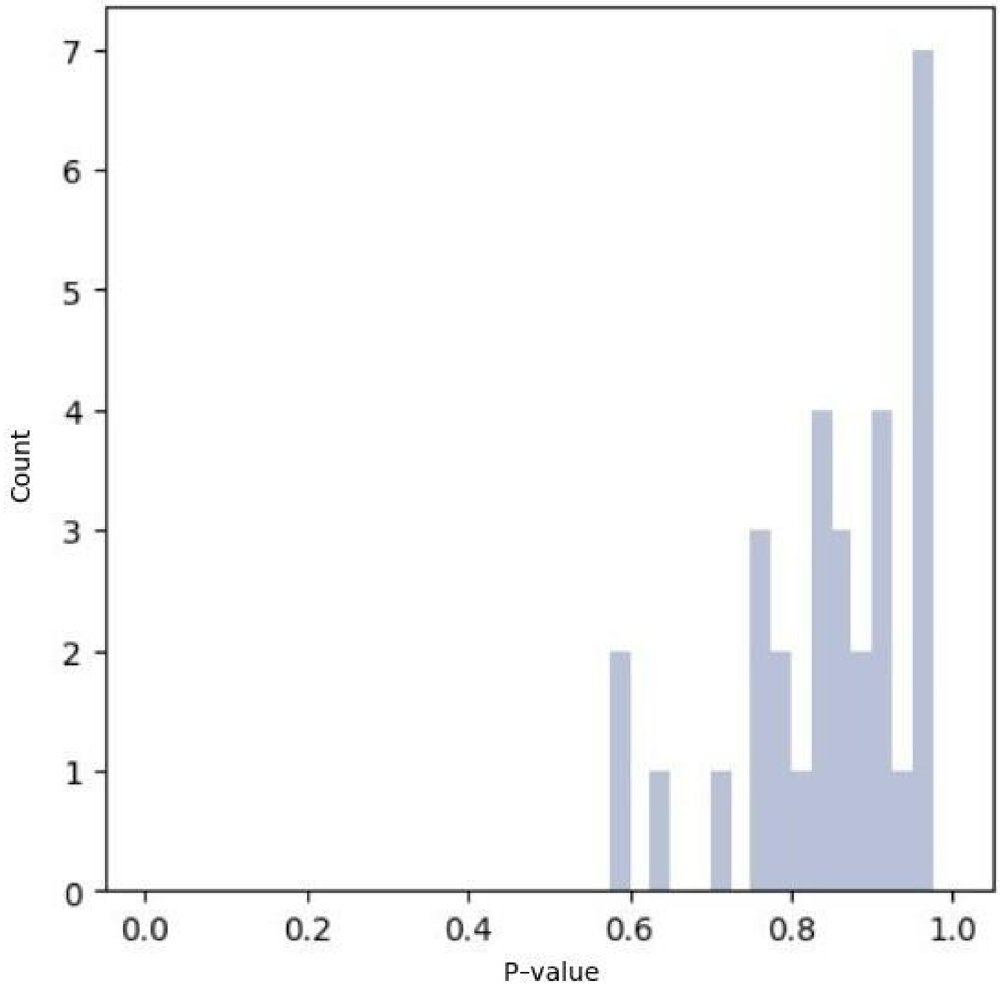
Histogram of p-values in the Mann-Whitney test on samples of P-wave and QRS complex neuron activation for T-wave specialized neurons:



- The analyzed neurons are actually specialized only in T-wave.
- The percentage of specialized neurons is **0.29%.**
- Experiments on changing architecture of autoencoder (kernel size, the number of convolutional layers, the number of channels) showed that a stable appearance of specialized neurons for the T-wave continued to be observed.

Conclusion

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- Our study of a well-trained autoencoder revealed that statistical specialization of neurons for fragments of the cardiac cycle important for diagnosis is very small.
- The number of specialized neurons for different fragments of the cardiac cycle is different, which shows problems with the interpretability of the convolutional network representation of the data.
- Experiments were also conducted to vary the architecture of the autoencoder, showing that the detected tendencies remain invariant to architecture changes.
- A further direction of research could be to use the knowledge of neuron specialization in developing new transfer learning techniques for training neural networks for electrocarodiagram markup and diagnosing to improve the interpretability of the results.

Thank you for your attention!

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References

1. Y. Wang, Q. Yao, J. Kwok, and L. Ni, "Generalizing from a few examples: A survey on few-shot learning," ACM Computing Surveys, vol. 53, pp. 1–34, June 2020.
2. Y. Song, T. Wang, P. Cai, S. Mondal, and J. Sahoo, "A comprehensive survey of few-shot learning: Evolution, applications, challenges, and opportunities," ACM Computing Surveys, vol. 55, February 2023.
3. Y. Li and J. Huang, "Explore pretraining for few-shot learning," Multimedia Tools and Applications, vol. 83, pp. 1–12, May 2023.
4. C.-Y. Chen, H.-T. Lin, G. Niu, and M. Sugiyama, "On the role of pre-training for meta few-shot learning," 2021, accessed 7-8-24. [Online]. Available: https://openreview.net/forum?id=TwkEGci1Y-
5. T. Liu, Y. Yang, W. Fan, and A. Chen, "Few-shot learning for cardiac arrhythmia detection based on electrocardiogram data from wearable devices," Digital Signal Processing, vol. 116, p. 103094, May 2021.
6. W. Zhang, S. Geng, Z. Fu, L. Zheng, C. Jiang, and linda Qiao, "Metava: Curriculum meta-learning and pre-fine-tuning of deep neural networks for detecting ventricular arrhythmias based on ecgs," ArXiv, vol. abs/2202.12450, 2022. [Online]. Available: https://api.semanticscholar.org/CorpusID:247155183
7. P. Gupta, S. Bhaskarpandit, and M. Gupta, "Similarity learning based few shot learning for ecg time series classification," in 2021 Digital Image Computing: Techniques and Applications (DICTA), 2021, pp. 1– 8.
8. H. Quan, X. Li, D. Hu, T. Nan, and X. Cui, "Dual-channel prototype network for few-shot pathology image classification," IEEE Journal of Biomedical and Health Informatics, vol. 28, no. 7, pp. 4132–4144, 2024.
9. B. T. Jin, R. Palleti, S. Shi, A. Y. Ng, J. V. Quinn, P. Rajpurkar, and D. Kim, "Transfer learning enables prediction of myocardial injury from continuous single-lead electrocardiography," Journal of the American Medical Informatics Association, vol. 29, no. 11, pp. 1908–1918, August 2022. [Online]. Available: https://doi.org/10.1093/jamia/ocac135
10. G. Wang, Q. Wang, G. N. Iyer, A. Nag, and D. John, "Unsupervised pre-training using masked autoencoders for ecg analysis," 2023, accessed 7-8-24. [Online]. Available: https://arxiv.org/abs/2310.11153
11. N. Nachar, "The mann-whitney u: A test for assessing whether two independent samples come from the same distribution," Tutorials in Quantitative Methods for Psychology, vol. 4, March 2008.
12. A. Kalyakulina, I. Yusipov, V. Moskalenko, A. Nikolskiy, K. Kosonogov, G. Osipov, N. Zolotykh, and M. Ivanchenko, "Ludb: A new openaccess validation tool for electrocardiogram delineation algorithms," IEEE Access, vol. 8, pp. 186 181–186 190, January 2020.
13. Y. Zhang, "A better autoencoder for image: Convolutional autoencoder," in ICONIP17-DCEC, 2018. [Online]. Available: https://api.semanticscholar.org/CorpusID:209442203