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Analysis of Electrocardiograms via Artificial Neural Networks For a Reliable Assessment of a Possible Myocardial Infarction

Alexey Gavryushin
Guglielmo Pacifico
Juan Fernandez de la Garza
Sunho Kim

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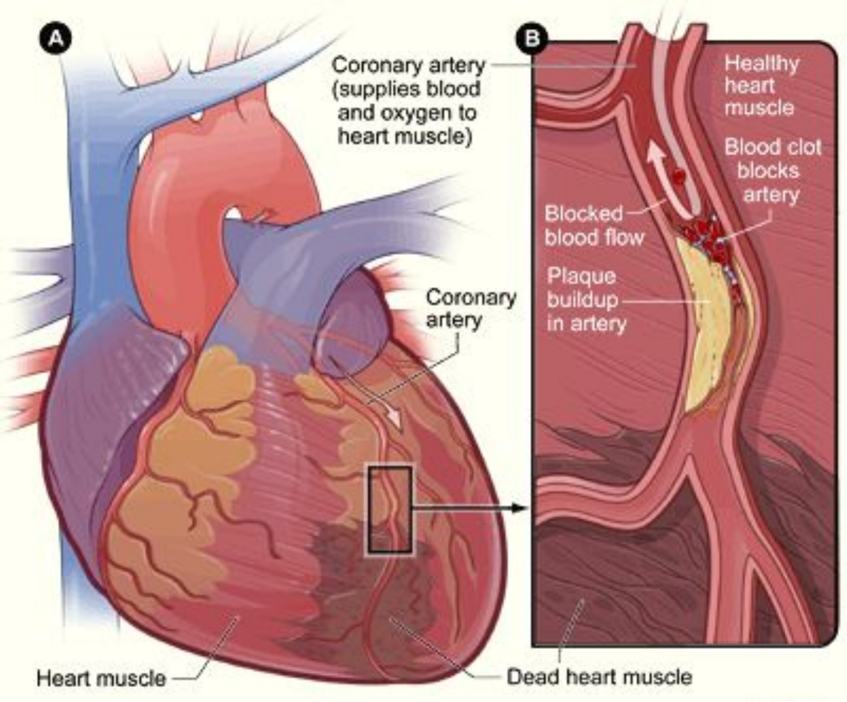
1.1 Problem Setting

What is Myocardial Infarction?

The presence of acute myocardial injury, detected by abnormal cardiac biomarkers in the setting of evidence of acute myocardial ischemia.



⇩

Happens when one or more areas of the heart muscle don’t get enough oxygen. This happens when blood flow to the heart muscle is blocked.

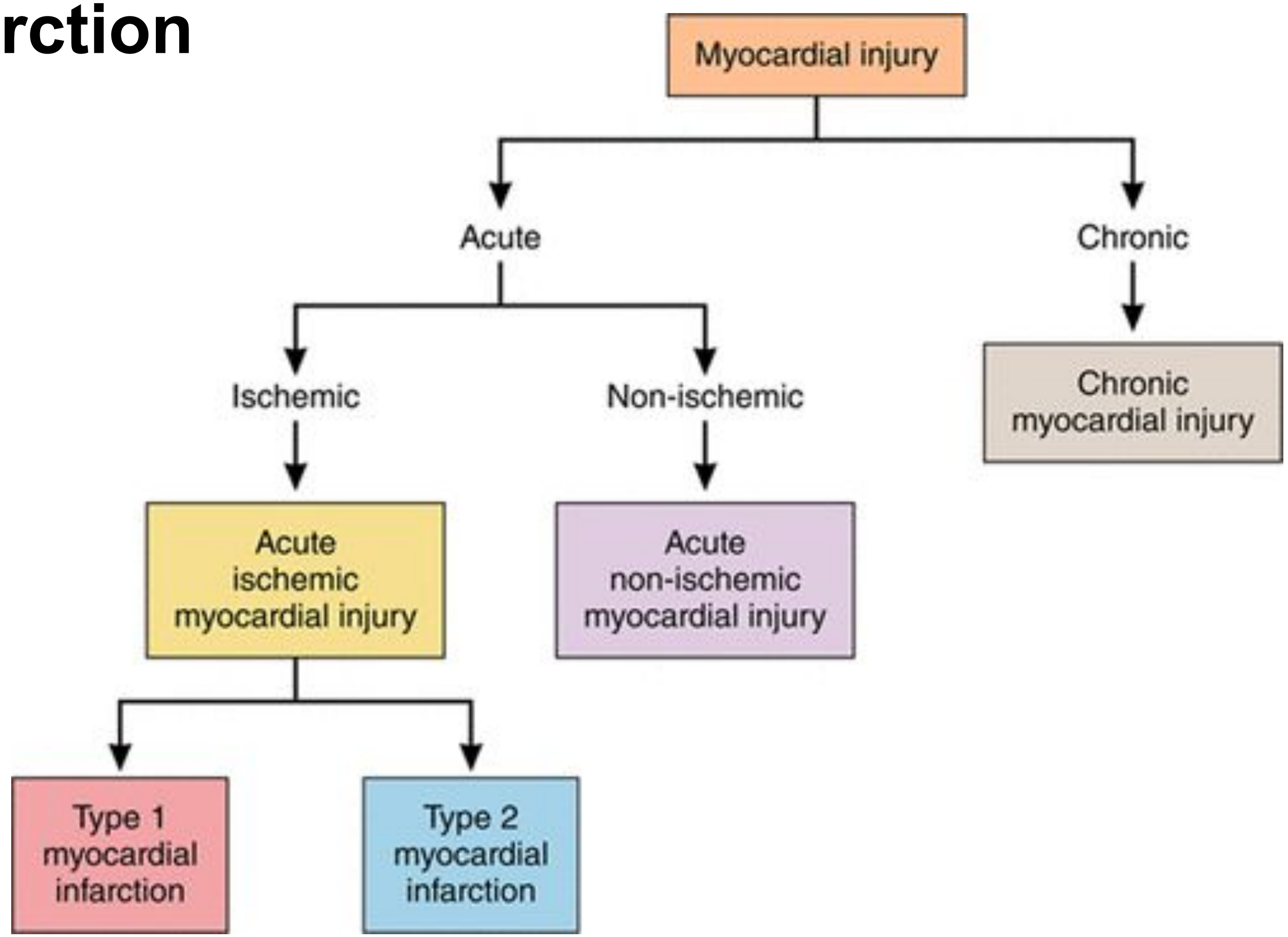
1) https://doi.org/10.1161/CIRCULATIONAHA.119.040631 Circulation. 2019;140:1661–1678
2) https://www.hopkinsmedicine.org/health/conditions-and-diseases/heart-attack

1.1 Problem Setting

Subtypes of Myocardial Infarction

Ischemic?

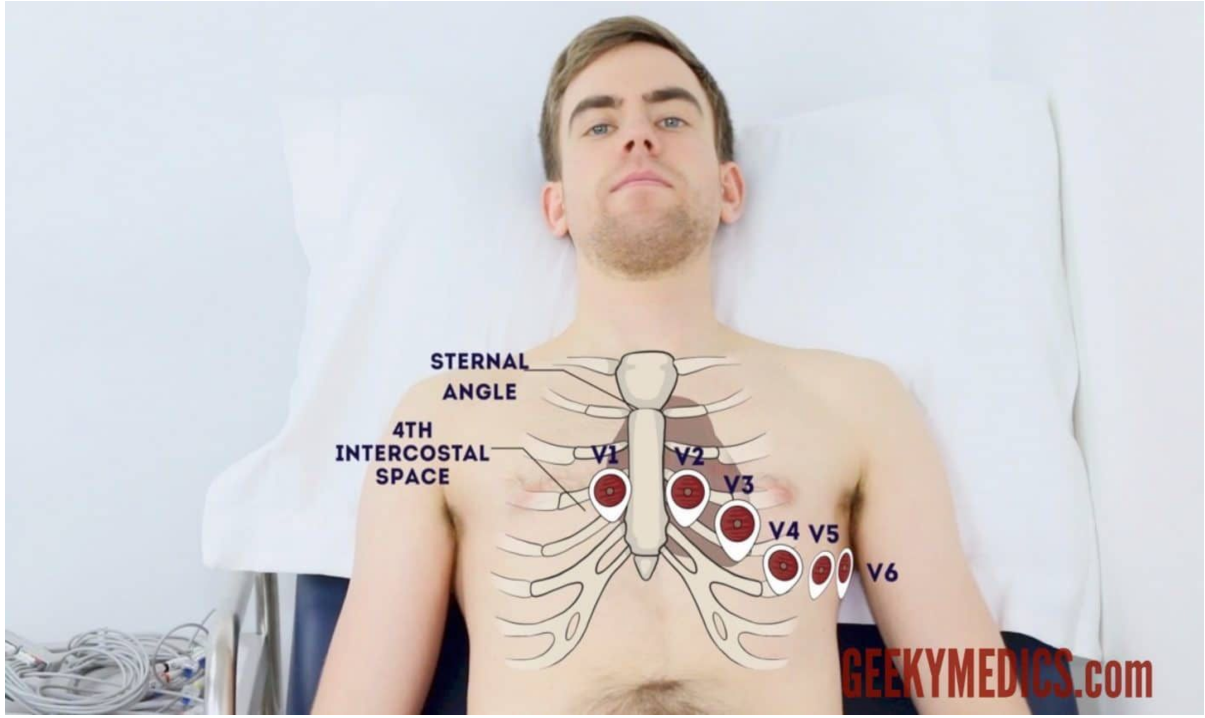
Deficient supply of blood to a body part that is due to obstruction of the inflow of arterial blood.

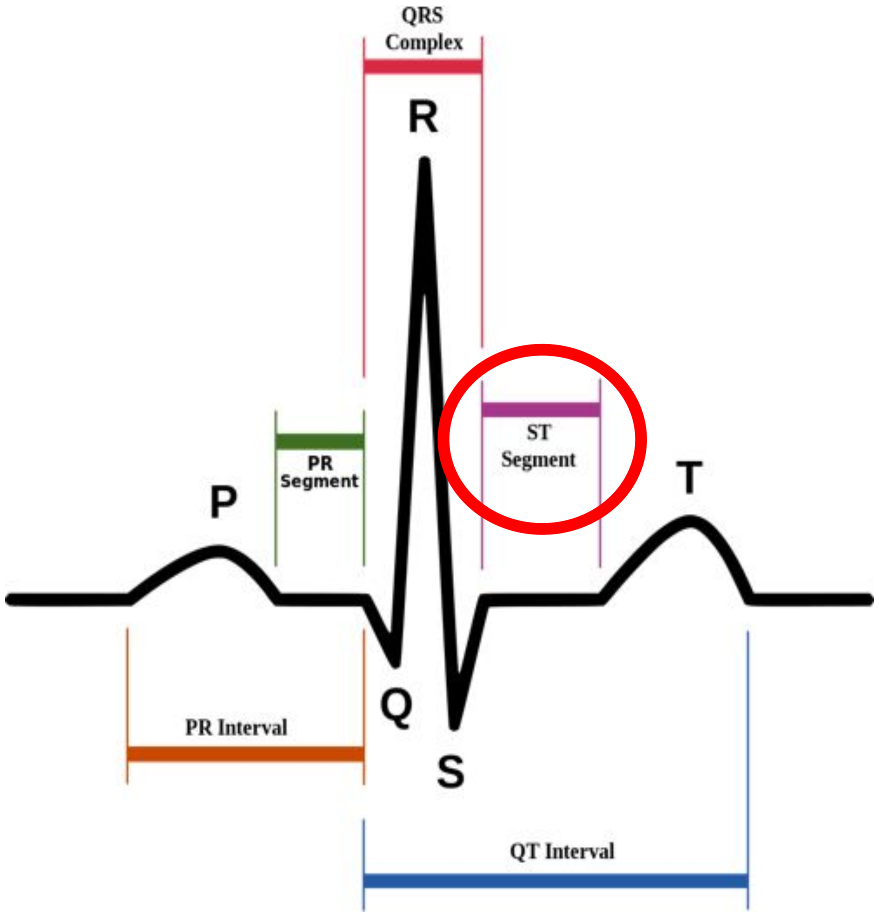


DeFilippis, A. P., Chapman, A. R., Mills, N. L., de Lemos, J. A., Arbab-Zadeh, A., Newby, L. K., & Morrow, D. A. (2019). Assessment and Treatment of Patients With Type 2 Myocardial Infarction and Acute Nonischemic Myocardial Injury. *Circulation*, *140*(20), 1661–1678. https://doi.org/10.1161/CIRCULATIONAHA.119.04063, Figure 1. Myocardial injury taxonomy.

1.1 Problem Setting

How can we detect MI? - ECG data





STEMI: ST-elevation myocardial infarction
NSTEMI: heart attack that usually happens when your heart needs oxygen can't be met

1.1 Problem Setting

How can we detect MI?

Figure 1) http://what-when-how.com/paramedic-care/the-monitoring-ecg-clinical-essentials-paramedic-care-part-1
Figure 2) https://www.samsung.com/global/galaxy/galaxy-watch4/
Figure 3) https://www.apple.com/uk/newsroom/2019/03/ecg-app-and-irregular-rhythm-notification-on-apple-watch-available-today-across-europe-and-hong-kong/

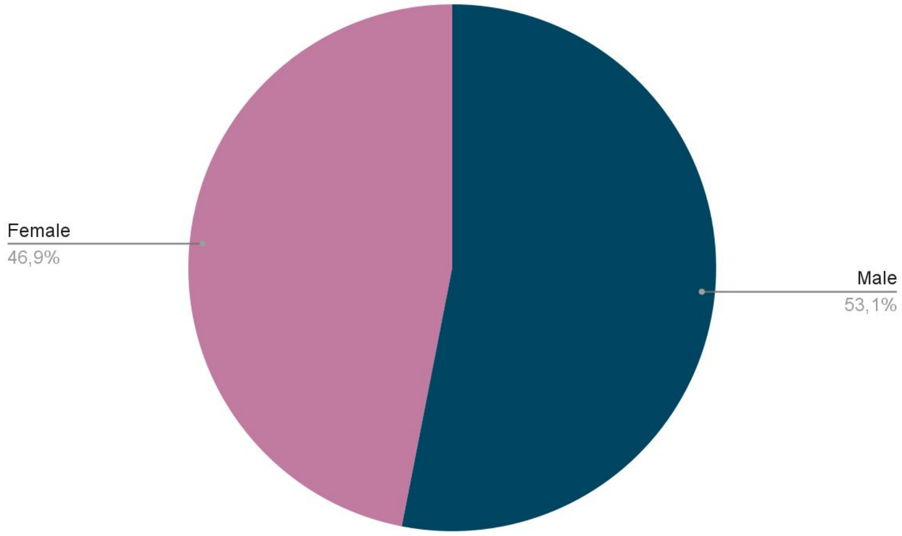
1.2 Project Idea

Why do we need a reliable ECG assessment?

"In Tanzania, I was involved in [training and equipping taxi drivers](https://www.hmpgloballearningnetwork.com/site/emsworld/article/12101337/the-struggles-of-ems-in-other-countries) in the place of ambulances and using motorcycle taxi riders as first responders."

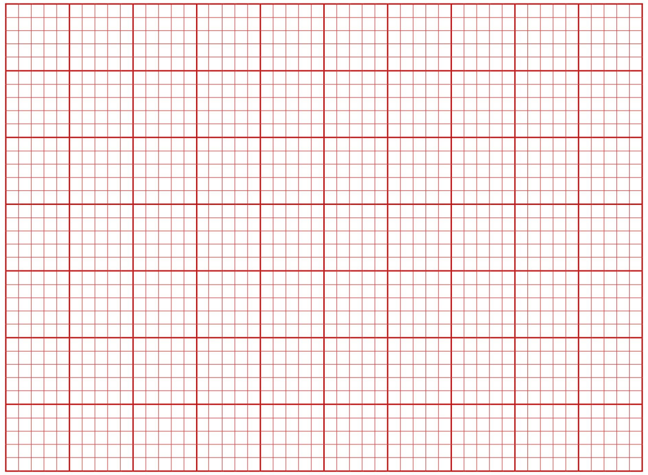
Figure 1) https://www.aljazeera.com/gallery/2019/4/1/ugandas-bicycle-ambulances-help-the-pregnant-sick-and-injured
https://www.hmpgloballearningnetwork.com/site/emsworld/article/12101337/the-struggles-of-ems-in-other-countries

2.1 Datasets

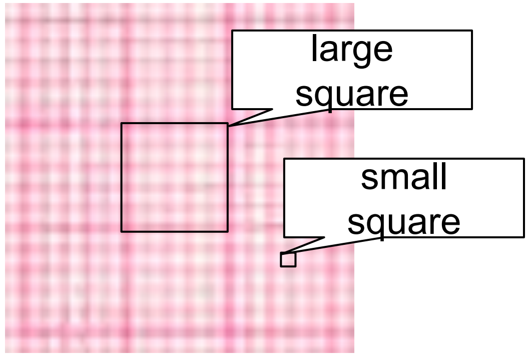


- PTB-XL ECG dataset
  - 21837 clinical 12-lead ECGs
  - 18885 patients, between 0 and 95 years old
  - 10 second length
  - 71 total different ECG statements conform to the SCP-ECG s

- Generate new “**PTB-V**” (“PTB-Visualized”) dataset
  - From time series to images
  - Python library “PIL” (Pillow) and the classes `Image` and `ImageDraw`



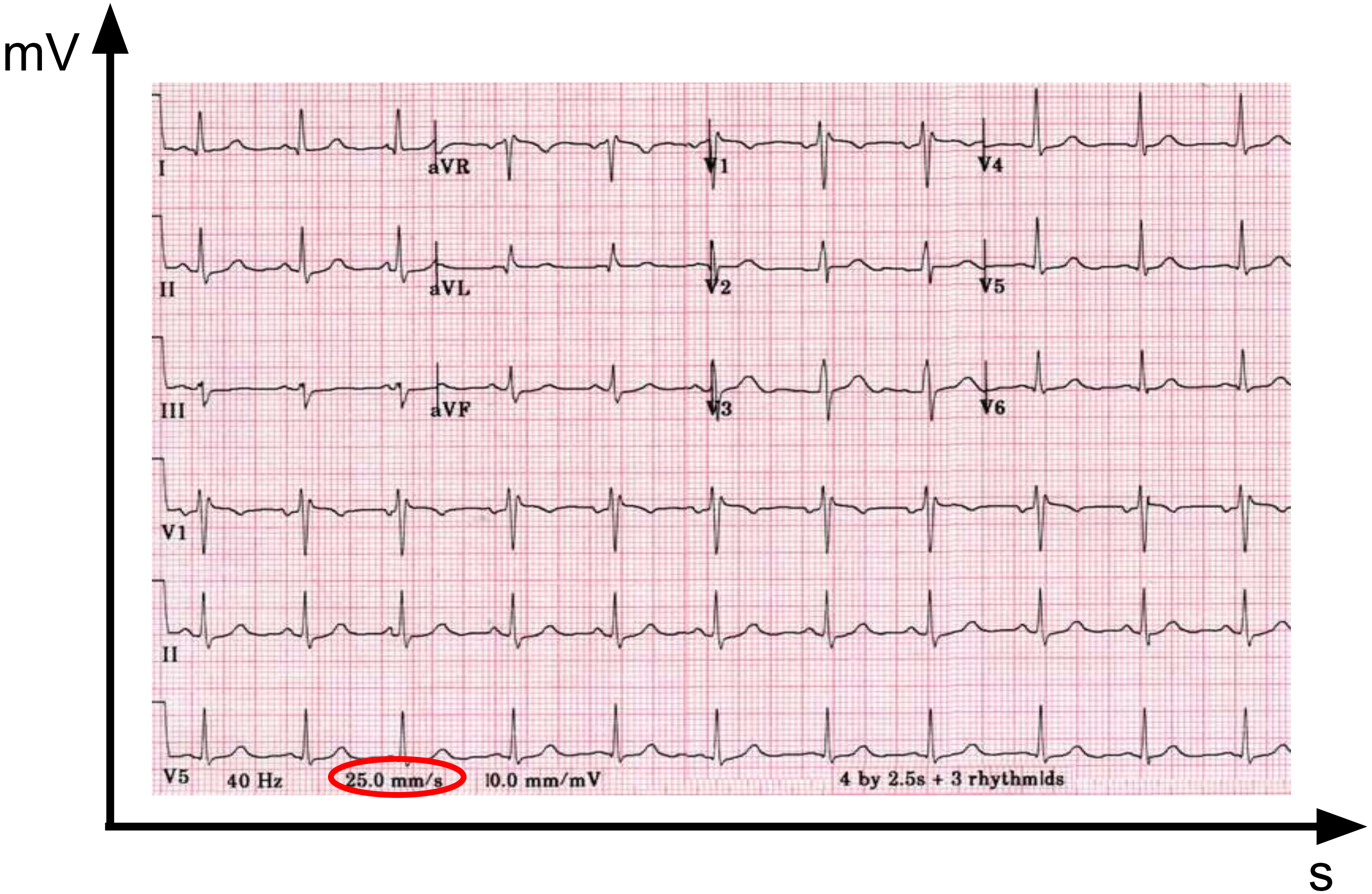
2.2 How to Read an ECG

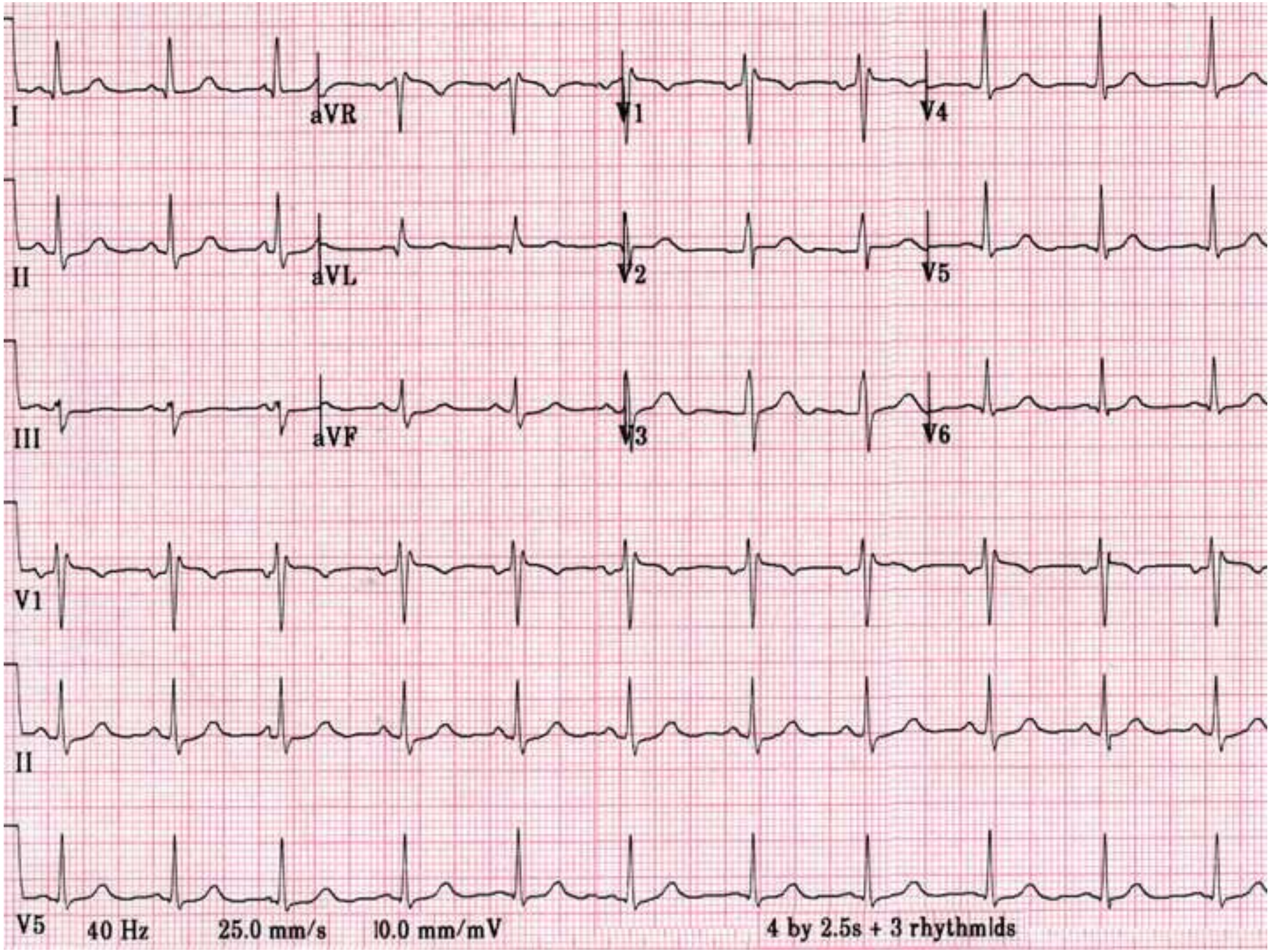


Default paper speed of 25mm/s:

- Each small square is 1 mm^2
- Each small square represents 0.04 s
- Each large square represents 0.2 s
- 5 large squares = 1 s
- 10 squares high = 1 mV

- **Chest leads**
  - V1: septal view of the heart
  - V2: septal view of the heart
  - V3: anterior view of the heart
  - V4: anterior view of the heart
  - V5: lateral view of the heart
  - V6: lateral view of the heart
- **Other leads**
  - Lead I: lateral view
  - Lead II: inferior view
  - Lead III: inferior view
  - aVR: lateral view
  - aVL: lateral view
  - aVF: inferior view

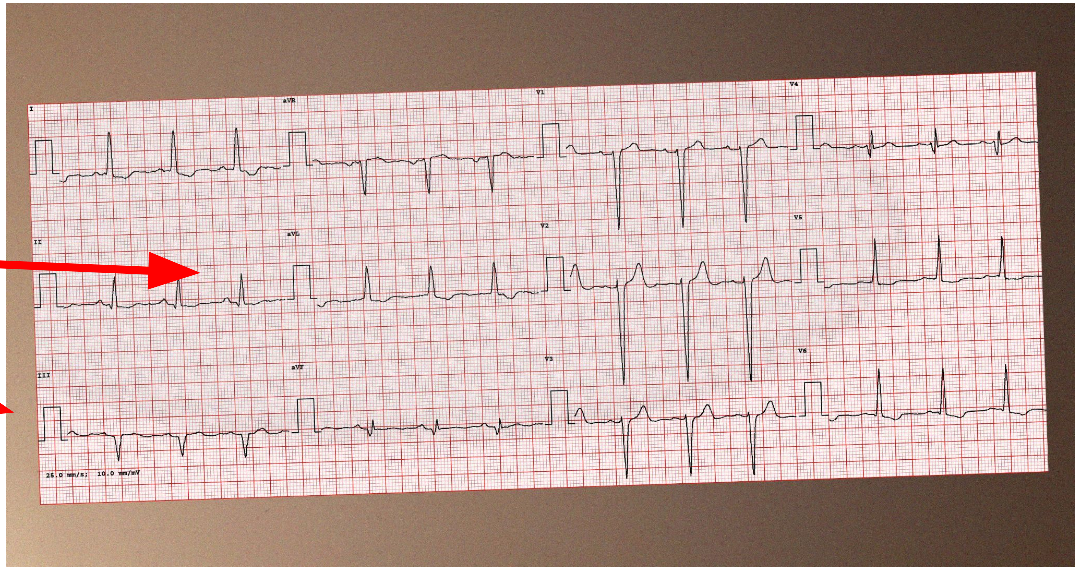


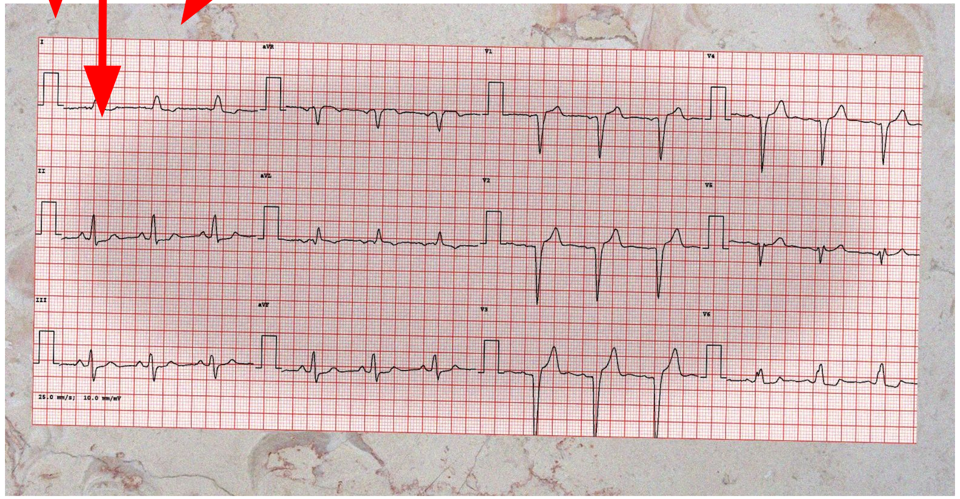

I
aVR
V1
V4
II
aVL
V2
V5
III
aVF
V3
V6
V1
II
V5
40 Hz
25.0 mm/s
10.0 mm/mV
4 by 2.5s + 3 rhythmlds

2.3 Data augmentation

Goal : making the segmentation network more robust to different kinds of inputs

- shearing
- rotation
- blurring
- noise
- shadows and flashes
- different backgrounds

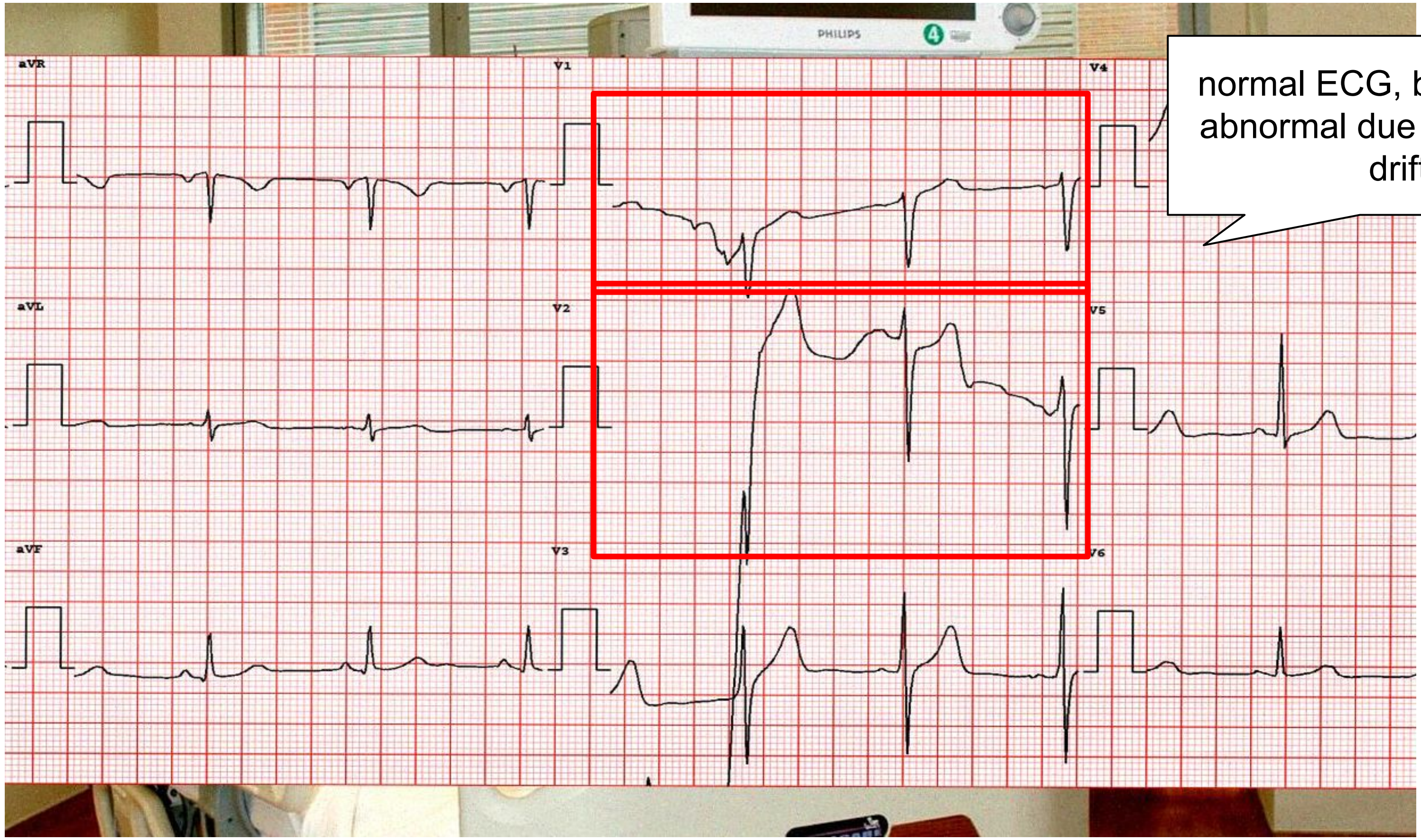




→ as a result we also generate more pictures

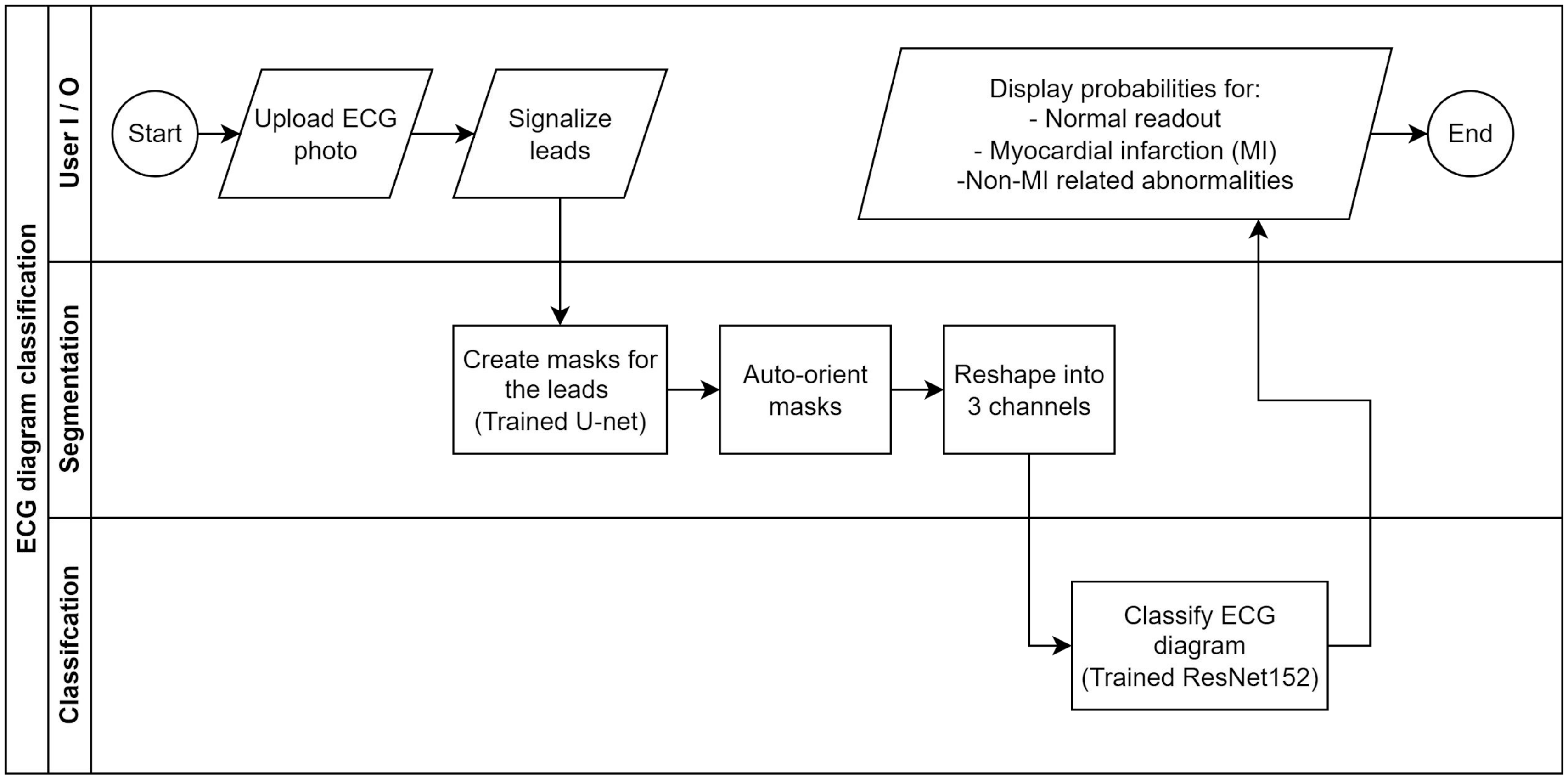
2.4 Problems with the data

- **Baseline drift**: Patient moving during the measurement



normal ECG, but appears abnormal due to baseline drift

3 ECG Processing Overview



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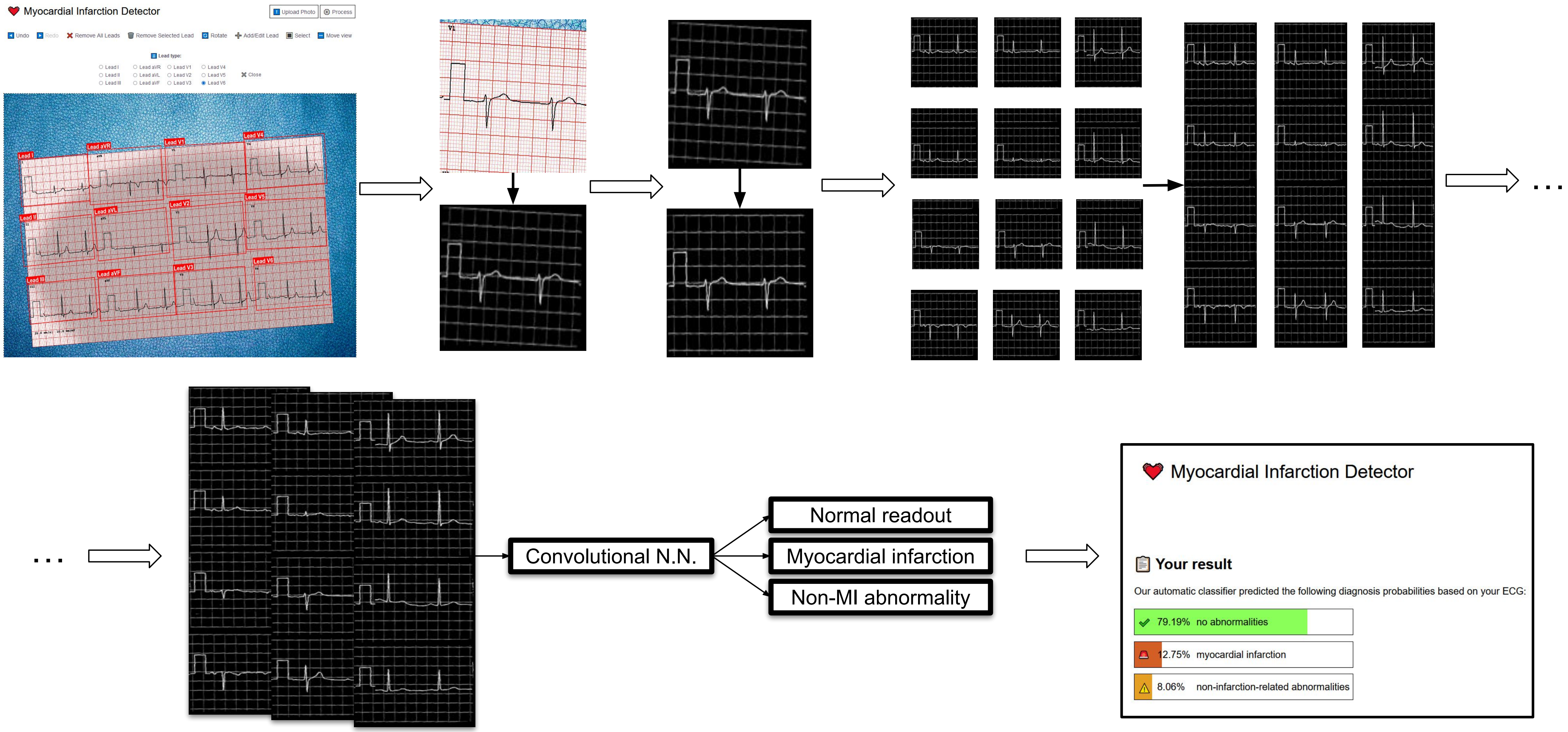

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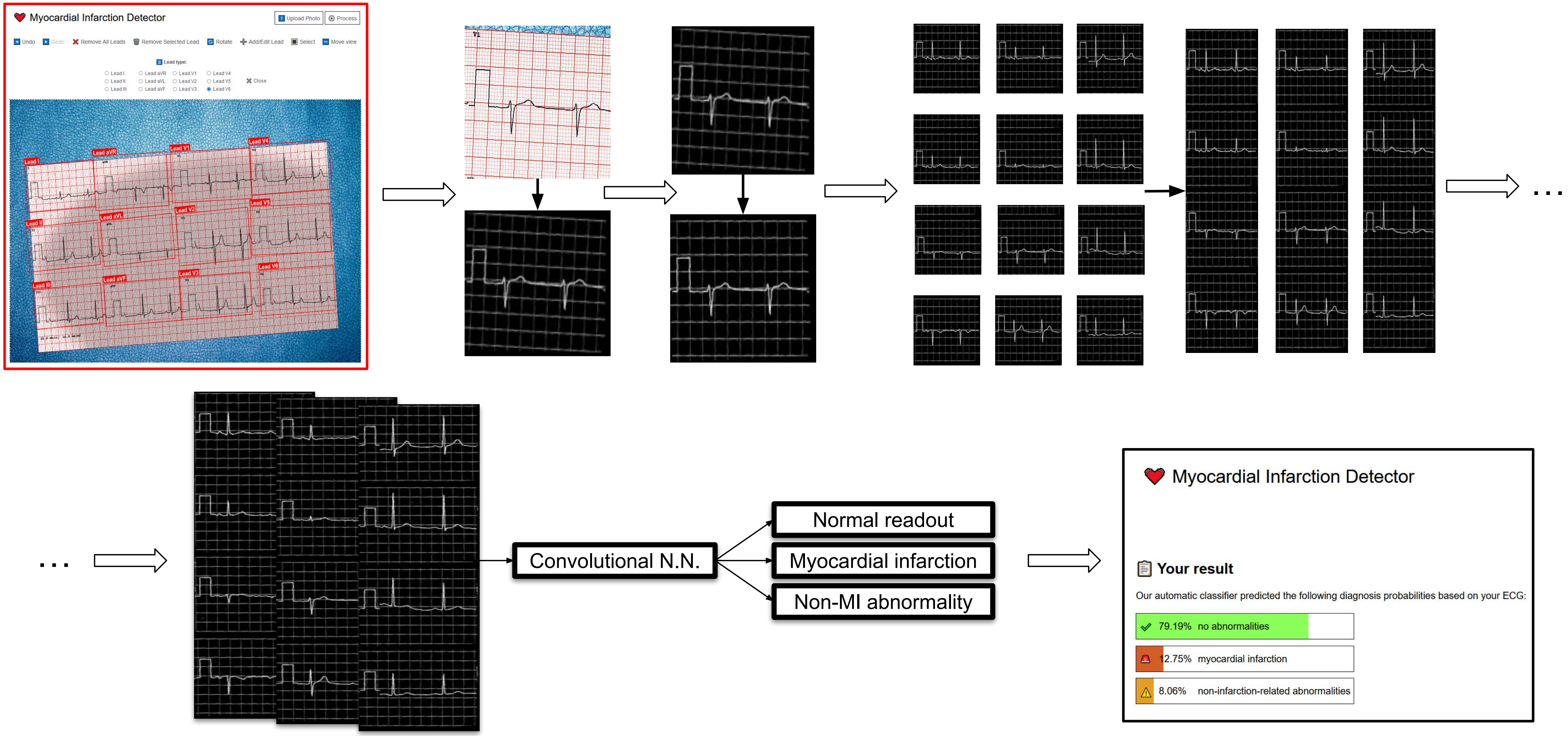

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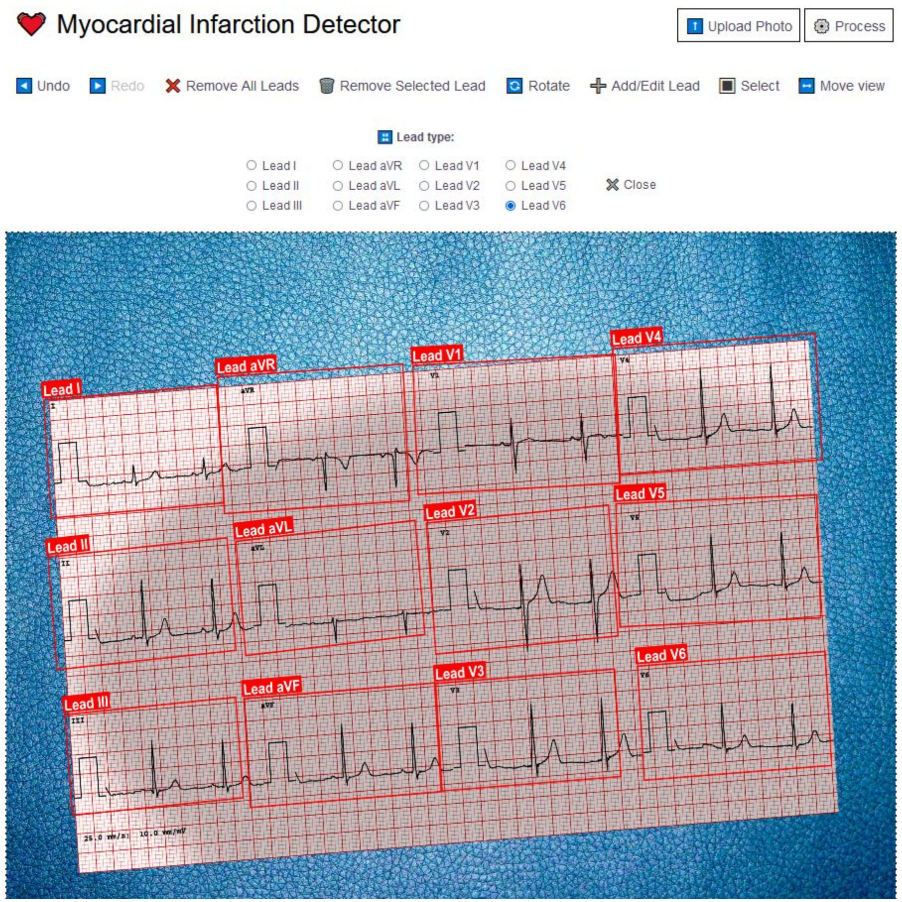

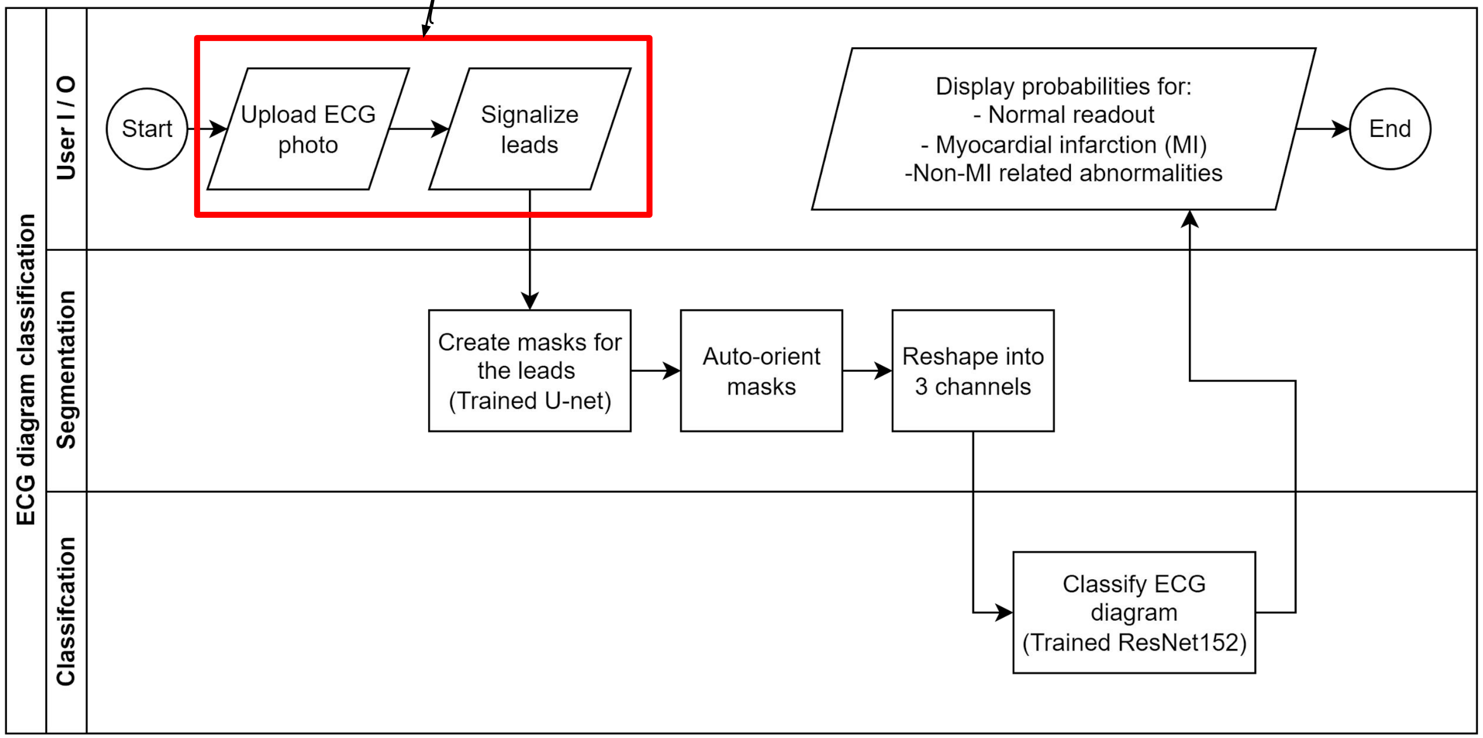

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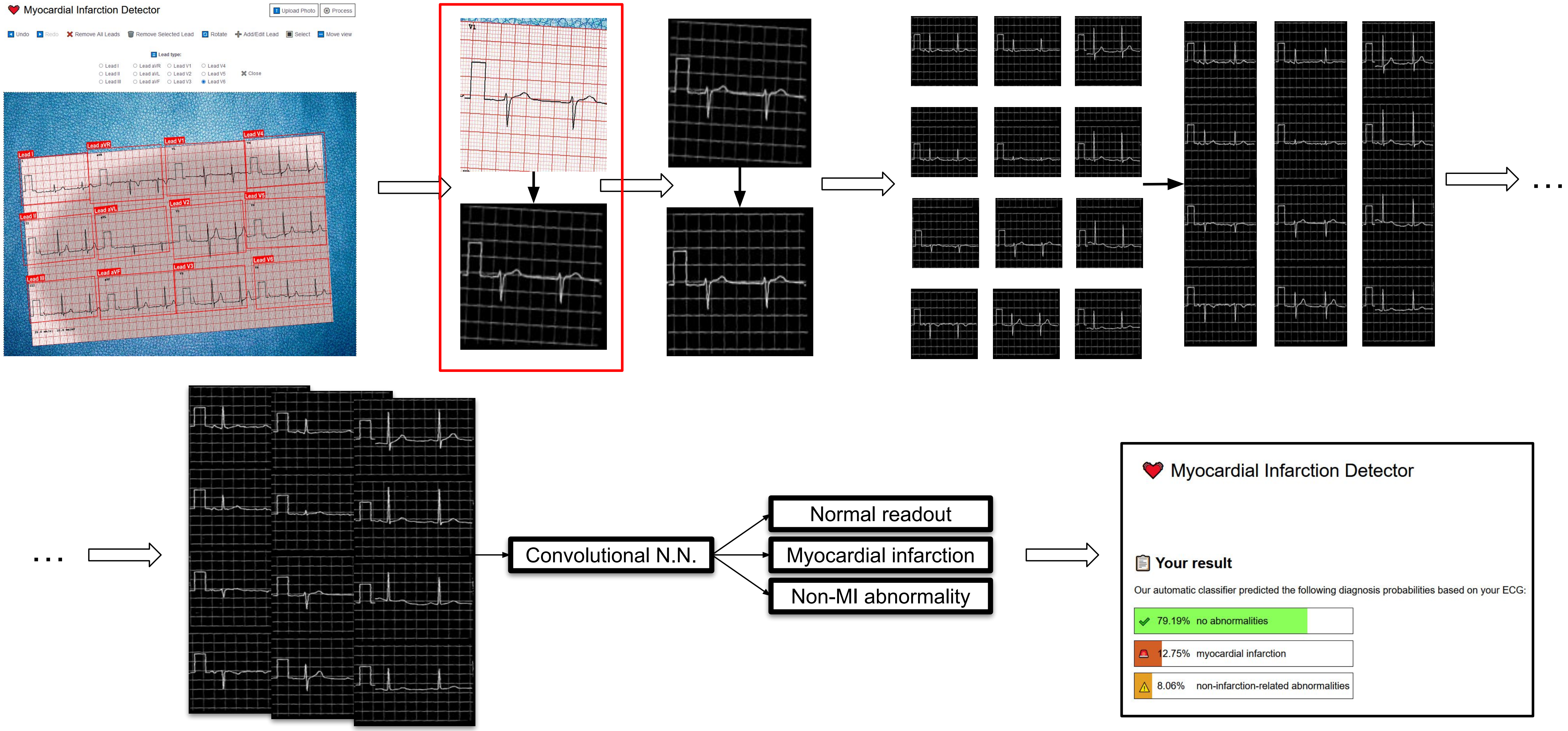

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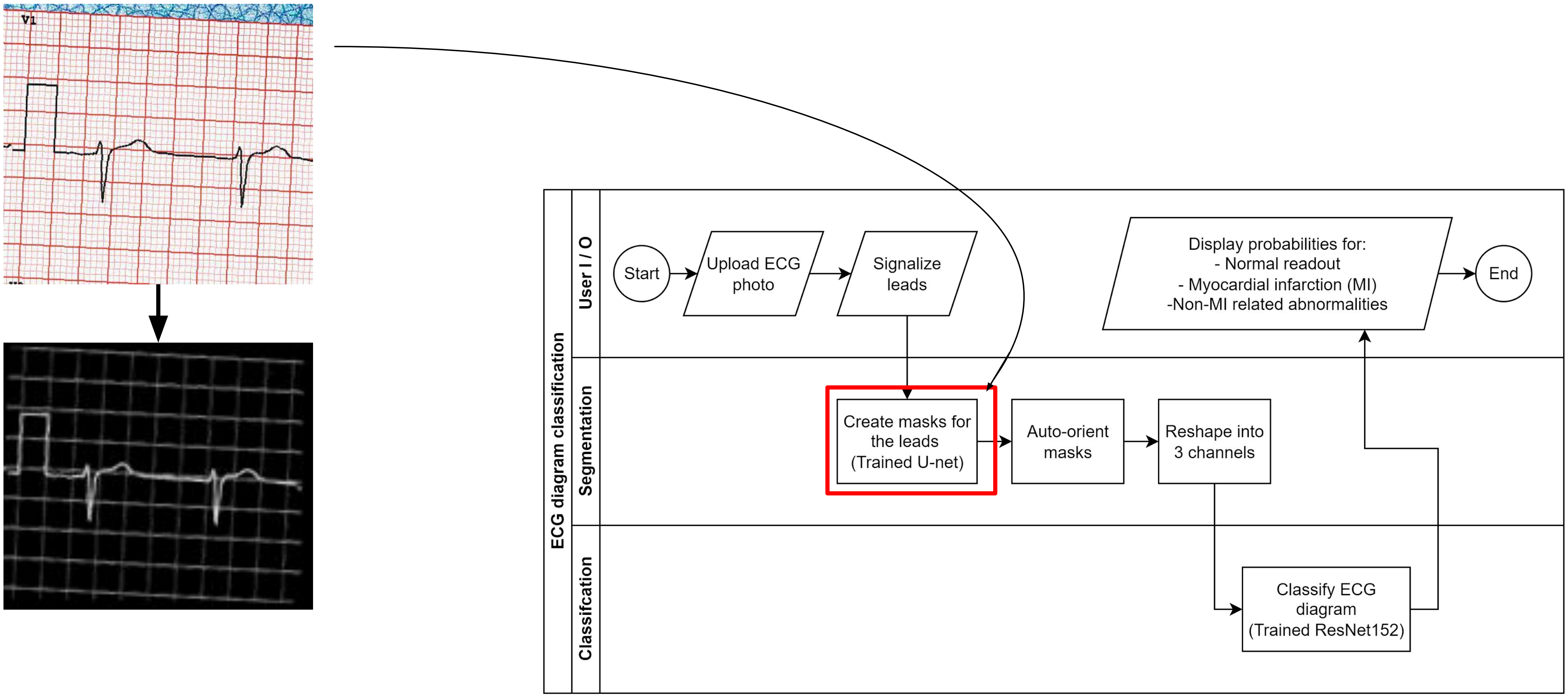
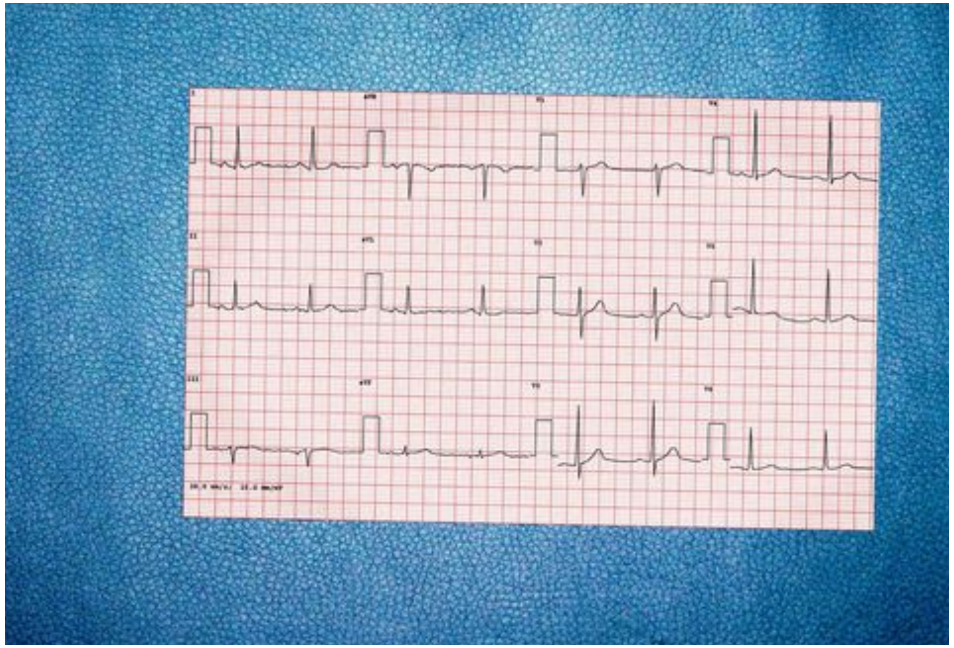
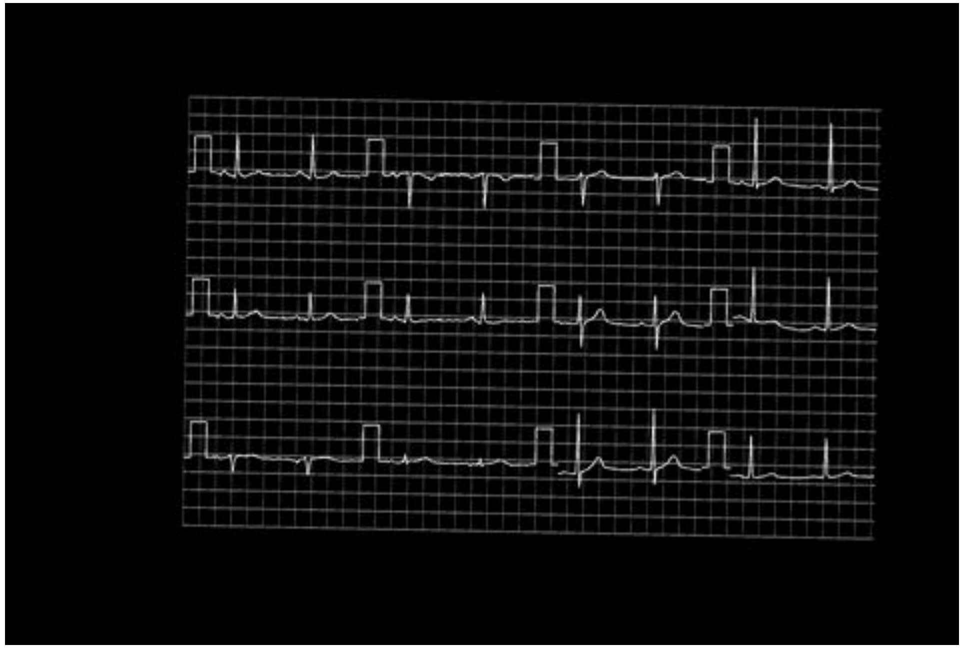


Ronneberger, O., Fischer, P., & Brox, T.. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. : https://arxiv.org/abs/1505.04597

3.1 ECG Segmentation

The U-Net was trained with pairs of masks and generated ECG diagrams with data augmentation applied to them, notice that the mask corresponds to the training label.





Grid-lines are also captured in the training to be used for auto-orienting of diagrams during processing.

3.1 ECG Segmentation

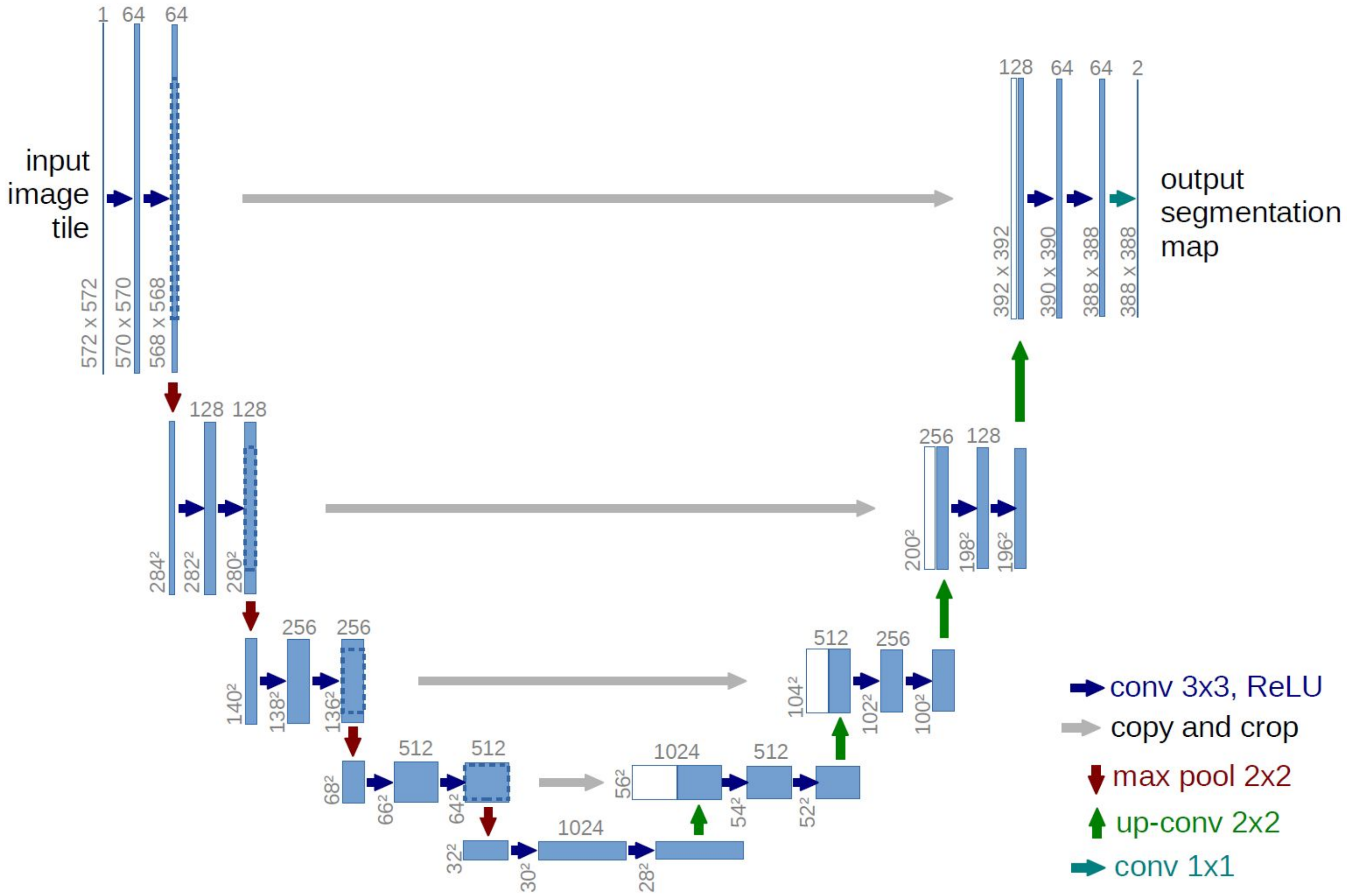


Figure taken from: Ronneberger, O., Fischer, P., & Brox, T.. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. : https://arxiv.org/abs/1505.04597

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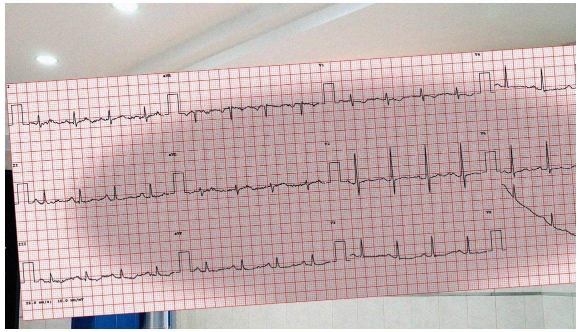

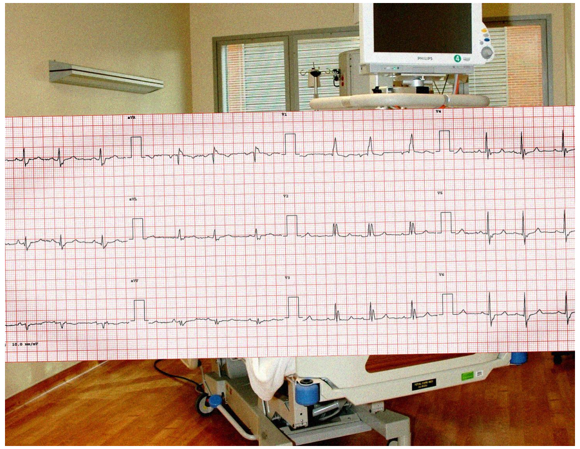

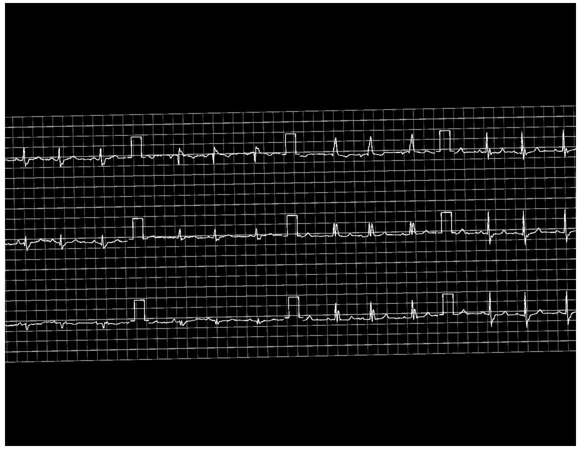

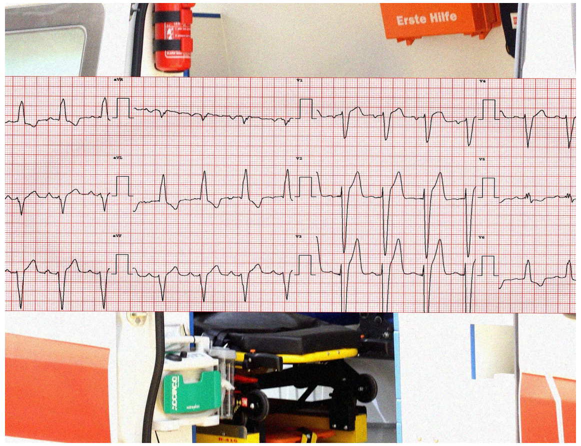

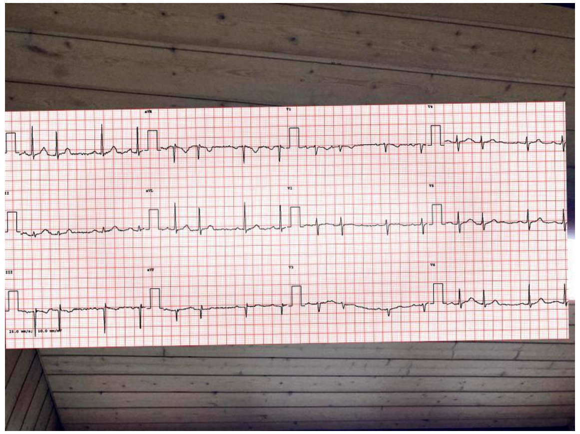

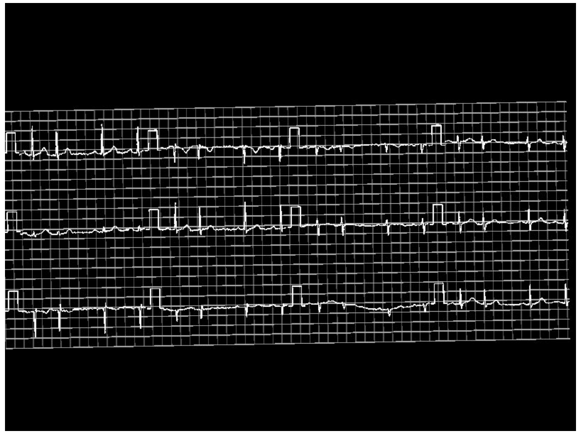

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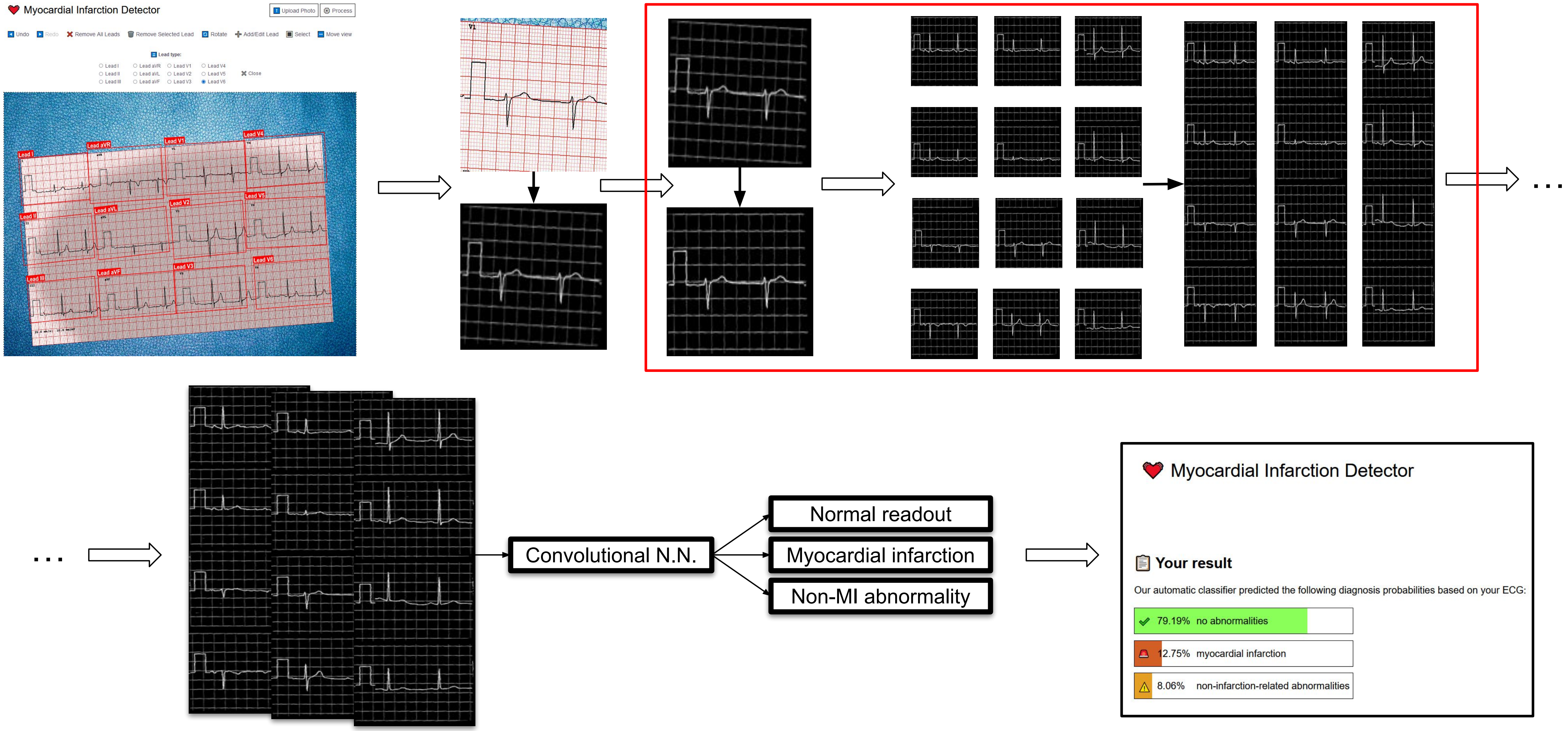
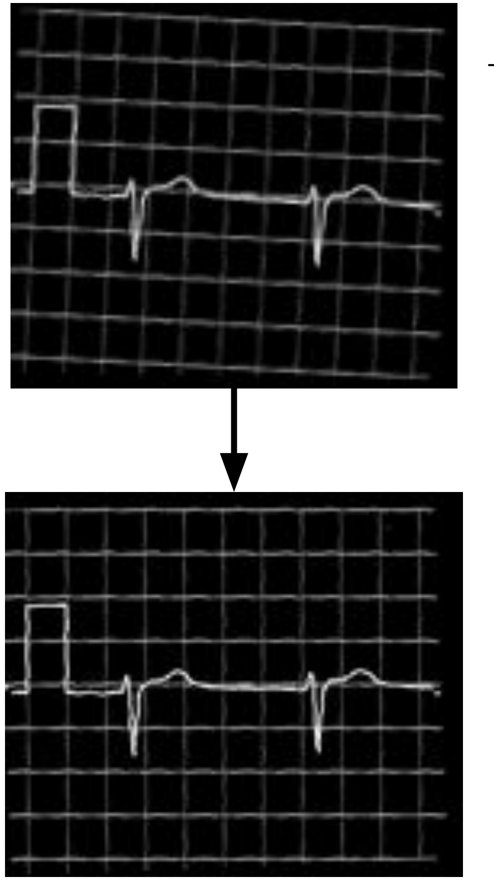
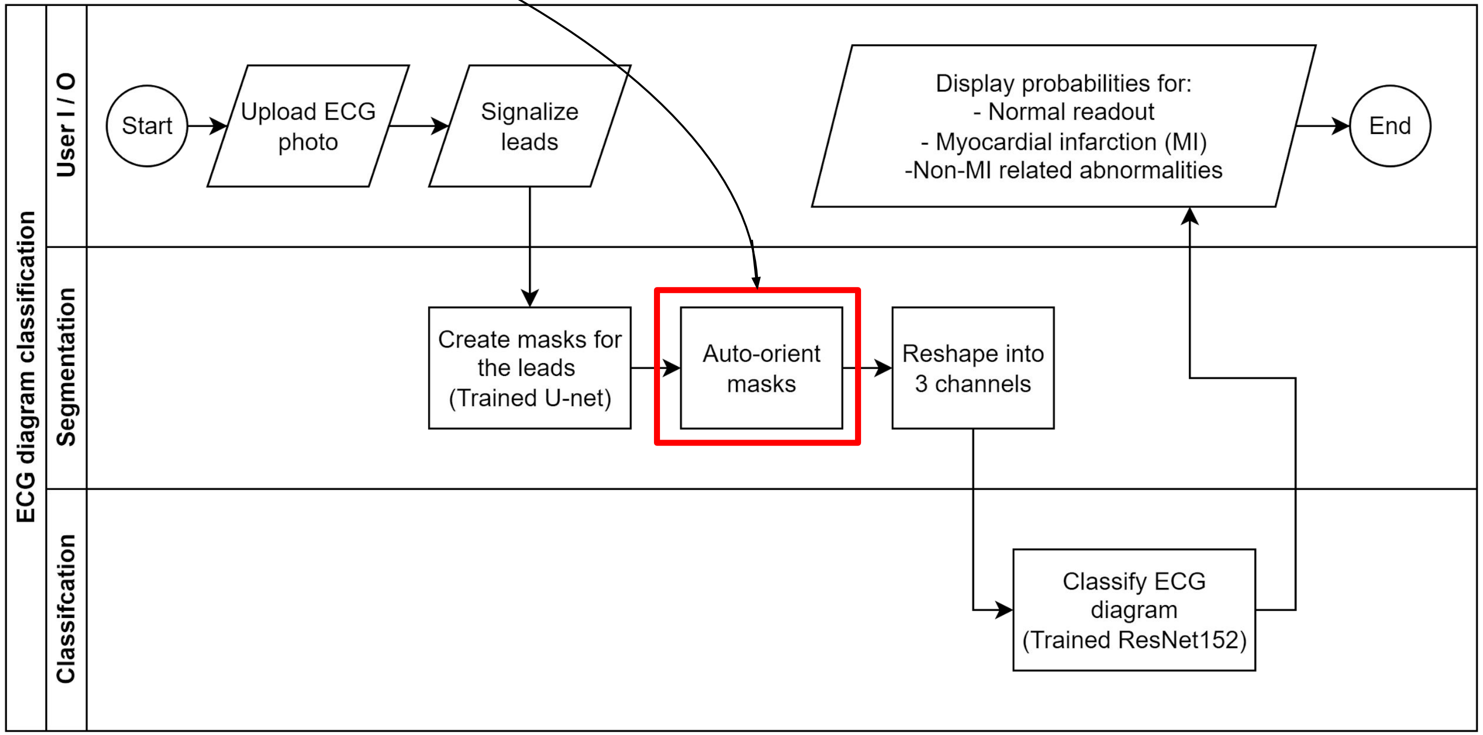
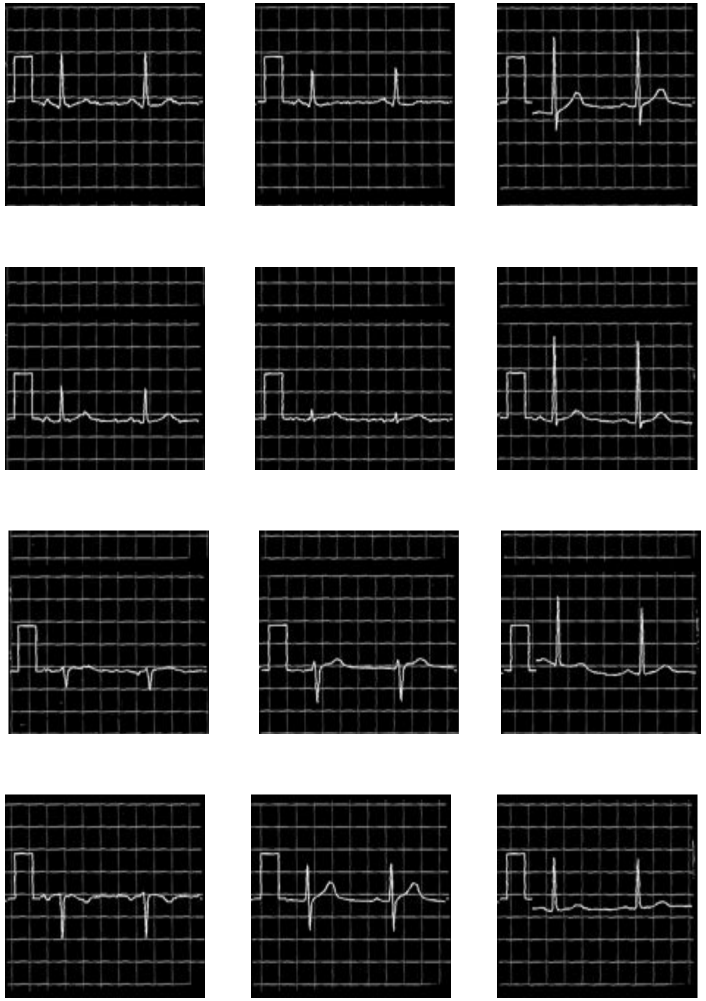


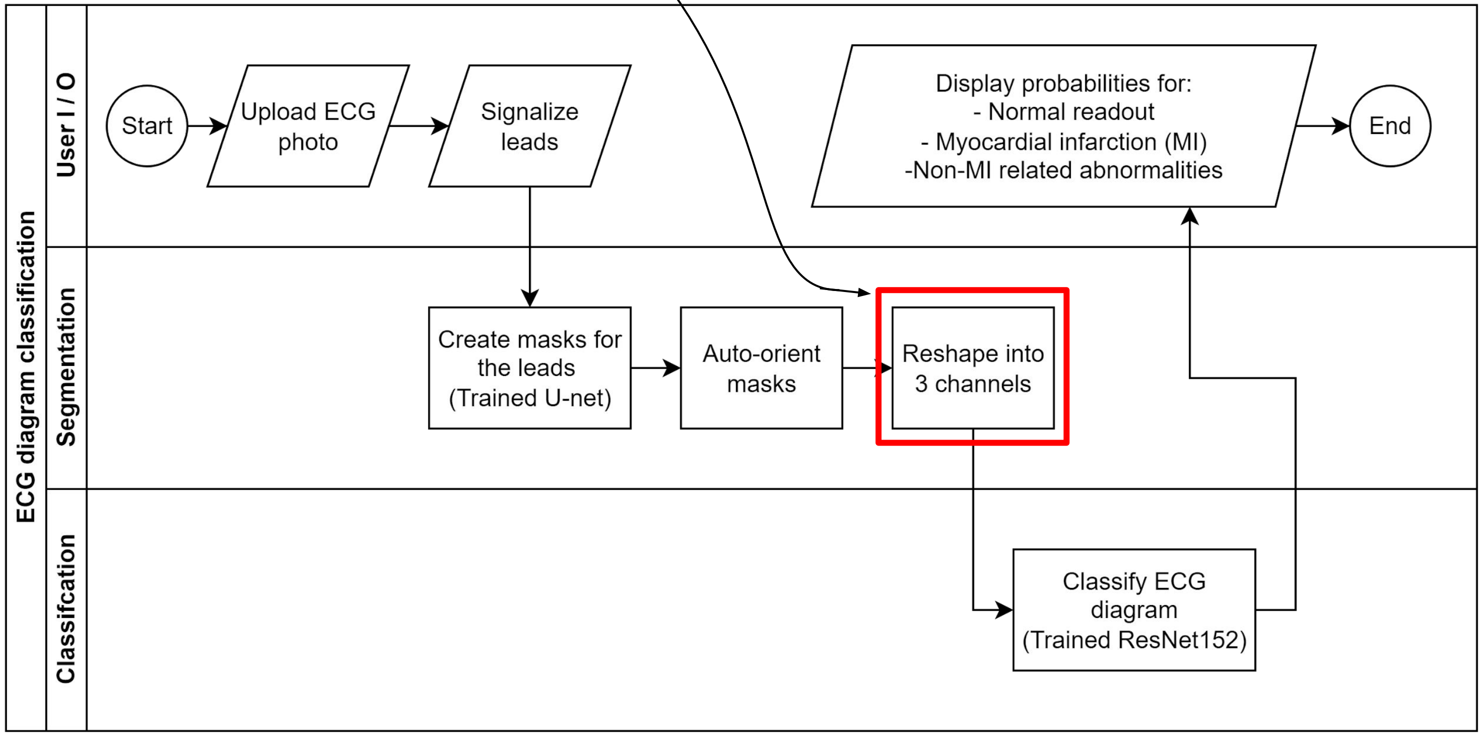
3 ECG Processing Overview





3 ECG Processing Overview





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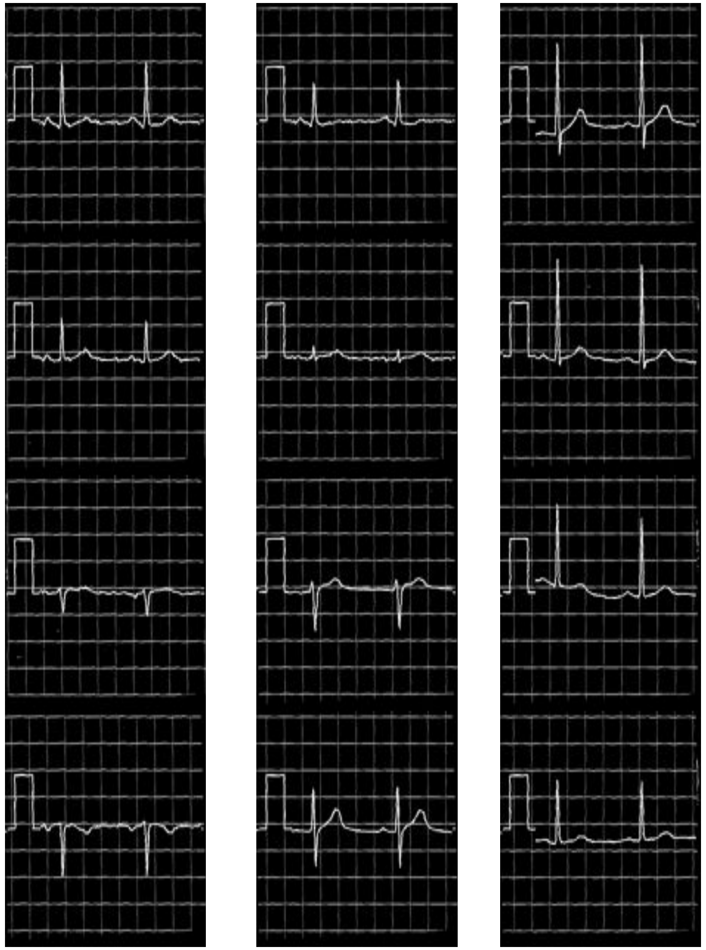
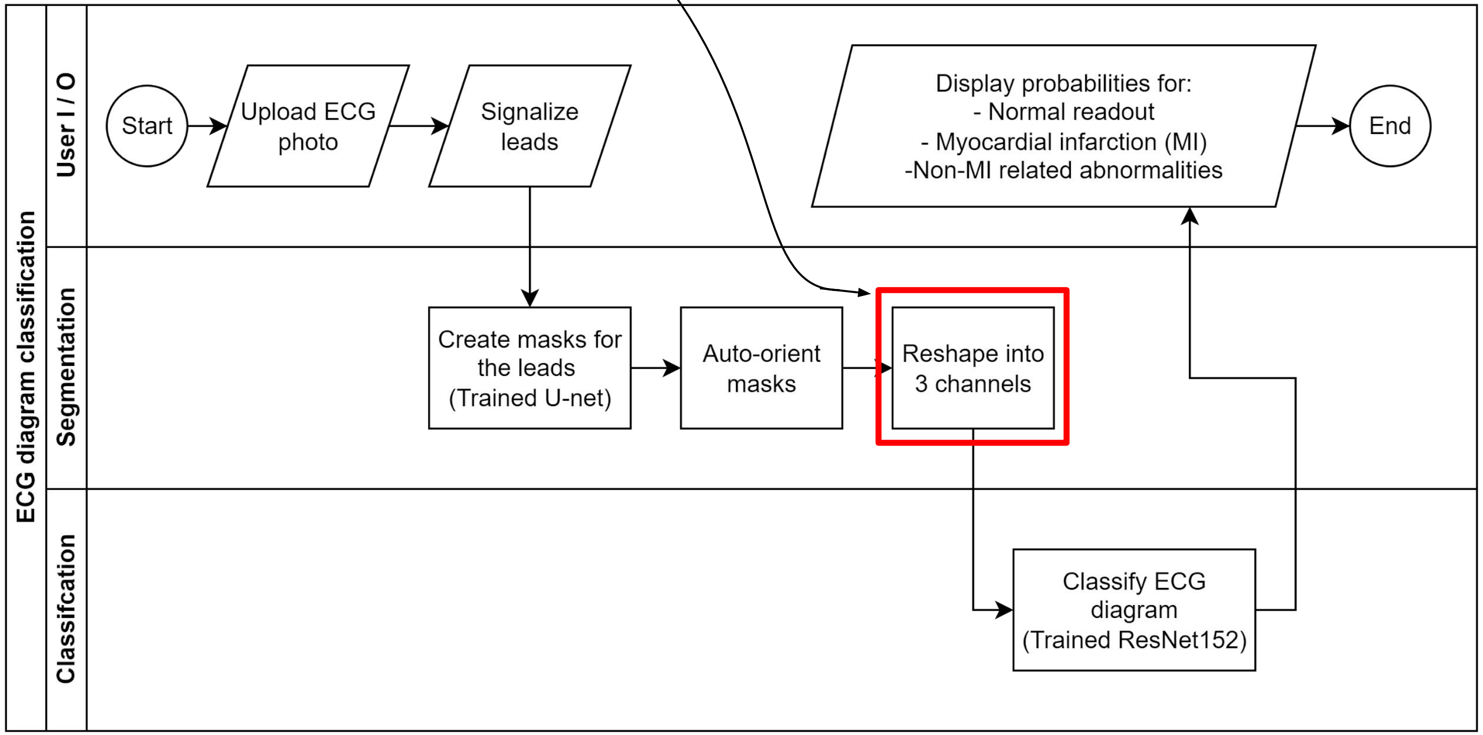
3 ECG Processing Overview

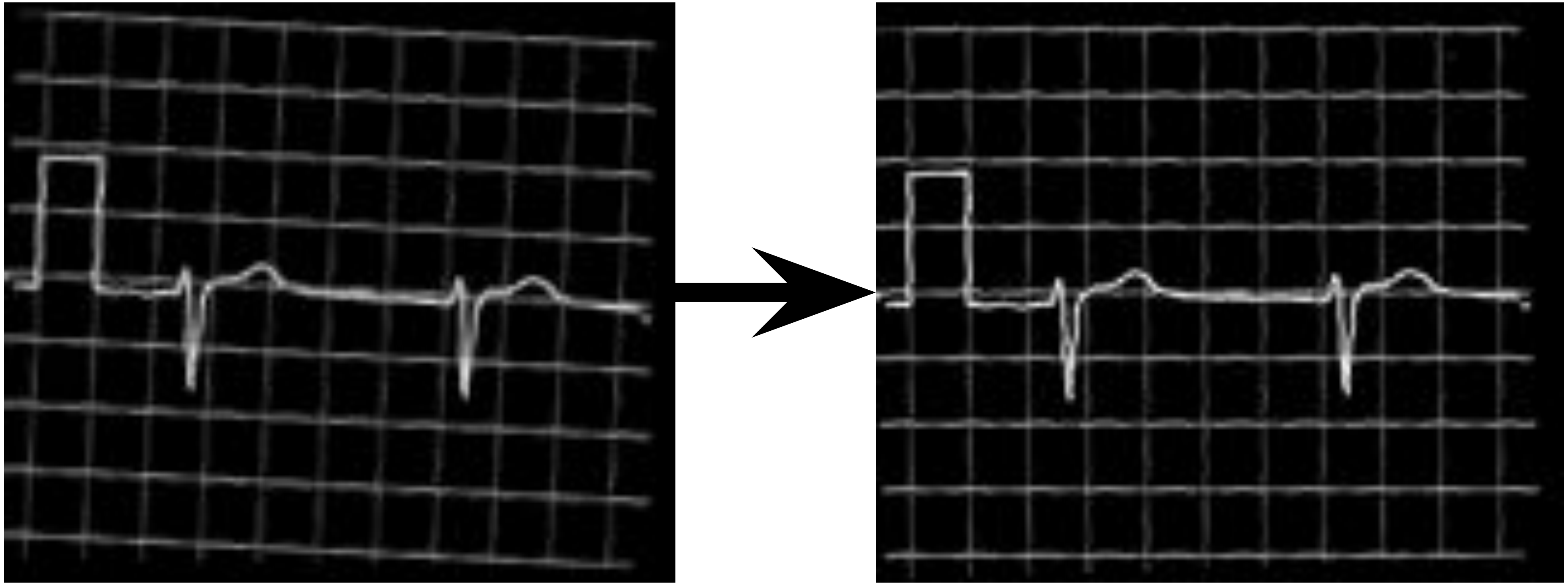


Channel 1 Channel 2 Channel 3



3.1 ECG Segmentation

The straightening algorithm is based on detecting horizontally the grid-lines on several heights and then correct the rotation

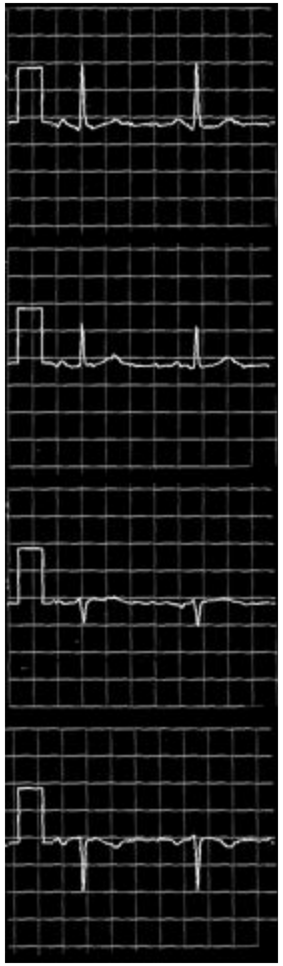


3.1 ECG Segmentation

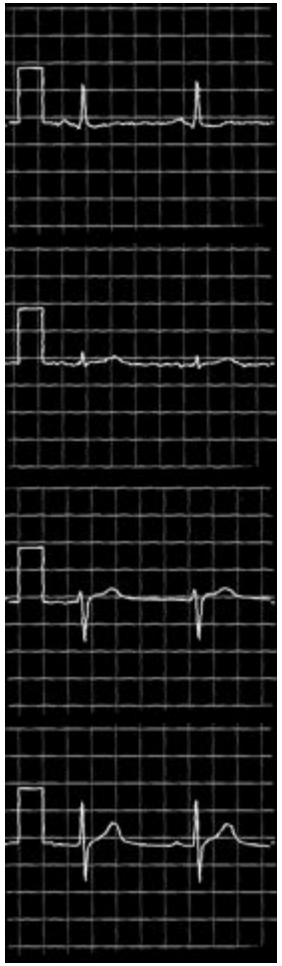
The 12 leads are divided in 3 groups, one for each channel fed into the convnet for classification.

If more leads are inserted, they are added in a **consistent** way to the different channels. **This is important because certain types of myocardial infarctions result in characteristic changes to certain leads.**

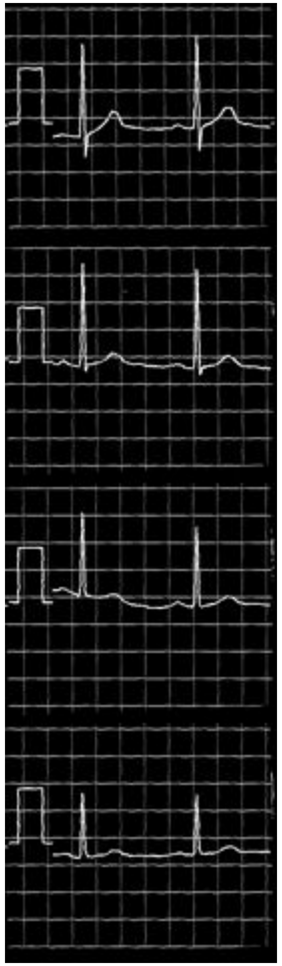
The grid lines are kept also fed to the classifying convnet. We expect that this helps with detecting correlations of different lead values at equal times.



Channel 1

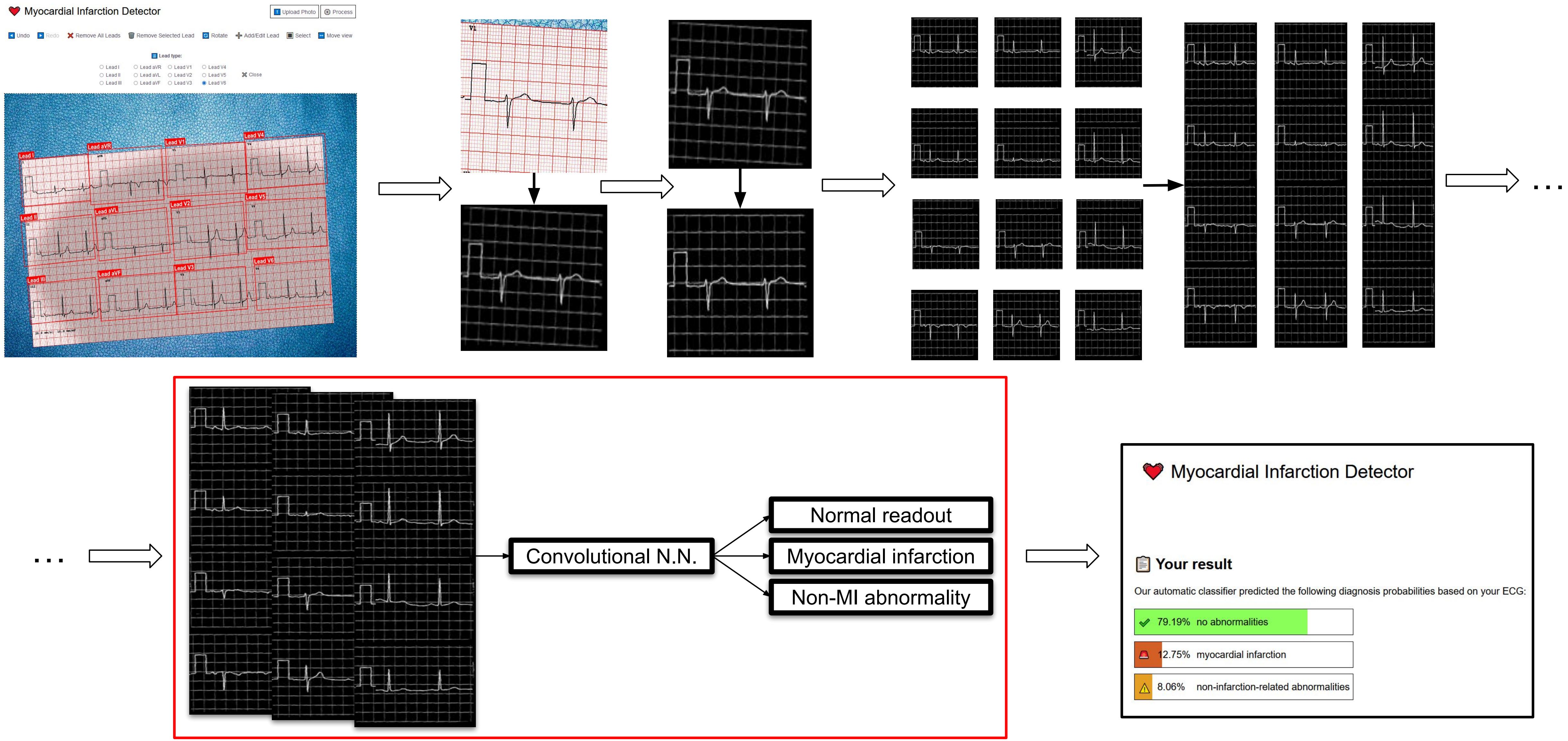


Channel 2



Channel 3

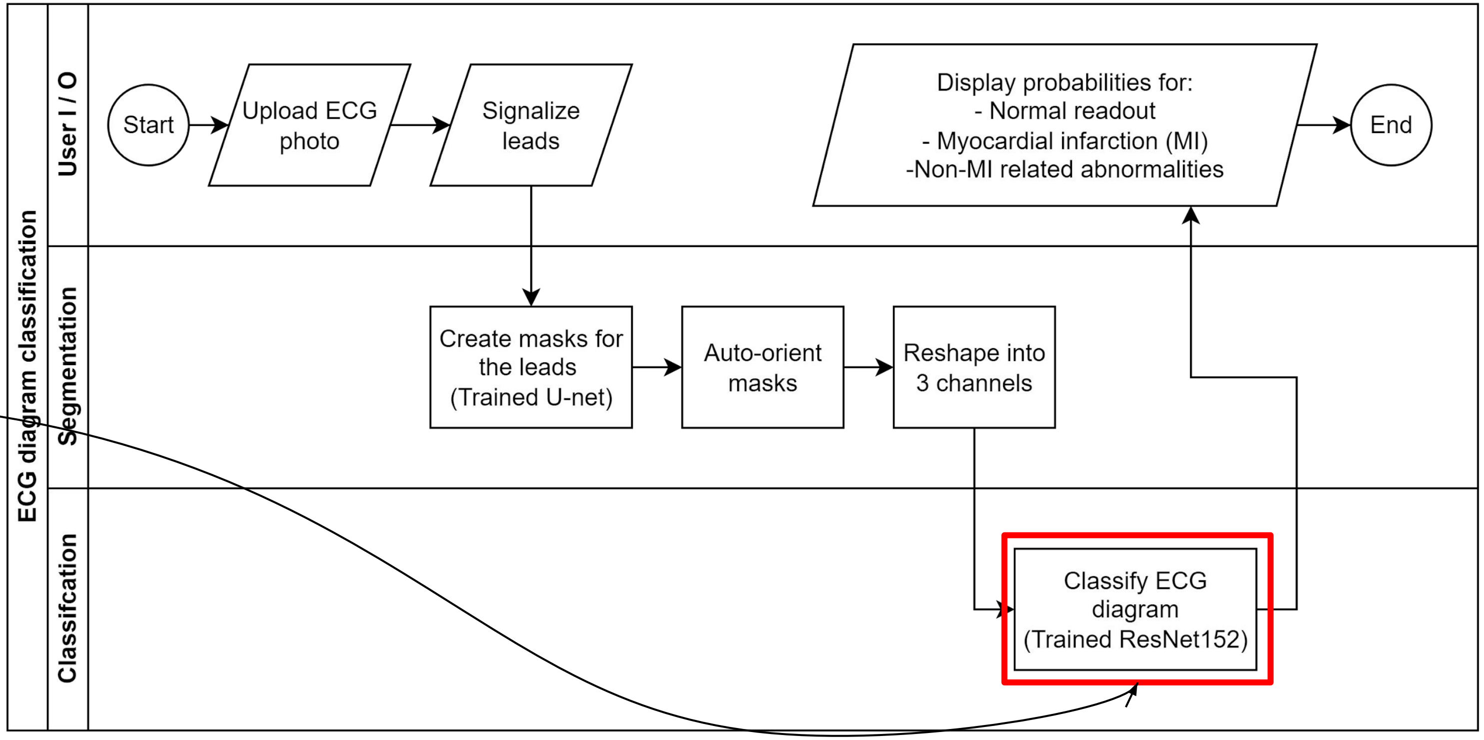
3 ECG Processing Overview



3 ECG Processing Overview

Channel 1 Channel 2 Channel 3

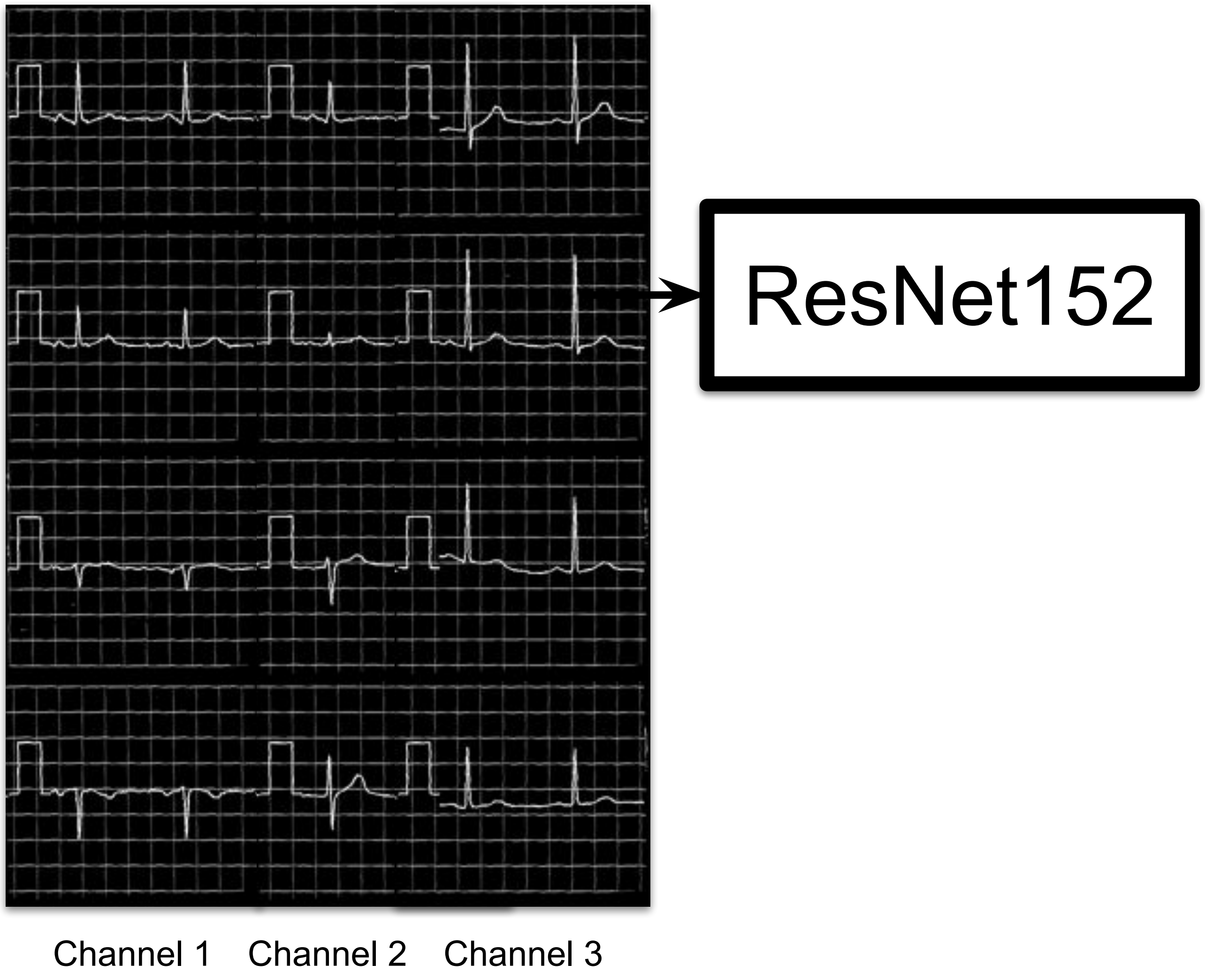
ResNet152



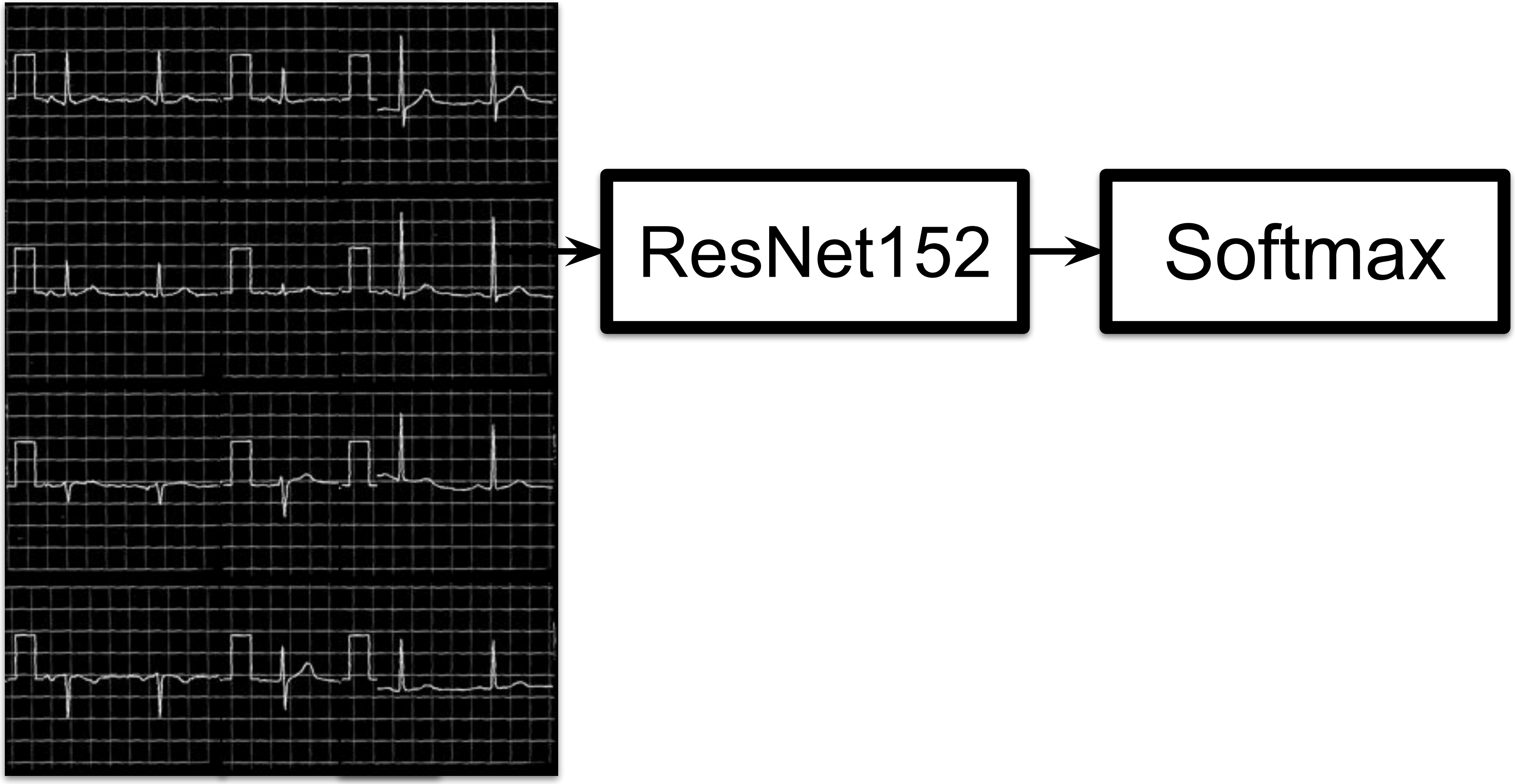
3.2 ECG Classification

Channel 1 Channel 2 Channel 3

3.2 ECG Classification



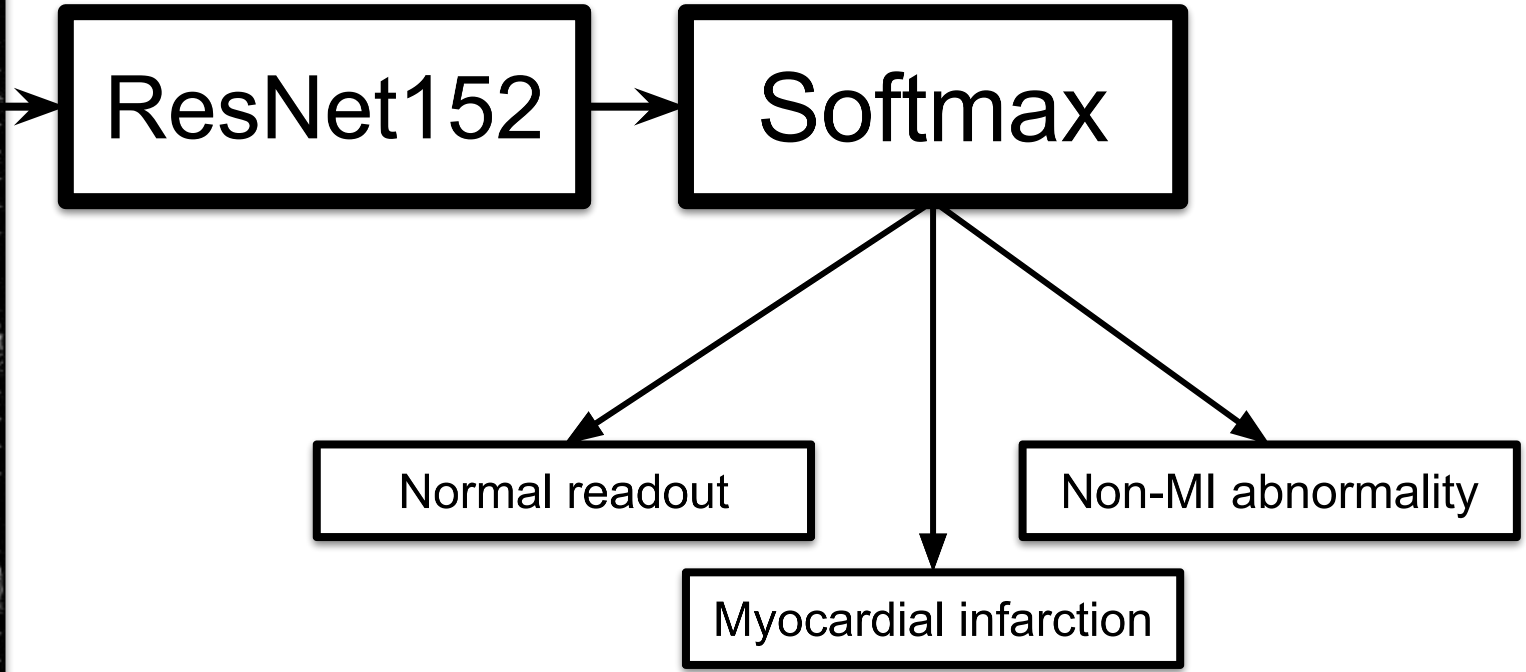
3.2 ECG Classification



Channel 1 Channel 2 Channel 3

3.2 ECG Classification

Channel 1 Channel 2 Channel 3



3.2 ECG Classification: ResNet152 architecture

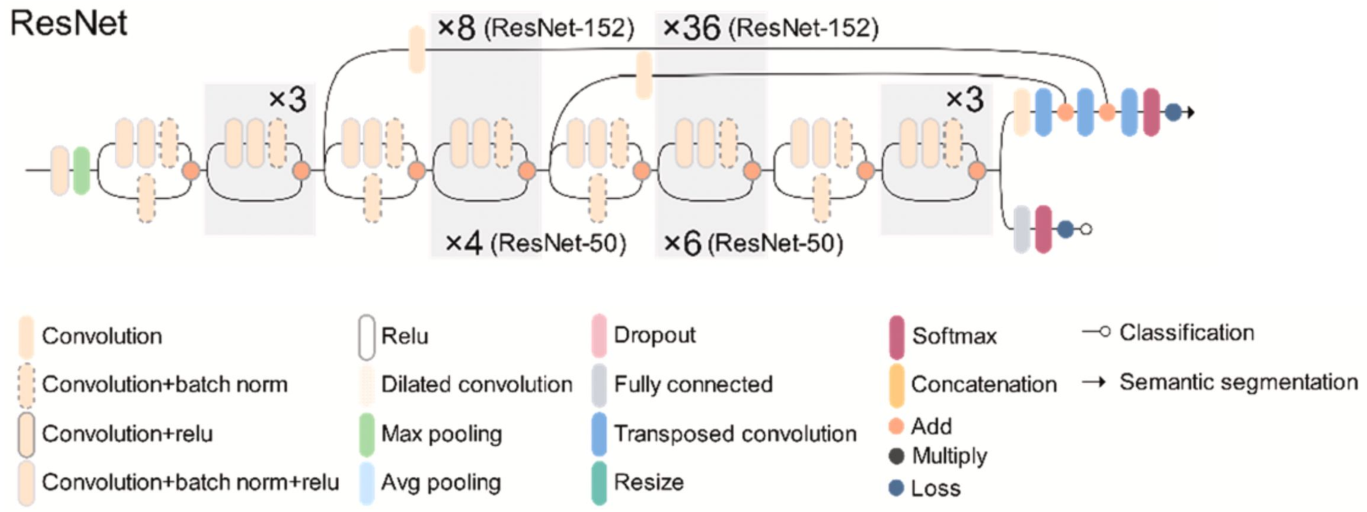


Figure 1: ResNet152 architecture diagram

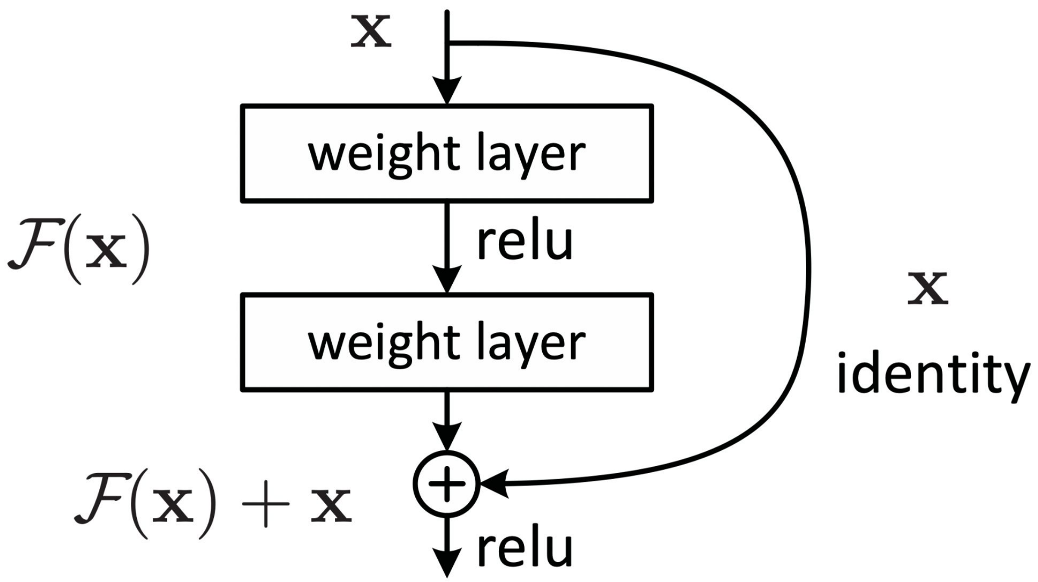
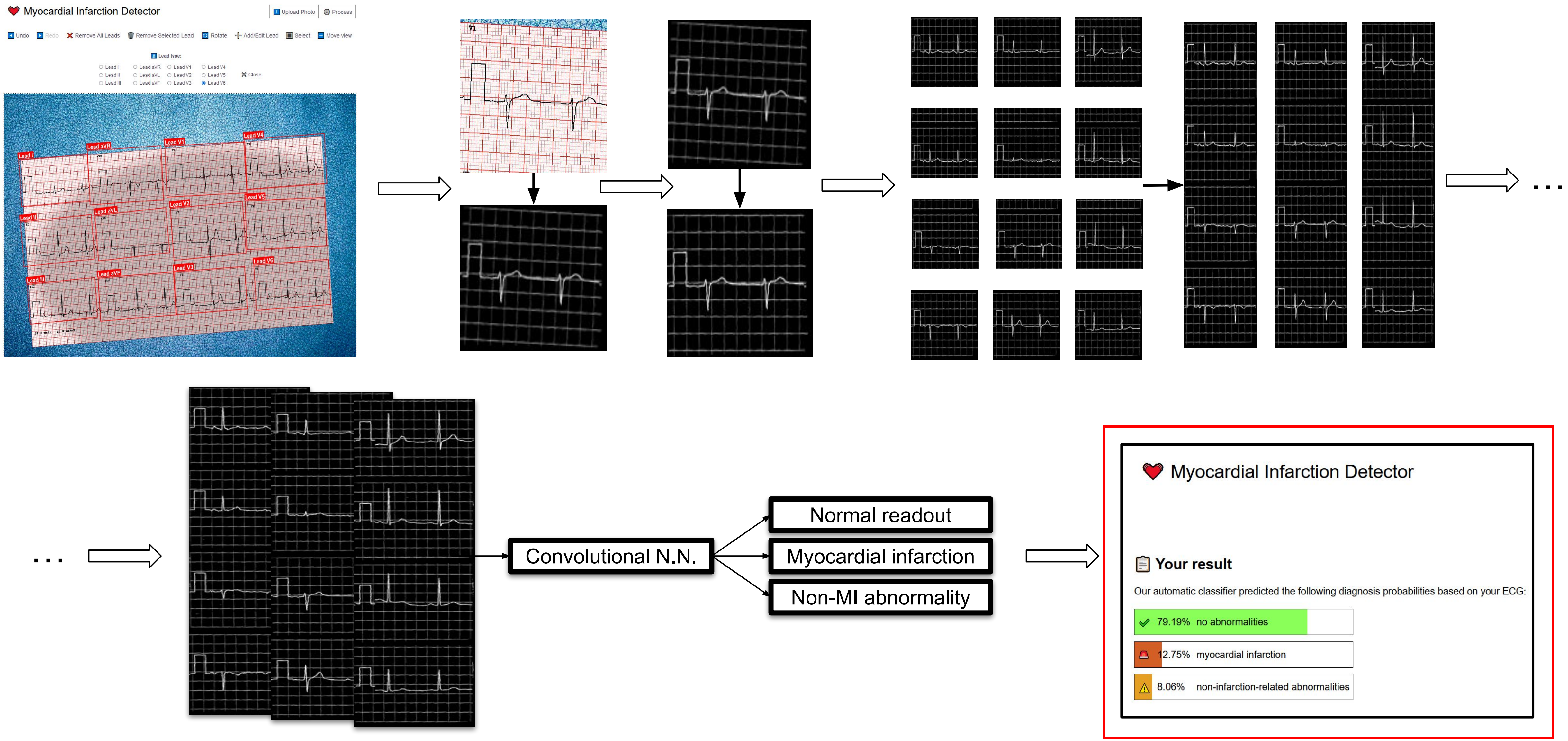


Figure 2: Residual learning building block

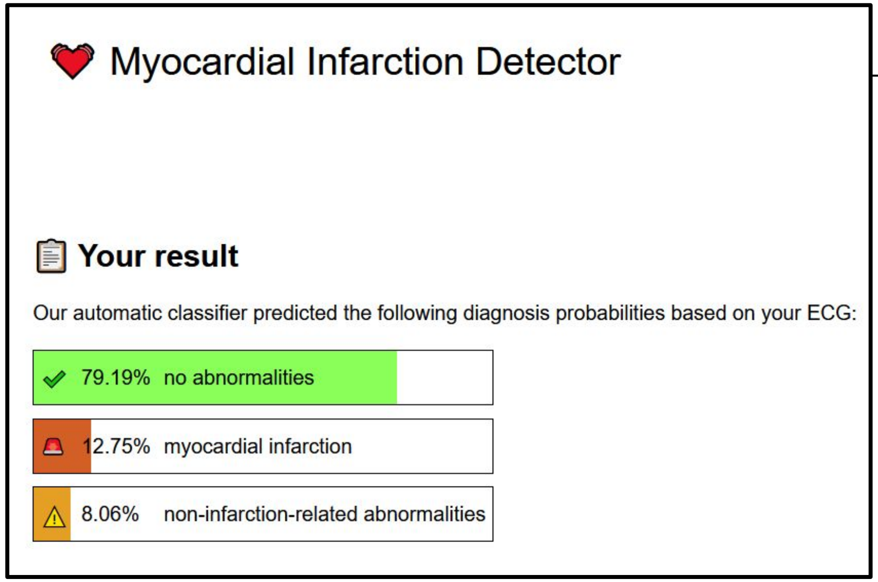
Figure 1 taken from: Zhouxin Xi, Chris Hopkinson, Stewart B. Rood, & Derek R. Peddle (2020). See the forest and the trees: Effective machine and deep learning algorithms for wood filtering and tree species classification from terrestrial laser scanning. ISPRS Journal of Photogrammetry and Remote Sensing, 168, 1-16.

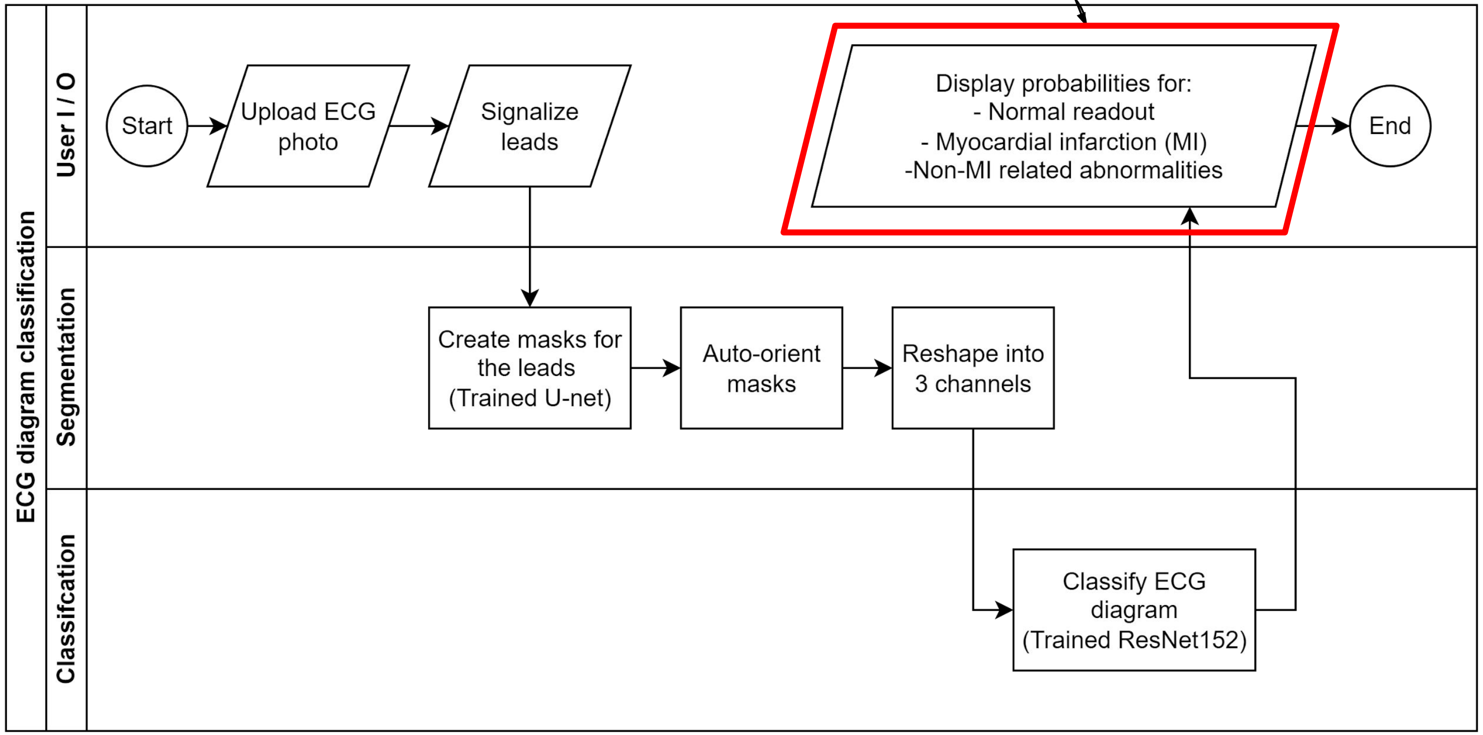
Figure 2 taken from: Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun (2015). Deep Residual Learning for Image Recognition. CoRR, https://arxiv.org/abs/1512.03385v1

3 ECG Processing Overview



3 ECG Processing Overview

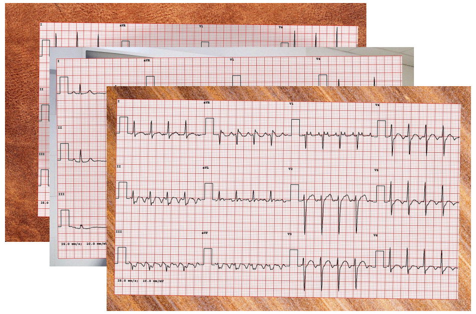


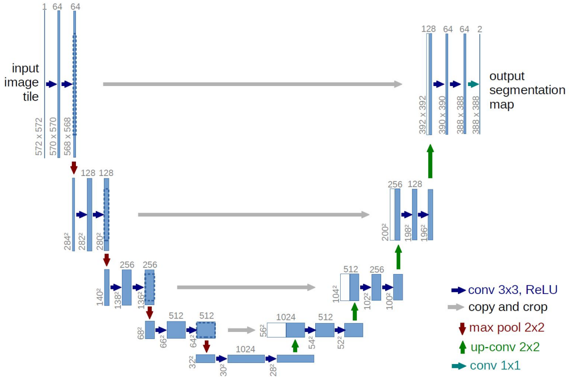


This will be presented with detail later on.

3.3 Classification Network Training

Extraction of segmentation images

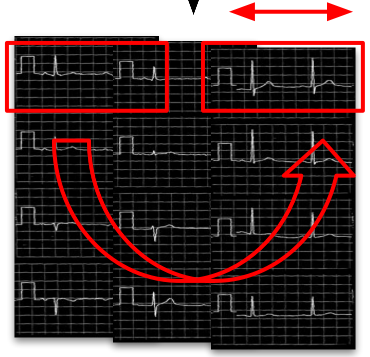




<u>dataset stats:</u>

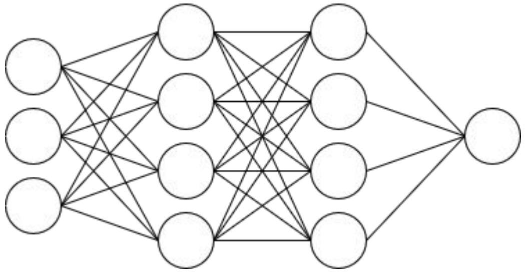
<u>before augmentation: 13826 ECGs</u>
6152 normal ECGs
4752 ECGs with non-MI abnormalities
2922 ECGs showing MIs

<u>after augmentation: 41478 ECGs</u>
18456 normal ECGs
14256 ECGs with non-MI abnormalities
8766 ECGs showing MIs



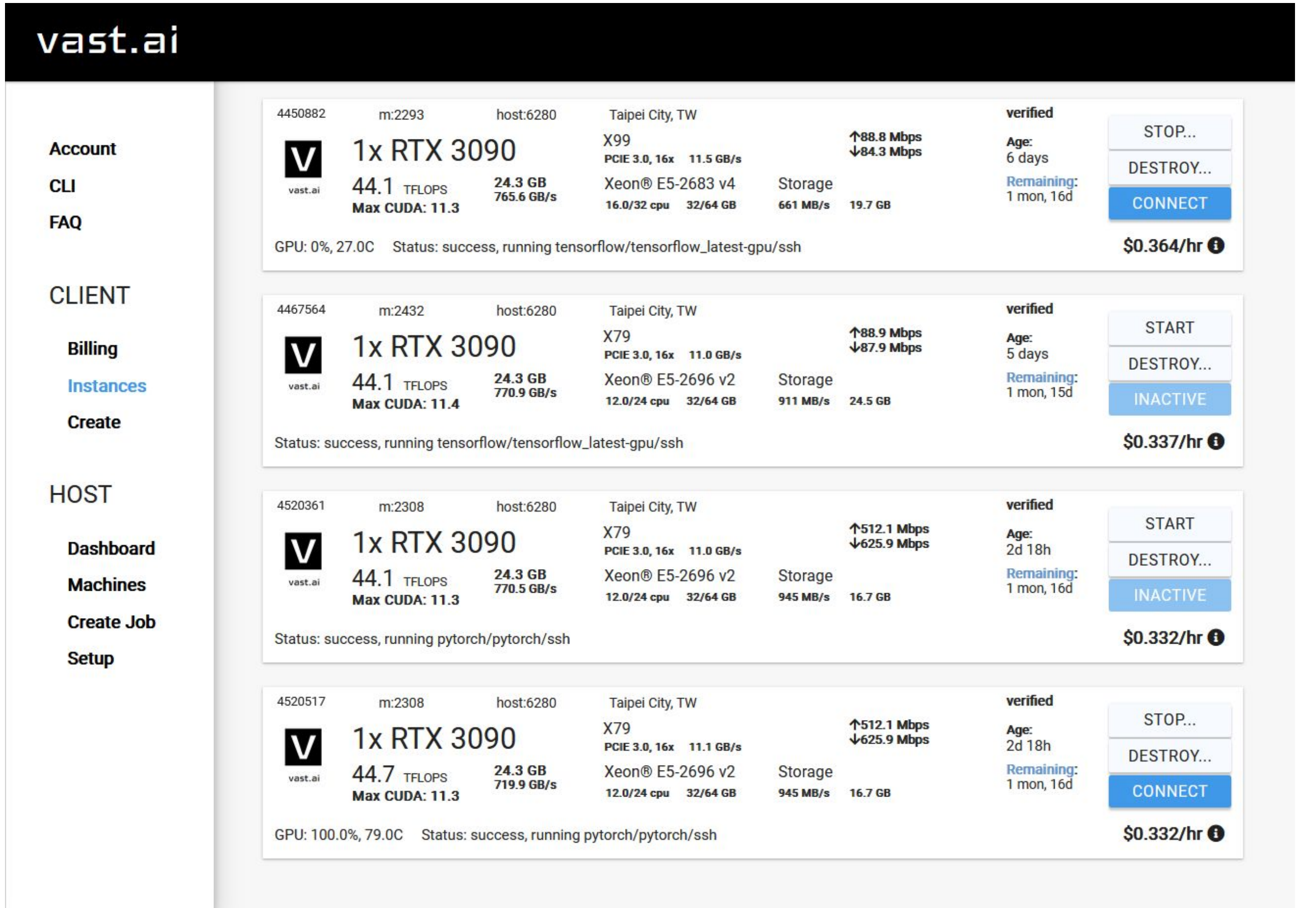
Swapping and stretching of leads

Data augmentation



Training on augmented segmentation images

3.3 Classification & Segmentation Network Training: Training Environment



Remote development & training using vast.ai

3.3 Classification & Segmentation Network Training: Training Frameworks

Frameworks:

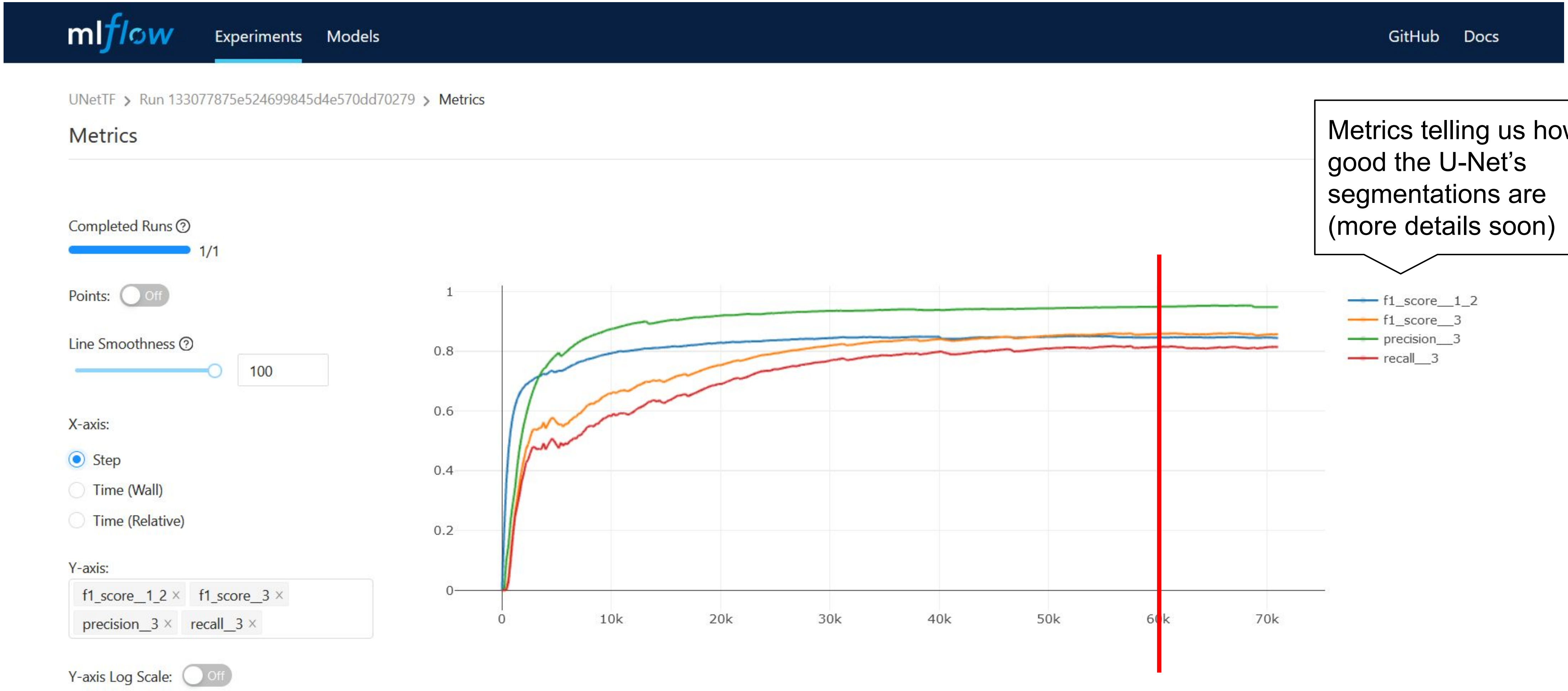
fast.ai

mlflow™

TensorFlow

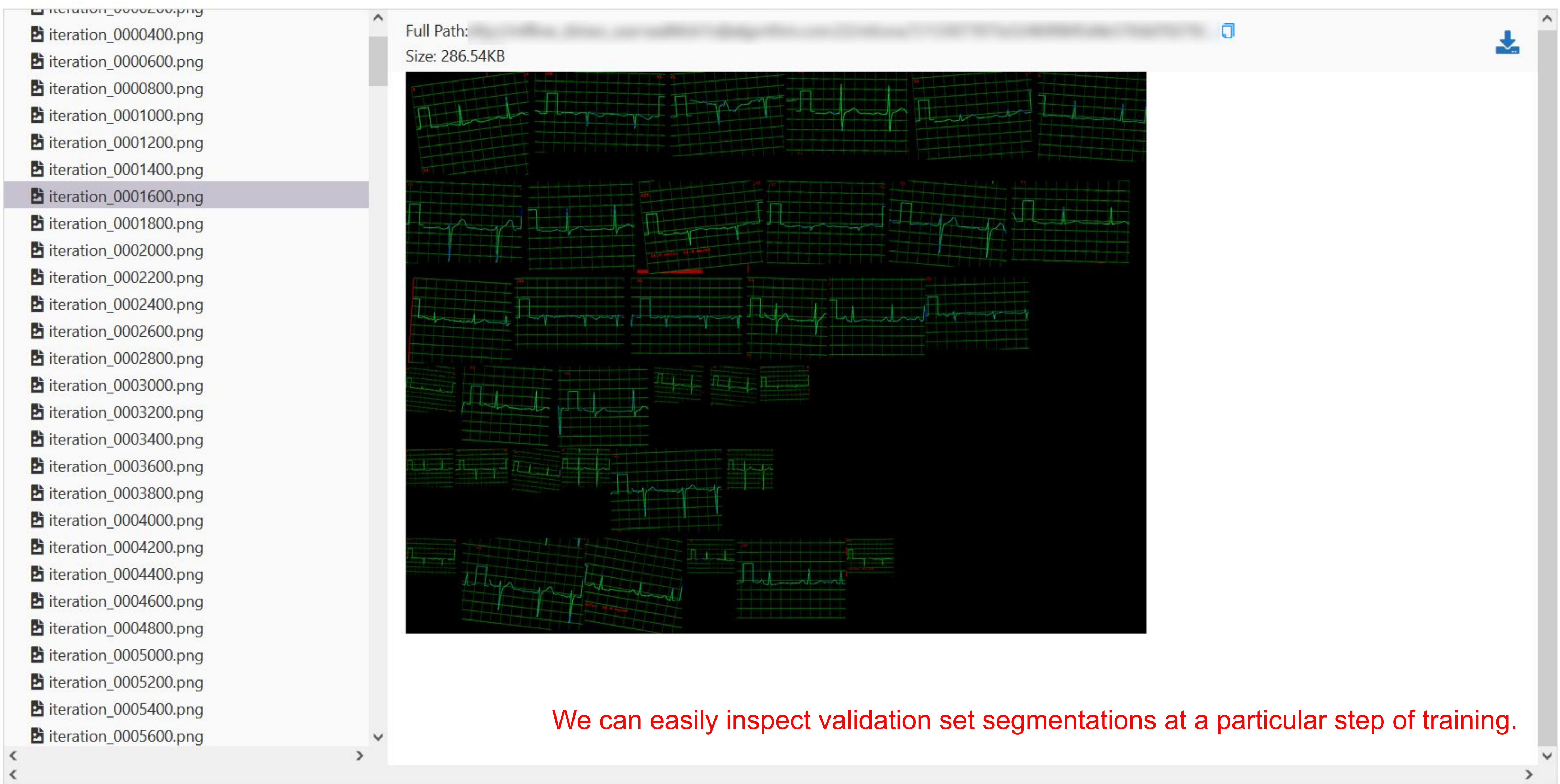
For classification network

For segmentation network



Metrics telling us how good the U-Net's segmentations are (more details soon)

We can easily see (approximate) the step at which convergence is achieved.



We can easily inspect validation set segmentations at a particular step of training.

iteration_0058200.png
iteration_0058400.png
iteration_0058600.png
iteration_0058800.png
iteration_0059000.png
iteration_0059200.png
iteration_0059400.png
iteration_0059600.png
iteration_0059800.png
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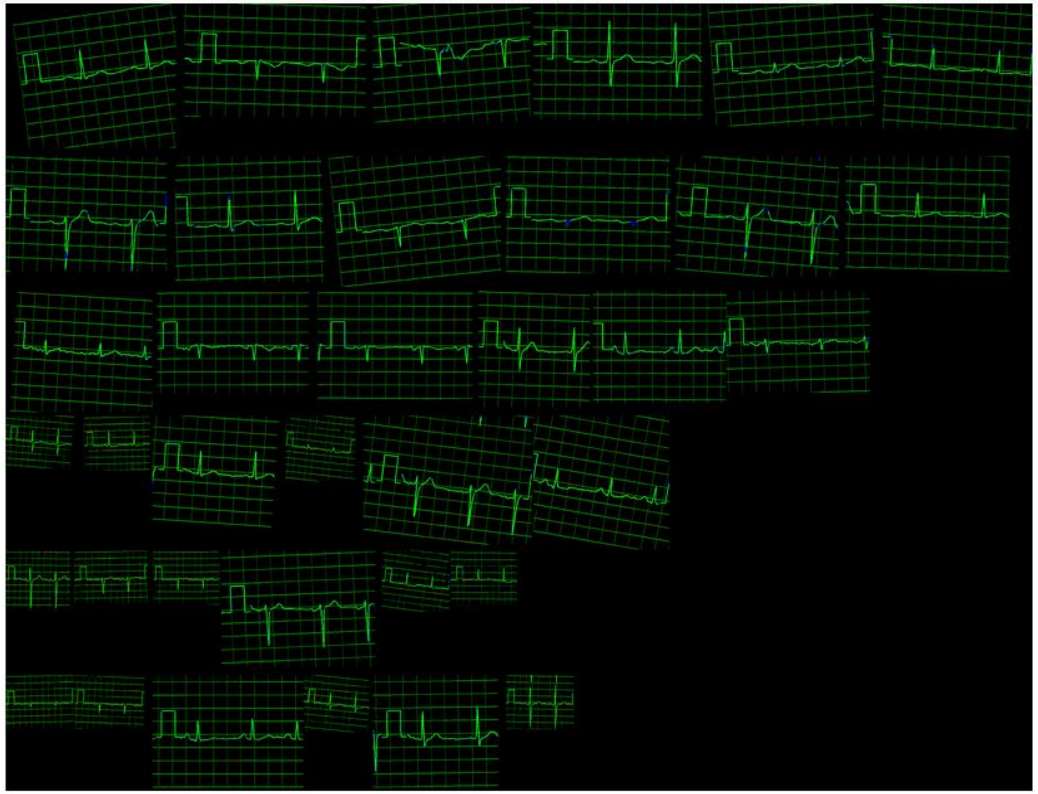
iteration_0060800.png
iteration_0061000.png
iteration_0061200.png
iteration_0061400.png
iteration_0061600.png
iteration_0061800.png
iteration_0062000.png
iteration_0062200.png
iteration_0062400.png
iteration_0062600.png
iteration_0062800.png
iteration_0063000.png
iteration_0063200.png
iteration_0063400.png
iteration_0063600.png

Full Path: [redacted]

Size: 249.8KB



…after convergence, visualizations look as they should (no red spots ➔ no errors)

3.3 Classification Network Training: Metrics

Precision:

$$\frac{\#\ \text{True positives}}{\#\ \text{True positives} + \#\ \text{False positives}} \quad \in [0, 1]$$

i.e. "if the classifier predicts an MI, how likely is it really an MI?"

Recall:

- - -

F1 score:

- - -

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i.e. “if there is an MI, how likely is the classifier to say so?”

F1 score:

$$\frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad \in [0, 1]$$

harmonic mean of precision and recall; means to combine the two scores

3.3 Classification Network Training: Results

Class	Precision	Recall	F1 Score
Normal ECG	73.17%	88.87%	0.8027
Non-MI-related abnormalities	- - -	- - -	- - -
Myocardial Infarction	- - -	- - -	- - -

Results on validation dataset of augmented ECG segmentation images

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Results on validation dataset of augmented ECG segmentation images

validation dataset:
1331 ECG segmentations

581 normal ECGs (43.7%)

462 ECGs w/ **non-MI abnormalities** (34.7%)

288 ECGs w/ **MI** (21.6%)

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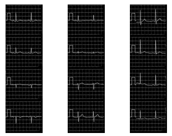
- Big problem: **classification networks overfit!**
  - Cannot perform data augmentation on ECG segmentation images easily on-the-fly
    - Need to **synthesize new ECG photographs**
    - **Time-consuming** process!



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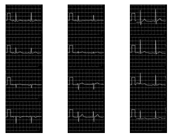

- ➢ One study (https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8273385/) using **10-second time series data** (raw PTB-XL dataset) achieved **precision of 78.9%**, **recall of 81.8%**, **F1 score of 0.825 on MIs (*binary* classification)**

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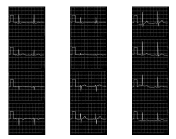


    - ➢ Need to **synthesize new ECG photographs**
    - ➢ **Time-consuming** process!
- ➢ One study (https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8273385/) using **10-second time series data** (raw PTB-XL dataset) achieved **precision of 78.9%**, **recall of 81.8%**, **F1 score of 0.825 on MIs (*binary* classification)**
- ➢ We view our **result** as a **reasonable proof-of-concept**, considering we **only take snippets of ~3 seconds** for each lead and **use *distorted image data*** rather than pure time series, and did not perform hyperparameter tuning
  - ➢ **Shorter lead recordings** are much more **common in practice**

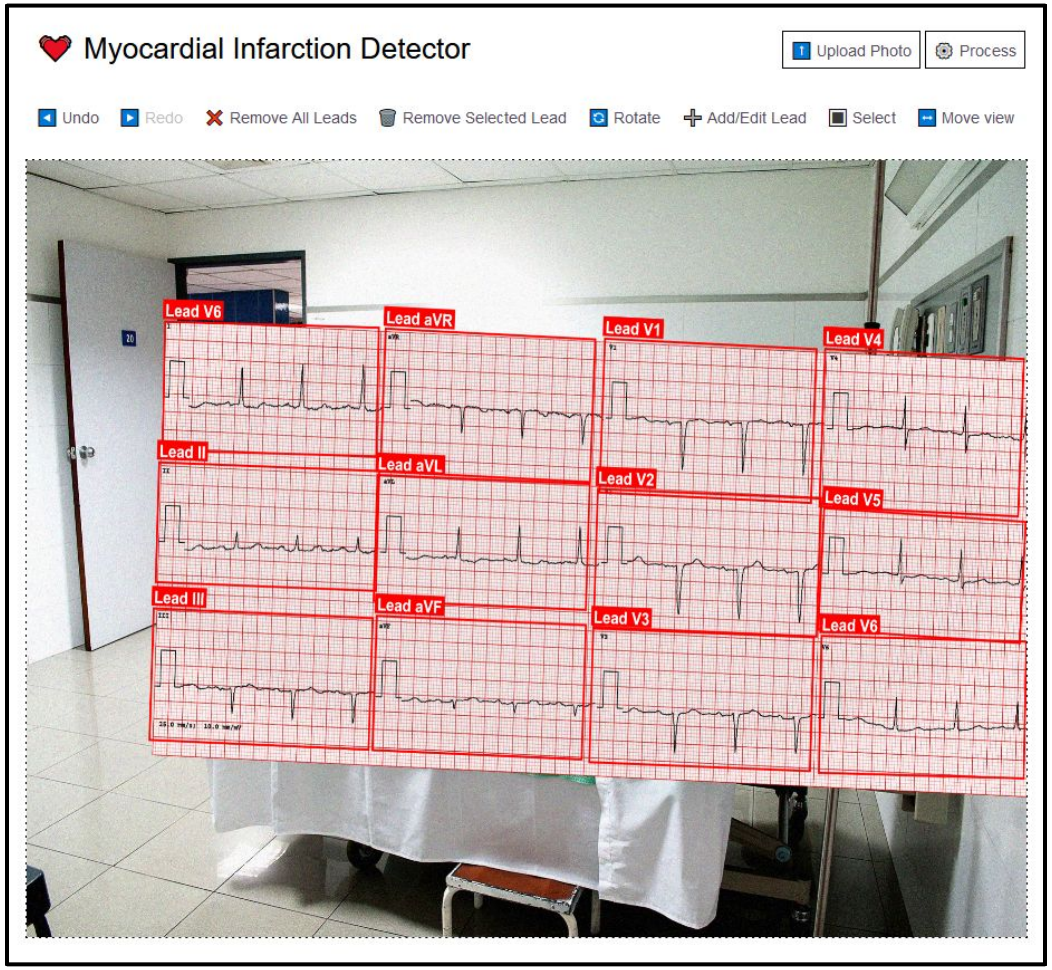
3.3 Classification Network Training: Precision-Recall-F1 Table For MI Class

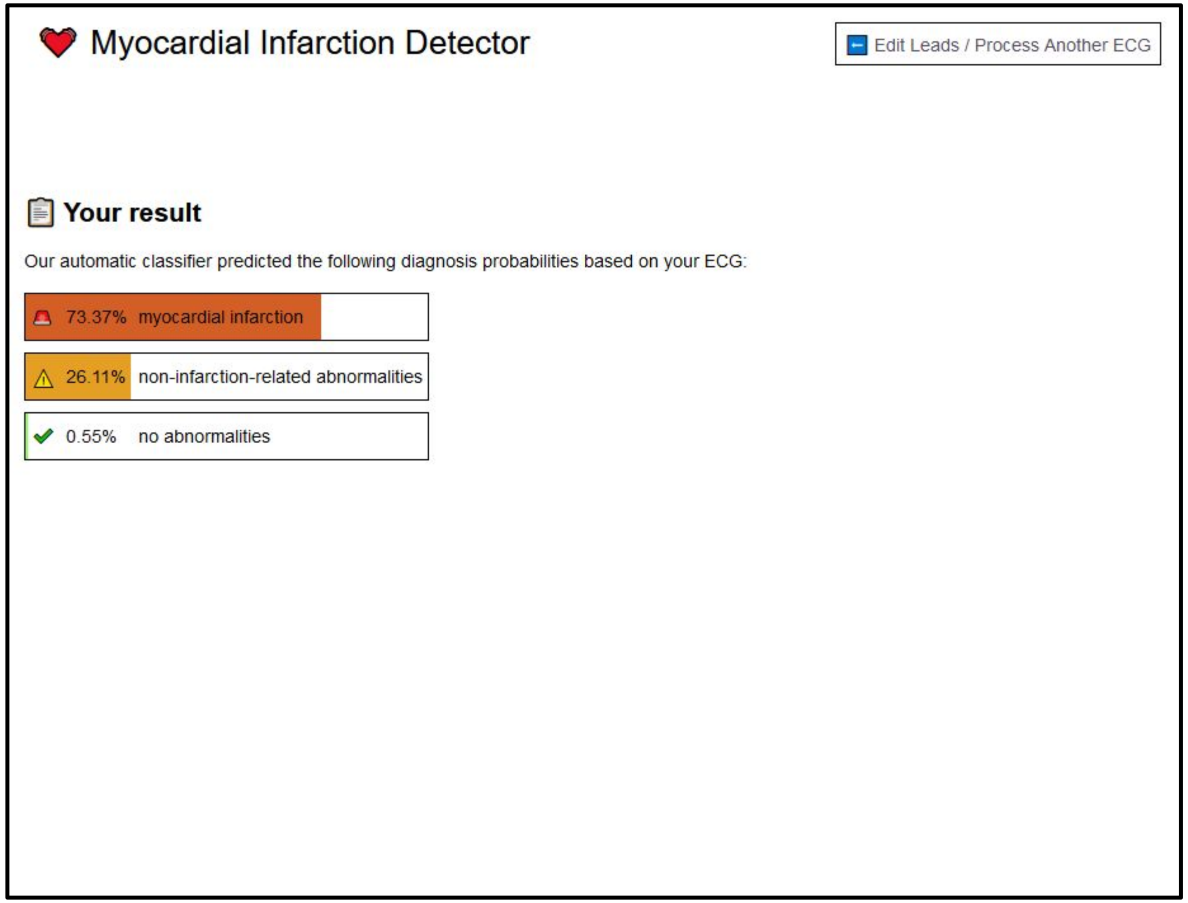
Precision	Recall	F1 Score
68.93%	49.31%	0.5749
67.44%	50.69%	0.5788
65.46%	52.20%	0.5808
63.61%	54.17%	0.5851
62.14%	55.97%	0.5890
60.81%	57.64%	0.5918
59.31%	59.08%	0.5919
58.02%	60.46%	0.5921

Precision	Recall	F1 Score
56.66%	61.84%	0.5914
55.38%	63.60%	0.5907
54.16%	64.74%	0.5898
52.81%	**66.00%**	**0.5868**
51.45%	67.28%	0.5831
50.11%	68.58%	0.5791
48.75%	69.79%	0.5741
47.42%	70.94%	56.85%

➔ add artificial bias to classifier’s score for MI class (start: +0; Δ: +0.0263 with each row)
➔ determine optimal / good boost: **should prioritize recall over precision!**
➔ how to trade off? cost of human life (false negative) vs. wasted time/wrong treatment (false positive)

3.4 Web Tool





Current address (temporary): http://algvrithm.com:8080/

4. Future Work

- Use even more data!
  - Can generate nearly unlimited data, but: computationally expensive
  - Move image generation logic to GPU
- Diversify training set
  - Use different lead layouts & lengths
  - Use only subset of 12 leads
- Add support for paper speeds other than default 25mm/s
- Try more architectures, perform hyperparameter tuning for segmentation and classification
- Try to detect lead locations automatically, or provide initial suggestion for user to correct
- Implement noise removal algorithms
  - e.g. correction of baseline drift
- **Test using real ECGs!**

DEMO

ETH zürich

THANK YOU!

💓

Q&A

ETH zürich

Backup slides

3.3 ECG Network Training: Training Frameworks