Kjersti Engan, professor, Dept. of Electrical Eng. and Computer Science, UiS

Artificial Intelligence in medical applications

from analysis of urinary bladder cancer to newborn resuscitation

BMDLab - Biomedical Data Analysis Lab
www.ux.uis.no/bmdlab

Norwegian Smart Care Cluster, Hvordan kan bruk av kunstig intelligens (AI) hjelpe pasienter og helsevesen? 09.05.19

Artificial intelligence in medical applications

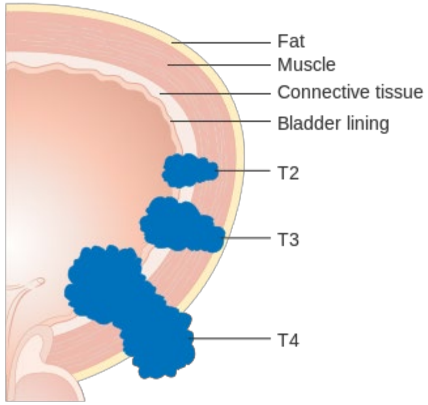
Deep neural networks and deep learning – Impressive success in later years all thorugh the worlds of computer vision, image processing, signal processing, computer science etc.

Challenges with data access in medical applications.
Combining domain knowledge and data learning!

This short talk will focus on two medical applications:

histopathological images, and safer births

Urinary bladder cancer



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- In 2015 it resulted in 188,000 deaths globally
- Fourth most common cancer type among men in Europe
- 70% increase in incidence past four decades in Norway
- Patients diagnosed with bladder cancer:
  - **Recurrence rate:** 50-70% will experience one or more recurrences
  - **Progression:** 10-30% will progress to a higher cancer stage

- Biopsy of the cancer tumour
- Determining the cancer grade/stage manually is time-consuming, subjective and low reproducibility.

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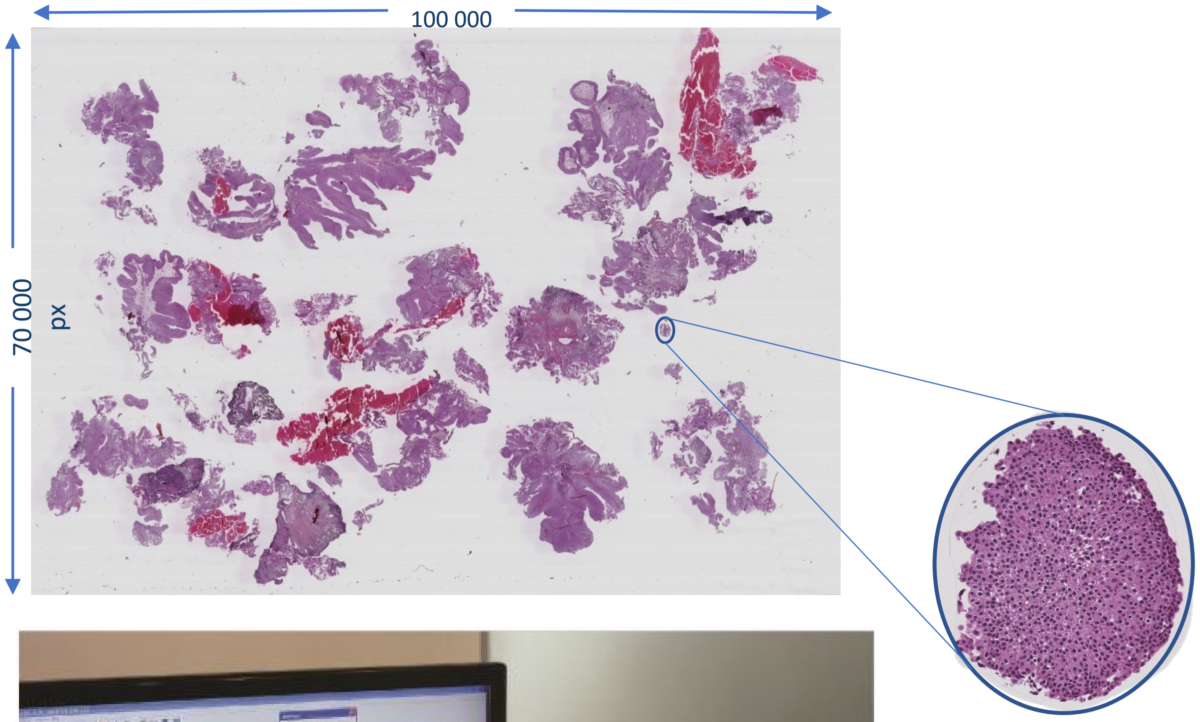
Automated analysis of histopathological images of unrinary bladder cancer



- **Digital pathology:** scanned whole slide images (WSI) opens new possibilities
- **Norway in a unique position** to exploit this since first country digitizing all pathology labs, collecting all WSI in a centralized database
- **Automated analysis for:**
  - Time efficient, objective, reproducible interpretation
  - Region of interest extraction for further analyses and/or visualization
  - Segmentation of cancer areas, and classification of cancer grade and diagnoses
  - Prediction of recurrence and progression risks

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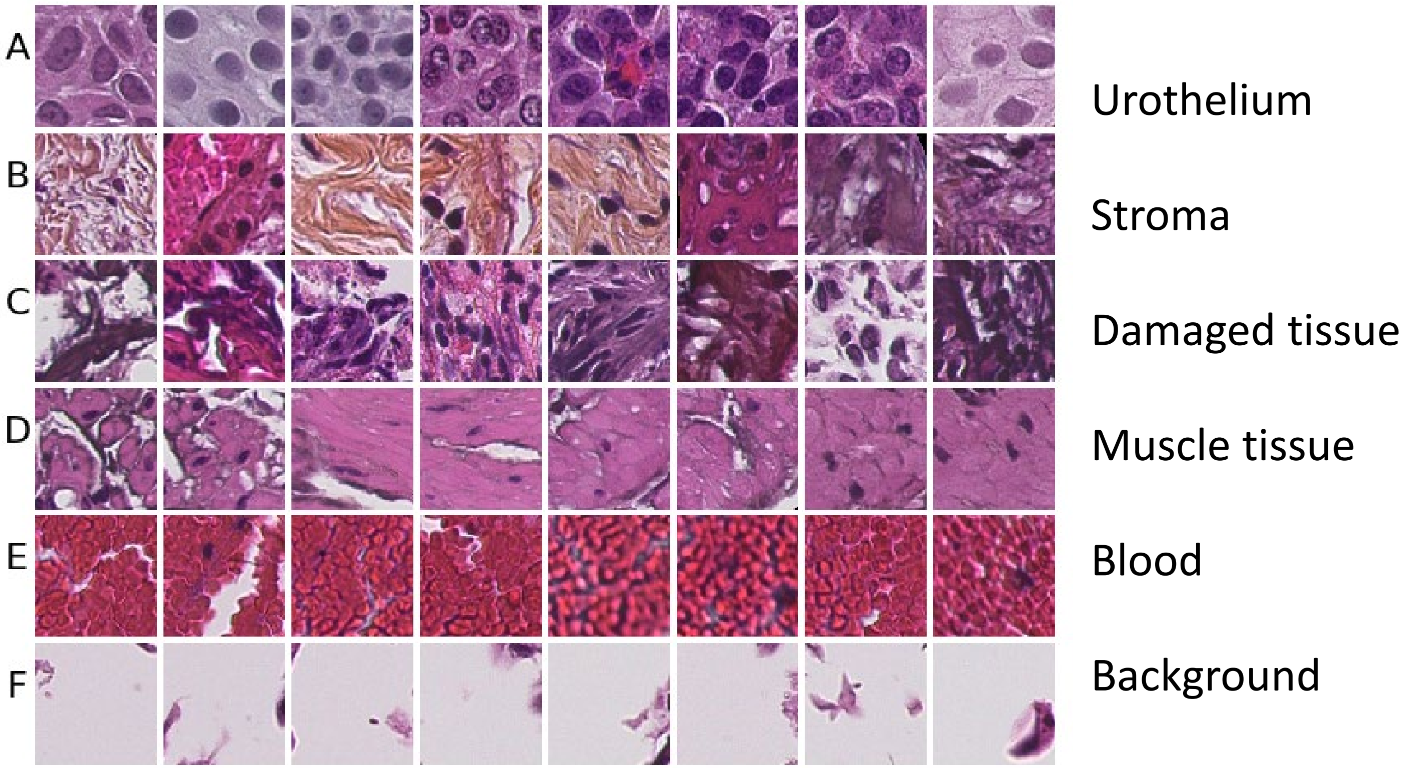
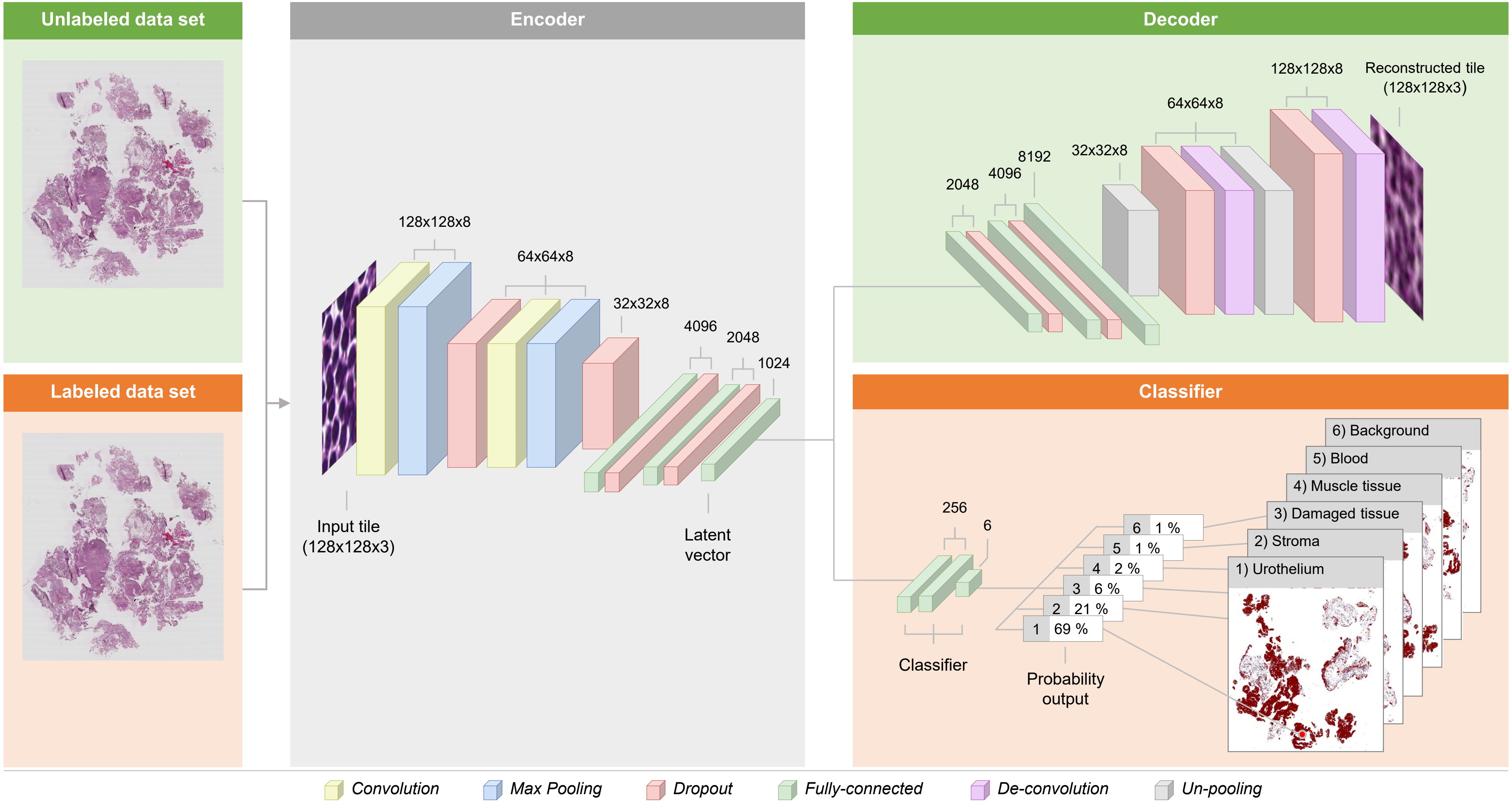
Region of interest extraction

Want to classify different parts of the image into different categories. The interesting parts can later be used with an other new network for diagnosisor prognosis prediction



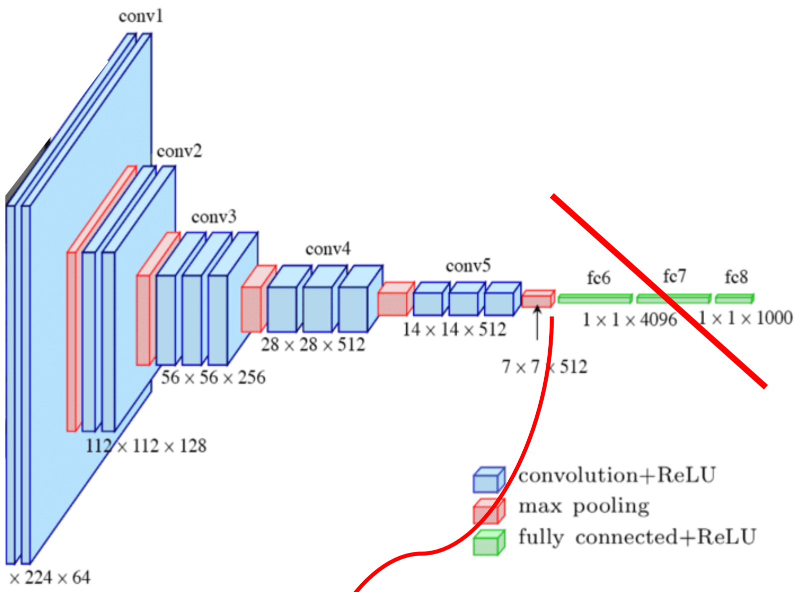
ROI extraction / segmentation 1:

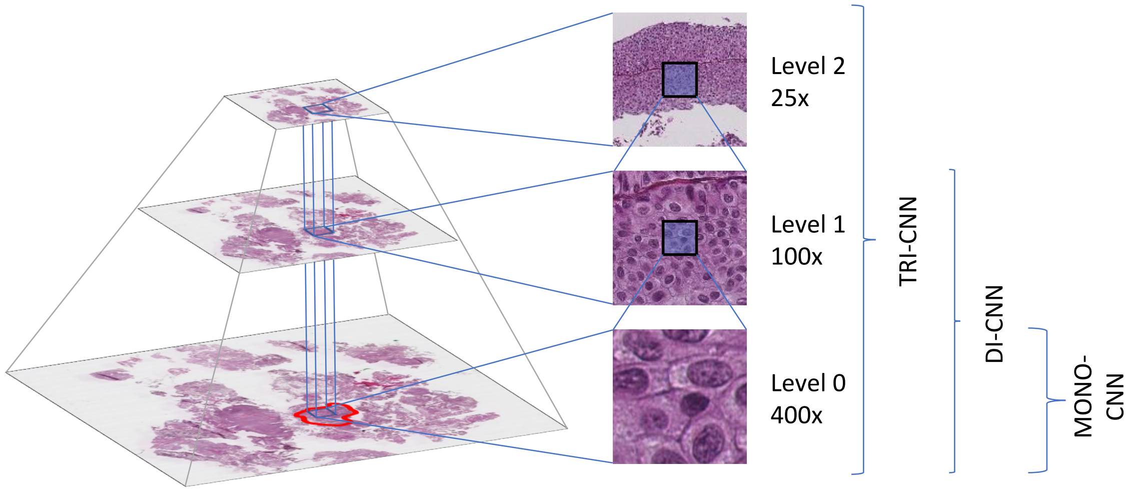
Learning relatively small networks from scratch on few and sparsly labelled data utilizing autoencoders

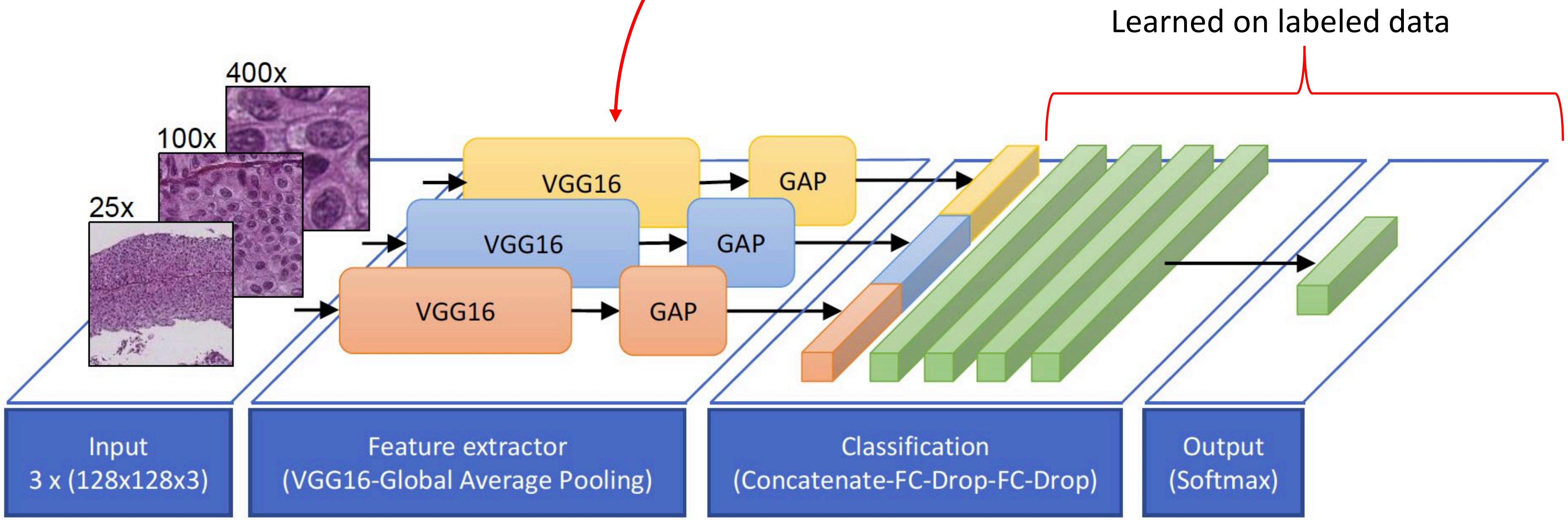


ROI extraction 2:

Using transfer-learning in multiscale.
VGG16 networks at three different scale, concatenating FV + fully connected layers trained on (relatively small set of) labelled data

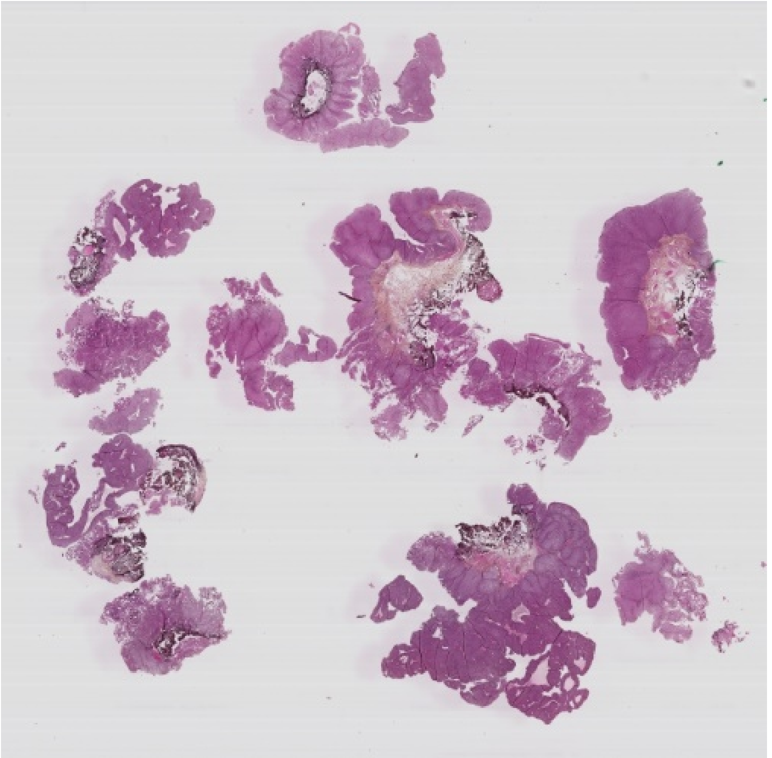




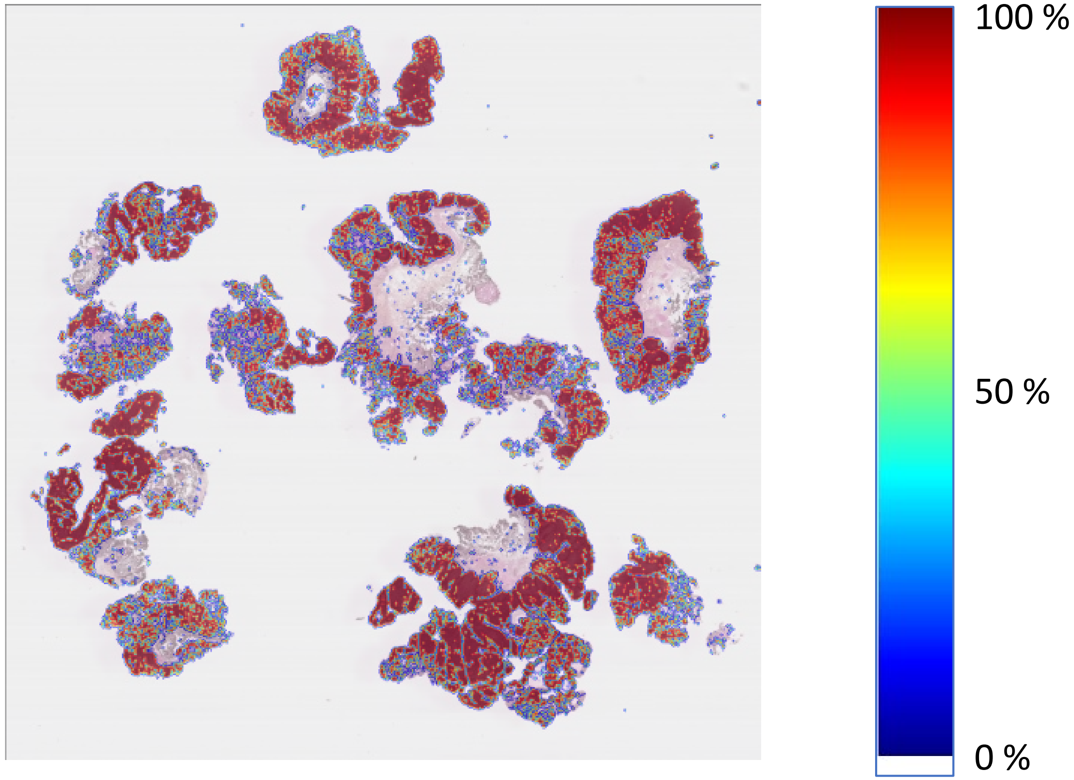


Heat Maps – example class

Original image



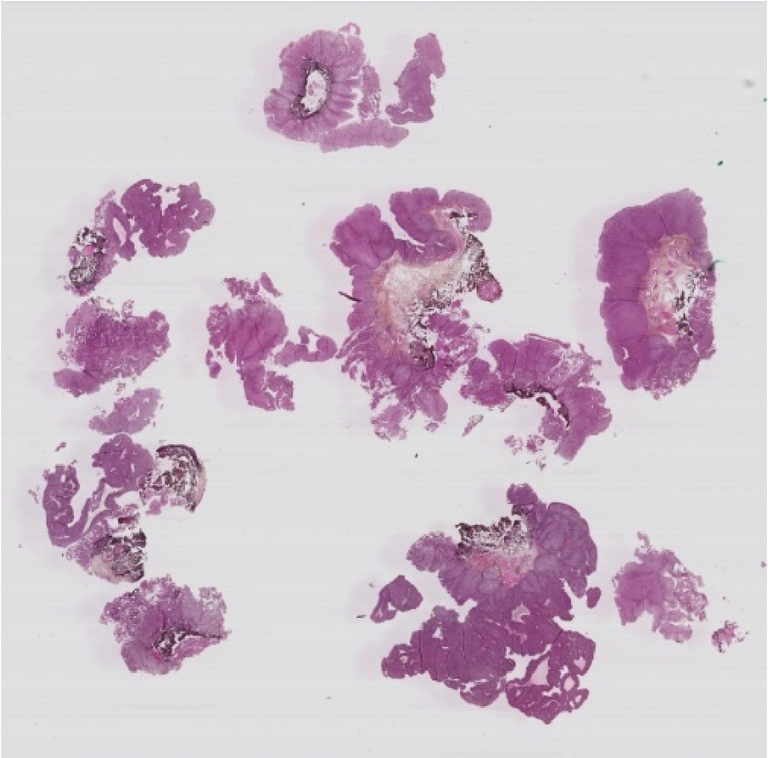
Urothelium tissue



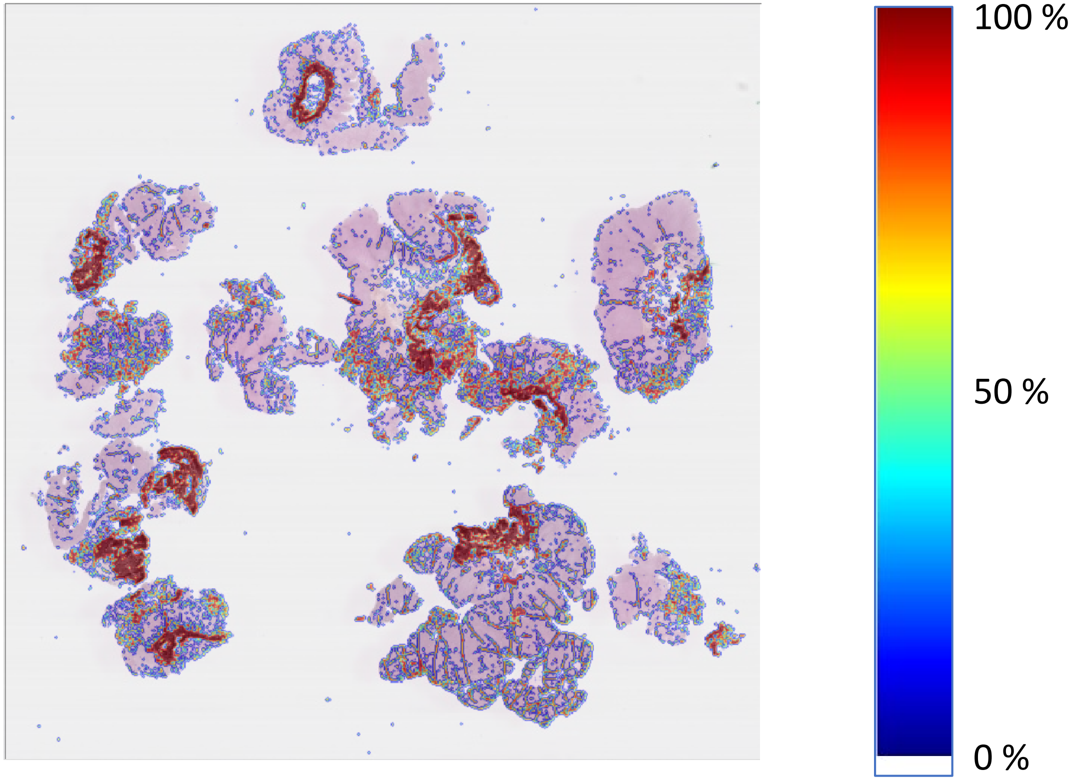
- Heat maps are post processed by applying a Gaussian filter kernel with standard deviation of $\sigma=0.6$ to smooth the image.

Heat Maps – example class

Original image



Damaged tissue



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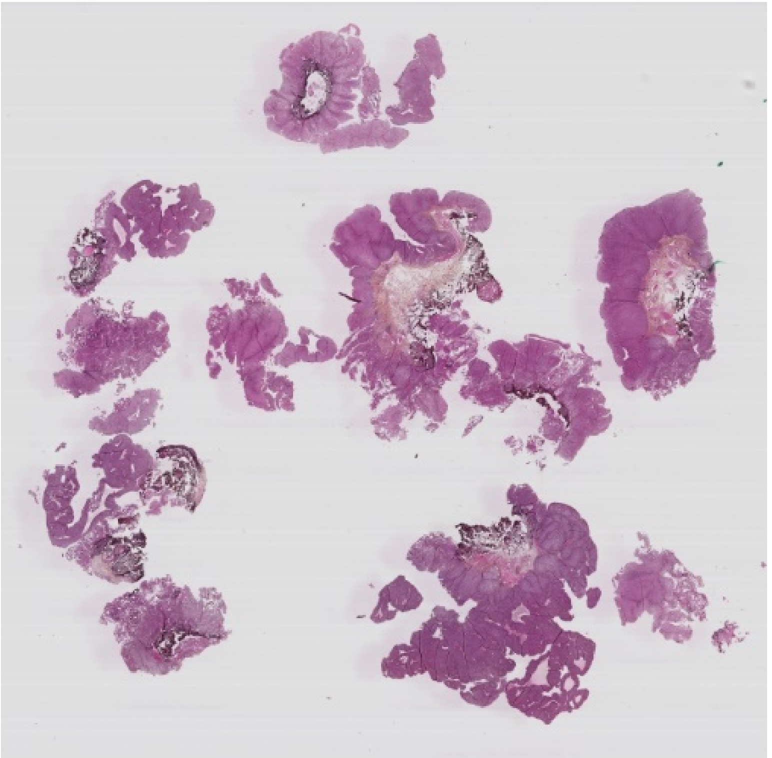
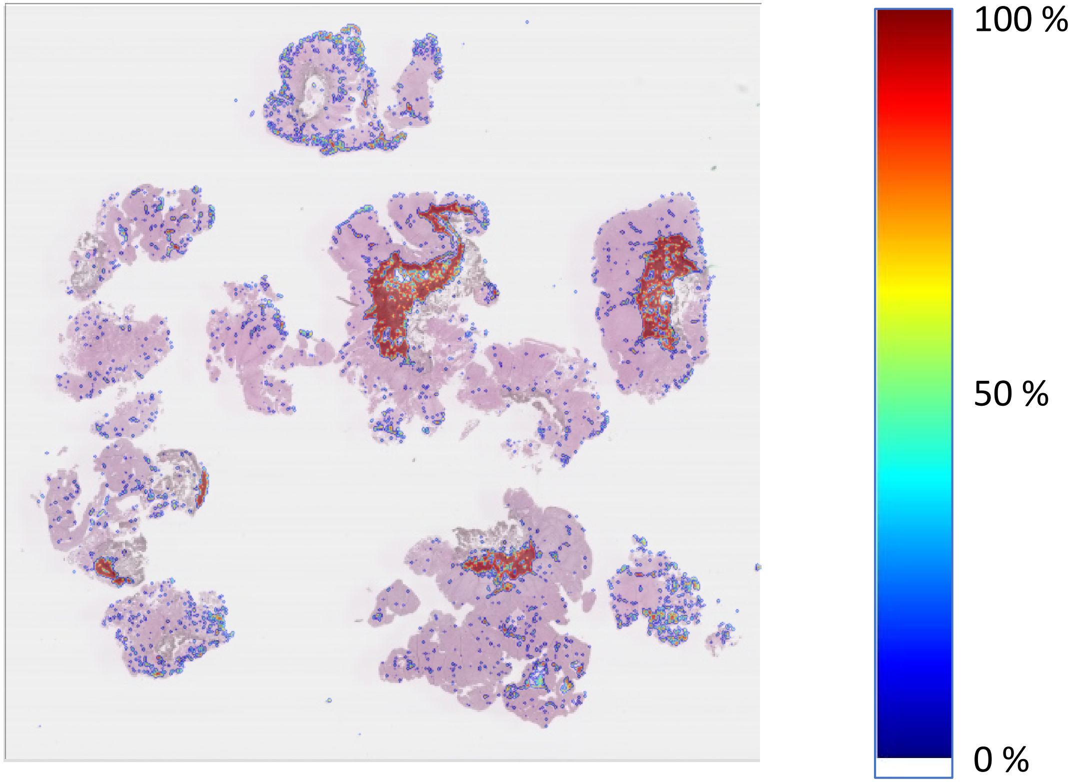
Heat Maps – example class

Original image

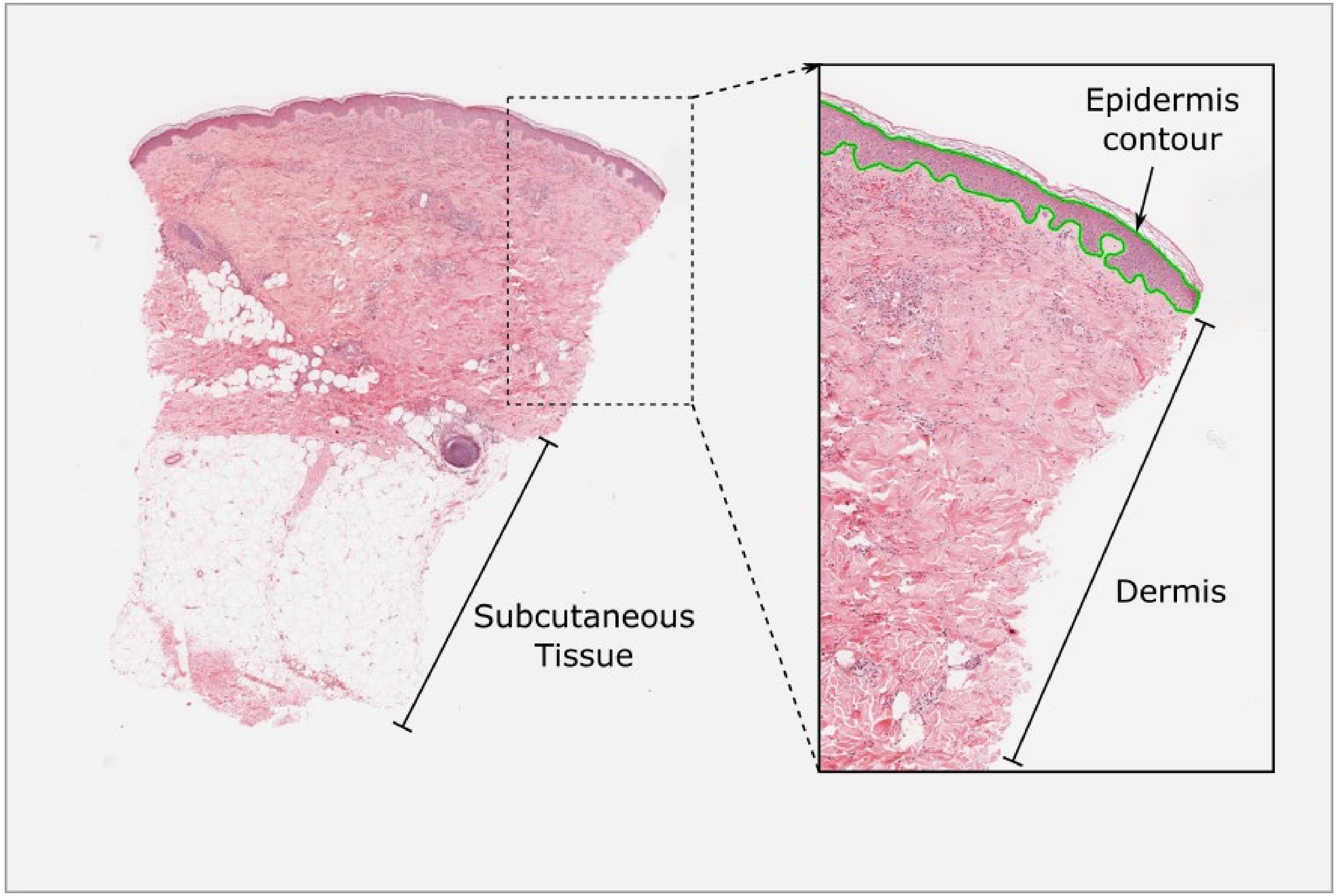


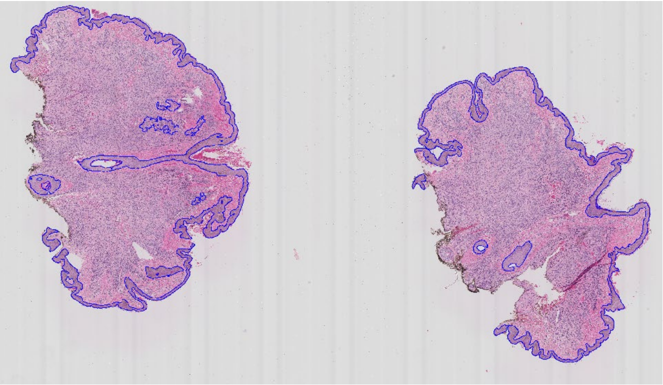
Stroma tissue



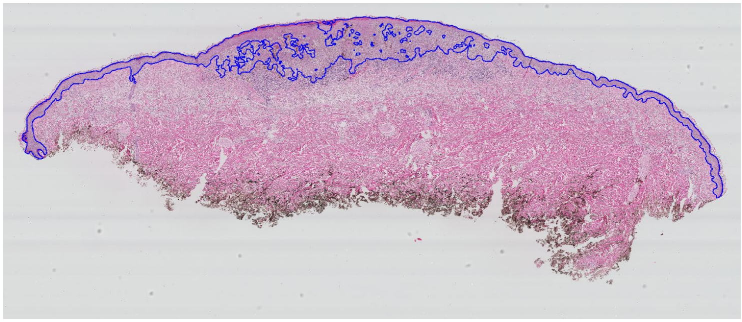
- Heat maps are post processed by applying a Gaussian filter kernel with standard deviation of σ=0.6 to smooth the image.

Melanoma : Epidermis segmentation





benign



Malignant

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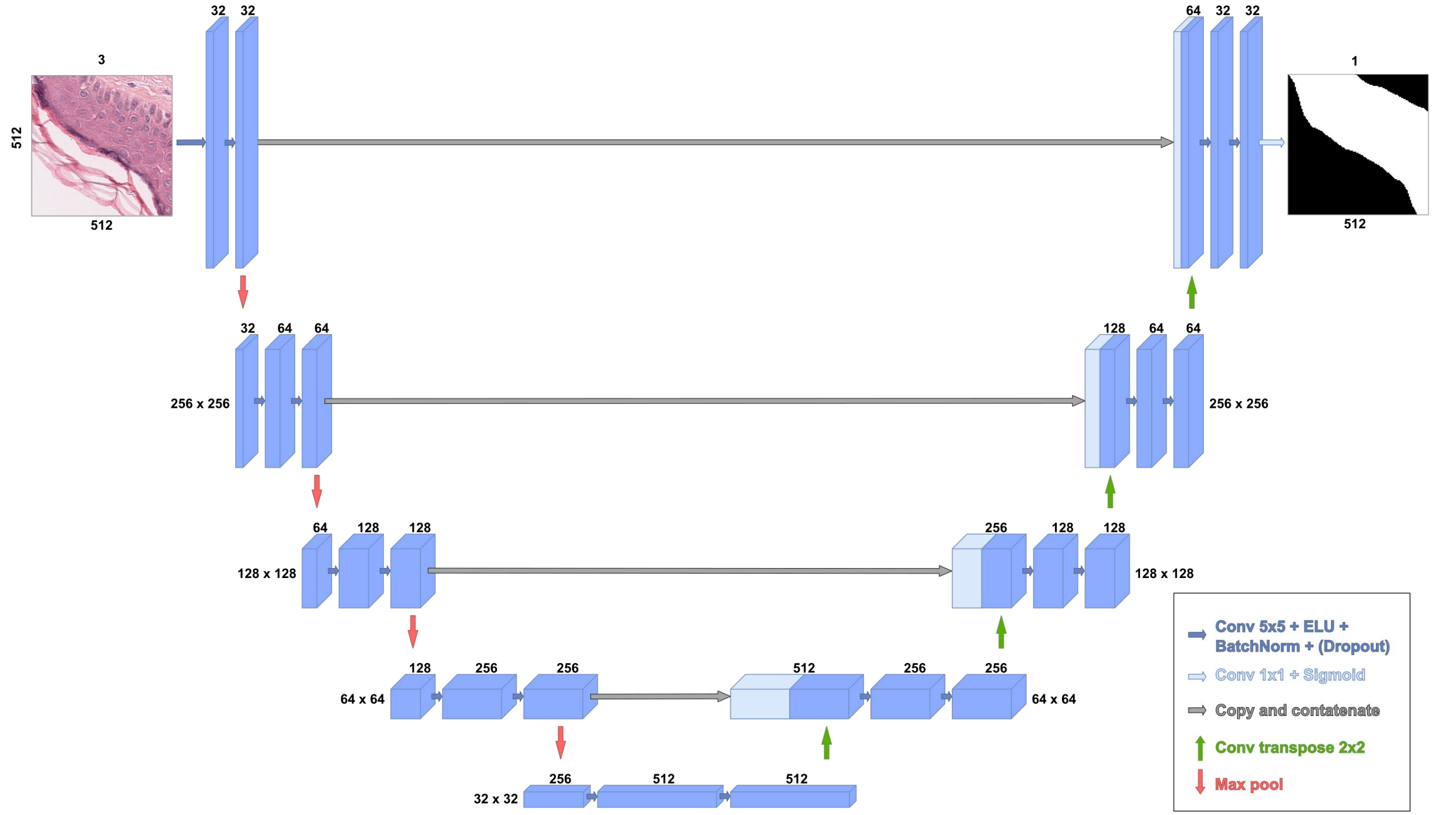
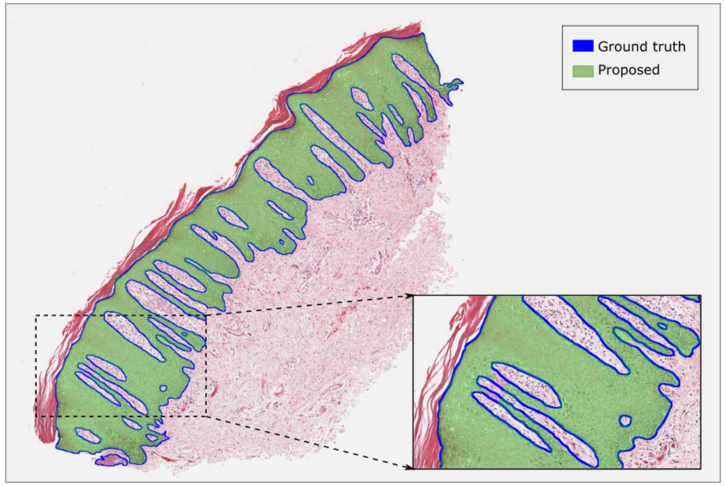
Epidermis segmentation – U-Net approach





Method	#failed	Mean value			
		$\mathcal{A}_{PPV}$	$\mathcal{A}_{SEN}$	$\mathcal{A}_{DSC}$	$\mathcal{A}_{MCC}$
CET	0	0.35	**0.99**	0.47	0.52
GTSA	21	0.73	0.31	0.39	0.42
THM	17	0.69	0.38	0.45	0.47
PASC	0	0.65	0.84	0.68	N/A
Proposed	0	**0.89**	0.92	**0.89**	**0.89**

Safer births

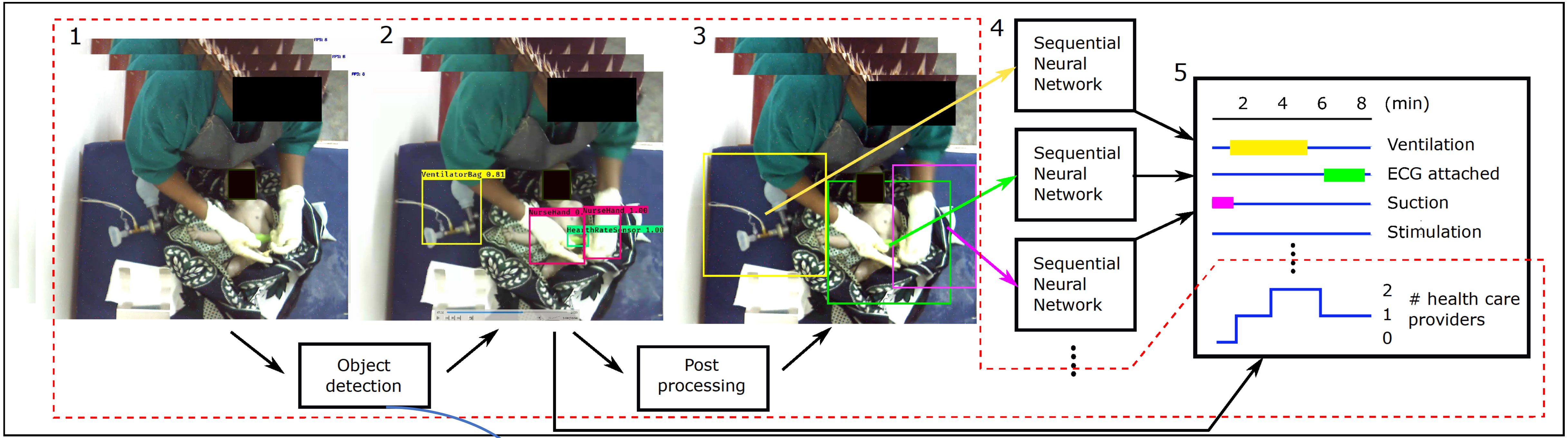
Sensor signals

- Fetal heart rate
- Resucitation signals (ECG, BMV)
- Video of rescucitation

Laerdal helping save lives HELSE STAVANGER Stavanger universitetssjukehus University of Stavanger ++

Video analysis

activity detection system for newborn resuscitation videos



Tried different things. So far best results using the pretrained model of YOLOV3, and continue training on our data

YOLOv3 Network Architecture

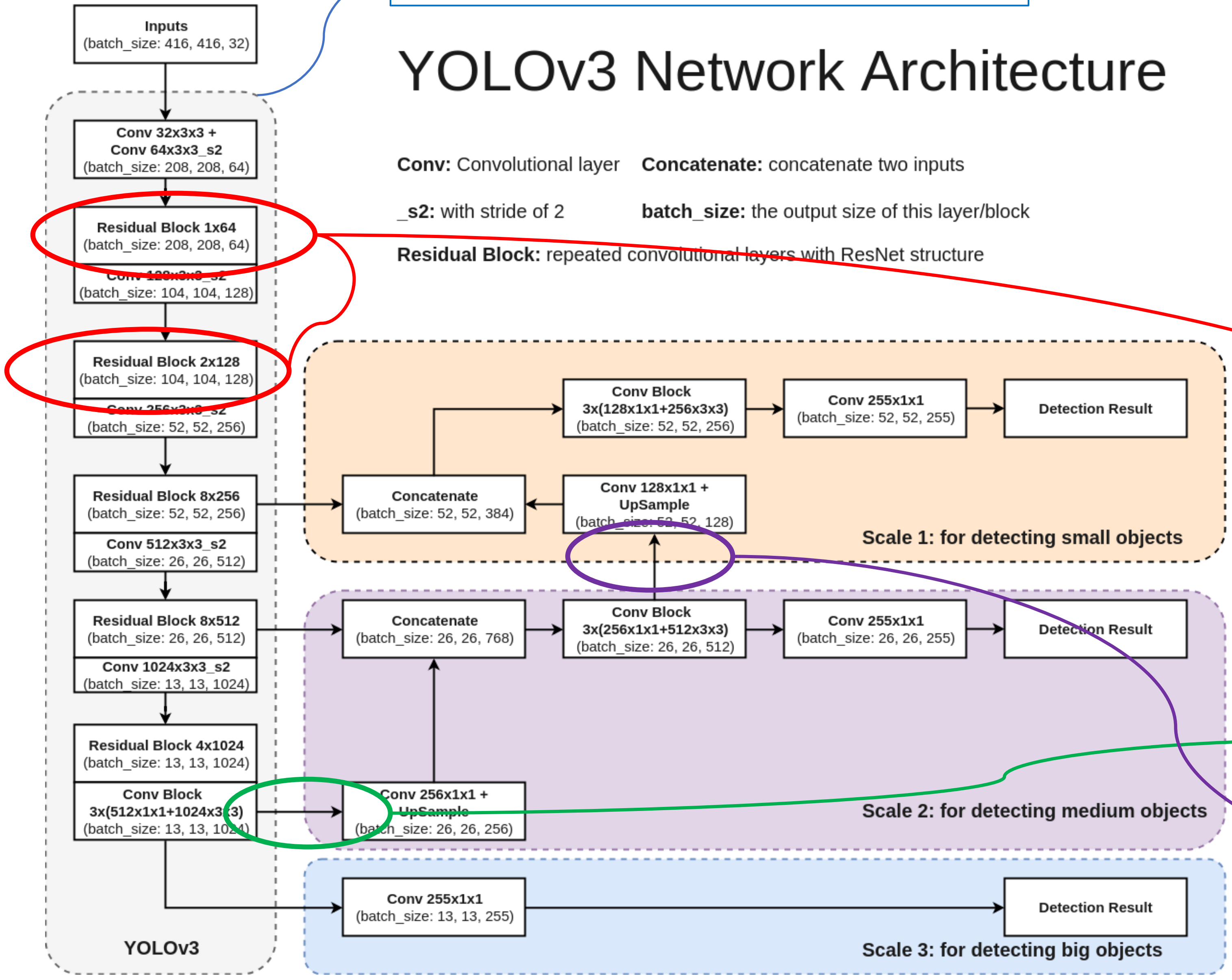
Darknet-53 (53 conv-layers) trained on Imagenet (feature extractor)

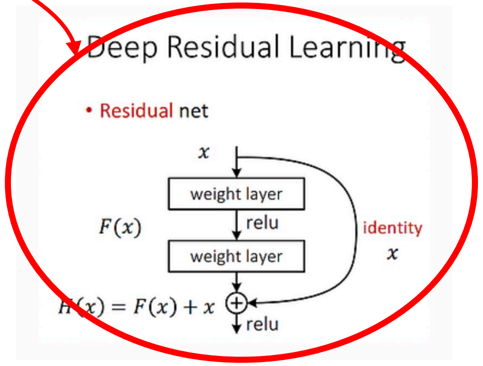
75 conv layers, no fully connected layers.
Conv layer with stride 2 is used for downsampling (no pooling)
ResNet for improved feature learning (skip connections)
FPN for utilizing multiscale
Multi-label classification

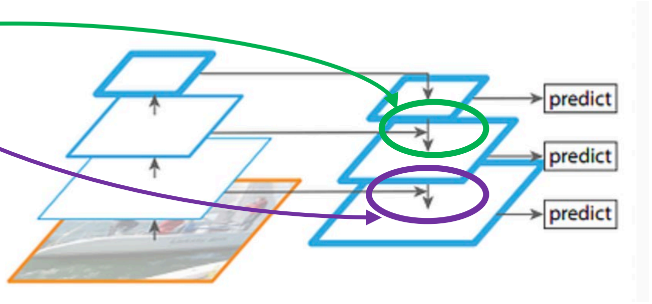
Conv: Convolutional layer **Concatenate:** concatenate two inputs

_s2: with stride of 2 **batch_size:** the output size of this layer/block

Residual Block: repeated convolutional layers with ResNet structure

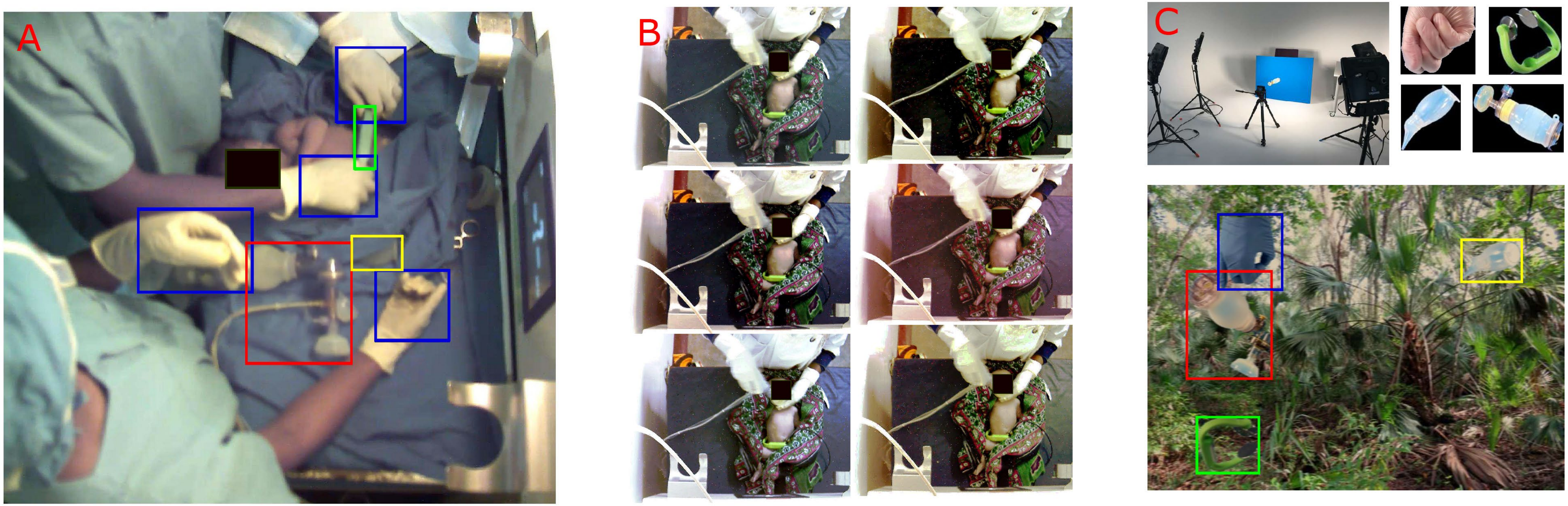






FPN: Feature Pyramid Network

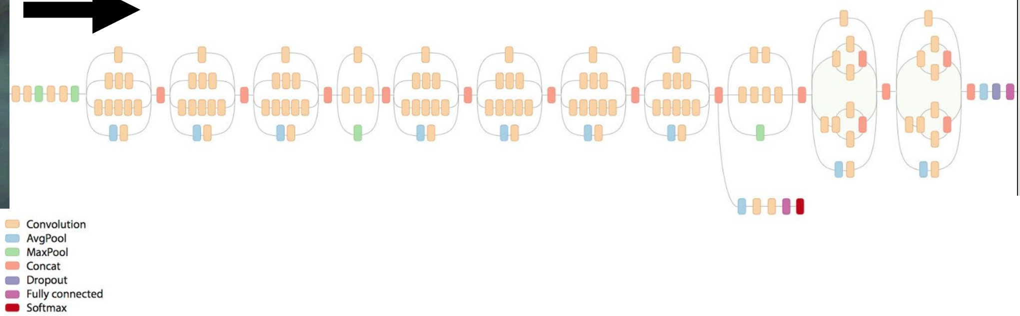
Never enough labeled data! Training data (video, augmented, synthetic)



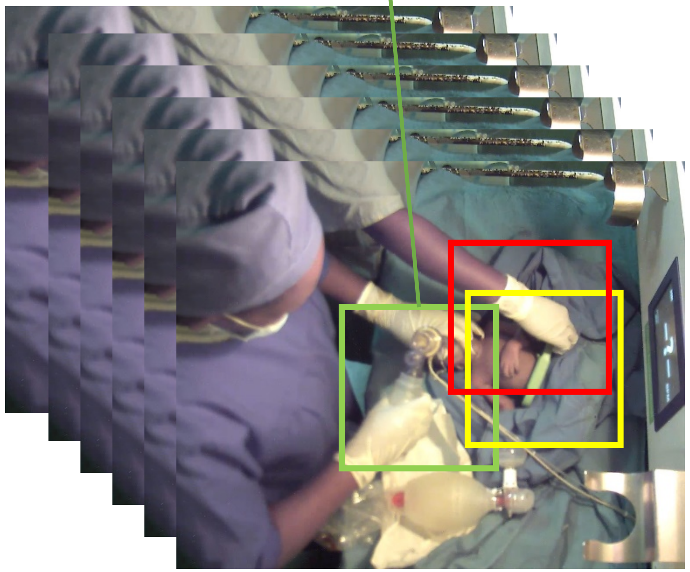
Object detection and tracking using YOLO v3 and post processing

Ventilations Not Ventilations

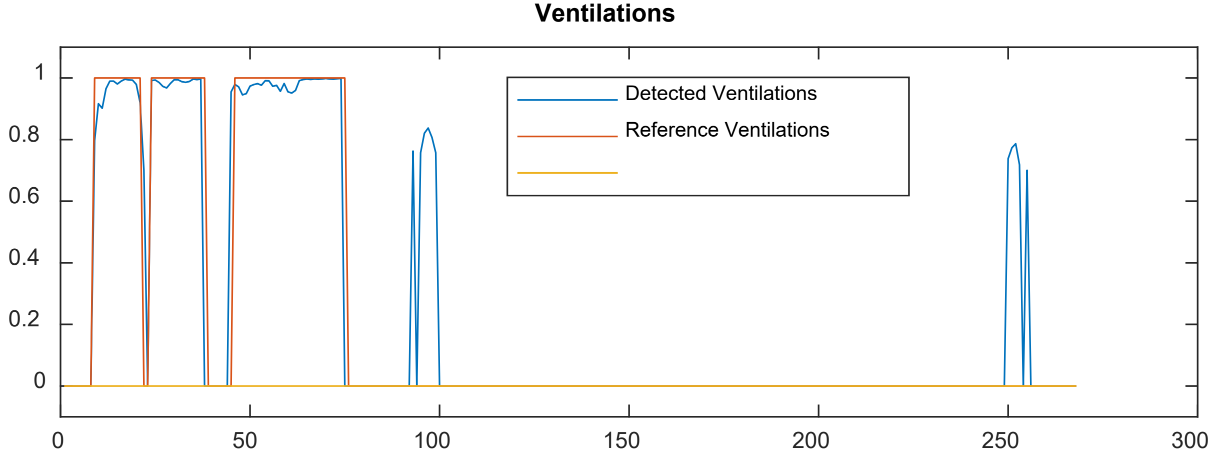
- Extract features from images using Inception_v3
- Input sequence of feature vectors to LSTM network trained on the idividual activities
  - Ex: ventilations or not
  - Augmentation (noise, blur, flip, rotate, crop)




```
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, 30, 2048)          33562624
_________________________________________________________________
lstm_2 (LSTM)                (None, 2048)              33562624
_________________________________________________________________
dense_1 (Dense)              (None, 512)               1049088
_________________________________________________________________
dropout_1 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_2 (Dense)              (None, 2)                 1026
=================================================================
Total params: 68,175,362
Trainable params: 68,175,362
Non-trainable params: 0
```



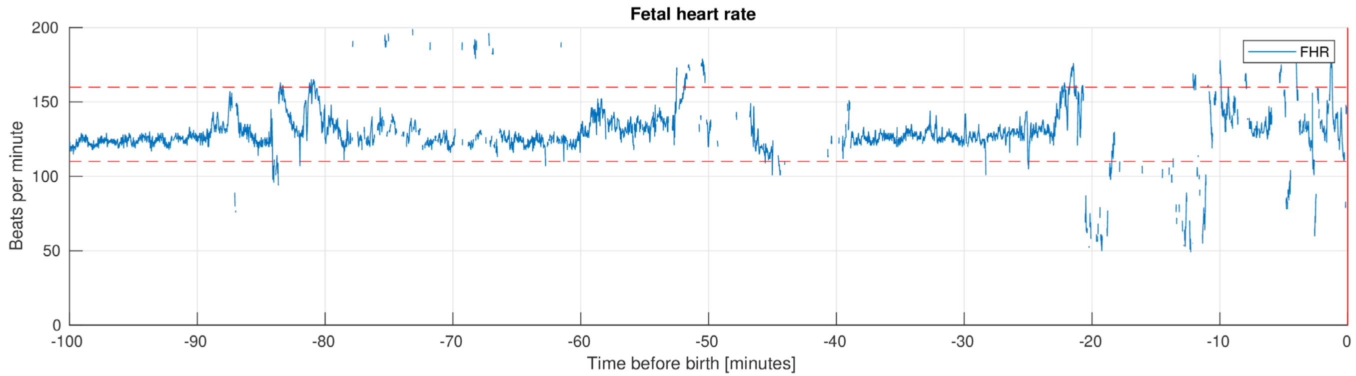
Validation acc 90% (using only RGB)

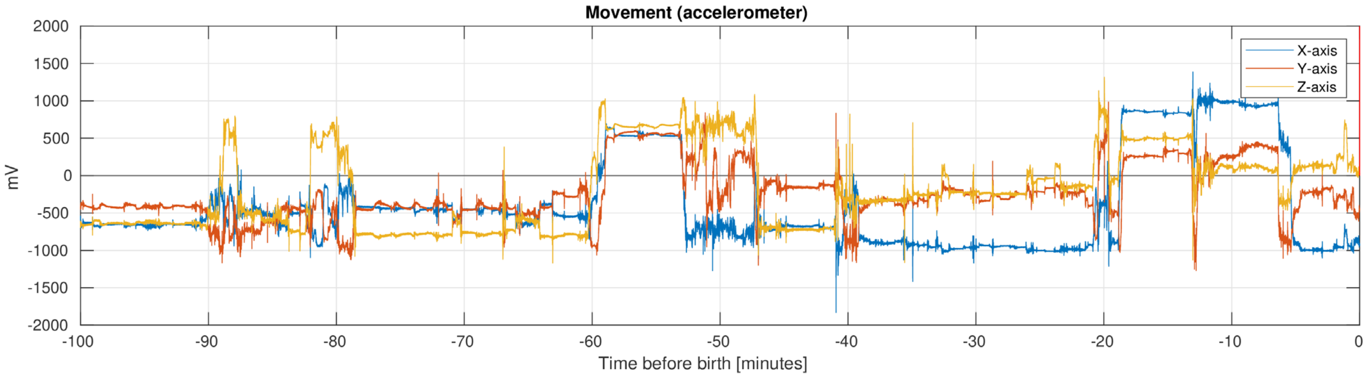


Working on: i3d (inception structure but for 3d (video) , one for RGB video and one for optical flow stream

Fetal heart rate - Moyo

Possible to predict outcome at earlier stage?
Detect fetus in need for care?
(Intrauterine intervention / C-section)





Other ongoing projects on deep learning at UiS

- Segmentation of myocardium in cardiac magnetic resconanse images
- Identifying areas at risk from perfusion CT images after cerebral ischemic stroke
- Identification and classification of dementia types from brain MRI
- Novel Deep Neural Network Architectures for Fake news Detection in Social Networks and News Media
- DeepRTP - Deep learning the real-time properties of strongly correlated quantum fields, deeprtp.uis.no
- Future Energy Hub – AI and Machine Learning in energy informatics and smart cities