Training of deep neural networks with incomplete training information on the example of recognition of tomographic images

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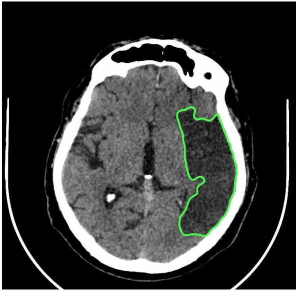
May 2021

Formulation of the problem



A large dataset of tomographic images of the brain is given. Each image is a section of the brain. Manual marking of such a dataset is very expensive, since only a highly qualified specialist can do this.

In this regard, it is necessary to create a model that will predict areas of stroke and select them on tomographic images of the brain. The model will be used as a "decision support system."

Complexity of the problem and scientific novelty

Complexity

- Very little labeled data available: only 34 images, which is clearly not enough for training classical deep convolutional neural networks;
- It is necessary not only to properly segment the image, but also to have high recognition accuracy;
- The model should be interpretable, otherwise doctors will not understand its decisions and will not trust it.

Scientific novelty

- All current solutions require a huge amount of training data;
- The interpretability of neural networks is poorly understood.

Initial data

- Images in DICOM format, labels in JPG format;
- Only 34 labeled images of brain slices;
- More than 30 GB of unlabeled images.

Segmentation task

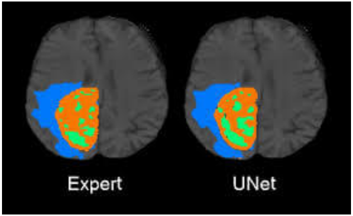
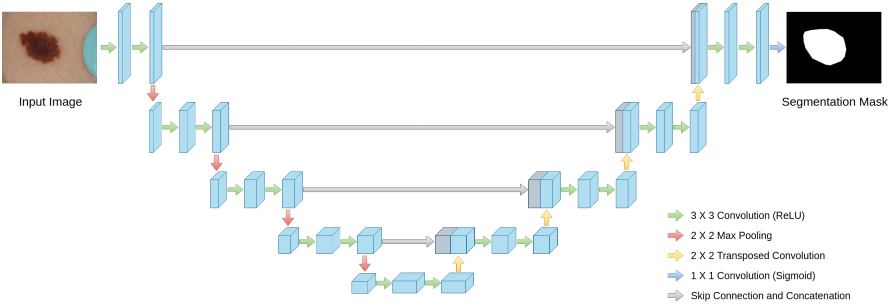


Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as image objects).

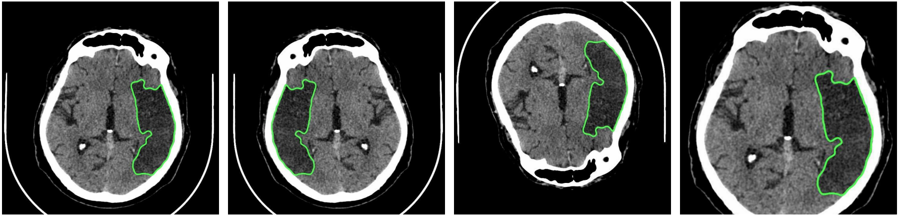
- **Automatic segmentation**: bad accuracy, doesn't work in medical image recognition tasks;
- **Semi-automatic segmentation**: requires the participation of a specialist during segmentation process, poorly suited for creating a decision-making system;
- **Trainable segmentation**: the most promising approach.

Trainable segmentation



- The model allows you to achieve high metrics;
- A lot of data is needed for training;
- Transfer learning doesn't work well for medical image recognition tasks;
- Inability to interpret model decisions.

Augmentations

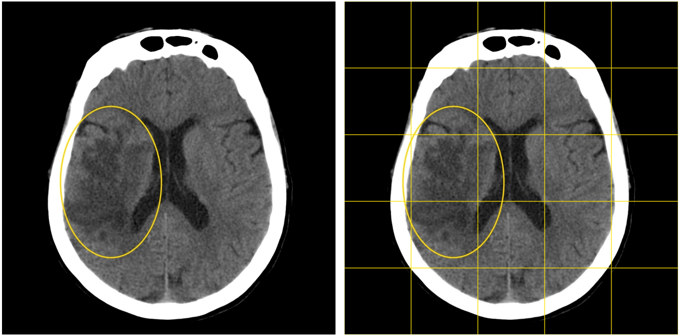


The only augmentations that have improved the quality:

- horizontal flips;
- vertical flips;
- small zoom;

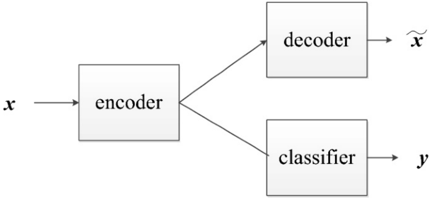
Instead of a random crop, which is a very popular augmentation in such problems, a slightly different approach was used.

Cutting the image into sub images



- Learning on crops smaller than the original image;
- To predict, we cut the picture into crop again, predict for them and collect the image back;
- We increase the dataset 16 times using a 4x4 grid.

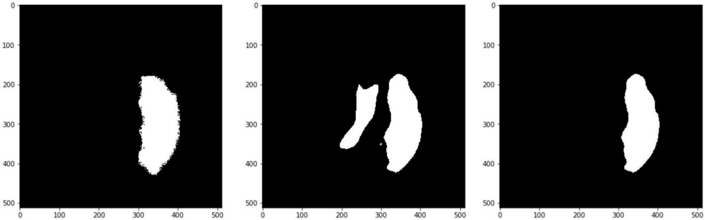
Network Architecture



To improve the accuracy of stroke diagnosis, the model includes two parts: a segmentator and a classifier. Thus, segmentation is performed only if the classifier reveals a stroke in the image.

- **Segmentator**: an architecture including an encoder and a decoder with skip-connections and higher dilation parameter;
- **Classifier**: a linear layer with sigmoid at the output of the encoder;
- **Loss function**: sum of the weighted cross-entropy of the classifier and the weighted cross-entropy of the segmentator.

Model Prediction Processing



Left image - ground truth, middle image - all components, right image - only the maximum connected component

- **Using TTA**: augmentations (horizontal flips) are applied not only during training, but also during prediction, then the predictions for the images are averaged;
- To increase the quality of segmentation, the model **leaves only the maximum connected component** in the resulting segmented image;
- In addition to this, **the remaining component is removed if it is less than a certain size** (currently less than 1200 pixels).

Results of Experiments

Table: Validation and Test Results

Metric	Validation	Test
Accuracy	0.922	0.890
IoU	0.727	0.675

- **Validation**: 8 (4+4) images (128 sub images);
- **Test**: 6 images (92 sub images).

Results of Experiments

Table: Comparison of the proposed algorithm with the baseline

Approach	IoU	FPR
U-Net (baseline)	0.541	1
Proposed algorithm	0.727	0.2

Conclusion

We managed to build a model for the diagnosis of stroke with good quality, having only 34 labeled images. To do this, we used various techniques:

- cutting the image into sub images;
- a convolutional neural network with a high dilation parameter, consisting of a segmenter and a classifier;
- processing model predictions by cutting off small components of connectivity.

To increase the interpretability of the model, it is assumed in the future to use well-interpreted algorithms, such as: decision tree, k-nearest neighbors, linear regression etc instead of the classifier layer.

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