Convolutional Neural Networks in Medical Imaging

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Introduction

- Convolutional neural networks or CNNs, have seen a rise in popularity in image related fields.
- CNNs have been having great success in biological segmentation tasks.
- These tasks include:
  - The automated detection of lymph nodes
  - Segmentation of knee cartilage
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- The goal of this work is to provide unsegmented MRIs to the network and receive properly segmented MRIs as output.
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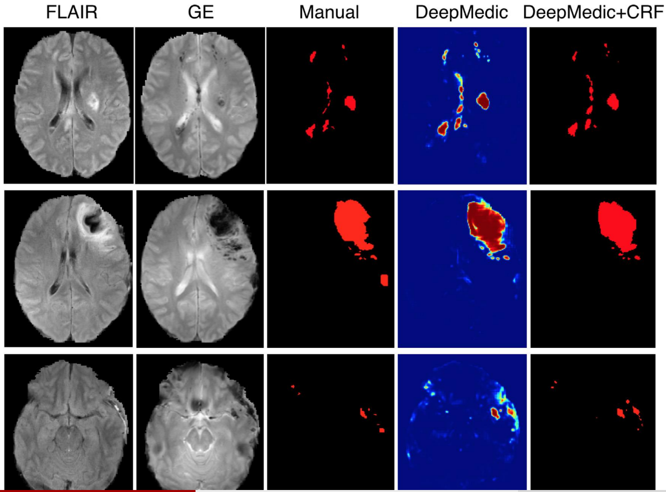
Input Output Example



Outline

- Background - Information about basic structural concepts for CNNs
- Methods used by Havaei, et al.
- Methods used by Kamnitsas, et al.
- Results
- Conclusions

Biological Segmentation

- Segmentation is the process of identifying the boundaries of different structures and classifying them
- Segmentation is loosely defined and can have a wide range of granularities.
  - Rough graularity such as identifying the different bones in a leg xray.
  - Smooth granularity such as determining the differing regions of a tumor.

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Neural Network Structure

- Comprised of layers of nodes
- Each node has an activation function that triggers when it recognizes something in the input.
- These activations are then passed to neighboring nodes through weighted connections eventually leading to some type of output.
- The network can 'learn' by altering the weights of its connections based on the accuracy of the output to the goal result.

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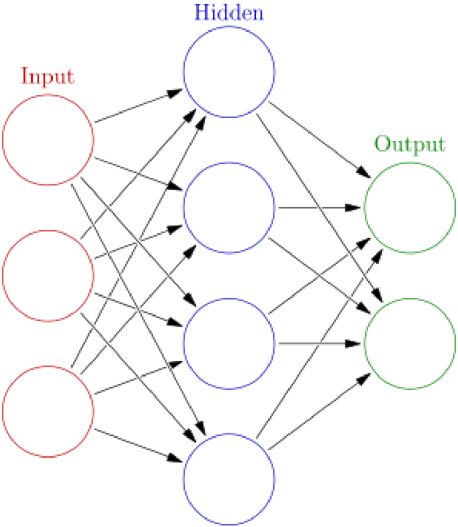
Hidden
Input
Output

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Kernels

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
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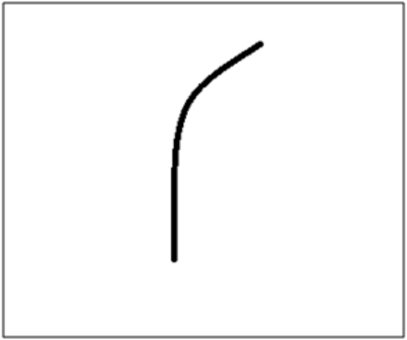
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter



Visualization of a curve detector filter

Kernel
`https://adeshpande3.github.io/`

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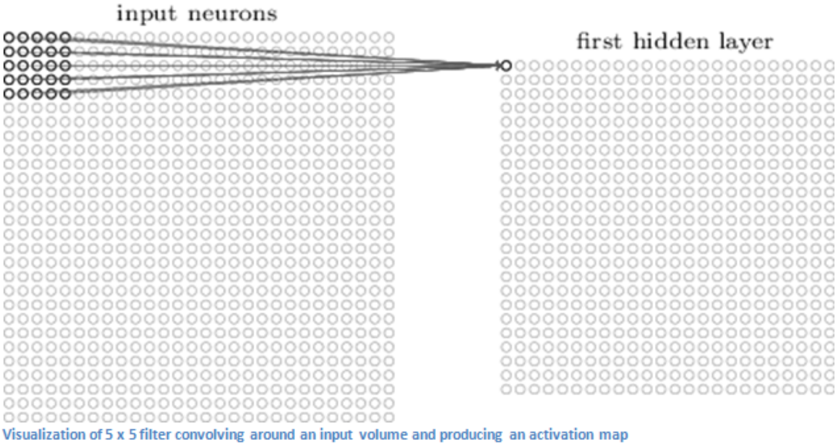

Feature Map
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- Their job is to convert the feature maps from previous layers into label probabilities.
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Training

- Training is the crux that makes everything work
- Training requires data that has already been properly segmented.
- Network is initialized with random kernel weights
- Training has four main steps:
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  - The backward pass
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  - Two pathways
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  - The local pathway with a smaller 7x7 receptive field'
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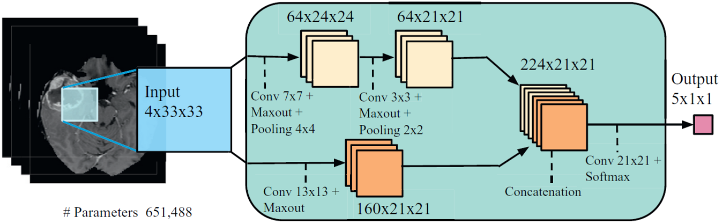

Cascaded Architectures

- The second approach implemented by Havaei, et al. is their use of a 'cascaded architecture'.
- In this approach they take the output one of one CNN and concatenate it into a layer of another.
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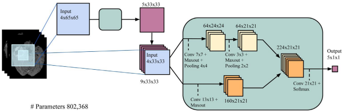
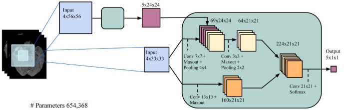
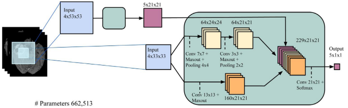


(a) Cascaded architecture, using input concatenation (InputCascadeCNN).



(b) Cascaded architecture, using local pathway concatenation (LocalCascadeCNN).



(c) Cascaded architecture, using pre-output concatenation, which is an architecture with properties similar to that of learning using a limited number of mean-field inference iterations in a CRF (MFCascadeCNN).

Two Phase Training

- The last approach implemented by Havaei, et al. is a two phase training system.
- This is done to alleviate the relative abundance of healthy tissue versus the small quantity of tumor tissue in each image.
- The two phases consist of:
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  - 3D kernels
  - Dense training
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  - Deeper networks
  - 3D conditional random fields on the output

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