Motivation

Vessel segmentation in the brain is a critical yet underexplored area in the health industry. Unlocking insights into this field can lead to breakthroughs across various medical domains. Specifically:

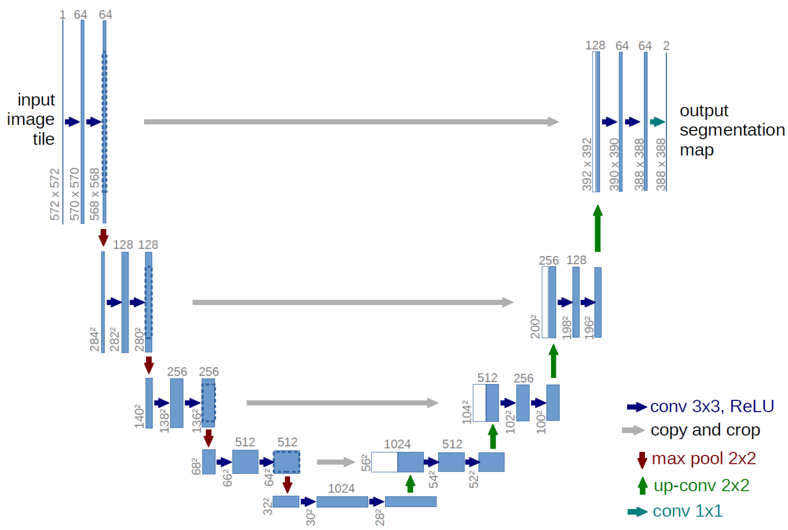
- **Nutrient and Oxygen Transport:** Vascular networks deliver oxygen and nutrients to tissues while removing waste. Analyzing these networks helps us understand homeostasis and its disruptions in diseases.
- **Growth and Development:** Angiogenesis, or the formation of new blood vessels, plays a crucial role in growth, wound healing, and adaptation to low-oxygen environments.
- **Cardiovascular Diseases:** Conditions like atherosclerosis, hypertension, and stroke are directly linked to vascular abnormalities. Enhanced vessel segmentation can aid in earlier diagnosis and targeted treatment strategies.
- **Cancer:** Tumor growth relies on angiogenesis. Accurate segmentation of vascular networks can facilitate the development of therapies to inhibit blood supply to tumors.
- **Diabetes:** Diabetic complications, such as retinopathy and nephropathy, involve vascular damage. Studying brain vasculature may provide insights into managing these complications.
- **Neurodegenerative Diseases:** Disorders like Alzheimer's disease involve reduced cerebral blood flow. Vessel segmentation can uncover patterns that might aid in early diagnosis and intervention.
- **Regenerative Medicine and Tissue Engineering:** Understanding and replicating vascular structures are critical for creating functional artificial tissues and organs.
- **Drug Delivery:** Insights into vascular structure and permeability can enhance the precision of targeted drug delivery systems.
- **Aging:** Age-related deterioration of vascular networks reduces tissue repair and organ function. Improved segmentation methods may help study these processes and extend healthy lifespans.
- **Global Health Impact:** Cardiovascular diseases remain the leading cause of death worldwide. Enhanced segmentation techniques can improve diagnostics, inform prevention strategies, and reduce healthcare costs.

Method

This project focuses on improving current machine learning methods for vessel segmentation by refining neural network models, specifically by using **U-Net architectures** to enhance **Convolutional Neural Networks (CNNs).**

Approach Overview

U-Nets are designed to process images in a way that **preserves important details** while **analyzing spatial patterns**. The process has two main stages: **compression and reconstruction**, forming the "U" shape of the network.



[source]

Compression Phase:

1. **Image Reduction:** The U-Net will reduce the input image size by grouping every 9 pixels into a single pixel and identifying the patterns between the groups.
2. **Layer Creation:** Patterns like color, edges, shapes, and size are stored in layers. These layers keep the important details of the original image while reducing its size. For every layer creation, it would evaluate the different patterns we are looking for and find the amount of information gained based on how much each layer will bring in new information. It will then saveW the layer with the highest information gain. For the next step, it would take in the next highest information gained based on the remaining patterns.

3. **Pattern Analysis:** This process continues until the image reaches a set lower limit, such as a single pixel or a small grid (e.g., 3x3 pixels). This limit will be adjusted for vessel segmentation tasks.

Reconstruction Phase:

1. **Rebuilding the Image:** The U-Net uses the compressed image and the stored layers to reconstruct the original image.
2. **Final Output:** The reconstructed image matches the size of the original image but highlights important features like vessel edges and shapes while reducing unnecessary details.

How we are improving CNNs using U-Net

- They keep spatial details by linking compression and reconstruction steps.
- The output is more accurate and captures small details that regular CNNs miss.
- They are tailored for vessel-specific features, making them better for tasks like detecting edges and complex shapes.

By combining feature extraction and detailed reconstruction, **U-Nets provide a clear improvement over traditional CNNs**. This approach will lead to **more reliable and accurate vessel segmentation**, which is useful in medical imaging and similar applications. Specifically the improvement is made during the layer section as it would accurately prioritize the information gained on certain layers over other layers so that we would retain the most amount of information possible given the image that the algorithm receives. This is way faster and better than traditional CNNs.

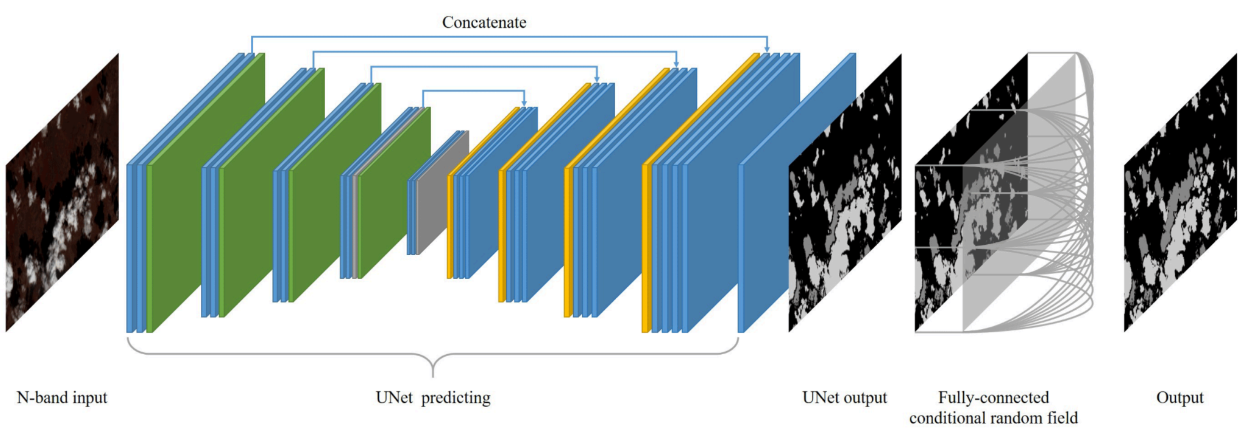
Intended Experiments

Comparison of CNN vs. U-Nets: We will compare CNN-based algorithms and U-Net-based algorithms using brain MRI scans that include noise and vessel structures. The process will involve:

1. **Data Collection:** Collecting multiple MRI scan images with significant noise and visible vessels.
2. **Baseline Creation:** Manually segmenting the vessels in the images to create a baseline for comparison. While our manual segmentation may not be perfect, it will serve as a reliable reference point.
3. **Algorithm Testing:** Running both CNN and U-Net algorithms on the same dataset and comparing their outputs against the manually segmented images. The goal is to determine which algorithm produces results closer to the baseline.

Real-World Applications:

1. **Noise Evaluation:** Testing the algorithms to understand how noise impacts their performance and determining if a threshold is needed to decide which parts of the vessel should or shouldn't be segmented.
2. **Disease Detection:** Using the improved algorithm to identify anomalies or similarities in the segmented vessels, aiding in the detection of potential diseases.



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Dataset + Prior Research

https://pmc.ncbi.nlm.nih.gov/articles/PMC7339138/

The authors employed established methods like **Independent Component Analysis (ICA)** and dual regression to analyze fMRI data. Their novelty lies in the **experimental design using concurrent neuronal and vascular stimuli**. They suggest exploring alternative approaches like **Tensor ICA and temporal ICA** in future research.

https://pmc.ncbi.nlm.nih.gov/articles/PMC3595043/

The paper focuses on the **vascular neural network** as a new way for understanding stroke pathophysiology. The authors argue that the **traditional** neurovascular unit model **is limited** because it **doesn't account for the roles of vascular smooth muscle cells**, arterial endothelium, and perivascular nerve fibers upstream of the cerebral microcirculation. They propose the vascular neural network, which **incorporates the neurovascular unit along with these upstream elements**, as a more comprehensive model.

https://www.sciencedirect.com/science/article/pii/S089662731400645X

The paper describes a computational tool used to analyze 3D confocal images of the vascular structure in mouse brains. This tool automatically quantifies: Vessel density, Vessel diameter, Branching patterns. There are several steps: Image smoothing and adaptive thresholding to identify vessel pixels, removal of incorrectly classified pixels based on size, skeletonization of the blood vessels, representing them as a network, removal of spurious short segments and measurement of segment length, estimation of vessel radius based on the cross-sectional area of the binary vessel image.

The researchers validated analysis by creating 3D images that combined the original image with the final skeletons. This allowed them to verify the accuracy of the skeletons in representing the blood vessel structure.