Gradient Segmentation for Enhanced Visualization of blood vessels in medical imaging

Deepak Menon K DEEPAK.K@SIEMENS-HEALTHINEERS.COM
Rashmitha R Mabiyan RASHMITHA.MABIYAN7@GMAIL.COM
Siemens Healthineers, Bengaluru

Editors: Under Review for MIDL 2025

Abstract

Traditional medical imaging segmentation classifies anatomical structures distinctly but fails to capture gradual transitions. We propose a gradient segmentation approach for smoother, more realistic boundaries, improving visualization and aiding clinical decisions. Using arteriovenous fistula (AVF) as an example, we modify neural network segmentation models to retain probability scores, applying gradient-based color mapping—red for arteries, blue for veins, and blended gradients for overlapping regions. This technique enhances vessel visualization and can be extended to other anatomical structures, providing a more intuitive approach to medical imaging.

Keywords: Arteriovenous fistula, Gradient Segmentation, Artificial Intelligence.

1. Introduction

Traditional segmentation techniques in medical imaging classify regions into well-defined, sharply demarcated groups but struggle to represent natural, gradual transitions on biological tissues. Gradient segmentation addresses this shortcoming by providing smooth, continuous borders that closely mimic anatomical intersections, improving the clarity of visualization and potentially enhancing clinical decision-making and treatment planning.

2. Methodology

In this paper, we present a novel gradient segmentation methodology to effectively visualize regions of interest in ArterioVenous Fistula (AVF), a clinical condition characterized by abnormal connections between arteries and veins.

Figure 1: Arteriovenous fistula(Clinic, 2022).

We take example of neural networks which can segment arteries and veins separately. The segmentation model architecture of these neural networks is slightly modified by removing the output layer i.e., the activation function in these models. In general, the output layer of neural networks provides the raw probabilities of each class label (target output), following this a post processing step such as argmax or thresholding is applied to determine the actual class label using these probabilities.

In case of an artery or veins segmentation model, the output layer consists of the probability of each pixel in input image belonging to artery or vein in their respective models. In the post-processing step, we introduce a new approach called gradient segmentation for getting the appropriate segmentation masks.

2.1. Post processing for Artery segmentation

At first, a thresholding technique will be applied to determine the positive class i.e., artery which the model is confident about. A threshold of say 't' (experimental) is selected - a confidence score above 't' for a pixel is 'artery'. Next, if the probability score of a pixel is below 0.5(experimental), we consider it as a negative class. This means that the model is confident that the pixel is not belonging to 'artery'.

If a pixel has a probability between '0.5' and the threshold 't', the model is predicting that the pixel might be close enough to be an 'artery' but not very confident. This might be a case where artery and veins do intersect. This set of pixels might be an area of uncertainty which probably means that it also could be an AVF where there are both arteries and veins interlinked.

For the positive class we color code the pixels as red(RGB 255,0,0) and for the pixels between 0.5 and 't' we apply gradient of red(in RGB). The gradient transitions from a light red(RGB) color at 0.5 to a darker red(RGB) at 't'. The proposed gradient segmentation for artery is explained with the help of Figure 2 where the threshold 't' is assumed as 0.9.

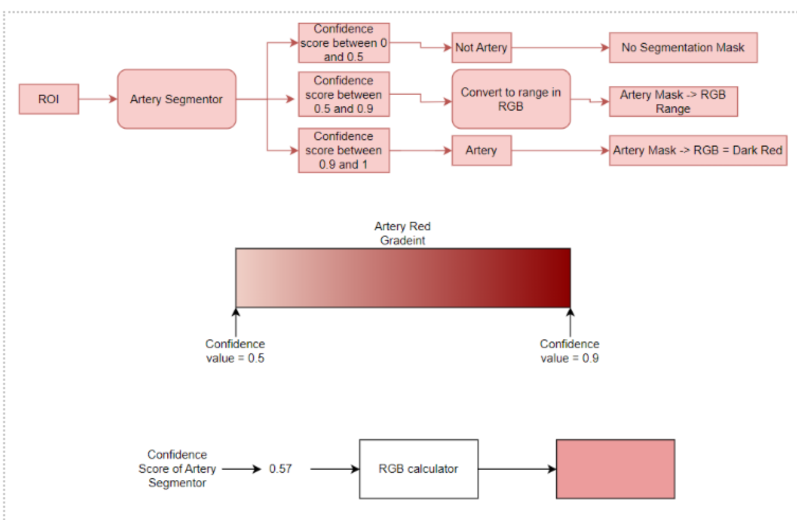

Figure 2: Color coding artery with gradient of red.

In the step above, for a particular ROI we have the confidence score of 0.57 for the artery segmentor. This confidence value is converted to a red color gradient.

2.2. Post processing for veins segmentation

Post processing for veins segmentation also follows similar steps. Pixels above the threshold 't' are colored in blue (RGB 0,0,255) indicating that they belong to veins and pixels with probability score of below 0.5 are considered as negative class. Gradient of blue is applied for the pixels with probability score between 0.5 and 't'. Gradient transitions from a light blue (in RGB) color at 0.5 to a darker blue (in RGB) at 't'.

The proposed gradient segmentation for veins is explained with the help of Figure 3 where the threshold 't' is assumed as 0.9.

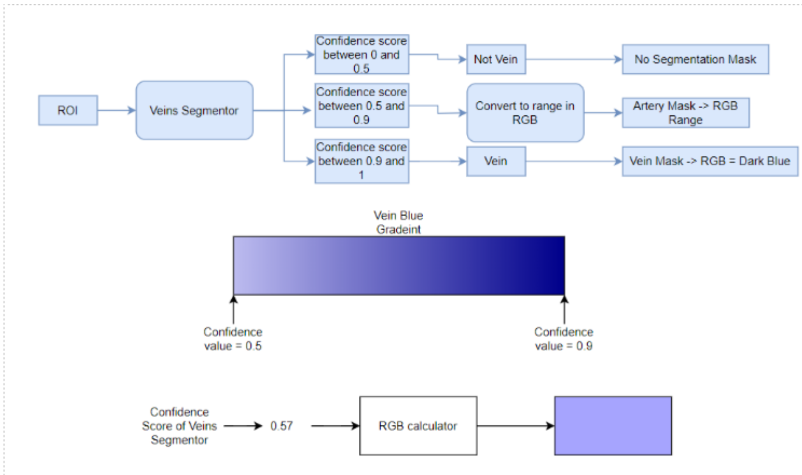

Figure 3: Color coding vein with gradient of blue.

In the step above, for the same ROI we have the confidence score of 0.57 for the vein segmentor. This confidence value is converted to a blue color gradient.

In Figure 4, we superimpose the RGB values for the same ROI provided by artery and veins segmentors to create a superimposed RGB value. Same technique is applied for the entire segmentation of arteries and veins. When the colored masks from both the segmentors are superimposed on the original images, a clear distinction of arteries, veins and a smooth transition of these at fistula can be visualized.

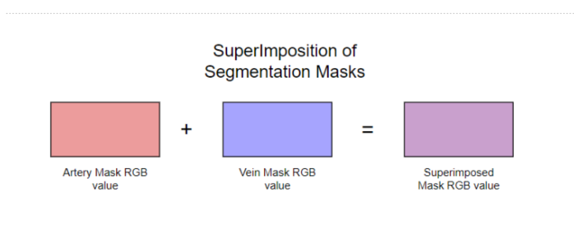

Figure 4: Super-imposed artery and vein segmentation mask.

To explain the proposal in detail, we used the example of fistula of blood vessels. The same can be applied to any other connecting organs or fistula.

References

Mayo Clinic. Arteriovenous fistula, 2022. URL https://www.mayoclinic.org/diseases-conditions/arteriovenous-fistula/symptoms-causes/syc-20369567. Retrieved March 23, 2025.