# A Divide-and-Conquer Approach Towards Understanding Deep Networks

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## Motivation

- Aim to improve the interpretation of Artificial Neural Networks (ANN).
- Construct an explainable network pipeline with high performance according to the known operator theory [1, 2].
- Experiment design follows the divide-and-conquer approach using the U-Net [3] as a universal operator.

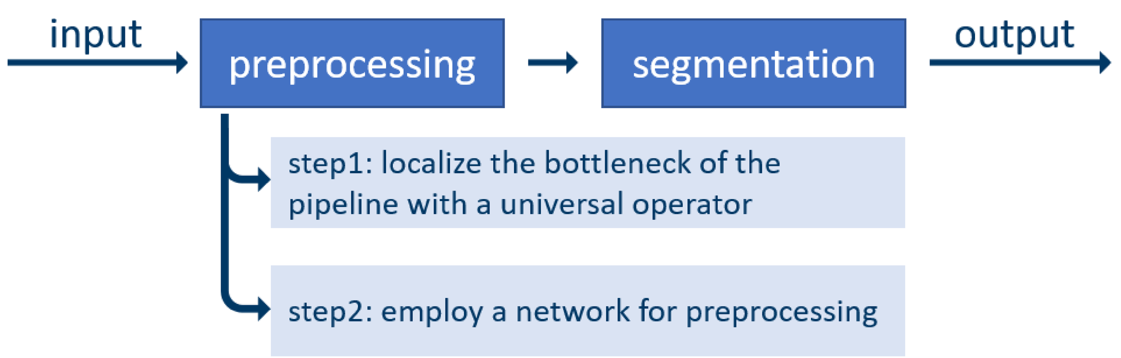


**Fig 1: Proposed workflow.**

## Segmentation Network: Frangi-Net

- An trainable ANN counterpart of the Frangi vesselness filter [4].
- A Frangi-Net across 8 scales contains $6,525$ parameters.

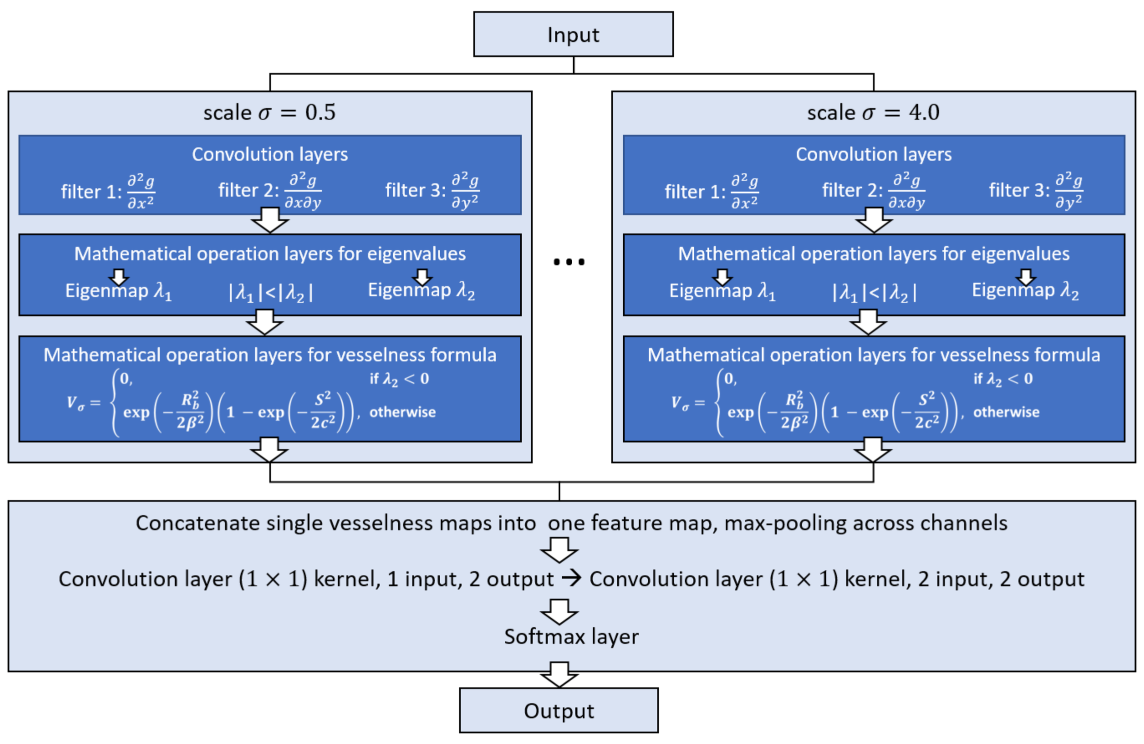


**Fig 2: Frangi-Net architecture.**

## Universal Operator: U-Net

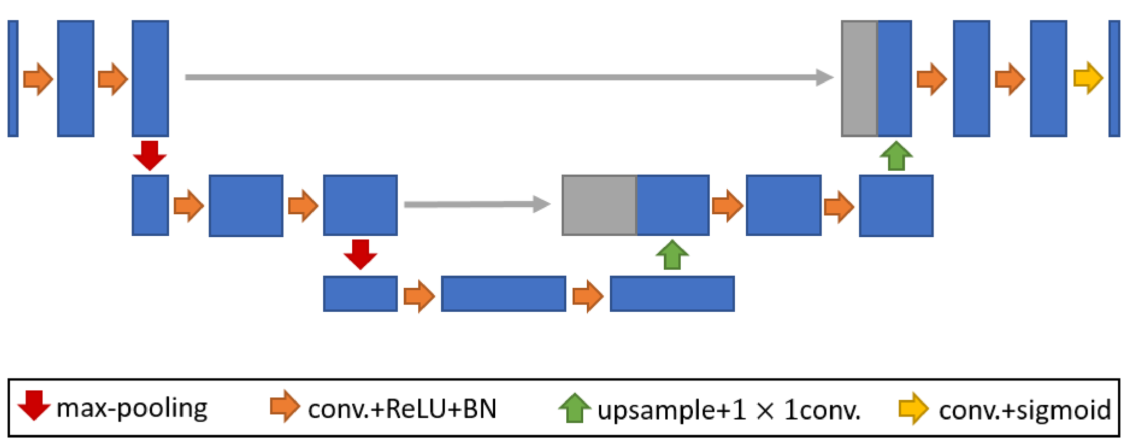


**Fig 3: U-Net architecture.**

- Add BN Layers, replace DeConv with Upsampling and Conv Layers.
- U-Net with 3 levels and 16 initial filters contains $111,536$ parameters.

## Preprocessing Network: Guided Filter Net

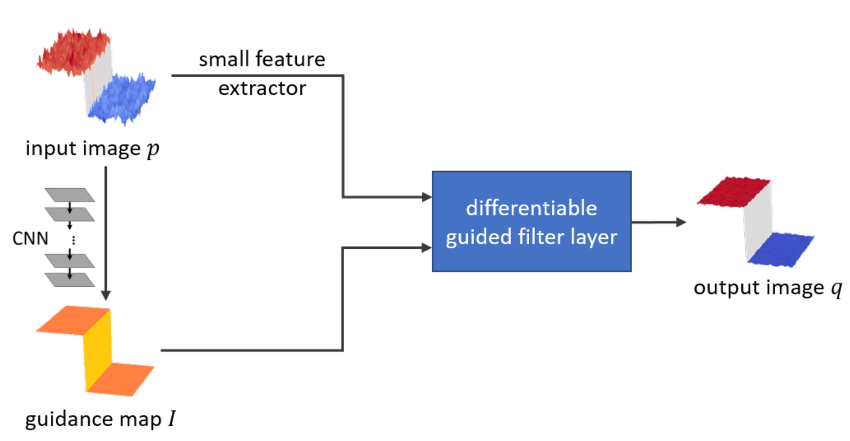


**Fig 4: Guided filter block architecture.**

- Use Context Aggregation Network to generate the guidance map $I$.
- The overall architecture contains $3,050$ parameters.

## Quantitative Results

- Frangi-Net (FN) boosts from the original Frangi filter.
- The universal operator, i.e. the U-Net, improves the pipeline performance when used for preprocessing (UP).
- Using the Guided Filter Net (GF) for preprocessing maintains the performance enhancement.

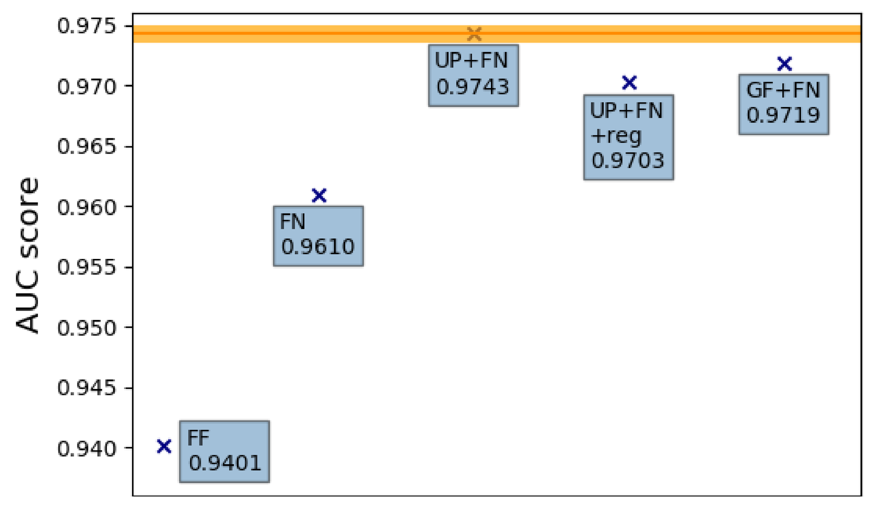


**Fig 5: AUC score of various pipelines.**

## Qualitative Results

- UP performs as a edge-preserving denoising filter.
- Increasing the regularizer enforces the output of the preprocessing network to resemble the input.
- GF behaves as a band-pass filter rather than a denoising filter.
- The probability maps of pipelines with preprocessing networks are comparably good, and are superior to that without.

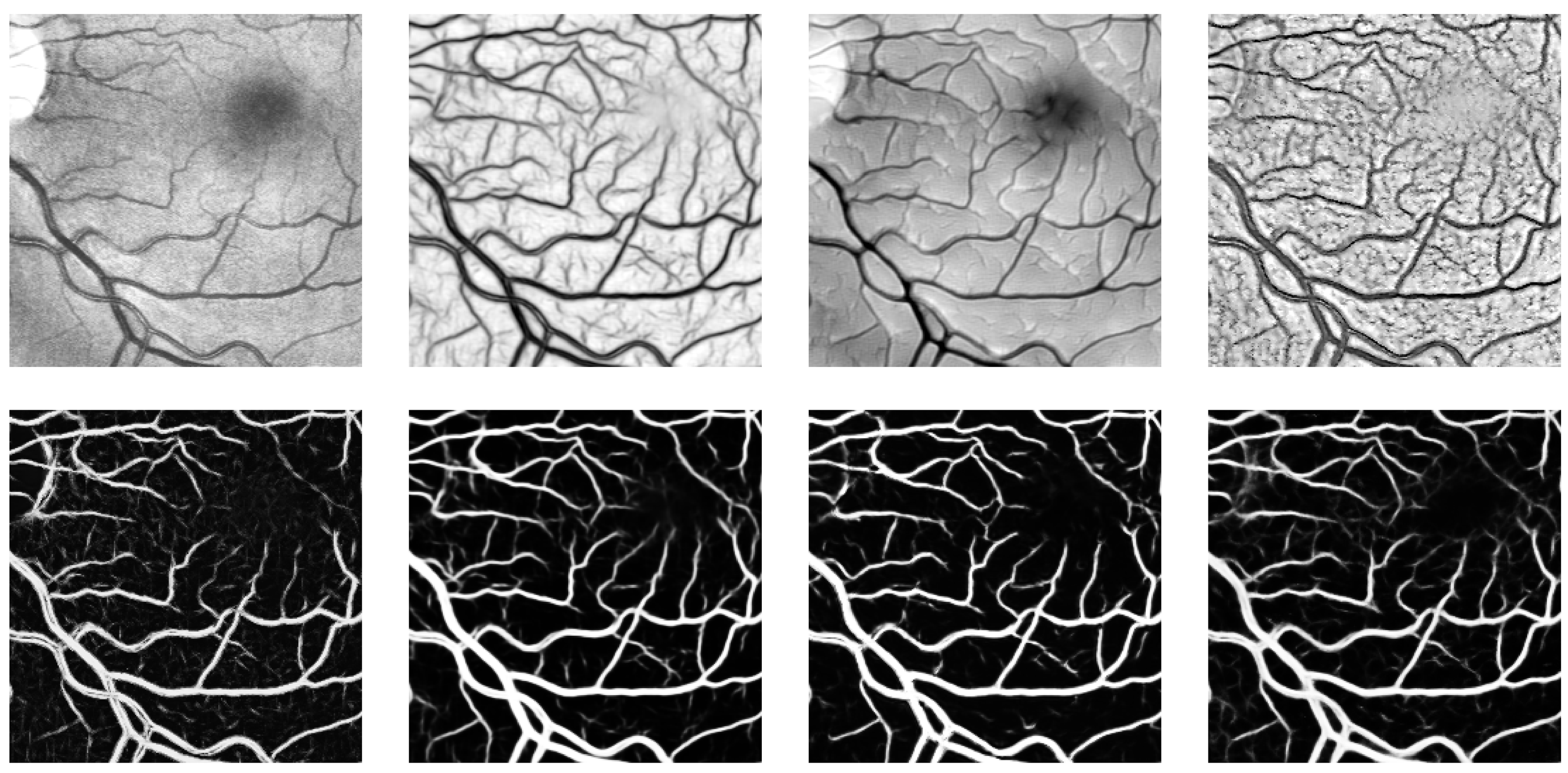

**Fig 6: Input (upper row) and output (lower row) to the segmentation network. Pipelines from left to right: FN, UP+FN, UP+FN+reg, and GF+FN.**

## Conclusion

- Using a universal operator as a tool to locate the bottleneck of a network pipeline is feasible. This confirms the known operator theory.
- The different UP outputs with varied regularizers give an example of the dilemma between ANN interpretability and performance.
- A network pipeline with well-interpretable component blocks as well as high performance is constructed.

## References

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