Semi-Supervised Learning for Biomedical Image Segmentation via Forest Oriented Super Pixels(Voxels)

Motivation

- Collecting massive biomedical data is easy, but annotating them is expensive as it necessitates specific knowledge.
- How to predict the pathological region without training data.

Our Solution

Key observation is that the homogeneous connected areas of low con-fidence (Fig.1(b)) tends to confuse the classifier with limited training data.

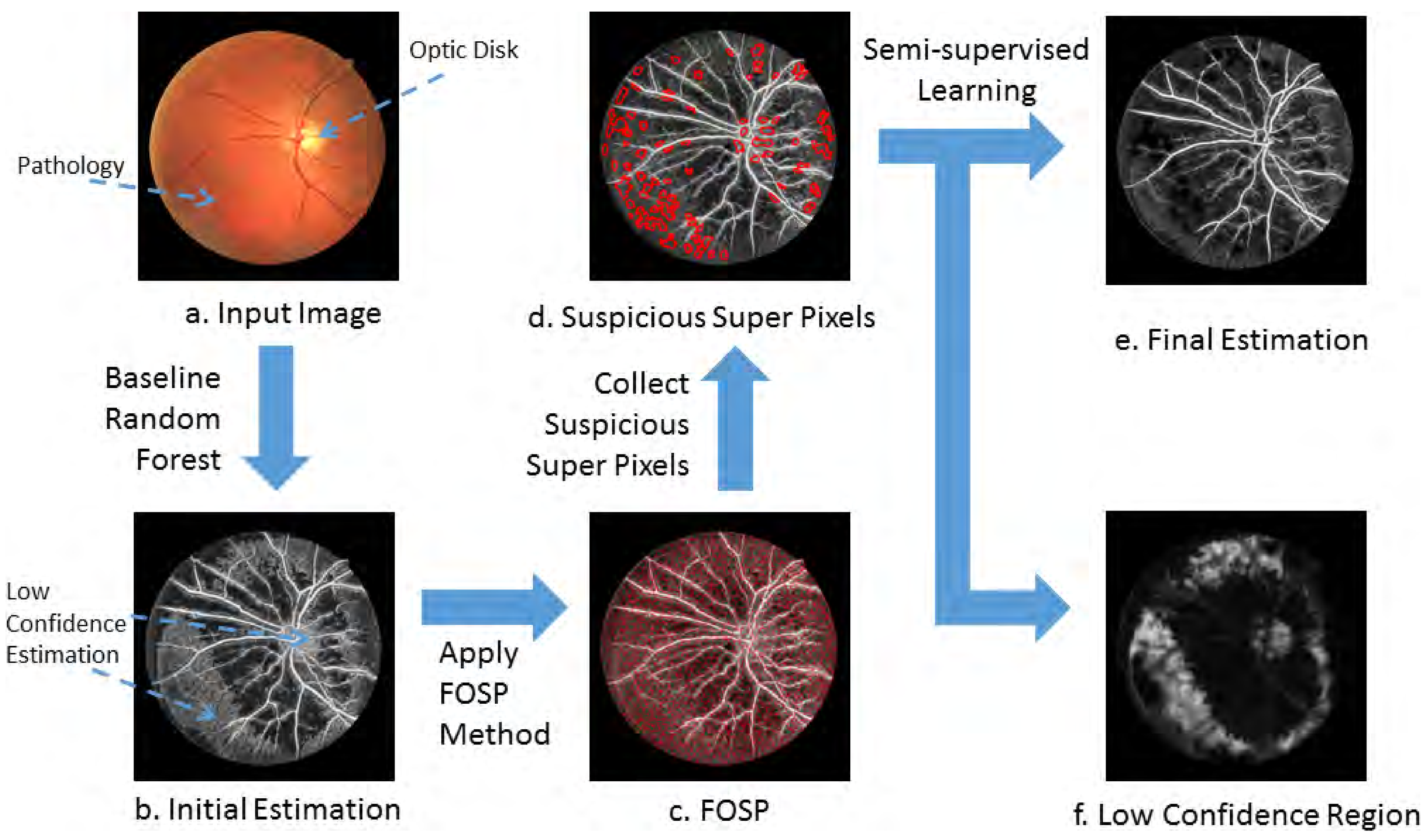


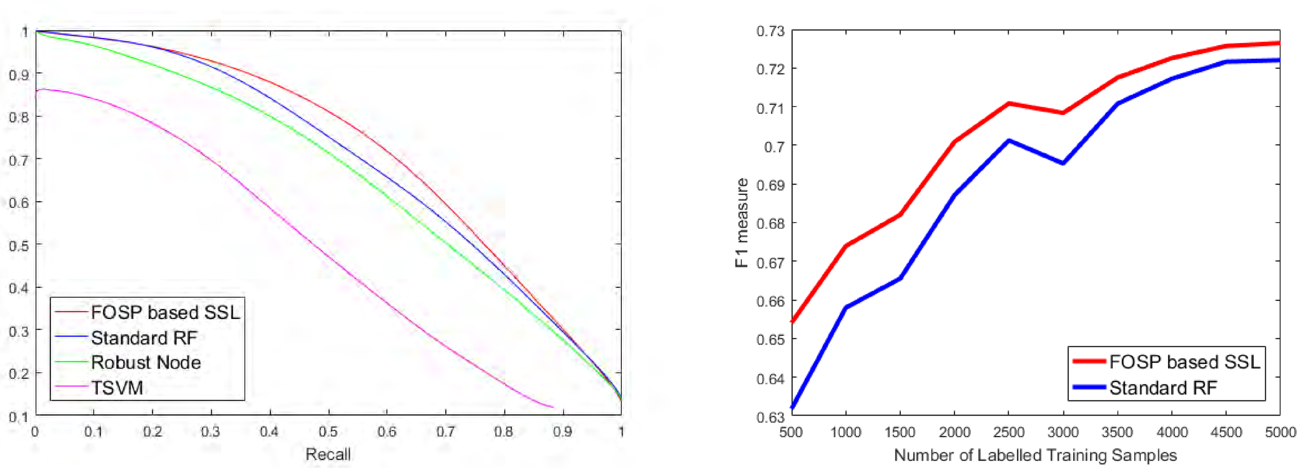
Figure 1: The pipeline.

1. Our method segments the images into super pixels(voxels) (Fig.1(c)) to pick up the low confidence samples.
2. From suspicious super pixels (Fig.1(d)), we train a Random Forest to predict the low confidence areas (Fig.1(f)).
3. By suppressing found low confidence area, our proposed method shows superior performance on challenging 2D retinal and X-ray im-ages and 3D Neuron Data.

Our Key Contribution

Unlike existing methods, such as SLIC[1], based on unsupervised colour space, our Forest Oriented Super Pixels(Voxels) works on the distance defined on forest based code.

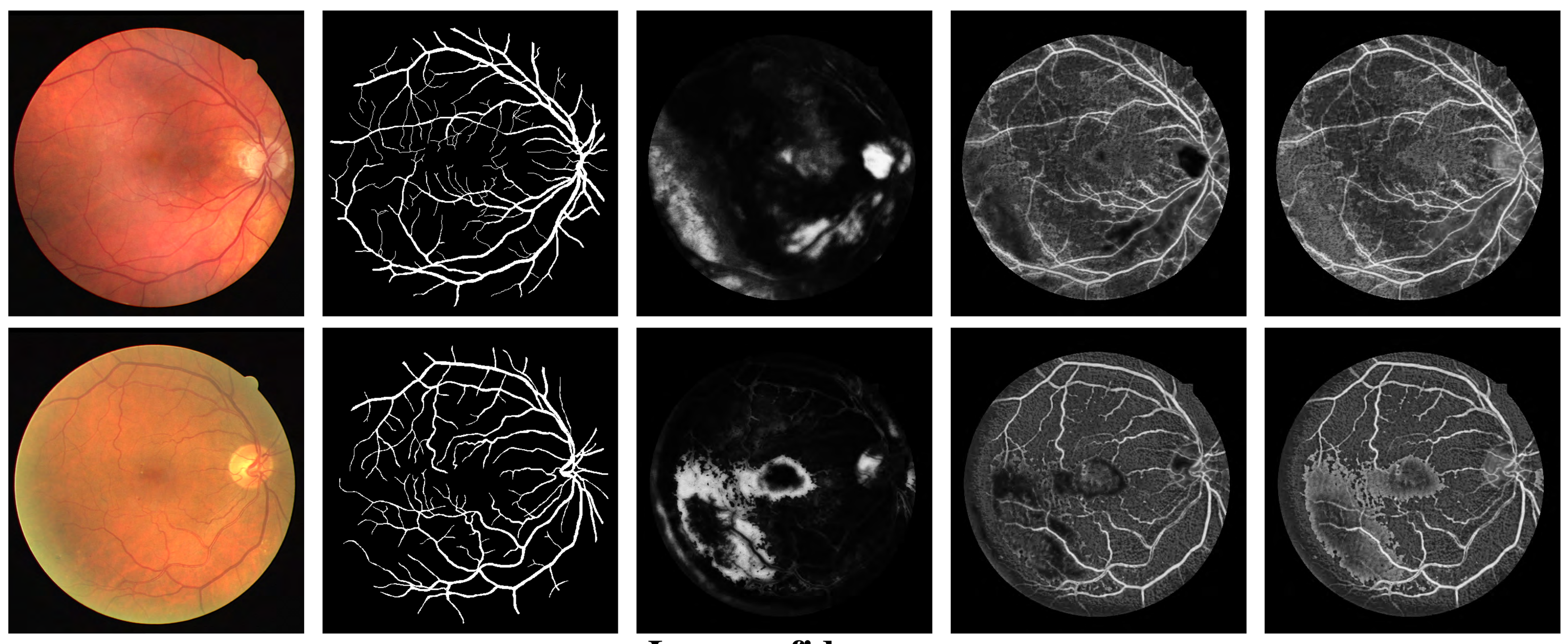
Results



PR Curves **F1 vs Labelled Data Size**

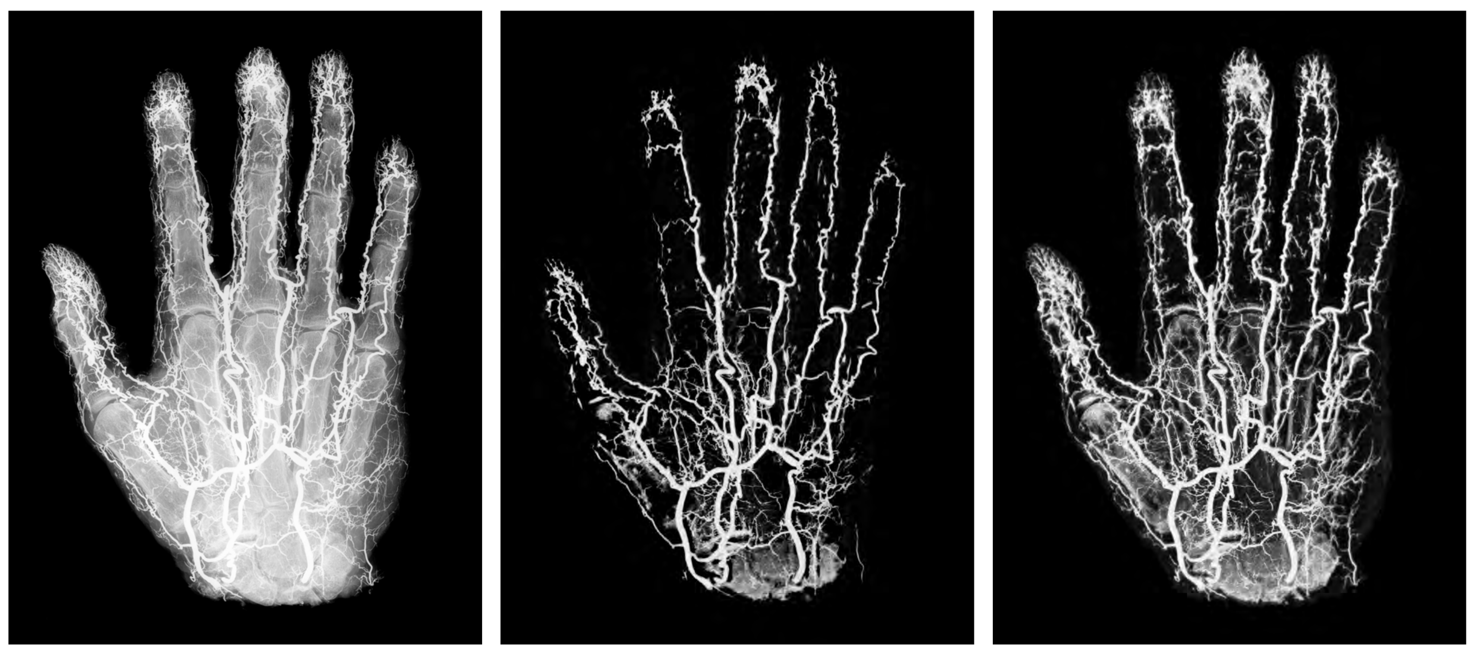
Figure 2: Quanatative Comparision on DRIVE dataset.

We evaluate our method on the retinal dataset DRIVE, X-ray hand image and 3D Big Neuron Challenge[4]. We compare the segmenta-tion performance with two semi-supervised method: TSVM[2], Ro-bust Node Random Forest[3]. All of the methods are trained with only 500 labelled samples.



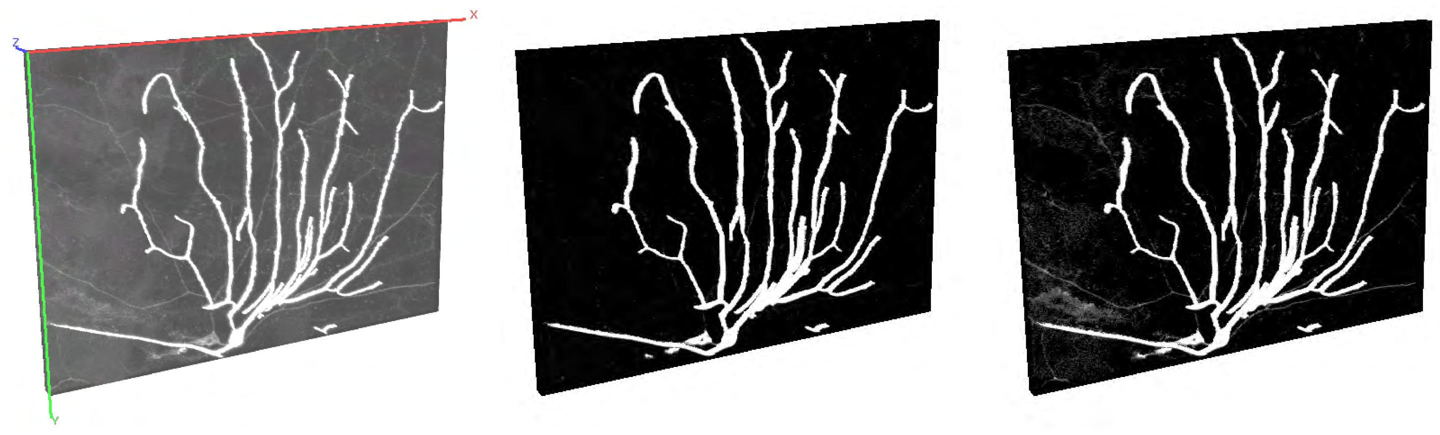
Input images **Ground-truth** **Low confidence** **Our method** **Standard RF**

Figure 3:



Input Image **Our Method** **Standard RF**

Figure 4: X-ray images of hand.



Input Image **Our Method** **Standard RF**

Figure 5: BigNeuron dataset [4].

Our Contributions

1. We propose a novel Forest Oriented Super Pixels (Voxels) to capture the complementary information of random forest, offering an advan-tage in the random forest based semi-supervised learning.
2. Our super pixel (voxel) is discriminant to segmentation task.
3. We succeed in unsupervised prediction of the suspicious regions i.e. pathological regions that would otherwise confuse the classifier.
4. We have made our source code public available at GitHub, please check https://github.com/lingucv/ssl superpixels

Figure 6: Please scan our QR

References

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Acknowledgements

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