2D Retinal Vessel Segmentation using Convolutional Neural Networks

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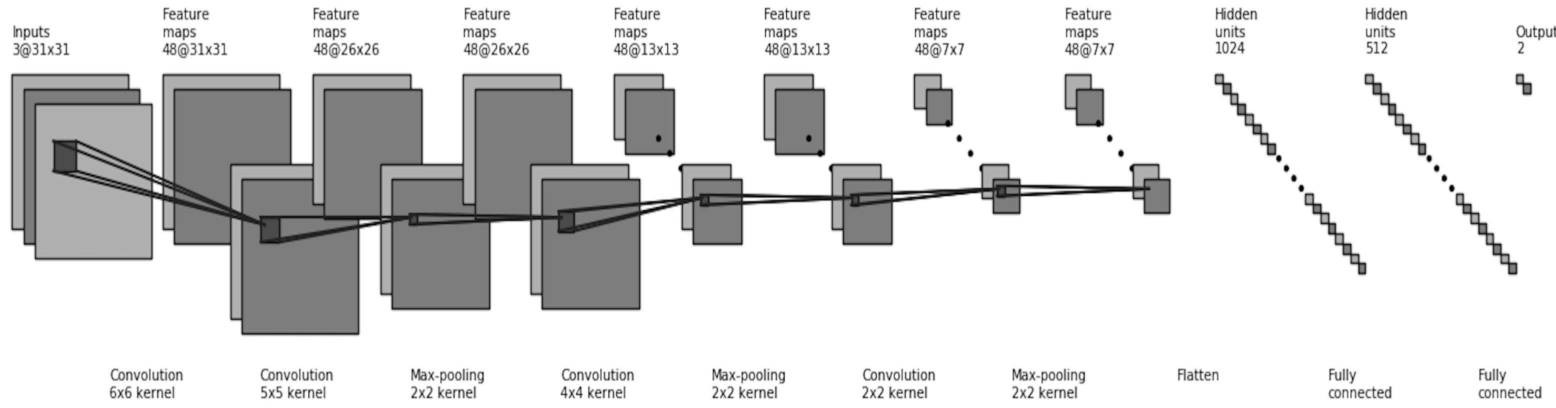
Background

- In the medical domain, 2D retinal vessel imaging using fundus cameras is an integral tool in diagnosing various diseases.
- To extract more relevant medical information from these types of images, it is necessary to segment them, separating the retina blood vessels from the non-vessel tissue surrounding them.
- The highest-performing models of late are based upon the max-pooling convolutional neural network (CNN) [1].
- A max-pooling convolutional neural network is a CNN that alternates between convolutional filtering layers and max-pooling layers before finally outputting to a fully connected layer that predicts the most probable class of the pixel [3]. Because the filters extract local features from the images, CNNs do particularly well for retinal vessel image segmentation [1].

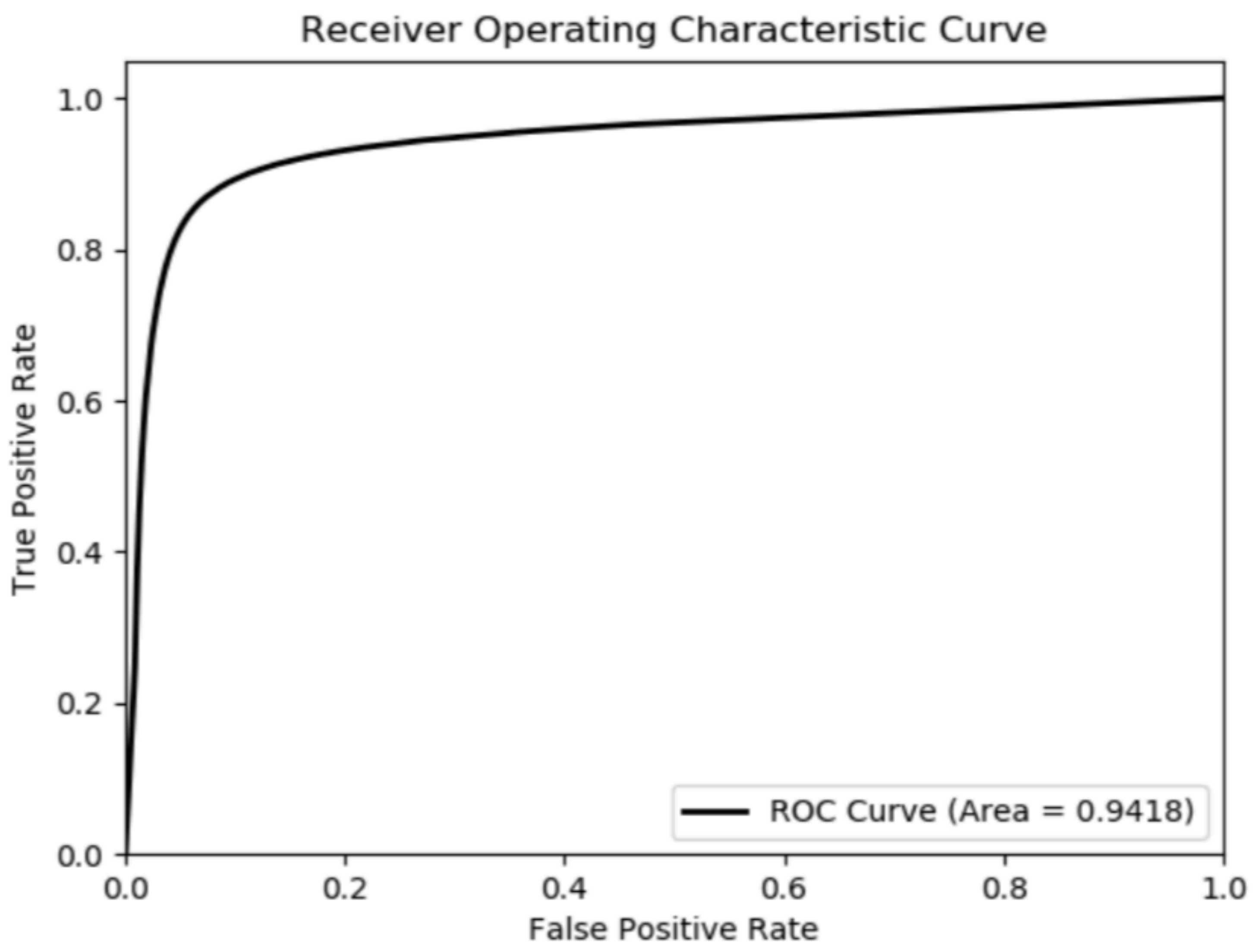
Methods

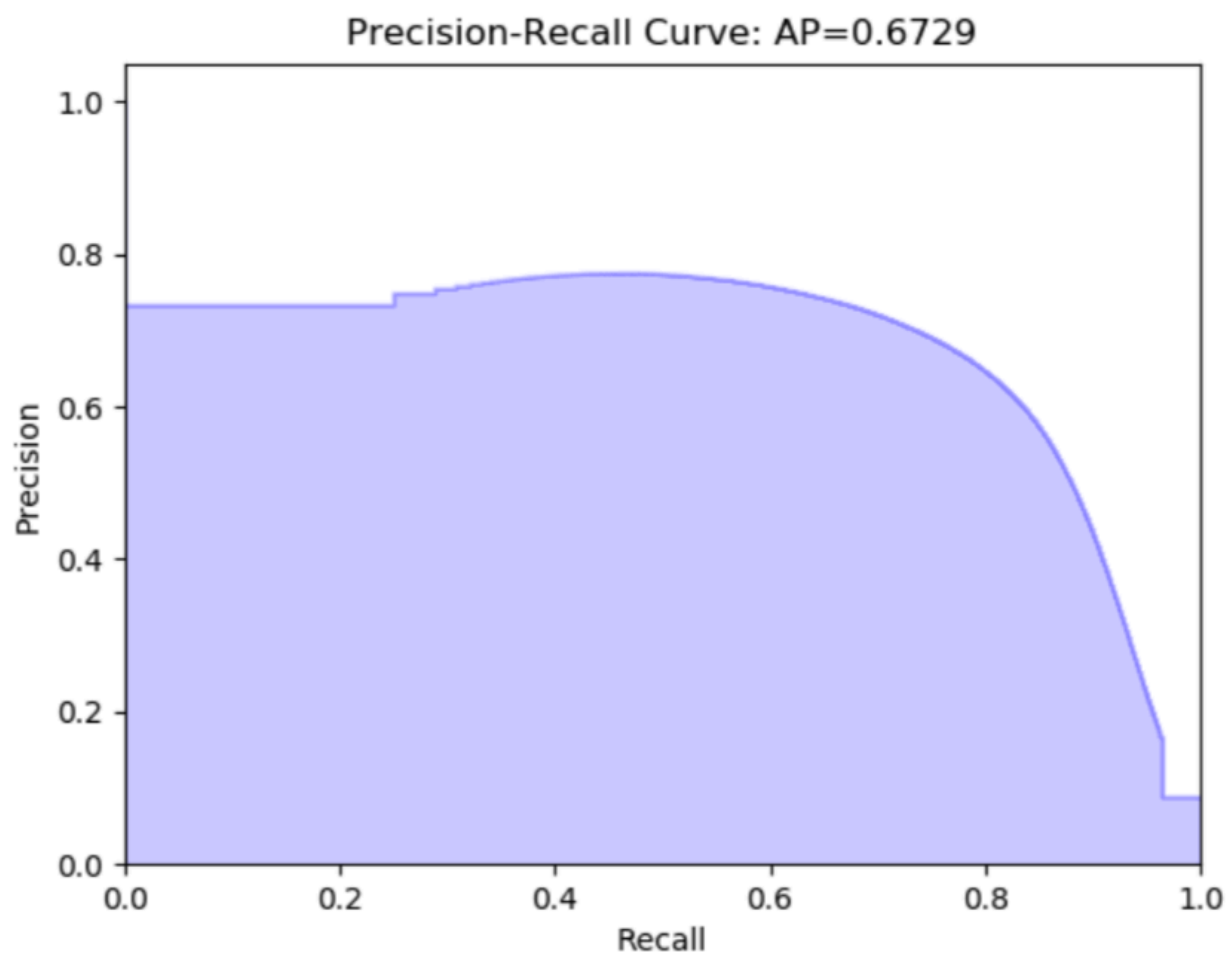
- We built a machine learning model, specifically a max-pooling convolutional neural network [3], to automatically segment 2D retinal blood vessel images.
- We trained and tested our model on the publicly available dataset DRIVE: Digital Retinal Images for Vessel Extraction [4]. This dataset consists of 20 training and testing retinal images along with manual blood vessel segmentations completed by a human expert.
- Before training the model, we divided our images into 120,000 patches and normalized the images by subtracting the mean intensity of the pixels.
- We trained 13 models of differing number of hidden units and dropout probabilities, and then ran cross-validation, choosing the version with the highest mean accuracy on the testing images as our model.



Results

- We segmented the images by classifying each pixel as a part of a retina blood vessel or not. We then used metrics including the receiver operating characteristic (ROC) curve, the precision-recall curve, maximum average accuracy score, and Cohen Kappa score to measure the performance of our model.





Comparisons to other State-of-the-Art Models [2]

Model	Max. Avg. Accuracy	Kappa Score
Our Proposed CNN	**0.9430**	**0.6795**
Maji et al.	0.9470	0.7031
Sheet et al.	0.9766	0.6287
Second Manual Annotator	0.9473	0.8213
Staal et al.	0.9422	-
Niemeijer et al.	0.9416	0.7145
Zana et al.	0.9377	0.6971
Jiang et al.	0.9212	0.6399
Martinez-Perez et al.	0.9181	0.6389
Chaudhuri et al.	0.8773	0.3357

Conclusion

- Our CNN does not beat the state-of-the-art; however, it is comparable and performs very well considering its simple architecture.
- Our model can be improved by appending more data to our training set by pre-processing the images more complexly, including rotating and scaling the images before obtaining the image patches.
- We can further tune the hyper-parameters by changing the filter sizes and strides of the convolutional and max-pooling in our model. With an un-optimal filter size, the most discriminative features may not be extractable. Thus, fine-tuning the filter size can improve our model's performance as it plays an important role in local feature extraction.
- Automatic image segmentation tools such as ours can be extremely useful as an assistant for healthcare professionals who must manually segment 2D retina blood vessel images every day.

References

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