Table 1. Results of OD segmentation on images with PPA for the proposed method as compared with other works.

Method	μ_e
EHT [4]	12.2%
MCV [2]	14.2%
MDM [3]	12.4%
Superpixels [1]	10.3%
ODD_{auto} + NN	10.5%
ODD_{manual} + SAE	8.2%
ODD_{auto} + SAE	**9.7%**

performances of all the methods. Third row has PPA looking similar to the OD and all other methods got confused between OD and PPA except the proposed method which segmented the OD fairly accurately ($E = 6.7\%$). In the last row it's hard to distinguish between PPA and OD even visually and all the methods failed. These results bring out the need to further work on improving segmentation performance on cases with subtle difference between PPA and OD region.

In Table 1, a comparison has also been made with a conventional neural network with 626 input units and 1 hidden layer with 100 units (sigmoid activation function). For this case ($ODD_{auto} + NN$), it is interesting to note that the value of μ_e before using ASM was 15.3% as compared to 12.6% using the proposed method. However ASM reduced the error drastically for $ODD_{auto} + NN$ due to which the final value of μ_e was 10.5% as compared to 9.7% for the proposed method. This reduction in error also justifies using ASM.

OD segmentation is affected by the accuracy in OD detection due to which we also ran experiments assuming that OD detection will be 100% accurate. This meant using the manually marked ground truth for OD centers instead of detecting them automatically. The corresponding results (ODD_{manual}+ SAE) clearly show that due to errors in OD detection, OD segmentation error increased by 1.5%.

As mentioned in sec. 2.2, just intensity features were insufficient so we included distance feature. Figure 5(b) shows an example to illustrate the need for including distance feature. It can be seen that including the distance feature reduced both the false positives outside and false negatives inside the OD region. This is because the value of the distance feature was high for OD region which is close to the center of the image while it was lower for region outside the OD.

4. CONCLUSIONS AND FUTURE WORK

This paper proposed a novel approach to Optic Disc (OD) segmentation using deep learning, aiming at robustness to the presence of Parapapillary Atrophy (PPA). Experiments were performed on 230 images containing varying amounts of PPA. Results for OD segmentation showed lower error than the related state-of-the-art methods. Intensity features alone were found insufficient in distinguishing between PPA and OD. To deal with this problem we used a distance feature in addition to the intensity features. The proposed work still had problems in handling cases where PPA looked very similar to the OD. This issue will be studied as a part of future work. It is observed that results relied on accurate OD center detection since errors in OD detection led to a 1.5% increase in OD segmentation error. This opens up possibility for improving the currently available OD detection methods.

References

[1] J. Cheng, J. Liu, Y. Xu, F. Yin, D. W. K. Wong, N. M. Tan, D. Tao, C. Y. Cheng, T. Aung, and T. Y. Wong, "Superpixel classification based optic disc and optic cup segmentation for glaucoma screening," *IEEE Tran Med Imaging*, vol. 32, no. 6, pp. 1019–1032, 2013.

[2] G Joshi, J. Sivaswamy, and SR Krishnadas, "Optic disk and cup segmentation from monocular color retinal images for glaucoma assessment," *IEEE Tran Med Imaging*, vol. 30, no. 6, pp. 1192–1205, 2011.

[3] J. Xu, O. Chutatape, E. Sung, C. Zheng, and P. Chew Tec Kuan, "Optic disk feature extraction via modified deformable model technique for glaucoma analysis," *Pattern recognition*, vol. 40, no. 7, pp. 2063–2076, 2007.

[4] J. Cheng, J. Liu, D. W. K. Wong, F. Yin, C. Cheung, M. Baskaran, T. Aung, and T. Y. Wong, "Automatic optic disc segmentation with peripapillary atrophy elimination," in *EMBC*, 2011.

[5] R. B. Palm, "Prediction as a candidate for learning deep hierarchical models of data," M.S. thesis, Technical University of Denmark, 2012.

[6] S. Lu, "Accurate and efficient optic disc detection and segmentation by a circular transformation," *IEEE Tran Med Imaging*, vol. 30, no. 12, pp. 2126–2133, 2011.

[7] F. Yin, J. Liu, S. H. Ong, Y. Sun, D. W. K. Wong, N. M. Tan, C. Cheung, M. Baskaran, T. Aung, and T. Y. Wong, "Model-based optic nerve head segmentation on retinal fundus images," in *EMBC*, 2011.

[8] Z. Zhang, B. H. Lee, J. Liu, D. W. K. Wong, N. M. Tan, J. H. Lim, F. Yin, W. Huang, H. Li, and T. Y. Wong, "Optic disc region of interest localization in fundus image for glaucoma detection in argali," in *Industrial Electronics and Applications (ICIEA), IEEE Conference on*, 2010.

[9] G. Hinton, S. Osindero, and Y-W Teh, "A fast learning algorithm for deep belief nets," *Neural computation*, vol. 18, no. 7, pp. 1527–1554, 2006.

[10] A. WP Foong, S. M. Saw, J. L. Loo, S. Shen, S. C. Loon, M. Rosman, T. Aung, D. TH Tan, E. S. Tai, and T. Y. Wong, "Rationale and methodology for a population-based study of eye diseases in Malay people: The Singapore Malay eye study (SiMES)," *Ophthalmic epidemiology*, vol. 14, no. 1, pp. 25–35, 2007.