Deep Learning for Diabetic Retinopathy Grading

Nirthika, R., Manivannan, S., and Ramanan, A.
Department of Computer Science, University of Jaffna, Jaffna, Sri Lanka
{nirthika, siyam, a.ramanan}@univ.jfn.ac.lk

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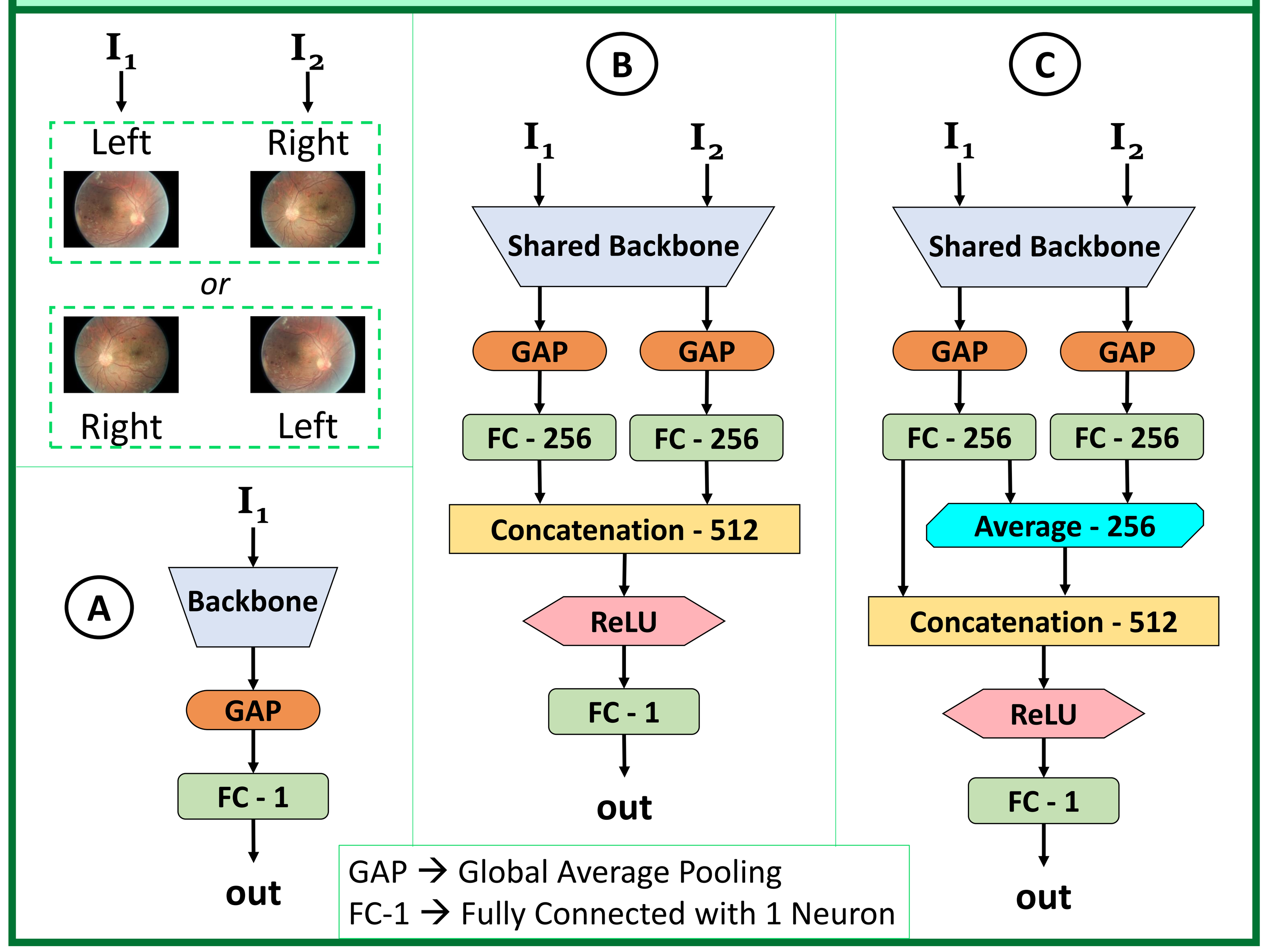
Introduction

Diabetic Retinopathy (DR) grading is used to identify the severity level of diabetic in retina of a patient to determine the type of treatment. Although deep learning achieved remarkable success for DR grading, it is challenging to detect small lesions which have similar visual appearance. Different feature fusion strategies like concatenation of features [1] are used to integrate information from both (left and right) eyes to determine DR grade of a particular eye. We found that a simple approach which concatenates the average-pooled features from both eyes with the features of particular eye gives considerable improvement in results. While comparing cross-entropy (CE), mean squared error (MSE), ordinal regression (OR) [2], and quadratic weighted kappa (QWK) [3] losses, CE gives best accuracy and MSE gives best kappa score. Global attention block (GAB) [4] consists of channel and spatial attentions, is applied to capture crucial information of small lesions in DR. It shows improvement in the results when using single eye in small dataset and no significant improvement when considering both eyes in large dataset as the results are saturated already.

Feature Fusion



Loss Functions for Ordinal Classification

CE Loss

$$\mathcal{L}_{CE} = -\sum_{i=1}^{n}\sum_{l=1}^{c}\left(\mathbb{1}_{(y_i=l)}\log P_{il}\right)$$

MSE

$$\mathcal{L}_{MSE} = \frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}_i)^2$$

OR Loss

$$S_{il} = softmax(-(\hat{y}_i - c_l)^2)$$

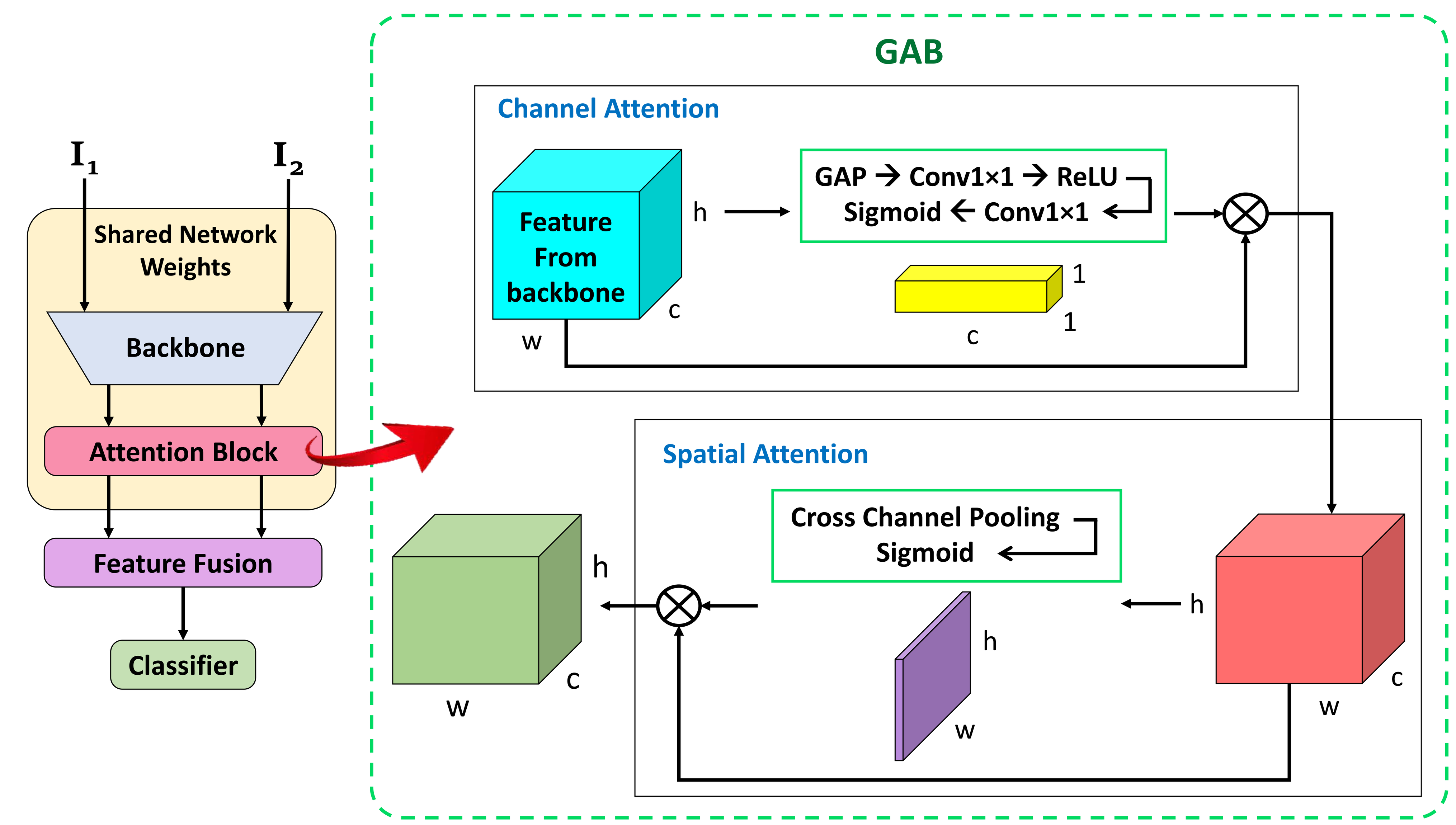
$$\mathcal{L}_{OR} = -\sum_{i=1}^{n}\sum_{l=1}^{c}\left(\mathbb{1}_{(y_i=l)}\log S_{il}\right)$$

QWK Loss

$$\mathcal{L}_{QWK} = \frac{\sum_{ij\epsilon c} W_{ij} O_{ij}}{\sum_{ij\epsilon c} W_{ij} E_{ij}}$$

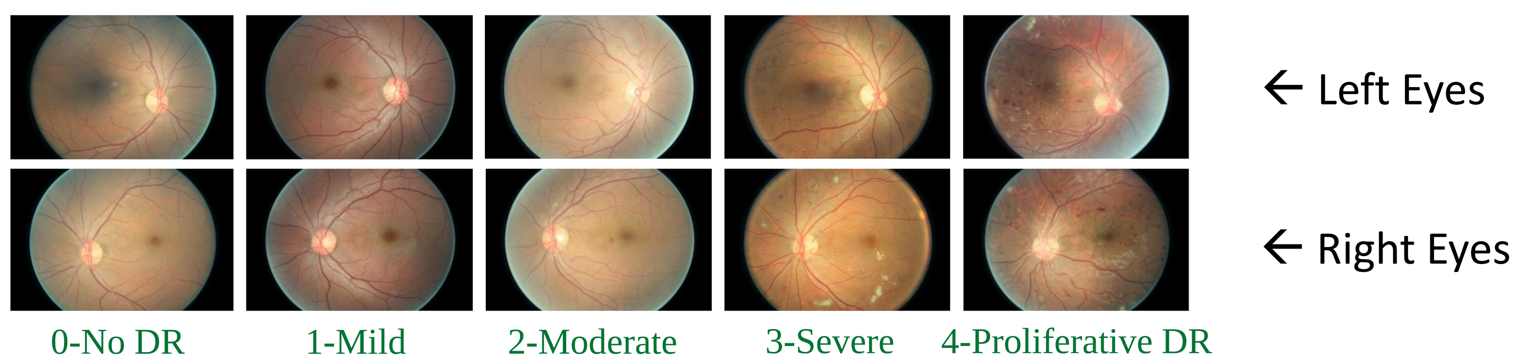
where,
- y_i – Actual label
- $\hat{y}_i$ – Predicted value
- n – Total number of images
- c = {0, 1, 2, 3, 4} – classes
- P_{il} – Probability of i^{th} image belonging to class l
- W_{ij} – The cost associated with misclassifying class *i* as class *j* and vice-versa
- O_{ij} – Number of times rater A classifies an image as class *i* and rater B classifies the same image as class *j*
- E_{ij} – Outer product between the actual histogram vector of outcomes and the predicted histogram vector

Attention



Dataset & Experimental Setup

DR Dataset [5] has five classes indicating the presence of diabetic retinopathy



Backbone – ResNet18 except GAB and FC
Objective function – MSE

Large dataset – Training → 35,126, Testing → 10,906
Small dataset – Training → 8,782, Testing → 10,906

Single Eye vs. Both Eyes

Method		Kappa	Accuracy
Single Eye (A)		0.832 ± 0.002	82.79 ± 0.17
Both Eyes	Concatenation (B)	0.845 ± 0.001	83.85 ± 0.19
	Pooling & Concatenation (C)	**0.853 ± 0.001**	**84.89 ± 0.16**

Considering information of both eyes with pooling and concatenation (ours) feature fusion techniques, performs better than considering single eye in DR grading of particular eye image.

Comparing Loss Functions in (C)

Loss	Kappa	Accuracy
CE	0.826 ± 0.001	**86.42 ± 0.19**
QWK	0.836 ± 0.003	84.23 ± 0.96
OR	0.844 ± 0.001	85.01 ± 0.04
MSE	**0.853 ± 0.001**	84.89 ± 0.16

CE gives best accuracy and MSE gives best kappa than other loss functions.

Attention on Small & Large Dataset

Method	Kappa	Accuracy
Small Dataset – Single Eye		
(A)	0.790 ± 0.002	80.66 ± 0.04
(A) + GAB	**0.802 ± 0.001**	**81.92 ± 0.27**
Large Dataset – Both Eyes		
(C)	**0.853 ± 0.001**	**84.89 ± 0.16**
(C) + GAB	0.851 ± 0.001	84.72 ± 0.26

GAB shows improvement on small dataset with single eye.

Conclusion

Our work shows that, DR grading can perform well while integrating the information of both eyes, especially with our pooling and concatenation approach. CE gives high accuracy as it considers only correctly classified instances, the other loss functions consider the ordering information of the classes, therefore show better QWK score. OR loss shows better QWK score than CE and better accuracy than MSE, as it is calculating soft probabilities for each classes. GAB improves the results for single eye on small dataset but no considerable improvement for both eyes fusion on large dataset as we have reached saturated performance already on DR grading.

References

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[2] Diaz, R., *et al.*, "Soft labels for ordinal regression", IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 4738-4747, 2019.
[3] Nirthika, R., *et al.*, "Loss functions for optimizing Kappa as the evaluation measure for classifying diabetic retinopathy and prostate cancer images", IEEE 15th International Conference on Industrial and Information Systems, pp. 144-149, 2020.
[4] He, A., *et al.*, "CABNet: Category attention block for imbalanced diabetic retinopathy grading", IEEE Transactions on Medical Imaging, pp.143-153, 2020.
[5] https://www.kaggle.com/c/diabetic-retinopathy-detection/data