Regression Constraint for an Explainable Cervical Cancer Classifier

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Introduction

We address the problem of automatic squamous cells severity classification for cervical cancer screening using deep learning methods. We also use an attribution method to show which cytomorphological features are relevant to classify severity at inference, and show that outputted explanation maps match with medical consensus.

Herlev Dataset

We merged normal images into a single class in order to study the medical severity only, thus building a 5 classes dataset (out of the usual 7). We call Herlev severity the challenge consisting in classifying into **normal**, **light dysplastic**, **moderate dysplastic, severe dysplastic**, or **carcinoma in situ**.

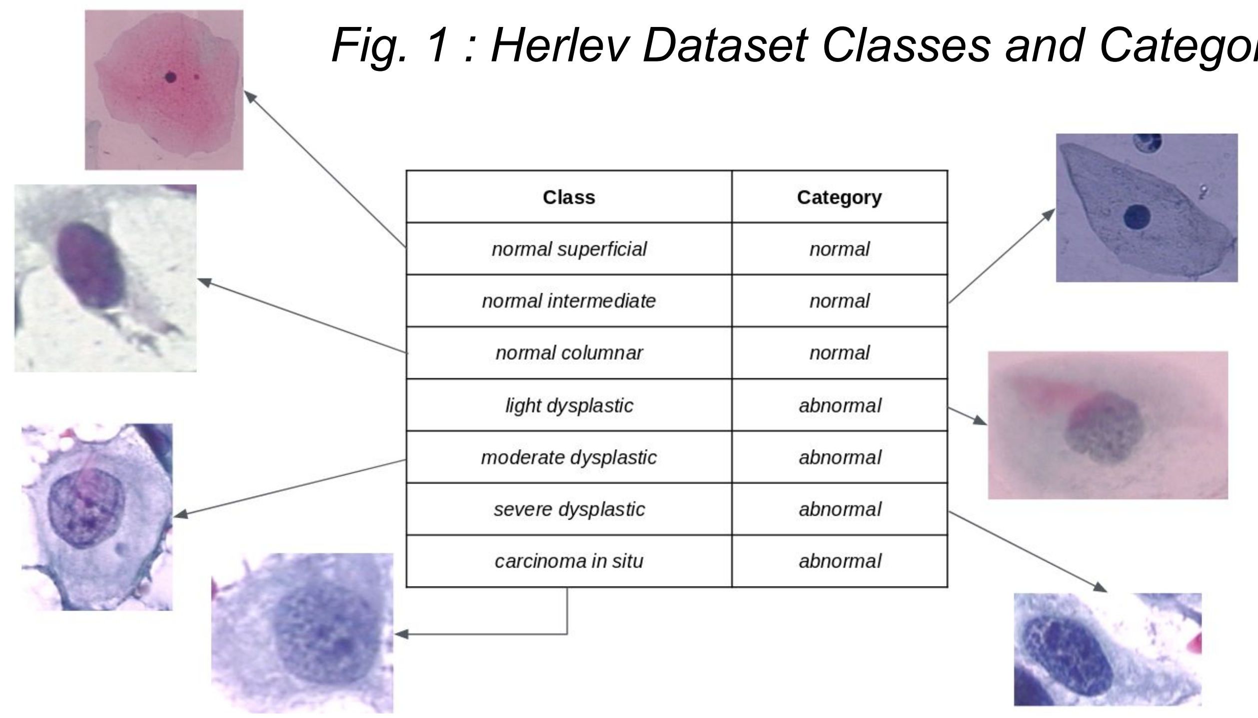
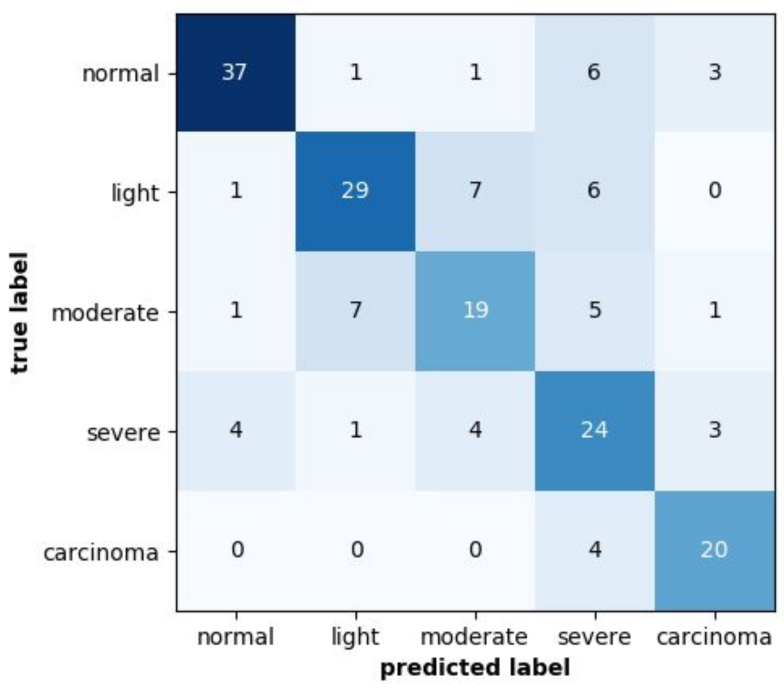


Fig. 1 : Herlev Dataset Classes and Categories

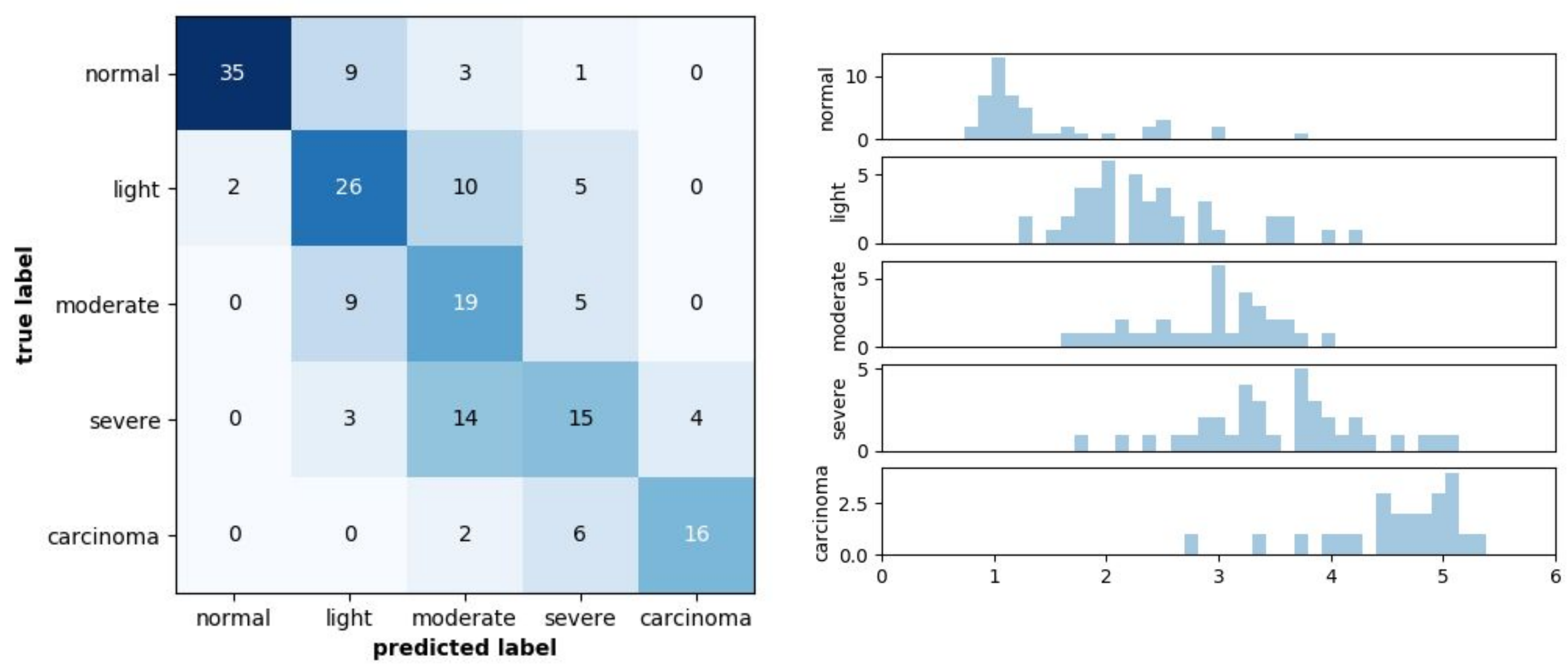
Classification Methods

We compare three pipelines based on a Resnet-101 [1] backbone: **classification** (softmax cross entropy), **regression** (mean square error) and a method we propose and call **classification with regression constraint** (unifying both losses). It consists in predicting, through a fixed weights fully connected layer, the **severity score based on the classes probabilities** and optimizing both losses during training.



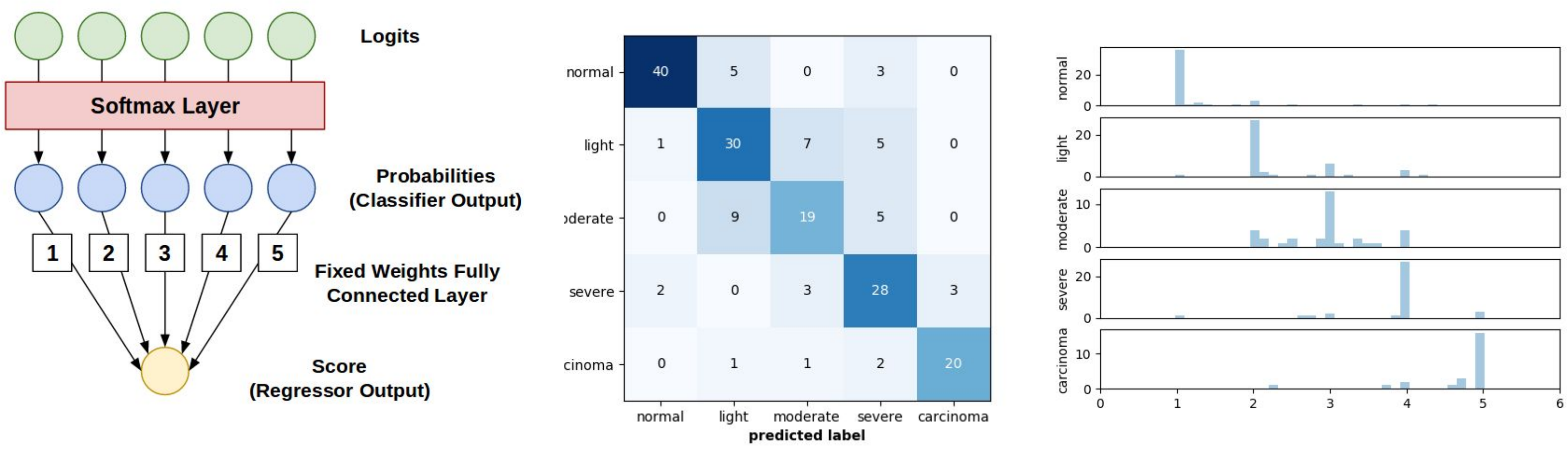
Classification gives acceptable results but tends to confuse normal samples and carcinoma in situ.

Fig. 2 : Classification Pipeline Confusion Matrix



Regression avoids classification pipeline big mistakes but performs worse regarding class accuracy.

Fig. 3 : Regression Pipeline Confusion Matrix and Score Distribution



	Accuracy (%)	Binary Accuracy (%)	AUC-ROC	MSE
Cls	67.6	90.3	0.9	/
Reg	58.2	89.3	/	0.71
Cls+Reg	**72.6**	**95**	**0.94**	**0.59**

Fig. 4 : Regression Constrained Architecture, Confusion Matrix, Score Distribution and Average metrics from 4 radom folds for each pipeline

Interpretability

We used a saliency method called **Integrated Gradient** [2] to compute the attribution of each pixel with regards to the predicted class. It highlights the **nucleus region** and this is in accordance with WHO and Bethesda guidelines. Thus giving confidence that the model learned actual relevant features.

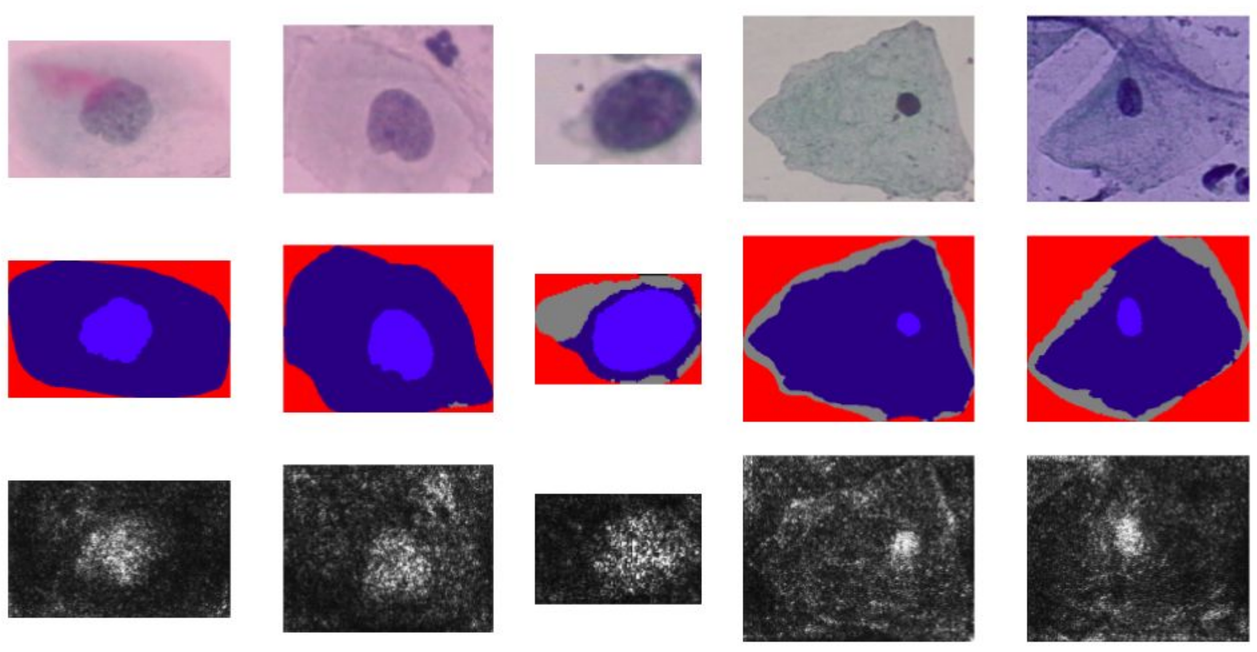


Fig. 7 : Integrated Gradient Qualitative Results

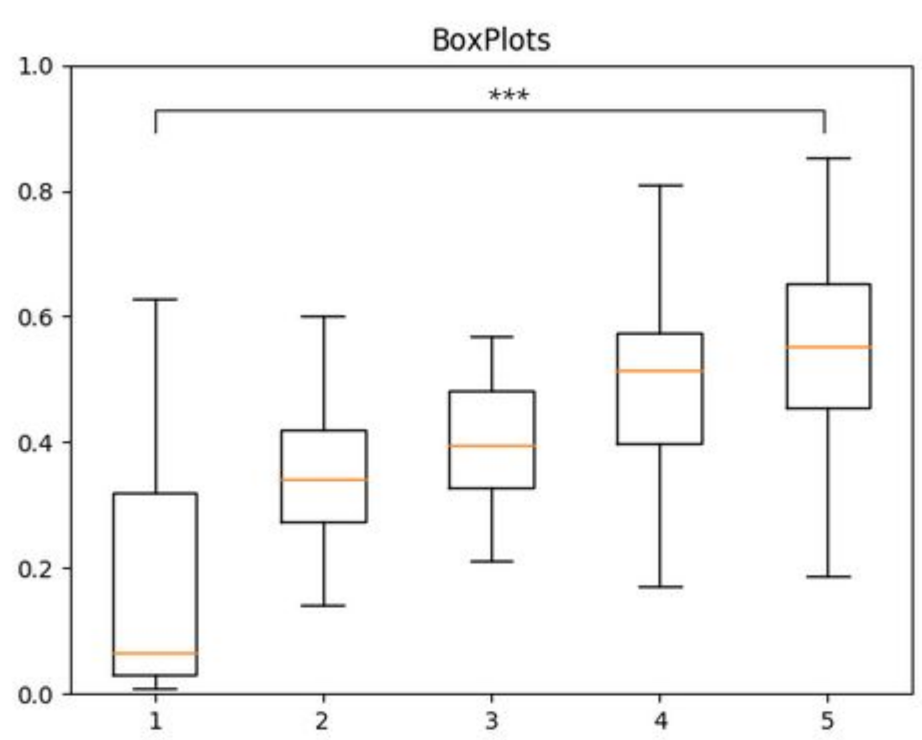


Fig. 8 : Integrated Gradient Quantitative Results

References

[1] Kaiming He, Xiangyu Zhang, Shaoqing Ren and Jian Sun. Deep Residual Learning for Image Recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR).
[2] Mukund Sundararajan,Ankur Taly et al. Axiomatic Attribution for Deep Networks. International Conference on Machine Learning (ICML) 2017.

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