Deep Learning approach for classification of prostate cancer morphology features on whole mount digital pathology specimens

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Problem: Aggressive growth features linked to poor prostate cancer (PCa) outcomes are ignored in current grading criteria, and already poor inter-reader agreement makes reporting all observations infeasible in clinical workflow. We aim to automatically classify PCa architectural morphology on digital pathology images by combining novel image processing and deep learning techniques.

Methods: Morphological growth patterns previously described [McKenney et al, Am J Surg Path 2016] were annotated by an expert pathologist on digital pathology images of PCa radical prostatectomy. Staining was normalized to independent reference prostate specimen using Macenko method. Classification tasks were performed for all independent patterns (N=20) and by grouping patterns of similar prognostic risk, including a two-class risk-based stratification (high/ low risk) and four-class risk-based stratification with multiple intermediate groups. Classification was performed using a ResNet101 architecture from Fast.Ai library on both stain-normalized RGB input images and custom 3-channel image comprised of grey-scale RGB image and deconvolved Hematoxylin and Eosin images, derived using Stain Color Descriptor method.

Results: 5404 annotations from 21 patients were used for model development and validation, with 10% of annotations plus all slides from one patient as independent hold-out test sets. Classification accuracy was moderate for all classes: 74% in RGB images and 75% in custom deconvolved images. This improved for risk-based classification tasks to 88% and 95% in four- and two-class models, respectively. Custom deconvolved images demonstrated 1-3% improvement in model performances.

Conclusions: These early results show feasibility of deep learning-based classification of PCa morphology, with preliminary results demonstrating a role for advanced image processing techniques.

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