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Predictive Analytics from Onward Health

Deep Learning Based Mitoses Recognition and Concordance Study With Pathologists

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BACKGROUND

Deep learning based mitosis detection in H&E biopsies can benefit in the early diagnosis and prognosis of cancer. Most of the approaches published so far have utilized publicly available ideal datasets, which usually come from expensive WSI scanners or microscopes. Moreover, very few validation studies have compared the efficacy of these algorithms with respect to inter-pathologist variability. In this study we compare the performance of multiple pathologists with respect to the algorithm and inter-observer variation.

MATERIALS AND METHODS

The dataset in this study consisted of 358 High Power Field (HPF) images that were used for training the deep learning algorithm while 301 HPFs were taken for testing. Two pathologists annotated the mitotic cells in these cases for this study. The images were collected from a low-cost CMOS camera attached to a microscope. We used deep learning based segmentation models like UNet supported with various pre and post processing techniques to develop our algorithm.

RESULTS

The performance of the model as well as the inter-pathologist variability were measured using different reliable performance metrics. Our ML algorithm showed encouraging results with f-scores of 73.2% w.r.t pathologist 1 and 74% w.r.t pathologist 2. Whereas, the f-score of pathologist 1 w.r.t pathologist 2 was 76.8% while pathologist 2 w.r.t pathologist 1 scored 76.5%.

CONCLUSION

The machine learning model's performance was quite close to that of a pathologist. Pathologists may be prone to inter-observer variations in mitoses counts due to subjectivity and accepting this while making an AI model can help in setting realistic goals for production-ready models. In our future studies, we aim to increase the scale in terms of the numbers of training and testing images.

PIPELINE OVERVIEW

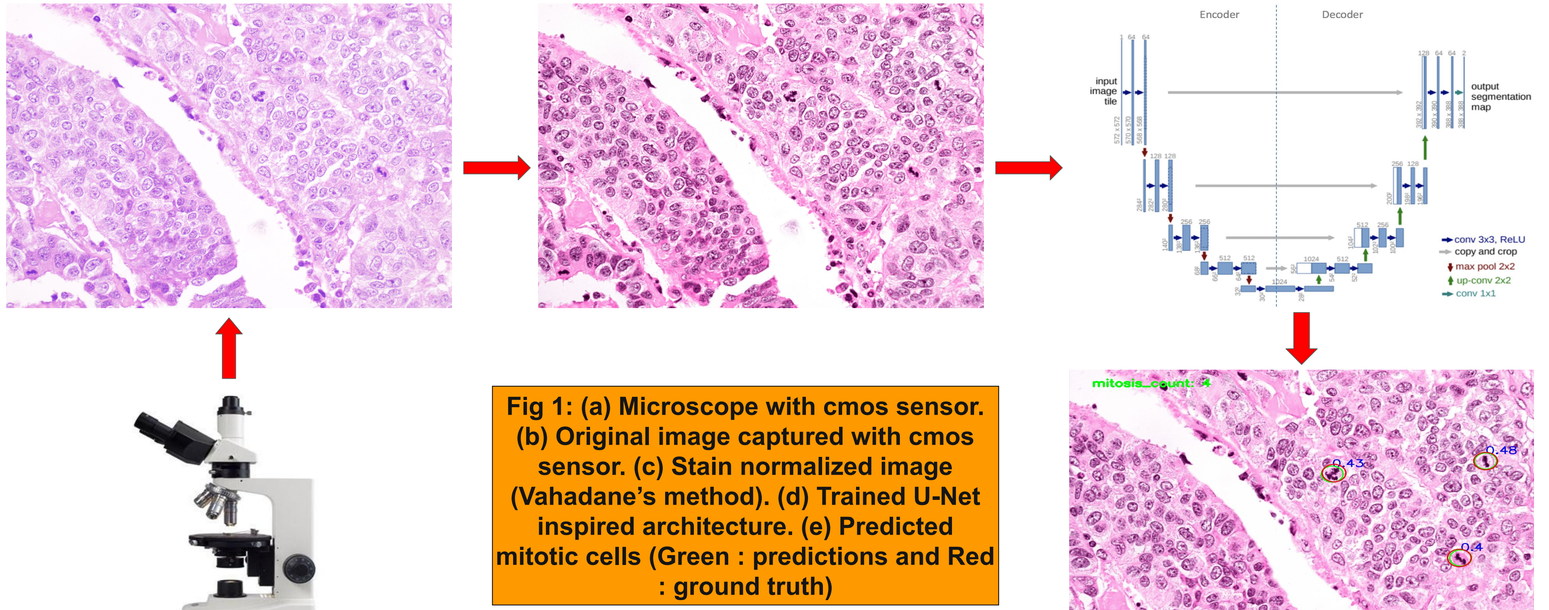

Fig 1: (a) Microscope with cmos sensor. (b) Original image captured with cmos sensor. (c) Stain normalized image (Vahadane's method). (d) Trained U-Net inspired architecture. (e) Predicted mitotic cells (Green : predictions and Red : ground truth)

Table 1: Machine Learning Model and Pathologists Comparison. 'Path' in table refers to 'Pathologist'.

Component	Category	score
Precision	Path 1 w.r.t Path 2	0.768
	Path 2 w.r.t Path 1	0.766
	ML Model w.r.t Path 1	0.690
	ML Model w.r.t Path 2	0.703
Recall	Path 1 w.r.t Path 2	0.769
	Path 2 w.r.t Path 1	0.765
	ML Model w.r.t Path 1	0.780
	ML Model w.r.t Path 2	0.780
F-Score	Path 1 w.r.t Path 2	0.768
	Path 2 w.r.t Path 1	0.765
	ML Model w.r.t Path 1	0.732
	ML Model w.r.t Path 2	0.740

REFERENCES

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