Deep Learning Identifies Microsatellite Instability in H&E Whole Slide Images from Prostate, Esophageal and Gastric Cancers and Generalizes across Cancer Types

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INTRODUCTION

Defective mismatch repair (dMMR) proteins and high microsatellite instability (MSI-H) are associated with a positive response to checkpoint inhibitor therapy in colorectal and non-colorectal cancers. Because of the low prevalence in certain non-colorectal cancers, testing for dMMR and/or MSI-H is not routinely performed, particularly at the time of initial biopsy. Here, we tested the ability to predict MSI status from H&E whole slide images (WSIs) in prostate cancer and to generalize model predictions to gastric and esophageal cancers.

METHODS

WSIs and MSI labels (MSI-H or microsatellite stable [MSS]; obtained via next-generation sequencing) were collected from primary and metastatic colorectal, endometrial, and prostate cancer specimens (Figure 1).



Figure 1. An attention-based convolutional neural network was trained to predict MSI status for each WSI in the training set. Hyperparameters and operating points were selected using the optimization set, targeting prostate cancer prediction (prostate cancer model) or simultaneous prostate, endometrial, and colorectal cancer prediction (gastric/esophageal cancer model). Results are reported on a fully-independent holdout set (prostate cancer model) or independently collected datasets (gastric and esophageal cancer model) to assess generalizability.

SUMMARY

enrich for patients who are likely to have actionable findings.

RESULTS

Demonstrating the predictive accuracy of trained Illustration of deep learning pipeline for predicting MSI status from WSIs models in a binary classification task **Tile Positions: Prostate Cance** (x_1, y_1) $(\mathbf{x}_n, \mathbf{y}_n)$ Predicted MSS Predicted MSI-H Overall Deep Learning **Deep Learning** Slide Label Prediction **Classifier Mode Attention Model** Total (MSS vs MSI-H) Summary Metri Tile Matrices Esophageal **Figure 2**. Whole slide images (WSIs) are broken up into 20x magnification tiles. Tile data and positions are Cancer recorded and passed to attention and classifier deep learning modules to create a prediction. During the training process, the weights of the deep learning models are iteratively updated until the area under the receiver Predicted MSS operating characteristic curve (ROC-AUC) for the validation set no longer improves. Predicted MSI-H Total Deep learning models discriminate MSI-H from MSS in **Dataset overview Prostate, Esophageal, and Gastric Cancer** Summary Metrie Gastric Cancer Prostate Cancer Esophageal Cancer — ROC-AUC 0.767 ROC-AUC 0.804 0.8 **Gastric Cancer** Predicted MSS y 0.4 Predicted MSI-H Total — Mean ROC (AUC = 0.72 ± 0.12 ± 1 std. dev. Summary Metrie 1.0 0.0 1.0 0.0 0.6 0.8 0.8 1.0 0.6 0.8 0.4 0.6 0.4 0.2 0.4 0.2 0.2 1 - specificity 1 - specificity 1 - specificity **Table 1**. A subset of Tempus data was allocated across training, optimization, **Figure 3**. Receiver operating characteristics demonstrate the predictive accuracy of our models. For prostate cancer, there were Table 2. Mode and holdout/external sets. Cancer types enough cases available to perform training and holdout testing with in which MSI-H is more prevalent determined ba cross-validation. The models distinguish MSI-H and MSS in prostate (colorectal and endometrial) were sensitivity for



Characteristic	MSI-H	MSS
Overall	441	5779
Development		
Colorectal	231	3132
Endometrial	126	430
Prostate	43	1322
External		
Gastric	26	320
Esophageal	15	575

leveraged in training to improve prediction for cancers with lower MSI-H prevalence (prostate) or fewer data (gastric, esophageal). "Development" data were used in both models whereas "External" data were used in the gastric/esophageal model.



cancer despite low prevalence, and esophageal and gastric cancer despite not being trained on these cancer types.

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Computational modeling can predict MSI status from H&E images, demonstrating the ability to Our modeling framework detects MSI in prostate cancer (despite its low prevalence) and generalizes to gastric and esophageal cancers while not being trained on these types.

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er	True Status			
	MSS	MSI-H	Total	
	193	0	193	
	81	8	89	
	274	8		
CS	Sensitivity = 100% (95% CI: 63–100%) Specificity = 70% (95% CI: 65–76%) Positive Likelihood Ratio = 3.4 (95% CI: 2.8–4.0)			
	True Status		Total	
	MSS	MSI-H		
	423	3	426	
	152	12	164	
	575	15		
CS	Sensitivity = 80% (95% CI: 52–96%) Specificity = 74% (95% CI: 70–77%) Positive Likelihood Ratio = 3.0 (95% CI: 2.3–4.0)			
	MSS	MSI-H	Total	
	185	5	190	
	135	21	156	
	320	26		
CS	Sensitivity = 81% (95% CI: 61–93%) Specificity = 58% (95% CI: 52–63%) Positive Likelihood Ratio = 1.9 (95% CI: 1.5–2.4)			
els w asec a sc	vere trained an d on the optimizer of th	d the operating zation set, with est. Here, confu	g points were a target of high ision matrices	

show model predictions and operating point application to the holdout/external sets. Using estimated real-world prevalences of 5%, 2%, and 20% of MSI-H (in prostate, esophageal, and gastric cancers, respectively), we expect that 15%, 6%, and 32% (respectively) of patients would have detectable MSI-H status on follow-up NGS testing after a positive model result.