Inferring PDL-1 status from H&E images using digital pathology to identify patients responsive to anti-PD(L)-1 immuno-oncology (IO) therapy for bladder cancer trials.

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KEY TAKEAWAYS

We developed **MIA:PDL1**, an AI algorithm to infer PDL-1 expression from routine **H&E** images and rapidly assess the likelihood of a patient responding to anti PD(L)-1 therapies

KEY TAKEAWAY
CONCLUSIONS
INTRODUCTION
METHODS
Study Design Diagram
RESULTS
FIGURE 1 PDL-1 Output Heatmap
FIGURE 2 Patient Stratification
APPENDIX

NAVIGATION

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CONCLUSIONS



We leveraged a pretrained Foundation Model and finetuned it to predict PDL-1 expression from routine H&E images to demonstrate the algorithm's potential use for selecting patients likely to respond to anti-PDL-1 immunotherapy.

We show that the model achieves a **strong performance** at classifying PDL1 status and proficiency in inferring outcomes to PDL-1 therapy in a small bladder cancer data set.

The algorithm represents a novel approach to rapidly and accurately assess the likelihood that a patient will respond to PDL-1 therapies from common H&E-stained images. More validation is warranted to establish the power of this model to guide treatment.

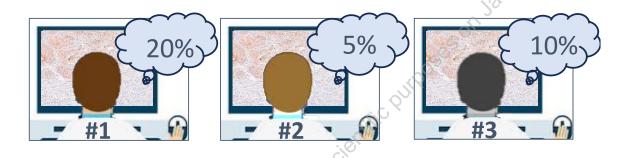
NAVIGATION
KEY TAKEAWAY
CONCLUSIONS
INTRODUCTION
METHODS
Study Design Diagram
RESULTS
FIGURE 1 PDL-1 Output Heatmap
FIGURE 2 Patient Stratification
APPENDIX

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Albert Juan Ramon, Brandon Ginley, Madhawa Saranadasa, Chaityana Parmar, Neil Beeharry, Shibu Thomas, Bolan Linghu, Joel Greshock, Kristopher Standish

INTRODUCTION

- Targeted IO therapies are available to inhibit the PDL-1 pathway and improve therapeutic response.
- Immunohistochemistry (IHC) testing is used to assess PDL-1 expression and guide IO therapy, but an
 alternative is warranted on limited tumor samples and to avoid pathologist subjectivity.



 We developed MIA:PDL1, an AI algorithm to infer PDL-1 expression from routine H&E images and identify patients that may respond to IO therapies



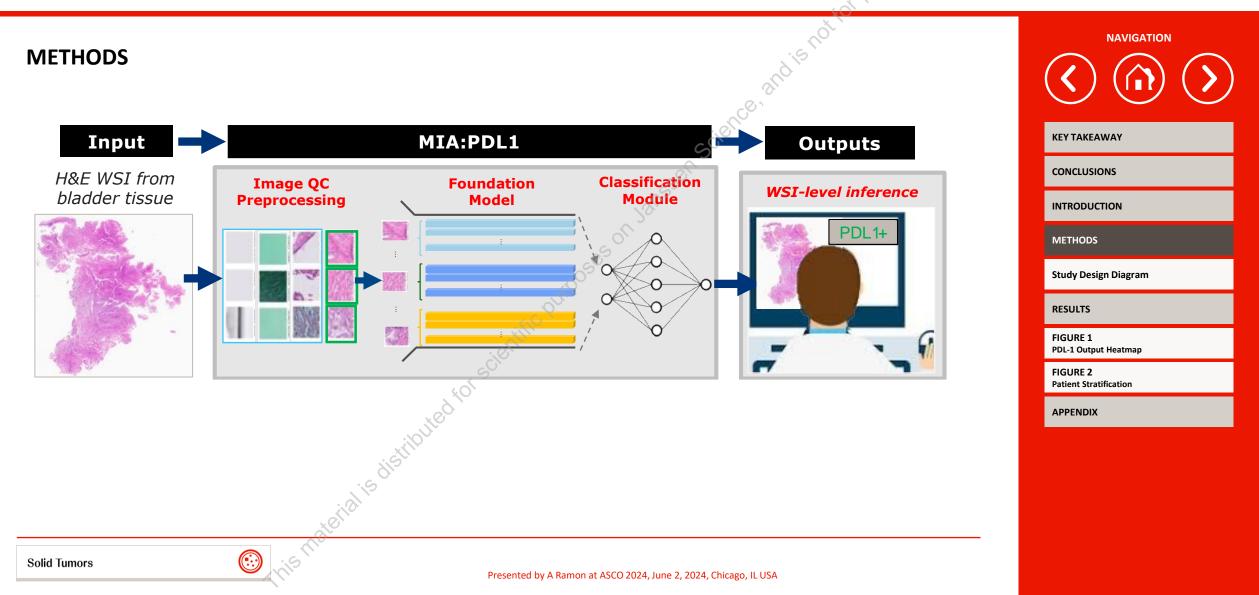
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METHODS

- Pretrained a Foundation Model (FM) using ~55k whole slide images (WSIs) from various data sources (multiple scanners, hospitals/labs, diseases, tissue types).
- Fine-tuned the pretrained model on 1546 WSIs with PDL-1 labels from corresponding IHC stained tissues, where appropriate thresholds for various included antibodies were used:
- PDL1-High: TPS>= 10% (22C3), CPS>=10% (22C3), CPS>=1% (28-8), IC>=5% (SP142), IC>=1% (SP263, LDT)
- We evaluated the performance at predicting PDL1-High vs. PDL1-Low, quantified by the Area Under ROC Curve (auROC) on a holdout set (n=388) and an independent set (n=93)
- Then, we applied the model to WSIs of biopsies taken prior to anti-PDL-1 treatment (i.e., pembrolizumab) and evaluated treatment response for the two groups (PDL1-High vs. PDL1-Low)
- We compared it to patients stratified based on IHC-based pathology readouts using the thresholds for corresponding antibodies (TPS>=10% vs. TPS<10%)

NAVIGATION
KEY TAKEAWAY
CONCLUSIONS
INTRODUCTION
METHODS
Study Design Diagram
RESULTS
FIGURE 1 PDL-1 Output Heatmap
FIGURE 2 Patient Stratification
APPENDIX

Albert Juan Ramon, Brandon Ginley, Madhawa Saranadasa, Chaityana Parmar, Neil Beeharry, Shibu Thomas, Bolan Linghu, Joel Greshock, Kristopher Standish

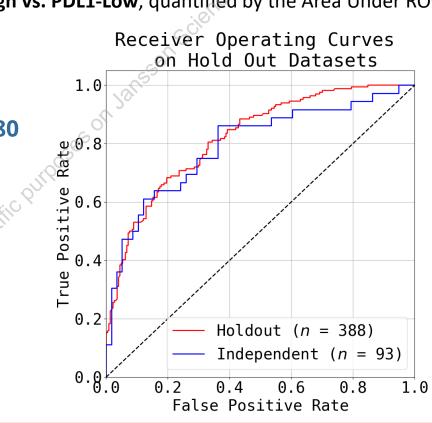


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RESULTS

 We evaluated the performance at predicting PDL1-High vs. PDL1-Low, quantified by the Area Under ROC Curve (auROC) on:

o a holdout set (n=388): auROC=0.82
o an independent set (n=93): auROC=0.80

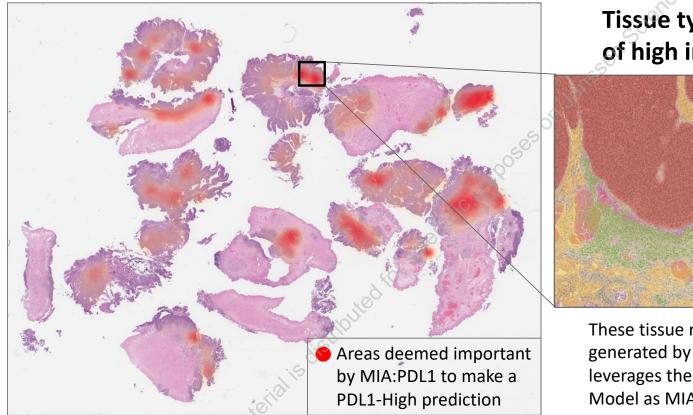


NAVIGATION **KEY TAKEAWAY** CONCLUSIONS INTRODUCTION METHODS Study Design Diagram RESULTS FIGURE 1 PDL-1 Output Heatmag FIGURE 2 Patient Stratification APPENDIX

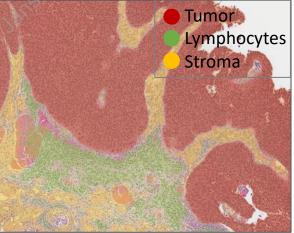
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RESULTS

MIA:PDL1 Output Heatmap



Tissue types in area of high importance



These tissue regions were generated by an algorithm that leverages the same Foundation Model as MIA:PDL1

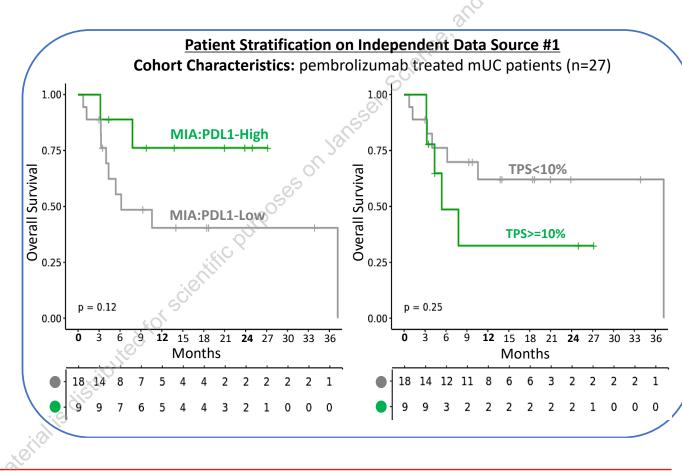


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RESULTS

- The figure shows the survival analysis results upon pembrolizumab treatment (n=27) when stratifying patients using MIA:PDL1 (left) vs. IHCbased readouts (right)
- Note that the survival probability for MIA:PDL1-High patients is higher than MIA:PDL1-Low patients, as opposed to IHCbased stratification.

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KEY TAKEAWAY CONCLUSIONS INTRODUCTION METHODS Study Design Diagram RESULTS FIGURE 1 PDL-1 Output Heatmap FIGURE X Figure Title (short title can be used) APPENDIX

NAVIGATION

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APPENDIX

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Solid Tumors



NAVIGATION

KEY TAKEAWAY

CONCLUSIONS

INTRODUCTION

Study Design Diagram

PDL-1 Output Heatmap

METHODS

RESULTS

FIGURE 1

FIGURE 2 Patient Stratification

APPENDIX