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#### **KEY TAKEAWAYS**



We developed algorithms to generate a risk categorization from H&E tissues of bladder cancer which predict patient survival under anti-PD-1 immunotherapies. The algorithm, which incorporates inferred PDL-1 status, tissue and cell features, age, and sex, demonstrated that low-risk patients have significantly higher survival probabilities compared to high-risk patients.

NAVIGATION



H&E: Hematoxylin and eosin; PD(L)-1: Programmed death protein (ligand) 1

**Urothelial Cancer** 



Brandon Ginley, Bolan Linghu, Chaitanya Parmar, Neil Beeharry, Shibu Thomas, Patricia Raciti, Joel Greshock, Kristopher Standish, Albert Juan Ramon

#### CONCLUSIONS



We developed algorithms to infer PDL-1 status and tumor microenvironment features from a digitized H&E slide typically used for disease diagnosis.



An algorithm combining inferred PDL-1 status, demographics, and tumor microenvironment (lymphocyte, stroma, tumor, and necrosis morphology and texture) can estimate survival risk under anti-PD-1 therapies.



This method offers a cheaper and faster alternative to immunohistochemistry, potentially aiding in the selection of patients who would benefit most from PD-(L)-1 therapy.

PD(L)-1: programmed death protein (ligand) 1, H&E: hematoxylin and eosin, AUC: area under the curve, BC: bladder cancer





Brandon Ginley, Bolan Linghu, Chaitanya Parmar, Neil Beeharry, Shibu Thomas, Patricia Raciti, Joel Greshock, Kristopher Standish, Albert Juan Ramon

#### INTRODUCTION

Bladder cancer is a significant health challenge, ranking among the most common malignancies worldwide. The use of checkpoint inhibitors has shown to be effective, but patient response is variable. This underscores the need for advanced tools to better understand and optimize treatment outcomes. In this work, we aimed to develop an artificial intelligence (AI) algorithm to evaluate the overall survival of bladder cancer patients treated with anti-PD-1 therapies, to identify patients with high likelihood of durable outcomes and recognize patients that may require different or combination therapies to achieve better outcomes. Our research leverages patient treatment history, demographics, AI-based PDL-1 positivity, and digitally derived features of the tumor microenvironment, a method proved to be effective though exploration in larger sample sizes is warranted.



PD(L)-1: programmed death protein (ligand) 1, Al/ML: artificial intelligence/machine learning



Brandon Ginley, Bolan Linghu, Chaitanya Parmar, Neil Beeharry, Shibu Thomas, Patricia Raciti, Joel Greshock, Kristopher Standish, Albert Juan Ramon

#### **METHODS**

A foundation model was trained on ~100k WSIs from various sources. H&E and PDL-1 IHC slides were used to fine-tune a model (MIA-PDL1<sup>1</sup>), which infers PDL-1 expression levels from H&E. Individualized IHC thresholds (TPS/CPS>=10% for 22C3, CPS>=1% on 28-8, etc) from pathologist reads created training labels. AI inferred probabilities >=0.5 were considered a positive result. We then trained MIA-Tissue to identify tissue regions of tumor, stroma, necrosis and lymphocytes. An open-source model (CellViT<sup>2</sup>) was used to identify neoplastic, inflammatory, connective, epithelial, and dead cells. 617 biologically inspired features were derived from the segmentations. A random survival forest (MIA-IO) was trained with outputs from each model along with patient age and sex to estimate overall survival from treatment start. This model was first developed with bladder cancer patients treated with any type of immunotherapy and further evaluated on a subset of anti-PD-1 treated patients (Pembrolizumab and Nivolumab). Log-rank test was used to determine statistical significance of inferred high-risk and low-risk event times for each model.

WSIs: Whole slide images; H&E: Hematoxylin and eosin; IHC: Immunohistochemistry; MIA: Microscopy image analysis; TPS: Tumor proportion score; CPS: Combined positive score; PD(L)-1: programmed death protein (ligand) 1, AI: artificial intelligence; IO: Immunotherapy outcome

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**KEY TAKEAWAY** CONCLUSIONS INTRODUCTION METHODS RESULTS TABLE 1 Data breakdown TABLE 2 PDL-1 estimation performance FIGURE 1 Tissue segmentation performance FIGURE 2 Example segmentations FIGURE 3 OS: PDL-1 FIGURE 4 OS: Age and sex FIGURE 5 OS: all features, internal dataset FIGURE 6 OS: all features, independent dataset TABLE 3 Top important features APPENDIX

NAVIGATION

Brandon Ginley, Bolan Linghu, Chaitanya Parmar, Neil Beeharry, Shibu Thomas, Patricia Raciti, Joel Greshock, Kristopher Standish, Albert Juan Ramon

#### **GUIDED REVIEW OF RESULTS**

**Table 1** shows datasets used for this study. MIA-PDL1 achieved 0.82/0.8 AUC on internal/independent test sets (**Table 2**). **Figure 1** outlines (via box-plot of testing ROIs) MIA-Tissue performance, with best results seen for stroma, tumor, and lymphocyte, and rarity leading to lower performance for necrosis. **Figure 2** shows an example overlay of both tissue segmentation and cell segmentation outputs. **Figures 3&4** demonstrate that *algorithm estimated* PDL-1 status, age, and sex do not reliably determine survival outcomes in anti-PD-1 treated internal test cohort. Ground truth IHC PDL-1 was not available for comparison. **Figure 5** shows that significant survival separation is achieved with added histologic features of the tumor microenvironment in internal test, confirmed in the independent testing cohort (**Figure 6**). Finally, **Table 3** outlines the most important features for determining survival risk, with lymphocyte features holding the most overall power, but necrosis, tumor, and stroma features also having significant play.

IHC: Immunohistochemistry; MIA: Microscopy image analysis; PD(L)-1: programmed death protein (ligand) 1, AUC: area under receiver operator curve; ROIs: Regions of interest

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NAVIGATION

APPENDIX

Brandon Ginley, Bolan Linghu, Chaitanya Parmar, Neil Beeharry, Shibu Thomas, Patricia Raciti, Joel Greshock, Kristopher Standish, Albert Juan Ramon

#### RESULTS

Table 1: Data breakdown for cohorts used in model development of presented analyses

MIA: Microscopy image analysis; PD(L)-1: programmed death protein (ligand) 1; IO: Immunotherapy outcome

|                     | Analysis category                         | n    |  |
|---------------------|---|------|--|
|                     | MIA-PDL1 model (whole slides)             | 1639 |  |
|                     | Training                                  | 1158 |  |
|                     | Internal holdout                          | 388  |  |
|                     | Independent holdout                       | 93   |  |
|                     | MIA-Tissue model (patches)                | 1919 |  |
|                     | Training                                  | 1520 |  |
|                     | Validation                                | 321  |  |
|                     | Testing                                   | 78   |  |
|                     | CellVIT cell segmentation model (patches) | 7904 |  |
|                     | Training                                  | 5248 |  |
| <i>.</i> .(         | Testing                                   | 2656 |  |
| dill and the second | MIA-IO model (whole slides)               | 558  |  |
| scier               | All immunotherapies training – internal   | 264  |  |
| (O <sup>r</sup>     | All immunotherapies testing – internal    | 67   |  |
|                     | All immunotherapies testing – independent | 227  |  |
|                     | PD1 therapies training – internal         | 157  |  |
|                     | PD1 therapies testing – internal          | 39   |  |
| У                   | PD1 therapies testing – independent       | 182  |  |
|                     |   |      |  |

**KEY TAKEAWAY** CONCLUSIONS INTRODUCTION METHODS RESULTS TABLE 1 Data breakdown TABLE 2 PDL-1 estimation performance **FIGURE 1** Tissue segmentation performance FIGURE 2 Example segmentations FIGURE 3 OS: PDL-1 FIGURE 4 OS: Age and sex FIGURE 5 OS: all features, internal dataset FIGURE 6 OS: all features, independent dataset TABLE 3 Top important features

NAVIGATION

APPENDIX

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#### RESULTS

Table 2: Performance of AI-based PDL-1 estimation from H&E image<sup>1</sup>

| Dataset   | AUC                    |      |
|---|------------------------|------|
| Internal test set   | 0.82                   |      |
| Independent test set  | 0.80                   | Nec  |
| in the trained for  | scientific purposes on | 28.2 |
| noc. Hematoxymi and eosii, <b>Po(L)-1</b> . programmed death protein (ngand) 1, Al. arthroid intelligence |                        |      |

| KEY TAKEAWAY                                       |
|--|
| CONCLUSIONS  |
| INTRODUCTION                                       |
| METHODS  |
| RESULTS  |
| TABLE 1<br>Data breakdown                          |
| TABLE 2<br>PDL-1 estimation performance            |
| FIGURE 1<br>Tissue segmentation performance        |
| FIGURE 2<br>Example segmentations                  |
| FIGURE 3<br>OS: PDL-1                              |
| FIGURE 4<br>OS: Age and sex                        |
| FIGURE 5<br>OS : all features, internal dataset    |
| FIGURE 6<br>OS : all features, independent dataset |
| TABLE 3<br>Top important features                  |
| APPENDIX   |

Urothelial Cancer



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**NAVIGATION** 

**KEY TAKEAWAY** 

CONCLUSIONS

INTRODUCTION

METHODS

RESULTS

FIGURE 1

FIGURE 2

FIGURE 3

OS: PDL-1 FIGURE 4 OS: Age and sex FIGURE 5

**FIGURE 6** 

TABLE 3

APPENDIX

Top important features

Data breakdown

PDL-1 estimation performance

Example segmentations

Tissue segmentation performance

OS: all features, internal dataset

OS: all features, independent dataset

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#### RESULTS

#### Figure 1: Performance of tissue segmentation



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#### RESULTS

Figure 2: Example segmentation outputs on whole slide image





**NAVIGATION KEY TAKEAWAY** CONCLUSIONS INTRODUCTION METHODS RESULTS TABLE 1 Data breakdown TABLE 2 PDL-1 estimation performance **FIGURE 1** Tissue segmentation performance FIGURE 2 Example segmentations FIGURE 3 OS: PDL-1 FIGURE 4 OS: Age and sex FIGURE 5 OS: all features, internal dataset **FIGURE 6** OS: all features, independent dataset TABLE 3 Top important features APPENDIX

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Brandon Ginley, Bolan Linghu, Chaitanya Parmar, Neil Beeharry, Shibu Thomas, Patricia Raciti, Joel Greshock, Kristopher Standish, Albert Juan Ramon

#### RESULTS

Urothelial Cancer

Figure 3: Overall survival curves for anti-PD-1 treated patients using inferred PDL-1 status as risk score



**KEY TAKEAWAY** CONCLUSIONS INTRODUCTION METHODS RESULTS TABLE 1 Data breakdown TABLE 2 PDL-1 estimation performance FIGURE 1 Tissue segmentation performance FIGURE 2 Example segmentations FIGURE 3 OS: PDL-1 FIGURE 4 OS: Age and sex FIGURE 5 OS: all features, internal dataset FIGURE 6 OS: all features, independent dataset TABLE 3 Top important features APPENDIX

NAVIGATION

Brandon Ginley, Bolan Linghu, Chaitanya Parmar, Neil Beeharry, Shibu Thomas, Patricia Raciti, Joel Greshock, Kristopher Standish, Albert Juan Ramon

#### RESULTS

Figure 4: Overall survival curves for anti-PD-1 treated patients using median age or sex as risk scores





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#### RESULTS

Figure 5: Survival curves based on combined demographics, AI-based PDL-1 and tumor microenvironment risk score in internal anti-PD-1 treated test set, segregated by median survival forest (MIA-IO) score.



NAVIGATION

**KEY TAKEAWAY** 

CONCLUSIONS

INTRODUCTION

METHODS

RESULTS

FIGURE 1

FIGURE 2

FIGURE 3

OS: PDL-1

FIGURE 4 OS: Age and sex

FIGURE 5

FIGURE 6

TABLE 3

APPENDIX

Top important features

Data breakdown

PDL-1 estimation performance

Example segmentations

Tissue segmentation performance

OS: all features, internal dataset

OS: all features, independent dataset

MIA: Microscopy image analysis; PD(L)-1: programmed death protein (ligand) 1, AI: artificial intelligence; IO: Immunotherapy outcome

**Urothelial Cancer** 



Brandon Ginley, Bolan Linghu, Chaitanya Parmar, Neil Beeharry, Shibu Thomas, Patricia Raciti, Joel Greshock, Kristopher Standish, Albert Juan Ramon

#### RESULTS

Figure 6: Survival curves based on combined demographics, AI-based PDL-1 and tumor microenvironment risk score in independent anti-PD-1 treated test set, segregated by median survival forest (MIA-IO) score.



MIA: Microscopy image analysis; PD(L)-1: programmed death protein (ligand) 1, AI: artificial intelligence; IO: Immunotherapy outcome

**Urothelial Cancer** 



NAVIGATION **KEY TAKEAWAY** CONCLUSIONS INTRODUCTION METHODS RESULTS TABLE 1 Data breakdown TABLE 2 PDL-1 estimation performance FIGURE 1 Tissue segmentation performance FIGURE 2 Example segmentations FIGURE 3 OS: PDL-1 FIGURE 4 OS: Age and sex FIGURE 5 OS: all features, internal dataset FIGURE 6 OS: all features, dependent dataset TABLE 3 Top important features APPENDIX

Brandon Ginley, Bolan Linghu, Chaitanya Parmar, Neil Beeharry, Shibu Thomas, Patricia Raciti, Joel Greshock, Kristopher Standish, Albert Juan Ramon

#### RESULTS

Table 3: Top 5 important feature groups for overall survival estimation as a function of performance loss when features are dropped out

| Category                  | C-index drop |
|---------------------------|--------------|
| Lymphocyte shape factors  | 0.083 Medil  |
| Necrosis textures         | 0.067        |
| Lymphocyte textures       | 0.057        |
| Tumor shape factors       | 0.033        |
| Stroma textures           | 0.025        |
| -index: Concordance index | sdfor scier  |
|                           |              |

| KEY TAKEAWAY                                   |  |  |
|--|--|--|
| CONCLUSIONS                                    |  |  |
| INTRODUCTION                                   |  |  |
| METHODS  |  |  |
| RESULTS  |  |  |
| TABLE 1<br>Data breakdown                      |  |  |
| TABLE 2<br>PDL-1 estimation performance        |  |  |
| FIGURE 1                                       |  |  |
| FIGURE 2<br>Example segmentations              |  |  |
| FIGURE 3<br>OS: PDL-1                          |  |  |
| FIGURE 4<br>QS: Age and sex                    |  |  |
| FIGURE 5<br>OS: all features, internal dataset |  |  |
| FIGURE 6                                       |  |  |
| TABLE 3 Top important features                 |  |  |
| APPENDIX                                       |  |  |

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#### **APPENDIX**

#### **REFERENCES:**

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#### **ACKNOWLEDGMENTS:**

Special thanks go out to Brendon Lutnick for his help constructing the tissue segmentation pipeline, Erik Burlingame for his assistance quantifying tissue performance, to the entire bladder oncology team at Johnson and Johnson for project direction, guidance, and production of data specimens for the analyses, and to the Neogenomics team for segmentation annotation work.



**KEY TAKEAWAY** 

#### CONCLUSIONS INTRODUCTION METHODS RESULTS TABLE 1 Data breakdown TABLE 2 PDL-1 estimation performance FIGURE 1 Tissue segmentation performance FIGURE 2 Example segmentations FIGURE 3 OS: PDL-1 FIGURE 4 OS: Age and sex FIGURE 5 OS: all features, internal dataset FIGURE 6 OS: all features, independent dataset TABLE 3 Top important features

APPENDIX