

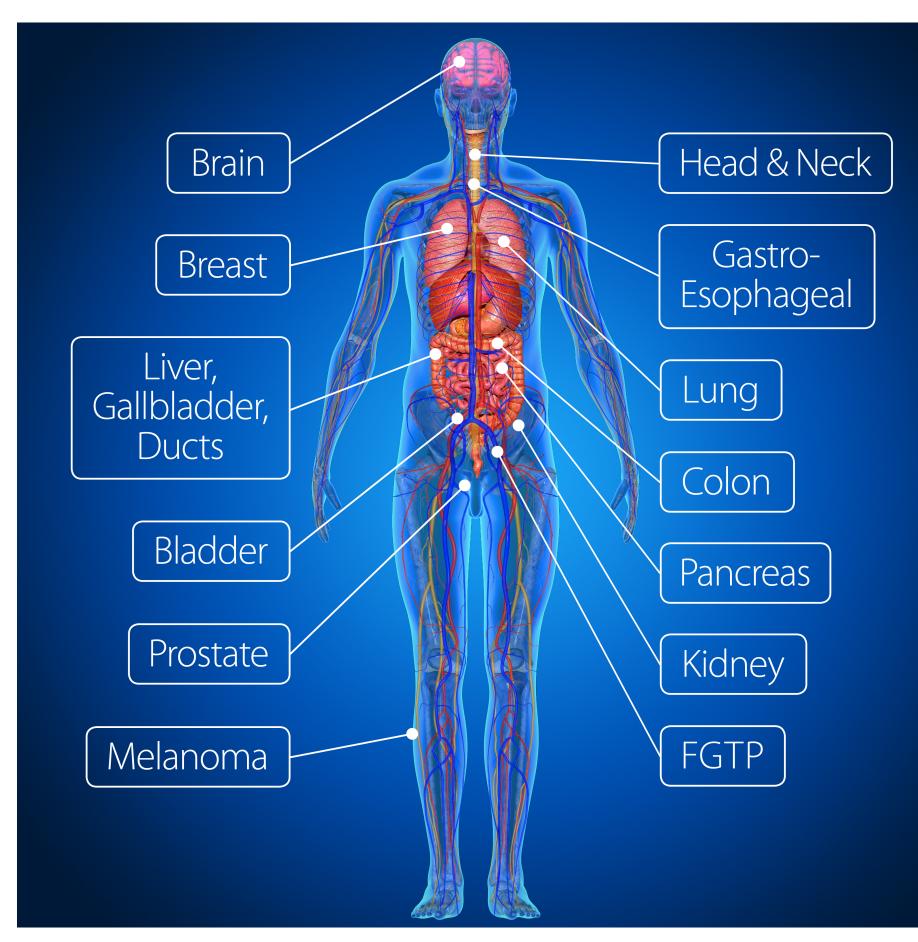
Machine Learning Algorithm Analysis using 55,780 Cases from a Commercial 592-gene NGS Panel to Accurately Predict Tumor Type for Carcinoma of Unknown Primary (CUP)

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Abstract

Background: The diagnosis of a malignancy is typically informed by clinical presentation and tumor tissue features including cell morphology, immunohistochemistry, cytogenetics, and molecular markers. However, in approximately 5-10% of cancers^{1,2}, ambiguity is high enough that no tissue of origin can be determined and the specimen is labeled as a Cancer of Occult/Unknown Primary (CUP). Lack of reliable classification of a tumor poses a significant treatment dilemma for the oncologist leading to inappropriate and/or delayed treatment. Gene expression profiling has been used to try to identify the tumor type for CUP patients, but suffers from a number of inherent limitations. Specifically, tumor percentage, variation in expression, and the dynamic nature of RNA all contribute to suboptimal performance. For example, one commercial RNA-based assay has sensitivity of 83% in a test set of 187 tumors and confirmed results on only 78% of a separate 300 sample validation set³.

Methods: 55,780 tumor patients with NGS data were used to construct a multiple parameter tumor type specific classification system using an advanced machine learning approach.



Tumor Types with Specific DNA Aberrations

Figure 1 – Tumor types that the algorithm is able to differentiate.

DNA Can Identify Tumor Type

Sensiti

90.0

Table 1 – Performance metrics of assay on an independent test set of 15,473 cases.

Robust to Metastasis and Tumor Percentage

Prim

Metast

20-50 Tume >50

Table 2 – Performance metrics on subsets of the test data from a primary site (N = 8,437), metastatic site (6,690), and samples with low (9,492) and high tumor percentages (5,945).

Performance Holds Across Multiple Tumor Types

Tumor Head, Fac Melar Pros Co Pancr Gastroesc Liver, Ga

ivity	Specificity	PPV	NPV	Accuracy	Call Rate
)%	98.0%	90.0%	98.6%	97.3%	97.5%

	Sensitivity	Specificity	PPV	NPV	Accuracy	Call Rate
ary	90.9%	98.0%	91.1%	98.9%	97.6%	97.3%
tatic	89.0%	97.9%	89.3%	98.2%	96.9%	97.6%
)% or	90.3%	98.2%	90.6%	98.5%	97.5%	97.1%
% or	90.3%	98.2%	90.6%	98.5%	97.5%	97.1%

Туре	Train N	Test N	Sensitivity	Specificity	PPV	NPV	Accuracy	Call Rate
e, Neck	299	144	45.4%	100.0%	96.4%	99.6%	99.6%	82.6%
oma	976	402	85.0%	99.9%	94.3%	99.6%	99.5%	96.3%
P	8,872	4,115	93.4%	98.3%	95.4%	97.6%	97.0%	98.8%
ate	785	477	96.1%	99.8%	94.7%	99.9%	99.7%	96.6%
in	1,554	479	93.3%	99.8%	93.5%	99.8%	99.6%	96.0%
on	5,805	2,532	94.5%	98.5%	92.9%	98.9%	97.9%	98.9%
ey	426	178	84.1%	99.9%	91.7%	99.8%	99.8%	88.2%
der	447	304	60.6%	99.9%	89.4%	99.3%	99.1%	91.8%
ast	3,324	1,386	90.9%	98.7%	87.9%	99.1%	98.0%	98.3%
g	7,744	3,540	96.0%	95.4%	86.3%	98.7%	95.5%	98.2%
eas	1,637	708	83.7%	99.3%	84.6%	99.2%	98.5%	98.3%
phageal	1,521	743	72.0%	99.3%	82.6%	98.6%	98.0%	93.8%
bladder, ts	734	364	57.7%	99.7%	82.2%	99.0%	98.8%	92.6%

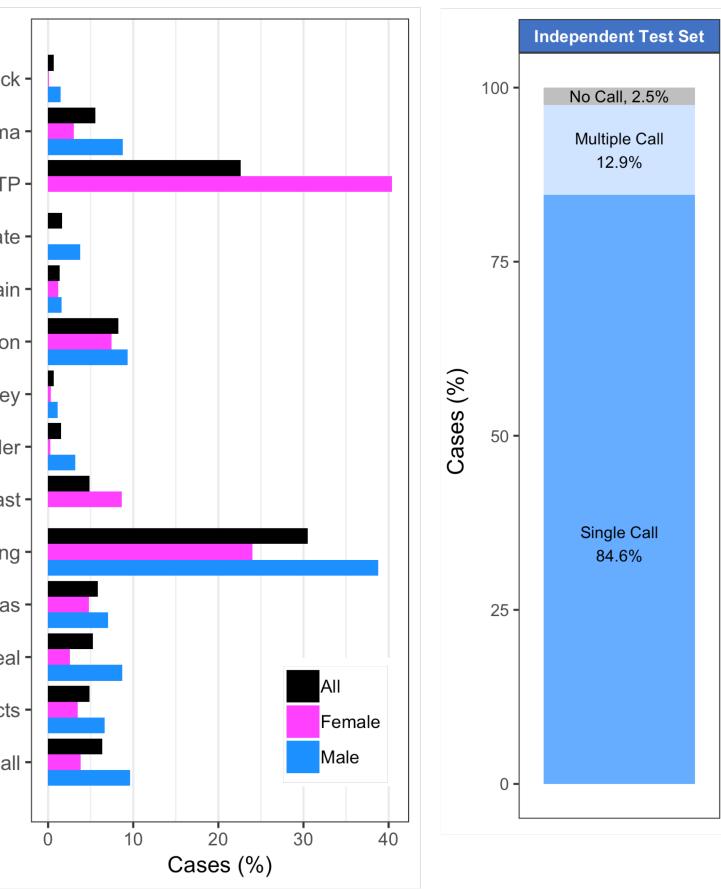
Table 3 – Performance metrics and cohort sizes of subsets of the independent test dataset where the primary tumor site is known.

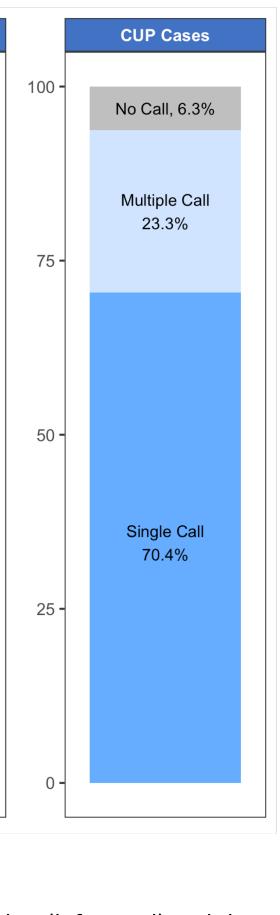
Algorithmic Classification of CUP Cases

	Head, Face, Neck -
	Melanoma -
	FGTP -
=	Prostate -
	Brain -
	Colon -
	Kidney -
	Bladder -
a he	Breast -
	Lung -
_	Pancreas -
	Gastroesophageal -
Liver,	Gallbladder, Ducts -
	No Call -
	2 – Percentages ution of required









True Tumor Type

Georgetown | Lombardi COMPREHENSIVE CANCER CENTER

Conclusions

- improve outcomes

References

- primary.html

s of tumor types identified in CUP cases (N = 5,955) by the algorithm (left panel) and the distribution of required calls in order to identify a tumor type with a sufficiently high probability (right panel).

Distribution of Calls Per Tumor Type Indicate Unique Molecular Subtypes

	Head, Face, Neck	FGTP	Prostate	Melanoma	Brain	Colon	Kidney	Bladder	Breast	
Face, Neck	0.96	0	0	0	0	0	0	0.04	0	
Melanoma	0.01	0.96	0.01	0	0	0.01	0	0	0	
FGTP	0	0	0.95	0	0	0.01	0	0	0.01	(
Prostate	0.01	0	0	0.95	0	0	0	0.01	0	(
Brain	0	0	0.03	0	0.93	0	0	0	0.01	
Colon	0	0	0.01	0	0	0.93	0	0	0	(
Kidney	0	0	0.01	0	0	0.01	0.92	0	0	(
Bladder	0.01	0.01	0.02	0	0	0	0.01	0.89	0.01	(
Breast	0	0	0.07	0	0	0	0	0.01	0.88	(
Lung	0.01	0.01	0.02	0	0	0.01	0	0.01	0.01	(
Pancreas	0	0	0.02	0	0	0.03	0	0	0	(
esophageal	0.01	0	0.02	0	0	0.05	0	0.01	0.01	(
dder, Ducts	0	0	0.02	0	0	0.01	0.01	0.01	0.02	(

Table 4 – Proportion of cases identified by the algorithm for each tumor type.



• Final performance of DNA-based tumor type identification on an independent test of 15,000+ patient samples is superior to current standards using gene expression based methods

 Unbiased training machine learning techniques applied to more than 45,000 enabled detection of tumor types independent of sampling location or tumor percentage • Tumor type predictors can render a histologic diagnosis to CUP cases that can inform treatment and potentially

 Cancer of unknown primary remains a substantial problem for both clinicians and patients, diagnosis can be aided with the algorithms presented here.

• Returning both diagnostic and therapeutic information that optimize patients treatment strategy from a single test is a substantial improvement over the current standard of multiple tests that require more tissue

1. https://www.mdanderson.org/cancer-types/cancer-of-unknown-

https://www.cancer.gov/types/unknown-primary/hp/unknownprimary-treatment-pdq#_1

Erlander MG, et al. Performance and clinical evaluation of the 92-gene real-time PCR assay for tumor classification. J Mol Diagn. 2011 Sep;13(5):493-503. doi: 10.1016/j.jmoldx.2011.04.004. Epub 2011 Jun

ung	Pancreas	Gastro- esophageal	Liver, Gallbladder, Ducts
0	0	0	0
0	0	0	0
.01	0	0	0
.01	0	0	0
0	0	0.01	0
.01	0.01	0.02	0.01
.03	0.01	0.01	0.01
.03	0.01	0.01	0.02
.01	0	0	0.01
.86	0.02	0.02	0.01
.03	0.85	0.02	0.05
.03	0.01	0.83	0.02
.03	0.04	0.03	0.82