

Applications of Deep Learning in Diagnostic Image Analysis

The National Academies of Sciences, Engineering, and Medicine
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Workshop on Digital Health
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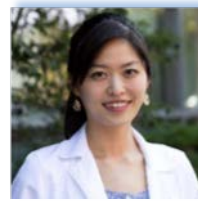
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Umrao, PhD



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Justin
Du



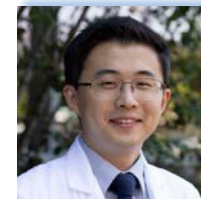
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Gao, MD



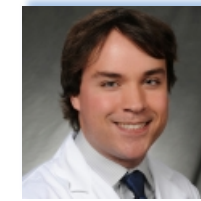
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Chang, BS



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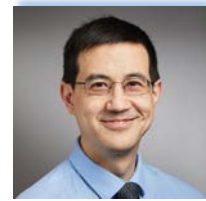
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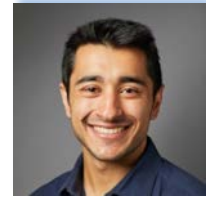
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CLINICIANS



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COMPUTER SCIENTISTS



MATHEMATICIANS



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RESEARCH AREAS

1. Machine learning algorithm development
2. Data science theory
3. Clinical applications of existing machine learning techniques



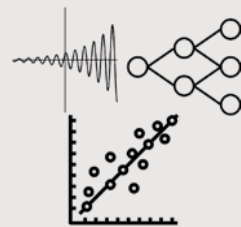
Pathway for Model Development



**GOOD CLINICAL
QUESTION**



**FIND & COLLECT
APPROPRIATE DATA**



**COMPARE MODEL
CANDIDATES
& GOLD STANDARD**



**EXTERNAL
VALIDATION**



**SURVEILLANCE &
VULNERABILITY
STUDIES**



Imaging Biomarkers

Lymph Node Classification

Multi-Institutional Validation of Deep Learning for Pretreatment Identification of Extranodal Extension in Head and Neck Squamous Cell Carcinoma

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SCIENTIFIC REPORTS

OPEN

Pretreatment Identification of Head and Neck Cancer Nodal Metastasis and Extranodal Extension Using Deep Learning Neural Networks

Received: 25 May 2018

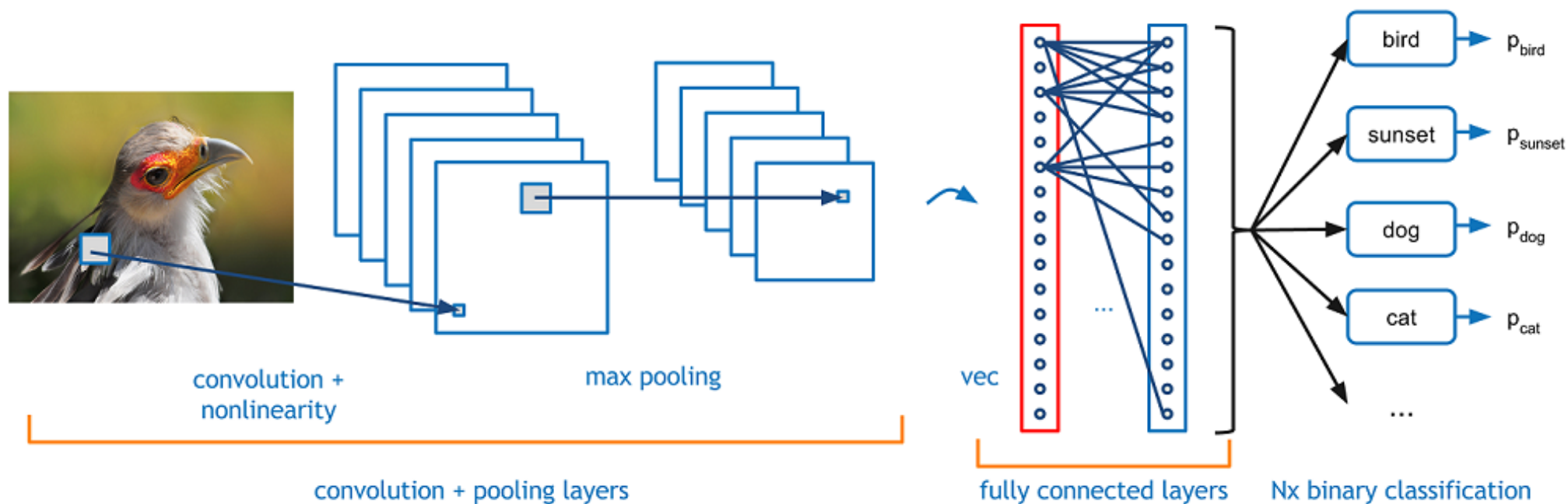
Accepted: 7 September 2018

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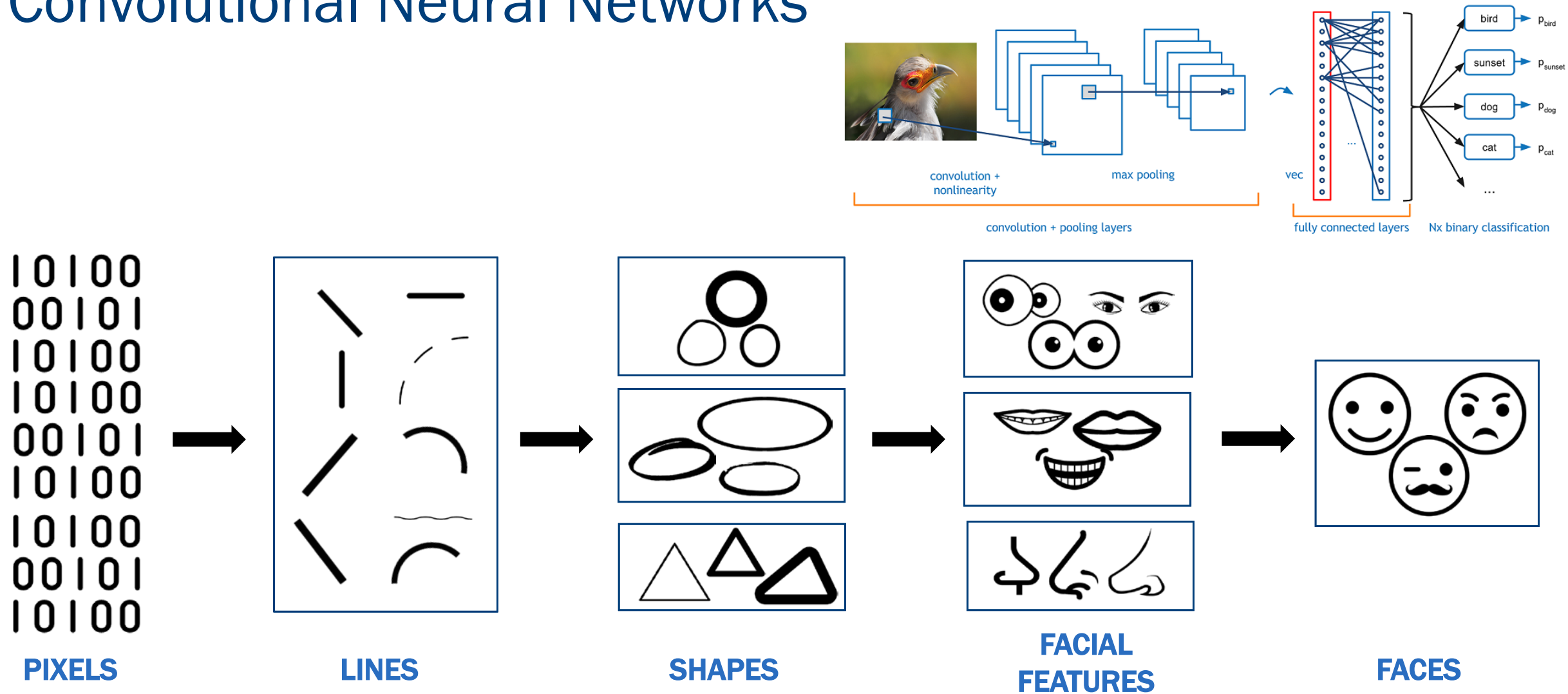
Benjamin H. Kann¹, Sanjay Aneja¹, Gokoulakrichenane V. Loganadane¹, Jacqueline R. Kelly¹, Stephen M. Smith², Roy H. Decker¹, James B. Yu¹, Henry S. Park¹, Wendell G. Yarbrough³, Ajay Malhotra⁴, Barbara A. Burtneess⁵ & Zain A. Husain¹



Convolutional Neural Networks

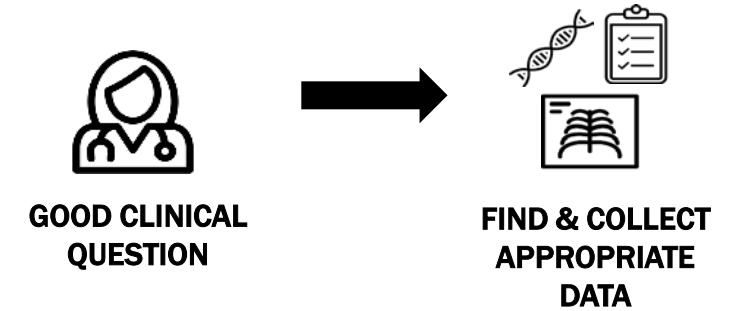


Convolutional Neural Networks



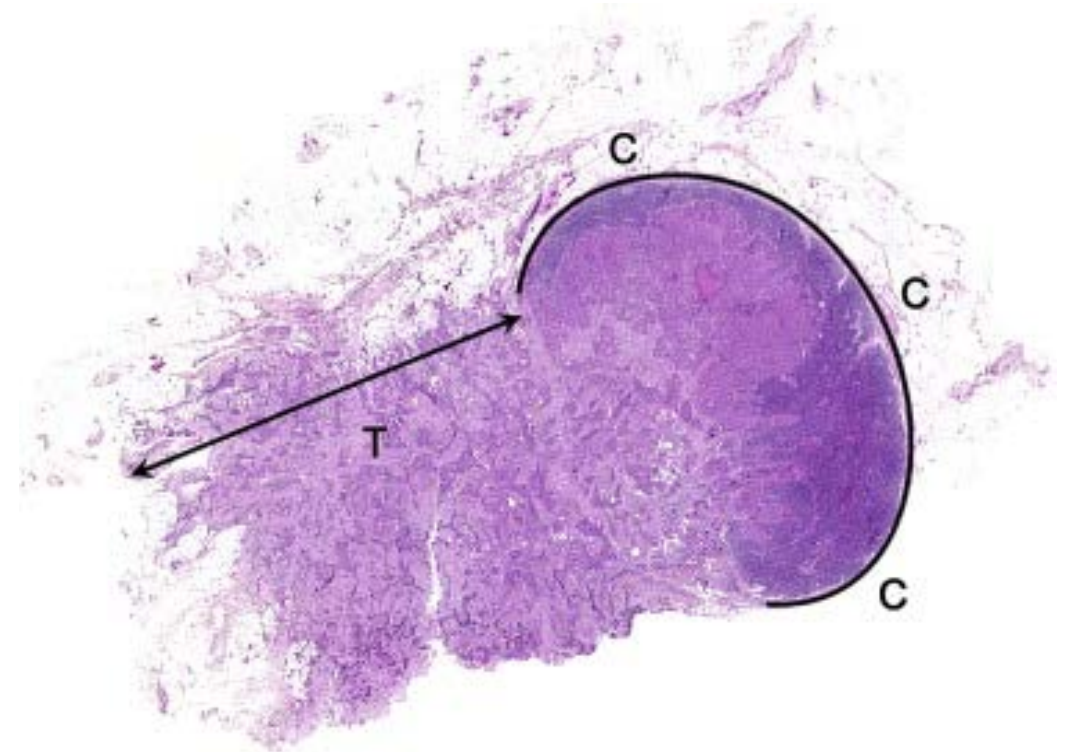
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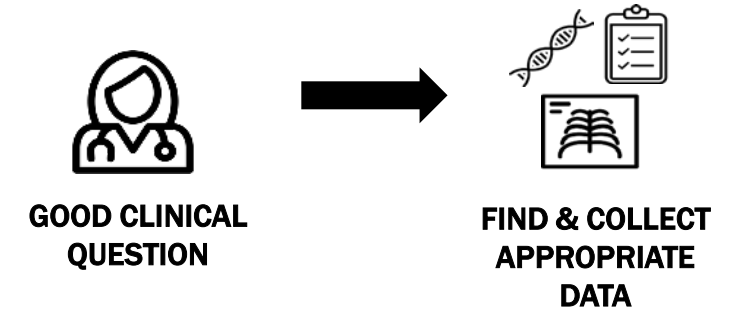
CLINICAL PROBLEM

- Presence of cancer within LNs affects prognosis
- Identification of cancer within LN is difficult to complete non-invasively
- The presence of extranodal extension (ENE) of cancer in LN is often requires adjuvant treatment escalation
- Preoperative identification of patients with ENE may reduce need for surgical interventions



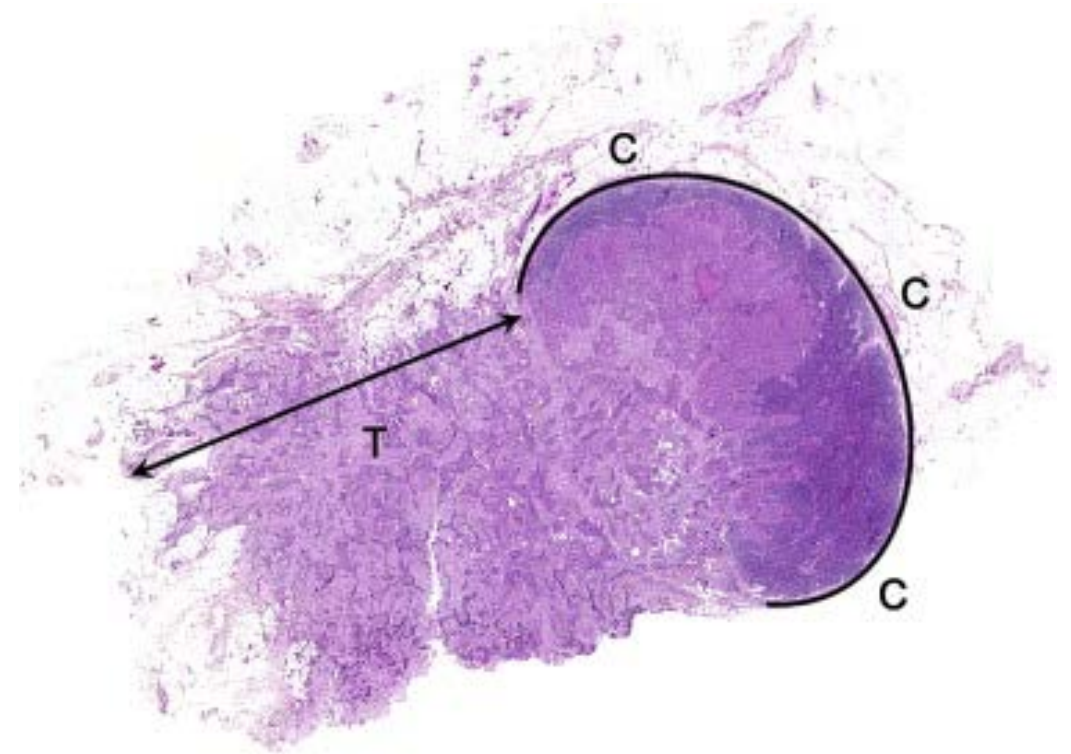
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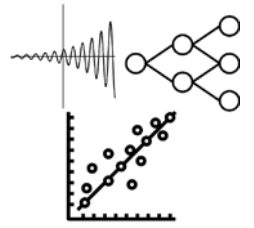
HYPOTHESIS

- Machine learning analysis of pre-operative diagnostic images could effectively classify LN in head and neck cancer patients
1. Identification of positive LN on preoperative CT imaging
 2. Identification of ENE within LN on preoperative CT imaging



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**COMPARE MODEL
CANDIDATES
& GOLD STANDARD**

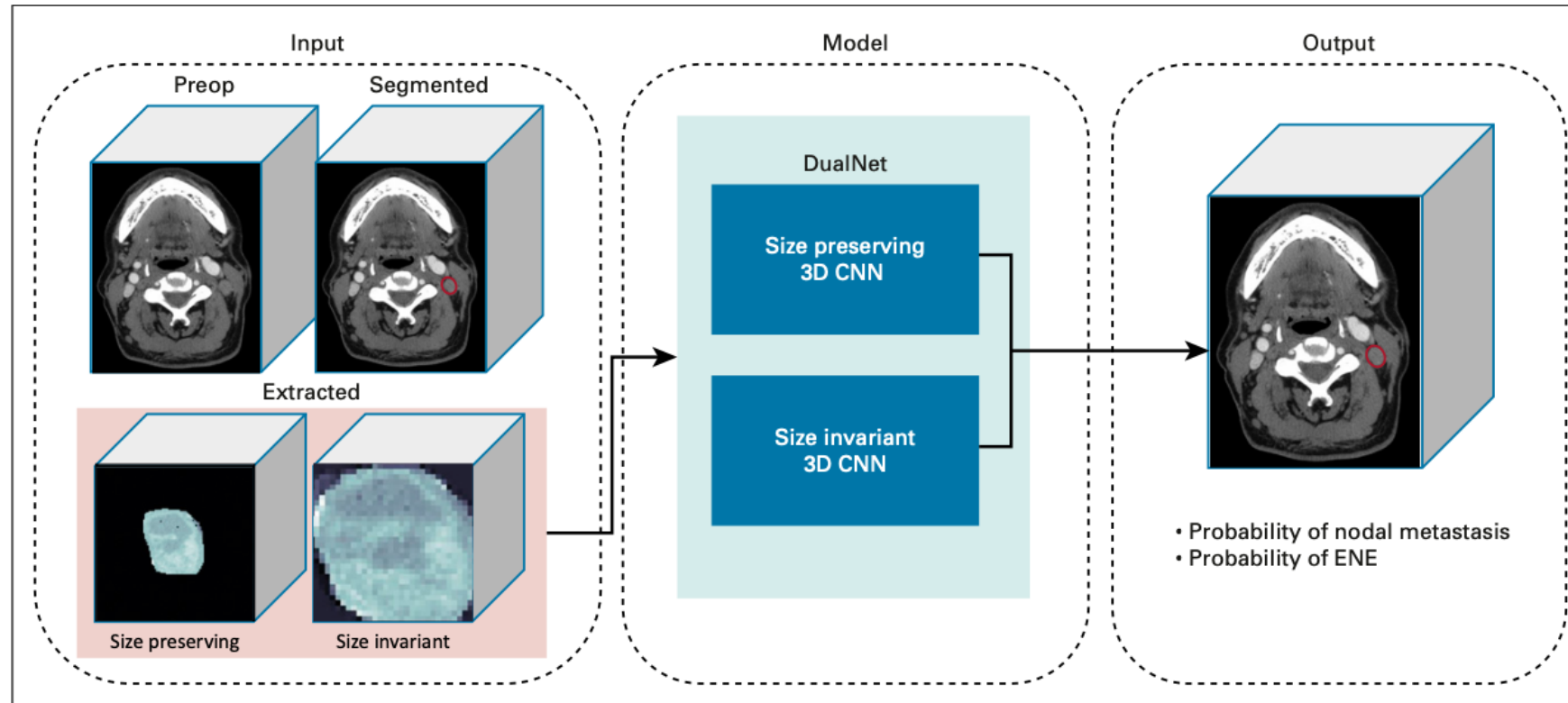
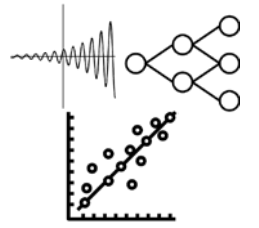


FIG 1. Deep learning algorithm framework. For each patient computed tomography scan, the algorithm uses 3-dimensional (3D) segmented lymph node region-of-interest inputs with two representations: a size-preserving input, and a size-invariant input. These inputs are fed into the DualNet 3D convolutional neural network (CNN), which outputs a probability of nodal metastasis and extranodal extension (ENE) for each input lymph node.

Imaging Biomarkers Lymph Node Classification



COMPARE MODEL
CANDIDATES
& GOLD STANDARD

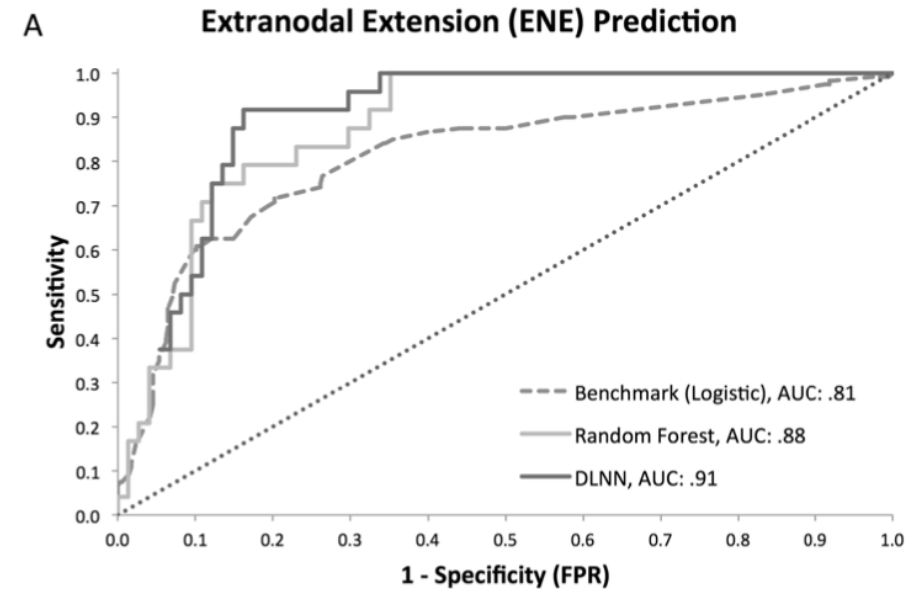
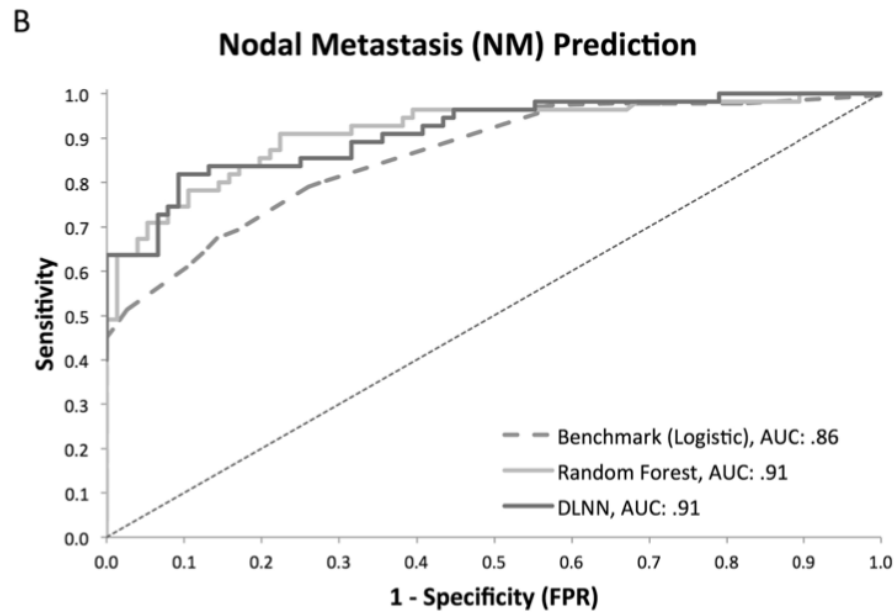


Figure 3. (A,B) Test Set ROC Curve Comparisons for Extranodal Extension (ENE) and Nodal Metastasis Prediction for Deep Learning Neural Network (DLNN), Radiomic Feature Random Forest, and Benchmark Logistic Model.

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EXTERNAL
VALIDATION



THE CANCER GENOME ATLAS

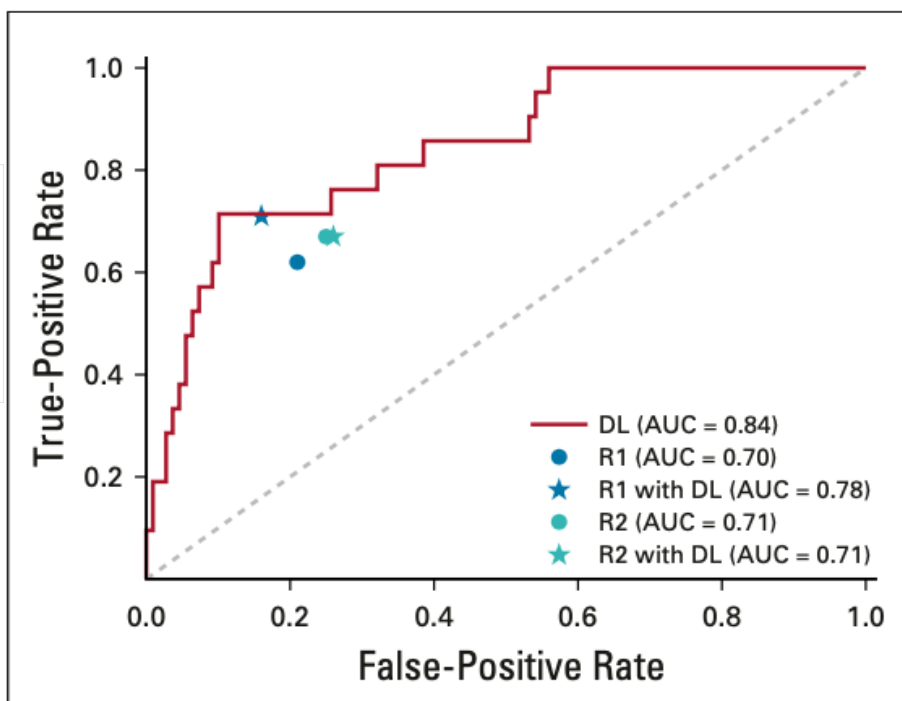


FIG 2. Receiver operating characteristic plots for extranodal extension identification for deep learning (DL [DualNet]) algorithm and radiologists (R1, R2): Mount Sinai Patients. AUC, area under the curve.

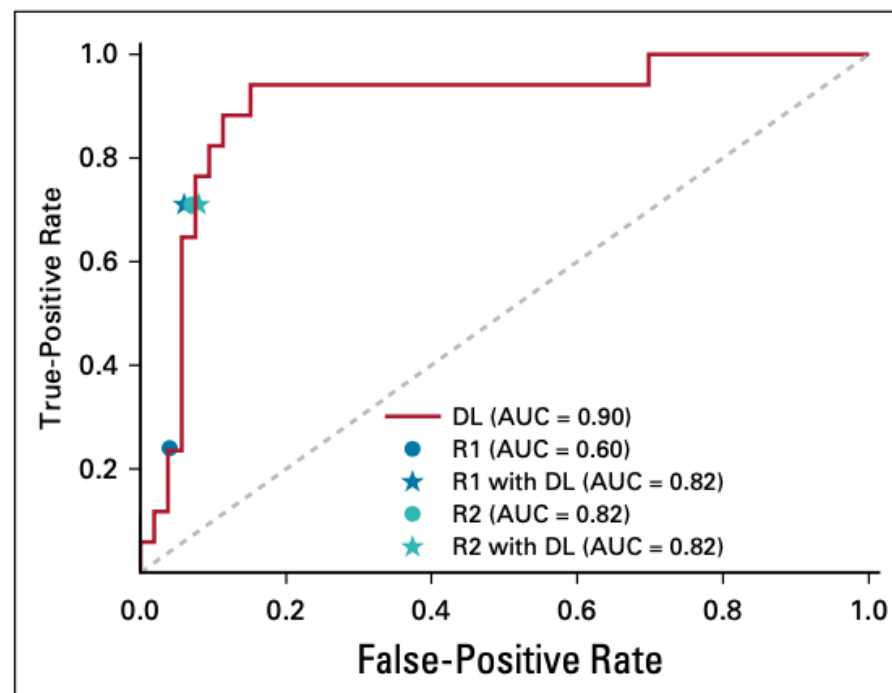


FIG 3. Receiver operating characteristic plots for extranodal extension identification for deep learning (DL [DualNet]) algorithm and radiologists (R1, R2): The Cancer Imaging Archive-The Cancer Genome Atlas patients.

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EXTERNAL
VALIDATION

TABLE 2. DL Algorithm Performance for ENE Identification and Radiologist Comparisons on External Test Sets

Performance Metric	Internal Test Set (n = 98)	Mount Sinai Validation (n = 130)				TCIA-TCGA Validation (n = 70)		
	DL	DL	R1	R2		DL	R1	R2
AUC (95% CI)	0.91 (0.86 to 0.96)	0.84 (0.75 to 0.93)	0.70 (0.59 to 0.82)	0.71 (0.60 to 0.82)		0.90 (0.81 to 0.99)	0.60 (0.49 to 0.71)	0.82 (0.71 to 0.94)
Accuracy, %	85.7	83.1	76.2	73.8		88.6	78.6	88.6
Sensitivity	0.88	0.71	0.62	0.67		0.82	0.24	0.71
Specificity	0.85	0.85	0.79	0.75		0.91	0.96	0.94
PPV	0.66	0.48	0.36	0.34		0.74	0.67	0.80
NPV	0.95	0.94	0.91	0.92		0.94	0.80	0.91
Youden index	0.73	0.56	0.41	0.42		0.73	0.20	0.65
Cohen κ score			0.43				0.29	

Abbreviations: AUC, area under the curve; DL, deep learning (DualNet algorithm); ENE, extranodal extension; NPV, negative predictive value; PPV, positive predictive value; R, radiologist.

TABLE 3. Radiologist Performance With DL Assistance

Performance Metric	Mount Sinai Validation		TCIA-TCGA Validation	
	R1 With DL	R2 With DL	R1 With DL	R2 With DL
AUC (95% CI)	0.78 (0.67 to 0.88)	0.71 (0.59 to 0.82)	0.82 (0.71 to 0.94)	0.82 (0.71 to 0.94)
Accuracy	82.3	73.1	88.6	88.6
Sensitivity	0.71	0.67	0.71	0.71
Specificity	0.84	0.74	0.94	0.94
PPV	0.47	0.33	0.80	0.80
NPV	0.94	0.92	0.91	0.91
Youden index	0.55	0.41	0.65	0.65
Cohen κ score		0.74		0.75

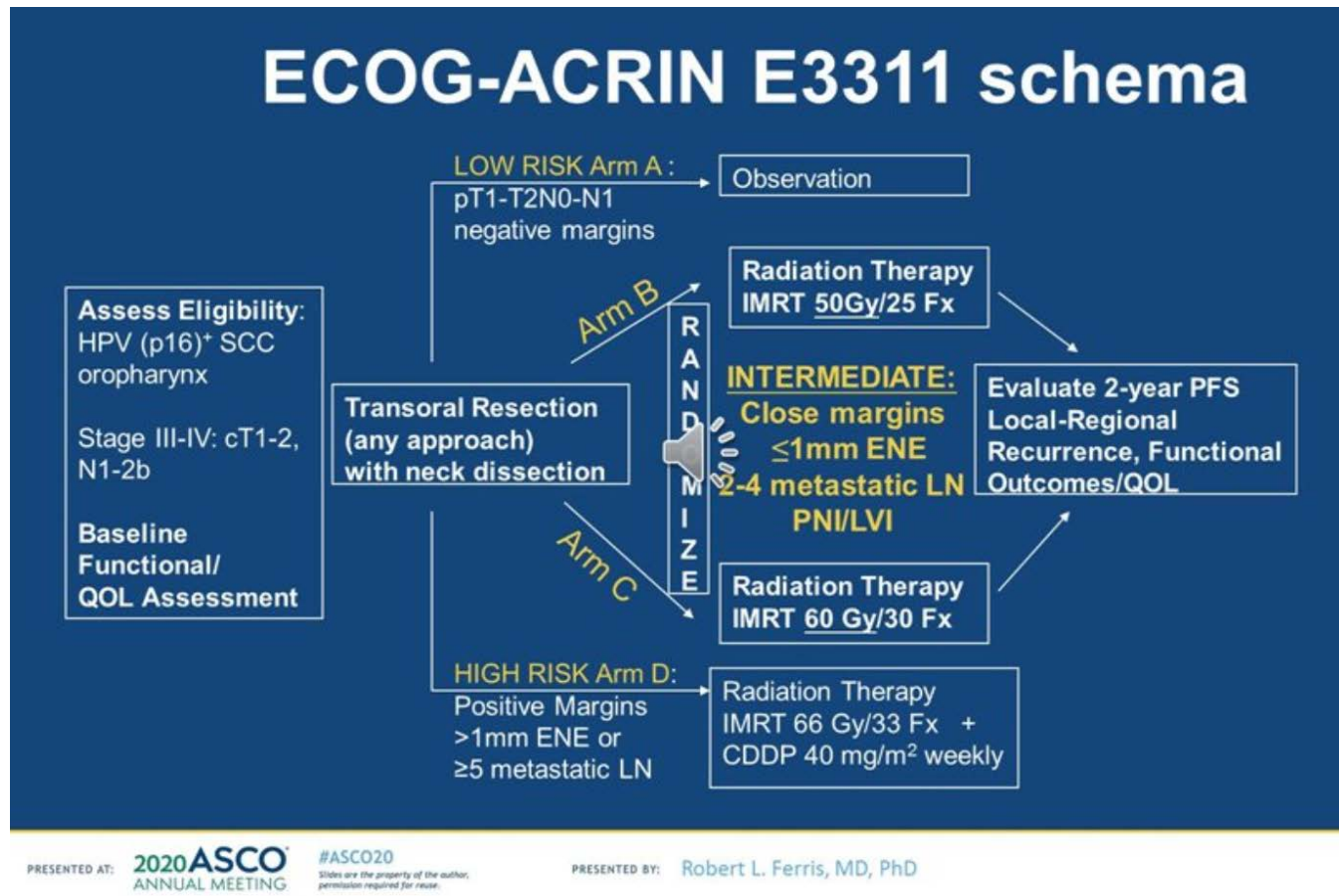
Abbreviations: AUC, area under the curve; DL, deep learning (DualNet algorithm); NPV, negative predictive value; PPV, positive predictive value; R, radiologist.

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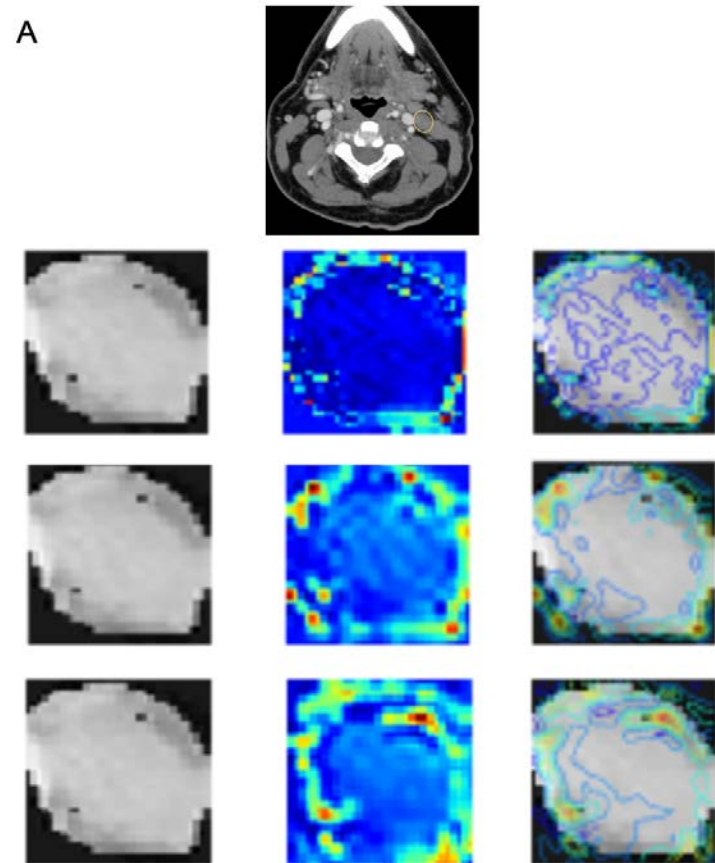
Lymph Node Classification



**SURVEILLANCE &
VULNERABILITY
STUDIES**



A



Final Thoughts

Quantitative imaging methods appear to have utility in clinical oncology

- Non-invasive risk stratification
- Clinical decision aids

Despite enthusiasm for machine learning methods, there are necessary steps before clinical implementation

- Rigorous external validation
- Interpretability and vulnerability studies

Questions

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Department of Statistics and Data Science

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