

# PHD IN INTELLIGENZA ARTIFICIALE IN MEDICINA E INNOVAZIONE NELLA RICERCA CLINICA E METODOLOGICA

**Coordinatore: Prof. Domenico Russo** 

Dipartimento di Scienze Cliniche e Sperimentali Viale Europa, 11 - 25123 Brescia, Italy

**XXXVIII Ciclo** 

Supervisor: Prof. Marco Fontanella

# OPTIMIZING PREOPERATIVE DIAGNOSIS AND TREATMENT OF PITUITARY ADENOMAS USING MACHINE LEARNING AND DEEP LEARNING ALGORITHMS: A RADIOMICS AND VIDEOMICS APPROACH

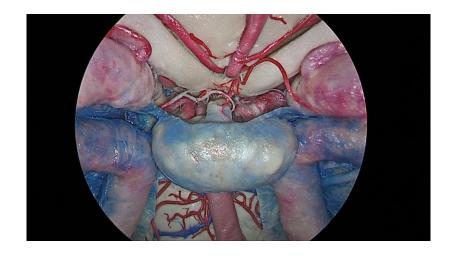
Edoardo Agosti, MD, PhDs<sup>1</sup>

<sup>&</sup>lt;sup>1</sup> Division of Neurosurgery, Department of Medical and Surgical Specialties, Radiological Sciences and Public Health, University of Brescia, Brescia, Italy

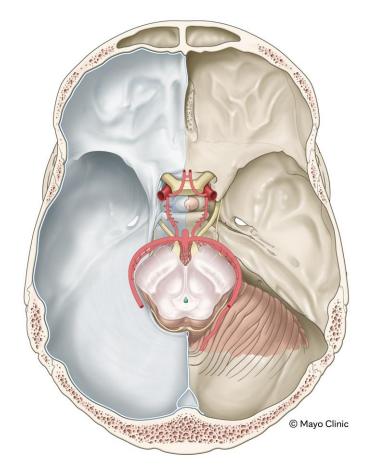


### **BACKGROUND**

- Sellar and parasellar regions are anatomically complex and contain vital neurovascular structures
- ➤ PAs are the most common tumors (15% of intracranial tumors, 85% of sellar and parasellar tumors)







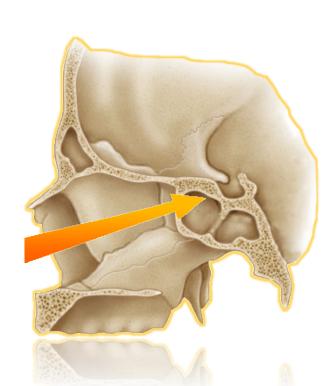


### **BACKGROUND**

Firstly MTAs, but now EEAs are commonly used for surgical treatment of PAs

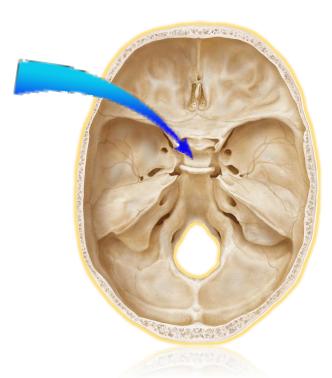














#### **BACKGROUND**

- > Pre- and intraoperative challenges require technological support and interdisciplinary collaboration
- ➤ AI, including ML and DL algorithms, is increasingly used in medical imaging to improve tumor diagnosis and treatment
- > Enhance:
- preoperative prediction of lesion features (consistency, relations with surrounding anatomy, histopathological and immunohistochemical patterns)
- intraoperative tumor detection



#### **BACKGROUND**

- ➤ Apply AI methods, specifically ML and DL algorithms, to enhance the diagnosis, endoscopic surgical treatment outcomes, and prognosis of **patients with PA**
- ➤ Radiomics → Preoperative assessment of PA features (i.e., consistency)
- Predict tumor relation with surrounding anatomy
- Minimize iatrogenic neurovascular injuries and postoperative CSF leaks
- ➤ Videomics → Real-time intraoperative detections of PA
- Reduce the risk of postoperative PA remnants
- Minimize iatrogenic neurovascular injuries and postoperative CSF leaks



### **PART 1: RADIOMICS FOR PAS**

# RADIOMICS FOR PREOPERATIVE ASSESSMENT OF PA CONSISTENCY WITH T2-WEIGHTED MRI: A MULTICENTER STUDY



#### **INTRODUCTION**

- > PA consistency can impact on surgical (i.e., EEA) outcome: softer tumors, easier to resect
- ➤ MRI could be a qualitative tool (e.g. T2-weighted and PA consistency prediction) to assess PA consistency

#### Prediction of Consistency of Pituitary Adenomas by Magnetic Resonance Imaging

Kyle A. Smith<sup>1</sup> John D. Leever<sup>2</sup> Roukoz B. Chamoun<sup>1</sup>

| Neurol Surg B 2015;76:340-343.

Address for correspondence Roukoz B. Chamoun, MD, Department of Neurosurgery, University of Kansas Medical Center, 3901 Rainbow Blvd., 3021, Kansas City, KS 66160, United States (e-mail: rchamoun@kumc.edu).

Tumor Consistency of Pituitary Macroadenomas: Predictive Analysis on the Basis of Imaging Features with Contrast-Enhanced 3D FIESTA at 3T

J. Yamamoto, S. Kakeda, S. Shimajiri, M. Takahashi, K. Watanabe, Y. Kai, J. Moriya, Y. Korogi and S. Nishizawa

AJNR Am J Neuroradiol 2014, 35 (2) 297-303

0148-396X/90/2605-0801\$02.00/0
NEUROSURGERY
Copyright © 1990 by the Congress of Neurological Surgeons

Printed in U.S.

### Is Magnetic Resonance Imaging Useful in Guiding the Operative Approach to Large Pituitary Tumors?

Robert B. Snow, M.D., Ph.D., Carl E. Johnson, M.D., Susan Morgello, M.D., Michael H. Lavyne, M.D., and Russel H. Patterson, Jr., M.D.

Divisions of Neurosurgery (RBS, MHL, RHP), Neuroradiology (CEJ), and Neuropathology (SM), The New York Hospital–Cornell Medical Center, New York, New York

Acta Neurochir (Wien) (1998) 140: 779-786

#### **MRI Prediction of Fibrous Pituitary Adenomas**

T. Iuchi, N. Saeki, M. Tanaka, K. Sunami, and A. Yamaura

Department of Neurological Surgery, Chiba University School of Medicine, Chiba, Japan

British Journal of Neurosurgery, October 2006; 20(5): 324-326

To assess the ability of MRI to predict consistency of pituitary macroadenomas

B. BAHULEYAN, L. RAGHURAM<sup>1</sup>, V. RAJSHEKHAR & A. G. CHACKO

Departments of Neurological Sciences and <sup>1</sup>Radiodiagnosis, Christian Medical College, Vellore, Tamil Nadu, India

### The Utility of Using Preoperative MRI as a Predictor for Intraoperative Pituitary Adenoma Consistency and Surgical Resection Technique

Jonathan J. Yun<sup>1</sup> Stephen J. Johans<sup>2</sup> Daniel J. Shepherd<sup>1</sup> Brendan Martin<sup>3</sup> Cara Joyce<sup>3</sup> Ewa Borys<sup>1,4</sup> A. Suresh Reddy<sup>5</sup> Chirag R. Patel<sup>1,5,6</sup> Anand V. Germanwala<sup>1,2,5,6</sup>

<sup>1</sup>Loyola University Chicago Stritch School of Medicine, Maywood, Illinois, United States

<sup>2</sup> Department of Neurological Surgery, Loyola University Medical Center, Maywood, Illinois, United States

<sup>3</sup>Clinical Research Office, Health Sciences Division, Loyola University Chicago, Maywood, Illinois, United States

<sup>4</sup>Department of Pathology, Loyola University Medical Center, Maywood, Illinois, United States

<sup>5</sup>Edward Hines, Jr. VA Hospital, Hines, Illinois, United States <sup>6</sup>Department of Otolaryngology, Loyola University Medical Center, Maywood, Illinois, United States

J Neurol Surg B 2020;81:651-658.

Address for correspondence Anand V. Germanwala, MD, Department of Neurological Surgery, Loyola University Medical Center, 2160 South First Avenue, Maywood, II. 60153, United States (e-mail: agermanwala@gmail.com).

<sup>&</sup>lt;sup>1</sup> Department of Neurosurgery, University of Kansas Medical Center, Kansas City, Kansas, United States

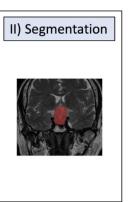
<sup>&</sup>lt;sup>2</sup> Department of Radiology, University of Kansas Medical Center, Kansas City, Kansas, United States

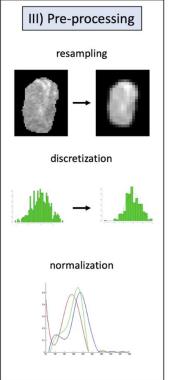


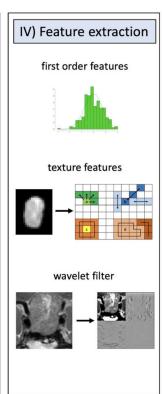
### **INTRODUCTION**

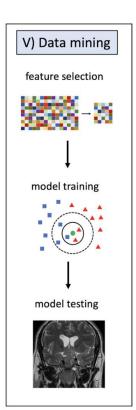
➤ Radiomics, an advanced imaging technique, transforms medical images into quantitative data, revealing tumor heterogeneity through texture analysis











The integration of **ML algorithms** into radiomics enhances predictive modeling, offering the potential to classify tumor consistency



### **OBJECTIVE**

- To assess the **performance** and **accuracy** of **radiomics-based models** trained with ML algorithms to **predict PA consistency** before endoscopic surgery using texture analysis from **T2-weighted MRI**
- ➤ Preoperatively predict **soft and fibrous** PA consistency, enhancing preoperative planning and reducing postoperative complications



### MATERIALS AND METHODS: Multicenter retrospective registry

- ➤ Ethical approval: Institutional Review Board (IRB-5924)
- ➤ Patients with **PA** who underwent **preoperative MRI** and **EEA** from January 2012 to December 2023
- Four centers included:
- University of Brescia, Spedali Civili of Brescia
- University of Naples "Federico II," University Hospital Federico II, Naples
- Ca' Foncello Hospital, Treviso
- University of Insubria, Circolo Hospital and Macchi Foundation of Varese



### MATERIALS AND METHODS: Multicenter retrospective registry

#### **Exclusion Criteria:**

- Pediatric patients
- Neoadjuvant RT or CT
- Other simultaneous sellar / parasellar lesions
- Extensive tumor necrosis or hemorrhage
- Significant MRI artifacts



### MATERIALS AND METHODS: MRI data acquisition

- ➤ MRI Equipment: 1.5T or 3T scanners from Philips (Gyroscan Intera) and Siemens (Magnetom Trio)
- ➤ MRI Protocol: Coronal T2-weighted Turbo Spin Echo (T2-w TSE) sequence

T2-w TSE s	necific aco	uisition	parameters
I WIDE	pooring acq	WIDI CIOII	parameters

	TR	TE	FOV	matrix	thk	ETL	Slice gap	Acquisition time
1.5 Tesla	2600 ms	89 ms	180x180 mm	288x288	3 mm	17	no gap	2 min 17 s
3 Tesla	3000 ms	98 ms	200x200 mm	384x384	3 mm	18	no gap	3 min 22 s

- Ensure consistent data for radiomics feature extraction
- Proven best sequence for radiomics prediction of tumor texture and heterogeneity

Neuroradiology https://doi.org/10.1007/s00234-019-02266-1

Prediction of high proliferative index in pituitary macroadenomas using MRI-based radiomics and machine learning

Lorenzo Ugga <sup>1</sup> · Renato Cuocolo <sup>1</sup> · Domenico Solari <sup>2</sup> · Elia Guadagno <sup>3</sup> · Alessandra D'Amico <sup>1</sup> · Teresa Somma <sup>2</sup> · Paolo Cappabianca <sup>2</sup> · Maria Laura del Basso de Caro <sup>3</sup> · Luigi Maria Cavallo <sup>2</sup> · Arturo Brunetti <sup>1</sup>

Neuroradiology (2020) 62:1649–1656 https://doi.org/10.1007/s00234-020-02502-z

Prediction of pituitary adenoma surgical consistency: radiomic data mining and machine learning on T2-weighted MRI

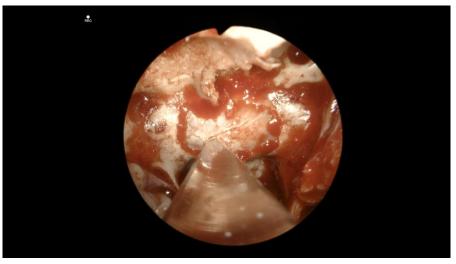
Renato Cuocolo<sup>1</sup> · Lorenzo Ugga<sup>1</sup> · Domenico Solari<sup>2</sup> · Sergio Corvino<sup>2</sup> · Alessandra D'Amico<sup>1</sup> · Daniela Russo<sup>1</sup> · Paolo Cappabianca<sup>2</sup> · Luigi Maria Cavallo<sup>2</sup> · Andrea Elefante<sup>1</sup>



### MATERIALS AND METHODS: Preoperative consistency assessment

- > Tumor consistency was independently assessed by two neurosurgeons (i.e., intraoperative report, surgical video)
- > The classification was based on intraoperative tumor texture and resistance to manipulation
- Soft PA: easily removed with standard surgical instruments like suction and curettage, deforming and fragmenting
- Fibrous PA: denser, requiring meticulous extracapsular dissection and microdissectors



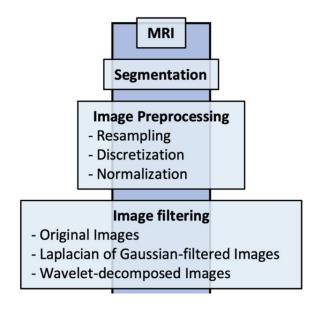




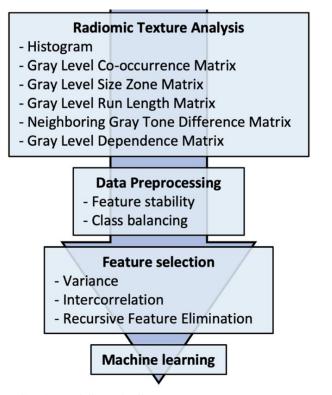
### MATERIALS AND METHODS: Radiomics analysis

> Description of the radiomics workflow pipeline

#### 1) Image processing



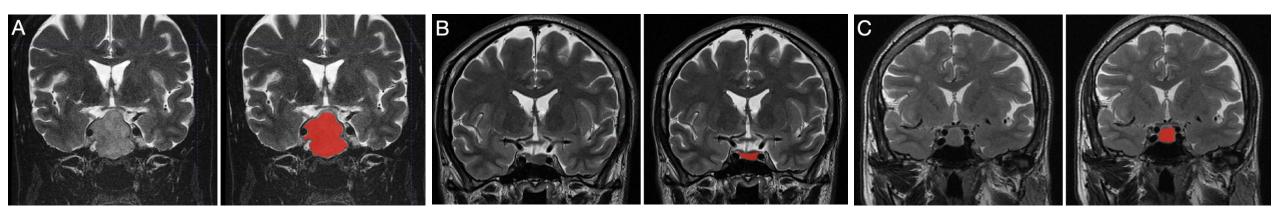
#### 2) Radiomics analysis





### MATERIALS AND METHODS: Imaging segmentation

- ➤ PA manual segmentation using ITK-SNAP software by one author
- Two additional authors independently repeated the segmentation to ensure unbiased and reproducible radiomic feature extraction



Case 1: Macro-PA Case 3: PA



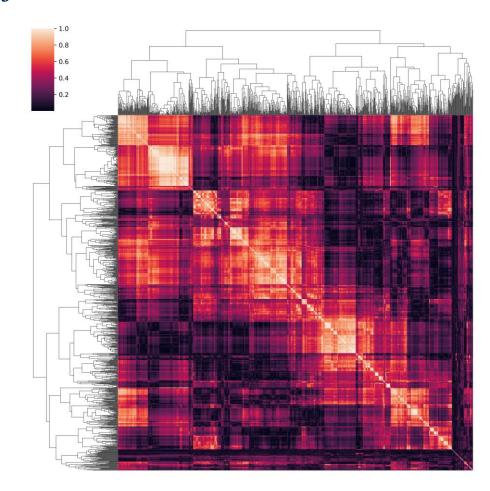
### MATERIALS AND METHODS: Radiomics analysis and ML algorithms

- ➤ Pyradiomics → image pre-processing and feature extraction
- ➤ Python → data processing
- Intraclass correlation coefficient (ICC)  $\rightarrow$  minimize inter-observer variability (threshold of  $\geq 1$  to confirm the consistency)
- Recursive Feature Elimination (RFE)  $\rightarrow$  select the most relevant features
- > SMOTE technique was applied to reduce class imbalance (rarity of fibrous PA)
- ➤ Model selected, Extra Trees (ET) classifier, was trained, estimating the AUC-ROC curve (classifier performance) and confusion matrix (classifier accuracy)



### **RESULTS:** Selected features

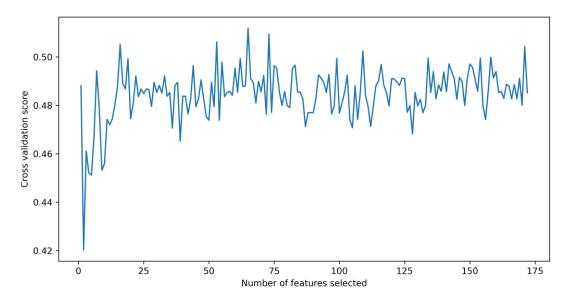
- ➤ 394 patients: 311 soft, 83 fibrous
- ➤ A total of 1,106 texture features were extracted
- > Features selection:
- Heatmap of the **correlation matrix** was produce using hierarchical clustering
- 767 features were selected showing **high ICC** (threshold  $\geq 1$ )





### **RESULTS:** Selected features

- ➤ Among these, 167 exhibited low variance
- > RFE subsequently identified a refined subset of 65 features as the most predictive

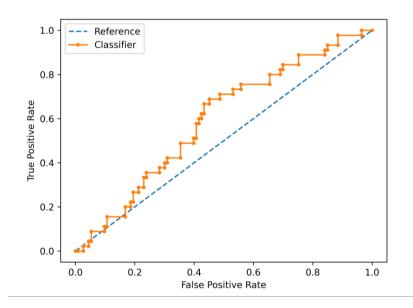


RFE plot: at each iteration, one feature is eliminated from the total number of features (x-axis); average cross-validation score for each feature total is shown on the y-axis



### RESULTS: ET classifier

➤ Model performance (AUC-ROC curve) was 0.59 with an accuracy of 63% (± 10%) in the test set



		Precision		F-score
Soft		0.74	0.74	0.74
Fibrous		0.36	0.36	0.36
Accuracy	Macro Avg	0.55	0.55	0.55
	Weighted Avg	0.63	0.63	0.63

Accuracy metrics for the ET classifier details

➤ Correctly classifying most lesions with a SE of 74% and a SP of 74%



### **CONCLUSION**

> T2-weighted MRI radiomics is a valid tool for preoperative prediction of PA consistency

> ET model provides modest classification performance and accuracy in distinguishing soft and fibrous PAs preoperatively



### **CONCLUSION**

- > Future perspectives to improve model accuracy and performance
- Objective methods to assess PA consistency intraoperatively  $\rightarrow$  E.g., elastography
- Further subcategorization of PAs → Fibrous, soft, and mixed
- DL approaches → Improve statistical power
- Automated segmentation methods → Reduce variability in tumor delineation



### **PART 2: VIDEOMICS FOR PAS**

# DEEP LEARNING FOR AUTOMATIC SEGMENTATION OF PITUITARY ADENOMAS: A VIDEOMICS STUDY



#### **INTRODUCTION**

- ➤ Videomics = Integration of AI (i.e., ML and DL algorithms) to video-endoscopy to enhance diagnostic accuracy (e.g. distinction of pathological from healthy tissue) by providing real-time video analysis during surgery
- > First application of videomics in videoendoscopy:
- GI lesions (Fig. 1)
- Laryngeal lesions (Fig. 2)

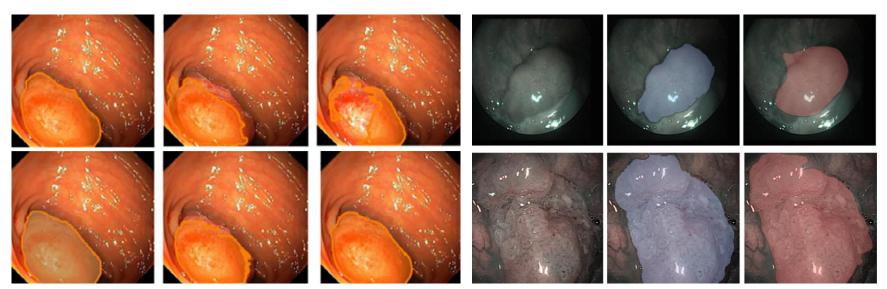


Fig. 1 Fig. 2



#### **INTRODUCTION**

- ➤ PA surgery (especially in final stages) pose unique challenges for accurate identification and differentiation of PA from healthy tissue:
- Technical issues: low contrast, obstructed views, or variable lighting
- Surgical issues: blood, fall of the arachnoid





#### **OBJECTIVE**

➤ Validate videomics techniques to create **models for automatic real-time intraoperative** recognition of PA

- > Translation to clinical applications, supporting surgeons in:
- Distinction of PA from other tissues
- Reduce the risk of intraoperative iatrogenic injury of neurovascular structures
- Reduce the risk of postoperative tumor remnants
- Enhance patient clinical outcomes



#### **MATERIALS AND METHODS**

#### Retrospective registry

- ➤ District Institutional Review Board (IRB-5925)
- ➤ Data were **retrospectively** collected from medical records of tertiary referring Institution (**Spedali** Civili, Brescia)
- > Inclusion criteria:
- Patients with histologically-confirmed PAs after EEA (January 2022 December 2023)
- Complete medical records, surgical documentation, and video-endoscopy
- **Exclusion Criteria:**
- Patients under 18 years of age
- Patients with a history of previous treatments for sellar or parasellar diseases
- Patients who had undergone prior treatments for PA or extensive tumor necrosis or hemorrhage



#### **MATERIALS AND METHODS**

#### Video-endoscopy data acquisition

➤ 0-degree **endoscope** (4 mm, 17.5 cm, Olympus Medical Systems Corporation) with both white light and NBI



➤ The endoscope was paired with CH-S400\_XZ-EB camera connected to an VISERA 4K UHD CLV-S400 light source (Olympus Medical Systems Corporation)



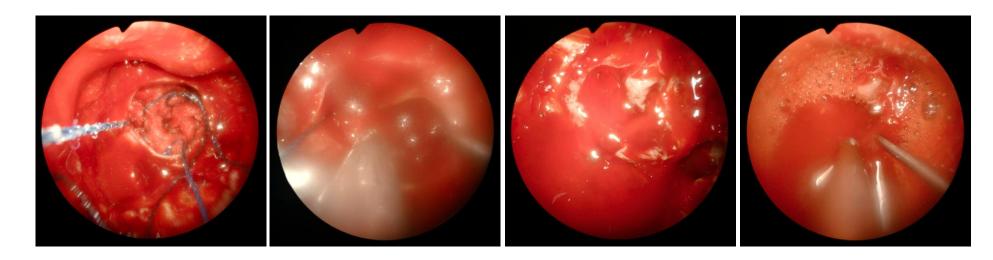




#### **MATERIALS AND METHODS**

#### Video-frames selection

- ➤ NBI video-frames were **manually selected** from PA video-endoscopies
- $\triangleright$  Video-frames dataset: 20 video-endoscopies  $\rightarrow$  35 video-frames per video  $\rightarrow$  700 video-frames
- Video-frames **exclusion criteria**: Out of focus, too dark, major bleeding, major interposition of cottonoids or other synthetic materials





#### **MATERIALS AND METHODS**

### Video-frames categorization

- ➤ Video-frames were randomly distributed into **3 subsets**:
- 80% for training
- 10% for validation
- 10% for testing
- ➤ Random distribution → Reduce selection bias



#### **MATERIALS AND METHODS**

#### Video-frames elaboration

➤ Preprocessing and augmentation techniques were applied to the selected video-frames to increase the effective dataset size

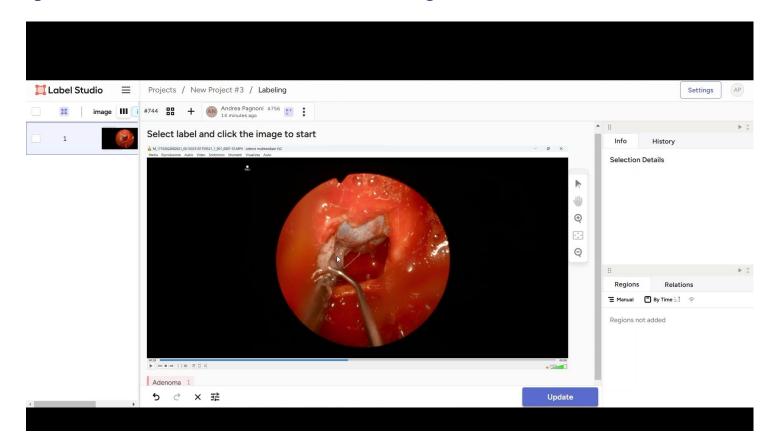
- Preprocessing: Images were resized using a fill method, incorporating a center crop to standardize dimensions to 640x640 pixels.
- Augmentation: Each image in the training set was augmented to generate five variants using the following transformations:
  - Flip: Horizontal and vertical flipping
  - Crop: 0% minimum zoom, 20% maximum zoom
  - Rotation: Between -15° and +15°
  - Hue: Between -20° and +20°
  - Saturation: Between -25% and +25%
  - Brightness: Between -15% and +15%
  - Exposure: Between -10% and +10%
  - Noise: Up to 1.68% of pixels



#### **MATERIALS AND METHODS**

#### PA segmentation on video-frames

➤ Video-frames were uploaded in **Label Studio** for semantic segmentation

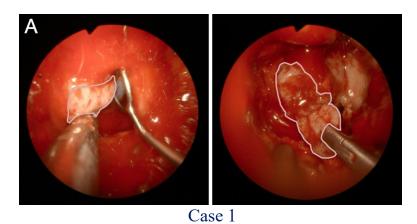




#### **MATERIALS AND METHODS**

#### PA segmentation on video-frames

The corresponding **masks** of the PA segmented were stored in **.json** format and used to train Fully Convolutional Neural Networks (FCNNs) for automatic segmentation (i.e., models for automatic segmentation)





Case 2

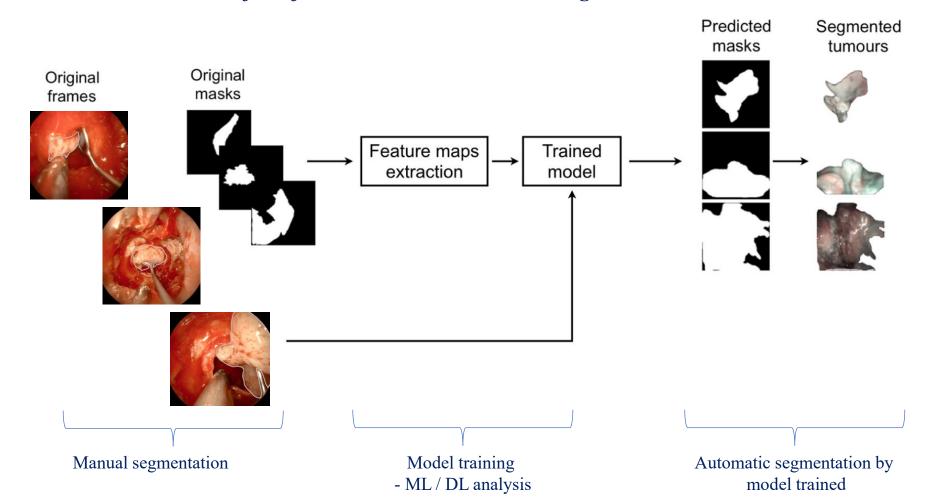
C

Case 3



#### **MATERIALS AND METHODS**

#### Workflow from manual to automatic segmentation models





#### **MATERIALS AND METHODS**

#### Automatic segmentation models selection

> Two DL frameworks were trained for image automatic segmentation:

#### 1) YOLO models $\rightarrow$ 6 models, including:

YOLOv8x-seg

• YOLOv9e-seg

• YOLOv8n-seg

YOLOv11x-seg

• YOLOv9c-seg

YOLOv11n-seg

### 2) MMDetection models $\rightarrow$ 3 models, including:

- Cascade Mask R-CNN 50
- Cascade Mask R-CNN 101
- Swin Transformer



#### **MATERIALS AND METHODS**

ML and DL analysis: Training set

- > All models were trained on an **NVIDIA RTX 3090 Ti GPU** software with:
- Adam optimizer protocol for YOLO models
- Stochastic Gradient Descent protocol for MMDetection models
- ➤ Model performance was assessed using the mean Average Precision (mAP) metric, calculated at an Intersection over Union (IoU) threshold of 0.5, as well as a weighted mAP across IoU values from 0.50 to 0.95
- Each model were trained for 100 epochs
- Epoch = complete pass through the entire training dataset



#### **MATERIALS AND METHODS**

ML analysis: Validation set and Test set

- ➤ Validation set (70 video-frames) → Monitor model overfitting
- Model performance was monitored across validation set, with **MMDetection** models showing overfitting beyond the **30th epoch**, indicated by increasing validation loss despite reduced training loss.
- To prevent overfitting, MMDetection models were truncated at 30 epochs
- While **YOLO** models had a more gradual training progression, their performance at 30 epochs was slightly lower than MMDetection models (truncated at **45 epochs**)
- ➤ Test set (70 video-frames) → Evaluate final model generalization, ensuring consistency and robustness



#### **MATERIALS AND METHODS**

#### Statistical analysis

- ➤ Models performance was evaluated against manual segmentation, using TP, TN, FP, and FN to calculate metrics like accuracy (Acc), recall (Rec), precision (Prec), and Dice Similarity Coefficient (DSC) to assess segmentation quality
- The **DSC** measured the **overlap between manual and automatic segmentations**, with values ranging from 0 (no overlap) to 1 (full overlap).
- The mAP was calculated as the average area under the Recall-Precision curve, and processing time for each frame was measured to assess tumor detection final performance.
- ➤ Statistical analyses, including the Kruskal-Wallis H-test, Mann-Whitney U test, ANOVA, and pairwise t-tests, were performed using Jupiter Notebooks to compare segmentation outcomes and identify significant differences between metrics at a significance level of 0.05



#### **RESULTS**

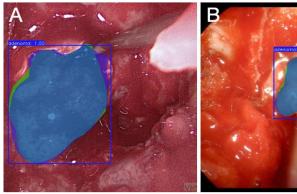
- ➤ YOLOv8x-seg (62 million parameters), was the top performer among YOLO models, with a validation box mAP[0.50] of 0.546, test segmentation mAP[0.50] of 0.921 and test mAP[0.50:0.95] of 0.509
- ➤ Cascade mask R-CNN 101 (135 million parameters), was the top performer among Cascade mask models, with a validation box mAP[0.50] of 0.610, test segmentation mAP[0.50] of 0.827 and test mAP[0.50:0.95] of 0.480
- Swin Transformer (70 million parameters), was the overall top performer model, with a validation box mAP[0.50] of 0.663, test segmentation mAP[0.50] of 0.911 and test mAP[0.50:0.95] of 0.601

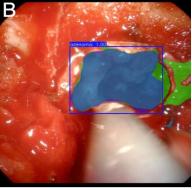
Model	N. params	Val box mAP	Val mAP[0.50]	Val mAP	Test mAP
YOLOv8x-seg	62M	0.546	0.921	0.579	0.509
YOLOv8n-seg	3M	0.536	0.827	0.466	0.452
YOLOv9c-seg	24M	0.629	0.919	0.554	0.483
YOLOv9e-seg	56M	0.116	0.216	0.070	0.000
YOLOv11x-seg	62M	NC	NC	NC	NC
YOLOv11n-seg	3M	0.600	0.882	0.513	0.480
C Mask R-CNN 50	77M	0.591	0.808	0.521	0.479
C Mask R-CNN 101	135M	0.610	0.827	0.550	0.480
Swin Transformer	70M	0.663	0.911	0.620	0.601

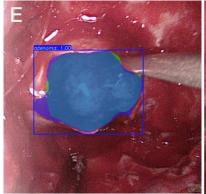


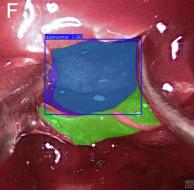
#### **RESULTS**

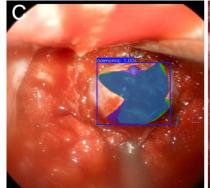
- The Swin Transformer model demonstrated strong **generalization capabilities** in recognizing a specific target, indicating the effectiveness of transformer-based models for automatic segmentation tasks
- Examples of six PA cases in which Swin Transformer model predicts PA localization in the surgical field:

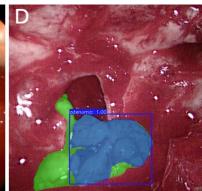






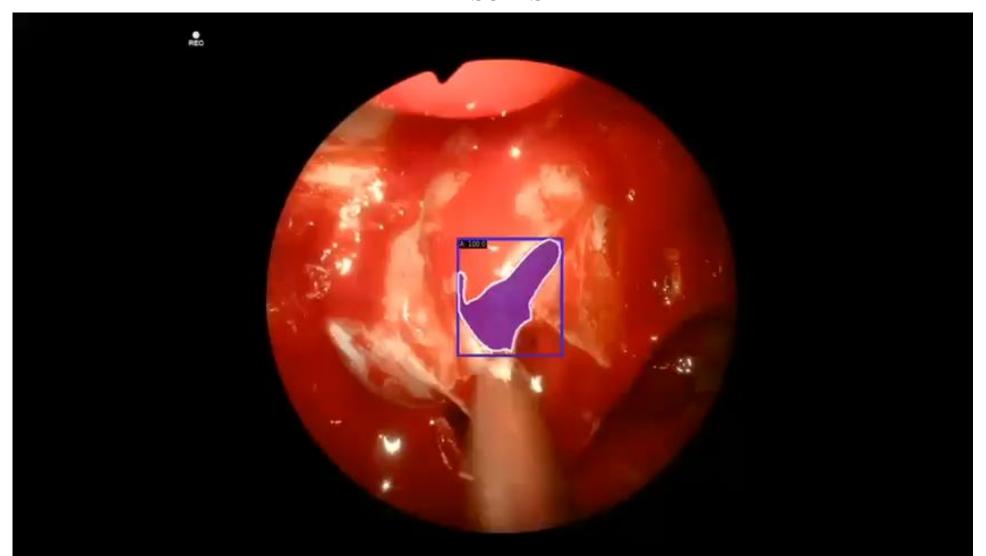








### **RESULTS**





#### **CONCLUSION**

This study demonstrated the **effectiveness** of a transformer-based model - **Swin Transformer** - for automatic segmentation of PAs, achieving the highest test mAP scores compared to YOLO and Mask R-CNN models

This model, with its advanced self-attention capabilities, allows for precise automatic segmentation and real-time detection of complex anatomical and pathological structures

➤ Ideal candidate for **clinical applications** in endoscopic endonasal PA surgery



#### Deep Learning for Automatic Segmentation of Pituitary Adenomas: A Videomics Study

Edoardo Agosti, MD<sup>1</sup>; Beshoy Guirges, BSc<sup>2</sup>; Francesco Carlo Tartaglia<sup>3</sup>; Andrea Pagnoni, BA<sup>1</sup>; Vittorio Rampinelli, MD, PhD<sup>4</sup>; Alessandro Fiorindi, MD, PhD<sup>1</sup>; Pier Paolo Panciani, MD, PhD<sup>1</sup>; Amedeo Piazza, MD<sup>5</sup>; Francesco Doglietto, MD, PhD<sup>6,7</sup>; Chris Holsinger, MD<sup>8</sup>; Cesare Piazza, MD<sup>4</sup>; Marco Maria Fontanella, MD<sup>1</sup>; Alberto Paderno, MD, PhD<sup>9</sup>

- <sup>1</sup> Division of Neurosurgery, Department of Medical and Surgical Specialties, Radiological Sciences and Public Health, University of Brescia, Brescia, Italy.
- <sup>2</sup> Department of Mathematics "Felice Casorati", University of Pavia, Pavia, Italy.
- <sup>3</sup> Department of Biomedical Sciences, Humanitas University, Milan, Italy.
- <sup>4</sup> Unit of Otolaryngology and Head and Surgery, ASST Spedali Civili di Brescia, University of Brescia, Italy.
- <sup>5</sup> Department of Neuroscience, Neurosurgery Division, "Sapienza" University of Rome, 00185 Rome, Italy.
- <sup>6</sup> Neurosurgery, Department of Neurosciences, Università Cattolica del Sacro Cuore, Rome, Italy.
- $^{7}$  Neurosurgery, Fondazione Policlinico Universitario Agostino Gemelli IRCCS, Rome, Italy.
- 8 Division of Head and Neck Surgery, Department of Otolaryngology, Stanford University, Palo Alto, California, USA.
- <sup>9</sup> Unit of Otorhinolaryngology, IRCCS Humanitas Research Hospital, Milan, Italy.

Radiomics for preoperative assessment of pituitary adenoma consistency with T2-weighted MRI: A multicenter study

Edoardo Agosti, MD<sup>1</sup>; Renato Cuocolo, MD, PhD<sup>2</sup>; Marcello Mangili, MS<sup>1</sup>; Vittorio Rampinelli, MD, PhD<sup>3</sup>; Pierlorenzo Veiceschi, MD<sup>4</sup>; Martina Cappelletti, MD<sup>5</sup>; Pier Paolo Panciani, MD, PhD<sup>1</sup>; Amedeo Piazza, MD<sup>6</sup>; Ilaria Bove, MD<sup>7</sup>; Domenico Solari, MD, PhD<sup>7</sup>; Luigi Maria Cavallo, MD, PhD<sup>7</sup>; Davide Locatelli, MD<sup>8</sup>; Francesco Doglietto, MD, PhD<sup>9,10</sup>; Alessandro Fiorindi, MD, PhD<sup>1</sup>; Marco Maria Fontanella, MD<sup>1</sup>; Lorenzo Ugga, MD, PhD<sup>11</sup>

- <sup>1</sup> Division of Neurosurgery, Department of Medical and Surgical Specialties, Radiological Sciences and Public Health, University of Brescia, Brescia, Italy.
- <sup>2</sup> Department of Medicine, Surgery and Dentistry, University of Salerno, Baronissi, Italy.
- <sup>3</sup> Unit of Otorhinolaryngology Head and Neck Surgery, ASST Spedali Civili, Department of Surgical and Medical Specialties, Radiological Sciences, and Public Health, University of Brescia, School of Medicine, Brescia, Italy.
- <sup>4</sup> Unit of Neurosurgery, ARNAS Ospedale Civico of Palermo, Palermo, Italy.
- <sup>5</sup> Unit of Neurosurgery, Ospedale Ca' Foncello, Treviso, Italy.
- <sup>6</sup> Department of Neuroscience, Neurosurgery Division, "Sapienza" University of Rome, 00185 Rome, Italy.
- Division of Neurosurgery, Department of Neurosciences, Reproductive and Odontostomatological Sciences, Università degli Studi di Napoli Federico II, Naples, Italy.
- <sup>8</sup> Division of Neurological Surgery, Department of Biotechnology and Life Sciences, University of Insubria-Varese, ASST Sette Laghi, Ospedale di Circolo e Fondazione Macchi, Varese, Italy.
- <sup>9</sup> Facoltà di Medicina e Chirurgia, Università Cattolica del Sacro Cuore, 00168 Rome, Italy.
- Neurosurgery, Department of Neuroscience, Fondazione Policlinico Universitario Agostino Gemelli IRCCS, 00168 Rome, Italy.
- Department of Advanced Medical and Surgical Sciences, University of Campania "Luigi Vanvitelli", P.zza L. Miraglia 2 80138 Naples, Italy



## Thank you

Email: edoardo\_agosti@libero.it

Twitter: @edoardo\_agosti