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**Optimizing Preoperative Diagnosis and Treatment of Pituitary Adenomas with Machine Learning
and Deep Learning Algorithms: A Radiomics and Videomics Approach**

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To my son Achille

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INTRODUCTION

Pituitary adenomas (PAs) represent one of the most prevalent intracranial tumors and still represent a challenge in skull base surgery due to their proximity to critical neurovascular structures. The advent of the endoscopic endonasal approach (EEA) has significantly improved visualization and surgical access to the sellar and parasellar regions. However, even in expert hands, intraoperative decision-making still relies heavily on the surgeon's experience, subjective interpretation of imaging, and subtle visual cues during tumor removal. These limitations underscore an urgent need for objective, reproducible, and data-driven tools capable of enhancing diagnostic precision and guiding surgical strategy.

In parallel with these clinical demands, artificial intelligence (AI) has rapidly evolved as a transformative force in modern medicine. Within neurosurgery, AI-based technologies now offer unprecedented opportunities to analyze complex, multimodal data and to uncover imaging patterns beyond the limits of human perception. Two of the most promising AI-driven methodologies applied to skull base surgery are radiomics and videomics. Radiomics enables the extraction of high-dimensional quantitative features from conventional magnetic resonance imaging (MRI), supporting tumor characterization, prediction of invasiveness, histotype classification, and preoperative assessment of tumor consistency. Videomics extends AI analysis into the operative field, leveraging deep learning-based computer vision to interpret endoscopic video in real time, facilitating tissue recognition, anatomical segmentation, and identification of residual adenoma during surgery.

The overarching purpose of this doctoral thesis is to explore, develop, and validate AI-based imaging strategies that augment the diagnostic and intraoperative management of PAs. In details, through a combined radiomics and videomics framework, this work aims to improve the precision of preoperative imaging evaluation, define imaging biomarkers predictive of surgical difficulty and oncological behavior, and enhance intraoperative visualization through automated recognition of PA. These parallel lines of research are supported by a strong anatomical foundation derived from extensive cadaveric dissections and by multicentric collaborations with neurosurgical and AI

laboratories in Italy and abroad.

By integrating quantitative MRI analysis with real-time computer vision applied to surgical videos, this thesis proposes a comprehensive, multimodal AI strategy for PA surgery. The findings presented here contribute to the evolving field of intelligent neurosurgery, paving the way for more objective, personalized, and technology-assisted approaches to skull base disease management.

PHD FLOW ACTIVITY

The rapid evolution of AI in medicine is transforming the way complex diseases are studied, diagnosed, and treated. In skull base pathology AI is emerging as a powerful instrument capable of providing objective, reproducible, and clinically actionable insights. From the beginning of this PhD program, my research has been positioned at the intersection of neurosurgery, medical imaging, and computer science, aiming to validate the role of machine learning (ML) and deep learning (DL) algorithms in the diagnosis and surgical management of PAs.

The initial years of my doctoral work allowed me to acquire a solid foundation in the principles of AI applied to medicine, including radiomics, videomics, classical ML pipelines, and state-of-the-art DL architectures such as convolutional neural networks (CNNs), Mask R-CNN, and transformer-based models. A significant portion of the project focused on validating the use of radiomic signatures for the prediction of clinically meaningful features of PAs, such as consistency and cavernous sinus invasion. This work required not only technical expertise in advanced data mining and feature extraction, but also rigorous methodological planning to ensure the reliability of multicentric retrospective datasets and the stability of radiomic features across segmentations.

In parallel, my PhD contributed to the formal development of videomics, an emerging field that applies advanced computer vision and DL-based segmentation and classification models to intraoperative endoscopic videos. Building the conceptual framework of videomics required an extensive review of the international literature, the

definition of methodological standards, and the creation of one of the first multicentric video-endoscopic registries dedicated to PAs. This effort was supported by collaborations with both national and international AI laboratories, including the University of Naples Federico II, other Italian research groups specializing in biomedical engineering, and international partners involved in computer vision research, such as Stanford University.

Beyond data acquisition, this PhD has required the establishment of a broad collaborative network spanning neurosurgical, radiological, engineering, and computational disciplines. Multicentric contributions from institutions across Italy (Brescia, Naples, Varese, Treviso, Salerno) and international centers enriched the radiomics and videomics datasets, ensured methodological robustness, and fostered the cultural exchange necessary to address the complexity of skull base pathology through interdisciplinary strategies. Technical collaborations with AI laboratories abroad enabled the development, training, and benchmarking of DL models on high-performance computing infrastructures, ultimately improving model accuracy and interpretability.

In addition, the anatomical expertise matured throughout the years, supported by extensive cadaveric dissections performed in Italian and U.S. laboratories, provided a crucial anatomical foundation for interpreting videomics data, understanding intraoperative variability, and developing DL models grounded in surgical reality rather than purely theoretical datasets.

Overall, this PhD journey has progressively consolidated the scientific basis for integrating AI into skull base surgery. The work presented in this thesis synthesizes the results of three years of multidisciplinary study, spanning radiomics, videomics, DL model development, multicentric data collection, and collaborative research.

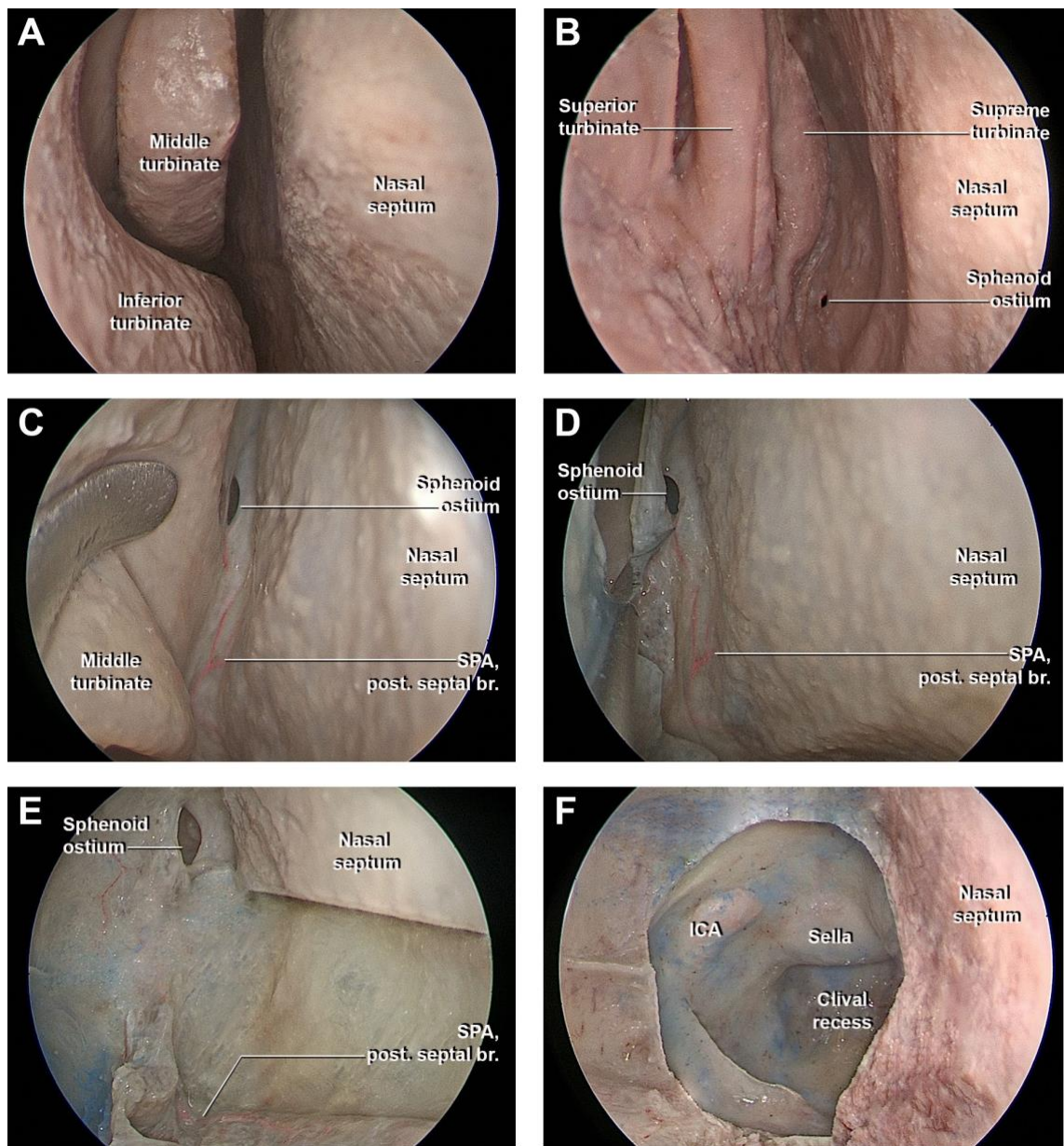
1. BACKGROUND

1.1 PRECLINICAL ANATOMICAL STUDY OF RELEVANT SURGICAL ANATOMY

A rigorous understanding of the complex anatomy of the sellar, parasellar, and skull base regions is a prerequisite for the safe and effective execution of EEAs. Within the framework of this doctoral project, a comprehensive preclinical anatomical investigation was undertaken to elucidate the endoscopic relationships that define these approaches. This work served not only to refine surgical expertise but also to establish a high-quality anatomical foundation for subsequent radiomics and videomics analyses, ensuring that all computational models developed later in the thesis were grounded in an accurate representation of endonasal surgical reality.

To replicate the operative environment and reproduce the visual and technical conditions encountered during videoendoscopic surgery, approximately thirty human cadaveric head specimens were meticulously dissected. These dissections were performed at two internationally recognized facilities: the Anatomical Training Center of the University of Brescia (Italy) and the Rhoton Surgical Anatomy Laboratory at the Mayo Clinic in Rochester, Minnesota (USA). All specimens were formalin-fixed and latex-injected using a standardized six-vessel technique to enhance the visualization of arterial and venous structures. A full set of rigid endoscopes (0°, 30°, and 45°; 4 mm, 18 cm, Hopkins II, Karl Storz, Tuttlingen, Germany) connected to a high-definition video system was used, together with standard microsurgical instruments and dedicated skull base equipment. Each dissection, performed entirely by the candidate, proceeded following a systematic step-by-step methodology designed to document every anatomical layer and surgical corridor with maximal clarity. Dissections were repeated until an optimal level of exposure and documentation was achieved. All completed specimens underwent high-resolution 3D photo-documentation through endoscopic imaging,

enabling the creation of a structured repository of anatomical landmarks and surgical variants (**Figures 1-5**).



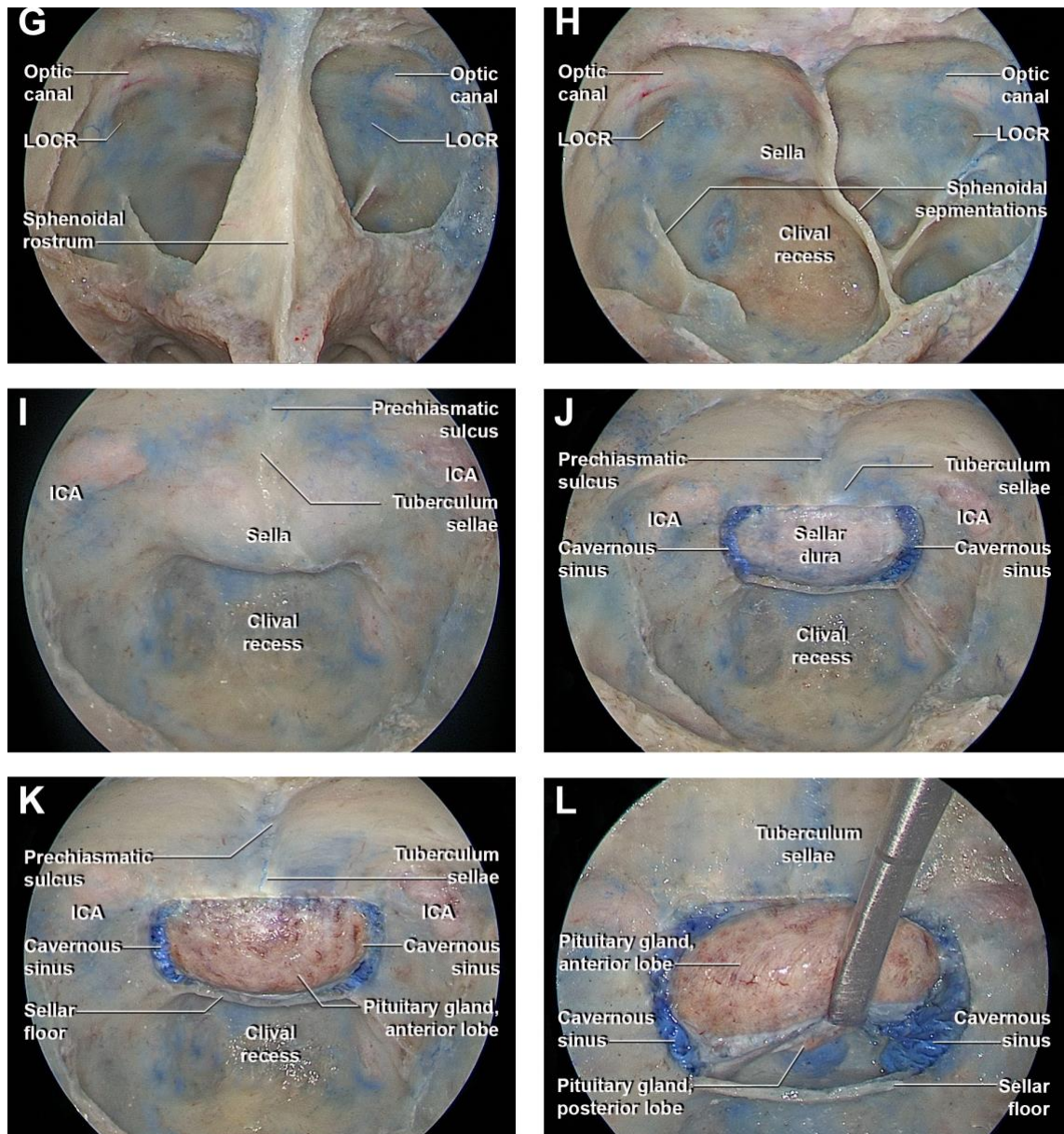
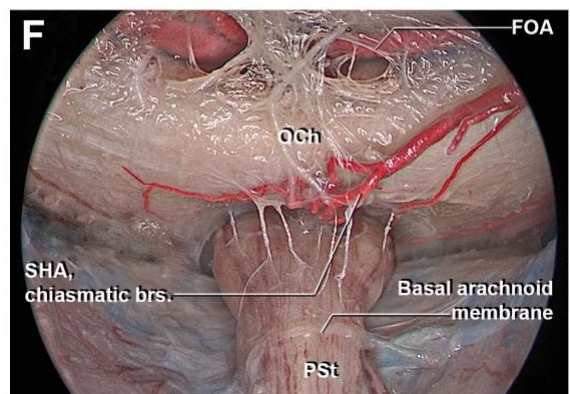
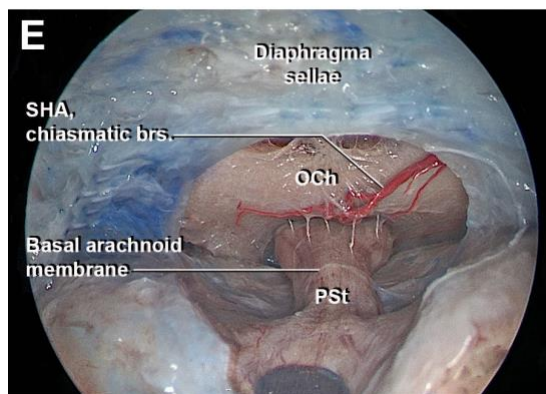
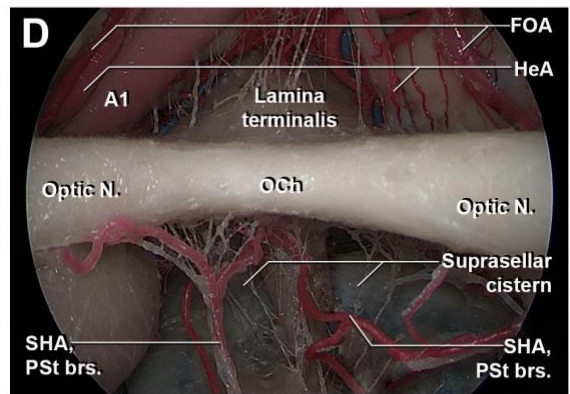
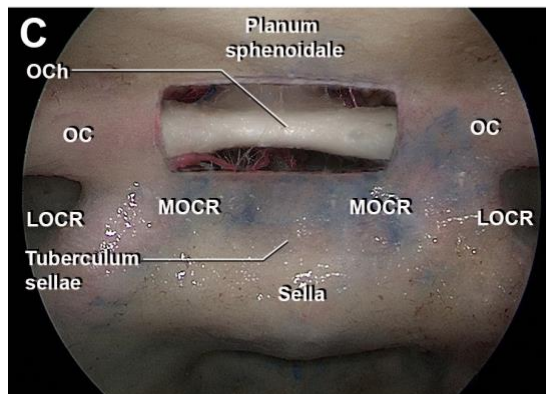
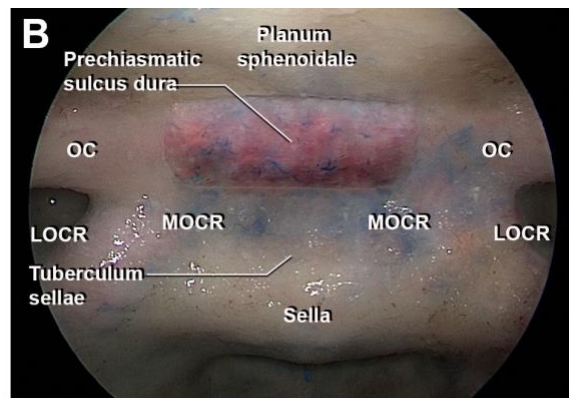
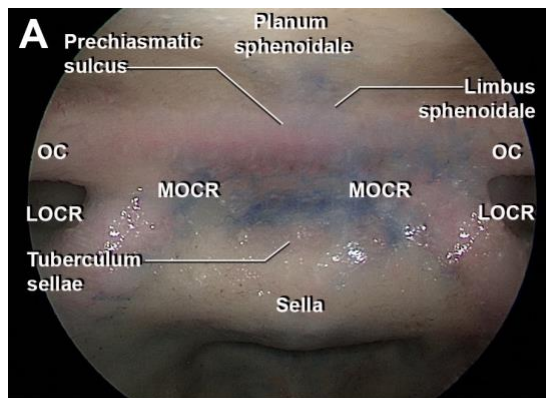


Figure 1 Stepwise dissection of the endoscopic endonasal transsphenoidal transsellar approach. (A) The 0-degree endoscope is inserted in the nasal cavities along the middle nasal corridor. The middle nasal corridor is bounded by bulbous portion of the middle turbinate laterally and the nasal septum medially. (B) The middle turbinate is gently lateralized, and, proceeding posteriorly through middle nasal corridor, the superior turbinate is identified. The sphenothmoidal recess is the space between the superior turbinate and the anterior wall of the sphenoid sinus, whose size varies according to the degree of pneumatization of the bulbous part of the superior turbinate. Superomedially to the superior turbinate, the supreme turbinate, if present, can be identified protruding into the sphenothmoidal recess. The sphenoid ostium is localized between the superior turbinate and the nasal septum. (C) The posterior septal branch of the sphenopalatine artery is localized in the sphenothmoid recess. It travels from lateral to medial between the sphenoid ostium superiorly and choana inferiorly, ultimately vascularizing the nasal septum. (D) The superior and supreme turbinates are removed. The rescue flap is harvested by a horizontal incision that starts in the inferior margin of the sphenoid ostium and proceeds anteriorly along the nasal septum. (E) The rescue flap is completed

by detaching and flipping down the mucosa from the nasal septum and anterior wall of the sphenoid sinus. (F) The anterior wall of the sphenoid sinus up to the sphenoid floor caudally, the planum sphenoidale and the laminar portion of the superior turbinate cranially, the sphenoid rostrum medially, and the posterior ethmoid laterally. (G) The anterior wall of the sphenoid is removed on the other side and a selective posterior septectomy is then performed between the sphenoid rostrum and perpendicular plate of the ethmoid bone, providing communication between two nasal cavities. (H) The sphenoidal septa are drilled flush with the posterior wall of the sphenoid sinus. (I) The bony landmarks of the posterior wall of the sphenoid sinus are exposed, including the sella, LOCR, MOCR, carotid protuberance, tuberculum sella, prechiasmatic sulcus, limbus sphenoidalis, planum sphenoidalis, and optic canals. (J) The bone covering the pituitary gland is fractured and removed from the tuberculum sellae superiorly to the sellar floor inferiorly. The bony removal is taken bilaterally until the medial portion of the anterior wall of the cavernous sinus is exposed. A C-shaped periosteal incision based superiorly is initiated with an inferior horizontal cut, followed by bilateral vertical cuts. (K) The periosteum covering the pituitary gland is removed and the anterior lobe of the pituitary gland is exposed. (L) By dissecting the corridor between the inferior margin of the pituitary gland and sellar floor, a limited exposure of the dorsum sellae is provided. The posterior lobe of the pituitary gland is visualized just anterior to the dorsum sellae. br.: branch, ICA: internal carotid artery, LOCR: lateral optic-carotid recess, post.: posterior, SPA: sphenopalatine artery.



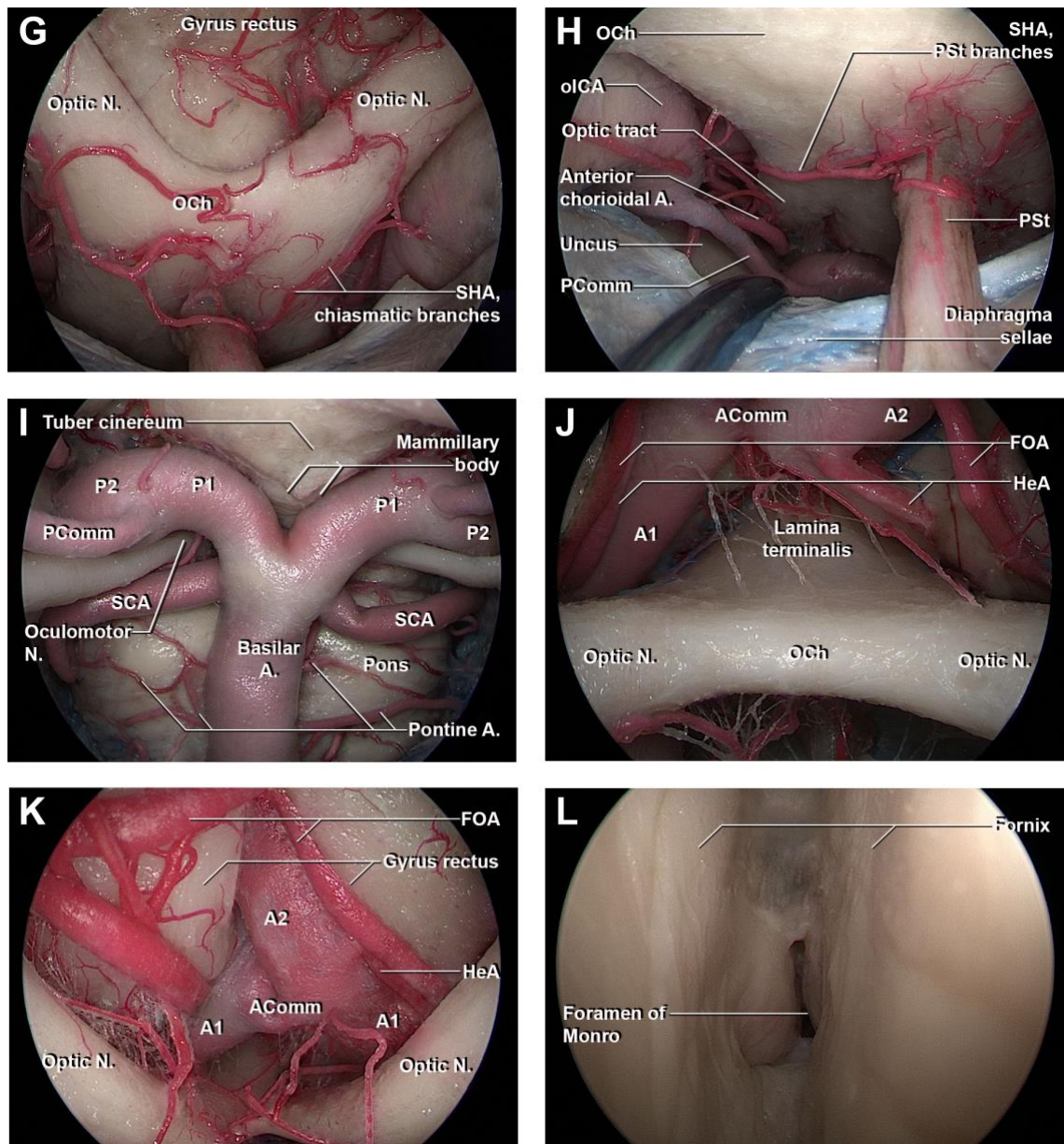


Figure 2 Endoscopic endonasal view of the suprachiasmatic and infrachiasmatic corridors from a selective removal of the prechiasmatic sulcus. (A) After the transsphenoidal approach has been finalized, with a 0-degree optic the prechiasmatic sulcus is identified on the posterior wall of the sphenoid sinus between the tuberculum sellae inferiorly and the planum sphenoidale superiorly. (B) A targeted osteotomy of the prechiasmatic sulcus is performed and the underlying dura is exposed. (C) The dura is incised and removed, exposing the chiasmatic cistern. (D) Within the suprasellar cistern, chiasmatic branches of the superior hypophyseal artery travel along the inferior surface of the optic chiasm and continue posteriorly and anteriorly, providing much of the vascularization of the optic chiasm and intracranial portion on the optic nerves. (E), view inferior to the sellar diaphragm. (F) The infrachiasmatic corridor is accessed and the anatomical details of the arachnoid membranes can be observed. The basal arachnoid membrane lies on the diaphragma sellae. It limits inferiorly the suprasellar cistern and wraps the base of the pituitary stalk. The pituitary stalk and superior hypophyseal arteries can be seen. (G) A 30-degree optic is positioned in the preinfundibular space and pointed superiorly, elucidating the superior hypophyseal arteries as they vascularize

the inferior portion of the optic chiasm. (H) After dissecting the cisternal arachnoid trabeculae of the suprasellar cistern posteriorly, access to the interpeduncular cistern is gained. The interpeduncular cistern is limited by the dorsum sella and mesencephalic leaf of the Liliequist's membrane inferiorly, the mammillary bodies and tuber cinereum posteriorly, posterior communicating arteries and oculomotor nerves laterally, and the diencephalic leaf of the Liliequist's membrane superiorly. (I) After the mesencephalic leaf of the Liliequist's membrane and the prepontine membrane have been removed, a 45-degree optic is pointed inferiorly. This maneuver allows to see vascular structures including the distal portion of the basilar artery and basilar tip, pontine arteries, and anterior pontomesencephalic and lateral pontomesencephalic segments of the superior cerebellar arteries. (J) Moving along the suprachiasmatic corridor, the cistern of the lamina terminalis is accessed. (K) Pointing a 30-degree optic superiorly, the fronto-orbital arteries, pre-communicating tract of the anterior cerebral arteries, anterior communicating artery, post-communicating tract of the anterior cerebral arteries, and recurrent arteries of Heubner are progressively identified. (L) View of the third ventricle after fenestration of the lamina terminalis. A.: artery; A1: pre-communicating segment of the anterior cerebral artery, A2: post-communicating segment of the anterior cerebral artery, AComm: anterior communicating artery, brs.: branches, FOA: fronto-orbital artery; HeA: recurrent artery of Heubner, LOCR: lateral optic-carotid recess, MOCR: medial optic-carotid recess, N.: nerve; OC: optic canal, OCh: optic chiasm, P1: pre-communicating segment of the posterior cerebral artery, P2: post-communicating segment of the posterior cerebral artery, PComm: posterior communicating artery, PSt: pituitary stalk, SCA: superior cerebral artery, SHA: superior hypophyseal artery.

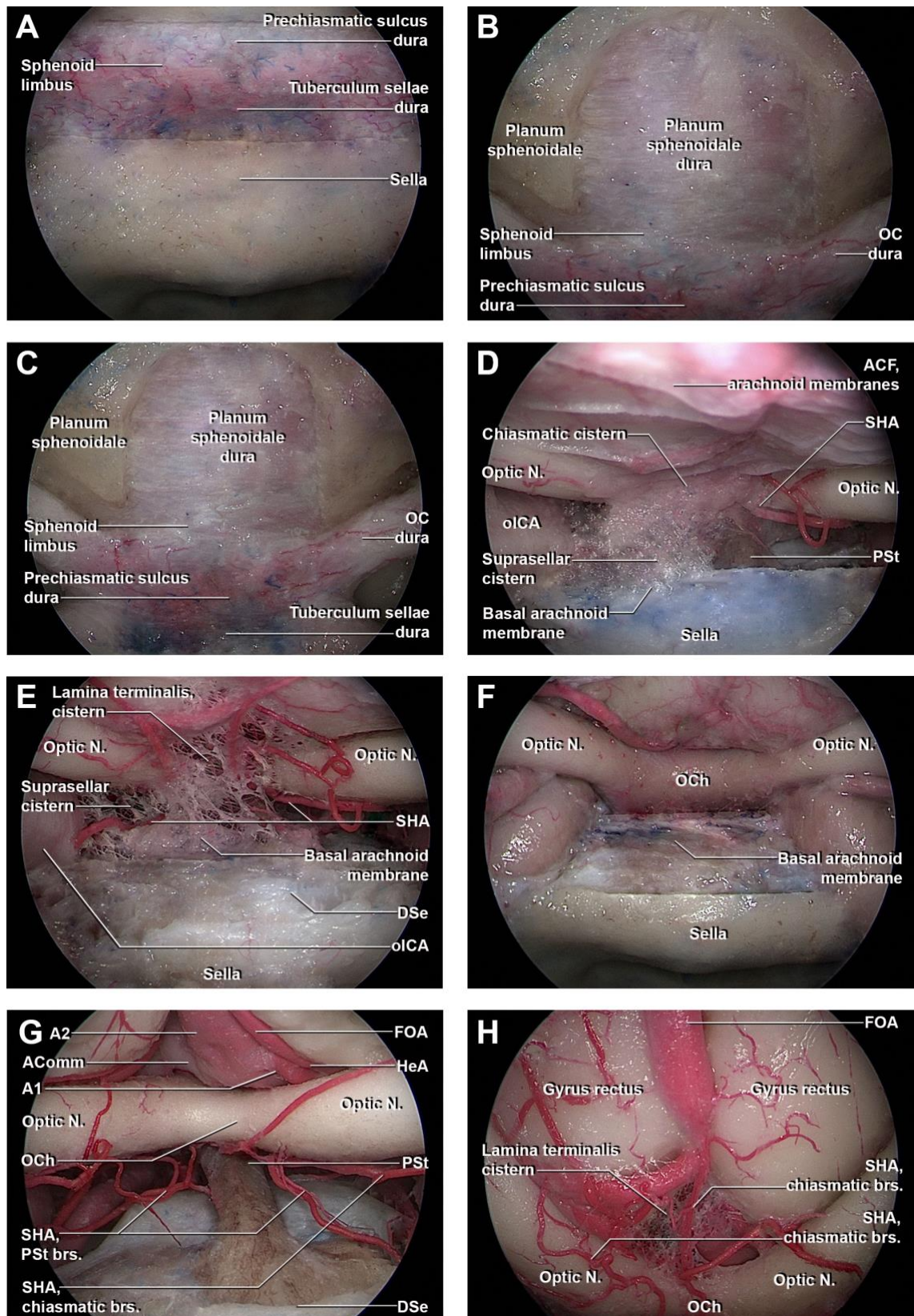
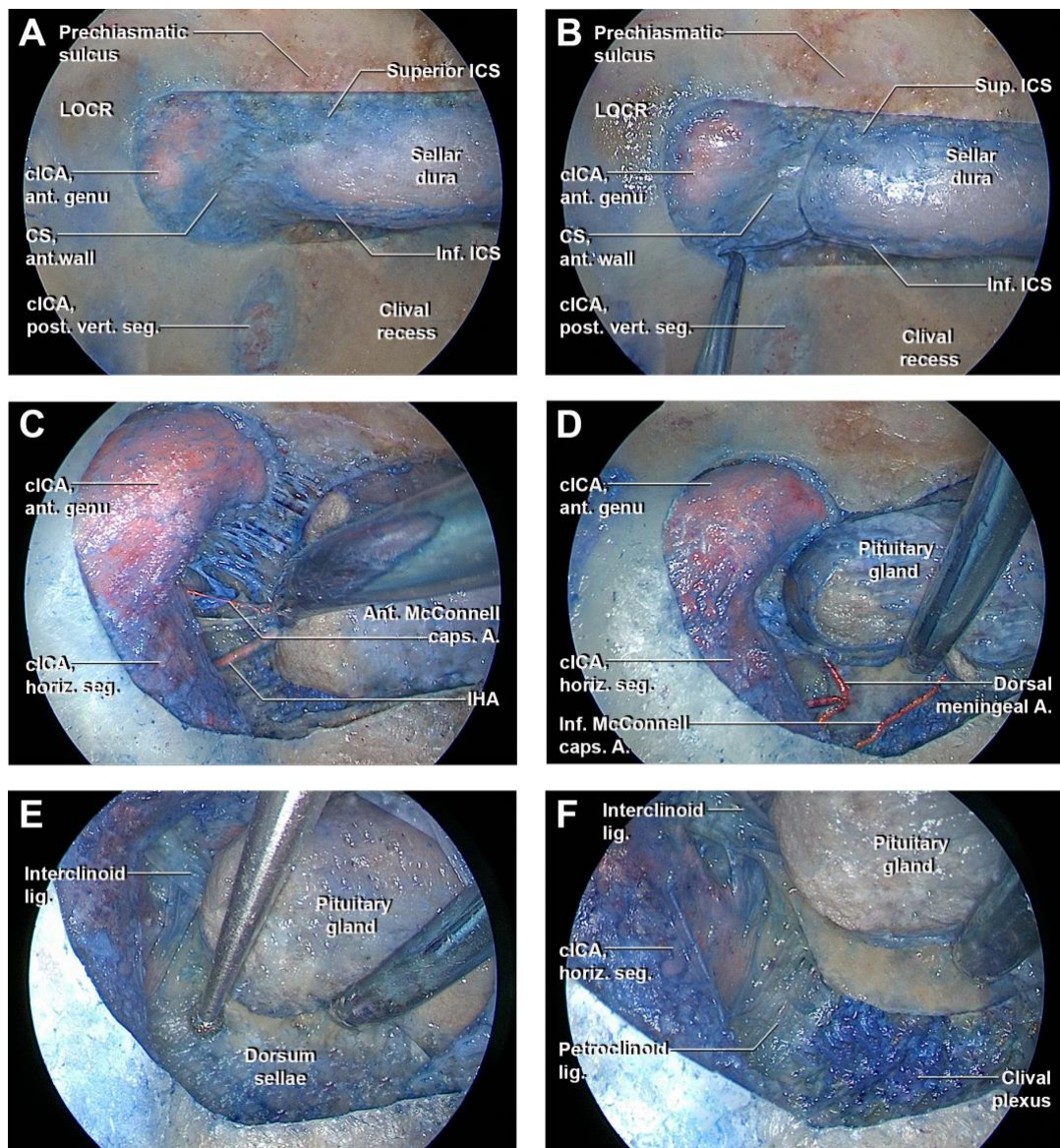


Figure 3 Endoscopic endonasal stepwise dissection of the transtuberculum transplanum approach. (A) The tuberculum sellae is removed. (B) Subsequently, with the aid of a 30-degree scope, the osteotomy is extended to the planum sphenoidale, exposing the underlying dura. (C) The dura is gently incised and removed, and the arachnoid membranes of the chiasmatic and suprasellar cisterns are exposed. (D) The dissection

of the suprasellar cistern proceeds along the infrachiasmatic corridor. (E) Branches of the superior hypophyseal artery supplying the optic chiasm and pituitary stalk are gently dissected from the arachnoidal trabeculae and isolated. (F) By turning a 30-degree optic superiorly, the intracranial vascular structures exposed by the transplanum approach can be visualized, including the proximal and distal course of the fronto-orbital arteries and the anterior cerebral artery complex. A.: artery, A1: pre-communicating tract of the anterior cerebral artery, A2: post-communicating tract of the anterior cerebral artery, ACF: anterior cranial fossa, AComm: anterior communicating artery, brs.: branches, DSe: diaphragm sellae, FOA: fronto-orbital artery, HeA: recurrent artery of Heubner, N.: nerve, OC: optic canal, OCh: optic chiasm, oICA: ophthalmic segment of the internal carotid artery, PSt: pituitary stalk, SHA: superior hypophyseal artery.



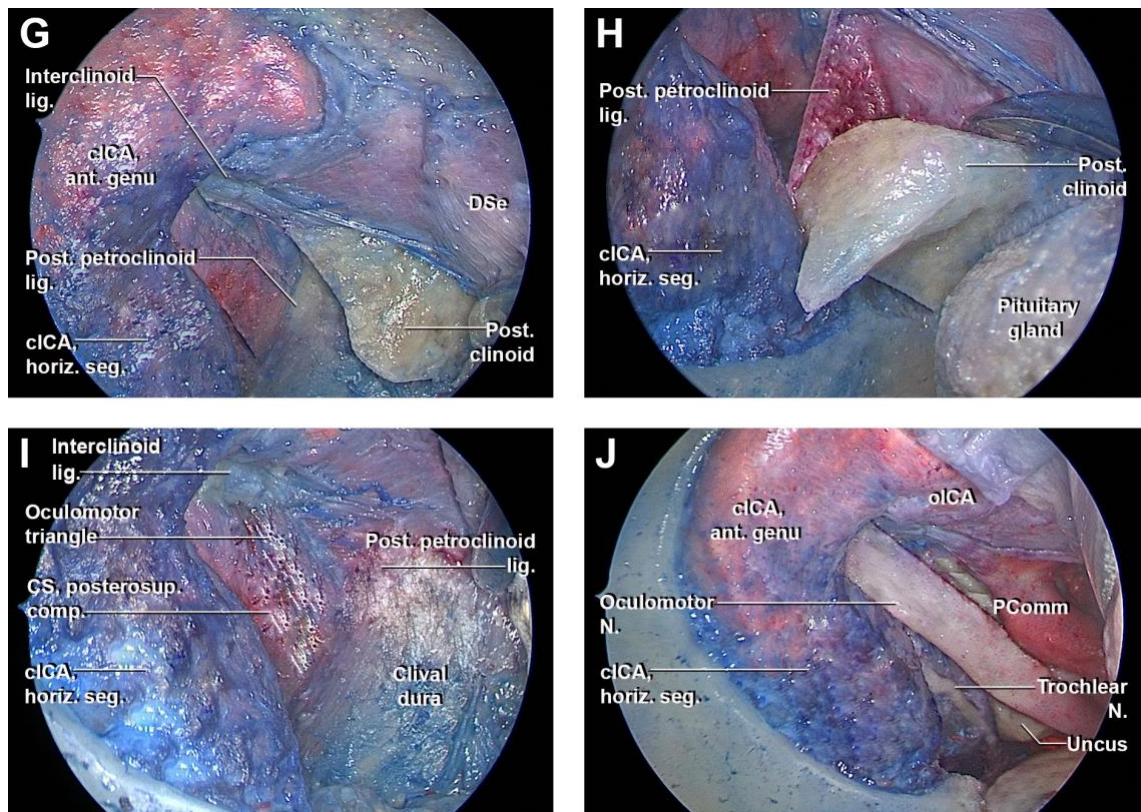


Figure 4 Endoscopic endonasal stepwise dissection of the transcavernous approach: medial compartment and posterior clinoidectomy. (A) After a sellar osteotomy has been performed, the craniectomy is extended laterally towards the carotid prominence, exposing the anterior wall of the cavernous sinus. The osteotomy is expanded inferiorly to the most inferior aspect of the anterior wall of the cavernous sinus, exposing the point where the lacerum ICA enters the cavernous sinus to become the posterior vertical segment of the cavernous ICA. (B) The periosteal layer of the inferior intercavernous sinus is incised from the midline moving laterally to the anterior wall of the cavernous sinus. In this way the cavernous sinus is indirectly reached and exposed, reducing the risk a direct damage to the cavernous ICA and its intracavernous branches. (C) The dissection proceeds along the medial compartment of the cavernous sinus, leaving the medial wall of the cavernous sinus attached to the lateral margin of the pituitary gland. The pituitary gland is gently transposed superomedially with an interdural technique, showing the anterior McConnell's capsular artery and inferolateral trunk. The anterior McConnell's capsular artery and inferior hypophyseal artery are sacrificed, allowing for better transposition of the pituitary. (D) The posterior clinoid and dorsum sellae are identified at the posterior limit of the medial compartment of the cavernous sinus. (E) The interclinoid ligament is identified, attaching on the anterior surface of the posterior clinoid. The interclinoid ligament connects the anterior and posterior clinoid processes and delimits superolaterally the cavernous sinus. It forms the anteromedial limit of the oculomotor triangle and is a reliable landmark to identify the course of the oculomotor nerve in the roof of the cavernous sinus. (F) The base of the posterior clinoid is drilled out, showing the clival dura. (G) The posterior petroclinoid ligament extends between the posterior clinoid process and petrous apex, anchoring the posterior clinoid process to the dura of the posterior cranial fossa, delimiting the cavernous sinus posteriorly. (H) After the superomedial transposition of the pituitary gland is maximized, with the aid of a dissector the posterior clinoid is fractured from the dorsum sellae and detached from

the clival dura. (I) The dura of the posterior compartment of the cavernous sinus and of the space behind the posterior genu of the ICA are completely exposed. (J) The dura is removed, exposing the lateral recess of the interpeduncular cistern. The oculomotor and trochlear nerves are identified before entering the roof and the posterior wall of the cavernous sinus, respectively. The posterior communicating artery travels with oculomotor nerve in the lateral recess of the interpeduncular cistern. A.: artery, ant.: anterior, caps.: capsular, cICA: cavernous segment of the internal carotid artery, comp.: compartment, CS: cavernous sinus, DSe: diaphragm sellae, ICS: intercavernous sinus, IHA: inferior hypophyseal artery, horiz.: horizontal, lig.: ligament, ligs.: ligaments, LOCR: lateral optic-carotid recess, N.: nerve, oICA: ophthalmic segment of the internal carotid artery, PComm: posterior communicating artery, post.: posterior, posterosup.: posterosuperior, sup.: superior, seg.: segment, vert.: vertical.

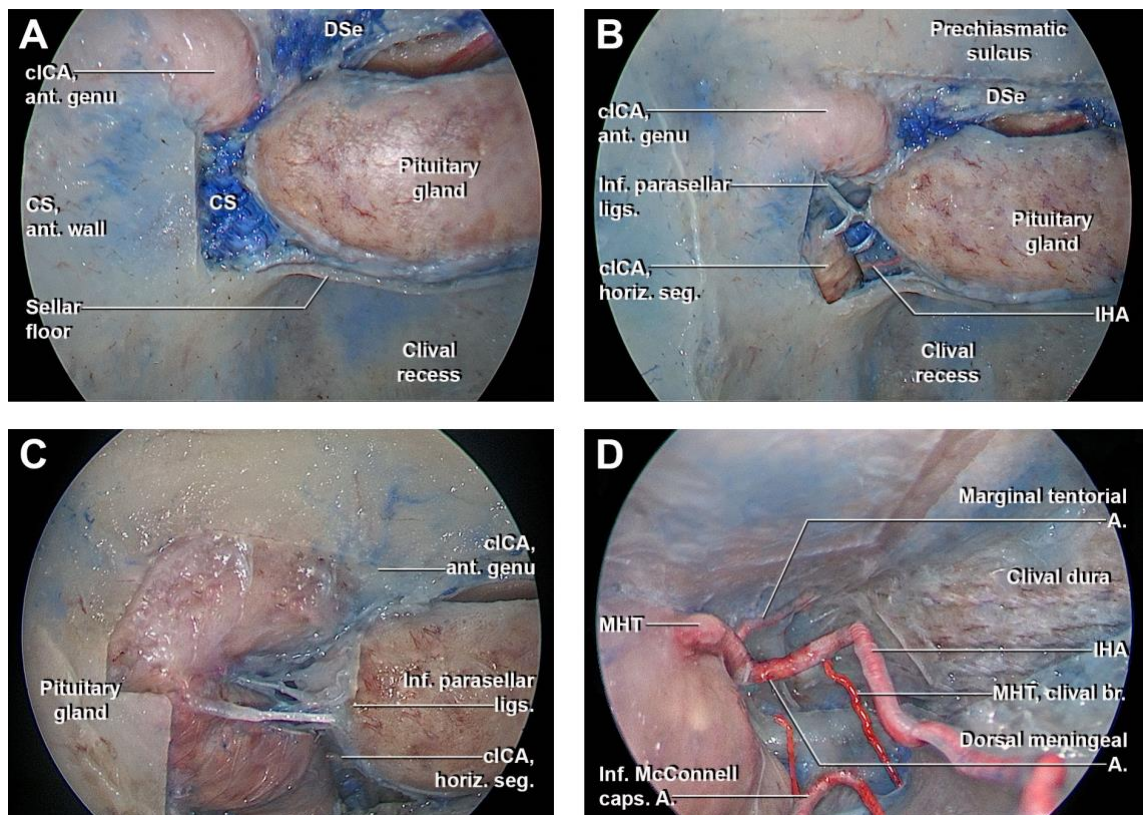


Figure 5 Anatomical overview of the endoscopic endonasal anatomy of the transsellar approach and transcavernous approach to the medial compartment of the cavernous sinus. (A) Transsellar approach with lateral extension of the osteotomy and exposure of the medial compartment of the cavernous sinus. (B) Medial transcavernous corridor, with a general view of the inferior parasellar ligaments and inferior hypophyseal artery (C) Removal of the carotid protuberance and exposure of the medial compartment of the cavernous sinus. (D) Anatomy of the meningo-hypophyseal trunk. The origin of the meningo-hypophyseal trunk is localized at the medial aspect of the posterior genu of the ICA. The meningo-hypophyseal trunk typically gives rise to three branches: the inferior hypophyseal artery, which runs medially to the posterior lobe of the pituitary gland; the marginal tentorial artery (or artery of Bernasconi-Cassinari), which travels laterally towards the tentorium; and the dorsal meningeal artery, which goes posteriorly through the cavernous sinus. A.: artery, ant.: anterior, caps.: capsular, cICA: cavernous segment of the internal carotid artery, CS: cavernous sinus, DSe: diaphragm sellae, horiz.:

horizontal, IHA: inferior hypophyseal artery, inf.: inferior, lig.: ligaments, MHT: meningohypophyseal trunk, post.: posterior, seg.: segment.

This extensive anatomical work resulted in a series of peer-reviewed scientific publications describing quantitative and qualitative analyses of skull base approaches, spanning regions such as Meckel's cave, the anterior cranial fossa, the petrous apex, the pterygopalatine fossa, and the sellar-parasellar compartment. For completeness, we provide below the list of published scientific articles:

- Agosti E, Zanin L, Ebner F, De Maria L, Belotti F, Buffoli B, Rezzani R, Hirt B, Ravanelli M, Ius T, Zeppieri M, Tatagiba MS, Fontanella MM, Doglietto F. Quantitative Anatomical Comparison of Surgical Approaches to Meckel's Cave. *J Clin Med* 2023;1:6847. doi: 3390/jcm12216847;
- Vilany L, Dang D, Agosti E, Leonel LCPC, Link MJ, Pinheiro-Neto CD, Peris-Celda M*. Anatomical Step-by- Step Dissection of Complex Skull Base Approaches for Trainees: Surgical Anatomy of the Transbasal Approach. *J Neurol Surg B Skull Base* 2023;84(S 01): S1-S344. doi: 10.1055/s-0043-1762235;
- Agosti E, Alexander AY, Leonel LCPC, Pinheiro-Neto CD, Peris-Celda M. Anatomical Step-by-Step Dissection of Complex Skull Base Approaches for Trainees: Surgical Anatomy of the Endoscopic Endonasal Approach to the Anterior Cranial Fossa. *J Neurol Surg B Skull Base* 2023; 84(S 01):S1-S344. doi: 10.1055/s-0043-1762097;
- Plou P, Serioli S, Leonel LCPC, Alexander AY, Agosti E, Vilany L, Graepel S, Choby G, Pinheiro-Neto CD, Peris- Celda M. Surgical Anatomy and Approaches of the Anterior Cranial Fossa from a Transcranial and Endonasal Perspective. *Cancers (Basel)*. 2023 May 1;15(9):2587. doi: 10.3390/cancers15092587;
- García-Lliberós A, Martin-Jimenez DI, Mondesir RJ, Agosti E, Alexander AY, Leonel LCPC, Choby G, Peris- Celda M, Pinheiro-Neto CD. Endoscopic-assisted en-bloc pterygomaxillectomy: Identifying an efficient and safe location for the pterygoid osteotomy. *Head Neck*. 2023;45(10):2718-2729. doi: 10.1002/hed.27465;
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MM, Doglietto F. Microsurgical transcranial approaches to the posterior surface of petrosal portion of the temporal bone: quantitative analysis of surgical volumes and exposed areas. *Neurosurg Rev.* 2023;46(1):48. doi: 10.1007/s10143-023-01956-y;

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- Agosti E, Cerqueira Rezende N, Leonel LCPC, Alexander AY, Pinheiro-Neto CD, Peris-Celda M. Anatomical Step-by-Step Dissection of Complex Skull Base Approaches for Trainees: Surgical Anatomy of the Endoscopic Endonasal and Endoscopic-Assisted Transmaxillary Transpterygoid Approaches. *J Neurol Surg B Skull Base.* 2022. doi: 10.1055/s-0042-1759874;
- Agosti E, Alexander AY, Leonel L, Van Gompel J, Link MJ, Pinheiro-Neto CD, Peris Celda M. Anatomical step-by-step dissection of complex skull base approaches for trainees: surgical anatomy of the endoscopic endonasal approach to the sellar and parasellar regions. *J Neurol Surg B Skull Base.* doi: 10.1055/a-1869-7532.

This preclinical anatomical program established a solid foundation for the subsequent computational components of the doctoral project. The visual and spatial insights acquired through these dissections not only supported surgical proficiency but also enabled a more informed and anatomically consistent design of the radiomics and videomics frameworks described in the following sections.

1.2 ROLE OF ARTIFICIAL INTELLIGENCE APPLIED TO PITUITARY ADENOMA NEUROIMAGING AND NEUROENDOSCOPY SURGERY

The sellar and parasellar regions represent one of the most anatomically intricate areas of the cranial base, where critical neurovascular structures (such as the internal carotid artery, cavernous sinus, optic apparatus, and pituitary gland) are confined within a narrow and functionally dense compartment. Lesions arising in this region, particularly PAs, which account for approximately 15% of all primary intracranial tumors, pose considerable diagnostic and therapeutic challenges.¹ The EEA has emerged as the preferred surgical route for many of these lesions, offering minimally invasive access and improved visualization of deep-seated structures. Nonetheless, even with advances in optical systems and surgical instrumentation, intraoperative navigation, prediction of tumor behaviour, and preservation of neurovascular integrity remain complex processes that depend heavily on the surgeon's experience and on the quality and interpretation of preoperative imaging.¹⁻³

In recent years, AI has begun to reshape the landscape of neurosurgical diagnostics and treatment, particularly in the field of head and neck pathology. The growing integration of AI-based systems reflects a broader paradigm shift in medicine, where the increasing availability of high-resolution imaging and video data necessitates analytical tools capable of extracting meaningful patterns beyond the limits of human perception. Within clinical oncology, medical imaging has transitioned from a predominantly descriptive discipline to a quantitative and predictive one, driven by the development of advanced computational techniques. Machine learning and DL algorithms now play a pivotal role in enhancing lesion detection, tissue characterization, automated segmentation, outcome prediction, and intraoperative decision support.^{4,5}

Traditionally, assessment of PAs has relied on conventional MRI and on the qualitative evaluation of intraoperative endoscopic video.³ Although these modalities provide essential anatomical information, their interpretation is often subjective and may fail to capture subtle imaging biomarkers associated with tumor consistency, invasiveness, proliferative potential, or surgical resectability. Moreover, the sheer volume of imaging and video data generated in modern neurosurgical practice frequently exceeds the

capacity for manual analysis. As a result, important features may remain underutilized, and preoperative predictions may lack reproducibility across institutions.⁵⁻⁸

Artificial intelligence-driven approaches offer a powerful solution to these limitations. In neuroimaging, radiomics has emerged as a discipline dedicated to the high-throughput extraction of quantitative features from medical images, converting conventional MRI into a rich source of structural, textural, and statistical descriptors with prognostic and predictive value.² Radiomics signatures derived from ML pipelines have shown promise in forecasting key pathological characteristics of PAs, including consistency, cavernous sinus invasion, hormonal activity, and postoperative residual risk. Similarly, DL architectures, particularly CNNs, enable automated segmentation and classification tasks that reduce interobserver variability and support more personalized surgical planning.⁹⁻¹¹

In parallel, recent years have seen the birth of videomics, an emerging field applying computer vision and DL to intraoperative endoscopic video.¹⁰ Videomics allows the transformation of unstructured surgical footage into analysable datasets capable of capturing dynamic interactions between surgical instruments, anatomical structures, and pathological tissue.³⁻¹² By enabling automated identification, segmentation, and tracking of the tumor and surrounding anatomy in real time, videomics algorithms have the potential to enhance intraoperative guidance, optimize surgical strategies, and reduce the risk of complications.¹³

Collectively, these advancements highlight how AI-based neuroimaging and neuroendoscopy are redefining the management of head and neck disorders. By integrating radiomics and videomics into the diagnostic and operative workflow, clinicians can benefit from more objective, reproducible, and data-driven insights, ultimately fostering personalized treatment strategies and improving surgical outcomes.^{1,5}

1.3 RADIOMICS APPLIED TO PITUITARY ADENOMA DIAGNOSIS

1.3.1 SUMMARY OF RADIOMICS-BASED APPROACHES FOR PITUITARY ADENOMA DIAGNOSIS

Magnetic resonance imaging remains the cornerstone of diagnostic evaluation for PAs, providing superior soft tissue contrast, multiplanar capability, and essential information regarding tumor size, morphology, and anatomical relationships. Magnetic resonance imaging is equally fundamental for long-term surveillance after treatment. However, conventional MRI interpretation is primarily qualitative and depends heavily on the experience of radiologists and neurosurgeons.⁸ This subjectivity contributes to inter-observer variability and may result in missed or underappreciated imaging biomarkers, especially in subtle or atypical presentations.¹⁴ These limitations have stimulated the development of quantitative, reproducible analytical methods capable of enhancing the diagnostic and prognostic value of neuroimaging.^{8,9}

Radiomics has emerged as a powerful quantitative imaging discipline designed to extract high-dimensional data from standard medical images. Through the computation of a wide array of features (including intensity-based metrics, texture descriptors, geometric parameters, and spatial heterogeneity indices), radiomics converts conventional MRI into a matrix of quantitative biomarkers that reflect underlying tumor biology. When combined with AI, particularly ML and DL algorithms, radiomics enables the construction of predictive models capable of handling complex, non-linear datasets and detecting patterns not visible to the human eye.¹¹ These models have demonstrated substantial potential in enhancing diagnostic precision, improving risk stratification, and guiding personalized treatment strategies.¹⁴

In the context of PAs, radiomics has been applied across several clinically relevant domains. Numerous studies have shown that radiomic signatures can differentiate PAs from other sellar and suprasellar lesions, such as craniopharyngiomas or Rathke cleft cysts, entities that often pose diagnostic challenges due to overlapping radiological

features. Radiomics has also proven valuable in preoperative histological and molecular characterization.¹⁵ Models trained on multiparametric MRI datasets have successfully distinguished several PA subtypes, including silent corticotroph adenomas and null-cell adenomas, which may present without overt endocrine symptoms yet carry distinct prognostic implications.^{3,6,15}

Furthermore, radiomics has contributed meaningfully to the evaluation of tumor invasiveness. Specific radiomic feature sets correlate with higher Knosp grades and cavernous sinus invasion, improving preoperative prediction beyond conventional visual assessment. Additional applications include predicting responsiveness to medical therapy (particularly somatostatin receptor ligands in the management of acromegaly), as well as forecasting the effects of radiotherapy or the likelihood of long-term recurrence and progression following surgical resection. Collectively, these advancements underline the potential of radiomics to complement clinical, biochemical, and imaging data, ultimately refining therapeutic decision-making.¹⁶

Despite rapid progress, the existing literature remains fragmented, with several studies addressing isolated aspects of radiomic application but without a comprehensive synthesis of methodologies, imaging protocols, feature extraction pipelines, and model performance metrics. This fragmentation highlights the need for systematic evaluation of the radiomics landscape and its current limitations.¹⁷

Among the various domains explored, one of the most clinically impactful applications is the preoperative prediction of PA consistency, a parameter that profoundly influences surgical strategy, tumor resectability, and overall operative risk.

1.3.2 RADIOMICS AND THE PREOPERATIVE PREDICTION OF PITUITARY ADENOMA CONSISTENCY

Pituitary adenoma consistency represents a fundamental parameter in the preoperative assessment and surgical management of sellar and parasellar tumors. The mechanical properties of the tumor (typically classified as soft versus fibrous) strongly influence the feasibility and extent of resection during endoscopic endonasal surgery. Soft PAs are

generally amenable to suction and curettage, allowing for more complete and efficient tumor removal. In contrast, fibrous PAs may adhere tightly to surrounding neurovascular structures, complicating dissection, prolonging operative time, and increasing the risk of intraoperative CSF leakage, vascular injury, and postoperative complications. Therefore, reliable preoperative prediction of PA consistency is essential for selecting the most appropriate surgical strategy, anticipating technical challenges, and counselling patients regarding expected outcomes.^{2,6,9}

Despite its clinical importance, accurately determining PA consistency prior to surgery remains challenging. Conventional MRI techniques offer crucial information on tumor size, margins, and invasiveness, yet their ability to predict texture or mechanical stiffness is limited.⁵ Qualitative MRI assessments (such as T2-weighted signal intensity, homogeneity, or contrast enhancement patterns) have been explored as potential surrogates for consistency; however, results have been inconsistent, and inter-observer variability remains substantial. These limitations underscore the need for objective, reproducible, and quantitative approaches capable of capturing microstructural differences that are not visually appreciable.¹⁶

Radiomics has emerged as a promising solution to this problem by transforming standard MRI scans into high-dimensional datasets composed of quantitative features that describe intensity, texture, shape, and spatial complexity. Through pixel-level and voxel-level analysis, radiomics can characterize tumor heterogeneity in a manner that greatly surpasses the descriptive capacity of human interpretation. Features derived from texture matrices (such as the grey-level co-occurrence, run-length, and size-zone matrices) may reflect underlying histopathological patterns, including fibrosis, collagen deposition, and microstructural arrangement, all of which contribute to tumor firmness.¹⁴⁻¹⁶

The integration of ML has further expanded the utility of radiomics in assessing PA consistency. Machine learning algorithms can handle large sets of radiomics features, identifying the most discriminative patterns, and constructing predictive models to classify tumors as soft or fibrous. Several studies have demonstrated the feasibility of this approach, reporting encouraging accuracy rates in preoperative consistency prediction. These advances align with the broader movement toward precision neurosurgery, where individualized operative planning is informed by quantitative

imaging biomarkers rather than subjective assessments.^{12,15}

However, despite these promising developments, current radiomics studies on PA consistency often suffer from methodological limitations, including retrospective design, single-center datasets, small sample sizes, and heterogeneous imaging protocols. These issues may limit generalizability, reduce model robustness, and hinder translation into clinical practice.^{15,16} Consequently, there is a pressing need for multicentric, standardized radiomics investigations capable of validating consistency-prediction models across diverse populations and imaging platforms. In this context, the radiomics analysis undertaken in this doctoral project addresses several of these gaps by incorporating large multicenter datasets, standardized segmentation workflows, and advanced ML pipelines.¹⁷

1.4 VIDEOMICS APPLIED TO PITUITARY ADENOMA MANAGEMENT

1.4.1 VIDEOMICS: ARTIFICIAL INTELLIGENCE APPLIED TO ENDOSCOPIC SURGERY

Videomics, the convergence of video-endoscopy and AI, is rapidly emerging as a transformative paradigm in surgical imaging and intraoperative decision support. Building on advances in computer vision and DL, videomics enables the automated analysis of endoscopic video streams, providing real-time recognition, segmentation, and characterization of anatomical structures and pathological tissue.^{17,18} Initially conceptualized and validated in fields such as gastrointestinal endoscopy, dermatology, and the upper aerodigestive tract, videomics has recently gained traction in skull base surgery, where the complexity of anatomical relationships and the narrow operative corridor present unique challenges for surgical navigation.¹⁹⁻²²

In early applications, CNNs demonstrated high accuracy in the detection and segmentation of colonic polyps, mucosal lesions, and other gastrointestinal

abnormalities.²³⁻²⁷ Similar successes were subsequently reported in laryngoscopy and sinonasal surgery, where DL models could delineate tumor margins, identifying nasal polyps, and segmenting papillomas with high precision.²⁸⁻³¹ These contributions provided the conceptual and methodological foundation for the expansion of videomics to the EEA, suggesting that automated analysis of intraoperative video could enhance diagnostic performance, improve spatial orientation, and support surgical decision-making across multiple anatomical domains.³²⁻³⁵

The EEA has become a cornerstone technique in skull base surgery, offering direct access to midline structures including the sellar, suprasellar, and clival regions.³⁶⁻³⁹ Despite its advantages, EEA presents several inherent limitations: restricted visual fields, complex and variable anatomy, bleeding and debris that obscure visibility, and dependence on suboptimal illumination.⁴⁰ These factors can hinder the surgeon's ability to identify critical neurovascular structures, differentiate tumor from normal tissue, or recognize residual disease during the final stages of resection.⁴¹⁻⁴³ Videomics provides a powerful technological solution to these challenges by integrating DL algorithms capable of processing intraoperative video in real time and delivering automated, high-resolution annotations directly within the endoscopic field of view.⁴⁴⁻⁴⁶

Among the most promising applications of videomics is automated tissue segmentation.⁴⁷ Through CNN-based architectures and state-of-the-art variants such as U-Net, Mask R-CNN, and transformer-based models, videomics enables the delineation of anatomical structures, identification of pathological regions, and detection of subtle residual tumor fragments that may be difficult to visualize with conventional endoscopy alone.^{23,28,45} The use of transfer learning, data augmentation, and frame-level annotation strategies further facilitates model training, even when clinical datasets are limited.⁴⁸⁻⁵⁰

1.4.2 VIDEOMICS APPLIED TO PITUITARY ADENOMA SURGICAL TREATMENT

The management of PAs stands to benefit significantly from videomics assistance. Although typically benign, PAs often present technical challenges during surgery due to

their proximity to the optic apparatus, cavernous sinuses, and the normal pituitary gland.^{25,33,51} The final phase of PA resection, when the goal is to identify and remove small remnants adherent to delicate structures, relies heavily on visual cues that may be subtle, subjective, or obscured.^{52,53} By augmenting the surgeon's intraoperative awareness, videomics tools have the potential to improve the completeness of tumor removal, reduce the risk of postoperative recurrence, and help prevent complications such as CSF leaks or neurovascular injury.⁴⁸

Despite these promising advancements, the clinical application of videomics in EEA remains in its early stages. Challenges persist, including heterogeneity in video quality, variations in surgical techniques and instruments, inconsistent annotation protocols, and limited large-scale datasets for training and validation. Methodological rigor and multicenter collaboration will be essential to ensure robust model performance and translation into routine practice.^{49,53}

2. AIM OF THE STUDY

The primary aim of this study is to apply AI methods, including ML and DL algorithms, to improve the management of PAs through both radiomics and videomics approaches. In radiomics, the main objective is to perform a preoperative assessment of PA characteristics, mainly represented by tumor consistency. This evaluation is intended to guide surgical planning, reduce the risk of neurovascular injuries, and minimize postoperative complications. In videomics, the primary objective is to implement real-time intraoperative analysis of the spatial relationships between PAs and surrounding

neurovascular structures, particularly during the final stages of tumor removal. This approach aims to provide a dynamic roadmap for surgeons, enhance differentiation between pathological and healthy tissue, and reduce residual tumor and surgical complications.

Secondary objectives include, for radiomics application in PA management, to review and synthesize current literature to provide an updated summary of state-of-the-art applications of radiomics for PAs and assess the predictive accuracy of these radiomics-based models. For videomics, the study seeks to summarize and validate DL-based computer vision techniques for intraoperative PA recognition reported in the literature, evaluating key anatomical and pathological targets, assessing performance across different architectures, and highlighting methodological challenges and considerations for clinical translation.

3. MATERIALS AND METHODS

3.1 SYSTEMATIC LITERATURE REVIEW

3.1.1 RADIOMICS STUDY

3.1.1.1 Research strategy

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines.⁵⁴ A comprehensive search of the PubMed, Scopus, and Web of Science databases was performed. The initial

search was conducted on 10 January 2024, with a final update on 5 May 2025. The articles identified through this search were published between 2018 and 2025. The search strategy utilized a combination of keywords and MeSH terms, including “radiomics,” “artificial intelligence,” “machine learning,” “pituitary adenoma,” “pituitary neuroendocrine tumor,” “PitNET,” “MRI,” and “magnetic resonance imaging.” Boolean operators (AND/OR) were employed to construct the search query as follows: (“radiomics” OR “machine learning” OR “artificial intelligence”) AND (“pituitary adenoma” OR “Pit-NET” OR “pituitary neuroendocrine tumor”) AND (“MRI” OR “magnetic resonance imaging”). Additional relevant studies were identified by manually screening the reference lists of all selected articles.

Studies were eligible for inclusion if they were published in English, involved human subjects, and investigated the application of radiomics (alone or in combination with AI-based methods) for the diagnosis, classification, prediction, or treatment response assessment of PAs using MRI-based features. Both retrospective and prospective original studies were considered. Articles were excluded if they were review articles, editorials, conference abstracts, purely technical or methodological papers without clinical data, or if they involved only phantom or animal models. Studies lacking clearly reported radiomic methodology, outcome measures, or validation procedures were also excluded. All references were managed using EndNote X9, and duplicate records were removed prior to screening. Titles and abstracts were screened for relevance. Full-text screening was then performed on all articles meeting initial inclusion criteria.

3.1.1.2 Data extraction

Data were extracted systematically from each included article using a pre-defined standardized data collection sheet. Extracted variables included: first author, year of publication, study design, population size, radiomics pipeline (including image acquisition, segmentation, feature extraction, and model development), type of MRI sequences used, clinical endpoint(s) investigated (e.g., differential diagnosis, subtype classification, tumor consistency, invasion, treatment response, or recurrence), and

performance metrics (e.g., accuracy, sensitivity, specificity, and area under the curve, i.e., AUC). Additional details were collected on validation methods (internal or external) and the use of AI or ML algorithms.

3.1.1.3 Outcomes

The primary objective of this review was to synthesize and characterize the current applications of radiomics in the clinical management of PAs, including diagnostic differentiation, subtype classification, prediction of invasiveness or consistency, treatment response forecasting, and recurrence risk stratification. Secondary outcomes included an evaluation of the types and performance of models developed, common methodological patterns, and the overall level of validation achieved across studies.

3.1.1.4 Radiomics Quality Assessment

A qualitative assessment using the Radiomics Quality Score (RQS) framework was performed with the aim of critically analyzing and comparing the clinical applicability and translational potential of the various radiomic models developed. Evaluation of the included studies was conducted according also to the IBSI compliance checklist to examine their reproducibility and adherence to technical standards. Since many items in the IBSI checklist overlap with those in the RQS checklists, we included only the items relevant to image pre-processing steps (**Table 1**).

Author, year	Method	RQS (36)	IBSI (%)
Zhang, 2018	Handcrafted	14	43
Niu, 2018	Handcrafted	16	43
Kocak, 2018	Handcrafted	12	86
Staatjes, 2018	Deep Learning	13	14
Zeynalova, 2019	Handcrafted	14	86
Ugga, 2019	Handcrafted	14	71
Fan, 2019	Handcrafted	16	43

Fan, 2019	Handcrafted	18	43
Fan, 2019	Handcrafted	17	43
Qian, 2020	Deep Learning	10	29
Peng, 2020	Handcrafted	12	43
Cuocolo, 2020	Handcrafted	14	71
Machado, 2020	Handcrafted	10	86
Park, 2020	Handcrafted	13	100
Zhu, 2020	Deep Learning	9	29
Chen, 2020	Handcrafted	14	43
Zhang, 2020	Handcrafted	11	4
Li, 2021	Deep Learning	13	71
Liu, 2021	Handcrafted	14	14
Park, 2021	Handcrafted	12	71
Wan, 2021	Handcrafted	12	100
Wang, 2021	Handcrafted	13	14
Zhang, 2021	Handcrafted	14	14
Zhang, 2021	Handcrafted	12	43
Baysal, 2022	Deep Learning	18	57
Chen, 2022	Multimodal	13	43
Fang, 2022	Deep Learning	14	29
Feng, 2022	Deep Learning	15	29
Kim, 2022	Deep Learning	14	57
Park, 2022	Deep Learning	13	57
Rui, 2022	Handcrafted	17	29
Shu, 2022	Deep Learning	13	57
Villalonga, 2022	Handcrafted	13	14
Zhang, 2022	Handcrafted	14	71
Gargya, 2023	Deep Learning	10	57
Shen, 2023	Handcrafted	16	86
Wang, 2023	Handcrafted	16	57
Wang, 2023	Handcrafted	15	86
Zhang, 2023	Handcrafted	16	86
Zhang, 2023	Deep Learning	17	14
Angus, 2024	Handcrafted	14	57
Behzadi, 2024	Deep Learning	15	43
Da Mullen, 2024	Deep Learning	13	43
Fang, 2024	Deep Learning	14	29
Ishimoto, 2024	Deep Learning	-2	71
Liu, 2024	Combined	19	86
Taslicay, 2024	Handcrafted	14	86
Zhang, 2024	Handcrafted	15	100
Agosti, 2025	Handcrafted	15	71

Table 1. Radiomics quality assessment through RQS and IBSI checklists.

3.1.1.5 Radiomics Quality Assessment

The quality of the observational studies included in the review was evaluated using the Newcastle-Ottawa Scale (NOS),⁵⁵ which assesses studies across three domains: selection, comparability, and outcome assessment (**Figure 6**).

MODIFIED NEWCASTLE - OTTAWA QUALITY ASSESSMENT SCALE

SELECTION

- 1) Representativeness of the exposed cohort
 - a) Consecutive eligible participants were selected, participants were randomly selected, or all participants were invited to participate from the source population,
 - b) Not satisfying requirements in part (a), or not stated.
- 2) Selection of the non-exposed cohort
 - a) Selected from the same source population,
 - b) Selected from a different source population,
 - c) No description.
- 3) Ascertainment of exposure
 - a) Medical record,
 - b) Structured interview,
 - c) No description.
- 4) Demonstration that outcome of interest was not present at the start of the study
 - a) Yes,
 - b) No or not explicitly stated.

COMPARABILITY

- 1) Were there clearly defined inclusion and exclusion criteria?
 - a) Yes,
 - b) No or not explicitly stated.

OUTCOME

- 1) Assessment of outcome
 - a) Independent or blind assessment stated, or confirmation of the outcome by reference to secure records,
 - b) Record linkage (e.g. identified through ICD codes on database records),
 - c) Self-report with no reference to original structured injury data or imaging,
 - d) No description.
- 2) Was follow-up long enough for outcomes to occur?
 - a) Yes (≥ 12 months),
 - b) No (< 3 months).
- 3) Adequacy of follow up
 - a) Complete follow up – all participants accounted for,
 - b) Subjects lost to follow up unlikely to introduce bias ($< 20\%$ lost to follow up or description provided of those lost),
 - c) Follow up rate $< 85\%$ and no description of those lost provided,
 - d) No statement.

Figure 6. Newcastle-Ottawa Scale variables.

Each study could receive a maximum of 9 points. Those scoring below 7 were classified as low quality and excluded from the analysis. Studies that met or exceeded this threshold were retained, and their quality scores were considered during subgroup analyses and narrative synthesis to explore potential sources of bias (**Table 2**).

Study	Year	Selection (4)	Comparability (2)	Outcome (3)	Total Score	Quality
Zhang	2018	3	1	3	7	High
Niu	2018	3	2	2	7	High
Kocak	2018	4	2	3	9	High
Staartjes	2018	3	2	2	7	High
Zeynalova	2019	3	2	3	8	High
Ugga	2019	3	1	3	7	High
Fan	2019	3	2	3	8	High
Fan	2019	4	2	3	9	High
Qian	2020	3	1	3	7	High
Peng	2020	3	2	3	8	High
Cuocolo	2020	3	2	3	8	High
Machado	2020	4	2	3	9	High
Park	2020	3	1	3	7	High
Zhu	2020	3	2	2	7	High
Chen	2020	3	2	3	8	High
Zhang	2020	3	2	2	7	High
Li	2021	4	2	3	9	High
Liu	2021	3	2	3	8	High
Park	2021	3	2	2	7	High
Wan	2021	4	2	3	9	High
Wang	2021	3	2	2	7	High
Zhang	2021	3	2	3	8	High
Zhang	2021	3	1	3	7	High
Baysal	2022	3	2	3	8	High
Chen	2022	3	2	2	7	High
Fang	2022	4	2	3	9	High
Feng	2022	3	2	3	8	High
Kim	2022	3	2	3	8	High
Park	2022	3	1	3	7	High
Rui	2022	3	2	3	8	High
Shu	2022	4	2	3	9	High
Villalonga	2022	3	2	2	7	High
Zhang	2022	3	1	3	7	High
Gargya	2023	3	2	3	8	High
Shen	2023	4	2	3	9	High
Wang	2023	3	2	2	7	High
Wang	2023	3	2	3	8	High
Zhang	2023	3	2	2	7	High
Zhang	2023	3	2	3	8	High
Sathya	2024	4	2	3	9	High
Behzadi	2024	3	2	2	7	High

Da Mullen	2024	3	2	3	8	High
Fang	2024	4	2	3	9	High
Ishimoto	2024	3	1	3	7	High
Liu	2024	3	2	3	8	High
Taslicay	2024	3	2	3	8	High
Zhang	2024	3	1	3	7	High
Agosti	2025	4	2	3	9	High

Table 2. Summary of NOS scores for each included study.

3.1.1.6 Statistical analysis

Descriptive statistics were used to summarize study characteristics, radiomics applications, and model performance metrics. Results were presented using medians, ranges, and proportions, where appropriate. Due to methodological heterogeneity across studies, - including differences in imaging protocols, feature selection methods, and outcome definitions - a formal meta-analysis was not performed. All data processing and visualization were conducted using R statistical software (version 4.2.0) (<https://www.r-project.org>).

3.1.2 VIDEOMICS STUDY

3.1.2.1 Study design

This systematic review was carried out following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines.⁵⁴ A comprehensive literature search was performed using three electronic databases: PubMed, Scopus, and Web of Science. The initial query was conducted on May 12, 2024, and a final search update was completed on June 28, 2025.

3.1.2.2 Search strategy

The search strategy was developed to capture studies investigating AI-based video analysis in the context of endoscopic endonasal procedures. A combination of keywords and Boolean operators was used to construct the search string as follows: (videomics OR artificial intelligence OR machine learning OR deep learning OR convolutional neural network OR segmentation) AND (endonasal OR nasal OR pituitary OR sella* OR parasellar) AND (endoscop*). Manual searches of the reference lists from relevant articles were also conducted to identify any additional studies not captured through the initial electronic search.

3.1.2.3 Eligibility criteria

Studies were included if they met the following criteria: (1) written in English; (2) involved human subjects undergoing endoscopic endonasal surgery; and (3) explored the use of videomics or DL-based video analysis techniques, particularly segmentation, during endoscopic procedures. Eligible studies had to present original data and describe applications such as anatomical recognition, intraoperative guidance, lesion segmentation, or tissue differentiation. No restrictions were placed on the type of DL architecture: CNNs, transformer-based models, and hybrid approaches were all considered eligible if applied to segmentation tasks in endoscopic endonasal surgery. This ensured comprehensiveness of included studies. Studies were included if they applied DL to segmentation in endoscopic endonasal surgery, even when certain methodological details (e.g., image resolution, validation split) were incompletely reported. This approach maximized comprehensiveness while making reporting gaps visible, underscoring the need for greater methodological transparency in future studies.

Exclusion criteria comprised: (1) review articles, editorials, or opinion pieces; (2) conference abstracts lacking peer review; (3) technical or methodological studies without clinical context or human data; and (4) animal or phantom-only research.

Additionally, studies were excluded if they did not clearly describe the AI methodology or failed to report clinically relevant outcomes.

3.1.2.4 Outcomes

The primary objective of this systematic review was to catalog and evaluate the current clinical applications of videomicroscopy and DL-based segmentation in endoscopic endonasal surgery. This included assessment of model functionality in real-time surgical guidance, anatomical structure identification, tumor or tissue boundary detection, and impact on intraoperative workflow or surgical outcomes. Secondary outcomes included classification of DL techniques used, dataset characteristics, and performance metrics reported.

3.1.2.5 Risk of Bias Assessment

To assess study quality and potential bias, the observational studies included were evaluated using the NOS,⁵⁵ which examines study methodology across three domains: participant selection, comparability of groups, and outcome assessment (**Figure 6**).

Each study was scored on a 9-point scale. According to the NOS scale paradigm, studies receiving a score lower than 7 will be excluded. Quality scores were considered during the synthesis process to explore the robustness of findings and identify possible sources of heterogeneity. A summary of NOS scores for each included study is presented in **Table 3**.

Study	Year	Selection (4)	Comparability (2)	Outcome (3)	Total Score	Quality
Li et al.	2018	3	2	2	7	High
Girdler et al.	2021	3	2	3	8	High
Bieck et al.	2022	4	2	3	9	High
Ay et al.	2022	3	1	3	7	High
Bi et al.	2023	4	2	3	9	High

Chen et al.	2023	3	2	2	7	High
Das et al.	2023	3	2	3	8	High
Yui et al.	2023	3	1	3	7	High
Fuse et al.	2023	3	2	3	8	High
Kwon et al.	2024	4	1	3	8	High
Phoommanee et al. (1)	2024	3	1	3	7	High
Phoommanee et al. (2)	2024	3	2	2	7	High
Tai et al.	2024	3	1	3	7	High
Mao et al. (1)	2024	4	2	3	9	High
Ganeshan et al.	2024	3	2	3	8	High
Rampinelli et al.	2024	4	2	3	9	High
Xu et al.	2024	3	2	3	8	High
Yue et al.	2024	3	1	3	7	High
Lei et al.	2025	4	2	3	9	High
Liu et al.	2025	3	1	3	7	High
Wang, X-S et al.	2025	3	2	2	7	High
Bidwell et al.	2025	3	2	3	8	High
He et al.	2025	4	2	3	9	High
Staartjes et al.	2025	3	1	3	7	High
Mao et al. (2)	2025	3	2	2	7	High
Levi et al.	2025	4	2	3	9	High
Wang W et al.	2025	3	1	3	7	High
Agosti et al.	2025	3	2	3	8	High

Table 3. Summary of NOS scores for each included study.

3.1.2.6 Statistical Analysis

Descriptive statistics were applied to summarize the characteristics of the included studies, videomics methodologies, and segmentation performance metrics. Results were presented using medians, ranges, and proportions as appropriate. Due to the methodological heterogeneity across studies, including differences in DL architectures, segmentation targets, validation techniques, and clinical endpoints, a meta-analysis was not performed. All statistical analysis and visualizations were performed using R (version 4.2.0; <https://www.r-project.org>).

3.2 RETROSPECTIVE REGISTRY

3.2.1 RADIOMICS STUDY

3.2.1.1 Multicenter Retrospective Registry

This retrospective study was conducted in accordance with the principles outlined in the 1964 Declaration of Helsinki and its subsequent amendments. The study protocol received approval from the Institutional Review Board (approval code: IRB-5924). Given the retrospective design of the study, the requirement for patient consent was waived by the Institutional Review Board, as all data were anonymized to protect patient privacy.

Data were collected from patients diagnosed with PAs who underwent preoperative MRI and subsequent endoscopic endonasal surgery at four collaborating institutions. The participating centers included University of Brescia, Spedali Civili of Brescia, Italy; University of Naples Federico II, University Hospital Federico II, Naples, Italy; Ca' Foncello Hospital, Treviso, Italy; and University of Insubria, Circolo and Macchi Foundation Hospital, Varese, Italy.

The study encompassed a patient selection period from January 2012 to December 2023. Only patients with complete medical records, including preoperative T2-weighted MRI scans and subsequent surgical documentation, were included. All collected data were anonymized to ensure patient privacy and confidentiality.

Exclusion criteria were defined to ensure the dataset clarity and consistency. Patients were excluded if they were under 18 years old, had a history of prior treatments for sellar or parasellar diseases, had undergone radiotherapy or medical therapy for pituitary adenoma at the time of the MRI, or had lesions smaller than 10 mm. Additionally, cases with extensive tumor necrosis, hemorrhage, or significant imaging artifacts that could compromise radiomic analysis were also excluded from the study.

3.2.1.2 MRI data acquisition

All patients included in the study underwent MRI scans using either a 1.5T or 3T magnetic resonance scanner, depending on the availability at the respective center. Scanners utilized in the study included models from Philips (Gyrosan Intera) and Siemens (Magnetom Trio). The imaging protocol was standardized across all centers and consistently incorporated a coronal T2-weighted Turbo Spin Echo (T2-w TSE) sequence, which served as the primary imaging modality for radiomic feature extraction. The specific acquisition parameters, such as repetition time (TR), echo time (TE), slice thickness, and field of view (FOV), were adjusted to ensure optimal image quality, enabling consistent texture analysis across different MRI platforms (**Table 4**).

	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

Table 4 Coronal T2-weighted Turbo Spin Echo sequence parameters for 1.5 and 3 Tesla scanners. TR: Repetition Time, TE: Echo Time, FOV: Field of View, thk: slice thickness, ETL: echo train length.

In addition to the T2-weighted sequence, standard pituitary imaging protocols often include other sequences, such as T1-weighted pre- and post-contrast images. However, these were not utilized in the texture analysis for this study. The focus remained on non-contrast T2-weighted images, as prior research has demonstrated their utility in capturing tissue heterogeneity associated with pituitary adenoma consistency.

3.2.1.3 Consistency evaluation

The consistency of PAs was documented in the operative reports and further evaluated through intraoperative videos. The candidate reviewed the videos to confirm the reported consistency. In cases where their evaluations differed, a consensus was reached through joint analysis of the videos with the surgeon.

Lesions classified as soft were characterized by their ease of removal using standard surgical instruments, such as suction and curettage. These tumors tended to deform and fragment readily, allowing for quick and uncomplicated resection. In contrast, fibrous PAs exhibited a denser structure, necessitating more meticulous extracapsular dissection, often requiring additional effort or alternative instruments such as microdissectors to ensure complete resection.

The classification relied on observable intraoperative properties, including tumor texture, resistance to surgical manipulation, and the instruments required for effective resection.

3.2.1.4 Radiomics analysis

Tumor segmentation was performed manually by an experienced neuroradiologist using ITKSnap (v4.0.2), an open-source software for medical image annotation. A two-dimensional polygonal region of interest (ROI) was delineated on the coronal slice that exhibited the largest cross-sectional area of the lesion (**Figure 7**).

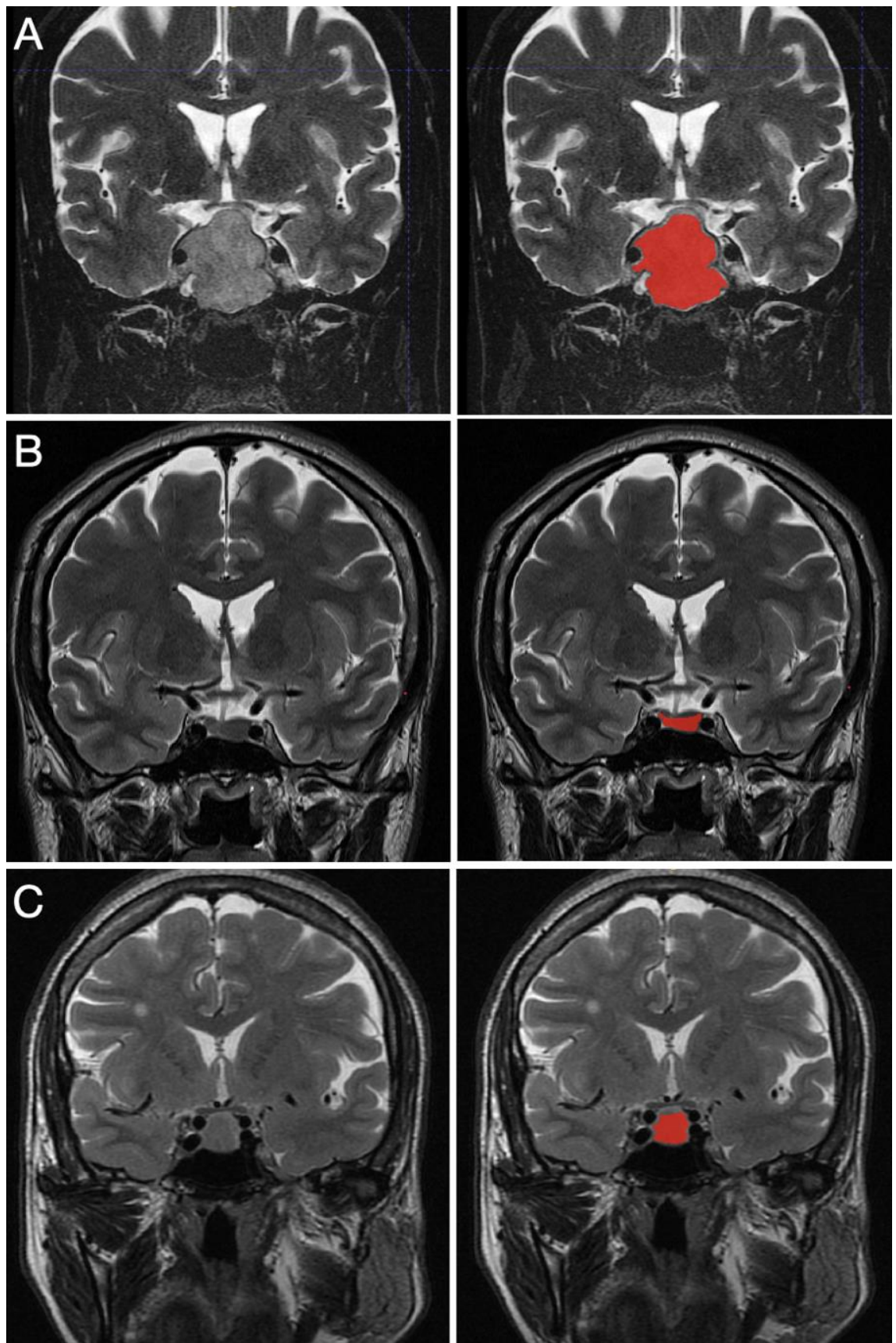


Figure 7. Example of pituitary adenoma segmentation on coronal T2-weighted, displaying ROI placement by hand. (A) Coronal T2-weighted MRI of a pituitary macroadenoma with the corresponding ROI (B). (C) Coronal T2-weighted MRI of a

pituitary microadenoma with the corresponding ROI (D). (E) Coronal T2-weighted MRI of a pituitary microadenoma with the corresponding ROI (F). MRI: magnetic resonance imaging, ROI: region of interest.

The candidate performed images segmentation. The extraction was performed by the candidate blinded to the initial neuroradiologist's annotations to ensure unbiased radiomics feature extraction and to validate the reproducibility of the segmentation process. To ensure consistency in radiomics analysis, inter-observer variability was measured using the intraclass correlation coefficient (ICC), with an acceptable threshold of ≥ 0.75 , ensuring stability across the features extracted from the multiple segmentations. This multi-reader approach was implemented to guarantee robust and reliable radiomic feature extraction for subsequent analysis.

A widely used, open-source Python software platform (Pyradiomics, v2.2.0) was utilized for image pre-processing and radiomics features extraction. Initially, images and ROIs were resampled to an isotropic voxel size of $2 \times 2 \times 2$ mm to ensure compatibility with subsequent pre-processing steps, such as the correct application of image filters. Voxel intensity values were normalized by subtracting the mean intensity and dividing by the standard deviation with a voxel array shift of 300, followed by discretization using a fixed bin count of 32.

Feature extraction was performed not only on the pre-processed original images but also on filtered images. Specifically, a Laplacian of Gaussian filter was applied with sigma values ranging from 2.0 (capturing finer textures) to 6.0 (capturing coarser textures) in 2.0 increments. Additionally, all possible combinations of high- and low-pass wavelet decompositions were applied along the x, y, and z dimensions.

3.2.1.5 Data mining and machine learning

The initial evaluation and processing of the extracted data were conducted in Python, utilizing the numpy, pandas, and scikit-learn libraries. Non-informative features with low variance (≤ 0.01) were excluded from further analysis. To address multicollinearity, a pairwise correlation matrix was generated, and features exhibiting an intercorrelation $\geq$

0.8 were removed. Then, a Recursive Feature Elimination with 10-fold cross validation was employed to select the final feature subset.

For model training and evaluation, 60% of the data was allocated for hyperparameter tuning through stratified 5-fold cross-validation, while the remaining 40% served as a hold-out test set for performance assessment on unseen data. Within the training set, a normalization scaler was first computed to mitigate feature scale biases and subsequently applied to the test set. Given the expected class imbalance due to the relative rarity of fibrous adenomas compared to soft ones, the Synthetic Minority Oversampling Technique (SMOTE) was employed to balance the training dataset.

The selected features were used to train an ensemble learning meta-algorithm, the ET Classifier, which has demonstrated strong performance in radiomic-based medical imaging studies. The model's predictive performance was evaluated on the test set, with accuracy metrics computed using scikit-learn and further analyzed in R (version 3.4.4, R Foundation for Statistical Computing, 2014). Specifically, DeLong's test (pROC package) was applied to estimate 95% confidence intervals (95% CI) for the area under the curve of the receiver operating characteristic (AUR-ROC) curve, while the confusion matrix function (caret package) was used to assess classifier accuracy and compare it to the no-information rate.

3.2.2 VIDEOMICS STUDY

3.2.2.1 Multicenter Retrospective Registry

This retrospective study was conducted in accordance with the principles outlined in the 1964 Declaration of Helsinki and its subsequent amendments. The study protocol received approval from the Institutional Review Board (approval code: IRB-5925). Given the retrospective design of the study, the requirement for patient consent was waived by the Institutional Review Board, as all data were anonymized to protect patient privacy. The study was also performed following the Transparent Reporting of a

multivariable prediction model for Individual Prognosis Or Diagnosis on Artificial Intelligence (TRIPOD+AI) statement.

Data were collected from patients diagnosed with PAs who underwent video-recorded endoscopic endonasal surgery. A dataset was retrospectively compiled from the institutional registry of a tertiary academic hospital, including patients treated between January 2022 and December 2023. Only those with complete medical records, including surgical documentation and video-endoscopies of histologically confirmed PAs, were included.

Exclusion criteria were applied to ensure dataset consistency: patients under 18 years of age, those with a prior history of treatment for sellar or parasellar diseases, and those who had received prior radiotherapy were excluded from the study.

3.2.2.2 Video-endoscopy data acquisition

All videos were captured using a rigid 0-degree endoscope (4 mm, 17.5 cm, Olympus Medical Systems Corporation, Tokyo, Japan), paired with an CH-S400_XZ-EB camera connected to an VISERA 4K UHD CLV-S400 light source (Olympus Medical Systems Corporation, Tokyo, Japan).

3.2.2.3 PA segmentation

Out of the 39 available video-endoscopies, 6 were excluded due to excessive out-of-focus sequences, 2 because of obscured sections within the video, and 11 for containing prolonged sequences of bleeding. Ultimately, 20 videos were selected for analysis.

Informative frames, referred to as original frames, showing images of PAs were manually selected from the videos by the candidate. From each video, 35 representative video-frames were manually chosen to capture the various PA portions and phases of PA removal. This process resulted in a dataset comprising a total of 700 video-frames. The

frames were then uploaded into Label Studio Enterprise (v. 1.10.1, Heartex, San Francisco, CA, USA), a specialized software for image annotation (Video 1). On each original frame, the lesion margins were manually outlined to create a corresponding mask, referred to as the original mask (**Figure 8**).

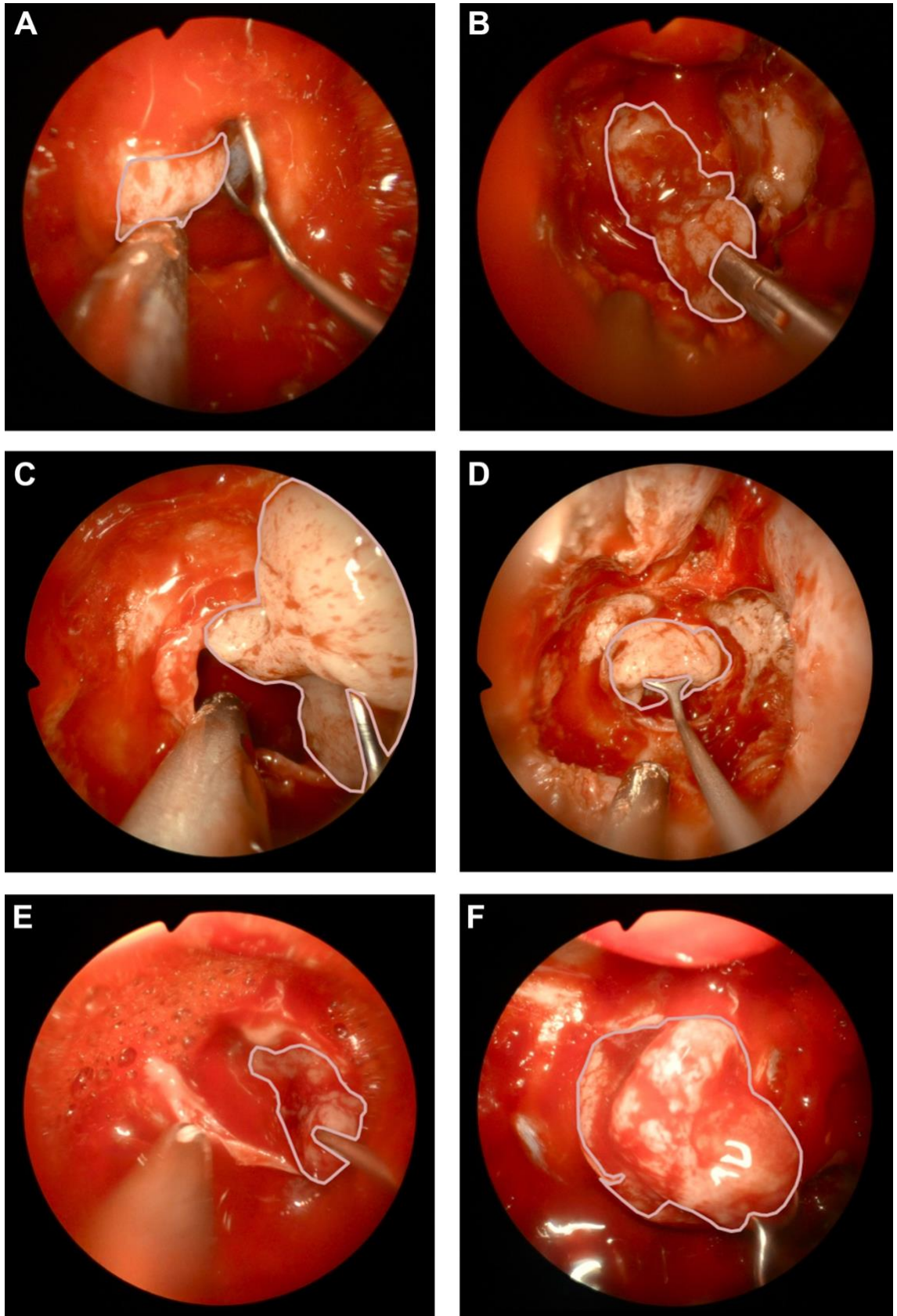


Figure 8 Endoscopic endonasal frames from six different clinical cases of PAs, with corresponding masks segmented using Label Studio. A) Case 1: segmentation of a remnant PA extending into the right cavernous sinus. B) Case 2: segmentation of a PA during the early stages of removal. C) Case 3: segmentation of a PA during the early

stages of removal. D) Case 4: segmentation of a PA in the early stages of removal using curettes. E) Case 5: segmentation of a remnant PA adherent to the left cavernous sinus. F) Case 6: segmentation of a PA during its initial stages of removal.

The resulting masks were then stored in .json format within a dedicated folder. These original frames and masks were then used to train the AI models for automatic tumor segmentation.

3.2.2.4 Dataset preparation

All the steps of dataset preparation, ML analysis, training and testing of the models are summarized in **Figure 9**.

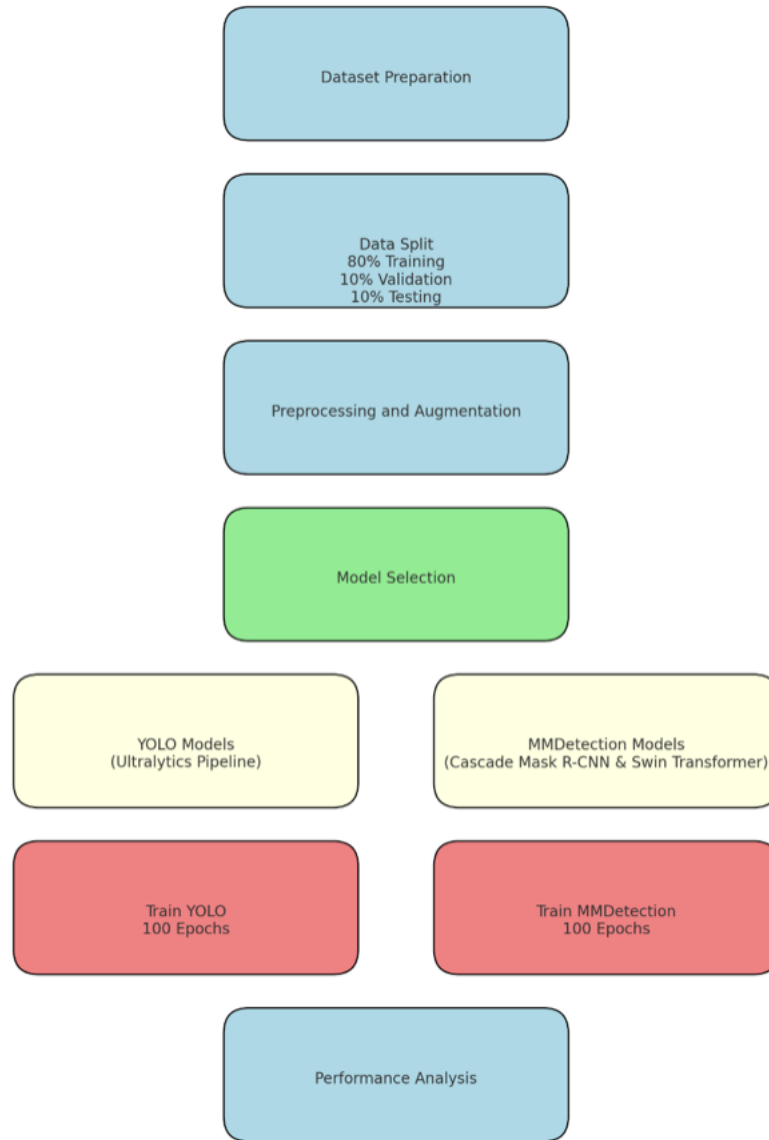


Figure 9 Schematic framework detailing the progressive steps of dataset preparation, training and testing of the models assessed in this work.

The dataset comprised 700 endoscopic endonasal images, specifically focused on the segmentation of PAs. To ensure broad applicability for DL model training, the dataset underwent pre-processing and was divided into three subsets: approximately 70% for training (from 14 videos), 15% for validation (from 3 videos), and 15% for testing (from 3 videos). To prevent data leakage and ensure a robust evaluation of model performance, all images derived from a given surgical case were assigned exclusively to a single subset (i.e., training, validation, or test). The original 487 training images were resized to a standard 640×640 pixels using a fill method with center cropping to ensure consistent dimensions. Each training image was then augmented to create

approximately two additional variations per sample, resulting in a total of 1462 images in the training.

These augmentations included random horizontal and vertical flips, zoom adjustments with a minimum of 0% and a maximum of 20%, and rotations between -15° and $+15^{\circ}$. Further adjustments were applied to hue (ranging from -20° to $+20^{\circ}$), saturation (between -25% and +25%), brightness (between -15% and +15%), and exposure (between -10% and +10%). Additionally, random noise affecting up to 1.68% of pixels was added to introduce variability. This augmentation strategy not only expanded the dataset significantly but also helped mitigate overfitting, thereby enhancing the model's generalization capabilities.

3.2.2.5 Image segmentation models

Two DL frameworks were employed for image segmentation: YOLO (You Only Look Once)-based segmentation models implemented through the Ultralytics pipeline, and models from the MMDetection library, specifically Cascade Mask R-CNN and Swin Transformer models.

3.2.2.5.1 YOLO segmentation models

The primary segmentation models used were based on the YOLO architecture, which is highly efficient for real-time object detection. The YOLO models were trained using the Ultralytics pipeline, which provided a streamlined process for consistent preprocessing, model configuration, and evaluation. Training was conducted for 100 epochs, with standard hyperparameters.

3.2.2.5.2 MMDetection models

In addition to the YOLO-based models, three models were trained using the MMDetection library: two Cascade Mask R-CNN models and one Swin Transformer-based model. The Cascade Mask R-CNN models were chosen for their multi-stage object detection refinement, which enhances segmentation accuracy. The Swin Transformer model was included for its advanced image segmentation capabilities, using self-attention to extract features effectively across multiple scales.

The initial training schedule spanned 100 epochs, but analysis of validation and test performance revealed overfitting tendencies after the 30th epoch, particularly for the MMDetection models. This was indicated by a divergence between training and validation losses beyond 30 epochs. Consequently, model selection was based on performance metrics at the 30th epoch, where accuracy and generalization were optimally balanced, minimizing overfitting.

3.2.2.6 Machine learning analysis

3.2.2.6.1 Training and evaluation protocol

All models were trained on an NVIDIA RTX 3090 Ti GPU (NVIDIA Corporation, Santa Clara, CA, USA) with 24GB of VRAM over a span of 100 epochs. The YOLO models were optimized using the Adam optimizer, while the MMDetection models were trained using the Stochastic Gradient Descent optimizer, both with learning rate schedules applied to facilitate convergence. A stepwise reduction in learning rate was triggered upon a plateau in validation loss, enhancing the ability of models to reach an optimal solution. The primary outcome was the quantification of models' performance. Model performance was evaluated using the mean Average Precision (mAP) metric. The mAP is standard for both detection and segmentation tasks.^{3,4,6} The mAP was measured

both at an IoU threshold of 0.50 (mAP[0.50]) and at IoU threshold range of 0.50-0.95 (mAP[0.50:0.95]). While the mAP[0.50:0.95] provides a thorough evaluation of detection performance, the mAP[0.50] concentrates on the model's accuracy in object detection.

The validation set was used for tuning hyperparameters and assessing model overfitting, while the test set was reserved for evaluating final model generalization. Emphasis was placed on the consistency between validation and test performances to ensure robustness in model selection.

3.2.2.6.2 Model selection and overfitting analysis

To determine the optimal training duration, model performance was assessed across validation and test sets, observing the occurrence of overfitting. We observed that the MMDetection models, particularly the Cascade Mask R-CNN and Swin Transformer variants, exhibited signs of overfitting beyond the 30th epoch. This overfitting was indicated by an increasing validation loss, despite a continued decrease in training loss. To counteract this overfitting, models trained using the MMDetection framework were truncated at 30 epochs, which provided the best balance between training accuracy and generalization capacity.

In comparison, the YOLO-based models demonstrated a more gradual training trajectory; however, their performance on the test set was marginally lower than that of the MMDetection models at the 30th epoch. As a result, the MMDetection models trained up to epoch 30 were prioritized for further evaluation and application in surgical contexts.

3.2.2.7 Image segmentation models

Every model's performance was evaluated against the gold standard, which was

composed of manual annotations made by medical professionals. The data were categorized into true positives (TPs), true negatives (TNs), false negatives (FNs), and false positives (FPs) using a contingency table. Overall accuracy was computed as the ratio of correctly segmented areas by the algorithm to regions annotated by experts, distinguishing positive (inside segmented area) and negative (outside segmented area) samples. Recall was defined as the percentage of actual positives correctly detected (i.e., TPs over FNs and TPs), whereas precision was defined as the percentage of correctly identified positive occurrences (i.e., TPs over TPs and FPs). The mAP, which represents the average of the area under the Recall-Precision curve, was finally computed. The overlap between the automatic and manual segmentations was measured using the Dice Similarity Coefficient, which has a value range of 0 (no overlap) to 1 (full overlap). The amount of time needed for each FCNN architecture to complete automatic segmentation on a single frame was measured to assess the tumor detection performance.

An overall comparison was conducted with the Kruskal-Wallis H-test, and pairwise comparisons were made with the Mann-Whitney U test. For broader metric comparison, an analysis of variance (ANOVA) was used at a significance level of 0.05. Pairwise t-tests were employed when significant differences emerged, providing comparisons between independent group metrics. Statistical analyses were performed in Jupyter Notebook 6.4.5 (Project Jupyter, <https://jupyter.org>) using the pandas 1.4.1 (Pandas development team, <https://pandas.pydata.org>) and SciPy 1.8.0 (SciPy community, <https://scipy.org>) libraries.

The datasets generated and/or analyzed during the current study, as well as the model codes, are available from the corresponding author upon reasonable request.

4. RESULTS

4.1 SYSTEMATIC LITERATURE REVIEW

4.1.1 RADIOMICS STUDY

4.1.2 Literature Review

After removing duplicates, 340 articles were identified. Following a review of titles and abstracts, 76 studies were selected for full-text screening. Of the 74 articles assessed for eligibility, 49 met the inclusion criteria and were retained for the final analysis. The remaining 25 studies were excluded based on the following reasons: 10 were systematic reviews or meta-analyses, 9 did not report selected outcomes and 6 were unrelated to the research question. The articles included in the final analysis were published between 2018 and 2025. An overview of the selection process is presented in the PRISMA flowchart (**Figure 10**).

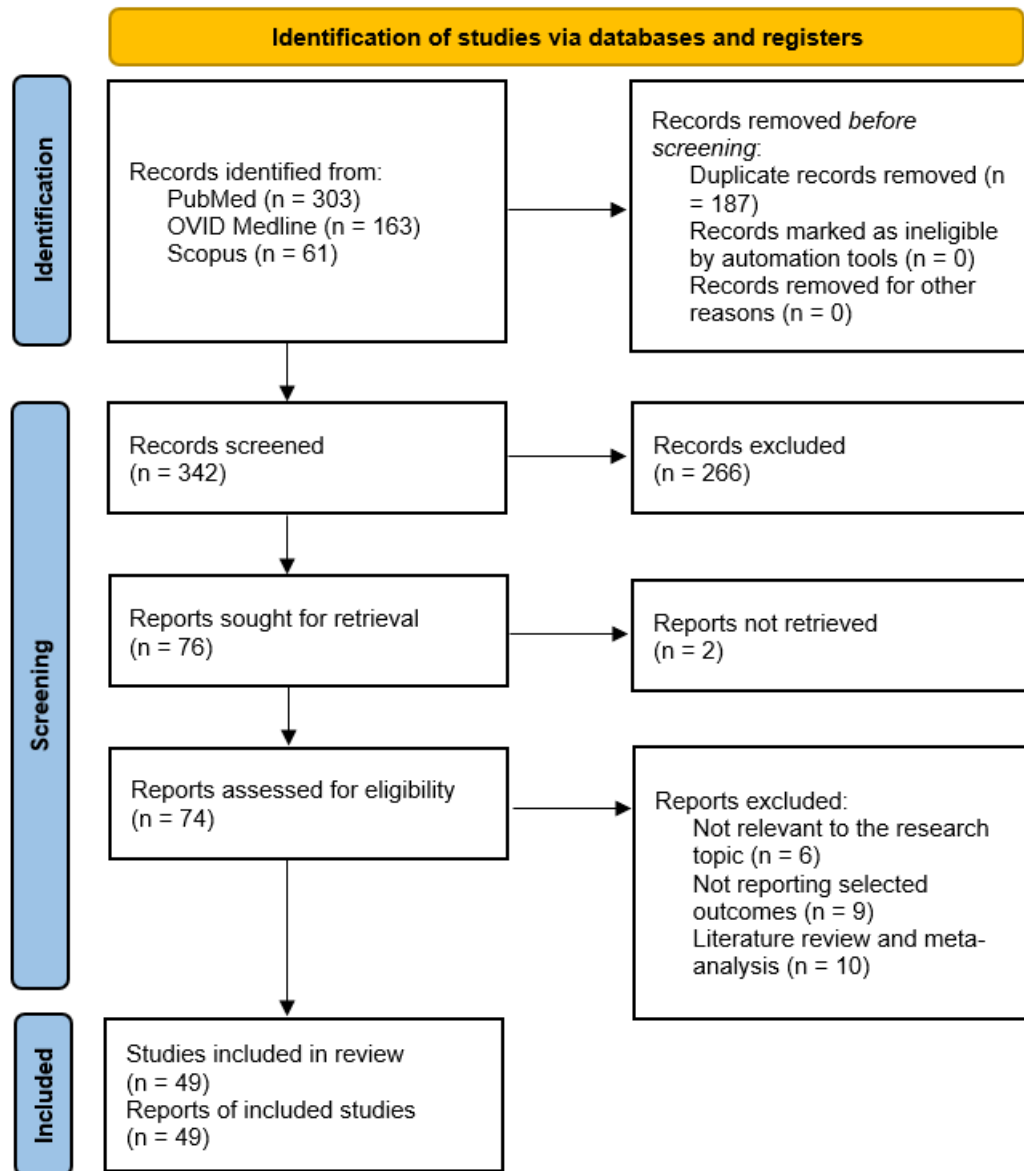


Figure 10 PRISMA flow chart.

4.1.3 Data Analysis

A total of 49 studies were included in the systematic review, published between 2018 and 2025, investigating the role of radiomics in the assessment and classification of PAs. The total patient population across all studies was approximately 9351, with individual study sample sizes ranging from 24 to 1045 patients. Of these, 30 studies (61%) reported explicit training and test data splits, with 6 studies (12%) including separate validation cohorts. Regarding MRI sequences, were used T1-weighted imaging (T1WI) in 21 studies

(43%), T2-weighted imaging (T2WI) in 35 studies (71%), contrast-enhanced T1WI (CE-T1WI) in 34 studies (69%) and T2-weighted imaging FLAIR (T2WI-FLAIR) in 1 study (2%). In terms of analytical methodology, shallow ML approaches were utilized in 43 studies (88%), while deep learning (DL) architectures were applied in 17 studies (34%), with some studies using both. The most common ML algorithms were support vector machine (SVM) (19 studies, 44%), random forest (RF) (8 studies, 19%), logistic regression (LR) (8 studies, 19%), and k-nearest neighbors (7 studies, 16%). For DL, convolutional neural networks (CNNs) were used in 8 studies (47%), with architectures such as ResNet, DenseNet, and U-net represented. Feature extraction was performed using PyRadiomics in 23 studies (47%), while Matlab-based custom tools were used in 4 studies (8%), and other platforms including 3D Slicer or proprietary scripts in the remaining cases.

The types of radiomic features extracted varied, but first-order statistics (FOS) were used in 18 studies (37%), shape-based features in 20 studies (41%), and texture features (e.g., GLCM, GLRLM, GLSZM, NGTDM, GLDM) in 25 studies (51%). Wavelet-transformed features were included in 10 studies (20%), and higher-order features (e.g., histo-gram-based or delta-radiomics) were reported in 5 studies (10%).

Regarding tumor subtype, 35 studies (72%) included PAs with any hormonal secretion profile, 7 studies (14%) focused on functional PAs, including GH-secreting, ACTH, TSH, FSH/LH, and prolactinomas, while other 7 (14%) focused on non-functioning PAs (NFPA). The diagnostic performance was reported using AUC or accuracy values in all studies, with AUCs ranging from 0.55 to 1.00. Most models demonstrated high performance, with 22 studies (45%) reporting AUC values ≥ 0.85 in the test set. Further-more, 6 studies (12%) included external validation, strengthening the generalizability of their findings (Table 5).

Auth or, year	Patients				MR seque nces	ML algori thms used or AI mode l (ML or DL)	Softw are used for featur es extrac tion	Type of radiomic features	Tu mo r sub typ e	AUC ROC (or accuracy %)		
	Tot al (N)	Trai ning data set (%)	Test data set (%)	Va lid ati on da ta set (%)								
Zhan g, 2018	112	67	33	-	T1WI CE- T1WI	RBF- SVM	MatL ab	Intensity Shape and size	NF	T1WI	Traini ng Test	0.831 0.804

								Texture Wavelet-based		CE-T1WI	Training	0.634
											Test	0.510
Niu, 2018	194	50	50	-	T2WI CE-T1WI	Linear SVM	MatLab	Intensity Shape and size Texture Wavelet-based ICA wrapped degree	Any		Training	0.852
											Test	0.826
Kocak, 2018	47	-	-	-	T2WI	kNN C4.5	PyRadiomics (3D-Slicer extension)	FOS GLCM GLRLM GLSZM NGTDM GLDM Wavelet-based	GH	Quantitative TA		0.847
										ROI-based quantitative rSI		0.581
Staartjes, 2018	140	-	-	-	CE-T1WI	MLP (DL) LR	-	-	Any	MLP (DL) LR		0.962
												0.86
Zeynalova, 2019	55	-	-	-	T2WI	ANN	PyRadiomics	-	Any (PMA)			0.710
Ugga, 2019	89	60	40	-	T2WI	kNN	PyRadiomics	Shape FOS GLCM GLRLM GLSZM NGTDM GLDM	Any			0.87
Fan, 2019	163	66	34	-	T1WI T2WI CE-T1WI	SVM	Inhouse program written in Matlab 2015b	Intensity Shape and size Texture Wavelet-based	Any (IFPA)	Training		0.832
										Validation		0.811
Fan, 2019	138	65	35	-	T1WI T2WI CE-T1WI	SVM	PyRadiomics	Shape FOS Texture Wavelet-based	GH	Training		0.96
										Validation		0.89
Fan, 2019	188	53	31	16	T1WI T2WI CE-T1WI	SVM LR	PyRadiomics	FOS Shape and size GLCM GLRLM GLSZM Wavelet-based	GH	Training		0.83
										Validation		0.81
Qian, 2020	149	80	20	-	T1WI T2WI	CNN	-	-	Any			-
Peng, 2020	235	-	-	-	T1WI T2WI CE-T1WI	SVM kNN NB	PyRadiomics	Shape GLCM GLRLM GLSZM	Any	SVM		T1WI 0.8762 T2WI 0.9549 CE-T1WI 0.8806

								GLDM		KNN	T1WI	0.8598
											T2WI	0.9266
											CE-T1WI	0.7947
										NB	T1WI	0.8492
											T2WI	0.9324
											CE-T1WI	0.8309
Cuocolo, 2020	89	80	20	-	T2WI	ET	PyRadiomics	Histogram GLCM GLRLM GLSZM NGTDM GLDM	Any		0.99	
Machado, 2020	27	-	-	-	CE-T1WI	kNN RF LR SVM MLP	PyRadiomics	FOS	NF	MLP	0.929	
								GLCM		RF	0.877	
								GLRLM		SVM	0.860	
								GLSZM		LR	0.929	
								NGTDM		kNN	0.979	
								GLDM FOSW FOSG				
Park, 2020	69	-	-	-	T2WI	-	PyRadiomics	Shape FOS GLCM GLRLM GLSZM NGTDM GLDM	GH		0.834	
Zhu, 2020	374	-	-	-	T1WI T2WI	-	DenseNet-ResNet based Autoencoder framework CRNN	-	Any		-	
Chen, 2020	101	71	29	-	T1WI T2WI CE-T1WI	-	-	-	Any	T1WI	Training	0.90
											Test	0.91
										T2WI	Training	0.86
											Test	0.83
										CE-T1WI	Training	0.90
											Test	0.89
										Combined	Training	0.92
											Test	0.91
Zhang, 2020	50	-	-	-	T2WI CE-T1WI	SVM	Python	SVR GLCM NGTDM	NF		0.87	
Li, 2021	185	54	Group 124	9	T1WI T2WI CE-T1WI	CNN	-	-	Any	Internal Validation 1	0.8063	

				Group 2 13	T2WI- FLAIR						Internal validation 2	0.7881
											External independent testing	0.8478
Liu, 2021	49	-	-	-	T1WI T2WI CE- T1WI	-	PyRadiomics	Shape FOS GLCM GLRLM GLSZM NGTDM GLDM	GH	ROI1	T1C	0.893
											T1WI	0.918
											T2WI	0.823
											Radio mics	0.908
										ROI2	T1C	0.860
											T1WI	0.898
											T2WI	0.812
											Radio mics	0.880
Park, 2021	17 7	80	20	-	T2WI	RF Light GBM ET	PyRadiomics	FOS GLCM GLRLM GLSZM	PRL	Training		0.81
										Test		0.81
Wan, 2021	15 6	69	31	-	T1WI T2WI CE- T1WI	RF SVM	MatLab	-	Any (PM A)			0.90
Wang , 2021	16 3	80	20	-	T1WI T2WI CE- T1WI	Linear SVM RF ET kNN DT GDBT AdaB oost MLP XGBoost	PyRadiomics	Knosp grade adenoma volume adenoma diameters OC height ICA contact degree	Any	Linear SVC		0.762
										RF		0.824
										ET		0.865
										KNN		0.920
										DT		0.597
										GDBT		0.807
										AdaB		0.817
										oost		
										MLP		0.856
										XGBoost		0.826
Zhang, 2021	10 45	80	20	-	T1WI T2WI CE- T1WI	GDBT RF AdaB oost XGBoost LR NB DT MLP	-	-	AC TH	XGBoost		0.712
										GDBT		0.734
										RF		0.726
										AdaB		0.699
										oost		
										NB		0.681
										LR		0.701
										DT		0.664
										MLP		0.700
										Stacking		0.743
Zhang, 2021	13 1	-	-	-	T2WI	SVM RF LDA	PyRadiomics	Shape FOS GLCM GLRLM GLSZM NGTDM GLDM	Any	SVM		0.824
										LDA		0.801
										RF		0.751

Baysal, 2022	130	70	15	15	T2WI	ANN (BFGS algorithm)	PyRadiomics	Shape FOS High order features	Any	NF	0.87
										GH	0.89
										PRL	0.95
										ACTH	0.94
										PH	0.74
										FSH-LH	0.96
Chen, 2022	78	80	-	20	T2WI CE-T1WI	MLP CNN	-	-	NF	TSH	0.95
										CNN	0.84
										MLP	0.73
										Multi modal CNN-MLP	0.85
Fang, 2022	371	-	-	-	CE-T1WI	CNN	-	-		Valid ation fold 1	0.89
										Valid ation fold 2	0.98
										Valid ation fold 3	0.89
										Valid ation fold 4	0.96
										Valid ation fold 5	0.93
Feng, 2022	695	-	-	-	CE-T1WI	CNN	-		Any		0,98
Kim, 2022	67	-	-	-	CE-T1WI	DL	-	Depth of Invasion Degree of contact with intracavernous ICA	Any	1-mm-slice MR	0.79
										3-mm-slice MR	0.61
Park, 2022	104	-	-	-	CE-T1WI	DL	-	-	Any	Read er 1	1-mm-slice MR 0.91
											3-mm-slice MR 0.88
										Read er 2	1-mm-slice MR 0.92
											3-mm-slice MR 0.87
Rui, 2022	302	80	20	-	T1WI T2WI CE-T1WI	LDA SVM RF GBM	PyRadiomics (3D-Slicer extension)	Shape (3D) Shape (2D) FOS GLCM GLRLM GLSZM NGTDM GLDM	NF	Ensemble	0.927
Shu, 2022	261	80	20	-	T2WI CE-T1WI	DL	U-net neural	-	Any	CE-T1WI	87.4%,
										T2WI	89.4%

							netwo rk			CE- T1WI + T2WI	89.2%	
Villal onga, 2022	14 4	80	20	-	T1WI T2WI CE- T1WI	IF local outlier factor oSVM	Pytho n	-	Any	-		
Zhan g, 2022	19 6	90	-	10	CE- T1WI	SVM	PyRa diomi cs	FOS Shape (3D) GLCM GLSZM GLRLM NGTDM GLDM	Any	0.86		
Garg ya, 2023	-	-	-	-	-	CNN (VGG 16, VGG 19, ResNe t-50, Incept ion V3) SVM kNN PNN	-	-	Any	VGG 16	89%	
										VGG 19	91.5%	
										Resne t 50	91%	
										Incept ion V3	96%	
Shen, 2023	11 4	70	30	-	T1WI T2WI CE- T1WI	LR	R softw are	Shape FOS GLCM GLRLM GLSZM NGTDM Wavelet- based	NF	Clinic al + radio mics featur es	0.929	
										Only radio mics featur es	0.844	
Wang , 2023	24 6	78	22	-	CE- T1WI	LR	LIFEx	SHAPE_Volum e (mL) SHAPE_Volum e (vx) SHAPE_Spher icity SHAPE_Surfa ce area SHAPE_Comp acity DISCRETIZED_ Q3 DISCRETIZED_ Kurtosis GLCM GLRM NGLDM GLZLM	Any	Traini ng	0.916	
										Test	0.935	
Wang , 2023	29 5	88	12	-	T1WI T2WI CE- T1WI	Elastic net Linear SVC RF ET	PyRa diomi cs	-	NF	Linear SVC	Traini ng	0.931
											Test	0.937
										Elastic net	Traini ng	0.908
											Test	0.915

						kNN DT GBDT AdaB oost MLP XGBo ost				RF	Traini ng Test	0.848 0.82
										ET	Traini ng Test	0.831 0.845
										KNN	Traini ng Test	0.836 0.762
										DT	Traini ng Test	0.615 0.622
										GBDT	Traini ng Test	0.862 0.819
										AdaB oost	Traini ng Test	0.667 0.793
										MLP	Traini ng Test	0.903 0.905
										XGBo ost	Traini ng Test	0.879 0.868
Zhan g, 2023	13 0	70	30	-	T2WI	Linear SVM	PyRa diomi cs	Shape Histogram Texture Wavelet- based	Any	Delta- radio mic model	Traini ng Test	0.821 0.811
										Comb ined model	Traini ng Test	0.841 0.840
Zhan g, 2023	22 0	80	20	-	T2WI	CNN	-	-	Any			-
A, 2024	22 2	67	33	-	T1WI T2WI CE- T1WI	SVM LR RF MLP	PyRa diomi cs	Shape features FOS GLCM GLRLM GLSZM	Any	Multi- seque nce (LR)	Traini ng Test Valid ation	0.935 0.886 0.840
									Any	Multi- seque nce (MLP)	Traini ng Test Valid ation	0.957 0.913 0.758
Behz adi, 2024	22 0	70	30	-	T1WI T2WI	CNN	-	-	Any			0.898
Da Mutte n, 2024	21 3	91	9	-	CE- T1WI	CNN	-	-	Any			-
Fang, 2024	72 9	89	11	-	CE- T1WI	CNN (ResN et-50)	-	-	Any			0.92
Ishim oto, 2024	24	-	-	-	CE- T1WI	DL	-	SNR CNR	Any			-
Liu, 2024	24 7	80	20	-	T1WI T2WI CE- T1WI	LR SVM MLP	PyRa diomi cs	FOS Shape Texture	Any	ML model	L R Training Test	0.7 89 0.5 47

							(ML model)			S Training	0.9
										V	0.4
										M Test	0.6
											45
							ResNe			M Training	0.8
							t50			L	12
							(DL model)			P Test	0.6
											20
								DL model	L Training	1.0	
									R	0.0	
									Test	0.8	
										0.8	
									S Training	1.0	
									V	0.0	
									M Test	0.8	
										12	
									M Training	1.0	
									L	0.0	
									P Test	0.7	
										65	
								DLR model	L Training	1.0	
									R	0.0	
									Test	0.8	
										10	
									S Training	1.0	
									V	0.0	
									M Test	0.8	
										10	
									M Training	0.9	
									L	94	
									P Test	0.7	
										78	
Taslicay, 2024	65	-	-	-	T1WI T2WI CE-T1WI	SVM LR LGB	PyRadiomics (3D-slicer)	FOS GLCM GLRLM GLSZM NGTDM GLDM	Any (CPA)	SVM LR LGB	0.956 0.956 0.951
Zhang, 2024	152	70	30	-	T1WI T2WI CE-T1WI	SVM	PyRadiomics	FOS Shape (3D) Shape (2D) GLCM GLRLM GLSZM NGTDM GLDM	Any	T1WI Training T1WI Test T2WI Training T2WI Test CE-T1WI Training CE-T1WI Test Multiparametric Training Multiparametric Test	0.784 0.767 0.724 0.763 0.822 0.794 0.851 0.847
Agosti, 2025	394	80	10	10	T2WI	ET	PyRadiomics	Shape FOS GLCM GLRLM GLSZM NGTDM Wavelet-based	Any		0.59

Gradient filtered images; CRNN, Convolutional Recurrent Neural Network. **Table 5** Summary of anamnestic and radiomics data of the studies included in the systematic review. Abbreviations: NF, non-functioning; OC, optic chiasm; ICA, internal carotid artery; GH, growth hormone; IFPA, invasive functional pituitary adenoma; PMA,

pituitary macro-adenoma; PRL, prolactin; ACTH, adrenocorticotrophic hormone; CPA, cystic pituitary adenoma; RBF-SVM, support vector machine with the radial basis function kernel; SVM, support vector machine; MLP, multi-layer perceptron; ANN, artificial neural network; CRNN, convolutional recurrent neural network; kNN, k-nearest neighbors; NB, Naïve Bayes; ET, Extra Trees; RF, Random Forest; LightGBM, light gradient boosting machine; DT, Decision Tree; AdaBoost, Adaptive Boosting; XGBoost, Extreme Gradient Boosting; GBDT, gradient boosting decision tree; BFGS, Broyden-Fletcher-Goldfarb-Shanno; IF, isolation forest; oSVM, one-class support vector machine; PNN, probabilistic neural network; SNR, signal-to-noise ratio; CNR, contrast-to-noise ratio; ICA, internal carotid artery; FOS, First Order Statistics; GLCM, Gray Level Co-occurrence Matrix; GLRLM, Gray Level Run Length Matrix; GLSZM, Gray Level Size Zone Matrix; NGTDM, Neighboring Gray Tone Difference Matrix; GLDM, Gray Level Dependence Matrix; FOSW, First Order Statistics applied over Wavelet-filtered images; FOSG, First Order Statistics applied over.

The most frequently represented field was the prediction of histopathological features, explored in 14 studies (29%), making it the dominant area of investigation. Within this category, the preoperative prediction of Ki-67 index was the most common specific endpoint, analyzed in 5 studies, followed by efforts to distinguish subtypes such as SCAs, NCAs, and Tpit/Pit-1/SF-1 families, and to classify functional versus non-functional adenomas. The second most common field was the prediction of response to surgical treatment, addressed in 13 studies (27%). Of these, post-surgical recurrence or regrowth was the most studied endpoint, featured in 4 studies, indicating its clinical relevance. This was followed by investigations into visual outcome, biochemical remission, and intraoperative cerebrospinal fluid leak prediction. The prediction of tumor consistency and prediction of invasiveness were respectively addressed in 8 and 7 studies (16% and 14%). For consistency, all studies focused on distinguishing soft from fibrous tumors, while the invasiveness category primarily targeted CS invasion (6 studies), and to a lesser extent suprasellar extension. Studies on diagnosis of PAs accounted for 4 publications (8%), with most evaluating automated tumor detection from brain MRI, and one study distinguishing cystic PAs from Rathke's cleft cysts. Lastly, prediction of response to non-surgical treatment, including somatostatin analogs and dopamine agonists (DAs), was investigated in 2 studies (4%), and automated tumor segmentation and volumetry was explored in 1 study (2%) (**Table 6**).

General Field of Application	Specific Endpoint	Author, year
Prediction of consistency		Zeynalova, 2019 Fan, 2019

Prediction of invasiveness	Distinction between soft and fibrous tumors	Cuocolo, 2020 Zhu, 2020 Chen, 2020 Wan, 2021 Wang, 2021 Agosti, 2025
	Prediction of CS invasion	Niu, 2018 Fang, 2022 Kim, 2022 Park, 2022 Zhang, 2022 Fang, 2024
	Prediction of SF invasion	Feng, 2022
Prediction of histopathological features	Preoperative prediction of Ki67	Ugga, 2019 Fan, 2019 Shu, 2022
	Prediction of Ki67 and PIT-1	Liu, 2024
	Distinction between high-risk and low-risk PitNETs (WHO 2021 classification)	A, 2024
	Distinction among Tpit, Pit-1, and SF-1 subfamilies	Peng, 2020
	Distinction between NCAs and other NFPA subtypes	Zhang, 2018
	Distinction between SCAs and other NFPA subtypes	Rui, 2022 Wang, 2023
	Distinction between functioning and nonfunctioning PAs	Li, 2021
	Prediction of aggressiveness (Ki-67 $\geq$ 3%, positive p53 staining, high mitotic count)	Wang, 2023
	Prediction of granulation pattern of GH-secreting PAs	Park, 2020 Liu, 2021
	Prediction of hormonal secretion patterns	Baysal, 2022
Prediction of response to surgical treatment	Prediction of post-surgical recurrence or regrowth	Machado, 2020 Zhang, 2020 Chen, 2022 Shen, 2023
	Prediction of post-surgical visual outcome	Zhang, 2021 Zhang, 2023 Zhang, 2023 Zhang, 2024
	Prediction of post-surgical biochemical remission	Fan, 2019 Zhang, 2021

Prediction of response to non-surgical treatment	Prediction of intraoperative CSF leak	Villalonga, 2022 Behzadi, 2024
	Prediction of the likelihood of GTR	Staartjes, 2018
	Prediction of response to SA in GH-secreting PMAs	Kocak, 2018
	Prediction of response to DAs	Park, 2021
Diagnose PAs	Detection of pituitary tumors from brain MRI	Qian, 2020 Gargya, 2023 Ishimoto, 2024
	Distinction between pituitary cystic adenomas and Rathke's cleft cysts	Taslicay, 2024
Automated tumor segmentation and volumetry	Lesion detection, evaluation of progression of pituitary incidentalomas and detection of residual tumor.	Da Muten, 2024

Table 6. Summary of radiomics applications for PAs. Abbreviations: CI, confidential interval; CS, cavernous sinus; SF, sellar floor; PIT-1, positive pituitary transcription factor 1; ICA, internal carotid artery; NFPA, non-functioning pituitary adenoma; NCA, null cell adenoma; CSF, cerebrospinal fluid; GTR, gross total resection; PMA, pituitary macroadenoma; SA, somatostatin analogues; DA, dopamine agonist; MRI, magnetic resonance imaging; GH, growth hormone; IFPA, invasive functional pituitary adenoma.

4.1.4 VIDEOMICS STUDY

4.1.5 Literature Review

Following the removal of duplicate records, a total of 223 articles were identified through database searching. After screening titles and abstracts, 44 studies were deemed potentially relevant and were retrieved for full-text evaluation. Upon detailed assessment, 28 studies satisfied the eligibility criteria and were included in the final review. The remaining 16 articles were excluded for the following reasons: 14 were not aligned with the core objectives of this review and 2 lacked relevant outcome data. A detailed summary of the study selection process is illustrated in the PRISMA flow

diagram (Figure 11).

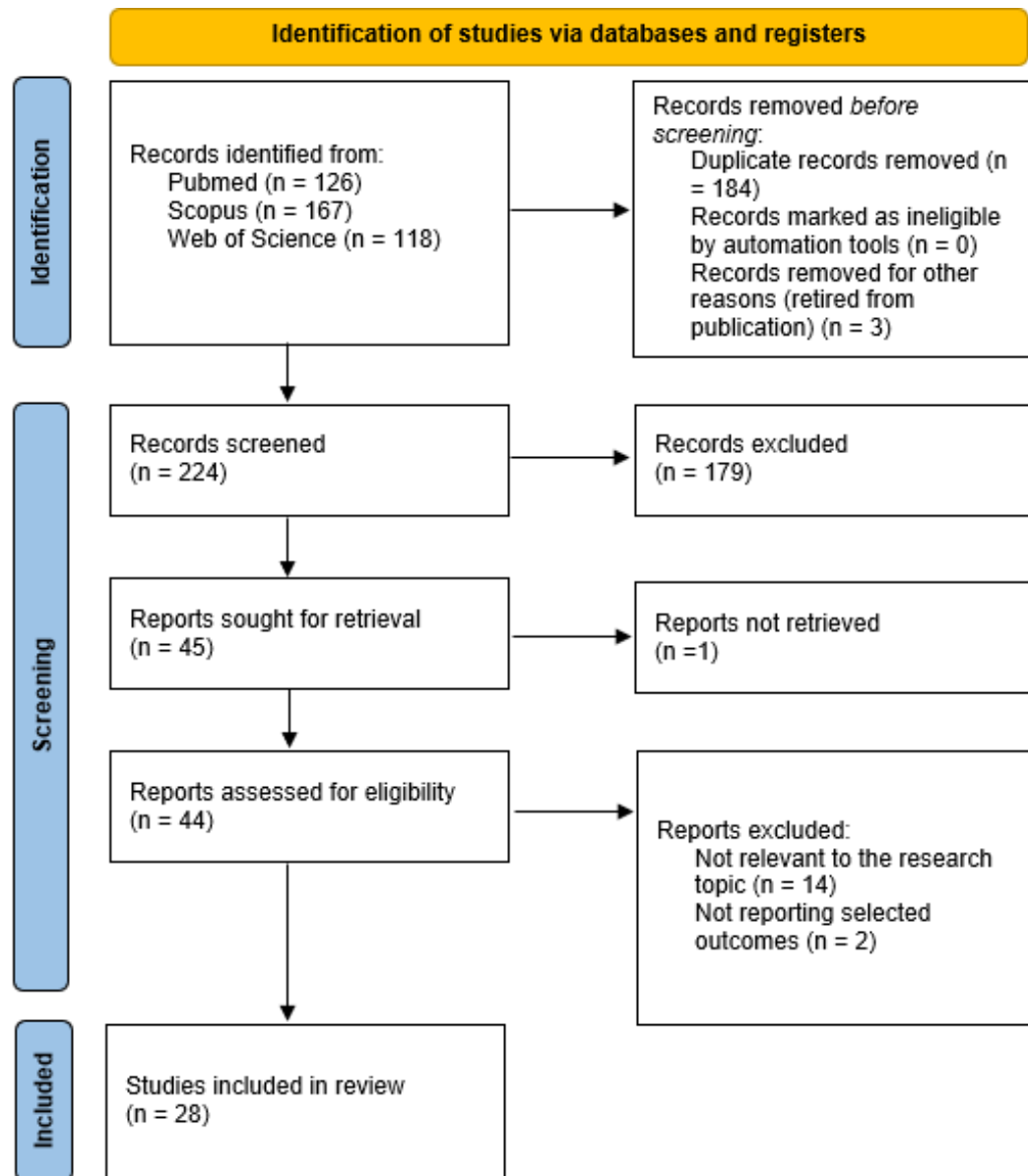


Figure 11 PRISMA flow chart.

4.1.6 Data Analysis

A total of 28 studies published between 2018 and 2025 were included, collectively analyzing 154,989 patients and 1,032,974 annotated endoscopic images. All studies

reported the use of annotated datasets, but the number of frames varied substantially, from fewer than 700 to more than 270,000 images. Data were typically split into training, validation, and testing sets in ratios ranging between 60-97%, 10-20%, and 3-40%, respectively, although several studies also reported absolute numbers (e.g., 400 images in validation sets). Studies allocating less than 10% of their data to test sets frequently reported disproportionately high-performance metrics, raising the possibility of overfitting and inflated accuracy estimates. This methodological weakness highlights the importance of balanced data splitting to ensure generalizable performance. Image resolution ranged from 128×128 to 1280×720 pixels, with 224×224 (28.6% of studies) being the most frequently used format. Despite the importance of annotation methodology, only 10 studies (35.7%) disclosed the software used, including LabelMe, VoTT, CocoAnnotator, Roboflow, OpenCV, Encord, and LabelStudio, whereas 64.3% omitted this information. These methodological differences illustrate a significant source of heterogeneity that affects reproducibility.

Segmentation targets were diverse, reflecting both oncologic and anatomical applications. Nasal polyps were the most frequent focus (7 studies, 25%), followed by nasopharyngeal carcinoma (6 studies, 21.4%). Other targets included sinonasal masses such as inverted papilloma (5 studies, 17.9%), inferior and/or middle turbinates (5 studies, 17.9%), clival/sellar landmarks (4 studies, 14.3%), adenoidal hypertrophy (3 studies, 10.7%), and PAs (2 studies, 7.1%). This distribution demonstrates the dual role of videomics in disease characterization and intraoperative navigation.

The included studies covered a wide spectrum of DL architectures, ranging from traditional CNNs (ResNet, Xception, InceptionResNetV2, MobileNet-V2)^{3,29,30} to object detection models (YOLOv7, YOLOv8)^{2,5,27,31} and emerging transformer-based frameworks (Swin Transformer, NasVLM, NaMA-Mamba).^{2,33,34,35,36} This distribution reflects the methodological diversity of the field. CNNs such as ResNet-50 and ResNet-152 were reported in 5 studies (17.9%), while YOLO-based architectures (YOLOv7, YOLOv8) were also used in 5 studies (17.9%). Other CNN-based models included Xception, InceptionResNetV2, MobileNet-V2, EfficientNet-B2, and nnUNet. More recently, transformer-based approaches were increasingly adopted, including Swin Transformer (3 studies), NasVLM (1 study), and NaMA-Mamba (1 study). This trend reflects a methodological shift toward architectures with greater capacity for multi-scale

contextual analysis. Models such as YOLOv8 and Swin Transformer achieved top-performing metrics and serve as benchmarks of both technical advancement and translational innovation in videomics.

Performance outcomes were generally high, but with considerable variability. Reported accuracy ranged from 71.1% to 98.6%, F1-score from 33.1% to 98.6%, and recall from 83.9% to 98.7%. AUC-ROC values spanned 87.4% to 99.2%. Segmentation-specific metrics demonstrated similar heterogeneity: IoU ranged from 45.1% to 94.6%, mIoU from 61.2% to 81.7%, mAP[0.50] from 53.4% to 94.9%, and MPCK-20 from 53.2% to 97.9%. Notably, studies with larger and higher-resolution datasets, or with standardized annotation protocols, tended to achieve superior boundary delineation and generalization ability.

Inference time was inconsistently reported, with only 8 studies (28.6%) providing data. Reported times ranged from 0.14 ms per image for lightweight SVM-based models to approximately 100 ms for more complex multi-stage networks. YOLOv8 achieved inference times as low as 9.8 ms per image, while transformer-based frameworks (e.g., Swin Transformer, NaMA-Mamba) reported longer but still clinically feasible times when optimized with engines such as TensorRT. These findings suggest a trade-off between segmentation accuracy and processing speed, with CNNs favoring efficiency and transformers excelling in precision. Reported inference times were not normalized to hardware specifications, as only a minority of studies provided full details of GPU type, memory, or acceleration engines. As a result, cross-study comparisons should be interpreted cautiously. Subgroup comparison of CNN-based versus transformer-based models showed that transformer architectures achieved superior segmentation accuracy (mAP[0.50], mIoU), whereas CNN-based models, particularly YOLO variants, consistently achieved faster inference times (**Table 7**).

Author, Year	Patients					Annotation dataset			DL model	Performance (%**)
	Total Patients N	Total images N	Training data set N (%)	Validation dataset (% or N*)	Testing data set N (%)	Image resolution (pixel x pixel)	Segmentation software	Evaluated target		
Li et al, 2018	7951	27536	70	20	10	500 x 500	NA	Nasopharyngeal malignancy	eNPM-DM	Accuracy: 88,7

Girdler et al, 2021	297	297	75	10	15	224 x 224	NA	IP, NP	ResNet-152	Accuracy: 74,2
Bieck et al, 2022	30	180 000	80	20	NA	NA	NA	Five anatomical landmarks during FESS	ResNet-50	F1-Score: 47,0
Ay et al, 2022	80	464 0	80	300*	20	550 x 550	NA	NP	3CH-CNN	Accuracy: 98,3
Bi et al, 2023	NA	317 9	80	996*	20	256 x 256	NA	AH grading	MIB-ANet	Accuracy: 76,8 F1-Score: 76,3 Inference time: 50 ms
Chen et al, 2023	NA	405	80	NA	20	765 x 570	LabelMe	Nasal bleeding	ETU-Net	IoU: 94,6 F1-Score: 97,2
Das et al, 2023	64	635	80	NA	20	1280 x 720	NA	Sella, clival recess, eight parasellar landmarks	PAINet	IoU sella: 66,1 IoU clival recess: 54,1 MPCK-20% eight landmarks : 53,2 Inference time: 100 ms
Yui et al, 2023	53	143 167	87,5	NA	12,5	224 x 224	NA	IP	MobileNet-V2	AUC-ROC: 87,4 Accuracy: 84,3
Fuse et al, 2023	50	605	60	20	20	128 x 128	VoTT	PA	ResNet-50	Accuracy: 75,1 F1-Score: 75,1
									wide-ResNet-50–2	Accuracy: 76,8 F1-Score: 76,6
									DenseNet-161	Accuracy: 75,3 F1-Score: 75,2
Kwon et al, 2024	434 0	434 0	60	400*	40	224 x 224 or 331 x 331	OpenCV	Normal nasal cavity, NP, benign tumor, malignant tumor	Xception	Accuracy: 82,0 F1-Score: 81,0

Phoommanee et al, 2024	73	8972	NA	NA	2257	384×384	NA	Nasal obstruction grading	ViT-tin	Accuracy validation set: 94,8 F1-Score validation test: 89,4 Accuracy testing test: 71,1 F1-Score testing set: 33,1 Inference time: 37,04 ms
									SVM	Accuracy validation set: 79,6 F1-Score validation test: 60,3 Accuracy testing test: 69,6 F1-Score testing set: 31,8 Inference time: 0,14 ms
Phoommanee et al, 2024	62	779	NA	NA	22	512 × 512	NA	Nasal septum, IT, MT, NP, others, airway	Mask2Former (Swin-T)	mIoU validation set: 81,7 mIoU testing set: 61,2 Inference time: 68,7 ms
Tai et al, 2024	1442	1442	70	10	20	256×256	NA	NP, IP	InceptionResNetV2	NP accuracy: 82,7 NP F1-Score: 84,1 IP accuracy: 82,7 IP F1-Score: 61,2
Mao et al, 2024	64	635	80	NA	20	1280 × 720	NA	Sella, clival recess, four parasellar landmarks	PitSurgRT	IoU sella: 67,0 IoU clival recess: 45,9 MPCK-20% four landmarks: 97,9
									PitSurgRT + TensorRT	Inference time (fps32): 44,1 ms Inference time (fps16): 33,5 ms

Ganeshan et al, 2024	NA	2111	80	15	5	1024 × 768	CocoAnn otator	IT, MT	YOLOv8	Accuracy: 91,5 F1-Score: 93,1
Rampinelli et al, 2024	52	342	80	10	10	640 × 640	Roboflow	NP	YOLOv8.0.28	Precision: 91,0 Recall: 83,9 mAP[0.50]: 94,9 IoU (mAP [0.50-0.95]): 67,9 Inference time: 9,8 ms
Xu et al, 2024	1050	6300	60	20	20	576 × 720	NA	NP, IP, fungal sinusitis, nasal malignant tumor	Att-Res2-UNet	Accuracy: 97,9
Yue et al, 2024	2134	38073	70	10	20	224 × 224	NA	NPC, AH, allergic rhinitis, chronic rhinosinusitis with nasal polyps, deviated nasal septum, NOR, rhinosinusitis	Nose-Keeper (Swin Transformer)	Accuracy: 92,3
Lei et al, 2025	NA	4000	NA	NA	NA	NA	NA	NOR	ResNet-50	Accuracy: 98,6 F1-Score: 98,6 Recall: 98,7
Liu et al, 2025	67900	271600	90	10	NA	224 × 224	NA	NOR, benign hyperplasia, NPC	NasVLM	NPC accuracy: 94,5 NPC AUC-ROC: 99,2
Wang 2025, X-S et al	NA	25278	97	NA	3	224 × 224	NA	AH grading	Xception	Accuracy: 95,5 AUC-ROC grade I: 93,0 AUC-ROC grade II: 94,0 AUC-ROC grade III: 97,0 AUC-ROC grade IV: 91,0
Bidwell et al, 2025	NA	2111	80	5	15	NA	CocoAnn otator	IT, MT	YOLOv8 (all)	Average: F1 score: 92,9 Accuracy: 87,0

										Inference time: 90,9 ms
									YOLOv8-nano	F1 score: 92,0 Accuracy: 86,0 Inference time: 25,6 ms
He et al, 2025	906	8816	70	10 + 2818*	20	512 × 512	LabelMe	NPC	NPC-SDNet	Diagnostic accuracy: 95,0 (WLI), 95,8 (NBI) Segmentation accuracy: 94,7 (WLI), 92,2 (NBI) IoU: 83,7 (WLI), 83,4 (NBI)
Staartjes et al, 2025	146	19000	NA	NA	20*	NA	VoTT	Anatomical landmarks in nasal and sellar phase of TSS approach	YOLOv7	mAP[0.50]: 53,4
Mao et al, 2025	64	635	80	NA	20	1280 × 720	NA	Sella, clival recess, four parasellar landmarks	ConsisTNet	IoU sella: 66,8 IoU clival recess: 45,1 F1-Score sella: 80,6 F1-Score clival recess: 60,2 MPCK-20% four landmarks: 96,3
									ConsisTNet + Tensor RT	Inference time (fps32): 8,8 ms Inference time (fps16): 5,0 ms
Levi et al, 2025	311	1242	80	10	10	224 × 224	Encord	Sinonasal masses	EfficientNet-B2	Accuracy: 90,5 F1-Score: 89,7
									nnUNet	Segmentation accuracy: 72,3 (polyp)

										and 72,8 (tumor)
Wang W et al, 2025	679 00	271 600	90	10	NA	224 × 224	NA	NOR, NPC	NaMA-Mamba	NPC accuracy: 92,7 NPC F1-Score: 90,7 NPC AUC-ROC: 96,3
Agosti et al, 2025	20	700	80	10	10	640 × 640	Label Studio	PA	YOLOv8x-seg	mAP[0.50]: 83,7 mAP[0.50:0.95]: 50,9 DSC: 83,0
									Swin Transformer	mAP[0.50]: 91,3 mAP[0.50:0.95]: 60,1 DSC: 89,0 Recall: 91,0 Precision: 88,0

Table 7 Summary of videomics data of the studies included in the systematic review. Abbreviations: AH: Adenoidal Hypertrophy, DL: Deep Learning, DSC: Dice Similarity Coefficient, FESS: Functional Endoscopic Sinus Surgery, IoU: Intersection over Union, IP: Inverted Papilloma, IT: Inferior Turbinate, mAP[0.50]: mean Average Precision at IoU threshold 0.50, mAP[0.50-0.95]: mean Average Precision across IoU thresholds from 0.50 to 0.95 in steps of 0.05, MPCK-20: Mean Percentage of Correct Keypoints within 20%, MT: Middle Turbinate, ms: milliseconds, N: Number, NA: Not Available, NBI: Narrow Band Imaging, NOR: NORMal nasal cavity and nasopharynx, NP: Nasal Polyps, NPC: NasoPharyngeal Carcinoma, PA: Pituitary Adenoma, TSS: Trans-Sphenoidal Surgery, VoTT: Visual object Tagging Tool, WLI: White Light Imaging. N*: Additional images out of the total images. **: The inference time is always specified to be measured in ms. When the articles reported it in frames per second (fps) (i.e., Mao et al, 2024 and Mao et al, 2025), it was converted to ms.

4.2 RETROSPECTIVE REGISTRY

4.2.1 RADIOMICS STUDY

A total of 1,106 texture features were extracted, encompassing both first- and higher-order texture features derived from the original and filtered images. A correlation

cluster map of the extracted features is presented in **Figure 12**, while a detailed description of these features is available in the Pyradiomics online documentation (<https://pyradiomics.readthedocs.io/en/latest/features.html>).

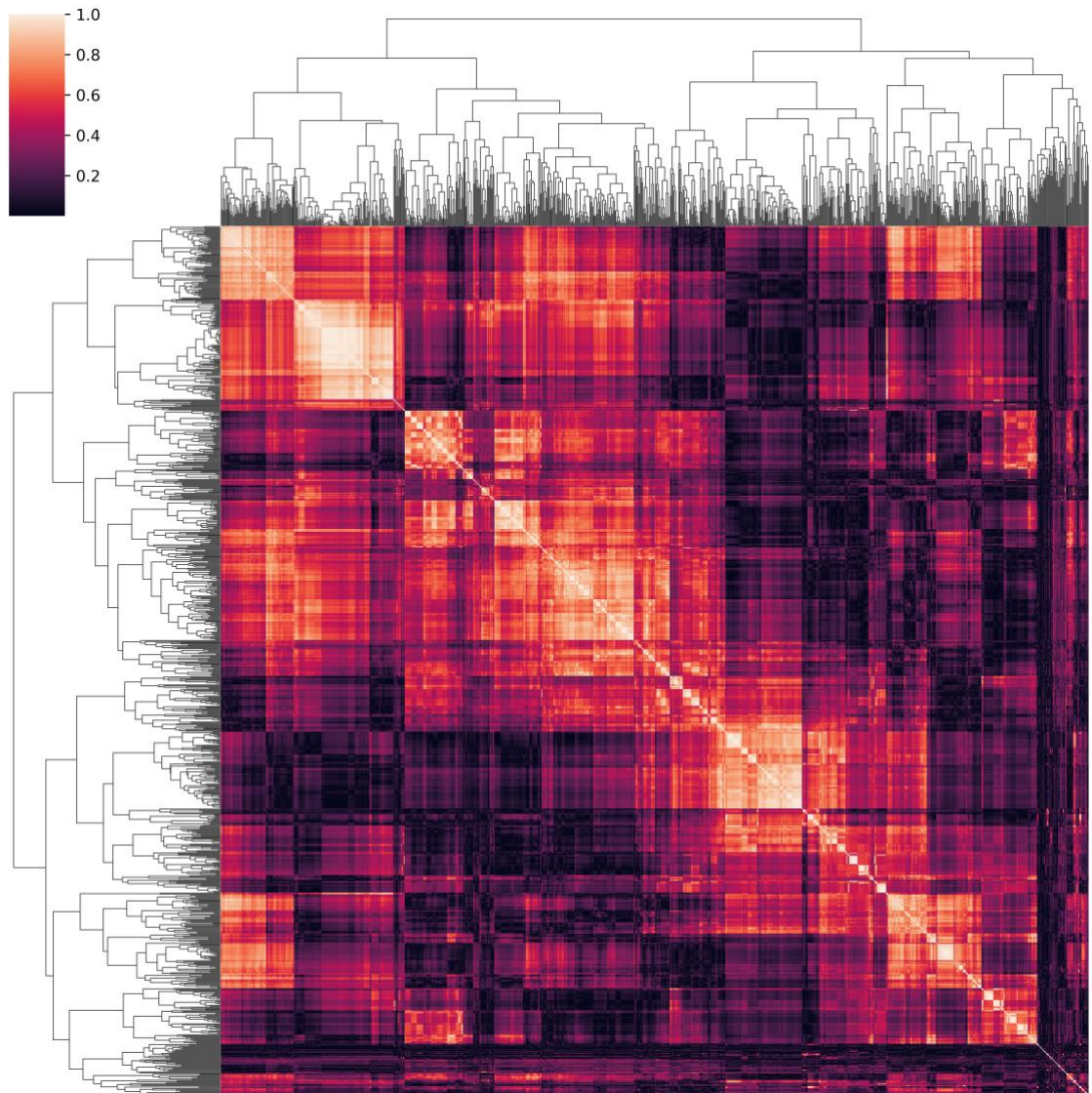


Figure 12 Heatmap of the feature correlation matrix using hierarchical clustering. The dataset was cleansed of features whose intercorrelation was greater than the chosen threshold (≥ 1).

Among these, 167 exhibited low variance, and 767 showed high intercorrelation. Recursive feature elimination (RFE) subsequently identified a refined subset of 65 features as the most predictive (**Figure 13**).

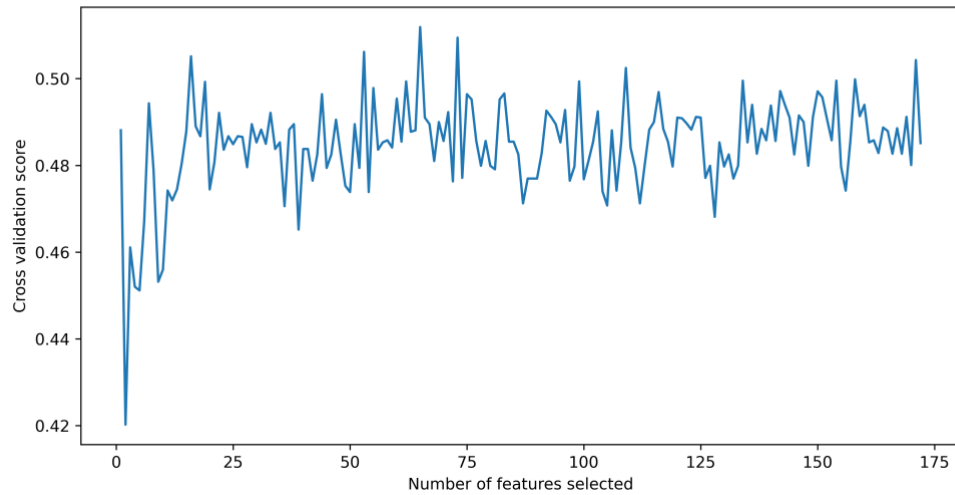


Figure 13 Recursive feature removal plot of the feature selection procedure. At each iteration, one feature is eliminated from the total number of features on the x-axis. The average cross-validation score for each feature total is shown on the y-axis.

The full feature list is provided below:

Optimal number of features: 65

[*'original_shape_Elongation'*, *'original_shape_Sphericity'*,
'original_firstorder_10Percentile', *'original_firstorder_Kurtosis'*,
'original_glszm_SizeZoneNonUniformityNormalized',
'original_ngtdm_Busyness', *'log-sigma-2-0-mm-3D_firstorder_90Percentile'*, *'log-*
sigma-2-0-mm-3D_firstorder_Maximum', *'log-sigma-2-0-mm-3D_firstorder_Skewness'*,
'logsigma-2-0-mm-3D_gldm_LargeDependenceLowGrayLevelEmphasis', *'log-sigma-4-*
0-mm-3D_firstorder_90Percentile',
'log-sigma-4-0-mm-3D_firstorder_Kurtosis', *'log-sigma-4-0-*
mm-3D_firstorder_Maximum', *'log-sigma-4-0-mm3D_gldm_Lmc2'*, *'log-sigma-4-0-mm-*
3D_gldm_Ldm', *'log-sigma-4-0-mm-3D_gldm_LongRunLowGrayLevelEmphasis'*,
'log-sigma-4-0-mm-3D_gldm_DependenceVariance', *'log-sigma-4-0-mm-*
3D_gldm_LargeDependenceLowGrayLevelEmphasis', *'log-sigma-6-0-mm-*
3D_firstorder_90Percentile', *'logsigma-6-0-mm-3D_firstorder_Kurtosis'*, *'log-sigma-6-0-*
mm3D_firstorder_Maximum', *'log-sigma-6-0-mm-3D_firstorder_Skewness'*, *'log-sigma-*
6-0-mm-3D_gldm_Contrast', *'logsigma-6-0-mm-3D_gldm_LongRunEmphasis'*, *'log-*
sigma-6-
0-mm-3D_glszm_LargeAreaHighGrayLevelEmphasis', *'logsigma-6-0-mm-*
3D_glszm_LowGrayLevelZoneEmphasis',
'log-sigma-6-0-mm-3D_glszm_SizeZoneNonUniformityNormalized', *'log-sigma-6-0-*
mm-3D_glszm_SmallAreaLowGrayLevelEmphasis', *'log-sigma-6-0-mm-*
3D_ngtdm_Strength',
'log-sigma-6-0-mm-3D_gldm_LargeDependenceHighGrayLevelEmphasis', *'wavelet-*
LLH_firstorder_Kurtosis', *'waveletLLH_firstorder_Minimum'*, *'wavelet-*
LLH_firstorder_Skewness', *'wavelet-LLH_glszm_SizeZoneNonUniformityNormalized'*,
'wavelet-LLH_ngtdm_Busyness', *'waveletLLH_ngtdm_Strength'*, *'wavelet-*
LHL_firstorder_90Percentile',

'wavelet-LHL_firstorder_Kurtosis', 'wavelet-LHL_firstorder_ -
 Maximum', 'wavelet-LHL_firstorder_Mean', 'waveletLHL_firstorder_Skewness',
 'wavelet-LHL_glcm_Correlation',
 'wavelet-LHH_firstorder_Skewness', 'wavelet-LHH_glcm_Correlation', 'wavelet-
 HLL_firstorder_10Percentile', 'waveletHLL_firstorder_90Percentile', 'wavelet-
 HLL_firstorder_Mean',
 'wavelet-HLL_glcm_Correlation', 'wavelet-HLL_glcm_DifferenceVariance', 'wavelet-
 HLL_glcm_Id', 'waveletHLL_gldm_LargeDependenceHighGrayLevelEmphasis', 'wavelet-
 HLH_glszm_LargeAreaHighGrayLevelEmphasis',
 'waveletHLH_gldm_LargeDependenceHighGrayLevelEmphasis',
 'wavelet-HHL_firstorder_10Percentile', 'wavelet-HHL_firstorder_Kurtosis', 'wavelet-
 HHL_firstorder_Maximum', 'waveletHHL_firstorder_RootMeanSquared', 'wavelet-
 HHL_firstorder_Skewness', 'wavelet-HHL_ngtdm_Strength',
 'waveletHHH_firstorder_Kurtosis', 'wavelet-HHH_firstorder_Skewness', 'wavelet-
 HHH_glcm_Autocorrelation', 'waveletHHH_glszm_SizeZoneNonUniformityNormalized',
 'waveletHHH_gldm_LargeDependenceHighGrayLevelEmphasis',
 'wavelet-LLL_firstorder_Kurtosis'].

The Extra Trees (ET) model achieved an overall accuracy of 63% ($\pm 10\%$) in the test set, correctly classifying most lesions with a sensitivity of 74% and a specificity of 74%. The optimized classifier parameters are detailed below:

Parameters: {'extratreesclassifier__bootstrap': True,
 'extratreesclassifier__class_weight': 'balanced', 'extratreesclassifier__criterion':
 'entropy', 'extratreesclassifier__max_depth':
 8, 'extratreesclassifier__max_features': 61, 'extratreesclassifier__max_samples':
 0.596850157946487, 'extratreesclassifier__n_estimators': 221}.

The AUC-ROC curve was 0.59 (**Figure 14**).

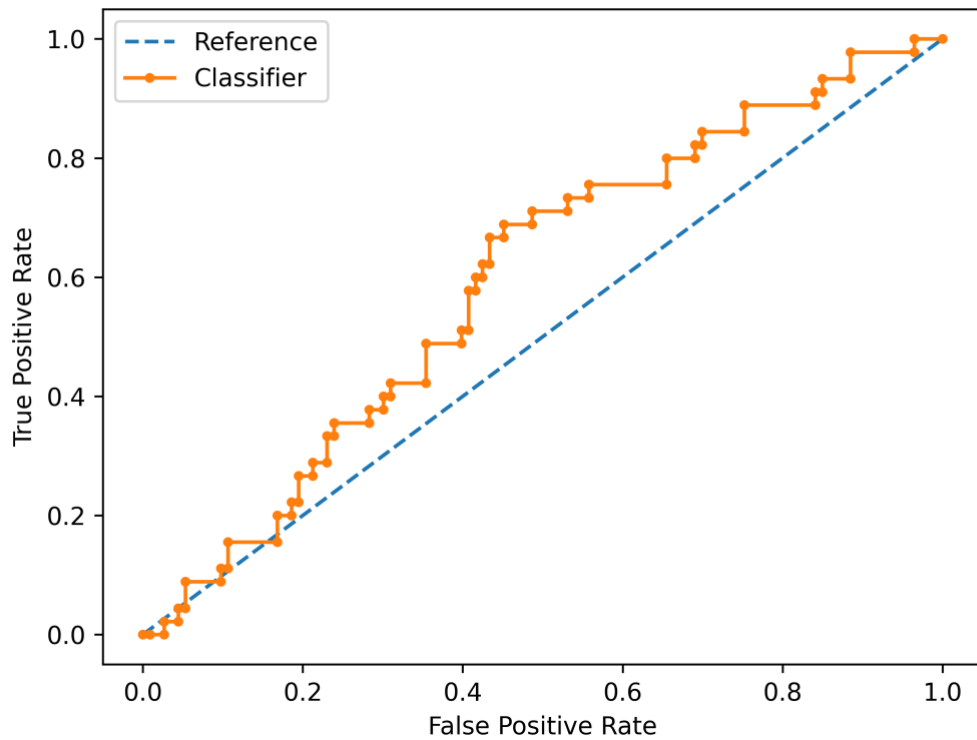


Figure 14 The accuracy of the Extra Trees classifier's receiver operating characteristics curve.

The classifier's performance was significantly superior to the no-information rate. The confusion matrix and a detailed breakdown of accuracy metrics are provided in **Table 8** and **Table 9**.

		Predicted class	
		Soft	Fibrous
Actual class	Soft	84	29
	Fibrous	29	16

Table 8 The test group's confusion matrix.

	Precision	Recall	<i>F</i> -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

Table 9 Accuracy metrics for the Extra Trees classifier.

4.2.2 VIDEOMICS STUDY

The Swin Transformer model, with 70M parameters, demonstrated strong performance across multiple metrics. It achieved a validation box mAP[0.50] of 0.864 and a validation segmentation mAP[0.50:0.95] of 0.593. On the test set, it reached a test segmentation mAP[0.50] of 0.607. These results indicate that transformer-based approaches are highly effective for object detection tasks, with solid generalization performance on unseen data (**Figure 15**).

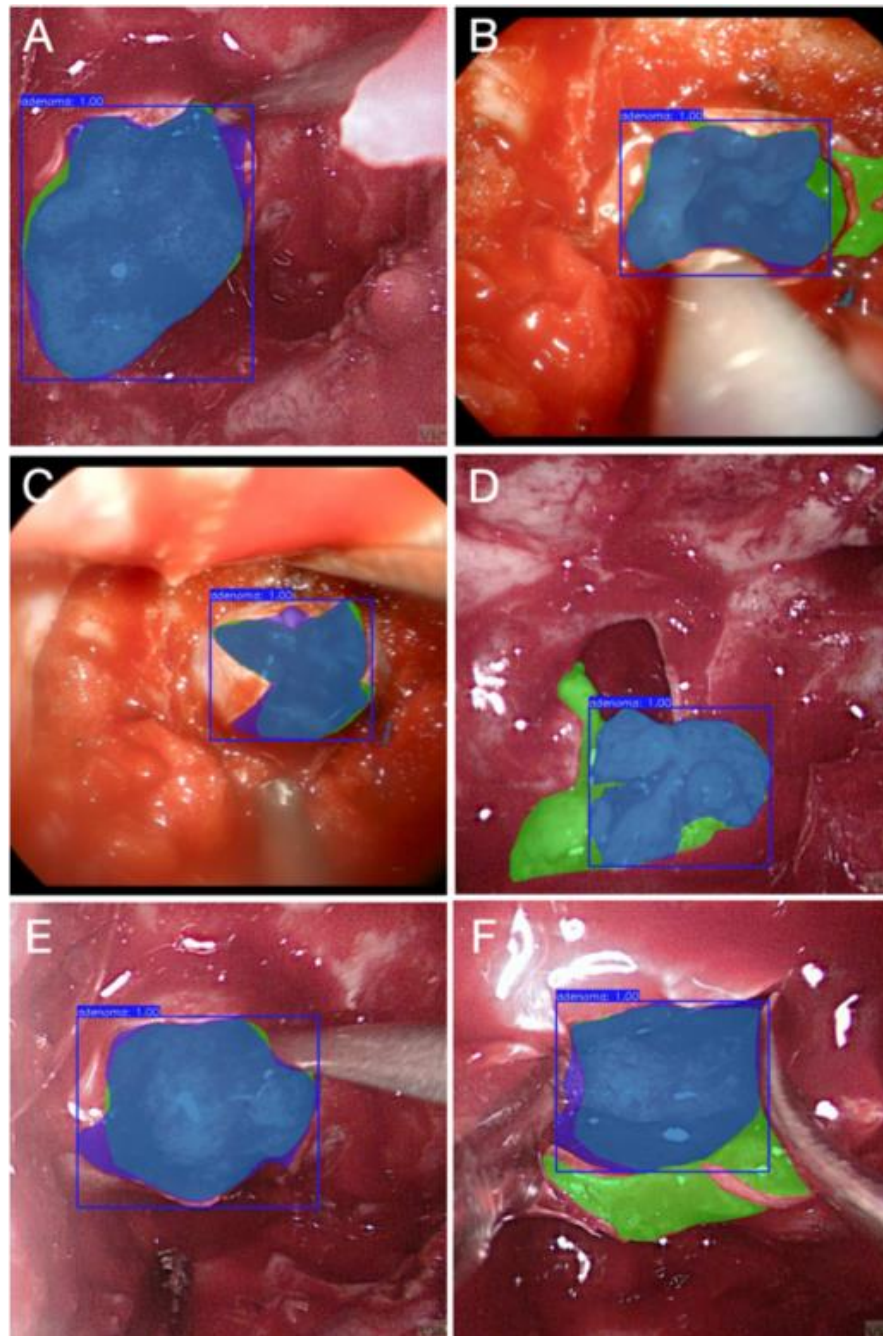


Figure 15 Sequential endoscopic endonasal frames from a video-endoscopy of a PA procedure were analyzed, utilizing the Swin Transformer model during the testing phase to predict PA localization within the surgical field. The green area represents the manually segmented PA, the purple area indicates the PA automatically segmented by the Swin Transformer model, and the blue area shows the overlap between the two. In all frames, the Swin Transformer model demonstrated a performance with an AUC of 1.00. A) Initial stage of surgery: identification of the PA at the dural opening. B) Initial stage of surgery: identification of the PA after folding the dural flaps. C) Intermediate stage of surgery: Removal of a portion of the PA near the left cavernous sinus using suction. D) Intermediate stage of surgery: identification and removal with curette of a PA portion closed to the medial wall of the right cavernous sinus distinctly segmented from the surrounding blood in the automatic segmentation. E) Final stage of surgery: identification of a PA remnant at the right upper corner hidden by the arachnoid. F) Final

stage of surgery: removal of a deep PA portion near the dorsum sellae, identified after elevating the arachnoid and distinguishing it from the pituitary gland.

Among the YOLO architectures, YOLOv8x-seg (62M parameters) achieved a validation box mAP[0.50] of 0.660 and a validation segmentation mAP[0.50] of 0.280, with a test segmentation mAP[0.50] of 0.416, being significantly outperformed by Swin Transformer model ($p = 0.02$, 95% CI: [0.56, 0.65]). YOLOv8n-seg (3M parameters) achieved a validation box mAP[0.50] of 0.619, but its performance on segmentation mAP[0.50:0.95] was notably lower, scoring 0.319. The test segmentation results were also modest, with a mAP[0.50] of 0.336 and a mAP[0.50:0.95] of 0.319. In contrast, YOLOv9c-seg (24M parameters) showed stronger performance, with a validation box mAP[0.50:0.95] of 0.402 and test segmentation mAP[0.50] was 0.399. YOLOv9e-seg (56M parameters) performed poorly across all metrics, with a particularly low validation segmentation mAP[0.50:0.95] of 0.293 and a test segmentation mAP[0.50] of 0.305. YOLOv11n-seg (3M parameters) performed reasonably well, with a validation box mAP[0.50:0.95] of 0.337 and a test segmentation mAP[0.50] of 0.316.

Finally, the Mask R-CNN models, traditionally considered strong performers for segmentation, showed moderate results but did not outperform the transformer-based Swin Transformer or even some YOLO variants in key metrics. Mask R-CNN 101, with 135M parameters, achieved a validation box mAP[0.50:0.95] of 0.356 and a test segmentation mAP[0.50] of 0.347, being significantly outperformed by Swin Transformer model ($p = 0.04$, 95% CI: [0.57, 0.64]), but failed to substantially exceed the performance of smaller models like YOLOv11n-seg, which achieved a test segmentation mAP[0.50] of 0.316 with only 3M parameters (**Table 10**).

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

Mask R-CNN	77M	0.591	0.808	0.521	0.479
50					
Mask R-CNN	135M	0.610	0.827	0.550	0.480
101					
SWIN	70M	0.663	0.911	0.620	0.601

Table 10 Performance metrics for various segmentation models. "mAP[0.50]" refers to the mean average precision at 0.50 IoU (intersection over union), while "mAP" stands for mean average precision at [0.50, 0.95] IoU interval with 0.05 steps. All the metrics except the "Val box mAP" refer to the segmentation task. Abbreviations: M: milion; mAP; mean avarage precision; N.: number; params: parameters; NC: not calculable; Val: validation.

The Swin Transformer model demonstrated superior segmentation capability, achieving a Dice Similarity Coefficient (DSC) of 0.89 ($p < 0.01$, 95% CI: [0.86, 0.92]), outperforming both YOLOv8x (DSC = 0.83) and Mask R-CNN (DSC = 0.81). In addition to its high overlap accuracy, the Swin Transformer achieved optimal recall of 0.91 ($p < 0.05$, 95% CI: [0.88, 0.94]) and precision of 0.88 ($p < 0.05$, 95% CI: [0.85, 0.91]). These results underscore the model's robustness and effectiveness in handling complex segmentation tasks, particularly in comparison to conventional CNN-based and real-time architectures.

5. DISCUSSION

5.1 FINDINGS OVERVIEW

The radiomics-based Extra Trees model achieved only moderate classification performance for PA consistency, with an overall test accuracy of 63% and balanced sensitivity and specificity of 74%. In contrast, videomics models showed substantial variability in segmentation performance in PA recognition. Notably, the transformer-based Swin Transformer significantly outperformed YOLOv8x-seg in segmentation performance ($p = 0.02$, 95% CI: 0.56–0.65) and surpassed Mask R-CNN 101 ($p = 0.04$,

95% CI: 0.57–0.64), emerging as the best-performing model overall. Despite their large number of parameters (135M), Mask R-CNN models achieved only moderate performance (test segmentation mAP[0.50] = 0.347) and failed to exceed either the Swin Transformer or smaller, more efficient YOLO variants such as YOLOv11n-seg (test segmentation mAP[0.50] = 0.316 with 3M parameters).

5.2 RADIOMICS: DIAGNOSTIC AND PROGNOSTIC PERFORMANCE

5.2.1 METHODOLOGICAL QUALITY, IBSI COMPLIANCE, AND RQS ANALYSIS

The systematic review revealed significant heterogeneity across radiomics studies, beginning with acquisition protocols and extending to segmentation strategies, feature extraction pipelines, classification algorithms, and validation frameworks.⁵⁶ IBSI compliance was explicitly reported in only a small minority of studies, with several others vaguely referencing “standardized extraction” without formal adherence to IBSI guidelines.¹² The absence of IBSI compliance raises concerns about feature stability and comparability, particularly given that MRI intensity values vary substantially between scanners, sequences, and institutions.⁵⁷

Similarly, RQS assessments showed that most studies achieved low to moderate scores, primarily due to the lack of phantom calibration, absence of test-retest analyses, insufficient external validation, limited use of prospective cohorts, and the absence of clinical utility assessments or cost-effectiveness analyses. No study demonstrated full model reproducibility by making code, data, or features publicly available.⁵⁸⁻⁶⁰ Although the RQS has recognized limitations, its application remains a useful benchmark to evaluate methodological transparency and robustness. In this context, even studies reporting high numerical performance often suffered from limited generalizability due to methodological constraints.^{4,7,61}

Segmentation strategies varied between manual, semi-automatic, and, in rare cases,

automatic methods. Manual segmentation was the most common approach but raises concerns related to interobserver variability and reproducibility, particularly given the intricate boundaries of PAs and the need to delineate fine-grained invasive patterns. Few studies provided detailed segmentation protocols or quantified interobserver variability through kappa coefficients or Dice similarity values.^{17,62-64}

The cumulative impression is that radiomics performance metrics are promising, but methodological weaknesses must be addressed before these models can be considered reliable for clinical implementation.⁶⁵

5.2.2 DIAGNOSTIC CLASSIFICATION AND SUBTYPE PREDICTION

Radiomics-based classification models showed generally encouraging results across a variety of diagnostic tasks, including differentiation between functioning and non-functioning adenomas, prediction of hormone-secreting subtypes, and histopathological characterization.^{5,11} Many studies reported AUCs between 0.75 and 0.90, suggesting that radiomics captures biological information not readily appreciable on conventional MRI. For instance, texture heterogeneity may correlate with hormonal activity, cellularity, or proliferation, although direct biological correlates remain underexplored.⁶⁶⁻⁶⁹

Subtype prediction studies demonstrated that texture features and shape descriptors can support diagnostic workflows before endocrine confirmation.^{70,71} Several models integrated radiomics with clinical variables (age, sex, symptom duration, hormonal levels), achieving higher performance than either modality alone. Such multimodal integration underscores the potential of radiomics as a complementary diagnostic tool.^{72,73}

Nevertheless, these studies were all retrospective and single-center, and the absence of standardized imaging protocols limits reproducibility. Hormonal subtypes often involve class imbalance, which may inflate performance metrics if inadequately addressed. Moreover, the reliance on single-sequence MRI (most commonly T2-weighted) in many studies reduces robustness because different MRI sequences capture different aspects

of tumor biology. Therefore, although radiomics-based diagnostic classification is promising, its role remains ancillary until larger multicenter datasets and standardized acquisition protocols become available.^{9,14,74-76}

5.2.3 PREDICTION OF TUMOR CONSISTENCY

Preoperative assessment of PA consistency is critical for surgical planning, as firm or fibrous adenomas are technically more challenging to resect and are associated with higher complication rates.^{72,77} Traditional qualitative MRI assessments - based on T2 signal intensity or enhancement patterns - have proven unreliable. Černý et al. reviewed 54 studies and found statistically significant correlations between T2 signal intensity and tumor consistency in only 55% of cases, with most studies reporting a negative correlation (softer tumors showing higher T2 signal).⁵⁸ Elastography and apparent diffusion coefficient (ADC) analyses yielded inconsistent results, and no technique demonstrated sufficient accuracy for clinical adoption.^{78,79}

Radiomics, by contrast, provides an objective, high-dimensional quantitative approach. Zeynalova et al.⁷⁴ developed a T2-weighted MRI-based model using first-order histogram features, achieving an AUC of 0.71 and 72.5% accuracy for predicting consistency. While informative, first-order features are limited in capturing tissue heterogeneity. Cuocolo et al.⁵⁷ combined multiparametric T1WI, T1CE, and T2WI sequences with ensemble classifiers (SVM and random forest), achieving near-perfect performance (AUC = 0.99, accuracy 93%). Similarly, Wan et al. reported a combined-sequence model with AUC 0.90 and accuracy 0.87, outperforming single-sequence models and demonstrating the added value of integrating multiple MRI contrasts.⁵⁹

Automatic segmentation using convolutional neural networks further improved predictive reliability. Wang et al. demonstrated that automatically segmented models achieved AUC 0.84, slightly outperforming manually segmented models (AUC 0.82), highlighting the potential of automated pipelines for scalable clinical use.⁹ The main limitations of these approaches remain limited multicenter validation and risk of overfitting, emphasizing the need for larger datasets and harmonized imaging protocols.

5.2.4 ASSESSMENT OF INVASIVENESS AND AGGRESSIVENESS

Cavernous sinus invasion, often graded by the Knosp scale, significantly influences surgical planning and prognosis. Radiomics-based predictive models have been successful in improving preoperative assessment, particularly in borderline Knosp grades. Niu et al.⁷⁶ developed a CE-T1WI radiomic-clinical nomogram integrating tumor sphericity and internal carotid artery wrapping, achieving an AUC of 0.90. Decision curve analysis (DCA) demonstrated superior net clinical benefit over conventional models at threshold probabilities above 20%.⁸⁰⁻⁸³

Radiomics has also been applied to broader markers of aggressiveness, including Ki-67 and p53 expression. Ugga et al. used T2WI-based features with a KNN classifier to predict high Ki-67 expression (AUC = 0.87). Multimodal models combining radiomics with Knosp grade achieved AUCs up to 0.94 for aggressive tumors, with Fan et al. demonstrating AUCs of 0.96 and 0.89 in training and test cohorts for acromegalic patients.⁵⁷ Liu et al. extended these approaches using dynamic contrast-enhanced MRI (DCE-MRI) to extract pharmacokinetic texture features, achieving an AUC of 0.96 for distinguishing aggressive from non-aggressive PitNETs.⁸⁴

5.2.5 PREDICTION OF SURGICAL OUTCOMES

Radiomics also contributes to predicting post-surgical outcomes, including recurrence risk and hormonal remission.⁸⁵⁻⁸⁷ Preoperative T1WI texture metrics were associated with recurrence in non-functioning adenomas (lower intensity linked to higher risk), while KNN and random forest models on CE-T1WI achieved AUCs of 0.96–0.98 for recurrence prediction.^{88,89} Radiomic scores derived from SVM classifiers were shown to be independent prognostic factors (AUC = 0.87), and delta-radiomics models combining pre- and post-operative imaging further improved predictive accuracy (AUC = 0.84 vs 0.65 for clinical models alone).^{90,91}

Hormonal remission has also been successfully modeled. Fan et al. analyzed over 13,000 CE-T1WI features, constructing a model with AUCs of 0.81–0.83 across training and

validation cohorts. DCA demonstrated meaningful clinical benefit for threshold probabilities >13% in primary cohorts and >25% in validation cohorts.^{3,6,92-94}

5.2.6 PREDICTION OF TREATMENT RESPONSE

Radiomics can further anticipate responsiveness to pharmacologic and radiotherapy interventions.⁹⁵⁻⁹⁸ In acromegaly, texture-based radiomic models predicted response to somatostatin receptor ligands with an AUC of 0.85, outperforming conventional signal intensity metrics.⁹⁹⁻¹⁰³ Similarly, for dopamine agonist treatment in prolactinomas, ensemble classifiers achieved AUC 0.81. CE-T1WI-based models for radiotherapy outcomes reached AUCs of 0.92, surpassing clinical-only models (AUC = 0.86). The combination of radiomic and clinical features improved predictive performance further (AUC = 0.96).¹⁰⁴⁻¹⁰⁶

5.3 VIDEOMICS IN PITUITARY ADENOMA SURGERY

5.3.1 DEEP LEARNING ARCHITECTURES FOR INTRAOPERATIVE SEGMENTATION

Recent advances in videomics have enabled precise, real-time analysis of endoscopic surgical footage for PA resection.¹⁰⁷ Across multiple studies, a wide variety of deep learning architectures were employed, ranging from CNNs such as ResNet-50, MobileNet-V2, YOLOv8, and Mask R-CNN, to transformer-based models including Swin Transformer, NasVLM, and NaMA-Mamba.¹⁰⁸

Convolutional neural networks demonstrated robust performance in small or heterogeneous datasets, providing rapid inference suitable for real-time surgical guidance.⁶³ However, their reliance on local receptive fields limited their ability to capture global anatomical context, often resulting in suboptimal boundary delineation

and reduced generalization. In contrast, transformer-based models leveraged self-attention mechanisms and hierarchical architectures to integrate local and global spatial information, achieving superior segmentation accuracy, precise tumor margin delineation, and greater resilience to intraoperative visual artifacts.¹⁰⁹⁻¹¹¹

Within retrospective registry analyses, the Swin Transformer consistently outperformed both CNN-based and other transformer models. In the tested datasets, it achieved a box mAP[0.50] of 0.843 and mAP[0.50:0.95] of 0.607, highlighting its ability to capture complex, multi-scale spatial features essential for precise boundary delineation. YOLOv9c-seg reached a test mAP[0.50] of only 0.399, demonstrating limitations in pixel-level segmentation despite rapid detection capability. Mask R-CNN, while effective in multi-stage segmentation, tended to overfit after extended training, reducing generalization. These findings underscore the superiority of transformer-based models in tasks requiring high-resolution, anatomically precise segmentation.¹¹²⁻¹¹⁶

5.3.2 CLINICAL APPLICATIONS OF VIDEOMICS

Accurate intraoperative segmentation enables precise differentiation between tumor tissue and normal pituitary gland, which is essential for maximizing resection while preserving gland function. Transformer-based models, particularly the Swin Transformer, excel in delineating complex anatomical boundaries such as residual adenoma margins, even under challenging operative conditions including low contrast, partial obstruction, or variable lighting.¹¹⁷

By providing continuous intraoperative guidance, these models help reduce the risk of damage to critical neurovascular structures, minimize cerebrospinal fluid leaks, and optimize tumor resection. Furthermore, real-time videomics has an educational role, offering trainees immediate visual feedback and supporting standardized surgical quality.²⁵ Real-time predictions can be overlaid directly on endoscopic video feeds, providing an intuitive interface while maintaining established surgical protocols.¹¹⁸

5.3.3 INTEGRATION INTO SURGICAL WORKFLOW

For clinical deployment, DL models can be integrated with existing endoscopic tower systems via HDMI or DVI splitters, allowing live video to be continuously analyzed. Transformer-based models such as Swin Transformer provide the spatial resolution and boundary accuracy necessary for practical intraoperative use, while CNNs can serve as lightweight, real-time support tools for rapid detection or general navigation.¹¹⁹⁻¹²¹ Implementation across multiple institutions may require fine-tuning to accommodate variations in video resolution, lighting conditions, color profiles, and endoscope optics.¹²² Multicenter validation is therefore crucial to ensure model robustness and generalizability. This approach also holds promise for more challenging applications, including the detection of subtle pituitary microadenomas, which are difficult to visualize intraoperatively.^{111,113}

5.3.4 PERFORMANCE COMPARISON AND COMPLEMENTARITY OF MODELS

While CNN-based architectures remain valuable for their speed and efficiency, particularly in smaller datasets or rapid detection tasks, transformer-based models provide superior spatial awareness, boundary precision, and generalization across patients and institutions. CNNs and transformers should be considered complementary: CNNs can serve as real-time support tools, while transformers handle high-precision segmentation tasks in complex anatomical regions.¹²³

Registry analyses confirm that transformer-based architectures outperform CNNs in segmentation accuracy and generalizability. Swin Transformer demonstrates robust edge detection, precise tumor margin delineation, and resilience to visual artifacts, making it highly suitable for integration into clinical workflows.¹⁴ The combination of preoperative knowledge from radiomics and intraoperative videomics output thus forms a comprehensive framework to support safe, efficient, and precise pituitary adenoma surgery.¹⁰⁸

5.4 INTEGRATION OF RADIOMICS AND VIDEORICS

The convergence of radiomics and videomics represents a promising frontier in precision neurosurgery, particularly in the management of pituitary adenomas.^{77,82} Radiomics provides a non-invasive, quantitative evaluation of tumor characteristics from preoperative imaging, encompassing information on tumor heterogeneity, consistency, invasiveness, and molecular signatures. Videomics enables real-time intraoperative visualization and segmentation, offering high-resolution guidance during resection. By integrating these two modalities, surgeons can benefit from a continuous feedback loop that spans from preoperative planning to intraoperative execution and postoperative assessment.¹²⁴

Preoperative radiomic analysis allows the stratification of tumors based on predicted consistency, aggressiveness, and potential surgical challenges. Features derived from T1WI, T2WI, and CE-T1WI sequences, combined with machine learning classifiers or deep learning architectures, can achieve AUC values up to 0.99 for tumor consistency prediction and 0.96 for aggressiveness and invasiveness. When integrated with videomics, these predictions can be directly mapped to intraoperative video, guiding the surgeon in identifying critical tumor margins, distinguishing between tumor and normal tissue, and avoiding complications.¹²⁵

Transformer-based architectures, such as the Swin Transformer, have shown superior performance in intraoperative segmentation due to their ability to capture both local and global spatial features.⁴ By overlaying real-time predictions onto the surgical field, these models complement radiomic insights with actionable visual guidance. This dual approach has the potential to reduce recurrence rates, minimize surgical complications, and optimize functional outcomes.^{112,120}

The integration of radiomics and videomics also facilitates advanced surgical planning through personalized, data-driven approaches. Nomograms combining radiomic features with clinical, histopathological, and genomic data can be linked with videomics outputs to create patient-specific surgical maps. These maps allow the anticipation of complex anatomical relationships and provide dynamic guidance during surgery.^{124,125} Furthermore, the combination of preoperative and intraoperative models can enhance research reproducibility, enabling multicenter validation and standardization of

protocols across institutions.¹¹²

5.5 LIMITATIONS OF THE STUDY

Despite the significant advances demonstrated in both radiomics and videomics for PA management, several limitations must be acknowledged. A primary concern is the relatively small sample sizes used in videomics study, which limits the generalizability of predictive models and increases the risk of overfitting. Many videomics studies included fewer than 400 annotated frames for validation. Radiomics investigations were predominantly single-center and retrospective. This limited dataset diversity may not adequately capture the variability encountered in routine clinical practice, emphasizing the need for larger, multicenter cohorts.

Manual segmentation remains the most common approach for both radiomics and videomics, introducing inter-observer variability that can affect feature extraction, model training, and subsequent predictive performance. Variations in delineation of tumor boundaries, anatomical landmarks, or tumor consistency may compromise reproducibility, particularly when datasets are relatively small. The reliance on manual annotation also constrains scalability, underscoring the potential benefits of semi-automated or fully automated segmentation pipelines that can reduce variability and enable processing of larger datasets. In many studies, methodological details, including segmentation software, deep learning pipeline parameters, and annotation protocols, were incompletely reported, further limiting the reproducibility and comparability of results across research groups.

Methodological heterogeneity constitutes another significant limitation. Radiomics studies exhibited variability in imaging acquisition, feature extraction techniques, classifier selection, and validation approaches, with only a small fraction implementing external validation or adherence to recognized standards such as IBSI or the RQS. Videomics analyses similarly lack systematic validation across multiple institutions and different endoscopic equipment, raising concerns regarding robustness and clinical applicability. The common practice of selecting representative frames prior to dataset

partitioning may introduce a bias toward clearer or more typical images, potentially inflating model performance relative to continuous, real-world intraoperative video streams.

Imaging limitations also constrain the predictive performance of current models. Radiomics-based consistency prediction has relied heavily on single MRI sequences, most often T2-weighted imaging, which may inadequately capture tumor heterogeneity. Intraoperative assessment of tumor consistency remains subjective, with no universally accepted quantitative standard, further complicating model development and interpretation. Future approaches incorporating multiparametric MRI, dynamic contrast-enhanced sequences, and automated segmentation may improve accuracy and reproducibility.

From a technical perspective, although transformer-based models such as the Swin Transformer achieve superior segmentation performance, their computational demands pose challenges for real-time intraoperative use. Variability in lighting conditions, endoscope optics, and video resolution further complicates deployment across institutions and surgical environments, highlighting the need for optimization and robust calibration.

Non-technical barriers also impede clinical translation. Regulatory approval, ethical governance, data privacy, and infrastructure costs are rarely addressed in current studies, limiting the immediate feasibility of implementing these models in routine practice. Prospective clinical trials and collaboration with regulatory authorities will be essential to ensure that these tools are safe, compliant, and scalable.

6. CONCLUSION

This study demonstrates the significant potential of AI-driven imaging analyses in the management of PAs, highlighting both radiomics and videomics as complementary approaches. In the radiomics domain, we developed and validated predictive models for tumor consistency based on multiparametric MRI, achieving robust accuracy and demonstrating that high-dimensional quantitative features can capture critical tissue characteristics not discernible with conventional imaging. These findings provide objective, reproducible metrics to support preoperative surgical planning and anticipate technical challenges associated with fibrous PAs. In the intraoperative setting, our retrospective videomics analyses confirmed the superiority of transformer-based architectures, particularly the Swin Transformer, in segmenting PAs and surrounding anatomical structures. The model demonstrated high precision, resilience to intraoperative variability, and practical applicability for real-time guidance, highlighting its potential to enhance surgical safety and maximize resection while preserving pituitary function. Collectively, these results underscore the feasibility and added value of integrating radiomics and videomics into a unified framework for personalized, data-driven management of pituitary adenomas.

7. FUTURE DIRECTIONS

Building on the findings of this study, future research in radiomics, videomics, and AI-driven imaging should pursue several key avenues to enhance clinical applicability and precision in pituitary and skull base surgery. First, large-scale, multi-institutional collaborations are essential to create diverse and representative datasets, which will improve model generalizability and robustness. In radiomics, integration of multiparametric MRI can capture complementary structural and functional tumor characteristics, while standardized preprocessing pipelines, feature extraction protocols, and automated segmentation methods will minimize variability and enable reproducible, high-quality analyses. Prospective studies should also explore the combination of radiomics features with clinical, histopathological, and genomic data, enabling personalized predictive models for tumor consistency, invasiveness, treatment response, and risk of recurrence.

In videomics, further development of transformer-based architectures such as Swin Transformer should focus on optimizing inference speed, model robustness to variable endoscopic optics, lighting conditions, and video resolutions, and seamless integration with intraoperative augmented reality platforms. Real-time overlays of predicted tumor margins and critical anatomical structures can support surgical decision-making, improve resection completeness, and reduce complications, particularly in challenging cases such as microadenomas or tumors invading the cavernous sinus. Standardized multicenter validation and prospective clinical trials are necessary to confirm the reliability, safety, and regulatory compliance of these AI tools, while attention to ethical considerations, data privacy, and cost-effectiveness will be essential for adoption in routine practice.

Finally, the convergence of radiomics and videomics offers a promising avenue for creating fully integrated, patient-specific workflows. Linking preoperative radiomic predictions with intraoperative videomics guidance can provide a continuous, data-

driven feedback loop from planning to execution, allowing surgeons to anticipate technical difficulties, adapt resection strategies in real-time, and improve functional outcomes. Beyond PAs, these approaches can be extended to other skull base pathologies, including meningiomas, chordomas, and complex sinonasal tumors, facilitating automated anatomical landmark detection, risk stratification, and precision-guided surgical planning. Ultimately, the integration of advanced AI-based imaging into skull base surgery represents a transformative step toward precision neurosurgery, enabling safer, more efficient, and personalized interventions for patients.

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FINAL CONSIDERATIONS

Throughout this PhD program, the work conducted has crystallized into a coherent journey across radiomics, videomics, and AI applied to PAs and skull base surgery. What began as a set of parallel research questions progressively evolved into an integrated framework, nourished by continuous collaboration between radiologists, neurosurgeons, engineers, data scientists, and clinical researchers. These interdisciplinary exchanges have been essential, not only for shaping the scientific direction of this thesis, but also for building a shared language capable of connecting imaging, surgical practice, and computational modelling. Such interactions, when sustained over time, have the potential to reshape routine clinical workflows and accelerate the adoption of quantitative and AI tools in neurosurgery.

The research activities developed during these years spanned the entire spectrum of translational investigation: from the extraction of radiomics features on MRI to the real-time analysis of endoscopic surgical videos, from systematic evaluations of the literature to the construction of an institutional videomics registry, and from meticulous manual annotations to the deployment of transformer-based deep learning models. Each component contributed a distinct layer of understanding, and together they delineate a roadmap for integrating computational intelligence into the diagnosis, characterization, and surgical treatment of PAs.

Radiomics offered an opportunity to challenge the traditional boundaries of MRI interpretation. By quantifying texture, geometry, and intensity patterns invisible to the naked eye, the studies performed in this thesis revealed that preoperative imaging contains more information about tumor phenotype and consistency than previously recognized. Even though heterogeneity in methodologies and standards limits the

consistency of published evidence, the work conducted here confirms that reliable prediction models are achievable when harmonized pipelines, robust feature selection, and standardized assessment are applied. This experience strengthened the notion that radiomics is not an abstract statistical exercise but a practical tool that, once refined, could support clinical decision-making in a reproducible and objective manner.

Videomics, in turn, represented a natural extension of this quantitative approach into the operating room. The creation of a large curated surgical video repository, the development of annotation guidelines, and the implementation of advanced deep learning architectures collectively marked a turning point in the exploration of intraoperative AI tools for pituitary surgery. Among the evaluated models, the Swin Transformer emerged as a reliable and accurate system for real-time segmentation of pituitary adenomas, validating the concept that intraoperative guidance can be augmented by computational vision without disrupting surgical workflow. This line of research not only opened new possibilities for surgical navigation but also highlighted the importance of institutional collaboration and the need for standardized videomics datasets.

Taken together, the work accomplished during these years underscores how technological innovation in neurosurgery is most effective when it remains grounded in clinical relevance. The aim was not to replace clinical judgment, but to complement it with objective, quantitative, and reproducible metrics. The integration of radiomics and videomics into a unified conceptual model reflects the broader paradigm shift currently taking place in medicine: a transition from descriptive interpretation to data-driven, precision-oriented care.

Most importantly, this PhD journey demonstrated that progress in such a rapidly evolving field relies as much on methodological rigor as on the willingness to explore uncharted territories. The experience gained in data curation, model development, interdisciplinary communication, and critical appraisal of the literature will remain foundational for future research. Many of the initiatives started during this thesis, including the videomics registry, the radiomics pipelines, and the cross-disciplinary collaborations, are intentionally designed to persist beyond the duration of the doctoral program and to serve as platforms for future investigations.

RESEARCH ACTIVITIES (2022-2025)

1) PUBLICATIONS

1. Agosti E, Pagnoni A, Zoia C*, Rampinelli V, Fiorindi A, Panciani PP, Paderno A, Fontanella MM. Deep Learning-Based Videomics for Automatic Segmentation in Endoscopic Endonasal Surgery. *Annali Italiani di Chirurgia*. 2025. To be published.
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- Scerrati A, De Bonis P, Locatelli D, Agosti E, Veiceschi P, Ceraudo M, Zona G, Gasparotti R, Terzi di Bergamo L, Rigamonti D. Preliminary Validation of FoRCaSco: A New Grading System for Cerebral and Cerebellar Cavernomas. *World Neurosurg.* 2022 Mar;S1878-8750(22)00361-8. doi: 10.1016/j.wneu.2022.03.070
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2) ABSTRACTS AT NATIONAL AND INTERNATIONAL CONGRESSES

1. 24/09/2025 – 27/09/2025 SINCH 2025, Brescia (Italy), 74° Annual Meeting
 - Poster: The role of radiation therapy in short- and long-term survival for craniopharyngiomas: An analysis of the national cancer database
 - Poster: Surgical management and postoperative outcomes of orbital cavernous malformations: A systematic review of the literature

- Oral presentation: Transcranial microsurgical resection of sphenoorbital meningioma with custom-made one-stage reconstruction using a cutting guide: surgical experience and technical advantages
 - Oral presentation: Endoscopic versus transcranial approaches for giant pituitary adenomas: meta-analysis of clinical and surgical outcomes
 - Oral presentation: Quantitative anatomical comparison of microscopic transcranial, endoscopic endonasal, and transorbital approaches to the orbit and adjacent regions of the skull base
 - Oral presentation: Automatic segmentation in endonasal endoscopy: A systematic review of deep learning models
 - Oral presentation: Navigare is necessary: The transorbital approach for temporal and insular intraparenchymal lesions – a systematic review and illustrative cases
 - Abstract coauthor: 360° to the petrous apex: comprehensive surgical anatomy and limitations of open and endoscopic endonasal approaches to the petrous apex
 - Abstract coauthor: The clock around the optic nerve. Quantitative anatomical comparison of approaches to the optic canal
 - Abstract coauthor: Automatic segmentation in endonasal endoscopy: A systematic review of deep learning models
 - Abstract coauthor: Endoscopic treatment of colloid cysts of the third ventricle: A national cooperative study of 146 patients
 - Abstract coauthor: Radiomics in Pituitary Adenomas: A Systematic Review of Predictive Models and Clinical Applications
 - Abstract coauthor: Step-by-step illustration of the 2-piece orbitozygomatic approach
2. 05/10/2025 – 09/10/2025 EANS 2025, Vienna (Austria)
 - Poster: Quantitative anatomical comparison of microsurgical transcranial, endoscopic endonasal, and endoscopic-assisted transorbital approaches to the orbit and surrounding skull base regions
 - Oral presentation: Deep Learning for Automatic Segmentation of Pituitary Adenomas: A Videomics Study
 - Oral presentation: Radiomics for preoperative assessment of pituitary adenoma consistency with T2-weighted MRI: A multicenter study
 3. 13/02/2025 – 16/02/2025 NASBS 2025, New Orleans, Louisiana (USA), 34th Annual Meeting
 - Oral presentation: Predicting Pituitary Adenoma Consistency Using Radiomic Data Mining And Machine Learning On T2weighted Mri: A Multicenter Retrospective Study

- Oral presentation: Quantitative Anatomical Comparison Of Microsurgical Transcranial, Endoscopic Endonasal, And Endoscopic-assisted Transorbital Approaches To The Orbit And Surrounding Skull Base Regions
 - Poster: Deep learning for automatic segmentation of pituitary adenomas using narrow band imaging: Preliminary experience in a clinical perspective
4. 23/10/2024 – 26/10/2024 SINCH 2024, Bari (Italy), 73° Annual Meeting
- Poster: Origin and course of the branches of the cavernous internal carotid artery from the endoscopic endonasal perspective: a cadaveric study
 - Poster: Advancing the management of skull base chondrosarcomas: A systematic review of targeted therapies
 - Poster: Chordoma genetic aberrations and targeted therapies panorama: A systematic literature review
 - Poster: Glioblastoma immunotherapy: A systematic review of the present strategies and prospects for advancements
 - Poster: Optimizing neurovascular-protective transposition of the pterygopalatine fossa through orbito-ptyerygo-sphenoidal ligament release and descending palatine canal decompression: Anatomical principles and surgical strategies
 - Poster: Anatomical step-by-step dissection of complex skull base approaches: surgical anatomy of the endoscopic endonasal superior ethmoidectomy
 - Poster: Anatomical step-by-step dissection of complex skull base approaches: surgical anatomy of the endoscopic endonasal and endoscopic-assisted transmaxillary transpterygoid approach to infratemporal fossa, Meckel's cave, and petrous apex
 - Poster: Comparative efficacy of transsphenoidal and transcranial approaches for treating tuberculum sellae meningiomas: A systematic review and meta-analysis
 - Poster: The role of radiotherapy in the management of craniopharyngiomas: A national cancer database analysis
 - Poster: Tumor microenvironment and stem cells in glioma: Current knowledge, therapeutic implications, and innovative perspectives
 - Oral presentation: Endoscopic-assisted anterior petrosectomy for a recurrent petrous chondrosarcoma in Ollier disease: 2D operative video
 - Oral presentation: Anatomical Step-by-Step Dissection of Complex Skull Base Approaches for Trainees: Surgical Anatomy of the Endoscopic Endonasal Clivectomy, Odontoidectomy, and Far Medial Approach
 - Oral presentation: Preliminary Validation of FoRCaSco: A New Grading System for Cerebral and Cerebellar Cavernomas
 - Oral presentation: The prognostic role of A β 1-42, T-Tau, and P-Tau in long term follow up for patients with shunted idiopathic normal pressure hydrocephalus

- Oral presentation: Combined endoscopic endonasal and sublabial transmaxillary approaches for resection of intracranially extended juvenile nasopharyngeal angiofibroma
 - Oral presentation: The precuneal interhemispheric, transtentorial corridor to the cerebello-mesencephalic fissure, pineal region, and dorsal brainstem: surgical anatomy and case illustration
 - Oral presentation: Predicting pituitary adenoma consistency using radiomic data mining and machine learning on T2- weighted MRI: A multicenter retrospective study
 - Oral presentation: Deep Learning for Automatic Segmentation of Pituitary Adenomas Using Narrow Band Imaging: Preliminary Experience in a Clinical Perspective
 - Oral presentation: Surgery versus endovascular treatment for spinal dural arteriovenous fistulas: A multicenter experience and systematic literature review
 - Oral presentation: Anatomical step-by-step dissections of complex skull base approaches for trainees: surgical anatomy of the approaches to the orbit and surrounding regions
 - Abstract coauthor: Gestione del glioblastoma ricorrente: revisione sistematica e studio retrospettivo multicentrico
 - Abstract coauthor: Applicabilità ed efficacia di un training cognitivo computerizzato per pazienti con tumore cerebrale
 - Abstract coauthor: Analisi delle funzioni cognitive e della qualità di vita dei pazienti sottoposti a chirurgia per tumore cerebrale primitivo: uno studio prospettico osservazionale
 - Abstract coauthor: Liquid biopsy in low-grade glioma: revisione sistematica della letteratura e una proposta di grading di utilità clinica
 - Abstract coauthor: Valore prognostico delle scale di dolore, ansia e depressione nella chirurgia vertebrale per patologia lombare degenerativa: uno studio osservazionale prospettico
 - Abstract coauthor: Gli indici pelvici nella chirurgia vertebrale strumentata: valore prognostico in una casistica retrospettiva degli ospedali civili di brescia
 - Abstract coauthor: Modello 3d dell osso temporale per il training neurochirurgico
5. 05/06/2024 – 08/06/2024 ESBS 2024, Maastricht (Netherlands), 15° Congress
- Oral presentation: Anatomical step-by-step dissection of complex skull base approaches for trainees: surgical anatomy of the microsurgical and endoscopic approaches to and through the orbit
 - Oral presentation: Optimizing neurovascular-protective transposition of the pterygopalatine fossa through orbito-pterygo-sphenoidal ligament release

- and descending palatine canal decompression: Anatomical principles and surgical strategies
- Oral presentation: Origin and course of the branches of the cavernous internal carotid artery from the endoscopic endonasal perspective: a cadaveric study
 - Oral presentation: Endoscopic-assisted anterior petrosectomy for a recurrent petrous chondrosarcoma
 - Oral presentation: Anatomical step-by-step dissection of complex skull base approaches for trainees: surgical anatomy of the endoscopic endonasal superior ethmoidectomy
6. 16/02/2024 – 18/02/2024 NASBS 2024, Atlanta, Georgia (USA), 33° Annual Meeting
- Poster: 360° To the Petrous Apex: Comprehensive Surgical Anatomy and Limitations of Open and Endoscopic Endonasal Approaches to the Petrous Apex
 - Poster: Anatomical step-by-step dissection of complex skull base approaches for trainees: surgical anatomy of the endoscopic endonasal superior ethmoidectomy
 - Poster: Anatomical step-by-step dissection of complex skull base approaches for trainees: surgical anatomy of the microsurgical and endoscopic approaches to and through the orbit
 - Oral presentation: Optimizing neurovascular-protective transposition of the pterygopalatine fossa through orbito-ptyerygo-sphenoidal ligament release and descending palatine canal decompression: Anatomical principles and surgical strategies
 - Oral presentation: Origin and course of the branches of the cavernous internal carotid artery from the endoscopic endonasal perspective: a cadaveric study
 - Oral presentation: Endoscopic-assisted anterior petrosectomy for a recurrent petrous chondrosarcoma
 - Abstract coauthor: Superior ethmoidal approach to an olfactory groove meningioma: a novel approach that maximizes preservation of nasal anatomy
 - Abstract coauthor: The role of radiotherapy in the short- and long-term survival for craniopharyngiomas: a national cancer database analysis
 - Abstract coauthor: 360° to the petrous apex: comprehensive surgical anatomy and limitations of open and endoscopic endonasal approaches to the petrous apex
7. 12/10/2023 – 14/10/2023 SINCH 2023, Padua (Italy), 72° Annual Meeting
- Poster: The role of radiotherapy in the management of craniopharyngiomas: A national cancer database analysis

- Poster: Tumor microenvironment and stem cells in glioma: Current knowledge, therapeutic implications, and innovative perspectives
 - Oral presentation: 360° approaches to the petrous apex: Anatomical indications of approaches to the petrous apex
 - Oral presentation: Origin and course of the branches of the cavernous internal carotid artery from the endoscopic endonasal perspective: a cadaveric study
 - Oral presentation: Anatomical step-by-step dissections of complex skull base approaches for trainees: Surgical anatomy of the approaches to the orbit and surrounding regions
 - Oral presentation: Anatomical step-by-step dissection of complex skull base approaches: Surgical anatomy of the endoscopic endonasal and endoscopic-assisted transmaxillary transpterygoid approach to infratemporal fossa, Meckel's cave, and petrous apex
 - Oral presentation: Endoscopic endonasal cribriform plate and planum sphenoidale inferior transposition to intracranial surface of the anterior cranial fossa with preservation of the olfactory apparatus: a technical note
 - Oral presentation: Combined endoscopic endonasal and sublabial transmaxillary approaches for resection of intracranially extended juvenile nasopharyngeal angiofibroma
8. 04/09/2023 – 06/09/2023 European Society of Minimally Invasive Neurological Therapy, Marseille, France, 15° Annual Meeting
- Abstract coauthor: The current diagnostic performance of MRI-based radiomics for glioma grading
 - Abstract coauthor: Cigarette smoking and intracranial aneurysms: CYP2A6 gene SNPs pilot analysis in the Italian population
9. 17/02/2023 – 19/02/2023 NASBS 2023, Tampa, Florida (USA), 32° Annual Meeting
- Poster: Origin and course of the branches of the cavernous internal carotid artery from the endoscopic endonasal perspective: a cadaveric study
 - Poster: Anatomical step-by-step dissection of complex skull base approaches for trainees: surgical anatomy of the endoscopic endonasal and endoscopic-assisted transmaxillary transpterygoid approach to infratemporal fossa, lateral recess of the sphenoid sinus, Meckel's cave, petrous apex, and surrounding anatomical regions
 - Poster: Improving endoscopic endonasal neurovascular sparing transposition of the pterygopalatine fossa by orbito-ptyergo-sphenoidal ligament releasing and descending palatine canal decompression: anatomical foundations and surgical techniques

- Oral presentation: Anatomical step-by-step dissection of complex skull base approaches for trainees: surgical anatomy of the endoscopic endonasal approach to the anterior cranial fossa
 - Oral presentation: Anatomical step-by-step dissection of complex skull base approaches for trainees: surgical anatomy of the endoscopic endonasal clivectomy, odontoidectomy, and far medial approach
 - Oral presentation: Preservation of the olfactory apparatus in endoscopic endonasal approaches to the anterior cranial fossa through inferior mobilization of the cribriform plate, planum sphenoidale, and olfactory apparatus: a technical note
 - Abstract coauthor: Surgical anatomy of the foramen lacerum and its ligaments: anatomical description and clinical relevance for expanded endonasal approaches
 - Abstract coauthor: Far lateral approach to a cerebellopontine angle hemangioblastoma: microsurgical anatomy and surgical principles
 - Abstract coauthor: Comparison between the supracerebellar infratentorial and precuneal interhemispheric, transtentorial approach to the cerebellomesencephalic fissure: an anatomoradiological study and illustrative cases
 - Abstract coauthor: Anchoring the anterior margin of the dural inlay graft: a technical note on endoscopic anterior skull base reconstruction
 - Abstract coauthor: Endoscopic-assisted en-bloc pterygomaxillectomy: identifying an efficient and safe location for the pterygoid osteotomy
 - Abstract coauthor: Anatomical step-by-step dissection of complex skull base approaches for trainees: surgical anatomy of the translabyrinthine, transotic, and transcochlear approaches
 - Abstract coauthor: Anatomical step-by-step dissection of complex skull base approaches for trainees - surgical anatomy of the transbasal approach
10. 15/10/2022 – 17/10/2022 SINCH 2022, Naples (Italy), 71° Annual Meeting
- Poster: The role of radiotherapy in the management of craniopharyngiomas: A national cancer database analysis
 - Poster: Step-by-step surgical resection of cavernous malformations of the spinal cord: principles, techniques, and pitfalls
 - Oral presentation: Principles and strategies for step-by-step AVM excision
 - Oral presentation: Combined endoscopic endonasal transpterygoid and sublabial anterior transmaxillary approaches for a large infratemporal fossa trigeminal schwannoma
 - Oral presentation: The prechiasmatic sulcus as a strategic surgical "window" to the suprachiasmatic and infrachiasmatic corridors in endoscopic endonasal surgery: from anatomical laboratory to clinical practice

- Oral presentation: Surgical versus endovascular treatment of the spinal dural arteriovenous fistula: a multicenter study and systematic literature review.
 - Oral presentation: Implications of intracranial and intracanalicular ophthalmic artery course in endoscopic endonasal surgery
 - Oral presentation: Quantitative anatomical comparison of endoscopic endonasal and microsurgical transcranial approaches to the anterior cranial fossa
 - Oral presentation: Quantitative anatomical comparison of microsurgical transcranial approaches to the posterior petrous bone
 - Oral presentation: Anatomical step-by-step dissections of complex skull base approaches: surgical anatomy of the endoscopic endonasal approaches to the sellar and parasellar regions
 - Oral presentation: The precuneal interhemispheric, transtentorial corridor to the pineal region and dorsal brainstem: surgical anatomy and case illustration
 - Oral presentation: Quantitative anatomical comparison of endoscopic endonasal, endoscopic transorbital, and microsurgical transcranial approaches to the spheno-orbital region
 - Oral presentation: Step-by-step surgical resection of cavernous malformations of the spinal cord: principles, techniques, and pitfalls
11. 17/02/2022 – 21/02/2022 NASBS 2022, Phoenix, Florida (USA), 71° Annual Meeting
- Poster: The Role of Bevacizumab for Recalcitrant Intracranial Meningiomas: a Single Institution's Experience and a Systematic Review of the Literature

3) BOOK CHAPTERS

1. Calbucci F, Fontanella MM, Agosti E. Posterior fossa meningiomas: 70 years later. Italia, Edizioni Minerva Medica, 2024
 - Agosti E, Belotti F, Fontanella MM. Epidemiology
 - Serioli S, Agosti E, Fontanella MM, Peris-Celda M. Pathogenesis of posterior cranial fossa meningiomas
 - Agosti E, Serioli S, De Notaris M, Leonel LCPC, Graepel S, Fontanella MM, Peris-Celda M. Anatomy of the posterior cranial fossa
 - Posterior cranial fossa meningioma imaging. Ugga L, Corvino S, Tranfa M, Scaravilli A, Agosti E MM Fontanella, E Agosti. Asymptomatic lesions
 - Agosti E, Fontanella MM, Panciani PP. Intraoperative neuronavigation and ultrasound
 - Calbucci F, Draghi R, Borghesi I, Ugga L, Fioravanti A, Giudici A, Serioli S, Fontanella MM, Agosti E. Posterior petrous bone meningiomas

2. Dionigi G. Dionigi Chirurgia: (opera in due volumi). Italia, Edra, 2022.
 - Agosti E, Locatelli D, Lanzino G. Patologia cerebrovascolare

4) BOOK EDITOR

- Posterior fossa meningiomas 70 years later. Book editors: Fabio Calbucci, Marco Maria Fontanella, Edoardo Agosti. Publisher: Edizioni Minerva Medica Spa. Publication year: 2024

5) FACULTY OF NATIONAL AND INTERNATIONAL CONGRESSES AND COURSES

- 07/11/2025 – 07/11/2025 Functional Neurosurgery Hands-On Course First Edition. Verona, Italy
- 30/10/2025 – 30/10/2025 Primo Corso Italiano di Anatomia Traslazione e Fotogrammetria: La Fossa Cranica Anteriore. Frosinone, Italy
- 31/10/2025 – 31/10/2025 Congresso La Patologia Sellare e Parasellare: Patologie e Approcci Clinici. Frosinone, Italy
- 02/10/2025 – 03/10/2025 In and Around the Orbit - Endonasal, Transorbital, and Supraorbital approaches, Salerno (Italy). Salerno, Italy
- 16/06/2025 – 20/06/2025 11° International Summer School: Transnasal endoscopic surgery: from sinuses to skull base. Brescia, Italy
- 29/05/2025 – 30/05/2025 Corso di Sezione di Neuro-oncologia e Neuroendoscopia SINch. Approcci endoscopici endonasali e transorbitari al seno cavernoso - Corso teorico-pratico. Brescia, Italy
- 07/05/2025 – 10/05/2025 64° Congresso Nazionale SNO - Scienze Neurologiche Ospedaliere. Rome, Italy
- 03/05/2025 – 05/05/2025 14th Annual EANS Young Neurosurgeons' Meeting and Research Course. Catania, Italy
- 03/04/2025 – 05/04/2025 Memorial Cantore, 9th Edition. Pozzilli, Italy
- 21/03/2025 Journal Club, IV Edition, Ospedale del Mare. Napoli, Italy
- 13/02/2025 – 16/02/2025 NASBS 2025 34° Annual Meeting. New Orleans, Louisiana, USA
- 07/10/2024 – 09/10/2024 5 International Workshop Endoscopic Transorbital Skull Base Surgery. Salerno, Italy
- 06/06/2024 Corso di Sezione di Neuroanatomia SINch, primo step tour anatomico 2024. Approcci Transcranici Antero-laterali: Approcci Transcranici VS Approcci Mini-invasivi. Salerno, Italy
- 15/03/2024 – 16/03/2024 FAST and CURIOUS in Neurooncology - Future Advances in Surgical Treatment. Reggio Emilia, Italy

- 16/02/2024 – 18/02/2024 NASBS 2024 33° Annual Meeting. Atlanta, Georgia, USA
- 02/02/2024 – 03/02/2024 3rd NEUROMED SKULL BASE COURSE WITH 3-D EXOSCOPES - HANDS-ON COURSE Anterior and Posterior Cranial Fossa. Pozzilli, Italy
- 14/09/2023 – 15/09/2023 Schola Anatomica Salernitana 2.0 Transorbital Translational Masterclass: A Neurosurgical Perspective. Salerno, Italy
- 21/06/2023 – 23/06/2023 Corso Tecnico-Pratico di Neuro-Oncologia, II Edizione. Innovazioni Teorico-pratiche sull'oncologia cranica e spinale. Brescia, Italy
- 06/06/2023 – 10/06/2023 9° International Summer School: Transnasal endoscopic surgery: from sinuses to skull base. Brescia, Italy
- 17/02/2023 – 19/02/2023 NASBS 2023 32° Annual Meeting. Tampa, Florida, USA
- 02/06/2022 – 05/06/2022 Mayo Clinic Open and Endoscopic Techniques in Cranial Base Surgery Course. Rochester, Minnesota, USA

6) ORAL PRESENTATIONS AT NATIONAL AND INTERNATIONAL COURSES AND CONGRESSES

- 06/03/2026 – 08/03/2026 NASBS 2026 35° Annual Meeting, San Diego, Florida (USA). 1) Rhoton room, Dueling section: Endoscopic versus microscopic surgical anatomy of the cavernous sinus, sellar and suprasellar areas, Meckel's cave, and petrous apex. 2) Endoscopic Endonasal Clivectomy for a Midline Middle Clivus Meningioma Removal
- 07/11/2025 – 07/11/2025 Functional Neurosurgery Hands-On Course First Edition, Verona, Italy. Temporal lobe anatomy: Cortical, subcortical, and vascular landmarks
- 31/10/2025 – 31/10/2025 La Patologia Sellare e Parasellare: Patologie e Approcci Clinici, Frosinone, Italy. Tumori della regione parasellare: Craniofaringioma
- 30/10/2025 – 30/10/2025 Primo Corso Italiano di Anatomia Traslazione e Fotogrammetria: La Fossa Cranica Anteriore, Frosinone, Italy. 1) Surgical Anatomy of the Subfrontal and Transbasal Approaches. 2) Surgical Anatomy of the Endoscopic Endonasal Transcribriform Approach
- 27/10/2025 – 28/10/2025 Surgical Neurovascular Angiography-Anatomy Course (SNAC), Rome, Italy. Interactive Workshop on Photogrammetry Applied to Neurovascular Anatomy

- 02/10/2025 – 03/10/2025 In and Around the Orbit - Endonasal, Transorbital, and Supraorbital approaches, Salerno (Italy). Anatomy of the transorbital approach
- 29/05/2025 – 30/05/2025 Corso di Sezione di Neuro-oncologia e Neuroendoscopia SINch. Approcci endoscopici endonasali e transorbitali al seno cavernoso - Corso teorico-pratico. 1) Approccio endoscopico endonasale transpterigoideo, landmarks chirurgici ossei ed endoscopici: anatomia chirurgica step-by-step. 2) Landmarks endoscopici degli approcci trans-orbitali: anatomia chirurgica
- 07/05/2025 – 10/05/2025 64° Congresso Nazionale SNO - Scienze Neurologiche Ospedaliere, Rome (Italy). Anatomia Chirurgica Step-by-Step dell'Angolo Ponto-Cerebellare: Confronto tra Landmarks Anatomici e Aree di Esposizione della Via Endoscopica Endonasale Anteriore e Microchirurgica Transcranica Posteriore
- 03/04/2025 – 05/04/2025 Memorial Cantore, 9th Edition. Surgical anatomy of para-suprasellar regions: MTAs, EEAs, and ETOAs dueling
- 21/03/2025 Journal Club, IV Edition, Ospedale del Mare, Napoli (Italy). Neuro-oncology section: The role of endoscopic transorbital approaches for intraparenchymal lesions.
- 13/02/2025 – 16/02/2025 NASBS 2025 34° Annual Meeting, New Orleans, Louisiana (USA). Rhoton room, Dueling section: Endoscopic versus Microscopic Surgical Anatomy of the Clinoid, Cavernous Sinus, Sellar, Suprasellar Areas, Meckel's Cave and Petrous Apex
- 07/10/2024 – 09/10/2024 5 International Workshop Endoscopic Transorbital Skull Base Surgery, Salerno (Italy). Transorbital step-by step approach anatomy
- 06/06/2024 Corso di Sezione di Neuroanatomia SiNch, primo step tour anatomico 2024. Approcci Transcranici Antero-laterali: Approcci Transcranici VS Approcci Mini-invasivi, Salerno (Italy). Pterional approach: Skin and temporal muscle incision and dissection techniques of the frontal branch of the facial nerve
- 15/03/2024 – 16/03/2024 FAST and CURIOUS in Neurooncology - Future Advances in Surgical Treatment, Reggio Emilia (Italy). Esperienze a confronto: trattamento recidive gliomi alto grado
- 16/02/2024 – 18/02/2024 NASBS 2024 33° Annual Meeting, Atlanta, Georgia (USA). Rhoton room, Dueling section: Endoscopic versus Microscopic Surgical Anatomy of the Clinoid, Cavernous Sinus, Sellar, Suprasellar Areas, Meckel's Cave and Petrous Apex
- 14/09/2023 – 15/09/2023 Schola Anatomica Salernitana 2.0 Transorbital Translational Masterclass: A Neurosurgical Perspective, Salerno (Italy). The anatomy of the transorbital route

- 17/02/2023 – 19/02/2023 NASBS 2023 32° Annual Meeting, Tampa, Florida (USA). Rhoton room, Dueling section: Endoscopic versus microscopic surgical anatomy of the cavernous sinus, sellar and suprasellar areas, Meckel's cave, and petrous apex
- 01/06/2022 – 04/06/2022 Mayo Clinic Open and Endoscopic Techniques in Cranial Base Surgery Course, Rochester, Minnesota (USA). Transsellar and transcavernous approach, posterior clinoidectomy Transpterygoid, transposition of the vidian nerve, lateral recess, Meckel's cave

7) COURSE DIRECTOR

- 30/10/2025 – 30/10/2025 Primo Corso Italiano di Anatomia Traslazione e Fotogrammetria: La Fossa Cranica Anteriore. Frosinone, Italy
- 29/05/2025 – 30/05/2025 Corso di Sezione di Neuro-oncologia e Neuroendoscopia SINch. Approcci endoscopici endonasali e transorbitari al seno cavernoso - Corso teorico-pratico. Brescia, Italy

8) GRANTS

- 24/09/2025 – 24/09/2025 Borsa di Studio Humanitas per la Chirurgia del Basicranio, 74° Congresso Nazionale SINch, Brescia, Italy
- 15/02/2025 Best abstract international award, NASBS 34th Annual Meeting, New Orleans, Louisiana, USA
- 25/10/2024 Borsa di studio Federico Bartolazzi, 73° Congresso Nazionale SINch, Bari, Italy

9) COLLABORATIONS WITH SCIENTIFIC JOURNALS

1. Editorial Board Member
 - Advances in Neuron Sciences - Section Editor of Neuro Oncology and Neurosurgical Oncology Section
 - Journal of Neuroscience and Clinical Neurology - Editorial Chief
 - Editorial Board Member
2. Reviewer
 - Frontiers in Surgery, Neurosurgery Section
 - Child's Nervous System
 - Journal of Precision Medicine
 - Diagnostics

- Journal of Functional Morphology and Kinesiology
- Biomedicines
- Neurology International
- World Neurosurgery
- World Neurosurgery X
- Journal of Clinical Medicine
- Journal of Pediatric Neurology
- Journal of Neurological Surgery Part B: Skull Base
- Journal of Neurological Surgery Part A: Central European Neurosurgery
- American Journal of Neuroradiology
- Laryngoscope
- Acta Neurochirurgica
- Neurochirurgie
- Neurosurgical Review
- Journal Stroke and Cerebrovascular Diseases