



## Artificial intelligence and pituitary adenomas: A review

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### Abstract

The aim of this review was to provide an overview of the main concepts in machine learning (ML) and to analyze the ML applications in the imaging of pituitary adenomas. After describing the clinical, pathological and imaging features of pituitary tumors, we defined the difference between ML and classical rule-based algorithms, we illustrated the fundamental ML techniques: supervised, unsupervised and reinforcement learning and explained the characteristic of deep learning, a ML approach employing networks inspired by brain's structure. Pre-treatment assessment and neurosurgical outcome prediction were the potential ML applications using magnetic resonance imaging. Regarding pre-treatment assessment, ML methods were used to have information about tumor consistency, predict cavernous sinus invasion and high proliferative index, discriminate null cell adenomas, which respond to neo-adjuvant radiotherapy from other subtypes, predict somatostatin analogues response and visual pathway injury. Regarding neurosurgical outcome prediction, the following applications were discussed: Gross total resection prediction, evaluation of Cushing disease recurrence after transsphenoidal surgery and prediction of cerebrospinal fluid fistula's formation after surgery. Although clinical applicability requires more replicability, generalizability and validation, results are promising, and ML software can be a potential power to facilitate better clinical decision making in pituitary tumor patients.

**Key Words:** Pituitary adenoma; Machine learning; Deep learning; Radiomics; Texture analysis; Magnetic resonance imaging

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**Core Tip:** Machine learning (ML) has seen an explosion of interest in medical imaging because of its capability of analyzing large amounts of data. Recent studies applied ML techniques to the imaging of pituitary adenomas. The purpose of our review was to describe the main concepts in ML and its current and potential applications in imaging

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## INTRODUCTION

Pituitary adenomas are benign tumors accounting for 15%-20% of all intracranial neoplasms, with an incidence of 80-90 cases per 100000 population<sup>[1,2]</sup>. Microadenomas are defined as tumors < 10 mm in maximum diameter, whereas larger adenomas are considered macroadenomas. Their peak age of presentation is between the fourth and seventh decades. Almost two-thirds of pituitary adenomas are hormone-secreting, prolactin most commonly, followed by growth hormone, corticotropin and thyrotropin, and cause typical hypersecretion syndromes. Non-functioning, small intrasellar tumors can be clinically silent and diagnosed only as incidental magnetic resonance findings, while bulky pituitary macroadenomas typically present with mass effect signs, such as headache, visual disturbances, and hypopituitarism<sup>[3,4]</sup>. The 2017 World Health Organization (WHO) classification adopted pituitary adenohypophyseal cell lineage as the main principle guiding the classification of adenomas. According to this principle we distinguish the acidophilic lineage (in which the involved transcription factor is PIT1), the corticotrope lineage (TPIT transcription factor), and the gonadotroph lineage (SF1 transcription factor). Null-cell adenomas (NCAs) are now defined as tumors that have no immunohistochemical evidence of cell-type-specific differentiation considering both pituitary hormones and transcription factors. Furthermore, in the new WHO classification the term "atypical adenoma" has been abandoned and replaced by "high risk adenoma", in reference to tumors with high proliferation index and tendency to invasion. In particular, emphasis is placed on the evaluation of tumor proliferation (mitotic count and Ki-67 index), tumor invasion, and on special adenomas variants for which clinical behavior has been shown to be more aggressive due to their intrinsic histological features: lactotroph adenoma in men, sparsely granulated somatotroph adenoma, the silent corticotroph adenoma, the Crooke's cell adenoma and the plurihormonal PIT1-positive adenoma<sup>[5]</sup>. Magnetic resonance imaging (MRI) is the investigation of choice for a complete evaluation of pituitary adenomas<sup>[6]</sup>. Various parameters regarding the extent, consistency, and contrast enhancement can be analyzed in order to help neurosurgeons in planning an appropriate surgical approach and long-term follow-up<sup>[7]</sup>.

Attempting to predict invasion (cavernous and/or sphenoid sinus involvement) based on imaging is an important challenge. The Knosp classification is one of the more commonly used systems to determine the likelihood of cavernous sinus invasion by pituitary macroadenomas, but the highest accuracy of this grading system is observed in extreme cases of overt invasion or non-invasion, while sensitivity and specificity are low in intermediate cases<sup>[8,9]</sup>.

Tumor consistency in pituitary macroadenomas has been known to be one of the main factors that determine the success rate of the transsphenoidal approach. The role of MRI in predicting the consistency of pituitary macroadenomas is controversial. Several studies suggested that relative signal intensity or signal intensity ratio on T2-weighted MRI correlates with the tumor consistency, while some others concluded that they have no predictive value<sup>[10-12]</sup>. A similar controversy has been reported in several studies which investigated the usefulness of diffusion-weighted imaging in tumor consistency prediction<sup>[13-15]</sup>.

Considering the above, it is still difficult to achieve an early identification of clinical and radiological features suggestive of an aggressive behavior, characterized by rapid growth, local invasion, and high ki-67 proliferation index.

In this setting, artificial intelligence (AI) has proved promising in recently published papers. Machine learning (ML) is a subfield of AI that employs algorithms to allow computers to learn directly from the data and subsequently perform predictions without explicit prior programming. The potential impact of ML on medicine, and particularly medical imaging, is relative to its ability to analyze large datasets including gray level textural features that humans do not consciously assess. Unlike

classical rule-based algorithms, machine learning can take advantage of increased exposure to new data and learn over time<sup>[16]</sup>. ML techniques can be further divided into supervised, unsupervised learning and reinforcement learning<sup>[17-20]</sup>. In supervised learning there is a ground truth which is directly used to guide the algorithm training process. The goal of the resulting model is usually to learn a general rule that maps inputs to outputs and is applicable to new, unseen cases. In unsupervised learning there is no preliminary labeling and therefore its goal is to cluster the given inputs based solely on the underlying data structure. Finally, reinforcement learning consists of a computer program performing an assigned task in a dynamic environment and consequently receiving feedback as a positive or negative reinforcement. To improve algorithm's performance, these approaches can be combined, some examples are semi-supervised, self-supervised and multi-instance learning.

Deep learning (DL) is an ML approach employing networks inspired by brain's structure, with a large number of simple interconnected units performing complicated tasks. The DL algorithms most applied to medical imaging are convolutional neural networks. Lower level information inputs, derived from imaging data transformed in feature vectors, form connections to the next level or "layer" of neurons. Each neuron in this second layer can combine the inputs from lower level neurons to form a newer, more complex output. As the number of intermediate or hidden layers increases, the final output from the highest layer becomes richer and more complex.

ML tasks are not limited to tumor property prediction but include many possible applications in other medical imaging and daily workflow fields, such as image acquisition, segmentation, image quality analytics, automated dose estimation and radiology reporting<sup>[21-23]</sup>. Despite the high number of recent ML successes, there are still many limitations in its clinical use<sup>[24-27]</sup>. First of all, an obstacle to AI adoption in the clinical setting is identifiable in its limited interpretability, especially true for DL. Clinicians are consequently reluctant to trust and to adopt something whose decision process is not fully understood. Secondly, ML research has to deal with issues due to the nature of the health domain, including the lack of large amounts of data, necessary during the training phase, the need for algorithm frequent updating and potential model overfitting.

This review aims to give an overview of the current applications of ML methods in pituitary adenomas evaluation.

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## PRETREATMENT ASSESSMENT

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Tumor consistency is one of the main factors that determine the success-rate of transsphenoidal adenomectomy. For this reason, pre-operative information about tumor consistency would help neurosurgeons in planning the most appropriate surgical approach. Zeynalova *et al*<sup>[28]</sup> demonstrated the utility of ML-based histogram analysis (from 55 pituitary adenoma patients) to predict tumor consistency and compared it with a conventional signal intensity ratio (SIR) evaluation. Histogram features were extracted from coronal T2-weighted original, filtered and transformed MRI images by manual segmentation. The high dimensionality of the histogram texture features was reduced with reproducibility analysis, collinearity analysis and wrapper-based feature selection. They employed the artificial neural network (ANN) as ML classifier. The reference-standard was consensual evaluations of neurosurgeons and pathologists. For histogram analysis, the ANN correctly classified 72.5% of pituitary macroadenomas with an area under the receiver operating characteristic (ROC) curve (AUC) value of 0.710. As for SIR evaluation, accuracy and AUC values were 74.5% and 0.551, respectively. Considering AUC values, ML-based histogram analysis performed better than SIR evaluation<sup>[28]</sup>.

Fan *et al*<sup>[29]</sup> demonstrated how a radiomics model can assist neurosurgeons in predicting tumor consistency in patients with acromegaly before surgery and facilitate the determination of an appropriate therapeutic approach. 158 patients (training group  $n = 100$ , validation group  $n = 58$ ) were included in this retrospective study, while 30 were enrolled in a prospective multi-center study for model validation. The consistency of the tumor was classified as soft or firm according to the neurosurgeon's evaluation. All patients underwent MRI examination which included T1-, T2- and contrast-enhanced T1-weighted sequences in the coronal plane, used for feature extraction. The radiomics features were collected based on the regions of interest drawn by an expert neuroradiologist and verified by a second expert. Total 1561 quantitative features were collected for every sequence. The radiomics features were determined using the elastic net feature selection algorithm, and the radiomics

signature was constructed. Next, a radiomics model was developed using the radiomics signature and clinical characteristics, which were further screened according to the Akaike information criterion. Then, 30 patients with acromegaly from three hospitals were enrolled for multicenter validation of the model. The prediction accuracy was then evaluated through ROC analyses and associated classification measures. The radiomics model constructed in this study showed an AUC of 0.83 and 0.81 in the primary and validation cohorts, respectively. In conclusion, this model was convenient to use and could accurately predict the tumor consistency in a multicenter prospective validation before surgery<sup>[29]</sup>.

The pre-operative prediction of cavernous sinus (CS) invasion by pituitary adenomas (Knosp grade 2-3) can help neurosurgeons in planning the surgical approach, follow-up, and long-term management. Niu *et al*<sup>[30]</sup> used a radiomics method to predict CS invasion, enrolling 194 patients with Knosp grade 2-3 (training set  $n = 97$ ; test set  $n = 97$ ) and extracting 2553 quantitative imaging texture features from contrast-enhanced T1- and T2-weighted MR images. A linear support vector machine (SVM) was used to fit the predictive model, then a nomogram was constructed incorporating radiomics signature and clinico-radiological risk factors. Radiomics model yielded an AUC of 0.852 and 0.826 for the training and test set, respectively. The nomogram yielded an AUC of 0.899 in the training test and 0.871 in the test set<sup>[30]</sup>.

According to the 2017 WHO classification, “high risk” pituitary adenomas are tumors with rapid growth, radiological invasion, and high Ki-67 proliferation index. MRI had already proved promising in proliferative index prediction, using diffusion-weighted imaging. Indeed, Tamrazi *et al*<sup>[31]</sup> performed a retrospective review of diffusion imaging and immunohistochemical characteristics of 17 with pituitary macroadenomas and demonstrated an inverse relationship between apparent diffusion coefficient values and Ki-67. In this context, machine learning can be effective for the early identification of “high risk” adenomas and could allow making a more accurate pre-operative assessment and long-term follow-up. Regarding the last, a recent study by Uggas *et al*<sup>[32]</sup> employed ML analysis of texture-derived parameters from pre-operative coronal T2-weighted MR images. A total of 89 patients that underwent endoscopic endonasal procedure were included. Pituitary adenomas were classified in high versus low Ki-67 proliferation index according to pathological data. Total 1128 features were extracted, and different supervised feature selection methods were employed to select the most informative features. A k-nearest neighbors (k-NN) classifier was used to predict the proliferative index, then algorithm validation was performed with a train-test approach. The accuracy of k-NN in the test group was 91.67% of correctly classified patients.

Non-functioning pituitary adenomas are a huge group of adenomas and can be divided in NCAs, oncocytomas and gonadotrophic adenomas. Patients with NCAs are more likely to respond to neo-adjuvant radiotherapy, so radiomics could play a role in discriminating preoperatively NCAs from other subtypes. Zhang *et al*<sup>[33]</sup> enrolled 112 patients (training set  $n = 75$ ; test set  $n = 37$ ) with non-functioning pituitary adenomas who underwent MR examination. In their retrospective study a SVM trained a predictive model that was validated using a ROC analysis on an independent test set. Then, a nomogram was constructed incorporating clinical characteristics and the radiomics signature for a more individualized predictive model. T1-weighted image features yielded an AUC value of 0.83 and 0.80 for the training and test sets, respectively. The nomogram incorporating sex and the T1 radiomics signature yielded good calibration in the training and test sets (concordance index of 0.854 and 0.857, respectively)<sup>[33]</sup>.

Somatostatin analogues (SAs) response prediction is an essential information in acromegalic patient medical treatment in the presence of GH-secreting pituitary adenomas. Indeed, this medical treatment can improve the surgical outcome, but it is burdened by high costs. Heck *et al*<sup>[34]</sup> showed how quantitative analysis of T2-weighted MR images could predict response to SAs in patients with acromegaly. However, they verified that conventional visual T2 intensity assessment achieved similar results. This retrospective cohort study included 58 newly diagnosed patients. Parameters from the T2 histogram analyses (T2 intensity ratio and T2 homogeneity ratio) were correlated to visually assessed T2 intensity (hypo-, iso- or hyperintense), baseline characteristics, response to SA treatment, and histological granulation pattern (anti-Cam5.2). T2 intensity ratio was lowest in the hypointense tumors and highest in the hyperintense tumors. T2 intensity at baseline correlated with reduction in GH ( $r = -0.67$ ) and IGF-1 ( $r = -0.36$ ) after primary SA treatment ( $n = 34$ ). The T2 homogeneity ratio correlated with adenoma size reduction ( $r = -0.45$ ). Sparsely granulated adenomas, which are typically associated to resistance to SAs, had a higher T2 intensity than densely or intermediately granulated adenomas. In conclusion, using T2 histogram analyses the

authors found that high T2 intensity correlated with more aggressive adenoma subtypes, larger adenoma size, lower GH and IGF-1 production, and blunted response to an octreotide test dose at baseline. Moreover, a better biochemical response to SA therapy was observed in adenomas with low T2 intensity. In their retrospective study, Kocak *et al*<sup>[35]</sup> demonstrated the potential role of ML-based high-dimensional quantitative texture analysis (qTA) in predicting SAs response in acromegalic patients with a GH-secreting pituitary adenoma. They showed how ML performs better than relative signal intensity (rSI) evaluation or immunohistochemical granulation pattern evaluation. Coronal T2-weighted images of 47 patients (24 SA responsive and 23 SA resistant patients) were used for qTA and quantitative and qualitative rSI evaluation, while the immunohistochemical evaluation was based on the granulation pattern of the adenomas. ML classifiers were k-NN and C4.5 algorithm. The reference standard was the biochemical response status (6 months post-therapy). Predictive performance of qTA was compared with that of the quantitative and qualitative rSI and immunohistochemical evaluation. For the qTA, k-NN correctly classified 85.1% macroadenomas with an AUC of 0.847. The accuracy and AUC ranges of the other methods were lower, equal to 57.4/70.2% and 0.575/0.704, respectively<sup>[35]</sup>.

Pituitary tumor growth can lead to compression of the anterior visual pathways, leading to visual impairment, which is the most common and earliest symptom in this pathology. In their retrospective study Lilja *et al*<sup>[36]</sup> demonstrated that diffusion Tensor imaging (DTI) and a prediction model may be an additional diagnostic tool that provides objective data about visual pathway injury, guiding treatment decisions. Total 23 patients with pituitary adenomas and 20 healthy patients underwent a complete neuro-ophthalmological examination and an MRI study, which included 3D T1-weighted and DTI sequences. A prediction model using logistic regression was constructed to test the capability of DTI parameters to correctly classify a subject as a patient (before surgery) or a control. Total 12 features quantifying mean DTI parameters from the optic tract regions were included. Based on the axial diffusivity and fractional anisotropy, the prediction model could separate patients from controls with high sensitivity. The prediction model correctly classified all patients with visual field defects (sensitivity = 1.0), 9 of 12 patients without visual field defects (sensitivity = 0.75), and 17 of 20 controls (specificity = 0.85)<sup>[36]</sup>.

## NEUROSURGICAL OUTCOME PREDICTION

Gross total resection (GTR) is the main surgical goal in transsphenoidal surgery for most pituitary adenomas. Predictive analytics for GTR may help in surgical decision-making, especially in intermediate cases (Knops grade 2-3A). In their retrospective study, Staartjes *et al*<sup>[37]</sup> investigated the potential value of deep neural network for predicting GTR in comparison with the Knops classification and logistic regression. They enrolled a total of 140 patients who underwent endoscopic transsphenoidal surgery and trained a deep neural network to predict GTR from 16 preoperatively available neuro-radiological and procedural variables. Their DL model (AUC = 0.96; accuracy = 91%; sensitivity = 94%; specificity = 89%) outperformed both the Knops classification (AUC = 0.87; accuracy = 81%; sensitivity = 92%; specificity = 70%) and logistic regression (AUC = 0.86; accuracy = 82%; sensitivity = 81%; specificity = 83%)<sup>[37]</sup>.

In their retrospective study, Liu *et al*<sup>[38]</sup> aimed to develop machine learning-based predictive models to evaluate Cushing disease recurrence after initial transsphenoidal surgery and to investigate their performance. Seventeen radiomic features including tumor volume computed from pre-operative MRI (contrast-enhanced T1-weighted MRI) and other pre/post-operative clinical variables were evaluated. Five supervised ML algorithms, including decision tree, gradient boosting decision tree, random forest (RF), adaptive boosting, and extreme gradient boost and 2 conventional models (Logistic regression, Naïve Bayes) were applied. Models were evaluated based on their AUC. The study demonstrated that ML-based predictive models for neurosurgical outcomes performed well, better than some conventional models such as logistic regression. Using 17 variables, several ML-based predictive models for recurrence were developed, and most of them (4/5) maintained high performance, with AUCs ranging from 0.694 to 0.781 which were much higher than that of conventional statistics. The best performance (AUC = 0.781) was obtained introducing 8 variables to RF algorithm, which was much better than that of logistic regression (AUC = 0.684) and that of using only postoperative morning serum cortisol (AUC = 0.635). According to the feature selection algorithms, the top predictors were age, postoperative serum cortisol, and postoperative ACTH<sup>[38]</sup>.

Cerebrospinal fluid (CSF) fistulas remain a major complication of transnasal transsphenoidal surgery for pituitary adenoma. Staartjes *et al*<sup>[39]</sup> developed a neural network-based model with the aim of classifying pituitary surgeries in having high versus low-risk of CSF leak. From a prospective registry, 154 patients who underwent endoscopic transnasal transsphenoidal surgery for pituitary adenoma were identified and underwent an MRI study. Moreover, risk factors for intraoperative CSF leaks were identified using conventional statistical methods. Selected features included both imaging features from inter-carotid distances and other clinical pre/post-operative variables. The authors built a predictive model for intraoperative CSF leaks based on a deep multilayer perceptron with 5 hidden layers. The deep neural network-based prediction model could identify patients at high risk for intraoperative CSF leak. It correctly classified 88% of patients in the test set, with an AUC of 0.84. Sensitivity and specificity were high, of 83% and 89% respectively. The positive predictive value was 71%, negative predictive value was 94%, and F1 score was 0.77<sup>[39]</sup>.

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## CONCLUSION

We reviewed a set of articles related to ML applications in pituitary adenomas. These studies showed that ML has a certain potential to improve the diagnostic performance of MRI in pre-treatment assessment and neurosurgical outcome prediction. In current studies there is not a standardized procedure, ML methodologies vary a lot, different types of classifiers are applied and only a few models are validated on an external set. The major limits of these studies are the replicability and generalizability. Publicly available datasets are needed, and clinical applicability still requires more robust validation across different sites, scanner vendors and field intensity. However, the research in the years is growing rapidly and ML software can be a potential power to facilitate better clinical decision making in pituitary tumor patients.

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## REFERENCES

- 1 **McDowell BD**, Wallace RB, Carnahan RM, Chrischilles EA, Lynch CF, Schlechte JA. Demographic differences in incidence for pituitary adenoma. *Pituitary* 2011; **14**: 23-30 [PMID: 20809113 DOI: 10.1007/s11102-010-0253-4]
- 2 **Fernandez A**, Karavitaki N, Wass JA. Prevalence of pituitary adenomas: a community-based, cross-sectional study in Banbury (Oxfordshire, UK). *Clin Endocrinol (Oxf)* 2010; **72**: 377-382 [PMID: 19650784 DOI: 10.1111/j.1365-2265.2009.03667.x]
- 3 **Chen L**, White WL, Spetzler RF, Xu B. A prospective study of nonfunctioning pituitary adenomas: presentation, management, and clinical outcome. *J Neurooncol* 2011; **102**: 129-138 [PMID: 20730474 DOI: 10.1007/s11060-010-0302-x]
- 4 **Asa SL**, Ezzat S. The pathogenesis of pituitary tumors. *Annu Rev Pathol* 2009; **4**: 97-126 [PMID: 19400692 DOI: 10.1146/annurev.pathol.4.110807.092259]
- 5 **Inoshita N**, Nishioka H. The 2017 WHO classification of pituitary adenoma: overview and comments. *Brain Tumor Pathol* 2018; **35**: 51-56 [PMID: 29687298 DOI: 10.1007/s10014-018-0314-3]
- 6 **Gupta K**, Sahni S, Sagar K, Vashisht G. Evaluation of Clinical and Magnetic Resonance Imaging Profile of Pituitary Macroadenoma: A Prospective Study. *J Nat Sci Biol Med* 2018; **9**: 34-38 [PMID: 29456390 DOI: 10.4103/jnsbm.JNSBM\_111\_17]
- 7 **Boxerman JL**, Rogg JM, Donahue JE, Machan JT, Goldman MA, Doberstein CE. Preoperative MRI evaluation of pituitary macroadenoma: imaging features predictive of successful transsphenoidal surgery. *AJR Am J Roentgenol* 2010; **195**: 720-728 [PMID: 20729452 DOI: 10.2214/AJR.09.4128]
- 8 **Knosp E**, Steiner E, Kitz K, Matula C. Pituitary adenomas with invasion of the cavernous sinus space: a magnetic resonance imaging classification compared with surgical findings. *Neurosurgery* 1993; **33**: 610-7; discussion 617-8 [PMID: 8232800 DOI: 10.1227/00006123-199310000-00008]
- 9 **Micko AS**, Wöhrer A, Wolfsberger S, Knosp E. Invasion of the cavernous sinus space in pituitary adenomas: endoscopic verification and its correlation with an MRI-based classification. *J Neurosurg* 2015; **122**: 803-811 [PMID: 25658782 DOI: 10.3171/2014.12.JNS141083]
- 10 **Bahuleyan B**, Raghuram L, Rajshekhar V, Chacko AG. To assess the ability of MRI to predict consistency of pituitary macroadenomas. *Br J Neurosurg* 2006; **20**: 324-326 [PMID: 17129884 DOI: 10.1080/02688690601000717]
- 11 **Hagiwara A**, Inoue Y, Wakasa K, Haba T, Tashiro T, Miyamoto T. Comparison of growth hormone-producing and non-growth hormone-producing pituitary adenomas: imaging characteristics and pathologic correlation. *Radiology* 2003; **228**: 533-538 [PMID: 12819334 DOI: 10.1148/radiol.2282020695]
- 12 **Snow RB**, Johnson CE, Morgello S, Lavyne MH, Patterson RH Jr. Is magnetic resonance imaging useful in guiding the operative approach to large pituitary tumors? *Neurosurgery* 1990; **26**: 801-803 [PMID: 2352598 DOI: 10.1097/00006123-199005000-00011]
- 13 **Pierallini A**, Caramia F, Falcone C, Tinelli E, Paonessa A, Ciddio AB, Fiorelli M, Bianco F, Natalizi S, Ferrante L, Bozzao L. Pituitary macroadenomas: preoperative evaluation of consistency with diffusion-weighted MR imaging--initial experience. *Radiology* 2006; **239**: 223-231 [PMID: 16452397 DOI: 10.1148/radiol.239200601000717]

- 10.1148/radiol.2383042204]
- 14 **Mohamed FF**, Abouhasheem S. Diagnostic value of apparent diffusion coefficient (ADC) in assessment of pituitary macroadenoma consistency. *Egypt J Radiol Nucl Med* 2013; **44**: 617–24 [DOI: [10.1016/j.ejmm.2013.05.012](https://doi.org/10.1016/j.ejmm.2013.05.012)]
  - 15 **Suzuki C**, Maeda M, Hori K, Kozuka Y, Sakuma H, Taki W, Takeda K. Apparent diffusion coefficient of pituitary macroadenoma evaluated with line-scan diffusion-weighted imaging. *J Neuroradiol* 2007; **34**: 228–235 [PMID: [17719632](https://pubmed.ncbi.nlm.nih.gov/17719632/) DOI: [10.1016/j.neurad.2007.06.007](https://doi.org/10.1016/j.neurad.2007.06.007)]
  - 16 **Erickson BJ**, Korfiatis P, Akkus Z, Kline TL. Machine Learning for Medical Imaging. *Radiographics* 2017; **37**: 505–515 [PMID: [28212054](https://pubmed.ncbi.nlm.nih.gov/28212054/) DOI: [10.1148/rg.2017160130](https://doi.org/10.1148/rg.2017160130)]
  - 17 **Choy G**, Khalilzadeh O, Michalski M, Do S, Samir AE, Pinykh OS, Geis JR, Pandharipande PV, Brink JA, Dreyer KJ. Current Applications and Future Impact of Machine Learning in Radiology. *Radiology* 2018; **288**: 318–328 [PMID: [29944078](https://pubmed.ncbi.nlm.nih.gov/29944078/) DOI: [10.1148/radiol.2018171820](https://doi.org/10.1148/radiol.2018171820)]
  - 18 **Wang S**, Summers RM. Machine learning and radiology. *Med Image Anal* 2012; **16**: 933–951 [PMID: [22465077](https://pubmed.ncbi.nlm.nih.gov/22465077/) DOI: [10.1016/j.media.2012.02.005](https://doi.org/10.1016/j.media.2012.02.005)]
  - 19 **Gillies RJ**, Kinahan PE, Hricak H. Radiomics: Images Are More than Pictures, They Are Data. *Radiology* 2016; **278**: 563–577 [PMID: [26579733](https://pubmed.ncbi.nlm.nih.gov/26579733/) DOI: [10.1148/radiol.2015151169](https://doi.org/10.1148/radiol.2015151169)]
  - 20 **Schmidt J**, Marques MRG, Botti S, Marques MAL. Recent advances and applications of machine learning in solid-state materials science. *NPJ Comput Mater* 2019; **5**: 83 [DOI: [10.1038/s41524-019-0221-0](https://doi.org/10.1038/s41524-019-0221-0)]
  - 21 **Zaharchuk G**, Gong E, Wintermark M, Rubin D, Langlotz CP. Deep Learning in Neuroradiology. *AJNR Am J Neuroradiol* 2018; **39**: 1776–1784 [PMID: [29419402](https://pubmed.ncbi.nlm.nih.gov/29419402/) DOI: [10.3174/ajnr.A5543](https://doi.org/10.3174/ajnr.A5543)]
  - 22 **Mazurowski MA**, Buda M, Saha A, Bashir MR. Deep learning in radiology: An overview of the concepts and a survey of the state of the art with focus on MRI. *J Magn Reson Imaging* 2019; **49**: 939–954 [PMID: [30575178](https://pubmed.ncbi.nlm.nih.gov/30575178/) DOI: [10.1002/jmri.26534](https://doi.org/10.1002/jmri.26534)]
  - 23 **McBee MP**, Awan OA, Colucci AT, Ghobadi CW, Kadom N, Kansagra AP, Tridandapani S, Auffermann WF. Deep Learning in Radiology. *Acad Radiol* 2018; **25**: 1472–1480 [PMID: [29606338](https://pubmed.ncbi.nlm.nih.gov/29606338/) DOI: [10.1016/j.acra.2018.02.018](https://doi.org/10.1016/j.acra.2018.02.018)]
  - 24 **Romeo V**, Ricciardi C, Cuocolo R, Stanzione A, Verde F, Sarno L, Improta G, Mainenti PP, D'Armiento M, Brunetti A, Maurea S. Machine learning analysis of MRI-derived texture features to predict placenta accreta spectrum in patients with placenta previa. *Magn Reson Imaging* 2019; **64**: 71–76 [PMID: [31102613](https://pubmed.ncbi.nlm.nih.gov/31102613/) DOI: [10.1016/j.mri.2019.05.017](https://doi.org/10.1016/j.mri.2019.05.017)]
  - 25 **Ciampi F**, Chung K, van Riel SJ, Setio AAA, Gerke PK, Jacobs C, Scholten ET, Schaefer-Prokop C, Wille MMW, Marchianò A, Pastorino U, Prokop M, van Ginneken B. Towards automatic pulmonary nodule management in lung cancer screening with deep learning. *Sci Rep* 2017; **7**: 46479 [PMID: [28422152](https://pubmed.ncbi.nlm.nih.gov/28422152/) DOI: [10.1038/srep46479](https://doi.org/10.1038/srep46479)]
  - 26 **Cuocolo R**, Perillo T, De Rosa E, Ugga L, Petretta M. Current applications of big data and machine learning in cardiology. *J Geriatr Cardiol* 2019; **16**: 601–607 [PMID: [31555327](https://pubmed.ncbi.nlm.nih.gov/31555327/) DOI: [10.11909/j.issn.1671-5411.2019.08.002](https://doi.org/10.11909/j.issn.1671-5411.2019.08.002)]
  - 27 **Islam MM**, Nasrin T, Walther BA, Wu CC, Yang HC, Li YC. Prediction of sepsis patients using machine learning approach: A meta-analysis. *Comput Methods Programs Biomed* 2019; **170**: 1–9 [PMID: [30712598](https://pubmed.ncbi.nlm.nih.gov/30712598/) DOI: [10.1016/j.cmpb.2018.12.027](https://doi.org/10.1016/j.cmpb.2018.12.027)]
  - 28 **Zeynalova A**, Kocak B, Durmaz ES, Comunoglu N, Ozcan K, Ozcan G, Turk O, Tanriover N, Kocer N, Kizilkilic O, Islak C. Preoperative evaluation of tumour consistency in pituitary macroadenomas: a machine learning-based histogram analysis on conventional T2-weighted MRI. *Neuroradiology* 2019; **61**: 767–774 [PMID: [31011772](https://pubmed.ncbi.nlm.nih.gov/31011772/) DOI: [10.1007/s00234-019-02211-2](https://doi.org/10.1007/s00234-019-02211-2)]
  - 29 **Fan Y**, Hua M, Mou A, Wu M, Liu X, Bao X, Wang R, Feng M. Preoperative Noninvasive Radiomics Approach Predicts Tumor Consistency in Patients With Acromegaly: Development and Multicenter Prospective Validation. *Front Endocrinol (Lausanne)* 2019; **10**: 403 [PMID: [31316464](https://pubmed.ncbi.nlm.nih.gov/31316464/) DOI: [10.3389/fendo.2019.00403](https://doi.org/10.3389/fendo.2019.00403)]
  - 30 **Niu J**, Zhang S, Ma S, Diao J, Zhou W, Tian J, Zang Y, Jia W. Preoperative prediction of cavernous sinus invasion by pituitary adenomas using a radiomics method based on magnetic resonance images. *Eur Radiol* 2019; **29**: 1625–1634 [PMID: [30255254](https://pubmed.ncbi.nlm.nih.gov/30255254/) DOI: [10.1007/s00330-018-5725-3](https://doi.org/10.1007/s00330-018-5725-3)]
  - 31 **Tamrazi B**, Pekmezci M, Aboian M, Tihan T, Glastonbury CM. Apparent diffusion coefficient and pituitary macroadenomas: pre-operative assessment of tumor atypia. *Pituitary* 2017; **20**: 195–200 [PMID: [27734275](https://pubmed.ncbi.nlm.nih.gov/27734275/) DOI: [10.1007/s11102-016-0759-5](https://doi.org/10.1007/s11102-016-0759-5)]
  - 32 **Ugga L**, Cuocolo R, Solari D, Guadagno E, D'Amico A, Somma T, Cappabianca P, Del Basso de Caro ML, Cavallo LM, Brunetti A. Prediction of high proliferative index in pituitary macroadenomas using MRI-based radiomics and machine learning. *Neuroradiology* 2019; **61**: 1365–1373 [PMID: [31375883](https://pubmed.ncbi.nlm.nih.gov/31375883/) DOI: [10.1007/s00234-019-02266-1](https://doi.org/10.1007/s00234-019-02266-1)]
  - 33 **Zhang S**, Song G, Zang Y, Jia J, Wang C, Li C, Tian J, Dong D, Zhang Y. Non-invasive radiomics approach potentially predicts non-functioning pituitary adenomas subtypes before surgery. *Eur Radiol* 2018; **28**: 3692–3701 [PMID: [29572634](https://pubmed.ncbi.nlm.nih.gov/29572634/) DOI: [10.1007/s00330-017-5180-6](https://doi.org/10.1007/s00330-017-5180-6)]
  - 34 **Heck A**, Emblem KE, Casar-Borota O, Bollerslev J, Ringstad G. Quantitative analyses of T2-weighted MRI as a potential marker for response to somatostatin analogs in newly diagnosed acromegaly. *Endocrine* 2016; **52**: 333–343 [PMID: [26475495](https://pubmed.ncbi.nlm.nih.gov/26475495/) DOI: [10.1007/s12020-015-0766-8](https://doi.org/10.1007/s12020-015-0766-8)]
  - 35 **Kocak B**, Durmaz ES, Kadioglu P, Polat Korkmaz O, Comunoglu N, Tanriover N, Kocer N, Islak C, Kizilkilic O. Predicting response to somatostatin analogues in acromegaly: machine learning-based high-dimensional quantitative texture analysis on T2-weighted MRI. *Eur Radiol* 2019; **29**: 2731–2739 [PMID: [30506213](https://pubmed.ncbi.nlm.nih.gov/30506213/) DOI: [10.1007/s00330-018-5876-2](https://doi.org/10.1007/s00330-018-5876-2)]
  - 36 **Lilja Y**, Gustafsson O, Ljungberg M, Starck G, Lindblom B, Skoglund T, Bergquist H, Jakobsson KE, Nilsson D. Visual pathway impairment by pituitary adenomas: quantitative diagnostics by diffusion tensor imaging. *J Neurosurg* 2017; **127**: 569–579 [PMID: [27885957](https://pubmed.ncbi.nlm.nih.gov/27885957/) DOI: [10.3171/2016.8.JNS161290](https://doi.org/10.3171/2016.8.JNS161290)]
  - 37 **Staatjes VE**, Serra C, Muscas G, Maldaner N, Akeret K, van Niftrik CHB, Fierstra J, Holzmann D, Regli L. Utility of deep neural networks in predicting gross-total resection after transsphenoidal surgery for pituitary adenoma: a pilot study. *Neurosurg Focus* 2018; **45**: E12 [PMID: [30453454](https://pubmed.ncbi.nlm.nih.gov/30453454/) DOI: [10.3171/2018.8.FOCUS18243](https://doi.org/10.3171/2018.8.FOCUS18243)]

- 38 **Liu Y**, Liu X, Hong X, Liu P, Bao X, Yao Y, Xing B, Li Y, Huang Y, Zhu H, Lu L, Wang R, Feng M. Prediction of Recurrence after Transsphenoidal Surgery for Cushing's Disease: The Use of Machine Learning Algorithms. *Neuroendocrinology* 2019; **108**: 201-210 [PMID: [30630181](#) DOI: [10.1159/000496753](#)]
- 39 **Staatjes VE**, Zattra CM, Akeret K, Maldaner N, Muscas G, Bas van Niftrik CH, Fierstra J, Regli L, Serra C. Neural network-based identification of patients at high risk for intraoperative cerebrospinal fluid leaks in endoscopic pituitary surgery. *J Neurosurg* 2019; 1-7 [PMID: [31226693](#) DOI: [10.3171/2019.4.JNS19477](#)]