Acta Biomed 2025; Vol. 96, N. 2: 16298 DOI: 10.23750/abm.v96i2.16298

Review

Diagnostic applications of artificial intelligence in chronic rhinosinusitis: A systematic review

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Abstract. *Background and aim:* Artificial Intelligence (AI) in healthcare is rapidly expanding and researchers are exploring its possible role in assisting physicians in early diagnosis, accurate prognosis prediction, and efficient treatment planning. This systematic review aims to summarize the evidence about the role of AI, Machine Learning (ML), and Deep Learning (DL) in the diagnostic imaging of chronic rhinosinusitis (CRS). *Methods:* The search strategy was performed according to PRISMA guidelines for systematic reviews. The authors searched all articles in three major medical databases (PubMed, Scopus, Cochrane Library) using the following key terms: "Artificial Intelligence" or "Machine Learning" or "Deep Learning" or "Neural Convolution Learning" or "Knowledge Engineering" and "Nose" or "Nasal" or "Septum" or "Turbinate" or "Sinus" or "Rhinology" or "Sinusitis" or "Rhinosinusitis" or "Chronic Rhinosinusitis" or "Chronic Sinusitis" or "CRS" and "CT" or "MRI" or "Computed Tomography" or "Images" or "CBCT" or "Magnetic Resonance Imaging" or "Imaging" or "Radiographs" or "X-ray". *Results:* Overall, 395 manuscripts were identified, and after duplicate removal (27 articles), excluding off-topic studies (298) and for other structural reasons (50) papers were assessed for eligibility; finally, only 20 papers were included and summarized in the review. *Conclusions:* Despite the growing interest in AI applications, due to the lack of standardized and unified validation procedures and the heterogeneity of patient cohorts, its practical role in rhinology, particularly in radiological image processing in CRS, is not yet well defined, and further research is needed. It should be crucial for physicians to use their knowledge and skills to critically assess the information provided by AI and make any final treatment decisions. (www.actabiomedica.it)

Key words: artificial intelligence, chronic rhinosinusitis, diagnostic imaging, deep learning, machine learning, systematic review, rhinology, radiology, computed tomography, paranasal sinuses

Introduction

Artificial intelligence (AI) is rapidly expanding in healthcare practices, and researchers are exploring its possible role in assisting physicians in early diagnosis, accurate prognosis prediction, and efficient treatment planning. First introduced in 1956, AI is a branch of computer science focused on developing algorithms and models that allow machines to perform tasks that typically require human intelligence, such as recognizing patterns, solving problems, learning from experiences, and making decisions (1, 2). There are several areas of AI and the most clinically relevant are machine learning (ML) and deep learning (DL). ML is a data-driven technique that enables algorithms to predict outcomes, make classifications, and recognize patterns by learning the inherent statistical patterns in a data set. ML algorithms mimic the human brain's neural networks to receive and analyze data, learning from experience and gradually becoming capable of performing tasks for which they were not even programmed (3, 4). DL is a subfield of ML in which multiple layers of algorithms are linked and stratified to process raw data. Unlike traditional ML algorithms, which generally just extract features, DL processes the raw data to define the representations needed for classification (5). DL systems can process large datasets, enabling accurate and efficient results. They also have the potential to minimize prediction errors and intra- and inter-observer variability (6). The first applications of AI in healthcare date back to the 1970s, when a rule-based system was developed to distinguish various bacterial infections and recommend antibiotic treatment options tailored to the patient's body weight (7). Since then, advances in AI have made unimaginable advances in the medical and healthcare fields, empowering the development of augmented reality to guide surgeons during procedures, the creation of robots for minimally invasive surgery, and the development of software that enables rapid and accurate diagnoses by analyzing patients' clinical and radiological features (8). Further evolution of AI and its ML and DL subsets are now being tested in clinical practice, and otolaryngology and rhinology are not immune from this evolution. In the literature, we are witnessing a great increase in studies on new AI applications in chronic rhinosinusitis (CRS) that analyze data from patients' symptoms, endoscopic images, nasal cytology, and radiological images. Although most of this research has focused on the symptoms and endotype of CRS (9-11), there is a growing interest in the role of AI in radiologic image processing (12). Recently, AI has demonstrated a functional capability in image processing and analysis equal to or superior to humans, leading to its application for the automation of multiple clinical processes (1, 3, 13-15). However, despite a growing interest in this area and the importance for rhinologists to understand the potential and flows of these analytical tools, there are still no systematic reviews in the literature on the role of AI in CRS imaging. Therefore, this systematic review aims to summarize the evidence about the role of ML, DL, and AI in the diagnostic imaging of CRS.

Methods

The search strategy for this systematic review was performed in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) guidelines for systematic reviews (16). The authors searched all articles in three major medical databases: PubMed (National Library of Medicine of the National Institutes of Health—NIH NLM), Scopus (Elsevier), and Cochrane Library (Wiley). All available articles on the topic from their inception until February 2024 were reviewed. In addition, the authors manually searched the main literature on otolaryngology conferences and citation chaining to ensure that no relevant papers were left out. The authors' search for articles was conducted in databases using a combination of the following key terms: "Artificial Intelligence" or "Machine Learning" or "Deep Learning" or "Neural Convolution Learning" or "Knowledge Engineering" and "Nose" or "Nasal" or "Septum" or "Turbinate" or "Sinus" or "Rhinology" or "Sinusitis" or "Rhinosinusitis" or "Chronic Rhinosinusitis" or "Chronic Sinusitis" or "CRS" and "CT" or "MRI" or "Computed Tomography" or "Images" or "CBCT" or "Magnetic Resonance Imaging" or "Imaging" or "Radiographs" or "X-ray". The inclusion criteria for the research were represented by original articles specifically focusing on the role of ML, DL, and AI in the diagnostic imaging of CRS. Articles in non-English language, letters to the editor, book chapters, single case reports, meta-analyses, systematic and narrative reviews, conference papers, and off-topic papers were excluded. Specifically, we defined off-topic articles as those works concerning different items, such as the use of AI in the radiological diagnosis of nasal and sinus tumors, but also those works on dental, oral, and maxillofacial surgery topics in which maxillary sinusitis is discussed in relation to issues not strictly related to otolaryngology, such as sinus lift and dental implantation. Two independent authors (AL and PD) conducted a selection of studies through a comprehensive screening of the titles and full abstracts retrieved from each manuscript to select eligible papers. After that, the detected articles were retrieved by further authors (RMM and EM) to perform full-text analysis. If there was any uncertainty about their inclusion, the documents were further analyzed by an additional team composed of experienced specialists (FS and ST). Then, senior experts (JZ and CC) were responsible for providing a final assessment and approval of the final revision version. The data extracted for each manuscript were authors, year of publication, nationality of the authors, type of paper (technical or clinical), dataset numerosity with the training:validation:testing split ratios, type of imaging assessed for each study, aim of each proposed AI model, learning method applied, type of AI models, algorithms and architectures employed, methods used for the interpretation and manipulation of the AI algorithm, and reliability for each AI model. Clinical studies were evaluated for both quality and methodological bias in accordance with the National Heart, Lung, and Blood Institute Study Quality Assessment Tools (NHISQAT) (17). The level of evidence for these prediction models that focus specifically on regression or ML methods was evaluated following the updated guidance of the statement Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis + AI (TRIPOD+AI) (18).

Results

The search strategy was performed according to the PRISMA guidelines, as shown in Figure 1.

A total of 395 manuscripts were identified, and after removal of duplicates (27 articles) and exclusion of off-topic studies based on title and abstract (298), 70 papers were assessed for eligibility; finally, after further removal of articles for other structural reasons (50), only 20 papers were included and summarized in the present systematic review. The eligible records included and summarized in this systematic review have a publication range between 2019 and 2024. The most frequent origin country was Korea (n = 8), with China being the second most productive nation (n = 6) and the United States the third (n = 3). The other papers included were written by researchers from Europe (n = 1), Taiwan (n = 1) and Saudi Arabia (n = 1).

Regarding the articles' type, nine had a technical structure, while the other eleven were clinical articles, specifically retrospective clinical studies, monocentric in seven cases, and multicentric in four cases. Clinical articles were rated as good (n = 6 papers) or fair (n = 5 papers) according to the NHI-SQAT tools, with no article being rated as low quality. Table 1 specifically reports the authors, year of publication, nationality of the authors, type of paper, and risk of bias for all manuscripts included in the systematic review.

Many of the papers included in this review investigated the use of AI models in imaging to diagnose maxillary sinusitis (MS) (n = 6 articles). Other works specifically assess the endotype of Chronic Rhinosinusitis with Nasal Polyps (CRSwNP) (n = 2 articles), while further manuscripts assessed the role of AI models to predict Eosinophilic Chronic Rhinosinusitis (ECR) and/or distinguish it from non-Eosinophilic Chronic Rhinosinusitis (NECRS) (n = 2 articles). Interestingly, in one paper, some researchers used AI models in imaging to predict CRS recurrence. Moreover, two manuscripts explored the potentiality of AI to distinguish cases of Maxillary sinus Fungus Ball (MFB) from CRS and healthy controls (HCs). In another paper, the authors used AI for Primary Ciliary Dyskinesia (PCD) screening by analyzing the computed tomography (CT) features of patients with PCD who had exudative otitis media and sinusitis through a DL model. Finally, four articles analyzed the accuracy of AI in predicting sinusitis; in one article, the authors applied AI to define the status of the osteomeatal complex (OMC) (occluded or not occluded), and in one paper, AI was used to detect imaging artifacts. In five studies, an automated sinus segmentation model was applied to perform volumetric quantification of paranasal sinuses and their opacification; the different models showed high reliability (Dice Similarity Coefficient: DSC 0.83-0.96) compared with standard manual segmentation performed

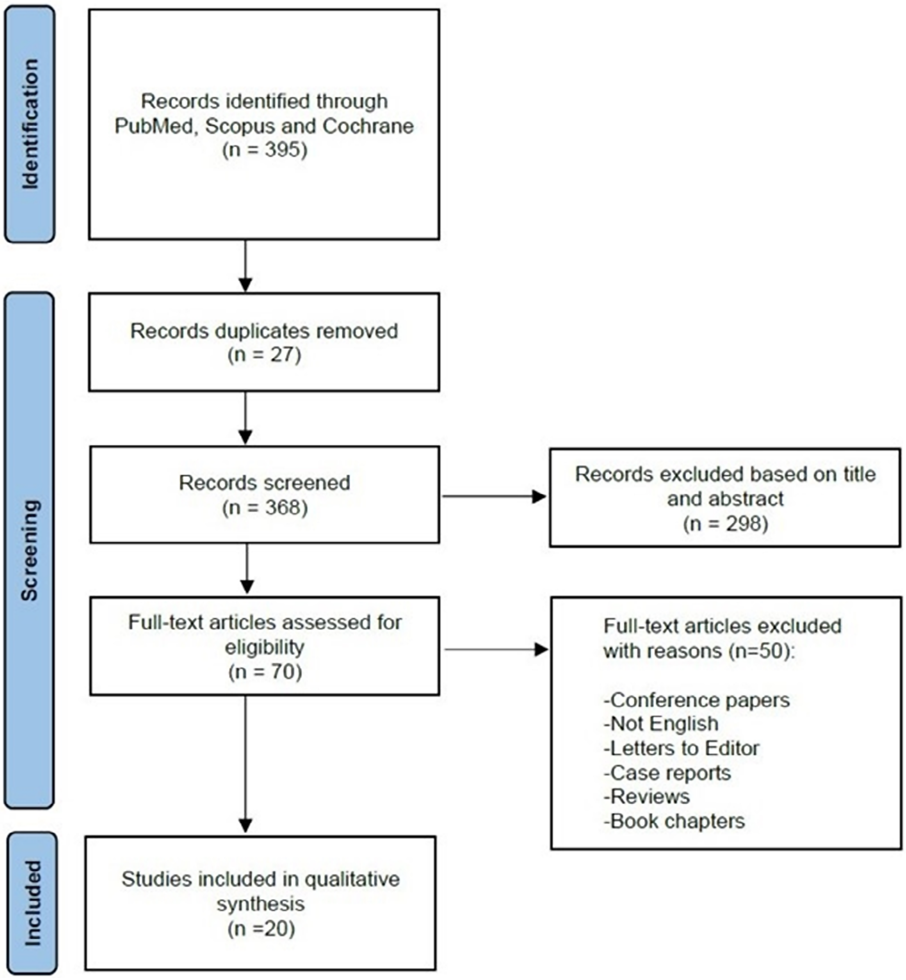

Figure 1. Search strategy.

by the radiologist, also much more time-consuming. In most articles, the authors used CT as a diagnostic tool for inflammatory nasal sinus diseases (n=14 articles). A few studies, all from Korea, were based on radiography (x-ray) (n=6 articles). The data set consisted of the number of patients (p) or the number of images (i), depending on the article, and the data set numerosity order of magnitude ranged from 10^1 to 10^4. Most authors (n=19 papers) performed training and validation of the proposed AI model, while in one case (Massey et al. (26)) the authors tested an AI model previously trained and validated by other authors (Humpries et al. (35)). Train:validation:test splits varied widely; the specific number of training, validation and test sets was available for most articles (n=16), except for two papers that reported the ratio as a percentage (Musleh (32), Chowdhury et al. (38)) and one article (Lim et al. (29)) in which the authors stated that they used five-fold cross-validation (5FCV) without reporting the numerosity of sets. Eight papers used external data to test or validate the performance of AI models, while two papers (Duan et al. (24) and Lim et al. (29)) conducted neither internal nor external test. Regarding the learning method applied, most authors (n=17 papers) considered DL, while in three articles, the learning method reported was ML. Concerning the AI models and architectures employed, the convolutional neural network (CNN) was the most frequently used (n=17 papers). In many papers (n=7 articles), the authors used Gradient-weighted Class

Table 1. Authors, year of publication, nationality, article type, and risk of bias of manuscripts.

Author	Year	Country	Type of paper	Center	NHISQAT rating
Xiong et al. (19)	2024	China	RCS	Multiple	G
Du et al. (20)	2024	China	RCS	Single	F
Alekseeva et al. (21)	2023	Ukraine	Technical	-	-
Kim K.S. et al. (22)	2023	Korea	Technical	-	-
He et al. (23)	2023	China	RCS	Multiple	G
Duan et al. (24)	2023	China	RCS	Single	F
Zhou et al. (25)	2023	China	RCS	Single	F
Massey et al. (26)	2022	USA	RCS	Single	F
Hua et al. (27)	2022	China	RCS	Single	G
Kong et al. (28)	2022	Korea	Technical	-	-
Lim et al. (29)	2022	Korea	Technical	-	-
Kuo et al. (30)	2022	Taiwan	Technical	-	-
Kim K.S. et al. (31)	2022	Korea	RCS	Single	F
Musleh (32)	2022	Saudi Arabia	Technical	-	-
Jeon et al. (33)	2021	Korea	RCS	Multiple	G
Oh et al. (34)	2021	Korea	Technical	-	-
Humphries et al. (35)	2020	USA	RCS	Single	G
Kim H.G. et al. (36)	2019	Korea	Technical	-	-
Kim Y. et al. (37)	2019	Korea	Technical	-	-
Chowdhury et al. (38)	2019	USA	RCS	Multiple	G

Abbreviations: NHISQAT: National Heart, Lung, And Blood Institute Study Quality Assessment Tools; RCS: Retrospective Clinical Study; G: Good; F: Fair.

Activation Mapping (Grad-CAM) to interpret the AI model, while nomogram was used in two papers. The authors chose different metrics for AI model reliability, with area under the curve (AUC) (0.63–0.98) and accuracy (ACC) (0.85–0.95) being the most frequently employed. A full report about the main features of the studies included in the present systematic review is available in Table 2.

Discussion

Recent advances in computer vision technology have enabled the rapid development of AI technology for image processing, automatic recognition, classification, and segmentation. This has resulted in increasingly efficient extraction of large amounts of image features from radiation images (13). Medical imaging evaluation is not limited to the qualitative diagnosis of diseases but also includes the acquisition and analysis of multiple quantitative information to provide data on disease severity, optimal treatment options, and patient prognostic outcomes. Thanks to continuous advancements in information technology and big data storage, AI is profoundly impacting various fields of the medical sciences. Considering otolaryngology and head and neck surgery, AI has been widely applied for disease diagnosis, pathology detection, and prognosis prediction (39). Specifically, most applications of AI in rhinology concern the diagnosis of nasal diseases, including nasal polyps (40), inverted papilloma (41), and other sinonasal tumors by combining AI with CT (42). Alternatively, AI has been applied in studies concerning magnetic resonance imaging (MRI) (43),

Table 2. Main features of the studies included in the present systematic review.

Author	Data set	Internal Training Set	Internal Validation Set	Internal Test Set	External Set	AIM of AI model	Type of Imaging	Learning Method	Type of Model	Model / Algorithm	Interpretation and Manipulation Method	Reliability of model
Xiong et al. 2024 (19)	437 p	215	n.a.	92	130	Predicting ECRS	CT	ML	n.a.	LR-LR RF GBDT DNN	Nomogram	AUC 0.84 LR-LR AUC 0.88 RF AUC 0.82 GBDT AUC 0.83 DNN
Du et al. 2024 (20)	29993 i (251 p)	17995	5998	6000	n.a.	Identifying CRSwNP endotype	CT	DL	CNN	ResNet-18	Grad-CAM	AUC 0.96 all AUC 0.96 eCRSwNP AUC 0.96 neCRSwNP
Alekseeva et al. 2023 (21)	162 i	130	16	16	n.a.	Identifying odontogenic MS	CT	DL	CNN	U-Net 23	ChatBot	ACC 0.90
Kim K.S. et al. 2023 (22)	678 p	512	102	n.a.	64	Discrimination between MFB, CRS and HCs	CBCT	DL	CNN	MUSC	Grad-CAM	AUC 0.94 MFB AUC 0.84 CRS AUC 0.97 HCs
He et al. 2023 (23)	265 p	160	40	n.a.	65	Sinus segmentation and CRS recurrence prediction	CT	DL	CNN	3D U-Net	Nomogram	AUC 0.74 DLR AUC 0.77 clinical AUC 0.84 combined DSC 0.83
Duan et al. 2023 (24)	64 p	52	12	n.a.	n.a.	PCD screening	CT	DL	CNN	VGG ResNet GoogLeNet ViT Swin-T ConvNeXt	Grad-CAM	ACC 0.94 GoogLeNet ACC 0.94 Swin-T ACC 0.95 ConvNeXt
Zhou et al. 2023 (25)	109 p	72	n.a.	37	n.a.	Identifying CRSwNP endotype	CT	ML	n.a.	ANN Binary LR	n.a.	AUC 0.98 ANN model 1 AUC 0.90 LR model 1

Massey et al. 2022 (26)	88 p	n.a.	n.a.	88	n.a.	Volumetric sinus segmentations with calculation of % sinus opacification, mHU of opacities and % of osteitis	CT	DL	CNN	n.a.	n.a.	n.a.
Hua et al. 2022 (27)	878 p	702	n.a.	176	n.a.	Discrimination between ECRS and NECRS	CT	DL	CNN	U-Net Deeplabv3 Efficientnet-b0 Resnet50 Inception-resnet-v2 Xception	Grad-CAM	DSC 0.95 U-Net DSC 0.96 Deeplabv3 AUC 0.89 Efficientnet-b0 AUC 0.90 Resnet50 AUC 0.88 Inception-resnet-v2 AUC 0.90 Xception
Kong et al. 2022 (28)	521 i	279	31	79	132	Data augmentation to improve the diagnosis of MS	X-ray	DL	CNN + GAN	ChexNet	n.a.	AUC 0.86 OD AUC 0.88 GCB AUC 0.91 GCB+CDA AUC 0.96 GCB+OMGDA
Lim et al. 2022 (29)	587 p	n.a.	n.a.	n.a.	n.a.	Diagnosis of MS usingWaters' and Caldwell's views	X-ray	DL	CNN	MVNet	Grad-CAM	AUC 0.72
Kuo et al. 2022 (30)	175 p	65	10	100	n.a.	Sinus inflammation assessment by calculating VMLMs	CT	DL	CNN	MobileNet SENet ResNet	n.a.	AUC 0.80 VMLMs DSC 0.92
Kim K.S. et al. 2022 (31)	1152 i (576 p)	818	206	n.a.	128	Discrimination between MFB, CRS and HCs	CT	DL	CNN	ResNet-18	Grad-CAM	AUC 0.97 Ext validation ACC 0.88 Ext validation
Musleh 2022 (32)	172 i (43 p)	60%	20%	20%	n.a.	Recognition of CT artifacts	CT	ML	n.a.	SVM	Algebric Method	AUC 0.91 Harding Beam AUC 0.88 Concentric Ring AUC 0.63 Rotation
Jeon et al. 2021 (33)	1535 i	1265	138	132	n.a.	Diagnosing FS, ES and MS using Waters' and Caldwell views	X-ray	DL	CNN	n.a.	Grad-CAM	AUC 0.71 FS AUC 0.78 ES AUC 0.88 MS

Author	Data set	Internal Training Set	Internal Validation Set	Internal Test Set	External Set	AIM of AI model	Type of Imaging	Learning Method	Type of Model	Model / Algorithm	Interpretation and Manipulation Method	Reliability of model
Oh et al. 2021 (34)	2822 i	1824	298	n.a.	700	Diagnosis of MS	X-ray	DL	CNN	YOLO v2	n.a.	AUC 0.80 Internal set AUC 0.82 Ext Validation set 1 AUC 0.82 Ext Validation set 2 AUC 0.74 Ext Validation set 3
Humphries et al. 2020 (35)	690 i	140	40	510	n.a.	Automatic quantitation of paranasal sinus opacification	CT	DL	CNN	n.a.	n.a.	DSC 0.93
Kim H.G. et al. 2019 (36)	5020 p	3402	729	729	160	MS diagnosis using Waters' views	X-ray	DL	CNN	VGG-16; VGG-19; ResNet-101	Activation Map	ACC 0.94 Internal set ACC 0.94 External set AUC 0.95 Internal set AUC 0.94 External set
Kim Y. et al. 2019 (37)	9340 i	8000	1000	n.a.	340	MS diagnosis using Waters' views	X-ray	DL	CNN	n.a.	CAM	AUC 0.93 Temporal ext test AUC 0.88 Geographic ext test
Chowdhury et al. 2019 (38)	239 p (956 i)	80%	10%	10%	n.a.	OMC occlusion classification	CT	DL	CNN	Inception-V3	n.a.	ACC 0.85 AUC 0.87

Abbreviations: p: patients; n.a.: not available; ECRS: Eosinophilic Chronic Rhinosinusitis; CT: Computed Tomography; ML: Machine Learning; LR-LR: Logistic Regression with Lasso Regularization; RF: Random Forest; GBDT: Gradient-Boosted Decision Tree; DNN: Deep Neural Network; AUC: Area Under Curve; i: images; CRSwNP: Chronic Rhinosinusitis with Nasal Polyps; DL: Deep Learning; CNN: Convolutional Neural Networks; ResNet: Residual Network; Grad-CAM: Gradient-weighted Class Activation Mapping; eCRSwNP: eosinophilic CRSwNP; neCRSwNP: non eosinophilic CRSwNP; MS: Maxillary Sinusitis; U-Net: U-shaped encoder-decoder NETwork architecture; ACC: Accuracy; CBCT: Cone-Beam Computed Tomography; MFB: Maxillary sinus Fungal Ball; CRS: Chronic Rhinosinusitis; HCs: Healthy Controls; MUSC: Multiscale U-Net-like Sparse Coding; DLR: Deep Learning Radiomic; DSC: Dice Similarity Coefficient; PCD: Primary Ciliary Dyskinesia; VGG: Visual Geometry Group; ViT: Vision Transformer; Swin-T: Shifted WINdows Transformer; ANN: Artificial Neural Network; Binary-LR: Binary Logistic Regression; mHU: mean Hounsfield Units; NECRS: Non-eosinophilic chronic rhinosinusitis; Xception: Extreme Inception; GAN: Generative Adversarial Networks; ChexNet: Chest X-ray Network; OD: Original Data; GCB: GAN-based Class Balancing method; CDA: Conventional Data Augmentation method; OMGDA: optimal multiple of GAN-based data augmentation method; MVNet: Multi-View Network; VMLMs: Volume based Modified Lund-Mackay score; SENet: Squeeze-and-Excitation Networks; SVM: Support Vector Machine; FS: Frontal Sinusitis; ES Ethmoid Sinusitis; YOLO-v2: You Only Look Once Version 2; OMC: Osteomeatal Complex.

endoscopic images (44), or positron emission tomography (PET)-CT (45). Some works have directly compared AI with the clinical skills of medical specialists and demonstrated its equivalence or superiority; in particular, it was found that AI takes much less time to reach a conclusive diagnosis (42). However, even if AI studies often boast efficiency and superiority over human analytical accuracy and speed, AI application to real-life scenarios remains distant thus highlighting the need for an analytical assessment of the technical content of articles. Our review has revealed that rhinology is not free from this significant challenge, and there is an increasing and growing interest in exploring the potential of various AI, ML and DL applications in daily clinical practice. Interestingly, a generic search on MedLine performed about the role of AI in medical diagnostics without specifying any medical specialty or disease ("artificial intelligence" AND ("diagnosis" OR " prediction")) revealed a total of 21133 articles in English over the past five years, indicative of an average of more than 11 publications per day. In particular, our review aims to summarize the evidence about the role of ML, DL, and AI in diagnostic imaging of CRS. CRS is a chronic inflammatory disorder that affects the nasal mucosa and has an overall prevalence in the general population in Europe of 10.9% (range 6.9%-27.1%), while in China it is 8%. This chronic disease is characterized by severe impairment of quality of life and a propensity to relapse that often requires multiple revision surgeries (46). According to the European Position Paper on Rhinosinusitis and Nasal Polyps 2020 (EPOS2020), CRS represents one of the ten most expensive health conditions for United States employers. Particularly, higher costs and worse quality of life are associated with patients with recurrent CRS after surgery (47). Identifying valid methods to accurately define CRS patients who fail adequate therapy and have a high risk of recurrence is critical in order to develop treatment recommendations to reduce the rate of relapse. In this regard, advanced knowledge of the risk of CRS recurrence has been gained in recent years. Lou et al. found that high numbers of tissue eosinophils play an essential role in polyp recurrence (48). Meng et al. suggested that the ratio of Lund-Mackay (LM) scores for the ethmoidal and maxillary sinus indicates CRSwNP recurrence (49). In addition, the presence of asthma and allergic rhinitis as comorbidities have been reported as risk factors for CRS relapse (50).

In our systematic review, we identified 395 manuscripts, but only 20 papers were included. This highlights the still relatively limited number of articles published on this topic despite a growing interest in every field of AI. Among the selected studies, some works have also specifically investigated the predictors of disease with the corresponding nomogram. Xiong et al. developed predictive models for ECRS based on specific clinical parameters of the patient, including history evaluation (age, sex, allergy, allergic rhinitis, asthma, smoking, surgical history), symptomatic evaluation including olfaction, presence and extent of nasal polyposis, nasal obstruction, purulent nasal discharge and visual analogue scale (VAS) score, CT evaluation by LM score and ethmoidal/maxillary (E/M) sinus density ratio, and blood tests (ratio of eosinophils in peripheral blood, absolute eosinophils in peripheral blood). As shown in the nomogram, the authors concluded that the AI algorithm identified the blood eosinophil ratio, the blood eosinophil count, and the E/M ratio as crucial predictors of ECRS (19). He et al. proposed an AI model to predict CRS recurrence by developing a comprehensive nomogram combining a deep learning signature and clinical factors. In this clinic-radiomic nomogram, the predictors of CRS recurrence included allergic rhinitis, asthma, circulating eosinophils, and a Deep Learning Radiomic (DLR) score (23). Zhou et al. aimed to evaluate the application of AI model to predict eCRSwNP based on clinical and radiological variables without the need for tissue biopsy. Specifically, the five most important variables for the prediction of tissue eosinophilia in eCRSwNP patients were the following: Peripheral Eosinophil Percentage (PEP), total Immunoglobulin E (IgE), Peripheral Eosinophil Absolute Count (PEAC), E/M ratio and nasal Nitric Oxide (nNO) (25). Humphries et al. aimed to use AI for fully automatic quantitation of paranasal sinus opacification in the diagnostic workup of patients with CRS, including the following parameters as predictors of disease: LM score, Forced Expiratory Volume in 1 second (FEV1) % predicted, Forced Expiratory Volume in 1 second / Forced Vital Capacity (FEV1/FVC), Fractional concentration of exhaled Nitric Oxide (FeNO), IgE, and blood eosinophils count (35). Furthermore, this systematic review demonstrates that no univocal information can be drawn regarding the size of the data pool, as collected papers suggest that models can rely on small numbers of subjects, although most data sets were between 10^2 and 10^4 items. Similarly, the training:test:validation split, which is required to evaluate the algorithm's performance with new data, is highly variable and uncorrelated with reliability. In contrast, the choice of AI model appears more uniform as convolutional neural network (CNN) has been the most widely used AI model. Specifically, CNN is composed of artificial neural networks that use a mathematical operation known as convolution to perform their task, which is to process pixel data for image detection and processing. We are aware of some intrinsic study limitations; the main one being related to the lack of uniformity of the included articles since both clinical and technical studies were collected to minimize data extraction bias. As a result, due to the lack of standardized and unified validation procedures and the heterogeneity of patient cohorts, at present no AI model can be broadly adopted in actual clinical practice. In the future, with the assumption of large sample sizes and multiple centers, it will be possible to further optimize algorithms and hyperparameter selection and promote ML and DL models to clinical use through online network calculators and other related methods. To the very best of our knowledge, this is the first systematic review in the literature concerning the role of AI in diagnostic imaging of inflammatory disorders of the nose and paranasal sinuses.

Conclusion

In conclusion, despite the growing interest in AI applications by researchers and clinicians, the practical role of AI in rhinology, particularly in radiological image processing in CRS, is not yet well defined, and further research is needed to investigate the topic adequately. An increasing influx of AI applications to medical challenges is expected, so specialists should be increasingly prepared to handle the constant changes. Finally, it should always be crucial for rhinologists and physicians in general, to use their knowledge and skills to critically assess the additional information given by AI and make final treatment decisions for each patient.

Conflict of Interest: Each author declares that he or she has no commercial associations (e.g. consultancies, stock ownership, equity interest, patent/licensing arrangement etc.) that might pose a conflict of interest in connection with the submitted article.

Authors Contribution: PD has given substantial contributions to study conception and design; RMM and EM to data acquisition; FS and ST to data analysis and interpretation; AL to manuscript writing; JZ to review and editing the paper; CC to supervision. All authors read and approved the final version of the manuscript.

Declaration on the Use of AI: None.

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Received: 10 July 2024
Accepted: 13 August 2024
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