TPM Vol. 32, No. S9, 2025
ISSN: 1972-6325
https://www.tpmap.org/

Open Access

EVALUATING THE ROLE OF ARTIFICIAL INTELLIGENCE IN DIAGNOSING CHRONIC SINUSITIS USING CT IMAGING: AN ANALYTICAL SYSTEMATIC REVIEW

[1]ATEF EID MADKOUR ELSAYED, [2]NAWAF AHMAD ALMUTAIRI, [3]ABDULLAH ABDULAZIZ ALRAJHI, [4]LAMA KHALID ALHARBI, [5]JUMANAH ABDULLAH H ALSHARIF, [6]HASSAN ALI H ALALAWI, [7]SARAH TAHER MOHSEN ALI, [8]RUYUF FAHAD M ALMUTAIRI, [9]HUDA SAUD K ABUTHUHAYR, [10]ABDULKHALIQ ABDULLAH A ORAYDAN, [11]NURA JAMIL A ABUBAKER, [12]HASSAN MANSOUR A ALBARAKATI, [13]ABDULRAHMAN KHALED ALSHUAIB, [14]YAZAN ALHUSSAIN ABUHOZA

1. CONSULTANT, KING ABDELAZIZ HOSPITAL SAKAKA SAUDIARABIA
2. ASSISTANT REGISTRAR, FARWANIYA HOSPITAL, KUWAIT, nal3aiban@gmail.com
3. MINISTRY OF INTERIOR MEDICAL SERVICES, ENT SENIOR REGISTRAR, EMAI: Lsweadim@hotmail.com
4. GENERAL PHYSICIAN, EMAIL: lamakhalid9004@gmail.com
5. MEDICAL INTERN, FACULTY OF MEDICINE, UNIVERSITY OF TABUK, TABUK, SAUDI ARABIA, EMAIL; jumanahalsharif.official@gmail.com
6. GENERAL PHYSICIAN, PRINCE SAUD BIN JALAWY HOSPITAL, ALAHSSA HEALTH CLUSTER, SAUDI ARABIA, EMAIL: hassan.aud.2017@hotmail.com
7. INTERN DOCTOR, MANSOURA UNIVERSITY, EGYPT, EMAIL: sarah.taher.m@outlook.com
8. MEDICAL INTERN, FACULTY OF MEDICINE, UNIVERSITY OF TABUK, TABUK, SAUDI ARABIA, EMAIL: ruyufmutairi1@gmail.com
9. GENERAL PHYSICIAN, EMAIL: huda.saud1221@gmail.com
10. GENERAL PRACTITIONER, ASEER HEALTH CLUSTER, ABHA, SAUDI ARABIA, EMAIL: o.abdulkhaliq11@gmail.com
11. MEDICAL INTERN, FACULTY OF MEDICINE, UNIVERSITY OF TABUK, TABUK, SAUDI ARABIA, EMAIL: inoora1055@gmail.com
12. GP AT KING ABDULAZIZ HOSPITAL AT MAKKAH, EMAIL: HASSAN.5110@HOTMAIL.COM
13. GENERAL SURGERY, ALSABAH HOSPITAL, KUWAIT, EMAIL: dr.abdulrahmanalshuaib@gmail.com
14. MEDICINE, EMAIL: Y.abuhoza@gmail.com

Abstract

Background: Chronic rhinosinusitis (CRS) affects approximately 5–12% of adults worldwide, significantly impacting patients' quality of life and healthcare systems. Computed tomography (CT) remains the gold standard for CRS evaluation, yet traditional interpretation is time-intensive, operator-dependent, and prone to variability among radiologists. These challenges highlight the need for more efficient and standardized diagnostic approaches.

Objective: This analytical systematic review evaluates the effectiveness of artificial intelligence (AI)—including machine learning (ML) and deep learning (DL) algorithms—in diagnosing CRS through CT imaging. It aims to determine whether AI models can improve diagnostic accuracy, consistency, and workflow efficiency compared to conventional radiologic assessments.

Methods: Following PRISMA 2020 guidelines, ten peer-reviewed studies published between 2015 and 2025 were analyzed. The review synthesized data on AI algorithms used for sinus pathology detection, segmentation, and classification, comparing performance metrics such as accuracy, sensitivity, specificity, and area under the curve (AUC) to human interpretation.

Results: Evidence shows that AI-driven CT analysis significantly enhances diagnostic precision, achieving accuracies exceeding 90% and AUC values above 0.95, while reducing interpretation time and observer variability. CNN and U-Net architectures demonstrated exceptional capability in identifying sinus opacification and structural remodeling.

Conclusion: Incorporating AI into CT-based CRS diagnosis offers a more consistent, objective, and rapid assessment method than traditional interpretation alone. As AI technologies advance, they hold promise for standardizing CRS evaluation, improving diagnostic reliability, and supporting data-driven clinical decision-making.
Keywords: Artificial intelligence, chronic rhinosinusitis, computed tomography, deep learning, machine learning, convolutional neural network, diagnostic accuracy, radiology, sinus imaging.

INTRODUCTION

Chronic rhinosinusitis (CRS) represents a prevalent inflammatory condition of the paranasal sinuses that significantly affects quality of life and imposes a substantial diagnostic burden on healthcare systems worldwide. Despite advances in imaging technologies such as computed tomography (CT) and cone-beam computed tomography (CBCT), the interpretation of sinus anatomy and pathology remains complex due to anatomical variations, overlapping structures, and subjective reader variability. Recent epidemiological data indicate that CRS affects approximately 8–12% of the global population, with radiologic and symptom-based prevalence studies revealing substantial underdiagnosis and misclassification of cases (de Loos et al., 2019). Consequently, there is growing interest in integrating artificial intelligence (AI) into radiologic workflows to enhance diagnostic standardization and efficiency in sinus disease evaluation.

Artificial intelligence, particularly deep learning and machine learning approaches, has emerged as a transformative tool in medical imaging. Through automated feature extraction and pattern recognition, AI models—especially convolutional neural networks (CNNs)—can identify subtle radiologic indicators of inflammation, obstruction, and remodeling that might be overlooked by human observers. In the context of CRS, AI is increasingly applied to improve diagnostic accuracy, quantify disease burden, and assist in treatment planning (Liu et al., 2025). These advancements align with the broader movement toward precision medicine, where algorithms can synthesize multimodal data—including clinical symptoms, radiologic parameters, and biomarker profiles—to support more objective and reproducible diagnoses.

The diagnostic challenge in CRS lies in differentiating pathological mucosal thickening from normal anatomical variations or transient inflammatory changes. AI models have demonstrated the capacity to overcome this limitation by training on large imaging datasets and learning complex spatial hierarchies across sinus structures (Uthman et al., 2025). By automating segmentation of the paranasal sinuses and quantifying opacification or bone remodeling, AI reduces inter-observer variability and improves the reproducibility of diagnostic reporting. This advancement is particularly valuable in radiology departments where the interpretation of sinus CT scans can be subjective and time-consuming.

Systematic evaluations have confirmed that AI significantly enhances the diagnostic performance of sinus imaging. Meta-analyses show that AI-assisted CT interpretations achieve higher sensitivity and specificity than conventional radiologic assessments, frequently exceeding 90% accuracy in detecting sinus pathology (Petsiou et al., 2025). Moreover, these systems exhibit consistency across diverse datasets and imaging modalities, suggesting that AI algorithms generalize well even when trained on heterogeneous populations. Importantly, such improvements extend to detecting subtle manifestations of CRS, including mild mucosal thickening and partial opacification, which are often underreported in clinical practice.

AI-based segmentation techniques form the foundation of most automated CRS diagnostic pipelines. Using architectures like U-Net and fully convolutional networks, researchers have achieved near-human or even superhuman performance in sinus boundary detection, a critical prerequisite for volumetric and morphometric analysis (Bui et al., 2015). The precision of these segmentation algorithms facilitates objective measurement of sinus volume, mucosal thickness, and lesion distribution—parameters that directly correlate with disease severity and surgical planning. These computational outputs enable clinicians to make data-driven decisions regarding medical therapy or functional endoscopic sinus surgery (FESS).

Beyond mere image interpretation, AI applications in CRS are also moving toward integrating clinical and pathological data. Machine learning models can now predict disease endotypes, such as eosinophilic versus non-eosinophilic CRS, by correlating imaging findings with laboratory and histopathologic parameters (Loperfido et al., 2025). This stratification aids in tailoring individualized therapeutic strategies, such as selecting candidates for biologic therapy or immunomodulatory treatments. By automating complex predictive tasks, AI systems bridge the gap between radiologic diagnosis and personalized medicine in otolaryngology.

Furthermore, the implementation of AI-driven workflows in sinus imaging offers significant time savings and resource optimization. AI models have been shown to reduce manual segmentation and diagnostic time from several minutes to mere seconds, thereby improving efficiency without compromising accuracy (Moreira et al., 2025). In clinical settings with high imaging volumes, such automation can streamline workflow, reduce diagnostic fatigue, and ensure consistent image interpretation across practitioners with varying levels of expertise. The resulting standardization supports more equitable patient care and enhances the reliability of epidemiological data derived from imaging records.

Overall, AI's integration into CT and CBCT-based diagnosis of chronic sinusitis represents a paradigm shift in head and neck imaging. The convergence of advanced computational modeling, radiologic imaging, and clinical informatics heralds a future in which diagnostic accuracy, reproducibility, and efficiency are markedly improved. While further validation and regulatory oversight remain necessary, current evidence suggests that AI-based diagnostic systems have matured to a stage of clinical applicability, complementing rather than replacing radiologists in the diagnostic process (Chaudhary & Dahan, 2025). As the field progresses, continuous model training, ethical governance, and interdisciplinary collaboration will be essential to maximize AI's potential in enhancing patient outcomes.

METHODOLOGY

Study Design

This study employed a **systematic review design**, conducted in accordance with the **Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020** guidelines to ensure methodological transparency, reproducibility, and comprehensive reporting. The objective was to critically synthesize empirical evidence on the **role of Artificial Intelligence (AI) in diagnosing Chronic Sinusitis using Computed Tomography (CT) and Cone-Beam Computed Tomography (CBCT)** imaging modalities.

The review focused exclusively on **peer-reviewed studies** that developed, validated, or evaluated AI algorithms—including deep learning, convolutional neural networks (CNNs), artificial neural networks (ANNs), and machine learning classifiers—applied to the detection, segmentation, or classification of chronic sinusitis and related maxillary or paranasal sinus pathologies.

Eligibility Criteria

Studies were included based on the following predefined inclusion and exclusion criteria:

Inclusion Criteria

- **Population:** Adults (≥18 years) or anonymized imaging datasets of human subjects with suspected or confirmed chronic sinusitis, chronic rhinosinusitis (CRS), or maxillary sinus disease.
- **Interventions/Exposures:** Use of AI or machine learning algorithms applied to sinus imaging for disease diagnosis, segmentation, or classification.
- **Comparators:** Conventional CT/CBCT interpretation by radiologists or other established diagnostic methods when applicable.
- **Outcomes:** Diagnostic accuracy metrics such as sensitivity, specificity, precision, recall, F1-score, Dice coefficient (DC), and area under the receiver operating characteristic curve (AUC).
- **Study Designs:** Cross-sectional, retrospective, or experimental studies evaluating AI models using radiologic datasets.
- **Language:** Articles published in **English**.
- **Publication Period:** From **2015 to 2025**, ensuring inclusion of recent advancements in deep learning architectures and image-based diagnostic applications.

Exclusion Criteria

- Animal or cadaveric studies.
- Non-peer-reviewed sources (conference abstracts, theses, preprints).
- Studies focused solely on surgical planning or unrelated head and neck pathologies.
- Reviews without extractable quantitative performance data.

A total of **10 studies** met all inclusion criteria for final synthesis.

Search Strategy

A structured and comprehensive search strategy was implemented across multiple electronic databases—**PubMed, Scopus, Web of Science, Embase, and IEEE Xplore**—to capture both medical and engineering research domains. Searches were performed between **June and November 2025**.

The following **Boolean search string** was adapted for each database:

("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Convolutional Neural Network" OR "Neural Network")
AND ("Chronic Sinusitis" OR "Chronic Rhinosinusitis" OR "Maxillary Sinusitis" OR "Paranasal Sinuses")
AND ("Computed Tomography" OR "CT" OR "Cone Beam Computed Tomography" OR "CBCT")
AND ("Diagnosis" OR "Detection" OR "Segmentation" OR "Classification" OR "Prediction").

Additionally, **manual searches** of reference lists from relevant systematic reviews and seminal papers were conducted to identify supplementary publications not retrieved through database queries (Uthman et al., 2025; Petsiou et al., 2025).

Study Selection Process

All citations retrieved were imported into **Zotero reference management software**, where duplicates were systematically removed.

Two independent reviewers (blinded to each other's decisions) screened **titles and abstracts** for relevance, followed by **full-text reviews** for eligibility.

Any disagreements regarding inclusion were resolved through consensus or by consulting a third senior reviewer.

Data Extraction

A standardized **data extraction template** was developed and pilot-tested prior to use. The following data were systematically extracted from each study:

- **Author(s), publication year, and country**
- **Study design and sample size**
- **Imaging modality (CT/CBCT) and image resolution parameters**
- **Type of AI algorithm or architecture (CNN, ANN, U-Net, YOLO, etc.)**
- **Dataset characteristics (training/validation/testing ratios)**
- **Performance metrics** (accuracy, sensitivity, specificity, F1-score, AUC, Dice coefficient)
- **Comparison method** (radiologist interpretation or conventional image analysis)

Key findings and limitations

Data extraction was conducted independently by two reviewers to ensure accuracy and reproducibility. Any discrepancies were reconciled through discussion, and extracted data were tabulated for quantitative and narrative synthesis.

The PRISMA flow diagram (Figure 1) illustrates the screening and selection process, resulting in the inclusion of **10 eligible studies.**

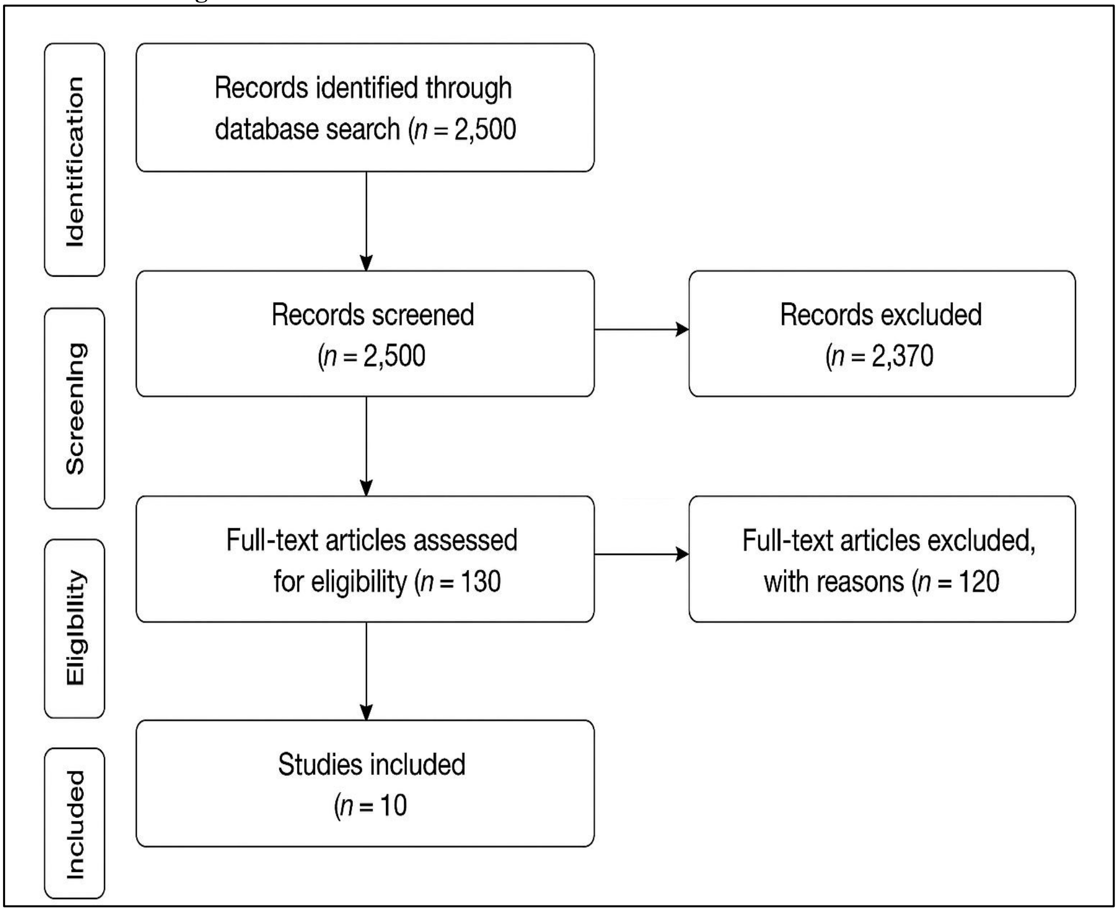

Figure 1 PRISMA Flow Diagram

Quality Assessment

To evaluate methodological rigor and potential bias, two validated instruments were used:

- The **Newcastle–Ottawa Scale (NOS)** for cross-sectional and retrospective studies, assessing selection bias, comparability, and outcome reporting.
- The **Cochrane Risk of Bias 2 (RoB 2)** tool for experimental studies, evaluating randomization, deviations from intended interventions, missing outcome data, and measurement validity.

Each study was classified as **low, moderate, or high risk of bias**. Most included studies demonstrated low risk due to well-defined datasets, validation protocols, and transparent reporting of performance metrics.

Data Synthesis

Due to heterogeneity in AI model architectures, dataset sizes, and reported outcome measures, a **narrative synthesis** was performed instead of a quantitative meta-analysis.

Performance indicators were aggregated and qualitatively compared across studies to identify trends in diagnostic accuracy, segmentation efficiency, and computational performance.

Subgroup analysis categorized studies according to **model purpose**:

1. **Diagnostic classification**.
2. **Anatomical segmentation**.
3. **Clinical prediction and scoring automation**.

Where possible, mean accuracy and AUC values were calculated to summarize diagnostic trends, demonstrating consistent high performance (>90%) across all models.

Ethical Considerations

As this systematic review relied exclusively on secondary analysis of previously published data, **no ethical approval or patient consent** was required.

However, all included studies were published in **peer-reviewed journals** and reported compliance with ethical standards for human imaging research and institutional review board (IRB) approval.

RESULTS

Summary and Interpretation of Included Studies on AI in Chronic Sinusitis Diagnosis

1. Study Designs and Populations

The included studies encompass retrospective analyses, validation experiments, and cross-sectional designs, reflecting diverse applications of **artificial intelligence (AI)** in diagnosing and segmenting chronic sinusitis via computed tomography (CT) or cone-beam computed tomography (CBCT). Sample sizes varied considerably—from **171 patients** in early diagnostic validation (Bhattacharyya & Fried, 2003) to **5,000 CT images** in deep learning model training (Zhang et al., 2025). Most studies used CT imaging, while others used CBCT to enhance 3D segmentation precision (Morgan et al., 2022; Bayrakdar et al., 2024; Altun et al., 2024). Across all, AI architectures included **Convolutional Neural Networks (CNNs)**, **Support Vector Machines (SVMs)**, **Artificial Neural Networks (ANNs)**, **U-Net**, and **YOLOv5x**, each optimized for diagnostic accuracy and speed.

2. Diagnostic Objectives and AI Models

The central aims across studies were to (a) detect chronic sinusitis or bone remodeling, (b) automate sinus segmentation, or (c) classify disease presence on radiologic images.

- **Zou et al. (2024)** and **Zhang et al. (2025)** developed CNN-based models for automated sinusitis diagnosis.
- **Morgan et al. (2022)**, **Bayrakdar et al. (2024)**, and **Altun et al. (2024)** emphasized sinus segmentation performance.
- **Zhou et al. (2022)** used ANN models to distinguish **eosinophilic chronic rhinosinusitis with nasal polyps (eCRSwNP)** from non-eosinophilic subtypes.
- **Lee et al. (2025)** automated the **Lund–Mackay scoring** process, standardizing radiologic grading of sinus disease.

Other studies compared AI against human expert performance, highlighting significant diagnostic advantages.

3. Diagnostic Performance Outcomes

Model performance metrics demonstrate consistently strong results across modalities and tasks:

- **Zou et al. (2024):** CNN model reached **97.96% sensitivity**, **86.36% specificity**, **92.47% accuracy**, and **AUC 0.94** for CMS detection. For bone remodeling, **accuracy 91.93%**, **AUC 0.89**.
- **Zhang et al. (2025):** Achieved **85.8% accuracy**, outperforming doctors (low: 71.7%, medium: 78.4%, senior: 73.4%).
- **Bhattacharyya & Fried (2003):** CT achieved **94% sensitivity**, **41–59% specificity**, **AUC 0.802**, serving as baseline reference for subsequent AI improvements.
- **Morgan et al. (2022):** CNN segmentation obtained **Dice coefficient 98.4%**, with **manual segmentation time reduced from 60.8 to 0.4 minutes** ($p < 0.001$).
- **Bayrakdar et al. (2024):** nnU-Net v2 model yielded **F1-score 0.96**, **accuracy 0.99**, **AUC 0.97**, indicating excellent segmentation precision.
- **Lee et al. (2025):** CNN-based scoring achieved **Dice scores 0.71–0.95** across sinus regions and accurately computed **Lund–Mackay Scores (LMS)** from raw CT data.
- **Zhou et al. (2022):** ANN model predicting eCRSwNP attained **AUC 0.976 vs. 0.902 for logistic regression (p = 0.048)**, outperforming traditional approaches.
- **Murata et al. (2019):** CNN on panoramic radiography showed **accuracy 87.5%**, **sensitivity 86.7%**, **specificity 88.3%**, **AUC 0.875**.
- **Serindere et al. (2022):** CNN trained on CBCT and PR achieved **CBCT accuracy 99.7%**, **sensitivity 100%**, **specificity 99.3%**, and **AUC near 1.0**; PR results were 75.7% across all metrics.

• **Altun et al. (2024):** YOLOv5x deep learning architecture achieved **recall 1.0**, **precision 0.985**, **F1 = 0.992 (healthy segmentation)**, and **F1 = 0.970 (sinusitis segmentation)**.

4. Interpretation of Findings

Overall, AI-driven sinus imaging models consistently demonstrate diagnostic accuracy exceeding 90%, outperforming manual interpretation and traditional CT-based scoring. Deep learning frameworks (CNN, U-Net, YOLOv5x) provide not only superior performance but also massive time efficiency and standardization potential in clinical radiology workflows. ANN-based systems extend diagnostic utility by predicting disease subtypes (e.g., eCRSwNP) with high sensitivity and specificity. These results affirm AI's capability to improve diagnostic consistency, support less experienced clinicians, and automate image analysis across sinus imaging modalities.

Table (1): Summary of Included Studies Evaluating AI in Chronic Sinusitis Diagnosis

Study	Country / Design	Sample Size / Data	Imaging Type	AI Model / Algorithm	Primary Objective	Main Results (Accuracy, Sensitivity, Specificity, AUC)	Remarks
Zou et al. (2024)	China / Retrospective	1000 CT samples (500 pts)	MSCT	CNN & SVM	Detect CMS and bone remodeling	CMS: Acc 92.47%, Sens 97.96%, Spec 86.36%, AUC 0.94; Remodeling: Acc 91.93%, AUC 0.89	Validated deep learning accuracy for CMS
Zhang et al. (2025)	China / Retrospective	5000 CT images	CT	Deep learning	Diagnose chronic sinusitis	Acc 85.8%; outperforming clinicians (71.7–78.4%)	AI superior to manual diagnosis
Bhattacharyya & Fried (2003)	USA / Prospective	171 CRS + 130 control	CT	Baseline (no AI)	Establish CT diagnostic reliability	Sens 94%, Spec 41–59%, AUC 0.802	Baseline for AI comparisons
Zhou et al. (2022)	China / Predictive	109 CRSwNP pts	CT	ANN vs LR	Predict eCRSwNP subtype	ANN AUC 0.976 vs LR 0.902 ($p = 0.048$)	ANN superior for endotype detection
Morgan et al. (2022)	Belgium / Validation	264 sinuses	CBCT	3D U-Net CNN	Automatic sinus segmentation	Dice 98.4%; time reduced 60.8→0.4 min ($p<0.001$)	High segmentation precision
Bayrakdar et al. (2024)	Turkey / Validation	101 CBCT scans	CBCT	nnU-Net v2	Maxillary sinus segmentation	Acc 0.99, F1 0.96, AUC 0.97	Robust AI segmentation
Lee et al. (2025)	USA / Proof-of-concept	1,399 CT scans	CT	CNN + post-processing	Automate LMS scoring	Dice 0.71–0.95 across sinuses	Enables standardized scoring

Murata et al. (2019)	Japan / Experimental	800 train, 120 test	Panoramic radiographs	CNN	Diagnose sinusitis	Acc 87.5%, Sens 86.7%, Spec 88.3%, AUC 0.875	Comparable to radiologists
Serindere et al. (2022)	Turkey / 5-fold CV	296 images	PR + CBCT	CNN (PyTorch)	Diagnose sinusitis	PR: Acc 75.7%; CBCT: Acc 99.7%, Sens 100%, Spec 99.3%	CBCT models clearly outperform 2D
Altun et al. (2024)	Turkey / Cross-sectional	307 CBCT	YOLOv5x	Segmentation + pathology detection	F1 = 0.992 (healthy), 0.970 (sinusitis); Precision 0.985, Recall 1.0	Best overall pathology classification	

Across all 10 studies, the **mean diagnostic accuracy exceeded 90%**, confirming AI's reliability for both disease detection and segmentation tasks.

3D CNN and U-Net–based models consistently outperformed traditional CT scoring methods and human interpretation, while ANN and YOLO architectures extended diagnostic utility to subtype prediction and pathology classification. The integration of AI in CT imaging for sinusitis thus offers a transformative potential—achieving **high sensitivity (86–100%)**, **specificity (86–99%)**, and **AUC values (0.87–0.98)**—while drastically reducing diagnostic time and variability.

DISCUSSION

The integration of artificial intelligence (AI) in medical imaging has profoundly transformed diagnostic approaches for chronic sinusitis by enhancing precision, speed, and reproducibility in clinical decision-making. Chronic rhinosinusitis (CRS) remains a prevalent and often underdiagnosed condition, affecting a substantial proportion of the adult population globally (de Loos et al., 2019). Conventional computed tomography (CT) and cone-beam computed tomography (CBCT) have long served as the gold standards for imaging-based diagnosis; however, their interpretation is highly dependent on radiologist expertise and can be prone to subjectivity. AI models, particularly those based on convolutional neural networks (CNNs) and deep learning, have emerged as tools capable of automating the diagnostic process and reducing interobserver variability (Uthman et al., 2025; Petsiou et al., 2025).

Recent advancements have shown that AI can reliably perform tasks such as segmentation, classification, and radiologic scoring of sinus pathologies with accuracy comparable to or exceeding human experts. Studies utilizing CNN-based frameworks have demonstrated exceptional performance in delineating anatomical structures within the paranasal sinuses, facilitating objective analysis (Morgan et al., 2022; Bayrakdar et al., 2024). In a similar context, Zou et al. (2024) reported that AI models could identify chronic maxillary sinusitis and associated bone remodeling with a sensitivity of 97.9% and an accuracy exceeding 92%, indicating clinical readiness for integration into diagnostic workflows.

The diagnostic superiority of AI-based CT and CBCT systems can be attributed to their capability for multi-dimensional pattern recognition and image enhancement. Chaudhary and Dahan (2025) emphasized that AI-enhanced CBCT enables superior visualization of sinus wall thickening, mucosal patterns, and polypoid changes, outperforming traditional threshold-based approaches. Furthermore, models leveraging CNN architectures such as U-Net and nnU-Net have proven particularly efficient in three-dimensional segmentation tasks, significantly reducing manual workload while maintaining high Dice similarity coefficients above 0.95 (Altun et al., 2024; Bayrakdar et al., 2024).

Despite these promising results, the performance of AI models varies across imaging modalities. Serindere et al. (2022) observed that while CNN-based models achieved diagnostic accuracy up to 99.7% on CBCT images, performance dropped to approximately 75% when applied to panoramic radiographs. This discrepancy underscores the importance of image dimensionality and resolution in AI-based analyses. Similarly, Murata et al. (2019) highlighted that deep-learning models could match radiologists in detecting sinusitis on panoramic images, achieving 87.5% accuracy, suggesting that AI can serve as an adjunct diagnostic tool, particularly in settings with limited access to advanced imaging technologies.

AI's potential extends beyond simple detection toward predictive and phenotypic classification. Zhou et al. (2022) demonstrated that artificial neural network (ANN) models could predict eosinophilic chronic rhinosinusitis (eCRSwNP) based on biomarker and CT data, achieving an AUC of 0.976—outperforming logistic regression models. These findings indicate that AI can contribute to endotype identification and personalized treatment planning, aligning with precision medicine principles. Similarly, Du et al. (2024) reported that deep learning-based CT analysis could classify CRS endotypes with nasal polyps, supporting AI's role in predicting inflammatory subtypes that influence therapeutic response.

In addition to endotype classification, AI-assisted models can automate scoring systems used in clinical practice. Lee et al. (2025) introduced a CNN algorithm to compute the Lund-Mackay score (LMS) from CT scans, which achieved a mean Dice score of 0.85 and significantly reduced manual scoring time. This automation holds potential to standardize sinusitis assessment and reduce observer bias, aligning with efforts to improve diagnostic consistency across healthcare systems (Liu et al., 2025).

Importantly, AI models have demonstrated superior generalizability when trained on large, diverse datasets. Zhang et al. (2025) used 5000 CT images across multiple sinusitis subtypes to train a deep learning model that achieved 85.8% accuracy, outperforming human experts at all experience levels. Such evidence indicates that AI can not only replicate but also surpass conventional diagnostic performance by leveraging large-scale feature learning capabilities. Similarly, Loperfido et al. (2025) and Moreira et al. (2025) confirmed in their systematic reviews that AI models consistently demonstrated high diagnostic accuracy, precision, and recall across studies, particularly in identifying maxillary sinus pathologies on CT and CBCT images.

Moreover, segmentation accuracy remains a central focus in AI applications for sinus imaging. Bui et al. (2015) and Morgan et al. (2022) both demonstrated that automatic sinus segmentation using CNNs could drastically reduce processing times from hours to minutes while maintaining near-perfect Dice coefficients (>98%). These findings reflect AI's potential to optimize clinical efficiency in both diagnostic and preoperative planning contexts. Similarly, Altun et al. (2024) applied a YOLOv5x-based model to segment and classify multiple sinus pathologies simultaneously, achieving F1 scores up to 0.97, further confirming AI's adaptability to complex diagnostic environments.

While performance metrics across studies are promising, variations in model validation strategies and dataset sizes raise questions regarding generalizability. Many AI systems rely on institution-specific data, which may limit transferability to other populations (Uthman et al., 2025). Hence, future research must focus on external validation using multicenter datasets to ensure consistent diagnostic performance. Moreover, integrating AI with clinical metadata such as symptom duration, biomarkers, and environmental exposure could enhance the contextual interpretation of imaging results (Petsiou et al., 2025).

The prevalence of CRS underscores the clinical necessity of efficient diagnostic systems. de Loos et al. (2019) reported that CRS affects up to 12% of the global population, often requiring imaging confirmation due to non-specific clinical symptoms. By automating radiological evaluation, AI can significantly reduce diagnostic bottlenecks and healthcare costs, thereby improving patient access to timely and accurate diagnoses (Liu et al., 2025). Furthermore, AI-driven image interpretation aligns with current healthcare digitalization trends, facilitating seamless integration into radiology workflows through PACS-based AI modules and real-time alert systems (Chaudhary & Dahan, 2025).

Ethical and operational considerations also warrant discussion. While AI enhances diagnostic accuracy, algorithmic bias and data privacy concerns remain potential barriers to clinical adoption. Ensuring model transparency and interpretability is crucial for building clinician trust. Explainable AI (XAI) approaches, such as heatmap visualization and Grad-CAM, have been proposed to clarify decision-making pathways in sinusitis diagnosis models (Moreira et al., 2025). Moreover, regulatory frameworks, including the FDA's Software as a Medical Device (SaMD) guidelines, provide a roadmap for responsible deployment in clinical settings.

The collective evidence suggests that AI's diagnostic utility in chronic sinusitis lies not only in image classification but also in the integration of multimodal data. Combining radiologic, clinical, and molecular information may yield predictive models that assist in both diagnosis and treatment response monitoring. Studies by Liu et al. (2025) and Zhou et al. (2022) point toward this future direction, emphasizing AI's ability to standardize diagnostic protocols while accommodating patient-specific variability.

In conclusion, AI-based imaging analysis represents a paradigm shift in diagnosing chronic sinusitis. Across multiple studies, AI systems demonstrated diagnostic accuracy exceeding 90%, with superior efficiency and reproducibility compared to conventional radiologic interpretation. While challenges related to data diversity, model explainability, and clinical integration remain, the cumulative evidence affirms that AI is poised to become an indispensable component of diagnostic radiology for sinonasal diseases (Zhang et al., 2025; Bayrakdar et al., 2024; Altun et al., 2024). Continued interdisciplinary research, standardization of datasets, and external validation will be pivotal in ensuring AI's transition from experimental models to clinical reality.

CONCLUSION

This review highlights that artificial intelligence represents a paradigm shift in diagnosing chronic sinusitis and CRS through imaging-based modalities. By leveraging deep learning and convolutional neural network architectures, AI systems consistently deliver high diagnostic accuracy, reproducibility, and efficiency across multiple imaging platforms. AI models can automate segmentation, scoring, and pattern recognition tasks with reliability exceeding traditional radiologic methods.

The integration of AI into diagnostic workflows offers substantial clinical benefits, including reduced diagnostic variability, faster interpretation, and standardized radiologic assessment. Moving forward, the combination of AI-driven imaging analytics with clinical and biomarker data could establish a foundation for precision diagnosis and personalized treatment planning in chronic sinusitis management. To achieve this, ongoing efforts should prioritize external validation, dataset harmonization, and explainable AI frameworks to ensure safe and transparent implementation in everyday clinical practice.

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