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Diagnostic accuracy of artificial intelligence in the detection of maxillary sinus pathology using computed tomography: A concise systematic review

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ABSTRACT

Purpose: This study was performed to assess the performance and accuracy of artificial intelligence (AI) in the detection and diagnosis of maxillary sinus pathologies using computed tomography (CT)/cone-beam computed tomography (CBCT) imaging.
Materials and Methods: A comprehensive literature search was conducted across 4 databases: Google Scholar, BioMed Central (BMC), ProQuest, and PubMed. Combinations of keywords such as “DCNN,” “deep learning,” “convolutional neural network,” “machine learning,” “predictive modeling,” and “data mining” were used to identify relevant articles. The study included articles that were published within the last 5 years, written in English, available in full text, and focused on diagnostic accuracy.
Results: Of an initial 530 records, 12 studies with a total of 3,349 patients (7,358 images) were included. All articles employed deep learning methods. The most commonly tested pathologies were maxillary rhinosinusitis and maxillary sinusitis, while the most frequently used AI models were convolutional neural network architectures, including ResNet and DenseNet, YOLO, and U-Net. DenseNet and ResNet architectures have demonstrated superior precision in detecting maxillary sinus pathologies due to their capacity to handle deeper networks without overfitting. The performance in detecting maxillary sinus pathology varied, with an accuracy ranging from 85% to 97%, a sensitivity of 87% to 100%, a specificity of 87.2% to 99.7%, and an area under the curve of 0.80 to 0.91.
Conclusion: AI with various architectures has been used to detect maxillary sinus abnormalities on CT/CBCT images, achieving near-perfect results. However, further improvements are needed to increase accuracy and consistency.
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KEY WORDS: Artificial Intelligence; Computed Tomography, X-Ray; Maxillary Sinus; Pathology

Introduction

The term “artificial intelligence” (AI) encompasses a range of concepts, including machine learning and deep learning. Neural networks, which form the basis of deep learning, are computational models that acquire, analyze, and associate input with output by constructing multiple hidden layers in nonlinear processing units. Deep learning differs from traditional machine learning in its capacity to evaluate larger amounts of data, exploring complex correlations between inputs and outputs. This capability stems from the proficiency of deep learning in handling abstract and detailed data.[1] Traditional machine learning employs computational methods and algorithms to extract insights and detect patterns within input data. It then provides a calculated assessment as a diagnostic result, based on the features and behavior of the lesion.[2] The integration of AI into medical imaging has revolutionized the diagnostic process, particularly regarding the assessment of maxillary sinus pathologies using computed tomography (CT). The application of CT, especially cone-beam CT (CBCT), is recognized as the gold standard for visualizing the complex anatomy of the maxillary sinus. It offers

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superior spatial resolution and detailed imaging compared to conventional panoramic radiography.[3]

Recent research has examined the prevalence of various maxillary sinus pathologies, including mucosal thickening, sinusitis, and opacification, with significant relationships reported in diverse populations.[4,5] The capacity of AI algorithms, especially those employing deep learning techniques, to interpret CT images has shown promise in improving diagnostic accuracy. For instance, AI models have been developed to detect maxillary sinus abnormalities with high sensitivity and specificity, often outperforming human radiologists.[6] This capability is crucial, as accurate diagnosis can facilitate timely interventions and lead to better patient outcomes, especially when sinus pathologies are secondary to dental issues.[7] As AI in medical imaging continues to evolve, ongoing research is essential to validate these technologies and establish standardized protocols for their incorporation into routine clinical workflows.[6,8]

In summary, the diagnostic accuracy of AI in detecting maxillary sinus pathology through CT is a notable advancement in radiological practice. This systematic review synthesizes current evidence to provide a comprehensive understanding of the role of AI in improving diagnostic capabilities, with the aim of benefiting patient care in the context of maxillary sinus conditions. Additionally, this review assesses the diagnostic accuracy of AI applications in identifying maxillary sinus pathology using various convolutional neural network (CNN) architectures.

Materials and Methods

The conduct of this review adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement,[9] guided by the following study question: "Can deep learning algorithms improve the accuracy, consistency, and reliability of maxillary sinus disease detection using CT and CBCT imaging?"

The research question was formulated in accordance with the PICO (population, intervention, comparison, and outcome) criteria. The population (P) comprised individuals undergoing maxillary sinus imaging with CT and CBCT; the intervention (I) was the application of deep learning for the detection of maxillary sinus pathology; the comparison (C) was made between traditional/conventional screening methods for maxillary sinus pathology and deep learning methods; and the outcome (O) was the diagnostic accuracy of deep learning in identifying maxillary sinus pathology, compared to traditional methods.

Literature search strategy

A comprehensive literature search was conducted across 4 databases: Google Scholar, BioMed Central (BMC), ProQuest, and PubMed. To ensure the screening of all relevant articles, the search employed a set of keyword combinations (DCNN OR "deep learning" OR "convolutional neural network" OR "neural networks") AND (machine learning OR "predictive modeling" OR "data mining") AND ("maxillary sinus pathology" OR "maxillary sinus diseases" OR sinusitis OR "maxillary sinus disorders").

The selection criteria required articles to be published no more than 5 years ago (that is, in 2019 or later), with the aim of incorporating the most recent developments in the field. BMC provided access to documents published in relevant journals within the biomedical domain. ProQuest's database facilitated the exploration of a diverse range of sources, including theses, dissertations, and articles. PubMed, a specialized database for biomedical literature, offered extensive access to a large collection of peer-reviewed articles and research papers. The search yielded an extensive compilation of findings, methodologies, and perspectives, providing a detailed overview of the current research landscape in this area. The analysis incorporated articles published within the last 5 years, in English, with full text available, and with a focus on diagnostic accuracy. The exclusion criteria ruled out non-English texts, abstracts, posters, and papers published before 2019.

Study selection and data extraction

Three evaluators independently assessed the titles, abstracts, and full texts of relevant studies, resolving any discrepancies by consensus. The examiners extracted essential information from the eligible articles. Data on the author, year, country, sample type, sample size, CNN architecture, statistical findings—including accuracy, sensitivity, specificity, and area under the curve (AUC)—and primary outcomes were collected when available.

Assessment of risk of bias and study quality

The Prediction Model Risk of Bias Assessment Tool (PROBAST) for nonrandomized studies[10] was utilized to evaluate the risk of bias and applicability of the studies (Table 1). This tool examines 4 key domains—participants, predictors, outcome and analysis—to help researchers measure the robustness and generalizability of the predictive models under examination. The tool emphasizes the importance of external validation in model development to mitigate potential bias. Models that lack external validation or are based on limited datasets may be considered at high

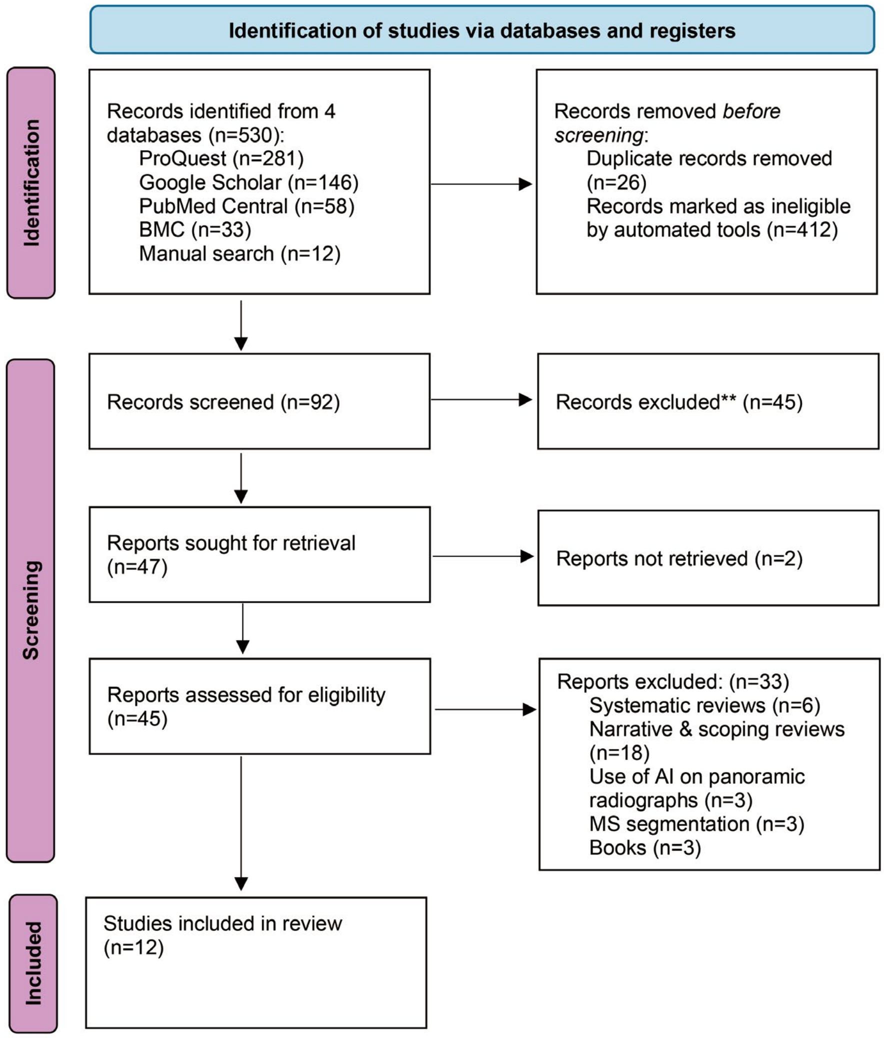

Fig. 1. PRISMA flowchart for systematic review. PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses, BMC: BioMed Central, AI: artificial intelligence, MS: maxillary sinus.

risk of bias unless they are supported by adequate internal validation. Moreover, the tool facilitates the identification of specific areas where bias may exist, enabling researchers to address these issues and improve the reliability of their predictive models. Rigorous application of the PROBAST tool can help foster transparency and rigor in the evaluation of prediction models, thereby increasing the quality of evidence used in clinical decision-making.

Results

A total of 530 articles were identified: 146 from Google Scholar, 33 from BMC, 281 from ProQuest, 58 from PubMed Central, and 12 from a manual search. After 26 duplicates were removed, 504 articles remained. The titles and abstracts of these articles were screened based on the predetermined inclusion criteria. Consequently, 412 articles were excluded due to their lack of relevance to the topic. The remaining 92 articles underwent further examination and were evaluated by 3 experts to determine their eligibility for inclusion. Two articles were not retrieved, and 45 studies were excluded because they did not utilize AI in the detection of maxillary sinus diseases. An additional 33 publications were eliminated based on reasons outlined in the PRISMA model (Fig. 1). Ultimately, 12 papers were included in the systematic review.

Using the PROBAST checklist, 6 studies were assessed as having a low risk of bias, 3 were rated as having a medium risk of bias, and 3 were considered to display a high risk of bias. Regarding applicability, all 12 studies were deemed reasonably applicable (Table 1).

Table 1. PROBAST tool for assessing risk of bias and applicability

Authors (year)	Participants	Predictor	Outcome	Analysis	Overall
Kim et al.[11] (2022)	Low	Low	Low	Low	Low
Massey et al.[12] (2022)	Low	Low	Low	Medium	Medium
Humphries et al.[13] (2020)	Low	Low	Low	Low	Low
Nechyporenko et al.[14] (2022)	Low	Low	Low	High	High
Alekseeva et al.[15] (2023)	Low	Low	Low	Low	Low
Yoo et al.[16] (2023)	Low	High	Low	High	High
Ozbay and Tunc[17] (2022)	Low	High	Low	High	High
Zeng et al.[18] (2023)	Low	Low	Low	Medium	Medium
Aboelmaaty et al.[19] (2024)	Low	Low	Low	Medium	Medium
Serindere et al.[20] (2022)	Low	Low	Low	Low	Low
Hung et al.[21] (2022)	Low	Low	Low	Low	Low
Chowdhury et al.[22] (2019)	Low	Low	Low	Low	Low

PROBAST: Prediction Model Risk of Bias Assessment Tool

Study characteristics

The total number of patients across the included studies was 3,349, with 7,358 images analyzed. These studies were conducted in 7 countries, with 2 studies each from Korea, China, Turkey, Ukraine, and the United States and 1 study each from Saudi Arabia and Italy. The sample sizes were determined based on the number of patients participating in the research. The largest sample included 1,000 patients, while the smallest comprised 67 patients. Regarding the images, the smallest set contained 67 images, with the largest set encompassing 2,000 images (Table 2).

All the selected studies were clinical trials. Five were comparative studies, 3 were retrospective studies, and 4 were model testing studies. Several employed various statistical procedures to evaluate a range of AI technologies. Collectively, the studies examined 9 different forms of AI, including multiple deep learning approaches.

Study comparator

Three studies proposed a deep learning method for the diagnosis of maxillary chronic rhinosinusitis (CRS),[11-13] while 2 studies suggested a CNN model for the identification of odontogenic maxillary sinusitis.[14,15] Various AI models were created to enable faster and more efficient diagnosis of maxillary sinus pathologies, as well as other anatomical identification tasks.

Study outcome

Several statistical tests have been utilized to evaluate the efficacy of AI in diagnosing maxillary sinus pathologies. In this review, most studies employed accuracy, sensitivity, specificity, and AUC. Analyzing each article individually revealed that different pathologies were examined, leading to distinct limitations and results (Table 2). For instance, Massey et al.[12] studied CRS using the Lund-Mackay scoring system, observing a correlation of approximately 0.85 with CNN-determined percentage sinus opacification. In research conducted by Zeng et al.,[18] an AUC of 0.95 was attained using CNN YOLOv5 to identify sinus abnormalities in the context of maxillary sinus lift and implant surgery.

Hung et al.[21] investigated mucosal thickening and mucosal retention cysts of the maxillary sinus, reporting AUC values of 0.91 and 0.84 on low-dose CBCT scans and 0.89 and 0.93 on full-dose scans, respectively. Limitations of the study included the evaluation of only 1 CNN architecture, the general-purpose DenseNet model; thus, future customization may be necessary to improve performance. Ozbay and Tunc[17] studied abnormalities in the paranasal sinuses, achieving an accuracy of 98.52% and a sensitivity of 100% for detecting sinusitis and rhinosinusitis using CNN convolutional layers and ReLU layers. However, their ability to assess comparative performance was limited by a lack of directly related studies. Kim et al.[11] explored the detection of maxillary sinus fungal ball using the ResNet-18 model, with an accuracy ranging from 87.5% to 88.4%. Nechyporenko et al.[14] focused on identifying odontogenic maxillary sinusitis, achieving an accuracy of 93.78%, but faced challenges in setting optimal model parameter values using the U-Net architecture. In a 2024 study, Aboelmaaty et al.[19] assessed sinus mucosal thickness in relation to periapical lesions, using the posterior superior alveolar artery (PSAA) as a reference, and reported accuracies ranging from 60.58% to 87%. They determined that the AI tool employed, e-Vol DXS, had a 100% success rate in identifying the PSAA. As described in a 2022 report, Serindere et al.[20] developed a CNN model to diagnose maxillary sinusitis using panoramic radiographs and CBCT images, finding that the diagnostic efficacy of the CNN was significantly higher for CBCT images than for panoramic radiographs.

In 2023, Alekseeva et al.[15] proposed an intelligent information system to improve clinician efficiency in the differential diagnosis of chronic odontogenic rhinosinusitis. This system combined patient interview and examination data with an image processing model using the U-Net network, achieving an overall accuracy of 90.09%. However, the researchers noted that while the decision support system could identify patterns indicative of CRS on imaging tests, its diagnostic accuracy may fall short of that of a trained physician, and factors such as the precision of imaging studies or the presence of other conditions with similar symptoms could affect the system's diagnostic precision. Humphries et al.[13] demonstrated the technical viability of a fully automated, volumetric assessment of sinus opacification on CT using a CNN, which produced a clinically significant severity index. They concluded that incorporating this objective approach into sinus CT evaluations could provide valuable additional insights for physicians and researchers. Chowdhury et al.[22] employed the Google Inception-V3 model to classify the ostiomeatal complex (OMC). They obtained preoperative coronal sections of the OMC from 239 patients participating in 2 prospective CRS outcome studies, yielding a total of 956 images through mirroring. The classification layer of Inception-V3 was retrained in Python using transfer learning to adapt the CNN for analyzing sinonasal CT images. The receiver operating characteristic curve analysis on the test set validated the robust classification capability of the CNN, with an AUC of 0.87.

Deep learning models have demonstrated impressive accuracy across various tasks, including segmentation, classification, and detection. For instance, in segmentation tasks, both semi-automatic and automatic approaches have been associated with significant time reduction, achieving accuracies as high as 96.3% and 95.1% for certain anatomical structures. Classification accuracies have been reported to range from 87.5% to 97.04%, with a specific model configuration reaching an accuracy of 93.78%. These findings underscore the effectiveness of deep learning methodologies in improving both efficiency and accuracy in the analysis of medical images, as evidenced by the shorter segmentation time and high classification accuracies found across various studies. Regarding the overall performance of deep learning, an accuracy of greater than 90% was reported in 6 studies,[14-16,18,20,22] with 3 of these employing the U-Net architecture.

Accuracy of AI in interpreting CT/CBCT images

AI systems are highly proficient in processing large datasets, which facilitates the detection of abnormalities within the maxillary sinus. In this review, 6 studies utilized CT,[11,12,14,15,17,22] while another 6 employed CBCT.[13,16,18-21] Ozbay and Tunc[17] used CT images to present a deep learning framework for the automated recognition of inverted papilloma and nasal polyp, achieving a classification accuracy of 89.30%. Moreover, their study achieved an accuracy of 98.52% in classifying paranasal sinus conditions. However, the comparative performance of the proposed method was difficult to assess. Zeng et al.[18] developed a deep learning model using the YOLOv5 architecture for object detection, designed specifically to localize the maxillary sinus region within CBCT images by leveraging the high inherent contrast of the relevant anatomical structures. A classification module was then implemented to diagnose various abnormalities in the maxillary sinus, incorporating strategies such as network architecture adaptation, transfer learning, and data augmentation to improve model performance and robustness. The findings indicated that the deep learning framework effectively identified maxillary sinus abnormalities, achieving high accuracy rates in both detection and classification tasks. The authors reported that their model outperformed traditional diagnostic methods, offering a more reliable assessment of sinus conditions.

In a study by Aboelmaaty et al.,[19] patients with diagnosed periapical lesions were examined. The results suggested that the AI tool used demonstrated high accuracy and reliability in detecting the location of the PSAA, which could aid in clinical decision-making and surgical planning. However, the study's cross-sectional nature was considered a limitation in validating the results. Serindere et al.[20] utilized a CNN model designed to automatically detect and classify sinusitis based on imaging features. They employed various performance metrics, including accuracy, sensitivity, specificity, and AUC, to assess the model's effectiveness. The findings revealed that the CNN model achieved high diagnostic accuracy for both panoramic radiographs and CBCT images, with significantly better performance on the latter. The AUC for CBCT images was notably higher, indicating that CBCT provides more detailed anatomical information that in turn enhances the model's detection capabilities. Additionally, the study highlighted the potential of CNNs as valuable adjuncts in clinical practice, assisting

Table 2. Study characteristics

Authors (year)	Sample size, imaging modality	Country	CNN type	Predictor	Performance metrics	Main findings
Kim et al.[11] (2022)	512 CT images	Korea	ResNet 18	MFB, CRS, healthy controls	Accuracy = 87.5%-88.4%	– AI system for classifying 2-stage AI model developed: 2-D CNN selects maxillary sinus slices; 3-D CNN classifies MFB, CRS, and healthy controls – Strong generalizability between different datasets – Performance similar to human experts – Potential for use in areas with limited specialist availability – Represents a reliable diagnostic tool for primary care physicians
Massey et al.[12] (2022)	88 patients 88 CT images	USA	CNN-based algorithm Not specified	CRS	Lund-Mackay score = 0.85	– Aimed to validate and extend an automated deep learning-based algorithm using a CNN for quantitative sinus CT analysis – Successfully segmented 100% of scans from various scanners and protocols – Provided detailed quantitative results exceeding visual scoring methods in sensitivity and reproducibility
Humphries et al.[13](2020)	690 patients 510 CT images	Italy	CNN-based algorithm Not specified	CRS	DSC = 0.93 Accuracy = 0.86-0.97	– CNN opacification scores showed strong correlation with Lund-Mackay visual scores and clinical metrics – CNN required only about 1 minute per scan for automated segmentation, showing superior practicality over traditional manual methods – Automated opacification scores provided an objective measure of disease severity, distinguishing between patients with CRS and those with or without a history of sinus surgery
Nechyporenko et al.[14] (2022)	100 patients 320 CT images	Ukraine	U-Net	Odontogenic maxillary sinusitis	Accuracy = 93.78%	– Six training models were used; model 6 achieved the highest accuracy of 93.78% with a batch size of 2 and 500 epochs – Significance: standard operating procedure for CT image segmentation, aiding in the diagnosis of odontogenic maxillary sinusitis – Enhances diagnostic efficiency, unifies tomographic results, and helps ensure accurate assessment
Alekseeva et al.[15] (2023)	162 MSCT images	Ukraine	U-Net	Chronic odontogenic rhinosinusitis	Accuracy = 90.09%	– Developed a computer vision model for MSCT image analysis and a chatbot for patient data collection – Developed a U-Net architecture-based segmentation model for MSCT image analysis, achieving high accuracy – Demonstrated effective performance in diagnosing complex and diagnostically challenging cases
Yoo et al.[16] (2023)	67 patients 67 CBCT images	Korea	U-Net, V-Net	Maxillary sinus lesions	DSC = 0.787 Precision = 0.875 Recall = 0.897	– Superior performance attributed to its ensemble learning approach, which combined predictions from 3 orthogonal planes – 2.5D network demonstrated greater robustness in accurately segmenting maxillary sinus lesions with large variations in size, shape, and location –2.5D networks can improve automatic segmentation of maxillary sinus structures in dental clinical settings, facilitating preoperative planning and minimizing surgical complications.

Table 2. Continued

Authors (year)	Sample size, imaging modality	Country	CNN type	Predictor	Performance metrics	Main findings
Ozbay and Tunc[17] (2022)	140 patients 340 CT images	Turkey	ReLU	Paranasal sinus pathology	Accuracy = 98.52% Sensitivity = 100% Specificity = 97.22% F1 score = 98.45%	– Introduces a fully automated system for diagnosing paranasal sinus conditions using CT images – Employs a CNN for automatic segmentation and classification – Enables automatic segmentation of paranasal sinus regions without manual cropping – Outperforms existing approaches in accuracy and automation – Demonstrates superior accuracy in automatic segmentation and classification tasks
Zeng et al.[18] (2023)	1000 patients 2000 CBCT images	China	YOLOv5, Res-Net 34, GoogleNet, InceptionV3, Res-NeXt101	Maxillary sinus abnormalities	AUC = 0.953 Precision = 83.3% Recall = 87.0% Specificity = 83.3% Accuracy = 90%	– Model uses a 2-stage strategy: object detection and classification modules – Object detection module minimizes background noise, focusing on sinus region – Classification module diagnoses abnormalities like mucosal thickening, polypoid lesions, effusion, and opacification – Model provides an efficient tool for identifying maxillary sinus abnormalities, thus improving diagnosis and treatment planning
Aboelmaaty et al.[19] (2024)	240 CBCT images	Saudi Arabia	CNN-based algorithm Not specified	Mucosal thickening	Accuracy = 60.58%-87%	– Utilized e-Vol DXS to locate the PSAA – PSAA location was classified into intraosseous, beneath the membrane, and over the external cortex – Significant correlation observed between PSAA location and mucosal thickening – Study group exhibited higher rates of mucosal thickening, especially when the PSAA was beneath the membrane
Serindere et al.[20] (2022)	148 patients with sinusitis 148 healthy participants 296 CBCT images	Turkey	CNN-based algorithm Not specified	Maxillary sinusitis	Accuracy = 99.7% Sensitivity = 100% Specificity = 99.3%	– A CNN-based AI model was developed to diagnose maxillary sinusitis on panoramic radiographs and CBCT images. – The model was evaluated using a 5-fold cross-validation technique and implemented using the PyTorch library. – CBCT was confirmed as a gold standard due to its higher diagnostic accuracy. – The study suggests AI could be an effective diagnostic aid, especially for less experienced practitioners.
Hung et al.[21] (2022)	445 patients 445 CBCT images	China	DenseNet	MT, MRC	DSC = 0.95 AUC = 0.91-0.84	– A 3-step CNN algorithm was developed for the automatic detection and segmentation of mucosal thickening and mucosal retention cysts in the maxillary sinus using CBCT images. – The algorithm achieved high diagnostic accuracy, with AUC values of 0.91 for MT and 0.84 for MRCs on low-dose CBCT scans and 0.89 for MT and 0.93 for MRCs on full-dose scans. – The CNN algorithm demonstrated potential for clinical use as an automated diagnostic and reporting tool for maxillary sinus evaluation. – The algorithm showed robustness across different CBCT dose settings and field-of-view sizes.

Table 2. Continued

Authors (year)	Sample size, imaging modality	Country	CNN type	Predictor	Performance metrics	Main findings
Chowdhury et al.[22] (2019)	239 patients 956 CT images	USA	Google Inception-V3	Ostiomeatal complex diseases	AUC = 0.87 Accuracy = 85%	– Utilized Google's Inception-V3 CNN model, trained on 1.28 million images and retrained on 956 labeled CT images – CNN learned clinically relevant features from 2-dimensional CT images, demonstrating the feasibility of machine learning in medical imaging – Misclassifications occurred due to ambiguous OMC status in borderline cases – Study provides proof of concept for AI systems in automating OMC classification, potentially reducing clinical workload and enabling efficient analysis of medical imaging data archives

CBCT: cone-beam computed tomography, CT: computed tomography, MSCT: multispiral computed tomography, AUC: area under the curve, CNN: convolutional neural network, AI: artificial intelligence, PSAA: posterior superior alveolar artery, DSC: dice similarity coefficient, MFB: maxillary sinus fungal ball, CRS: chronic rhinosinusitis, MT: mucosal thickening, MRC: mucosal retention cyst, OMC: ostiomeatal complex.

radiologists and clinicians in the timely diagnosis of maxillary sinusitis. The authors concluded that integrating CNN technology into routine radiographic evaluations could improve diagnostic efficiency and accuracy, ultimately benefiting patient care. However, the small size of the dataset was acknowledged as a limitation of the study.

Discussion

The primary purpose of this systematic review was to evaluate the performance and accuracy of different AI models in diagnosing maxillary sinus pathologies using CT/CBCT imaging. The studies assessed in this systematic review largely demonstrated that AI models could identify maxillary sinus pathologies quickly, efficiently, and with excellent accuracy. The primary benefit of these models is their non-invasive approach to detecting pathologies, offering patients ease and convenience. Although the models are still in the early stages, efforts have been underway to continuously improve their results and efficiency for their designated tasks. In this review, to assess the potential for bias in the included studies, the PROBAST checklist was utilized. This tool prompts researchers to evaluate the clinical relevance of prediction models by examining criteria such as participant characteristics and predictor variables. This comprehensive methodology ensured that the prediction models were not only statistically robust but also applicable and useful in real-world clinical settings. The tool promotes transparency and repeatability by examining the analysis methodologies used in model creation, thus fostering confidence in the predictions made. In summary, the systematic application of the PROBAST tool provided a valuable framework for evaluating the quality and reliability of prediction models, potentially aiding in the development of specific and clinically relevant decision support systems for healthcare. A CNN is a type of artificial neural network widely used for image recognition and processing due to its capacity to identify patterns within images. U-Net is a specific CNN designed for image segmentation. This network employs a fully convolutional architecture that has been modified and optimized to achieve more precise segmentation with a smaller number of training images.

The U-Net architecture has emerged as a critical tool in the analysis of CBCT images, particularly for assessing maxillary sinus pathology. This deep learning model is designed to facilitate precise segmentation of anatomical structures, which is essential for diagnosing various conditions that affect the maxillary sinus. This application of U-Net aims to increase image quality, improve diagnostic accuracy, and help elucidate the relationship between dental health and maxillary sinus conditions.[23] Yalcin and Ozturk[5] emphasize that CBCT is particularly effective in visualizing sinonasal anatomy, including the maxillary sinus, due to its high image quality and comparatively minimal metal artifacts from dental restorations. This capability is crucial for accurately diagnosing maxillary sinus pathologies, such as mucosal thickening and sinusitis, which can be influenced by adjacent dental conditions.[5] The U-Net architecture is particularly suited for segmenting complex anatomical structures, including the maxillary sinus and its associated pathologies. Its encoder-decoder structure captures both local and global features, enabling it to delineate the boundaries of the sinus and effectively identify pathological changes. The segmentation capabilities of U-Net can facilitate the identification of maxillary sinus pathologies. Thus, integrating U-Net in the analysis of relevant CBCT images represents a notable advancement in dental imaging. The associated image quality, diagnostic accuracy, and insights regarding oral health and sinus conditions underscore its importance in clinical practice.

Chowdhury et al.[22] employed a deep learning approach to classify the opacification of the OMC on specific 2-dimensional coronal sections. They analyzed 956 preoperative coronal sections of the OMC from 239 patients in 2 prospective CRS outcome studies, classified by OMC status. Their method, which utilized a CNN trained on 296 CT scans from patients with CRS, accurately detected OMC opacification 85% of the time. In a study by Massey et al.,[12] an initial CNN was created, trained, evaluated, and validated. The algorithm segmented each sinus cavity individually while incorporating the left and right sides, apart from the maxillary sinuses, which are segmented separately. A visual, qualitative evaluation was conducted on each segmentation generated by the algorithm to thoroughly verify its accuracy. The researchers concluded that quantitative processing of sinus CT images generates objective metrics consistent with established visual scoring methods. The benefits of automation are clear; however, validation in a prospective, multi-institutional setting may be necessary. The limitation of that study was the inability to validate the algorithm using diverse scans. Zeng et al.[18] developed another deep learning-based screening model that incorporated object detection and a straightforward classification strategy to identify maxillary sinus abnormalities on CBCT images. Their model achieved more than 90% accuracy at the optimal cutoff. However, the study's limitations included the challenges of exploring all types of CNNs for training and testing. Based on another study by Kim et al.,[11] the most representative CT finding associated with maxillary sinus fungal ball is the presence of intralesional calcifications, which can be effectively detected using deep learning algorithms like ResNet. ResNet improves the accuracy and resilience of medical image processing by extracting and classifying complex features from these images. Furthermore, ResNet's depth and accuracy make it an excellent choice for various medical image processing tasks. Its architecture enables the construction of deep networks that can recognize complex patterns in imaging data via skip connections. However, a limitation of this research was its use of a small dataset.

Overall, the studies explored various AI approaches for detecting maxillary sinus pathology using CBCT. The efficacy of AI in identifying such pathology is subject to clinician evaluation. In the diagnostic process, clinicians rely on specific features to assess abnormalities and determine the severity of the condition. However, manual assessment poses the risk of error, as the need to precisely quantify diagnostic criteria may result in inaccuracies.[1] The advent of AI technologies has addressed these challenges by reducing errors and increasing the effectiveness and precision of maxillary sinus pathology detection.

Recent studies have demonstrated that deep learning significantly facilitates the screening of maxillary sinus pathologies. This capability not only enables teams to devise tailored treatment plans but also streamlines their workload. Moreover, deep learning models can stratify patients into high- or low-risk groups, assisting surgeons in determining whether a conservative or aggressive treatment approach is appropriate. This strategic classification may spare low-risk patients from the potential adverse effects of aggressive treatment.

Despite these promising prospects for integrating AI-driven research into maxillary sinus pathology, several challenges persist. Privacy concerns and the confidentiality of patient data pose substantial obstacles to the widespread adoption of AI in practice. Furthermore, the lines of responsibility must be clarified regarding instances of error in AI-driven analyses—whether the onus lies with the physician or the software. Additionally, the introduction of AI in pathology practice raises questions about patient autonomy and the dynamics of the patient-clinician relationship.

In conclusion, this systematic review provides robust evidence supporting the effectiveness of deep learning in accurately detecting maxillary sinus pathologies using CBCT or CT imaging. The findings suggest that various deep learning techniques yield accurate results, assisting clinicians and pathologists in improving diagnostic outcomes and minimizing the chance of error. As such, the integration of machine learning, especially deep learning methods, holds considerable promise for improving diagnostic accuracy and efficiency in the field of maxillary sinus pathology.

Conflicts of Interest: None

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