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Artificial Intelligence-Based Diagnosis of Obstructive Sleep Apnea Syndrome: A Scoping Review

Diagnóstico Basado en Inteligencia Artificial para el Síndrome Obstructivo de Apnea del Sueño: Una Revisión de Alcance

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SUMMARY: To diagnose obstructive sleep apnea syndrome (OSAS), polysomnography is used, an expensive and extensive study requiring the patient to sleep in a laboratory. OSAS has been associated with features of facial morphology, and a preliminary diagnosis could be made using an artificial intelligence (AI) predictive model. This study aimed to analyze, using a scoping review, the AI-based technological options applied to diagnosing OSAS and the parameters evaluated in such analyses on craniofacial structures. A systematic search of the literature was carried out up to February 2024, and, using inclusion and exclusion criteria, the studies to be analyzed were determined. Titles and abstracts were independently selected by two researchers. Fourteen studies were selected, including a total of 13,293 subjects analyzed. The age of the sample ranged from 18 to 90 years. 9,912 (74.56 %) subjects were male, and 3,381 (25.43 %) were female. The included studies presented a diagnosis of OSAS by polysomnography; seven presented a control group of subjects without OSAS and another group with OSAS. The remaining studies presented OSAS groups in relation to their severity. All studies had a mean accuracy of 80 % in predicting OSAS using variables such as age, gender, measurements, and/or imaging measurements. There are no tests before diagnosis by polysomnography to guide the user in the likely presence of OSAS. In this sense, there are risk factors for developing OSA linked to facial shape, obesity, age, and other conditions, which, together with the advances in AI for diagnosis and guidance in OSAS, could be used for early detection.

KEY WORDS: Artificial intelligence; Obstructive sleep apnea syndrome; Facial morphology.

INTRODUCTION

The facial skeleton determines the shape of the face and its vital functions. Currently, obstructive sleep syndrome has been associated with some features of facial morphology (Sutherland *et al*., 2020). Moreover, this condition is present worldwide, affecting all social levels and ages. Approximately 10 % of the population presents differing degrees of alteration in the shape of the face (Bailey *et al*., 2004). This consists of a group of signs and symptoms that determine the function and aesthetics involved in vital activities such as phonation, chewing, swallowing, and breathing, even altering the craniocervical posture, which is ultimately expressed as orofacial and temporomandibular pain, in addition to changes in psychological and social characteristics in people with these facial anomalies (Van Sickels & D'Addario, 2007; Ryan *et al*., 2012).

Among facial form anomalies (FFA), there are three-dimensional changes. From the sagittal point of view, these are characterized by anteroposterior deficiencyor excess of the maxilla and/or mandible. Vertical deficiencies, on the other hand, are presented as short and long facial syndromes. Finally, transverse deficiencies include maxillary or mandibular compressions and facial asymmetries. FFA, therefore, are characterized by involving the maxilla, mandible, or both, with concomitant alterations in the temporomandibular joint (TMJ), piriform opening, and facial soft tissues, presenting different levels of involvement and alterations of various degrees of complexity in some vital functions such as breathing, where the type II anomaly has been associated with snoring and sleep apnea, which in turn can produce some sequelae such as arterial

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hypertension, heart attacks, and other metabolic pathologies (Kim *et al*., 2020).

On the other hand, 2D imaging studies have made a fundamental contribution to the analysis and diagnosis of subjects with facial alterations. Although cephalometric radiographs are useful for skeletal analysis, they have several limitations when taking measurements, such as the overlapping of structures and the absence of Hounsfield correspondence in soft tissues, making it difficult to visualize structures like the airway (Bag, 2014). In this sense, when comparing 2D and 3D images, the latter can obtain more reliable and accurate dimensions than conventional cephalometrics in hard tissues, soft tissues, and airway measurements (Burkhard *et al*., 2014). Moreover, there is no correlation between the values obtained by the two, making 3D measurements a more accurate tool in the evaluation of these parameters (Sears *et al*., 2011); however, they must be performed uniformly regarding the positioning of the head to ensure accurate outcomes (Cevidanes *et al*., 2015; Ruellas *et al*., 2016a,b).

Obstructive sleep apnea syndrome (OSAS) is related to an anatomical condition that causes obstructed breathing. Some common characteristics and symptoms of OSAS are: 1. Snoring; 2. Daytime sleepiness; 3. Nighttime awakenings; 4. Difficulty in concentrating; and 5. Rapid mood swings. This heterogeneity of symptoms and the difficulty in diagnosing them make OSAS a difficult pathology to diagnose and, therefore, currently underdiagnosed. The diagnosis of OSAS is usually made with polysomnography. This costly and extensive study requires the patient to sleep in a laboratory to analyze the type and quality of sleep. It involves using an electroencephalogram and other elements to define the patient's condition. Although the study is thorough and reliable, the high costs and lengthy application periods necessitate exploring alternate methods for screening individuals with a likelihood of OSAS.

Artificial intelligence (AI) is a widely used tool in healthcare and is currently under development. In the case of OSAS, some technological developments aim to record the nocturnal sounds of suspected patients. In these cases, the predictive AI model detects breath sounds during sleep, which vary according to airway patency and can be associated with the presence and severity of apnea (Emoto *et al*., 2012; Cho *et al*., 2022). The study aimed to analyze the AI-based technological options applied to the diagnosis of OSAS and the parameters analyzed in these analyses through a literature review.

MATERIAL AND METHOD

Study design. A scoping review was conducted following the recommendations described in the transparency report of systematic reviews and meta-analyses (PRISMA-ScR) (Tricco *et al*., 2018) to answer the following research question: What variables are considered when diagnosing OSAS using AI?

Eligibility Criteria. We included primary studies in persons over 18, with a sample equal to or greater than 100, that evaluated craniofacial anthropometric characteristics or neck circumference in subjects diagnosed with OSAS by polysomnography. These studies contained training and validation of AI models and AI performance quantification measurements. There were no limitations on the population's ethnicity or the locations where the study was conducted. Studies on subjects with syndromes or surgical interventions, narrative or systematic reviews, letters to the editor, opinion articles, and conference abstracts were excluded.

Search strategy. A systematic literature search was conducted up to February 2024 using the Medline, Embase, Lilacs, Scopus, and Web of Science databases. Studies in English, Spanish, and Portuguese were selected; the publication date and type of study design were not limited.

The following search strategy was used: (((((((obstructive sleep apnea[MeSH Terms]) OR (apnea, obstructive sleep[MeSH Terms])) OR (obstructive sleep apnea syndrome[MeSH Terms])) OR (OSA)) OR (obstructive apnea during sleep)) OR (obstructive sleep-disordered breathing)) OR (sleep apnea, obstructive)) AND ((((((artificial intelligence[MeSH Terms]) OR (machine learning[MeSH Terms])) OR (computer-aided)) OR (deep learning)) OR (neural networks)) OR (machine intelligence[MeSH Terms]))

Study selection. The complete list of identified references was entered into the Mendeley 2.90.0 software (Reference Management, Elsevier, London, England), where duplicates were automatically removed. Titles and abstracts were independently screened for eligibility by two investigators. In case of discrepancy, consensus was achieved by discussion or consultation with a third reviewer. References that appeared to fulfill the inclusion criteria were reviewed in full text by the same reviewers.

Data extraction. Data extraction was performed by two reviewers using a predefined and standardized data form, following the recommendations of Green *et al*. (2006). A pilot test was used to ensure homogeneity of criteria among reviewers in the selection of the following data:

a) Study group data (number of patients, sex, age, race);
b) Research data (prospective or retrospective nature of the study, AI architecture, validation of the AI method);

c) Type of data analyzed (clinical methods to determine the presence of OSAS, type of tomography and analysis performed, software and anatomical references used in the studies);
d) Type of image captures (computed tomography (CT), cone beam computed tomography (CBCT), 3D stereophotogrammetry, facial scanner, and others).

RESULTS

The systematic review identified 1339 articles. After excluding 795 duplicates, 544 articles were selected for title and abstract review, yielding 17 articles for full-text review (Table I). Of the final 17 articles, 3 were excluded for not fulfilling the inclusion criteria. This results in 14 studies to be analyzed in this article (Fig. 1).

The selected articles included a total of 13,293 subjects analyzed. The age range of the included studies ranged from 18 to 90 years. 9,912 (74.56 %) subjects were male, and 3,381 (25.43 %) were female. Concerning ethnicity, three studies presented a sample originating in Taiwan, three studies were on a population in China, three studies were in Hungary, one study was in Japan, one study was in France, one study was in Turkey and Japan, and one study was on a population from the United States and Canada (Table II). Thirteen studies had a retrospective design, and one (Monna *et al*., 2022) used a prospective model.

At the diagnostic stage, eight studies noted a control group of subjects without OSAS and another group with OSAS. In contrast, the other studies presented OSAS groups in terms of their severity. Overall, the diagnostic stage of the sample of the included studies comprised 8,077 subjects with OSAS, which were used for the training and validation of the algorithm to predict the diagnosis of OSAS, and 1,219 subjects without OSAS, which were used as a control group for the final test of the algorithm in the differentiation of subjects with OSAS.

Studies had an average accuracy of 80 % in predicting OSAS using variables such as age, gender, anthropometric measurements (body mass index, neck, or waist circumference), and/or imaging measurements (computed tomography, facial scan, photographs, magnetic resonance imaging, or cervical ultrasound) (Table III).

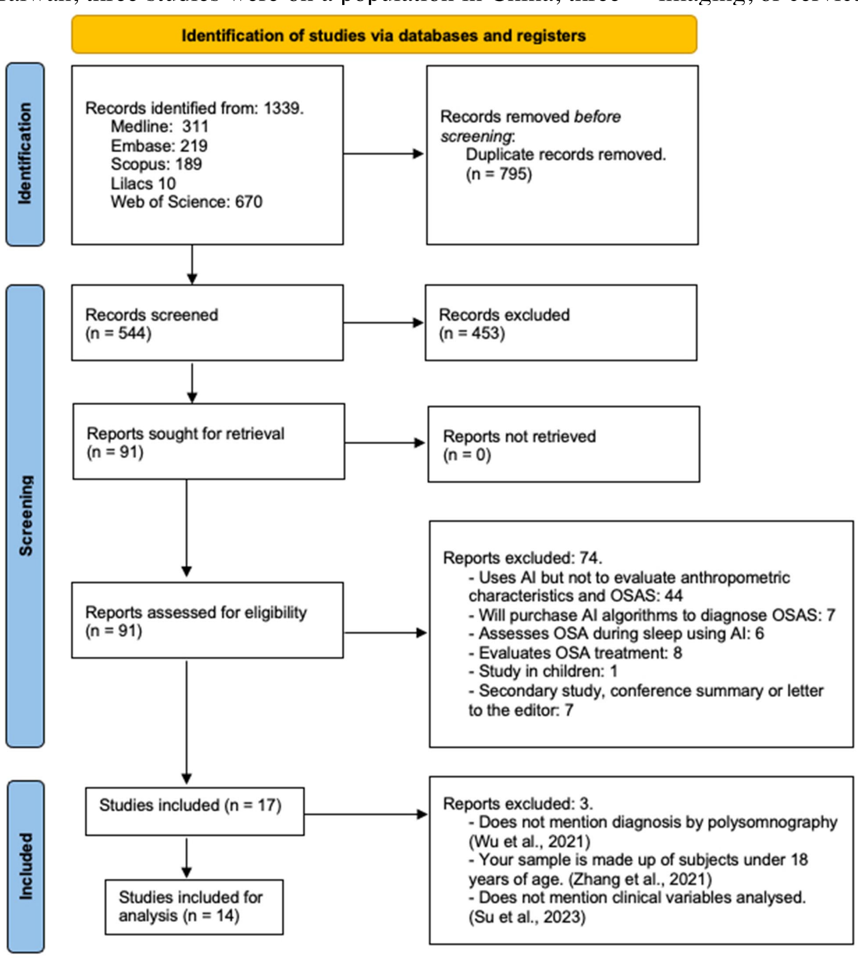

Fig. 1. Flow chart of the systematic review.

Table I. Characteristics of the 17 potential articles related to the study objective and patients included.

Author and year	Objective	N	Sex (M/F)	Age (years)	Type of analysis
Wang *et al.*, 2016	The aim was to develop and compare algorithms for diagnosing OSAS severity based on a nthropometric characteristics and questionnaire data.	3345	ND	ND	Cervical and body anthropometric measurements and questionnaire
Liu *et al.*, 2017	The aim was to apply a machine learning method to diagnose OSAS and predict its severity using anthropometric characteristics.	5245	4003 - 1242	20 to 80	Cervical and body anthropometric measurements and questionnaire
Hanif *et al.*, 2021	This study aimed to p redict the apnea-hypopnea syndrome index by deep learning of craniofacial features.	1366	724 - 642	45.9 ± 14.8	Facial scan measurements and anthropometric measurements
Ryu *et al.*, 2023	This study aimed to apply machine learning methods derived from upper airway morphology with automatic segmentation using deep learning.	173	ND	20 to 75	Upper airway analysis
Tsuiki *e t al.*, 2021	The aim was to use a machine learning model using two-dimensional images of craniofacial features to differentiate subjects with and without OSAS.	1389	1389-0	Over 20 years	Cephalometric analysis
Wu *et al.*, 2021	The aim was to propose an algorithm for diagnosing OSAS by upper airway analysis using cone beam computed tomography data.	154	ND	ND	Upper airway analysis
Zhang *e t al.*, 2023	This study aimed to use a ma chine learning model to detect moderate to severe OSAS based on body and neck anthropometric measurements.	481	325-156	14 to 77	Cervical and body anthropometric measurements and questionnaire
He *et al.*, 2022	Their objective was to develop a deep learning-based model to detect OSAS using facial photographs.	393	308 - 85	18 to 68	Cervical and body anthropometric measurements and facial photographs
Molnár *et al.*, 2022	This study aimed to analyze the thickness of adipose tissue around the upper airways with anthropometric parameters for OSAS and airway collapse.	100	74-26	42.15-± 11.7	Cervical anthropometric measurements and cervical MRI.
Molnár *e t al.*, 2022	This study evaluated anthropometric analyses and subcutaneous neck circumference measurements in subjects with OSAS.	100	74-26	42.15-± 11.7	Cervical anthropometric measurements and cervical ultrasound.
Monna *e t al.*, 2022	The study aimed to investigate the reliability of the OSAS diagnosis using 3 D geometric morphometric analysis of maxillofacial scans combined with machine learning analysis.	267	267-0	40 to 75	Geometric analysis of the neck and submandibular area with 3D facial scanning
Orhan *et al.*, 2022	The objective was to use AI software to generate and validate an automatic pharyngeal airway detection algorithm in cone beam computed tomography data from OSAS patients.	200	ND	46.4 to 54.2	Computed tomography airway analysis
Tsai *et al.*, 2022	Their objective was to develop machine learning models based on anthropometric features to detect OSAS risk.	3503	2324 - 1179	18 to 90	Cervical and body anthropometric measurements and questionnaire
He *et al.*, 2023	The study aimed to propose a d eep-learning model using craniofacial photographs to detect the risk and severity of OSAS.	530	407 - 123	18 to 68	Cervical and body anthropometric measurements, and craniofacial photographs
Molnár *et al.*, 2023	The objective was to i nvestigate the applicability of AI in preliminary screening based on anthropometric, demographic, and questionnaire parameters to d iagnose mild, moderate, and severe OSAS.	100	74 - 26	Over 18 years old	Cervical and body anthropometric measurements and questionnaire
Su *et al.*, 2023	Their goal is to propose a machine-learning model of frontal view craniofacial images to predict the severity of OSAS.	280	ND	Over 18 years old	Frontal view craniofacial images and clinical variables
Zhang *e t al.*, 2023	The objective was to develop an AI method to predict OSAS by airway, bone tissue, and so ft tissue analysis.	300	268 - 32	Over 18 years old	Upper airway, bone, and soft tissue analysis

Table II. Descriptive characteristics of the 14 studies based on clinical and imaging features used to predict obstructive sleep apnea based on artificial intelligence.

Author and year	Ethnicity	Study design	Diagnosis of the sample	2D or 3D imaging analysis	Cervical circumference analysis
Wang *et al*., 2016	Taiwan	Retrospective	1) 480 subjects without OSAS. 2) 728 mild OSAS. 3) 706 moderate OSAS. 4) 1432 severe OSAS	ND	Neck C: 1) mild OSAS 34.87 cm. 2) Moderate OSAS 37.71 cm. 3) Severe OSAS 39.86 cm.
Liu *et al*., 2017	Taiwan	Retrospective	1) 1141 mild SAOS. 2) 730 moderate OSAS. 3) 2132 severe OSAS	ND	Male: 39 cm ±3.4 / female: 33.4 cm ±3.4
Hanif *et al*., 2021	United States and Canada	Retrospective	Patients with and without OSAS (does not describe the number of subjects per group).	3D Craniofacial 3D Scanner (Structure Sensor from Occipital Inc.)	ND
Ryu *et al*., 2023	Korea	Retrospective	1) 46 have normal levels and mild OSAS. 2) 127 present moderate OSAS	Computed tomography of the upper airway	ND
Tsuiki *et al*., 2021	Japan	Retrospective	1) 522 without OSAS. 2) 867 with severe OSAS.	Lateral cephalometry	ND
He *et al*., 2022	China	Retrospective	Subjects with mild OSAS and those with moderate OSAS	Facial photographs using frontal and profile shots	39.3 cm 4.2
Molnár *et al*., 2022	Hungary	Retrospective	1) 36 control group. 2) 32 subjects with mild OSAS. 3) 32 subjects with moderate to severe OSAS.	Parapharyngeal adipose tissue: 1) 509.66 cm^2 ± 121.96 control group. 2) 555.34 cm^2 ± 141.88 mild SAOS. 3) 616.21 cm^2 ± 110.07 moderate-severe OSAS	Neck C: 1) Without OSAS 37.95 cm ±4.12. 2) Mild OSAS 40.69 cm ± 3.42. 3) Moderate- severe OSAS 42.73 cm ± 3.33.
Molnár *et al*., 2022	Hungary	Retrospective	1) 36 control group. 2) 32 subjects with mild OSAS. 3) 32 subjects with moderate to severe OSAS.	Subcutaneous adipose tissue: 1) 0.33 cm ± 0.11 in group without OSAS. 2) 0.38 cm ± 0.37 cm mild OSAS. 3) 0.40 cm ± 0.11.	Neck C: 1) Without OSAS 37.95 cm ±4.12. 2) Mild OSAS 40.69 cm ± 3.42. 3) Moderate-severe OSAS 42.73 cm ± 3.33
Monna *et al*., 2022	France	Prospective	267 subjects with OSAS	A 3D facial scanner was used to analyze the lobe of each ear, the subnasal, and the tip of the chin, noting that this group has specific characteristics.	Neck C 40.3 cm
Orhan *et al*., 2022	Turkey	Retrospective	100 subjects without OSAS and 100 subjects with OSAS	CBCT was used to analyze the upper airway.	ND
Tsai *et al*., 2022	Taiwan	Retrospective	1) 951 subjects with normal to mild OSAS. 2) 969 subjects with moderate OSAS. 3) 1583 subjects with severe OSAS.	ND	Neck C: 1) normal to mild subject 33.96 cm ± 3.12. 2) moderate OSAS 37.36 cm ± 3.34. 3) severe OSAS 39.85 cm ± 3.48.
He *et al*., 2023	China	Retrospective	Subjects with mild, moderate, and severe OSAS.	Facial photographs using frontal and profile shots	Neck C: 1) subject OSAS mild 39.79 cm ± 4.23. 2) moderate OSAS 39.86 cm ± 4.18. 3) severe OSAS 39.81 cm ± 4.37.
Molnár *et al*., 2023	Hungary	Retrospective	1) 36 control group. 2) 32 subjects with mild OSAS. 3) 32 subjects with moderate to severe OSAS.	ND	Neck C: 1) No OSAS 37.95 cm ± 4.12. 2) Mild OSAS 40.69 cm ± 3.42. 3) Moderate-severe OSAS 42.73 cm ± 3.33.
Zhang *et al*., 2023	China	Retrospective	1) 81 subjects as a control group without OSAS. 2) 219 subjects with OSAS.	Uses computed tomography	ND

Table III. Characteristics of the studies according to the algorithm model for applying AI.

Author and year	Software or language for machine learning or deep learning	Machine learning or deep learning model	Sample number for training	Sample number for validation
Wang *et al*., 2016	ND	A C4.5 fuzzy decision model was used and complemented with a SMOTE oversampling approach.	ND	ND
Liu *et al*., 2017	Matlab R2014b	The support vector machine (SVM) model was used.	ND	ND
Hanif *et al*., 2021	Python 3.7.4 and pytorch 1.3.1	Multi-view learning of convolutional neural network ResNet 18	ND	ND
Ryu *et al*., 2023	MathWork, softMax.	Convolutional neural networks were used using a 3D UNet model and a support vector machine (SVM) model.	73	15
Tsuiki *et al*., 2021	Keras, TensorFlow, written in Python	Deep convolutional neural network model VVG-19	1) 470 subjects for the training of absence of OSAS. 2) 781 subjects for training of OSAS.	1) 52 subjects were used to validate the absence of OSAS. 2) 86 subjects for OSAS validation.
He *et al*., 2022	Pytorch	Convolutional neural network, EfficientNet B4 model.	275 randomized subjects participated in the training	58 randomized subjects participated in the validation
Molnár *et al*., 2022	DeepNet R software	Multivariate Adaptative Regression Splines	ND	ND
Molnár *et al*., 2022	DeepNet R software	Multivariate Adaptative Regression Splines	ND	ND
Monna *et al*., 2022	R V3.3 software	Neural network with support vector analysis with different kernels and an animated cross-validation method to evaluate performance.	The software divided the sample into 4 parts, one for training and the other for validation (the amount of sample for each procedure is not described).	
Orhan *et al*., 2022	Python U-net	A 3D U-net automatic segmentation model was used centered on the region of interest.	90 % of the data, equivalent to 180 subjects, was used for training.	10 % of the data, equivalent to 20 subjects, was used for validation.
Tsai *et al*., 2022	Python version 3.9.7	Logistic regression models, k-nearest neighbors, naïve Bayes, random forest, support vector machine, and extreme gradient boosting were used.	80 % of the sample, equivalent to 2,802 subjects, was used for training.	20 % of the sample, equivalent to 701 subjects, was used for validation and testing.
He et *al*., 2023	Python 3.7.4 and pytorch 1.12.1	A ResNet-101 deep neural network was used.	A total of 371 training samples were used.	53 subjects were used for validation and 106 subjects for testing.
Molnár *et al*., 2023	R software	Flexible discrimination analysis	ND	ND
Zhang *et al*., 2023	Pytorch	They used the ResNet-18 convolutional neural network, and each model was optimized with AdamW	175 subjects were used for training.	44 subjects were used for validation and 81 subjects for testing.

DISCUSSION

Eguía & Cascante (2007) defined apnea as an absence or reduction of more than 90 % in the amplitude of the respiratory flow signal lasting more than 10 seconds. Apnea is obstructive if accompanied by respiratory effort measured by thoracoabdominal bands, central when there is no respiratory effort, and mixed when it begins as central and ends with effort. Conversely, hypopnea is a reduction in the respiratory flow signal between 30 % and 90 % lasting more than 10 seconds and accompanied by desaturation equal to or greater than 3 %, an EEG-detected microarousal, or both. From this point of view, there is a set of signs and symptoms that can be detected prior to a specific examination, and alert to the presence of one of these clinical pictures.

Senaratna *et al*. (2017), describe OSAS as a condition that occurs in 4-6 % of men and 2-4 % of women in the US and Europe; moreover, this condition increases with age and obesity, where subjects over 70 years old present 30 % higher apnea-hypopnea rates. These results are consistent with those found in this review, where a larger group of male participants in the studies and individuals in different age groups were observed, including a large group of people over 60 years of age, which suggests a greater presence of the condition in men and, despite the heterogeneity of age, significant involvement in older people.

Polysomnography is the gold standard for identifying OSAS. This test is performed in specialized clinics, takes about 5 to 6 hours, and requires equipment, infrastructure, and specialized personnel for its performance; therefore, other alternatives with better cost-effectiveness should be obtained. All the included studies diagnosed OSAS by polysomnography, but only the studies by Wang *et al*. (2016), Hanif *et al*. (2021), Tsuiki *et al*. (2021), Molnár *et al*. (2022), Orhan *et al*. (2022), Molnár *et al*. (2023) and Zhang *et al*. (2023) were able to perform a comparison of imaging or anthropometric analyses on subjects with and without OSAS. No study combined airway analysis, computed tomography, facial scan, and anthropometric measurements to increase diagnostic accuracy using AI.

The physiopathology of OSAS indicates that there are factors associated with its diagnosis. One of the keys is the upper airway (mainly in the oropharynx), which, when its volume decreases, produces a collapse and/or blockage leading to apnea. Airway caliber is produced by the structural stability of muscles activated during the respiratory process. Given the circumstances, the local component holds significant importance in this procedure. Comparing different groups of subjects, Opdebeeck *et al*. (1978), established some differences between individuals with short and long facial syndrome. The main morphological difference was associated with mandibular rotation, where patients with long facial syndrome presented mandibular rotation inferiorly and posteriorly (clockwise) and patients with short facial syndrome in an anterior and superior direction (counterclockwise). Changes in condylar position were also observed, possibly associated with mandibular rotation. Different positions of the hyoid bone accompanied this rotation and, consequently, different positions of the tongue; the oropharynx also presented positions related to the hyoid bone and the mandible, with a significant decrease in patients with long face syndrome. These signs seem relevant when analyzing individuals with suspected OSAS, since facial morphology would be associated with variations in several structures that would determine the airway volume. This could be an important starting point for a screening that includes AI in diagnosing these conditions (Opdebeeck *et al*., 1987).

Regarding the acquisition of radiographic images, Rückschloß *et al*. (2019), point out that while most studies use a natural head position as a reference for radiography examinations, it is crucial to ascertain if this position affects airway volume during image acquisition. This is mainly associated with changes in the craniocervical position and angle, which modify the volume of the airway and the position of the hyoid bone. This is an important variable to be considered when analyzing the data, especially those that seem controversial.

In this regard, de Oliveira Pinto *et al*. (2020), noted that in 3D tomographic examinations, the image acquisition time can vary between 20 and 38 seconds, which may be considered too long a processing time to ask the individual not to breathe and maintain the airway soft tissue position. From this point of view, the airway volume in the 3D image may be influenced by muscle, postural, and morphological movements specific to the breathing cycle; this should be considered in the results for this analysis.

When relating cephalometric analyses to airway volume, our studies (Ravelo *et al*., 2020, 2021) indicated that subjects with an Angle class II occlusal alteration have lower airway volume than subjects with an Angle class III deformity. The results of the 3D airway analysis also showed that these differences were statistically significant, which agrees with the results found by Cheng *et al*. (2019), who noted that Class III subjects have greater airway volume than Class I and II subjects both preoperatively and postoperatively in orthognathic surgery. The above confirms the need to include the facial skeletal pattern and objectively assess its severity correlation with OSAS.

Unberath *et al*., (2021) and Nguyen *et al*. (2022), pointed out that both 2D and 3D images provide relevant information associated with bone structures and include airway and soft tissue analyses, which afford an objective and automated assessment. In this review, only two studies (Tsuiki *et al*., 2021; Zhang *et al*., 2023) performed a skeletal analysis based on bone positions to determine the severity of OSAS, while Zhang *et al*. (2023), was the only study to assess the airway, bone tissue, and soft tissue in subjects with and without OSAS, observing that with these three variables, there is an 88.2 % prediction and accuracy for the diagnosis of OSAS. Therefore, we can assume that by incorporating anthropometric measurements, better predictive results could be obtained with AI.

In this study, 10 of the 14 articles analyzed performed imaging analysis, of which three used craniofacial computed tomography. Ryu *et al*. (2023) and Orhan *et al*. (2022), performed upper airway measurements, while Zhang *et al*. (2023), took soft tissue, bone tissue, and airway measurements. Two studies performed facial scanning, Henif *et al*. (2021) and Monna *et al*. (2022), and one study performed 2D cephalometry (Tsuiki *et al*., 2021).

On the other hand, Molnár *et al*. (2022) took measurements of subcutaneous adipose tissue and parapharyngeal adipose tissue. Concerning anthropometric analyses, nine studies performed neck circumference measurements, observing that subjects with OSAS had a larger neck circumference than control group subjects with no OSAS. In addition, the neck circumference of subjects with OSAS increased in length in relation to its severity, with subjects with moderate and severe OSAS having the largest neck circumference. Only five studies performed imaging and anthropometric analyses together (He *et al*., 2022; Molnár *et al*., 2022; Monna *et al*., 2022; He *et al*., 2023). This agrees with Cillo Jr. *et al*. (2012), who mention that craniofacial alterations are not always related to the decrease in airway volume since, in addition to facial variables, there are other determining factors such as body mass index (BMI) and height of the subjects, which influence airway volume. Therefore, in addition to considering the individual's skeletal-facial pattern, possible screening should consider the height and BMI of the individuals to be analyzed (Supmaneenukul *et al*., 2024).

In terms of studies that relied on facial scanning (Hanif *et al*., 2021; Monna *et al*., 2022) or facial photographs, He *et al*. (2022) and He *et al*. (2023), point out that in the sagittal analysis of the lower third with the presence of retrognathism, decreased height, and neck thickness are variables that are most frequently repeated in subjects with OSAS. However, they do not mention reference points for replicating these measurements, and variables such as dermal, adipose, and muscle tissue thickness can affect an individual's facial features, as well as compensate for sagittal skeletal abnormalities such as facial asymmetries (Supmaneenukul *et al*., 2024). Therefore, a skeletal analysis must be included as a complement to a soft tissue analysis.

From the studies analyzed, we noted that the variables with the highest frequency in subjects with OSAS are males aged 50 years or older, profiles with mandibular retrognathism, neck circumferences over 37.71 mm, and decreased airway volumes. Ishiguro *et al*. (2009), examined the impact of factors such as obesity and craniofacial morphology on the severity of OSAS, finding that obesity, along with increased neck circumference and certain skeletal conditions like mandibular retrognathism and a short mandibular body, contribute to airway collapse and the severity of OSAS.

According to the studies by Shen *et al*. (2020) and Le *et al*. (2023), models based on snoring recognition are very accurate in predicting OSAS, as well as being able to classify and identify between the absence of OSAS and the presence of apnea but have difficulty in accurately determining the presence of hypopnea, representing a proven option in the initial classification of this condition, as well as in the determination of its absence. On the other hand, Thomas *et al*. (2007) and Zhao *et al*. (2021), show that respiratory control dysfunction affects heart rate and blood pressure, so assessing electromyography signals can help evaluate sleep status. Following the recommendations of Bahr-Hamm *et al*. (2023), the use of predictive algorithms, along with the inclusion of variables such as snoring, low frequencies of electromyography or thoracoabdominal effort signals, variations in blood pressure, and heart rate, has the potential to generate more precise diagnoses through the implementation of AI. Furthermore, using validated questionnaires for OSA can enhance accuracy by up to 90 % (Table IV).

Regarding the algorithm models used, seven studies used Python as the software to analyze the data (Hanif *et al*., 2021; Tsuiki *et al*., 2021; He *et al*., 2022; Orhan *et al*., 2022; Tsai *et al*., 2022; He *et al*., 2023; Zhang *et al*., 2023); four studies used the R software (Molnár *et al*., 2022; Monna *et al*., 2022; Molnár *et al*., 2023); while the study by Liu *et al*. (2017) used Matlab R2014b; and Ryu *et al*. (2023), used MathWork, softMax. When looking at the model used, each study performed individualized algorithms incorporating multiple sequences and adding codes in relation to their sample; hence, we found a method repeated across articles. However, we noted that the support vector machine-based model and the convolutional neural network ResNet were the most prevalent among its algorithms. Of the 14 studies, nine described the sample number for training and the sample number for algorithm validation, but only three studies (Tsai *et al*., 2022; He *et al*., 2023; Zhang *et al*., 2023) performed training, validation, and incorporation of a third final test method. On average, they used 70 % to 80 % of the sample for training and 30 % to 20 % for validation and final testing of the prediction algorithm.

CONCLUSION

Polysomnography is currently the test indicated for diagnosing OSAS; however, it is expensive and requires infrastructure and trained personnel for its interpretation, making its application difficult. Nevertheless, there are no tests prior to the diagnosis by polysomnography to guide the user in the likely presence of OSAS. In this sense, some characteristics increase the likelihood of acquiring OSAS, such as facial shape, obesity, age, and other medical

Table IV. Characteristics of the measurement method and the results of the items included.

Author and year	Measurement method	Main results
Wang *et al*., 2016	Cranial and body anthropometric measurements were used and compared with algorithms to determine which was more accurate in diagnosing OSAS.	Based on the algorithms used, they observed that age is a risk factor for OSAS diagnosis, while weight gain and waist circumference correlate with neck circumference, and all three variables increased in relation to the severity of OSAS.
Liu *et al*., 2017	Cervical and body anthropometric measurements were used to assess the severity of OSAS in relation to male and female gender.	Based on the support vector machine test, it was observed that waist circumference, body mass index, and neck circumference correlated with the severity of OSAS. Being over age 50 also correlated with the severity of OSAS.
Hanif *et al*., 2021	A portable facial scanner was used to analyze the faces and necks of subjects with and without OSAS to train the convolutional neural network.	The scanned craniofacial variables provide information for the diagnosis of OSAS, but anthropometric measurements and OSAS diagnostic questionnaires must be incorporated to increase their specificity and validation.
Ryu *et al*., 2023	Using computed tomography analysis of the upper airway, the anteroposterior width of the nasopharyngeal, the lateral width at the minimal area, the anteroposterior width at the minimal area, and the length from the nasopharyngeal to the minimal area were evaluated. Changes in flow characteristics according to airway changes were also analyzed.	A 3D airway analysis and flow dynamics showed that in subjects with OSAS, the minimum anteroposterior and the minimum lateral areas were affected. Thus, upper airway obstruction is influenced by the shape and hydrodynamic properties of the air passing through it.
Tsuiki *et al*., 2021	Automatic learning was performed using lateral cephalometry in subjects with and without OSAS.	The trained machine learning algorithm could identify subjects with severe OSAS by analyzing a 2D image of lateral cephalometry, where it is not necessary to explore the entire image, since there was a higher accuracy of the analysis only when analyzing the region of interest.
He *et al*., 2022	To conduct the training on diagnosing mild and moderate OSAS, frontal and profile facial photographs were analyzed using the RetinaFace software.	When training, the diagnostic threshold for OSAS was higher in mild OSAS with a sensitivity of 0.9 and specificity of 0.8 compared to moderate OSAS. 90° and 45° profile photographs provide more information to predict OSAS.
Molnár *et al*., 2022	The neck circumference of subjects with and without OSA was measured with a tape measure. Magnetic resonance imaging was used to evaluate the parapharyngeal adipose tissue, and its area was calculated using the region of interest tool.	Significant differences were observed in relation to age, weight, neck circumference, and parapharyngeal adipose tissue. As the severity of OSAS increases, the value of the variables with the greatest upper airway compression increases.
Molnár *et al*., 2022	Neck circumference was measured with a tape measure, and subcutaneous adipose tissue was assessed by ultrasound in subjects without OSAS and with mild and moderate to severe OSAS.	Significant differences were noted in relation to age, weight, neck circumference, and subcutaneous adipose tissue. As the severity of OSAS increases, the value of the variables increases.
Monna *et al*., 2022	A 3D facial scan was performed using points from the middle and lower third of the face in subjects diagnosed with OSAS to train and validate facial recognition using artificial intelligence.	The algorithm was able to differentiate subjects with OSAS, who have a shorter and thicker neck and greater retrognathism, from subjects without OSAS.
Orhan *et al*., 2022	Using cone beam computed tomography, the morphology of the upper airway in subjects with and without OSAS was compared, classifying based on severity.	The artificial intelligence-based algorithm can identify airway area and volume patterns in subjects with and without OSAS. In contrast, subjects with OSAS have less airway area and volume than subjects without OSAS.
Tsai *et al*., 2022	Cervical and body anthropometric measurements were used in different OSAS groups to develop an algorithm to detect mild, moderate, and severe OSAS.	It was observed that the group with severe OSAS presented higher mean BMI and neck circumference values, where the machine learning performance showed an accuracy of over 80 % in their models.
He *et al*., 2023	An analysis of frontal and profile facial photographs and anthropometric analysis to diagnose mild, moderate, and severe OSAS using artificial intelligence.	When analyzed from the front, the model used the middle and lower areas, whereas in profile, it focuses on analyzing the mandible, ear, and neck to determine the presence and severity of OSAS. In addition, the performance of this algorithm improved when OSAS-related anthropometric measurements were incorporated.
Molnár *et al*., 2023	Diagnostic tests were performed using anthropometric patterns on people with and without OSAS to assess the prediction of OSAS and its severity.	Using parameters of age, gender, BMI, neck circumference, and questionnaires, a prediction of OSAS can be made, but not its severity, so it is necessary to incorporate more information on the characteristics of subjects with OSAS to determine whether it is moderate or severe.
Zhang *et al*., 2023	Soft tissue, bone, and airway variables were assessed using computed tomography to predict moderate and severe OSAS. The three variables were trained and validated to ascertain whether they were necessary to make the diagnosis.	The information provided by a CT scan allows for prediction and accuracy of 88.2 % in diagnosing OSAS. Here, soft tissue was the most accurate for diagnosis of OSAS, followed by skeletal analysis, and finally, the airway.

conditions. The application of artificial intelligence (AI) in diagnosing and guiding treatment for OSAS has advanced significantly, and it can be used for the early detection of OSAS. However, there are still many limitations to using AI both as a diagnostic model and as a pre-diagnostic screening model.

RAVELO, V.; FUENTES, J.; PARRA, M.; MUÑOZ, G.; OLATE, S. Diagnóstico basado en inteligencia artificial para el síndrome obstructivo de apnea del sueño: Una revisión de alcance. *Int. J. Morphol., 42(4)*:1150-1160, 2024.

RESUMEN: Para diagnosticar el Síndrome Apnea Obstructiva del Sueño (SAOS) se utiliza la polisomnografía, el cual es un costoso y extenso estudio que exige que el paciente duerma en un laboratorio. El SAOS ha sido asociado con características de la morfología facial y mediante un modelo predictivo de la Inteligencia Artificial (IA), se podría realizar un diagnóstico preliminar. El objetivo de este estudio fue analizar por medio de una revisión de alcance, las opciones tecnológicas basadas en IA aplicadas al diagnóstico del SAOS, y los parámetros evaluados en dichos análisis en las estructuras craneofaciales. Se realizó una búsqueda sistemática de la literatura hasta febrero del 2024 y mediante criterios de inclusión y exclusión se determino los estudios a analizar. Los títulos y resúmenes fueron seleccionados de forma independiente por dos investigadores. Se seleccionaron 14 estudios, incluyeron un total de 13.293 sujetos analizados. El rango edad de la muestra oscilo entre 18 y 90 años. 9.912 (74.56 %) sujetos eran de sexo masculino y 3.381 (25,43 %) eran de sexo femenino. Los estudios incluidos presentaron diagnóstico de SAOS mediante polisomnografía, siete estudios presentaron un grupo control de sujetos con ausencia de SAOS y otro grupo con presencia de SAOS. Mientras que los demás estudios, presentaron grupos de SAOS en relación con su severidad. Todos los estudios tuvieron una precisión media del 80 % en la predicción de SAOS utilizando variables como la edad, el género, mediciones y/o mediciones imagenológicas. no existen exámenes previos al diagnóstico por polisomnografía que permitan orientar al usuario en la probable presencia de SAOS. En este sentido, existen factores de riesgo para desarrollar SAOS vinculados a la forma facial, la obesidad, la edad y otras condiciones, que sumados a los avances con IA para diagnóstico y orientación en SAOS podrían ser utilizados para la detección precoz del mismo.

PALABRAS CLAVE: Inteligencia artificial; Síndrome de apnea obstructiva del sueño; Morfología facial.

REFERENCES

Bag, A. K.; Gaddikeri, S.; Singhal, A.; Hardin, S.; Tran, B. D.; Medina, J. A. & Curé, J. K. Imaging of the temporomandibular joint: An update. *World J. Radiol., 6(8)*:567-82, 2014.

Bahr-Hamm, K.; Abriani, A.; Anwar, A. R.; Ding, H.; Muthuraman, M. & Gouveris, H. Using entropy of snoring, respiratory effort and electrocardiography signals duringsleep for OSA detection and severity classification. *Sleep Med., 111*:21-7, 2023.

Bailey, L. T. J.; Cevidanes, L. H. S. & Proffit, W. R. Stability and predictability of orthognathic surgery. *Am. J. Orthod. Dentofacial Orthop., 126(3)*:273-7, 2004.

Burkhard, J. P. M.; Dietrich, A. D.; Jacobsen, C.; Roos, M.; Lübbers, H. T. & Obwegeser, J. A. Cephalometric and three-dimensional assessment of the posterior airway space and imaging software reliability analysis before and after orthognathic surgery. *J. Craniomaxillofac. Surg., 42(7)*:1428-36, 2014.

Cevidanes, L. H. S.; Ruellas, A. C. O.; Jomier, J.; Nguyen, T.; Pieper, S.; Budin, F.; Styner, M. & Paniagua, B. Incorporating 3-dimensional models in online articles. *Am. J. Orthod. Dentofacial Orthop., 147(5)*:195-204, 2015.

Cheng, J. H.; Chen, C. M.; Chen, P. H.; Chou, S. T.; Pan, C. Y. & Tseng, Y. C. Comparison of pharyngeal airway between mandibular setback surgery patients (skeletal class III) and non-surgery patients (skeletal classes I and II). *Biomed. Res. Int., 2019*:5012037, 2019.

Cho, S. W.; Jung, S. J.; Shin, J. H.; Won, T. B.; Rhee, C. S. & Kim, J. W. Evaluating prediction models of sleep apnea from smartphone-recorded sleep breathing sounds. *JAMA Otolaryngol. Head Neck Surg., 148(6)*:515-21, 2022.

Cillo Jr., J. E.; Thayer, S.; Dasheiff, R. M. & Finn, R. Relations between obstructive sleep apnea syndrome and specific cephalometric measurements, body mass index, and apnea-hypopnea index. *J. Oral Maxillofac. Surg., 70(4)*:e278-283, 2012.

de Oliveira Pinto, M. G.; Sousa Melo, S. L.; Cavalcanti, Y. W.; de Lima, E. D.; Bento, P. M. & de Melo, D. P. Influence of tooth position within the field of view on the intensity of cone-beam computed tomographic imaging artifacts when assessing teeth restored with various intracanal materials. *Imaging Sci. Dent., 50(2)*:141-51, 2020.

Eguía, V. M. & Cascante, J. A. Síndrome de apnea-hipopnea del sueño: Concepto, diagnóstico y tratamiento médico. *An. Sist. Sanit. Navar., 30(1)*:53-74, 2007.

Emoto, T.; Abeyratne, U. R.; Chen, Y.; Kawata, I.; Akutagawa, M. & Kinouchi, Y. Artificial neural networks for breathing and snoring episode detection in sleep sounds. *Physiol. Meas., 33(10)*:1675-89, 2012.

Green, B. N.; Johnson, C. D. & Adams, A. Writing narrative literature reviews for peer-reviewed journals: secrets of the trade. *J. Chiropr. Med., 5(3)*:101-17, 2006.

Hanif, U.; Leary, E.; Schneider, L.; Paulsen, R.; Morse, A. M.; Blackman, A.; Schweitzer, P.; Kushida, C. A.; Liu, S.; Jennum, P.; et al. Estimation of apnea-hypopnea index using deep learning on 3-d craniofacial scans. *IEEE J. Biomed. Health Inform., 25(11)*:4185-94, 2021.

He, S.; Li, Y.; Zhang, C.; Li, Z.; Ren, Y.; Li, T. & Wang, J. Deep learning technique to detect craniofacial anatomical abnormalities concentrated on middle and anterior of face in patients with sleep apnea. *Sleep Med., 112*:12-20, 2023.

He, S.; Su, H.; Li, Y.; Xu, W.; Wang, X. & Han, D. Detecting obstructive sleep apnea by craniofacial image-based deep learning. *Sleep Breath., 26(4)*:1885-95, 2022.

Ishiguro, K.; Kobayashi, T.; Kitamura, N. & Saito, C. Relationship between severity of sleep-disordered breathing and craniofacial morphology in Japanese male patients. *Oral Surg. Oral Med. Oral Pathol. Oral Radiol. Endod., 107(3)*:343-9, 2009.

Kim, S. J.; Ahn, H. W.; Hwang, K. J. & Kim, S. W. Respiratory and sleep characteristics based on frequency distribution of craniofacial skeletal patterns in Korean adult patients with obstructive sleep apnea. *PLoS One, 15(7)*:e0236284, 2020.

Le, V. L.; Kim, D.; Cho, E.; Jang, H.; Reyes, R. D.; Kim, H.; Lee, D.; Yoon, I. Y.; Hong, J. & Kim, J. W. Real-Time detection of sleep apnea based on breathing sounds and prediction reinforcement using home noises: Algorithm development and validation. *J. Med. Internet Res., 25*:e44818, 2023.

Liu, W. T.; Wu, H. T.; Juang, J. N.; Wisniewski, A.; Lee, H. C.; Wu, D. et al. Prediction of the severity of obstructive sleep apnea by anthropometric features via support vector machine. *PLoS One. 12(5)*:e0176991, 2017.

Molnár, V.; Kunos, L.; Tamás, L. & Lakner, Z. Evaluation of the applicability of artificial intelligence for the prediction of obstructive sleep apnoea. *Appl. Sci., 13(7)*:4231, 2023.

Molnár, V.; Lakner, Z.; Molnár, A.; Tárnoki, D. L.; Tárnoki, Á. D.; Kunos, L.; Jokkel, Z. & Tamás, L. The predictive role of the upper-airway adipose tissue in the pathogenesis of obstructive sleep apnoea. *Life (Basel), 12(10)*:1543, 2022.

Monna, F.; Ben Messaoud, R.; Navarro, N.; Baillieul. S.; Sanchez, L.; Loiodice, C.; Tamisier, R.; Joyeux-Faure, M. & Pépin, J. L. Machine learning and geometric morphometrics to predict obstructive sleep apnea from 3D craniofacial scans. *Sleep Med., 95*:76-83, 2022.

Nguyen, C.; Nicolai, E. S. J.; He, J. J.; Roshchupkin, G. V. & Corten, E. M. L. 3D surface imaging technology for objective automated assessment of facial interventions: A systematic review. *J. Plast. Reconstr. Aesthet. Surg., 75(11)*:4264-72, 2022.

Opdebeeck, H.; Bell, W. H.; Eisenfeld, J. & Mishelevich, D. Comparative study between the SFS and LFS rotation as a possible morphogenic mechanism. *Am. J. Orthod., 74(5)*:509-21, 1978.

Orhan, K.; Shamshiev, M.; Ezhov, M.; Plaksin, A.; Kurbanova, A.; Ünsal, G.; Gusarev, M.; Golitsyna, M.; Aksoy, S.; Mısırlı, M.; et al. AI-based automatic segmentation of craniomaxillofacial anatomy from CBCT scans for automatic detection of pharyngeal airway evaluations in OSA patients. *Sci Rep., 12(1)*:11863, 2022.

Ravelo, V.; Olate, G.; Moya, M. P.; Brito, L.; Garay, I. & Olate, S. 3-D airway analysis related to facial morphology. *Int. J. Morphol., 38(2)*:423-6, 2020.

Ravelo, V.; Olate, G.; Muñoz, G.; de Moraes, M. & Olate, S. The airway volume related to the maxillo-mandibular position using 3d analysis. *Biomed. Res. Int., 2021*:6670191, 2021.

Rückschloß, T.; Ristow, O.; Berger, M.; Engel, M.; Freudlsperger, C.; Hoffmann, J. et al. Relations between mandible-only advancement surgery, the extent of the posterior airway space, and the position of the hyoid bone in Class II patients: a three-dimensional analysis. *Br. J. Oral Maxillofac. Surg., 57(10)*:1032-8, 2019.

Ruellas, A. C. D. O.; Huanca Ghislanzoni, L. T.; Gomes, M. R.; Danesi, C.; Lione, R.; Nguyen, T.; McNamara Jr., J. A.; Cozza, P.; Franchi, L. & Cevidanes, L. H. Comparison and reproducibility of 2 regions of reference for maxillary regional registration with cone-beam computed tomography. *Am. J. Orthod. Dentofacial Orthop., 149(4)*:533-42, 2016a.

Ruellas, A. C. D. O.; Yatabe, M. S.; Souki, B. Q.; Benavides, E.; Nguyen, T.; Luiz, R. R.; Franchi, L. & Cevidanes, L. H. 3D mandibular superimposition: Comparison of regions of reference for voxel-based registration. *PLoS One, 11(6)*:e0157625, 2016b.

Ryan, F. S.; Barnard, M. & Cunningham, S. J. Impact of dentofacial deformity and motivation for treatment: a qualitative study. *Am. J. Orthod. Dentofacial Orthop., 141(6)*:734-42, 2012.

Ryu, J.; Kim, Y. H.; Kim, T. W. & Jung, S. K. Evaluation of artificial intelligence model for crowding categorization and extraction diagnosis using intraoral photographs. *Sci. Rep., 13(1)*:5177, 2023.

Sears, C. R.; Miller, A. J.; Chang, M. K.; Huang, J. C. & Lee, J. S. Comparison of pharyngeal airway changes on plain radiography and cone-beam computed tomography after orthognathic surgery. *J. Oral Maxillofac. Surg., 69(11)*:e385-394, 2011.

Senaratna, C. V.; Perret, J. L.; Lodge, C. J.; Lowe, A. J.; Campbell, B. E.; Matheson, M. C.; Hamilton, G. S. & Dharmage, S. C. Prevalence of obstructive sleep apnea in the general population: A systematic review. *Sleep Med. Rev., 34*:70-81, 2017.

Shen, F.; Cheng, S.; Li, Z.; Yue, K.; Li, W. & Dai, L. Detection of snore from OSAHS Patients based on deep learning. *J. Healthc. Eng., 2020*:8864863, 2020.

Supmaneenukul, Y.; Khemla, C. & Parakonthun, K. Soft tissue compensation evaluation in patients with facial asymmetry using cone-beam computed tomography combined with 3D facial photographs. *Heliyon, 10(6)*:e27720, 2024.

Sutherland, K.; Weichard, A. J.; Davey, M. J.; Horne, R. S.; Cistulli, P. A. & Nixon, G. M. Craniofacial photography and association with sleep-disordered breathing severity in children. *Sleep Breath., 24(3)*:1173-9, 2020.

Thomas, R. J.; Mietus, J. E.; Peng, C. K.; Gilmartin, G.; Daly, R. W.; Goldberger, A. L. & Gottlieb, D. J. Differentiating obstructive from central and complex sleep apnea using an automated electrocardiogram-based method. *Sleep, 30(12)*:1756-69, 2007.

Tricco, A. C.; Lillie, E.; Zarin, W.; O'Brien, K. K.; Colquhoun, H.; Levac, D.; Moher, D.; Peters, M. D. J.; Horsley, T.; Weeks, L.; et al. PRISMA extension for scoping reviews (PRISMA-ScR): Checklist and explanation. *Ann. Intern. Med., 169(7)*:467-73, 2018.

Tsai, C. Y.; Huang, H. T.; Cheng, H. C.; Wang, J.; Duh, P. J.; Hsu, W. H.; Stettler, M.; Kuan, Y. C.; Lin, Y. T.; Hsu, C. R.; et al. Screening for obstructive sleep apnea risk by using machine learning approaches and anthropometric features. *Sensors (Basel), 22(22)*:8630, 2022.

Tsuiki, S.; Nagaoka, T.; Fukuda, T.; Sakamoto, Y.; Almeida, F. R.; Nakayama, H.; Inoue, Y. & Enno, H. Machine learning for image-based detection of patients with obstructive sleep apnea: an exploratory study. *Sleep Breath., 25(4)*:2297-305, 2021.

Unberath, M.; Gao, C.; Hu, Y.; Judish, M.; Taylor, R. H.; Armand, M. & Grupp, R. The impact of machine learning on 2d/3d registration for image-guided interventions: asystematic review and perspective. *Front. Robot. AI, 8*:716007, 2021.

Van Sickels, J. E. & D'Addario, M. Esthetic options with two jaw surgery. Oral Maxillofac. *Surg. Clin. North Am., 19(3)*:423-33, 2007.

Wang, K. J.; Chen, K. H.; Huang, S. H. & Teng, N. C. A prognosis tool based on fuzzy anthropometric and questionnaire data for obstructive sleep apnea severity. *J. Med. Syst., 40(4)*:110, 2016.

Zhang, M.; Lyu, L.; Li, J.; Yan, H.; Zhu, Y.; Yu, T.; Wang, Y.; Zhao, Y.; Zhou, Y. & Liu, D. Subjective evaluation of facial asymmetry with three-dimensional simulated images among the orthodontists and laypersons: a cross-sectional study. *BMC Oral Health, 23(1)*:500, 2023.

Zhao, X.; Wang, X.; Yang, T.; Ji, S.; Wang, H.; Wang, J.; Wang, Y. & Wu, Q. Classification of sleep apnea based on EEG sub-band signal characteristics. *Sci Rep., 11(1)*:5824, 2021.

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