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Review

Performance of Artificial Intelligence (AI) Models Designed for Application in Pediatric Dentistry—A Systematic Review

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Abstract: Oral diseases are the most prevalent chronic childhood diseases, presenting as a major public health issue affecting children of all ages in the developing and developed countries. Early detection and control of these diseases is very crucial for a child's oral health and general wellbeing. The aim of this systematic review is to assess the performance of artificial intelligence models designed for application in pediatric dentistry. A systematic search of the literature was conducted using different electronic databases, primarily (PubMed, Scopus, Web of Science, Embase, Cochrane) and secondarily (Google Scholar and the Saudi Digital Library) for studies published from 1 January 2000, until 20 July 2022, related to the research topic. The quality of the twenty articles that satisfied the eligibility criteria were critically analyzed based on the QUADAS-2 guidelines. Artificial intelligence models have been utilized for the detection of plaque on primary teeth, prediction of children's oral health status (OHS) and treatment needs (TN); detection, classification and prediction of dental caries; detection and categorization of fissure sealants; determination of the chronological age; determination of the impact of oral health on adolescent's quality of life; automated detection and charting of teeth; and automated detection and classification of mesiodens and supernumerary teeth in primary or mixed dentition. Artificial intelligence has been widely applied in pediatric dentistry in order to help less-experienced clinicians in making more accurate diagnoses. These models are very efficient in identifying and categorizing children into various risk groups at the individual and community levels. They also aid in developing preventive strategies, including designing oral hygiene practices and adopting healthy eating habits for individuals.

Keywords: artificial intelligence; automated learning; machine learning; deep learning; pediatric dentistry; pedodontics; caries detection; age estimation; prediction

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Citation: Khanagar, S.B.; Alfouzan, K.; Alkadi, L.; Albalawi, F.; Iyer, K.; Awawdeh, M. Performance of Artificial Intelligence (AI) Models Designed for Application in Pediatric Dentistry—A Systematic Review. *Appl. Sci.* **2022**, *12*, 9819. https://doi.org/10.3390/app12199819

Academic Editors: Cristina Portalés Ricart, João M. F. Rodrigues and Pedro J. S. Cardoso

Received: 31 August 2022
Accepted: 26 September 2022
Published: 29 September 2022

1. Introduction

Oral diseases are the most prevalent chronic childhood diseases, presenting as a major public health issue affecting children of all ages in developing and developed countries. Early detection and control of these diseases are very crucial for a child's oral health and general wellbeing. Since oral diseases are preventable in nature, early and accurate identification of risk factors can be very useful for developing cost-effective measures to prevent oral diseases.

For identifying risk factors for oral diseases, such as dental caries, caries risk prediction models have been developed, which can lead potentially to the development of preventive measures that, in return, can improve patient care [1]. Caries risk assessment tool (CAT), caries management by risk assessment (CAMBRA) and the Cariogram are the most commonly used caries risk assessment models [2]. The Cariogram is regarded as a good caries risk prediction model; however, its sensitivity is reportedly in the range of 41–75% and its specificity is in the range of 65.8–88% [3].

Dental plaque is considered a precursor of most oral diseases, which include dental caries and gingivitis [4]. Hence, the prevention of accumulation of plaque on the oral hard and soft tissues is very critical in maintaining oral health among children [5,6]. The traditional method for the detection of dental plaque using an explorer (with or without a disclosing agent) is inconvenient to be used with children [7,8]. Several advanced methods, such as laser-induced autofluorescence spectroscopy and digital imaging analysis, had been reported in the literature, but their major drawbacks include equipment cost and the difficulty in technique standardization [9–11].

The newer developments in the field of science and technology have gained tremendous attention with the development of artificial intelligence (AI), a new breakthrough in technology that quickly became popular in the scientific world. AI technology has been widely put to use in the field of medical sciences and has demonstrated excellent performance in a variety of tasks related to patient care that include disease diagnoses and identification of patient's risk for developing a disease among many more [12]. AI has also demonstrated excellent performance in diagnosing and predicting the prognosis of COVID-19 and has contributed to its drug discoveries [13]. AI models have also gained attention with their use as ancillary tools, increasing the precision and accuracy of diagnoses. In dentistry, it is used in orthodontics, orthognathic surgeries and oral cancer for planning treatments and predicting their outcomes [14–16]. Hence, the aim of this systematic review is to assess the performance of AI models designed for application in pediatric dentistry.

2. Materials and Methods

2.1. Search Strategy

Before the start of the literature search, an ethical clearance (IRB Approval No-IRB/0741/22) was obtained from the Institutional Review Board (King Abdullah International Medical Research Center) and this protocol was registered in PROSPERO with ID number CRD42022360175. This systematic review was prepared in compliance with the guidelines set for Preferred Reporting Items for Systematic Reviews and Meta-Analysis—An Updated Guideline for Reporting Systematic Reviews [17]. A systematic search of the literature was conducted using different electronic databases, primarily (PubMed, Scopus, Web of Science, Embase, Cochrane) and secondarily (Google Scholar and the Saudi Digital Library) for studies published from 1 January 2000 until 20 July 2022, related to the research topic. The search strategy was mainly based on the Medical Subject Headings (MeSH), such as artificial intelligence, automated learning, unsupervised learning, deep learning, machine learning (ML), neural networks, pediatric dentistry, pedodontics, caries detection, age estimation, prediction and diagnosis. Boolean operators were further used for advanced search for developing a combination of these MeSH terms, with the year of publication and English as a language filter (Table A1 in Appendix A).

A manual search for articles was also performed simultaneously. Further, selected articles' reference lists were screened at the college library. The article search was based on the (problem/patient/population, intervention/indicator, comparison and outcome) PICO elements (Table 1).

Table 1. Description of the PICO (P = Population, I = Intervention, C = Comparison, O = Outcome) elements.

Research question	What is the performance of AI-based models designed for pediatric patients?
Population	Pediatric patients who underwent investigation for oral disease
Intervention	AI applications designed for detection, diagnosis, prediction of oral diseases in pediatric patients
Comparison	Expert/Specialist opinions, Reference standards/models
Outcome	Measurable or predictive outcomes, such as Accuracy, Sensitivity, Specificity, ROC = Receiver Operating Characteristic curve, AUC = Area Under the Curve, Area Under the Receiver Operating Characteristic = AUROC, ICC = Intraclass Correlation Coefficient, IOU = intersection-over-union, PRC = precision recall curve, Statistical Significance, F1 Scores, vDSC: Volumetric Dice Similarity Coefficient, sDSC: Surface Dice Similarity Coefficient, PPV = Positive Predictive Value, NPV = Negative Predictive Value, Mean Decreased Gini (MDG), Mean Decreased Accuracy (MDA) coefficients, Intersection over Union (IoU), Dice coefficient

2.2. Study Selection

Two phases were utilized to select articles for this study. First, the articles were selected according to their relevance to the research objective based on their titles and abstracts. In this phase, two authors (S.B.K. and F.A.) independently carried out the search process and 288 articles were selected. After screening, 128 articles were eliminated due to duplication and the rest of the articles (156 articles) were evaluated against the eligibility criteria.

2.3. Eligibility Criteria

The inclusion criteria were: (a) Original research articles with a clear mention of AI applications; (b) The data sets types used in training/validating the AI model are clearly mentioned; (c) The quantifiable outcome measures for performance assessment are clearly mentioned. The type of study design did not affect the articles' inclusion.

The exclusion criteria were: (a) Non-full text articles (abstracts only); (b) Non-peer-reviewed publications (such as conference papers and thesis projects); (c) Review articles, letters to editors, commentaries.

2.4. Data Extraction

After applying the eligibility criteria, the included articles decreased to 21. In the second phase, the identifiers of the journal and authors were removed and the articles were critically assessed by two independent authors who did not contribute to the initial search (L.A. and K.I.). The assessment of the quality of the articles was carried out based on Quality Assessment and Diagnostic Accuracy Tool (QUADAS-2) guidelines [18]. This tool is used to assess the quality of studies that report on diagnostic tools. The assessment is based on four domains (patient selection, index test, reference standard and flow and timing) each of which is evaluated for risk of bias and applicability. The inter-rater reliability was assessed on a sample of articles, where Cohen's kappa showed 82% agreement between the two authors. For one article, there was a disagreement regarding its inclusion, since the quantifiable outcome measures of performance were not clearly mentioned. This was resolved through a third opinion obtained from (M.A), after which, the article was excluded. Twenty articles finally underwent qualitative synthesis (Figure 1).

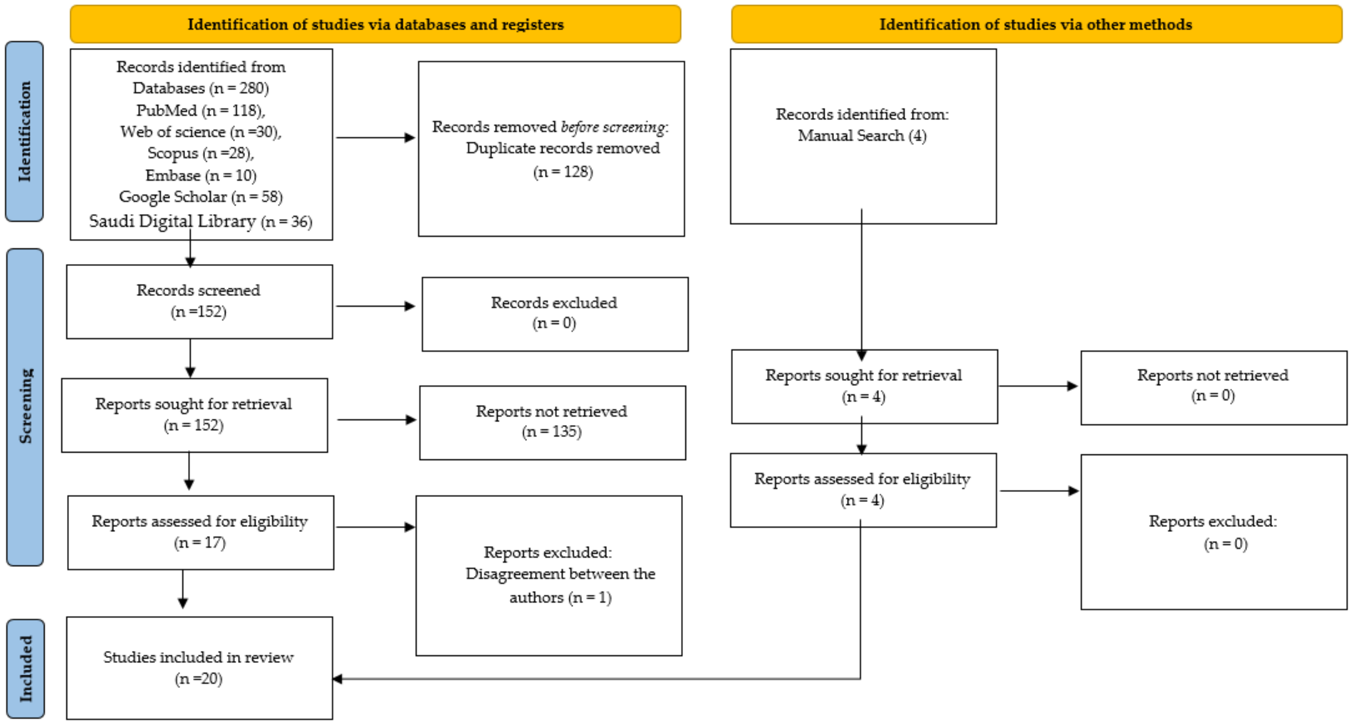

Figure 1. PRISMA flow chart for screening and selection of articles.

3. Results

The qualitative data synthesis was performed on the 20 articles [19–38] that met the set criteria (Table 2). There is a gradual increase in the research trend on the application of AI in pediatric dentistry.

Table 2. Details of the studies that have used AI-based models in pediatric dentistry.

Serial No.	Authors	Year of Publca-tion	Study Design	Algorithm Architecture	Objective of the Study	No. of Patients/Images/ Photographs for Testing	Study Factor	Modality	Comparison If Any	Evaluation Accuracy/Average Accuracy/Statistical Significance	Results (+) Effective, (−) Non effective (N) Neutral	Outcomes	Authors Sugges-tions/Conclusions
1	You, W., et al. [19]	2020	Comparative study	CNNs	To evaluate the accuracy of AI-based model for detecting plaque on primary teeth	886 samples for training, 98 for validation	Dental Plaque	Intra oral photographs	Experienced pediatric dentist	MIoU of 0.726 ± 0.165. There was no difference between the AI model and specialist ($p > 0.05$)	(+) Effective	CNNs-based model demonstrated high accuracy in detecting plaque, in comparison with the pediatric dentist	This model can help children to improve their oral health
2	Wang, Y., et al. [20]	2020	Comparative study	ANNs	To assess the performance of ML model (XGBoost) for predicting children's oral health status (OHS) and treatment needs (TN)	545 subjects (70% for training and 30% for validation)	Oral health status and treat-ment needs	Data sets	Dentist	Sensitivity of 93% and specificity of 49% for predicting referral for treatment needs (RFTN)	(+) Effective	These models were efficient in predicting OHS and TN	This model can be of great use in school oral health programs
3	Karhade, D.S., et al. [21]	2021	Retrospective cohort	ANNs	To evaluate the accuracy of an automated ML algorithm for classification of early childhood caries (ECC)	6040 (5123 subjects for training 1281 subjects for testing)	Dental caries	Data sets	External National Health and Nutrition Examination Survey (NHANES) dataset/ 10 trained and calibrated clinical examiners	AUC of (0.74), Sensitivity of (0.67) and PPV of (0.64)	(+) Effective	This ML model's performance was similar to the reference model	This model is valuable for ECC screening
4	Ramos-Gomez, F., et al. [22]	2021	Retrospective cohort	ANNs	ML algorithm (Random forest) for identifying survey items for predicting dental caries (DC)	182 subjects	Dental caries	Data sets	2 Trained dentists	For classifying active caries parent's age mean decreased Gini MDG = 0.84; mean decreased accuracy MDA = 1.97, unmet needs (MDG = 0.71; MDA = 2.06). Predictors of caries with parent's age (MDG = 2.97; MDA = 4.74), with oral health problems in past 12 months (MDG = 2.20; MDA = 4.04	(+) Effective	This model has potential for screening DC	This model is potential for screening for DC for children

Table 2. *Cont.*

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5	Schlickenrieder, A. [23]	2021	Comparative study	CNNs	To assess the performance of convolutional neural network (CNN) for detecting and categorizing fissure sealants	2352 permanent posterior teeth	Fissure sealants	Digital photographs	Experienced examiner	98.7% accuracy in detecting sealants with an AUC of 0.996. The diagnostic accuracy and AUC were 89.6% and 0.951 for Intact sealant; 83.2% and 0.888 for Sufficient sealant; 92.4 and 0.942 for insufficient sealant.	(+) Effective	CNN detected sealant intraoral photographs with an agreement of 98.7%, in comparison with reference decisions	Additional training of AI-based is required before clinical use
6	Zaborowicz, K. [24]	2021	Comparative study	ANNs	Three Radial Basis Function neural models RBF 22:22-15-1:1 RBF 13:13-1-1:1 RBF 18:18-1-1:1 for determining the chronological age	619 subjects (296 girls and 323 boys)	Age assessment	Digital pantomographic images	PNN (probabilistic neural network), GRNN (generalized regression neural network), and three-and four-layer MLP (multilayer perceptron) networks	This model demonstrated an accuracy of 99.7% for chronological age assessment	(+) Effective	RBF networks were characterized by the best quality indicators	This is an effective and innovative tool for the assessment of the chronological age
7	Zaorska, K., et al. [25]	2021	Prospective cohort	CNNs	AI model for predicting DC based on chosen polymorphisms	95 patients	DC lesions	Data sets	Logistic regression model	Sensitivity of 90, specificity of 96% overall accuracy of 93% ($p < 0.0001$), AUC was 0.970 ($p < 0.0001$). Prediction accuracy of 90.9–98.4%	(+) Effective	This model displayed high accuracy in predicting DC	The knowledge of potential risk status could be useful in designing oral hygiene and adopting eating habits for patients
8	Pang, L., et al. [26]	2021	Prospective cohort	ANNs	AI-based ML model for caries risk prediction based on environmental and genetic factors	953 patients (633 for training and 320 for testing)	DC lesions	Data sets	Logistic regression model	AUC of 0.73	(+) Effective	This model could accurately identify individuals at high and very high caries risk	This is a powerful tool for identifying individuals at high caries risk at community level

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9	Park, Y.H., et al. [27]	2021	Prospective cohort	ANNs	ML-based AI models (XGBoost, random forest, LightGBM algorithms and Final model) for predicting early childhood caries	4195 (2936 for training and 1259 for testing)	DC lesions	Data sets	Traditional regression model	AUROC = 0.774–0.785	(+) Effective	ML-based models showed favorable performance in predicting DC	Can be useful in identifying high risk groups and implementing preventive treatments
10	Koopaie, M., et al. [28]	2021	Comparative study Case-control study	ANNs	ML-based AI models feed-forward neural network (S1 and S2), for comparing the salivary level of cystatin S in ECC patients and caries-free (CF) children	20 cases of ECC and 20 caries free children as control	ECC prediction	Data sets	XGBoost, random forest and support vector machine	S1 model demonstrated an accuracy of 88.1%, sensitivity of 100% and specificity of 71.3%. S1 model demonstrated an accuracy of 90.9%, sensitivity of 100% and specificity of 72.1%	(+) Effective	The logistic regression model based on salivary cystatin S levels and birth weight had the most acceptable potential for discriminating early childhood caries from caries-free controls.	Considering clinical examination, demographic and socioeconomic factors, along with the salivary cystatin S levels, could be useful for early diagnosis of ECC
11	Gajic, M., et al. [29]	2021	Comparative study	ANNs	Determining the impact of oral health on adolescents' quality of life and comparison between standard statistical methods and AI algorithms	374 (128 male and 246 female)	Adolescent quality of life	Data sets	Standard statistical methods	Not clear	(+) Effective	Using artificial intelligence algorithms, the respondents can be clustered into characteristic groups	Dental education will need to accompany the introduction of clinical AI solutions by fostering digital literacy in the future dental workforce.
12	Kılıc, M.C., et al. [30]	2021	Observational study	CNNs	A deep-learning model for automated detection and enumeration of the deciduous teeth on panoramic radiographs	421	Tooth	Panoramic images	Not clear	Sensitivity of 0.9804, precision of 0.9571 and F1 score was 0.9686	(+) Effective	A promising tool for the automated charting of panoramic dental radiographs	It will aid clinicians by serving as a time-saving measure

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13	Ruff, R.R., et al. [31]	2021	Observational study	ANNs	An MI-based predictive model for treatment non-response to Silver diamine fluoride (SDF) therapy	20	Microbial analysis	Plaque samples and data sets	Lasso regression	Not clear	(+) Effective	These are the only possible models that could be useful in predicting non-response	There is a need of making predictions in larger, independent datasets
14	Ahn, Y., et al. [32]	2021	Comparative study	CNNs	Deep-learning models SqueezeNet, ResNet-18, ResNet-101 and Inception-ResNet-V2 for automatically classify mesiodens in primary or mixed dentition	1100 Images (1000 images for validating and 100 images for testing)	Mesiodens	Panoramic radiographs	Six pediatric dentists and six general dentists	The AUC values were 0.862 for SqueezeNet, 0.955 for ResNet-18, 0.941 for ResNet-101 and 0.932 for Inception-ResNet-V2	(+) Effective	These models delivered high accuracy in classifying the presence of mesiodens in the mixed dentition panoramic radiographs	Deep-learning technologies may help clinicians with insufficient clinical experience in more accurate and faster diagnosis
15	Mine, Y., et al. [33]	2021	Comparative study	CNNs	Deep-learning Models AlexNet, VGG16-TL and InceptionV3-TL for detecting the presence of supernumerary teeth during the early mixed dentition stage	220	Supernumerary teeth	Panoramic radiographs	Two experienced pediatric dentists	VGG16 model demonstrated high performance with AUC of 0.89, accuracy of 82.3%, sensitivity of 85.0% and specificity of 79.0%. AlexNet, VGG16-TL and InceptionV3-TL models achieved sensitivity values of 82.5%, 85.0% and 83.3%, respectively	(+) Effective	VGG16-TL model had the highest performance, in comparison with others.	CNN-based deep learning is a promising approach for detecting the presence of supernumerary teeth during the early mixed dentition stage.
16	Li, R.Z., et al. [34]	2021	Comparative study	CNNs	Deep learning-based image recognition system for detecting dental caries	712	Dental Caries	Intraoral photographs	Pediatric dentists	Sensitivity of 96.0% and specificity of 97.0% for caries with cavities, 95.8% and 99.0% for pit and fissure caries and 88.1% and 97.1% for approximal caries	(+) Effective	Demonstrated the ability to detect dental caries	AI system could accurately verify different types of dental caries.

Table 2. *Cont.*

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17	Zaborowicz, M., et al. [35]	2021	Comparative study	CNNs	Deep learning-based model for estimating the age	619 (296 male and 323 female)	Tooth and bone parameters	Digital pantomographs	Statistical 7.1 simulator	The MAE (mean squared error) error of the produced models, depending on the learning set used, is between 2.34 and 4.61 months, while the RMSE (root mean squared error) error is between 5.58 and 7.49 months. The correlation coefficient R2 ranges from 0.92 to 0.96.	(+) Effective	Deep neural models have higher quality already in the first iteration of learning the network using all the developed metrics	It is recommended to prepare deep neural networks based on the set of indicators used in the first stage of the research.
18	Bunyarit, S.S., et al. [36]	2021	Comparative study	ANNs	To develop reliable teeth maturity scores for age estimation based on artificial neural networks	1569	Dental age and chronological age	Panoramic radiographs	Demirjian's eight developmental stages—trained observers	Significant correlation was observed between chronological age and new dental maturity scores after ANN in both girls and boys ($p < 0.001$); R2 of 0.951 with predicting accuracy of 95.1% for boys (ANOVA, F $\frac{1}{4}$ 5096.6, $p < 0.001$); an adjusted R2 of 0.938 was found for girls, with an accuracy of 93.8% for predicting the actual age	(+) Effective	Demonstrated greater accuracy in age estimation	Can be applied for clinical and forensic cases.
19.	Galibourg, A., et al. [37]	2021	Comparative study	ANNs	To develop machine learning algorithms to predict dental age in children	3605 (1734 females and 1871 males)	Dental age	Panoramic radiographs	Demirjian's reference method	Mean absolute error (MAE) under 0.811 years	(+) Effective	The machine learning methods were significantly more accurate than the two reference methods.	These results support the use of ML algorithms instead of using standard population tables.

Table 2. *Cont.*

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20.	Shen, S., et al. [38]	2021	Comparative study	ANNs	Random forest (RF), support vector machine (SVM) and linear regression (LR) based on the Cameriere method to predict children's dental age	748 children (356 females and 392 males)	Dental age	Panoramic radiographs	Cameriere age estimation	ML models have better accuracy than the traditional Cameriere formula. The mean error (ME), mean absolute error (MAE), mean square error (MSE) and root mean square error (RMSE) values of the SVM model (0.004, 0.489, 0.392 and 0.625, respectively). In contrast, the ME, MAE, MSE and RMSE of the European Cameriere formula were 0.592, 0.846, 0.755 and 0.869, respectively, and those of the Chinese Cameriere formula were 0.748, 0.812, 0.890 and 0.943, respectively	(+) Effective	Compared to the Cameriere formula, ML methods based on the Cameriere's maturation stages were more accurate in estimating dental age	ML models have better accuracy than the traditional Cameriere formula

ANNs = artificial neural networks, CNNs = convolutional neural networks, DCNNs = deep neural networks, c-index = concordance index, CT = scans computed tomography, CBCT = cone-beam computed tomography.

3.1. Qualitative Synthesis of the Included Studies

AI models have been utilized for the detection of plaque on primary teeth (*n* = 1) [19], prediction of children's oral health status (OHS) and treatment needs (TN) (*n* = 1) [20], detection and classification of dental caries (*n* = 2) [21,34], prediction of dental caries (*n* = 5) [22,25–28], detection and categorization of fissure sealants (*n* = 1) [23], determination of the chronological age (*n* = 5) [24,35–38], determination of the impact of oral health on adolescents' quality of life (*n* = 1) [29], automated detection and charting of teeth (*n* = 1) [30], prediction of treatment non-response to Silver Diamine Fluoride (SDF) therapy (*n* = 1) [31] and automated detection and classification of mesiodens and supernumerary teeth in primary or mixed dentitions (*n* = 2) [32,33]. Data presented in the included articles were extracted and recorded in a data sheet. The heterogeneity of available data made a meta-analysis impossible, as studies varied with respect to software applications and the type of data sets used for assessing the performance of the AI models. Therefore, only a descriptive analysis of the data of the included studies was presented.

3.2. Study Characteristics

Author details, publication year, the type and architecture of the used algorithm, validating and testing details, study objectives, results and outcomes (such as accuracy averages and statistical significance) and conclusions were among the details recorded about each of the studies included.

3.3. Outcome Measures

Task performance efficiency was the outcome of interest in the selected studies. This included accuracy, sensitivity, specificity, Receiver Operating Characteristic (ROC) curve, Area Under the Curve (AUC), Mean Absolute Error (MAE), Mean Error (ME), Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Decreased Gini (MDG), Mean Decreased Accuracy (MDA), Area Under the Receiver Operating Characteristic (AUROC), F1 scores, Positive Predictive Value (PPV), Negative Predictive Value (NPV), Mean Decreased Gini (MDG), Mean Decreased Accuracy (MDA) coefficients, Intersection Over Union (IoU) and Dice Coefficient [19–38].

3.4. Risk of Bias Assessment and Applicability Concerns

Systematic reviews on diagnostic accuracy are in many cases affected by the heterogeneous nature of their outcomes based on sample selection, type of AI test, reference standards and validation methods. Appropriate quality assessment of the selected studies through risk of bias is, therefore, essential. Since 2003, the Quality Assessment of Diagnostic Accuracy Studies (QUADAS) has been put into application in numerous studies. QUADAS-2 assesses studies' quality in two essential areas: risk of bias and applicability (categorized as high, low or unclear), and four domains: patient selection, index test, reference standard, and flow and timing.

Assessment of included studies was conducted independently by two authors (KI and SBK), based on the above scale. A high risk of bias was reflected in patient selection, as most of the studies (47.3%) relied on secondary data and there was no mention of randomization being employed or considered in the primary studies. AI studies require a large sample for ML testing and reference. Usually, studies tend to use retrospective hospital records or survey data for this purpose, but authors need to go a step further in looking at sample selection methods.

Index test results were interpreted without a clear mention or no mention of a reference standard used in six (31.5%) of the studies assessed, which, in turn, raises concerns about bias related to the flow and timing of these studies. Overall, there was a moderate risk of bias and no concern on applicability, considering all three categories across all the studies included for review (Table A2 in Appendix A) (Figure 2).

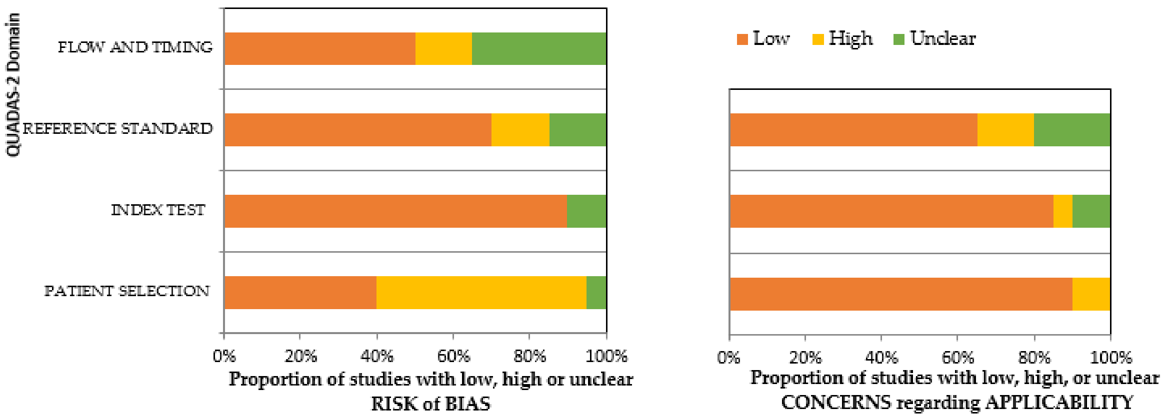

Figure 2. QUADAS-2 assessment of the individual risk of bias domains and applicability concerns.

4. Discussion

Oral health is an integral component of the overall health and well-being of an individual. The main focus of pediatric dentistry is on the prevention and treatment of various oral diseases in the early childhood stage with the intent of establishing an optimal oral health condition in young children. The most common oral diseases affecting children include dental caries, pulpal and periapical lesions, gingival disease and other conditions, including dental trauma and abnormal oral habits.

Untreated oral diseases, especially dental caries, may complicate the required treatment, result in pain, decreased masticatory function or asymmetrical mastication [39]. This could eventually result in compromised facial development, ultimately contributing to malocclusion and oro-facial deformities [40,41]. Evidence also suggests that severe caries experienced in children is associated with a more severe caries experience in permanent dentition during adulthood [42,43]. Severe caries experiences among children may also lead to malnutrition due to compromised masticatory function, affecting dietary preferences, and resulting in developmental delays [44]. Considering these facts, it is important for a pediatric dentist to be capable of assessing caries risk and applying various strategies designed for its prevention and intervention, which can contribute considerably to the health of their patients.

With the advancements in the field of technology, new AI-based applications have been widely utilized for the detection, diagnosis and prediction of the prognosis of oral diseases. These applications have demonstrated excellent performance, with accuracies similar to trained and experienced dental professionals [14,15]. In pediatric dentistry, these AI-based models have been applied for the detection of dental plaque, which is considered a precursor for most oral diseases, in particular, dental caries and gingival diseases [4]. The traditional method for the detection of dental plaque using an explorer (with or without a disclosing agent) is inconvenient to be used on children [7,8]. You, W., et al. [19] studied the application of CNNs-based AI model for the detection of dental plaque in primary teeth. This model demonstrated a higher accuracy in detecting dental plaque, in comparison with experienced pediatric dentists. However, this model had a few limitations related to the limited number of intraoral photographs used for training, which were all obtained using a single camera. Obtaining photographs through different equipment may result in differences in aspects, such as color and resolution, which might affect the accuracy of the trained model.

AI has also been applied for the detection and classification of dental caries. Dental caries is considered one of the most prevalent chronic childhood diseases [45]. Karhade, D.S., et al. [21] reported on an ANNs-based model for the classification of early childhood caries (ECC). The model demonstrated similar performance to the reference models and could be of great value in screening for ECC. However, the study population was a limiting factor, as it was only representative of high-risk children from low-income families from one state in the United States. Li, R.Z., et al. [34] also reported on a CNNs-based model for detecting dental caries. The model demonstrated a sensitivity of 96.0% and specificity of 97.0% for caries with cavities, 95.8 and 99.0% for pit and fissure caries and 88.1 and 97.1% for proximal caries. Ramos-Gomez, F., et al. [22] also reported on an ML-based model for predicting dental caries. This model demonstrated excellent performance, similar to that of trained dentists, and showed a great potential for screening dental caries in children. However, the small sample size and including a small number of children with active caries were limitations of this study. There are also chances of social desirability bias, since the parents were asked to complete the questionnaire related to their child's oral health. Zaorska, K., et al. [25] also reported on an AI model for predicting dental caries based on chosen polymorphisms. This model showed excellent performance with a sensitivity of 90%, specificity of 96% and overall accuracy of 93%. Pang, L., et al. [26] studied the possibility of predicting caries risk based on environmental and genetic factors using an AI-based ML model. This model recorded an AUC of 0.73 and was able to accurately categorize individuals with high and very high caries risk. However, the applicability of the studies' findings was affected by the authors' use of the cariostatic score to assess the cariogenicity of dental plaque, where the prediction performance can be affected by microbiome markers. Another limitation was that the sample was from one center. Park, Y.H., et al. [27] reported on ML-based AI models: XG Boost, random forest, Light GBM algorithms and final model for predicting early childhood caries. These models displayed a favorable performance in predicting dental caries and can be of great use in identifying high-risk groups and implementing preventive treatments.

Patients' age assessment is exceptionally useful for dentists in the planning and evaluation of treatment results. It is also useful in anthropology and forensic dentistry for determining the metric age of human remains [46,47]. The most conventional ways of dental age determination are through Demirjian's, Schour and Massler's, Ubelaker's, Moorres', Fanning and Hunt's, Noll's, or Gustafson and Koch's methods [47–53]. However, there were discrepancies between the chronological age, the age estimated through the charts and the tables developed using these methods. This could be due to the acceleration or growth spurts in the population [54–56].

AI models have also been widely designed for determining the chronological age of children. Zaborowicz, K., et al. [24] reported on AI-based neural models for determining the chronological age using digital pan tomographic images. The model demonstrated an excellent accuracy of 99.7% for chronological age assessment and is considered an innovative tool. However, it was developed using 2D images alone, which could be a possible limitation. Bunyarit, S.S., et al. [36] also reported on the AI-based model designed for age estimation. The model demonstrated an excellent accuracy of 93.8% for predicting the actual age and can be applied in forensic sciences. Galibourg, A., et al. [37] reported on ML algorithms designed for predicting dental age in children. This model demonstrated acceptable performance, and these ML methods were significantly more accurate than the two reference methods. Shen, S., et al. [38] reported on a random forest (RF), support vector machine (SVM), and linear regression (LR) based on the Cameriere method to predict the dental age of children [57]. This model demonstrated better accuracy than the traditional Cameriere formula. However, it requires further assessment using samples from different regions, as this sample was only from one region.

Wang, Y., et al. [20] reported on an AI model that has been designed for predicting the OHS and TN of children. This model demonstrated a sensitivity of 93% and could be of great assistance in school oral health programs. Gajic, M., et al. [29] reported on an AI model for determining the impact of oral health on adolescents' quality of life. This model has been found effective and can be useful in clustering children into different characteristic groups. Kılıc, M.C., et al. [39] reported on an AI model designed for automated detection and numbering of deciduous teeth on panoramic radiographs. It can be a promising tool for the automated charting of panoramic dental radiographs and can serve as a time-saving measure while dealing with pediatric patients.

AI models were also used in the automated detection and classification of mesiodens and supernumerary teeth in children with primary or mixed dentitions. Supernumerary teeth are teeth that are additional to the normal number of teeth. Their presence can lead to serious complications, such as crowding, root resorption of adjacent teeth, and dentigerous cysts, most of which require surgical correction [58]. To prevent these complications, early detection and extraction of supernumerary teeth at the appropriate time are mandatory. Ahn, Y., et al. [32] reported on deep learning models (SqueezeNet, ResNet-18, ResNet-101 and Inception-ResNet-V2) for automatically classifying mesiodens in primary or mixed dentitions. The performance of these models was assessed in comparison to six pediatric dentists and six general dentists. These models demonstrated high accuracy in classifying the presence of mesiodens in the mixed dentition. However, the limitation of this study was that the models were trained and evaluated with panoramic radiographs taken from a single piece of equipment from one single institution. This can be improved by utilizing radiographs from different institutions. Mine, Y., et al. [33] also reported on using deep-learning models (AlexNet, VGG16-TL and InceptionV3-TL) for the detection of supernumerary teeth in the early mixed dentition stage. These models were compared with two experienced pediatric dentists. The VGG16-TL model had the highest performance, in comparison with the others. However, this study had similar limitations related to the utilization of radiographs from one single institution.

This review article might have certain limitations. First, even though a comprehensive search for original research articles was conducted, some studies might have been missed. Second, there could be certain variations in subjective judgment with respect to the risk of bias assessment, as it may vary depending on individuals' perception. Considering the overall performances of AI models, there is a need for policy implications in order to accelerate the process of approving these AI models for marketing, which can eventually enhance clinicians daily functionalities and decision making processes.

5. Conclusions

AI has been widely applied in pediatric dentistry in order to help less-experienced clinicians in making more accurate diagnoses. These models are very efficient in identifying and categorizing children into various risk groups at the individual and community levels. They also aid in developing preventive strategies, including designing oral hygiene practices and adopting healthy eating habits for individuals. These models can also be of great value in the planning and evaluation of school oral health programs. They can help children become more aware of their own oral health and appreciate its improvement, which can increase their motivation. These reported models, however, have some limitations in relation to the samples used for their training and validation. This can be overcome by using datasets from multiple institutions and datasets collected by different individuals and various pieces of equipment.

Author Contributions: Conceptualization, S.B.K. and K.A.; methodology, L.A.; software, M.A.; validation, F.A., L.A. and K.I.; formal analysis, M.A.; investigation, S.B.K.; resources, K.A.; data curation, S.B.K.; writing—original draft preparation, S.B.K.; writing—review and editing, L.A.; visualization, F.A.; supervision, K.A.; project administration, K.I. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Structured search strategy carried out in electronic databases.

Search/Filters	Topic and Terms
"English" Language	"artificial intelligence" OR "neural networks" OR "deep learning" OR "machine learning" OR "supervised machine learning" OR "automated learning" OR "unsupervised machine learning" OR "computational intellegence" OR " machine intellegence" OR "expert systems" OR " fuzzy networks" OR " AI networks" OR " AI models" OR " computational systems" OR "dental plaque" OR "plaque detection" OR "dental caries" OR "caries prediction" OR " preventive dentistry" OR " supernumerary teeth" OR" fissure sealants" OR " fluorides" OR "pediatric dentistry" OR "pedodontics"OR "caries detection" OR "prediction" OR "diagnosis" OR "age estimation"
"English" Language	"artificial intelligence" AND "deep learning" AND "machine learning" AND "supervised machine learning" "computational intellegence" AND " machine intellegence" AND "expert systems" AND " fuzzy networks" AND " AI networks" AND " AI models" AND " computational systems" AND "dental plaque" AND "dental caries" AND "caries prediction" AND " preventive dentistry" AND " supernumerary teeth" AND" fissure sealants" AND " fluorides" AND "plaque detection" AND "automated learning" AND "unsupervised machine learning" AND "pediatric dentistry" AND "pedodontics" AND "caries detection" AND "prediction" AND "diagnosis" AND "prognosis" AND "age estimation"

Table A2. Assessment of risk of bias domains and applicability concerns.

	Risk of Bias				Applicability Concerns		
Author	**Patient Selection**	**Index Test**	**Reference Standard**	**Flow and Timing**	**Patient Selection**	**Index Test**	**Reference Standard**
You, W., et al. [19]	⊗	⊕	⊕	⊕	⊕	⊕	⊕
Wang, Y., et al. [20]	⊕	⊕	⊕	○	⊕	⊕	⊕
Karhade, D.S., et al. [21]	⊗	⊕	⊕	○	⊕	⊕	⊕
Ramos-Gomez, F., et al. [22]	⊕	⊕	⊕	⊕	⊕	⊕	⊕
Schlickenrieder, A. [23]	○	⊕	⊕	⊕	⊕	⊕	⊕
Zaborowicz, K. [24]	⊗	⊕	⊕	⊕	⊕	⊕	⊕
Zaorska, K., et al. [25]	⊕	⊕	○	○	⊕	⊕	○
Pang, L., et al. [26]	⊗	○	○	○	⊕	○	○
Park, Y.H., et al. [27]	⊕	⊕	⊗	○	⊕	⊕	○
Koopaie, M., et al. [28]	⊗	○	⊗	⊗	⊗	○	⊗
Gajic, M., et al. [29]	⊕	⊕	⊕	○	⊕	⊕	⊕
Kılıc, M.C., et al. [30]	⊕	⊕	⊕	⊕	⊕	⊕	⊕
Ruff, R.R., et al. [31]	⊗	⊕	⊗	⊗	⊗	⊕	⊗

Table A2. *Cont.*

	Risk of Bias				Applicability Concerns		
Author	**Patient Selection**	**Index Test**	**Reference Standard**	**Flow and Timing**	**Patient Selection**	**Index Test**	**Reference Standard**
Ahn, Y., et al. [32]	⊕	⊕	⊕	⊕	⊕	⊕	⊕
Mine, Y., et al. [33]	⊕	⊕	⊗	⊗	⊕	⊕	⊗
Li, R.Z., et al. [34]	⊗	⊕	⊕	⊕	⊕	⊗	⊗
Zaborowicz, M., et al. [35]	⊗	⊕	⊕	⊕	⊕	⊕	⊕
Bunyarit, S.S., et al. [36]	⊗	⊕	⊕	○	⊕	⊕	⊕
Galibourg, A., et al. [37]	⊗	⊕	⊕	⊕	⊕	⊕	⊕
Shen, S., et al. [38]	⊗	⊕	⊕	⊕	⊕	⊕	⊕

Footnotes: ⊗ = High Risk, ⊕ = Low Risk, ○ = Unclear.

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